Université de Montréal

A Multi-Modal, Modified-Feedback and Self-Paced Brain-Computer Interface (BCI) to Control an Embodied Avatar's Gait

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Thèse présentée en vue de l'obtention du grade de Philosophiae doctor – Doctorat (Ph.D.) en génie biomédical

Décembre 2020

Université de Montréal
Institut de Génie Biomédical

Cette thèse intitulée:

“A Multi-Modal, Modified-Feedback And Self-Paced Brain-Computer Interface (BCI) To Control An Embodied Avatar's Gait”

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Résumé:

Les interfaces cerveau-ordinateur (ICO) ont été utilisées pour contrôler la marche d'un égo-avatar virtuel dans le but d'être utilisées dans la réadaptation de la marche. Une ICO décode les signaux du cerveau représentant un désir de faire produire un mouvement et les transforme en une commande de contrôle pour contrôler des appareils externes.

Les sentiments décrits par les participants lorsqu'ils contrôlent un égo-avatar dans un environnement virtuel immersif démontrent que les humains peuvent être incarnés dans un corps d'un avatar (illusion de propriété). Il a été récemment démontré que provoquer l'illusion de propriété puis manipuler les mouvements de l'égo-avatar peut conduire à des stratégies de contrôle moteur compensatoire.

Afin de maximiser cet effet, il existe un besoin d'une méthode qui mesure et surveille les niveaux d'incarnation des participants immergés dans la réalité virtuelle (RV) pour induire et maintenir une forte illusion de propriété.

D'autre part, atteindre un niveau élevé de performances (taux de classification) ICO et d'incarnation est interconnecté. Pour atteindre l'un d'eux, le second doit également être atteint. Certaines limitations de plusieurs de ces systèmes entravent leur adoption pour la neuroréhabilitation: 1- certains utilisent l'imagerie motrice (IM) des mouvements autres que la marche; 2- la plupart des systèmes permettent à l'utilisateur de faire des pas simples ou de marcher mais pas les deux, ce qui ne permet pas à un utilisateur de passer des pas à la marche; 3- la plupart fonctionnent en un seul mode d'ICO, rythmé (*cue-paced*) ou auto-rythmé (*self-paced*).

Surmonter les limitations susmentionnées peut être fait en combinant différents modes et options de commande dans un seul système. Cependant, cela aurait un impact négatif sur les performances de l'ICO, diminuant ainsi son utilité en tant qu'outil potentiel de réhabilitation. Dans ce cas, il sera nécessaire d'améliorer les performances des ICO. À cette fin, de nombreuses techniques ont été utilisées dans la littérature, telles que la rétroaction modifiée, le recalibrage du classificateur et l'utilisation d'un classificateur générique.

Le projet de cette thèse a été réalisé en 3 études, avec objectif d'étudier dans l'étude 1, la possibilité de mesurer le niveau d'incarnation d'un égo-avatar immersif, lors de l'exécution, de l'observation et de l'imagination de la marche, à l'aide des techniques encéphalogramme (EEG), en présentant une rétroaction visuelle qui entre en conflit avec la commande du contrôle moteur des sujets incarnés.

L'objectif de l'étude 2 était de développer un BCI pour contrôler les pas et la marche vers l'avant d'un égo-avatar dans la réalité virtuelle immersive, en utilisant l'imagerie motrice de ces actions, dans des modes rythmés et auto-rythmés. Différentes stratégies d'amélioration des performances ont été mises en œuvre pour augmenter la performance (taux de classification) de l'ICO.

Les données de ces deux études ont ensuite été utilisées dans l'étude 3 pour construire des classificateurs génériques qui pourraient éliminer la calibration hors ligne pour les futurs utilisateurs et raccourcir le temps de formation.

Vingt participants sains différents ont participé aux études 1 et 2. Dans l'étude 1, les participants portaient un casque EEG et des marqueurs de capture de mouvement, avec un avatar affiché dans un casque de RV du point de vue de la première personne (1PP). Ils ont été invités à performer, à regarder ou à imaginer un seul pas en avant ou la marche vers l'avant (pour quelques secondes) sur le tapis roulant. Pour certains essais, l'avatar a fait un pas avec le membre controlatéral ou a arrêté de marcher avant que le participant ne s'arrête (rétroaction modifiée).

Dans l'étude 2, les participants ont participé à un entrainement séquentiel de 4 jours pour contrôler la marche d'un avatar dans les deux modes de l'ICO. En mode rythmé, ils ont imaginé un seul pas en avant, en utilisant leur pied droit ou gauche, ou la marche vers l'avant . En mode auto-rythmé, il leur a été demandé d'atteindre une cible en utilisant l'imagerie motrice (IM) de plusieurs pas (mode de contrôle intermittent) ou en maintenir l'IM de marche vers l'avant (mode de contrôle continu). L'avatar s'est déplacé en réponse à deux classificateurs '*Regularized Linear Discriminant Analysis*' (RLDA) calibrés qui utilisaient comme caractéristiques la densité spectrale de puissance (Power Spectral Density; PSD) des bandes de fréquences μ (8-12 Hz) sur la zone du pied du cortex moteur. Les classificateurs ont été recalibrés après chaque session. Au cours de l'entrainement et pour certains des essais, une rétroaction modifiée positive a été présentée à la moitié des participants, où l'avatar s'est déplacé correctement quelle que soit la performance réelle du participant. Dans les deux études, l'expérience subjective des participants a été analysée à l'aide d'un questionnaire.

Les résultats de l'étude 1 montrent que les niveaux subjectifs d'incarnation sont fortement corrélés à la différence de la puissance de la synchronisation liée à l'événement (Event-Related Synchronization; ERS) sur la bande de fréquence μ et sur le cortex moteur et prémoteur entre les essais de rétroaction modifiés et réguliers.

L'étude 2 a montré que tous les participants étaient capables d'utiliser le BCI rythmé et auto-rythmé dans les deux modes. Pour le BCI rythmé, la performance hors ligne moyenne au jour 1 était de 67±6,1% et 86±6,1% au jour 3, ce qui montre que le recalibrage des classificateurs a amélioré la performance hors ligne du BCI ($p < 0,01$). La performance en ligne moyenne était de 85,9±8,4% pour le groupe de rétroaction modifié (77-97%) contre 75% pour le groupe de rétroaction non modifié. Pour le BCI auto-rythmé, la performance moyenne était de 83% en commande de commutateur et de 92% en mode de commande continue, avec un maximum de 12 secondes de commande. Les performances de l'ICO ont été améliorées par la rétroaction modifiée ($p = 0,001$). Enfin, les résultats de l'étude 3 montrent que pour la classification des initialisations des pas et de la marche, il a été possible de construire des modèles génériques à partir de données hors ligne spécifiques aux participants. Les résultats montrent la possibilité de concevoir une ICO ne nécessitant aucun entraînement spécifique au participant.

Mots-clés : *Électroencéphalogramme (EEG), Interface cerveau-ordinateur (ICO), Synchronisation liée à l'événement, Imagination Motrice, Système Neuoronale Mirroire (SNM), Réalité Virtuelle (RV), Classification de EEG, Navigation, Réadaptation de la marche, Avatar, Incarnation.*

Abstract:

Brain-computer interfaces (BCI) have been used to control the gait of a virtual self-avatar with the aim of being used in gait rehabilitation. A BCI decodes the brain signals representing a desire to do something and transforms them into a control command for controlling external devices.

The feelings described by the participants when they control a self-avatar in an immersive virtual environment (VE) demonstrate that humans can be embodied in the surrogate body of an avatar (ownership illusion). It has recently been shown that inducing the ownership illusion and then manipulating the movements of one's self-avatar can lead to compensatory motor control strategies.

In order to maximize this effect, there is a need for a method that measures and monitors embodiment levels of participants immersed in virtual reality (VR) to induce and maintain a strong ownership illusion. This is particularly true given that reaching a high level of both BCI performance and embodiment are inter-connected. To reach one of them, the second must be reached as well. Some limitations of many existing systems hinder their adoption for neurorehabilitation: 1- some use motor imagery (MI) of movements other than gait; 2- most systems allow the user to take single steps or to walk but do not allow both, which prevents users from progressing from steps to gait; 3- most of them function in a single BCI mode (cue-paced or self-paced), which prevents users from progressing from machine-dependent to machine-independent walking. Overcoming the aforementioned limitations can be done by combining different control modes and options in one single system. However, this would have a negative impact on BCI performance, therefore diminishing its usefulness as a potential rehabilitation tool. In this case, there will be a need to enhance BCI performance. For such purpose, many techniques have been used in the literature, such as providing modified feedback (whereby the presented feedback is not consistent with the user's MI), sequential training (recalibrating the classifier as more data becomes available).

This thesis was developed over 3 studies. The objective in study 1 was to investigate the possibility of measuring the level of embodiment of an immersive self-avatar, during the performing, observing and imagining of gait, using electroencephalogram (EEG) techniques, by presenting visual feedback that conflicts with the desired movement of embodied participants.

The objective of study 2 was to develop and validate a BCI to control single steps and forward walking of an immersive virtual reality (VR) self-avatar, using mental imagery of these actions, in

cue-paced and self-paced modes. Different performance enhancement strategies were implemented to increase BCI performance.
The data of these two studies were then used in study 3 to construct a generic classifier that could eliminate offline calibration for future users and shorten training time.
Twenty different healthy participants took part in studies 1 and 2. In study 1, participants wore an EEG cap and motion capture markers, with an avatar displayed in a head-mounted display (HMD) from a first-person perspective (1PP). They were cued to either perform, watch or imagine a single step forward or to initiate walking on a treadmill. For some of the trials, the avatar took a step with the contralateral limb or stopped walking before the participant stopped (modified feedback).
In study 2, participants completed a 4-day sequential training to control the gait of an avatar in both BCI modes. In cue-paced mode, they were cued to imagine a single step forward, using their right or left foot, or to walk forward. In the self-paced mode, they were instructed to reach a target using the MI of multiple steps (switch control mode) or maintaining the MI of forward walking (continuous control mode). The avatar moved as a response to two calibrated regularized linear discriminant analysis (RLDA) classifiers that used the μ power spectral density (PSD) over the foot area of the motor cortex as features. The classifiers were retrained after every session. During the training, and for some of the trials, positive modified feedback was presented to half of the participants, where the avatar moved correctly regardless of the participant's real performance.
In both studies, the participants' subjective experience was analyzed using a questionnaire. Results of study 1 show that subjective levels of embodiment correlate strongly with the power differences of the event-related synchronization (ERS) within the μ frequency band, and over the motor and pre-motor cortices between the modified and regular feedback trials.
Results of study 2 show that all participants were able to operate the cued-paced BCI and the self-paced BCI in both modes. For the cue-paced BCI, the average offline performance (classification rate) on day 1 was 67±6.1% and 86±6.1% on day 3, showing that the recalibration of the classifiers enhanced the offline performance of the BCI ($p < 0.01$). The average online performance was 85.9±8.4% for the modified feedback group (77-97%) versus 75% for the non-modified feedback group. For self-paced BCI, the average performance was 83% at switch control and 92% at continuous control mode, with a maximum of 12 seconds of control. Modified feedback enhanced BCI performances ($p = 0.001$). Finally, results of study 3 show that the constructed generic models

performed as well as models obtained from participant-specific offline data. The results show that there it is possible to design a participant-independent zero-training BCI.

Keywords— *EEG, Brain-computer interface (BCI), Event-related synchronisation (ERS), Motor Imagery (MI), Mirror neuron system (MNS), Virtual reality (VR), EEG Classification, Navigation, Gait rehabilitation, Avatar, Embodiment.*

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List of Abbreviations

1PP	1st Person Perspective
3PP	3rd Person Perspective
ALS	Amyotrophic Lateral Sclerosis
AP	Anterior-Posterior
APA	Anticipatory postural adjustment
AR	Auto-Regression
As.R	Asymmetry Ratio
BCI	Brain-Computer Interface
BCI-MAFO	BCI driven motorized ankle-foot orthoses
BPr	Band-Power
CAR	Common Average Reference
CG	Center of Gravity
CM	Center of Mass
CNS	Central Nervous System
CP	Center of Pressure
CPG	Central Pattern Generators
CSP	Common Spatial Pattern
CV	Cross Validation
DFT	Discrete Fourier Transform
ECG	Electrocardiogram
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electrooculogram
ERD	Event Related De-synchronization
ERP	Event Related Potential
ERS	Event Related Synchronization
FDR	False Discovery Rate
FES	Functional Electrical Stimulation
FFT	Fourier Fast Transform
FPE	Foot Placement Estimator
GUI	Graphic User Interface
HMD	Head Mounted Display
ICA	Independent Component Analysis
IIR	Infinite Impulse Response
KNN	K-Nearest Neighbor
LDA	Linear Discriminant Analysis
LRM	Linear Regression Model
MDF	Modified Feedback
MI	Motor Imagery
ML	Medial-Lateral
MNS	Mirror Neuron System
NIRS	Near Infrared Spectroscopy
NN	Neural Networks
PCA	Principle Component Analysis

PCPG	Programmable Central Pattern Generators
PET	Positron Emission Tomography
PNS	Peripheral Nervous System
PSD	Power Spectral Density
RGF	Regular Feedback
RLDA	Regularized Linear Discriminant Analysis
RoGo	Robotic Gait Orthosis
SCI	Spinal Cord Injury
SCP	Slow Cortical Potential
SMA	Supplementary Motor Area
SMR	Sensory Motor Rhythm
SNR	Signal to Noise Ratio
SSVEP	Steady State Visual Evoked Potential
SVM	Support Vector Machine
TA	Tibialis Anterior
TFR	Time-Frequency Representation
VE	Virtual Environment
VEP	Visual Evoked Potential
VR	Virtual Reality

REMERCIEMENTS

Tout d'abord je tiens à remercier deux personnes spéciales qui m'ont soutenu pendant les dernières 5 ans dans le cadre de mon programme de doctorat. Prof. Jocelyn Faubert et Prof. David Labbé, vous étiez des directeurs uniques avec un magnifique sens de l'humour, qui m'avez donné de votre précieux temps et m'avez motivé à atteindre mes objectifs. Merci beaucoup de m'avoir accepté dans ce programme et de m'avoir permis de faire ce projet. Merci aussi pour la bourse que vous m'avez offerte. Merci David pour ton encouragement et pour les discussions tout au long de ces années, j'ai beaucoup appris de toi, surtout comment avoir une réflexion analytique. Merci à mon collègue Philippe Charbonneau, qui m'a aidé dans la programmation, et à Sara Saint-Pierre Côté de m'avoir aidé avec le système de gestion de la qualité du CRCHUM. Merci à toute l'équipe du Groupe GoAvatar pour votre soutien, vos encouragements et pour l'ambiance d'amitié que j'ai trouvé au labo. J'ai vraiment eu beaucoup de plaisir à travailler avec vous. Je tiens aussi à remercier les différents membres de mon jury d'avoir accepté de juger mon travail et ma thèse.

Merci mes chers parents, mes précieux cadeaux de Dieu. Sans vous, sans votre encouragement et sagesse, je n'aurais pas été ici et cette thèse n'aurait jamais été écrite. Vous m'avez toujours inspiré dans la recherche pour le savoir et la science. Je voulais vous rendre fiers de moi.

Merci à mon premier directeur de thèse à l'Université de Damas, Dr. Basel Douagi, qui m'a accepté au projet de l'année pré-finale du bac. Je ne t'oublierai jamais.

Les derniers sont les premiers …… Un merci spécial, un très gros merci à ma jolie femme adorable, mon amour et inspiration. Abir, je suis le plus heureux des hommes quand je suis avec toi, merci de m'aimer comme je suis, pour partager avec moi les plus beaux sentiments. Merci pour chaque jour et chaque moment, merci pour ton encouragement et soutien, et pour l'ambiance magnifique que tu as créée pour moi et nos 2 enfants magnifiques à notre maison. Merci surtout pour la fabuleuse cuisine, tu es une femme merveilleuse.

AVANT PROPOS

"*Le succès est un voyage, pas une destination*" (Arthur Ashe)

L'histoire a commencé à l'hiver 1994, dans la ville de Nancy en France. C'était une longue journée au CE2 à l'école, donc à mon retour à la maison, j'ai regardé un nouveau dessin animé. Le policier Alex Murphy a été tué par des gangsters, mais des ingénieurs ont construit une armoire humanoïde pour lui et elle était contrôlée par la puissance de son cerveau, pour devenir plus tard RoboCop. Depuis lors, mon rêve était de réaliser cela, de construire un système qui utiliserait la puissance du cerveau humain pour contrôler quelque chose qui pourrait aider les gens qui ont perdu certaines ou toutes les fonctions du corps, à déambuler.

Le premier pas vers mon rêve, c'était quelques années plus tard quand je suis rentré à l'école d'ingénieur, département de génie biomédical. Puis, pour mon premier projet de fin d'études, mon équipe a développé un système qui mesure l'activité cérébrale et la transmet sans fil. Dans mon deuxième projet de fin d'études, mon équipe a utilisé cet appareil pour développer un système de biofeedback pour les enfants avec TDAH.

L'histoire se poursuit lorsque j'ai fait un Skype avec le professeur Jocelyn Faubert qui m'a donné le privilège de me superviser dans un programme de maîtrise en Génie Biomédicale à l'UdeM, afin de travailler dans le chemin que j'ai toujours voulu et commencé : développer un système d'interface cerveau-ordinateur pour contrôler la navigation en RV. Des années plus tard, j'ai commencé, avec lui et le professeur David Labbé, un programme de doctorat en génie biomédical, encore à l'UdeM, pour développer un BCI qui contrôle la marche d'un avatar, en poursuivant le même chemin et le rêve que j'ai commencé il y a des années.

Introduction

Despite best available conventional physical rehabilitation programs to mitigate post-stroke gait impairment, there is still a great need for novel methods that can help improve gait rehabilitation results [1]. One suggested approach is to use the function of the brain as a control center for body motor functions such as gait in order to improve motor function in those with moderate impairment due to stroke [2, 3]. Post-stroke patients can modulate their EEG without doing any physical movement, and this can be exploited by a brain-computer interface (BCI).

A BCI is a system that measures the brain activity of an intention to do something and converts it into a control command that replaces, restores, enhances, supplements or improves natural brain activity output [4, 5]. This control command can be used to control external devices such as robotic and prosthetic devices [6], software [7], the movements of a cursor on a computer screen [8, 9] or even a virtual keyboard [10].

BCI systems appear to be a particularly promising communication channel for individuals suffering from motor impairment [3] or severe paralysis [11], such as those suffering from amyotrophic lateral sclerosis (ALS) [12] or spinal cord injury (SCI) [13]. In these populations, BCIs can make it possible to control assistive exoskeletons [13], navigate in virtual reality (VR) [14, 15] and move avatars within virtual environments (VE) [3, 16, 17]. One important and increasingly widespread application of BCI technology is in the field of neurorehabilitation [18, 19] where BCIs have been used for rehabilitation of upper limbs in post-stoke individuals [20-23] and to control the ambulation of a virtual self-avatar in VR, in a SCI patient [3]. Millions of people worldwide suffer from gait instability after SCI or stroke [24] and the improvement of gait is considered one of the primary objectives of the rehabilitation process. BCIs have been developed for this purpose [25], where users imagine the movement of a specific limb of their body and this motor imagery (MI) is detected by the BCI and translated into control commands that result in an action in VR or movements of an avatar [26].

When the movement of a self-avatar is the same as the movement that was imagined and the feedback is provided with sufficiently short latency, this results in visuomotor synchronicity between the user and his avatar [27, 28]. When this occurs, an illusion of embodiment of the virtual body can be induced [27, 29]. Embodiment is the gradual process of perceptual illusion whereby artificial body parts or full bodies are perceived by people as their own [30]. The induction of such an illusion is important in MI-BCIs, where reaching a high level of both BCI performance and embodiment are inter-connected. To reach one of them, the second must be reached as well [31, 32]. Thus, there is a high importance to measure the degree of embodiment while in the experiment.

Questionnaires are currently the most common method used to assess the different dimensions of embodiment [28, 33], but they do not enable real-time/in-task recordings of the level of embodiment [28]. Other methods used, such as positron emission tomography (PET) or functional magnetic resonance imaging (fMRI), are neither portable nor inexpensive [34, 35]; this is why recently some researchers have started to use electroencephalography (EEG). Researchers have measured the embodiment of an avatar's hand during the control of a BCI, such as Clemente et al. [34] who compared the levels of presence during observation and control of navigation within a VE using EEG, and Padrao et al. [36] who investigated the EEG and neurophysiological correlations of modified feedback. However, there is currently no way to measure the embodiment of human gait during the control of a MI-BCI.

Besides its role in inducing embodiment, MI of the intended limb movement also induces changes in the two EEG frequency bands: μ (8-12 Hz) and β (16-30 Hz) rhythms, over the corresponding sub-region of the sensorimotor cortex [37]. Combining virtual visual feedback with MI of the intended movements, patients can gradually recover from impairment through neuroplasticity [18], when combined with physiotherapy [38].
However, the beneficial effects of MI in motor control of lower limbs have not been as widely shown as for upper limbs because of the complexity of gait neural control [39]. Because of this complexity, several studies have used MI of upper limb movements in a BCI to control the feedback of navigation or of the lower limbs of an avatar [40-45] or of an exoskeleton [44]. For example, Hazrati and Hofmann [45] used the signals of MI of left/right hand movements to control the left/right navigation of an avatar. Such methods have been shown to allow a user to control the gait of an avatar but the fact that the imagined movement is different than the produced movement of the avatar prevents it's

use in gait rehabilitation. Indeed, such a BCI would not allow the user to benefit from the neural plasticity properties of MI training, which is a crucial part in rehabilitation and restoring or enhancing motor functions [23, 46]. Moreover, performing MI of one movement and receiving visual feedback of another movement, sometimes from a different limb, would not be conducive to the feeling of embodiment over the virtual avatar. This would therefore have a detrimental effect on BCI performance [28, 47].

To overcome this limitation, many studies have focused on the EEG signatures of gait, such as left and right foot discrimination [48, 49], gait initiation and gait termination in order to move forward and stop [50] and for normal cyclical walking [51]. They found that the brain areas employed by these commands are lateralized for steps, i.e. contralateral in sides between the foot in movement and the brain hemispheres [48, 52, 53], and centralized for walking i.e. over the central parts of the brain [50]. Nonetheless, there are few studies that use lower-limb MI in a BCI system to control walking feedback [3, 6, 54] and, to our knowledge, only two studies have used lower-limb MI in a BCI system to control the feedback of steps [55]. For example, Donati et al. [55] found that using long-term training of paralyzed patients with a lower-limb MI-BCI to control the left and right steps of a virtual self-avatar, and later of a lower-limb exoskeleton, led to partial neurological recovery. These studies show promising results, but they limit patients to only one type of command for walking: either individual left and right steps without allowing patients to progress using the imagination of walking in normal gait cycles, or allowing patients to progress using the imagination of walking in normal gait cycles, but without performing individual steps [3]. This is a limitation of such BCIs since normal gait is not controlled as a succession of left and right step motor commands [39].

Another limitation of existing gait MI-BCIs is that they mostly work in a single BCI mode. Usually, a user can control BCIs in different modes, such as cue-paced (where the user sends the mental command to the system after a cue) or self-paced modes (the user sends the mental command to the system at the time he desires) [56]. Self-paced BCIs can be devised into a brain switch control [57] and continuous control [58]. Each BCI control mode contributes its specific benefits to the rehabilitation process, and the current gait MI-BCIs lack the possibility to enable the user to control BCIs in different modes at the same time [59].

Thus, when designing a BCI for gait rehabilitation, a proposed way to overcome the aforementioned limitations is to use MI of left/right steps and of forward walking at the same time, and to map these signals to control the gait of an avatar in different modes (cue-paced, self-paced switch, self-paced continuous).

Each of these modes has its advantages in neurorehabilitation [60] so the concurrent implementation of all of them, in a way that would make it possible to run all modes or more than one mode at once, would allow to accommodate different rehabilitation programs and patient progression within them. However, the combination of more control options and several modes in a single system would result in diminished performance, which is already low in lower-limb MI-BCIs, compared to upper-limb MI-BCIs [59]. Lower performance of MI-BCI is particularly problematic when its intended use is in rehabilitation because receiving feedback that is incongruent with the imagined movement would diminish embodiment [61] and be detrimental to achieving neural plasticity benefits [23]. To overcome performance limitations, many enhancement techniques have been used in the literature, such as sequential training [62, 63] and modified feedback [64].

This thesis reports on our work towards the development of a BCI that could be used in a clinical setting to allow patients to control the gait of an embodied virtual self-avatar. Three studies were conducted in order to study this effect. In the first, we investigated the level of embodiment over a self-avatar whose steps and gait were imagined by participants. We also developed an objective EEG-based measure of this level of embodiment. In the second, we developed a BCI to control the steps and gait of the self-avatar through MI, in different modes that are useful for gait rehabilitation. In the third study, we generalized the training of the BCI to reduce the required duration of training, thus making its clinical use more feasible.

To present our work in this thesis, Chapter 1 will review the literature to present the fundamentals of gait biomechanics, gait motor and neural control, gait impairment rehabilitation methods and the recordings of brain activity in relation to brain anatomy and physiological functions, especially the gait functions. It will also introduce BCIs and explain the fundamental approaches of BCI design, control and enhancement techniques. The last section of this chapter will introduce the concept of the measure of embodiment. Chapter 2 will present the problem statement, objectives and hypotheses of this thesis. The third chapter will present the methodology and equipment that were common to our different studies. The details of the three studies for this work, as well as their results and discussions will be presented in Chapters 4, 5 and 6, respectively. Finally, a general discussion, limitations and future work will be presented in Chapter 7.

Chapter 1: Literature review

1.1 Introduction to human gait

Humans are different from other creatures because of the small organ that lies in their heads, the brain. The brain is a complex body part that functions as a control center that acquires, interprets, and dispatches sensory information all over the body [65]. It is the control center for most of our motor activities, amongst which is gait, a very important and complex body function. The ability to walk is one of the main aspects of a high quality of life and participation in social and economic life [66].

The main requirements of gait are [67]:

1) supporting the upper body during gait;
2) controlling the foot trajectory;
3) generating the mechanical energy to maintain or to increase the forward velocity;
4) absorbing the mechanical energy to reduce shock or to decrease the forward velocity;
5) ensuring balance and safe walking;
6) conserving energy measures during mobility.

1.2 Biomechanics of gait

1.2.1 Gait of forward walking

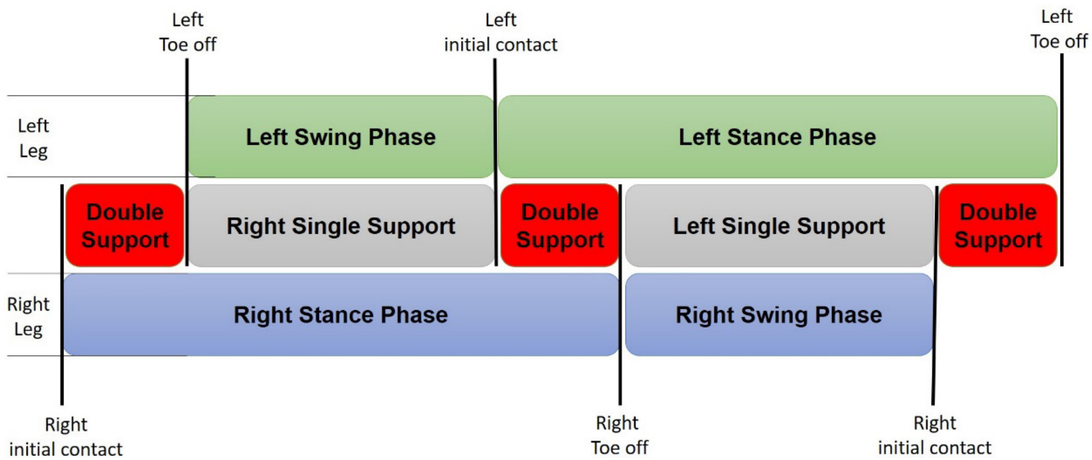


Figure 1.1 Illustration of the phases of one complete gait cycle with both legs and with respect to time (adapted from Whittle (1996) [90])

One complete gait cycle, as illustrated above in Figure 1.1 [68], is defined as being 'from the heel strike of the right or left foot to the subsequent heel strike of the same foot' [69]. During this gait cycle, the leg goes through the following phases:

1- Stance phase – Double support (0-10% of the gait cycle)

   It starts when both feet are touching the ground, with the heel touching the ground first. It ends with the contralateral toe off, when the opposite leg leaves the ground. To manage the body weight that is placed on the leg, the knee flexes, leading to the lowest height of the body's center of mass (CM).

2- Stance phase – Mid-stance (10-30% of the gait cycle)

   It starts with the contralateral toe off and ends when the center of gravity (CG) is directly over the reference foot. The knee extends to a straight leg as the body travels over the standing leg, leading to the maximum height of the CM [70].

3- Stance phase – Terminal Stance (30-50% of the gait cycle)

   It starts when the CG is over the supporting foot and ends when the contralateral foot contacts the ground. The heel rises from the ground as the opposite heel strike occurs, initiating the second double-support period. The ankle plantar flexors are actively involved in pushing the limb into swing, creating the second single limb support phase. They are also involved in providing body support, and in the forward kinetic energy of the trunk, and thus propelling the body forward [71, 72].

4- Stance phase – Double support (50-60% of the gait cycle)

It starts at the contralateral heel strike and ends at the toe off. Thus, both feet are again in contact with the ground.

5- Swing phase – Initial swing (60-70% of the gait cycle)

In this phase, the foot leaves the ground and the leg swings forward. It begins at toe off and continues until maximum knee flexion (60 degrees).

6- Swing phase – Mid swing (70-80% of the gait cycle)

The period from maximum knee flexion until the tibia is vertical or perpendicular to the ground.

7- Swing phase – Terminal swing (80-100% of the gait cycle)

It starts where the tibia is vertical and ends at initial contact. During swing, the knee flexes in order to help in swinging the limb forward, and the knee then extends for the next heel strike. As this subsequent heel strike occurs, the gait cycle is repeated once again.

1.2.2 Gait initiation and termination

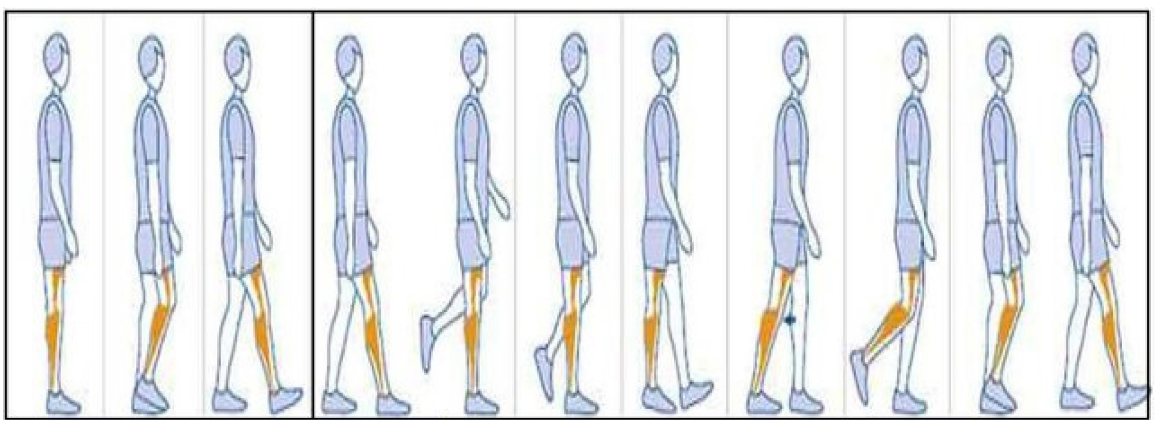


Figure 1.2 Illustration of human gait initiation, and a gait cycle.
It starts from a static standing position, to gait initiation, to a gait cycle (adapted from Cha et al. (2013) [69]).

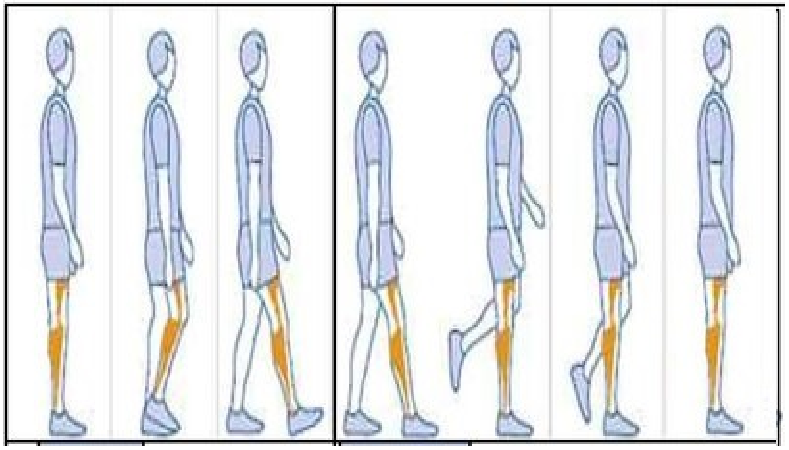


Figure 1.3 Illustration of stepping with the right foot.
It starts from a static standing position, to the initiation of stepping to performing one step, to terminating the step (adapted from Cha et al. (2013) [69])

Gait initiation is a sequence of postural movements that builds up to a forward step.

There is a difference between gait initiation (Figure 1.2) and stepping (Figure 1.3). The first is a transition between static and dynamic postural stability, while the second is mainly dynamically stabilized. In addition, the patterns of body destabilization and CM displacement underlying gait initiation [73, 74] and stepping [75] are stereotypic and well known.

There is also a difference between forward walking (Figure 1.1) and stepping (Figure 1.3). In the first, the termination of gait occurs after multiple gait cycles, while in the second, the termination of gait occurs in the middle of the first gait cycle. The termination of gait, either for forward walking or stepping, has also been shown to be biomechanically the reverse of gait initiation [76].

Rodgeret al. (1994) [77] recorded multiple gait initiations of each of 12 healthy adults, aged 20 to 82 years. They found that all participants showed almost identical patterns of gait initiation. Those patterns were so reproducible that it was possible for a computer to perform averaging of multiple steps by each person.

1.2.3 The control of gait kinematics

The main objective of walking is to drive the body forward in a stable movement while maintaining balance, preventing falls [78] and resisting gravity [68, 79]. In order to achieve this, walking is generated and controlled by the dynamically-changed and harmonized integration of many systems, which interact on different levels of interactions and different degrees of activation. These systems include, for example, the internal sensory systems (ex. vestibular and visual), the complex neural networks system and the neuromuscular interactions. Those interactions are based on a very complex hierarchical system, which includes several control networks located both at the spinal and supra-spinal levels, and that are activated on different levels. An important example of those networks would be the central pattern generators (CPG) network which can be located at the spinal level. This network plays its role in gait control by producing a precise and complex sequence of numerous muscle activations, called the motor pattern for stepping [80]. The spinal CPG network consists of coupled antagonist oscillators specifically dedicated to extensor or flexor muscles, acting at the different joints.

Mechanically, it is the control of the movements of the CM, in relation to the center of pressure (CP), CG and the center of support. Researchers have developed many models to describe the kinematic control of gait stability[81] . Their models describe walking with linear/non-linear inverted pendulum models. These models calculate specific estimations on where to place the foot relative to the body at quiet standing and at each phase of gait, such that gait is stabilized. They take into account many parameters such as CM velocity [82], muscle strength [83], foot placement estimator (FPE), collision dynamics [31] and step width [84].

Quiet standing is modeled as a single-link inverted pendulum that pivots at the ankle joint in the sagittal plane [85]. Because the CM is usually sustained in front of the ankle joints during quiet standing, gravity continuously acts on the pendulum to produce a forward toppling torque. At the same time, the ankle extensor muscles coupled to the pendulum by the series of elastic elements, pull the pendulum backward to prevent it from falling [86]. In this phase, each leg is loaded to about 50% of the body weight.

Then, gait initiation can be modeled as with the same previous models, by adding the CP motion under the feet in AP/ML directions, defined as the anticipatory postural adjustments (APA). APA is also defined as the kinematics of body segments and the kinetics applied under the activity of muscle contraction, such as the activation of the tibialis anterior [87].

At gait initiation, all body weight must be positioned over the stancing leg, liberating the other leg to perform a forward swing for the first step to be made. However, this sequence causes important challenges to balance, such as sufficient strength and control in the stance leg [88].

To keep up with the model of the inverted pendulum outlined above, the CP must move posteriorly in order to destabilize and push the CM forward via the APAs.

Gait initiation can be divided into three phases [87]:

1- Postural phase: APAs are activated. This would generate the dynamic reorganization of posture necessary for a stable whole-body progression. The CP is displaced backward, bilaterally by decreasing the activation of the soleus, and increasing the activation of the tibialis anterior (TA), and laterally towards the leading leg, by activating hip abductors.
2- Foot lift phase: M/A movement of the CP towards the stance leg, as body weight is transferred to it.
3- Execution phase: terminates right after foot contact.

Thus, gait stability while walking can also be controlled by APAs. Foot positioning is tuned to disparities in the CM position, principally by modulation of hip abductor muscle activity during the swing phase of gait. This specific sequence occurs at the level of spinal and cortical control. It also includes strategies to stabilize gait, which includes modulation of ankle moments in the stance leg and changes in body angular momentum.

All those sequences occur with repetitive patterns, suggesting a programmed control by the CPG. It was also found that the programs for gait initiation and walking overlap, with the latter beginning before the first has ended [89].

On the other hand, inspired by biological CPG, and thanks to the advancements in machine learning algorithms, researchers were able to develop new algorithms that are called programmable central pattern generators (PCPGs).

Those algorithms are specifically adapted for rehabilitation systems dedicated to walking. The PCPG can learn a gait pattern and automatically reproduce it [90]. The PCPG that was developed by Duvinage et al. (2011), produced naturalistic gait kinematic patterns in a range of walking speeds from 1.5 to 6 km/h [91].

1.2.4 Gait parameters

There are two types of parameters that characterize and quantify gait:

1- Spatiotemporal parameters:

Gait spatiotemporal parameters quantify the distance and time of the different phases of gait. For example, steady state walking velocity for healthy adults with average height and weight was found to be 1.3 to 1.5 m/s. This velocity relies on on weight, height and other non-morphological attributes (e.g. maximum oxygen consumption) [92]. Other common spatiotemporal parameters include cadence, step length/width and step total/double support/swing times [67].

Furthermore, most of these parameters are related to walking velocity. For example, if step length is increased, walking velocity will be increased too [92]. It was found that step width divergence, a gait attribute believed to be related to balance control, would be a better indicator of falls than step length divergence, a gait attribute related to the programmed and controlled stepping pattern. For people walking at a normal speed, step width is more variable, which makes it an indicator of fall risk in this population [93].

2- Kinetic and kinematic parameters:

Kinematic parameters quantify the positions and angles of joints and segments through each phase of gait, while kinetic parameters quantify the forces and torques that generate movement. Those forces and torques are the result of a combination of active muscle contractions, CPG and APA activations and passive forces across the joints and segments through each phase of gait.

1.3 Neuro-motor control system of gait

1.3.1 Overview

Figure 1.4 shows an illustration of the human motor control system of gait.

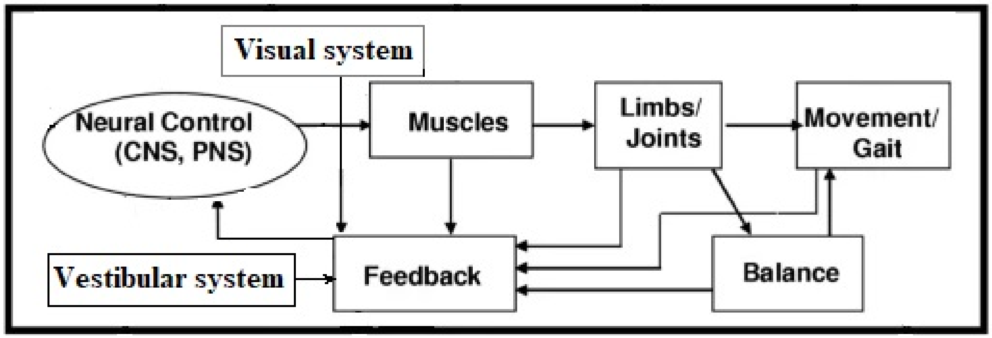


Figure 1.4 Simplified block diagram of human motor control of gait [94]

The human motor control of gait, including initiation, pattern of continuation and termination, all starts at the superior central nervous system, the brain [95].

Gait is characterized as successive, rhythmic, cyclical and symmetric movements generated and controlled by the dynamically-changed and harmonized integration of many systems, which interact on different levels of interactions and different degrees of activation. These systems include, for example, the internal sensory systems (ex. vestibular and visual), the complex neural networks system and the neuromuscular interactions. (Figure 1.5). Those interactions are based on a very complex hierarchical system, which includes several control networks located both at the spinal and supra-spinal levels, and that are activated on different levels. An important example of those networks would be the CPG [39]. Principally, the brain is responsible for the imitation of movements. It sends high-level motor commands to the spinal network that combines the CPG. The CPG network, as mentioned before, is composed of coupled antagonist oscillators that target extensor or flexor muscles acting at the different joints and generates rhythmic patterns of neural signals.

Those generated efferent neural signals, are released by the motoneurons and sent through the motor nerves to the muscles. Then, muscles contract in response to those nervous commands, which in turn produces active forces. Those forces are then sent to the skeleton through the tendons. The forces produce the movements of the legs. The feet interact with the ground, and external forces propels the body forward [96].

Concurrently, each level of motor control receives and sends peripheral sensory information (sensory feedback). This information then becomes a part in the harmony of the dynamically-changed integration of many systems located in the spinal and supra-spinal levels (such as the complex neural networks system and the neuromuscular interactions), with different levels of interactions and different degrees of activation. The output of this harmonized integration at each level of motor control is then used to modify the motor output at that level. This makes the spinal control, all along with the supraspinal control, responsible for generating gait and stepping patterns, at their different degrees of automaticity [39].

Eventually, the cerebral network, at every moment of gait, monitors, modulates and adjusts all gait parameters and phases (e.g. gait initiation, termination, stepping patterns, velocity, direction and spatial orientation). Furthermore, it controls balance and gait by the integration of multi-sensory information, which are vestibular, visual and somatosensory [97].

1.3.2 Gait equilibrium control

The spinal cord incorporates the feedback of the multi-sensory system. The transmition of this feedback stabilizes gait automatically via reflexes, without a direct intervention of the brain [80].

This process ensures that the reflex of a certain muscle is activated at the proper times in the step cycle, and is deactivated at other times [98]. This reflex activity, which modulates the timing and amplitude of the stepping patterns [99, 100], arises at very specific moments in the gait cycle.

For example, during normal walking, the tibialis anterior (TA) shows two activity periods. The first one occurs at the end of the stance, due to output of a spinal CPG. The second occurs at the end of the swing, and is more of cortical origin [101].

However, at the occurrence of a major perturbation, and to avoid a fall, the superior central nervous system and the vestibulo-oculomotor system have to intervene.

The multisensory inputs that contribute to gait control are:

1- Somatosensory input from the receptors of muscles and skin: Proprioceptive organs respond to mechanical stimuli by generating electrical signals [102].

   These signals are transmitted to the spinal cord through the afferent sensory nerves. The muscle spindles determine the muscle fiber lengths and velocities, while the Golgi tendon organs provide information about the muscle forces. Specific cutaneous mechanoreceptors located in the skin can detect tension, changes in texture, rapid vibrations, sustained touch, pressure and stretches. Additional mechanoreceptors are also found in the joints [102].

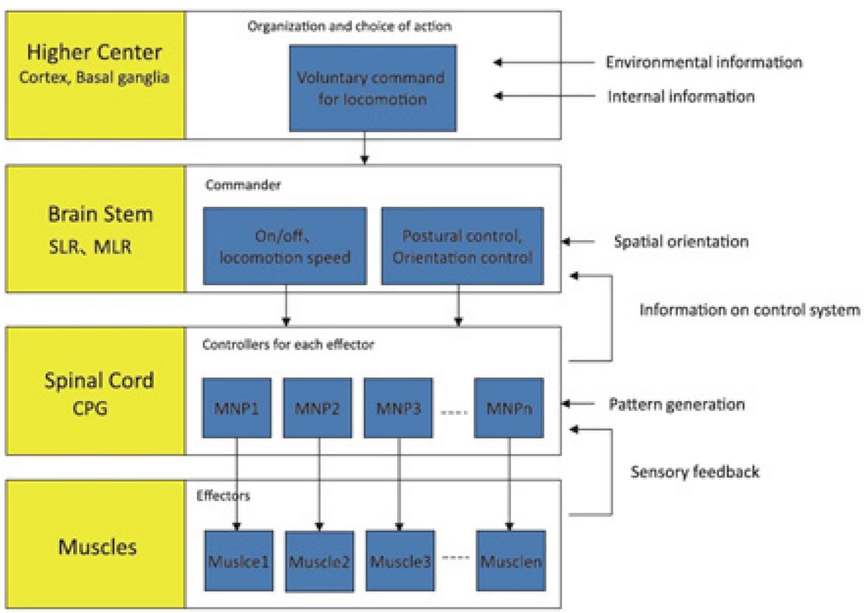


Figure 1.5 Illustration of human neuro-motor control of gait [103]

2- The vestibular system sends information about the orientation of the head in space. In concurrence with other sensory input, this information plays a role in initiating and maintaining body equilibrium [104, 105].

   However, this role is different across the different phases of gait. For example, during quiet standing, the head and joint motions are below physiological thresholds of the vestibular and proprioceptive systems [103]. Then, at the initiation phase of a forward step, Bent et al. (2002) [106] found that this phase is run without vestibular influence, where vestibular information are extended during the more dynamic phases. They also found that the level of extension may be different across step accomplishment, with a clear dependence on vestibular information for upper body alignment [107].

3- In another work, Bent et al. (2002) [108] studied the visual-vestibular interactions during the different phases of gait, and found that the vestibular information in standing contributes to maintaining postural stability. It also contributes to the aligned positioning of the body segments when preparing for regular movement task. Vision appeared to differentially attenuate these responses, depending on the phase of the movement.

To summarize, visual and vestibular feedback are integrated differently across the different phases of a forward-stepping movement.

1.4 Brain control of gait

1.4.1 Introduction

The human central nervous system is responsible for generating the locomotion of the body. While the spinal cord plays the largest role in the programmation of gait and stepping patterns, the brain is mainly responsible for the initiation of movements [95, 109].

1.4.2 Brain anatomy and function

The brain is organized into different parts, different networks and sub-networks (brain wiring) that contribute to every action, on very different levels of integrations, different levels of contribution, and different degrees of activation. However, for a centralized, high level of contribution and high degree of activation, to each specific task and function, the brain activation is very localized [110]. This enables splitting the brain into different areas that are in charge of different tasks. The human brain can be split up into 5 principal structures that are displayed in Figure 1.6:

1) **Brainstem** is responsible for autonomic nerve functions (respiration, heart rate, blood pressure).

2) **Cerebellum** integrates position and movement information from the vestibular system and uses this information to coordinate limb movements and maintain balance.
3) **Hypothalamus** is responsible for visceral functions, body temperature and behavioral responses such as feeding, drinking, sexual response, aggression and pleasure.
4) **Thalamus** modulates and generates rhythmic cortical activity.
5) **Cerebrum** consists of the cortices, large fiber tracts (corpus callosum) and some deeper structures (basal ganglia, amygdala, hippocampus). It integrates information from all the sense organs, initiates motor functions, controls emotions and holds memory and higher thought processes.

The cerebrum can be divided into two hemispheres: the left hemisphere and the right hemisphere. The corpus callosum links the two hemispheres to each other. The two hemispheres are contralateral in function. The left hemisphere receives sensory information from the right side of the body, and controls movement on the that side. Vice versa applies for the right hemisphere. Due to its surface position, the electrical activity of the cerebral cortex has the greatest influence on EEG recordings [111]. Each hemisphere can be split up into four lobes. They are:

1. Frontal Lobes, which are mainly responsible for planning, problem solving and decision making. The frontal lobes consist of:
   a. Prefrontal cortex: problem solving, emotion, complex thought.
   b. Motor cortex: mainly responsible for the initiation of voluntary movement, and plays a role in activating the dorsiflexors and plantar flexors during walking in humans [112]. The motor cortex consists of:
      I. Primary motor cortex: It generates neural signals that are transmitted to the spinal cord. It also controls the performance and accomplishment of movement such as leg movements and walking.
      II. Pre-motor cortex: mainly responsible for motor control. It controls the preparation for movement, the sensory and spatial guidance of movement. It also plans and coordinates complex movements, and contributes to the achievement of rhythmic foot or leg movements and walking [113].

III. Supplementary motor area (or SMA): This area plans the sequences of movement such as gait, and coordinates the two sides of the body such as in the control of postural stability during stance or walking [114, 115].

2. Parietal Lobes which mainly consist of:
   a. Posterior parietal cortex: this part contributes to motor planning, and transforms multisensory information into motor commands.
   b. Somatosensory cortex: which receives sensory and tactile information from the body.
3. Occipital Lobes with the visual cortex (complex processing of visual information.
4. Temporal Lobes (emotions, memory, and speech) [111, 116].

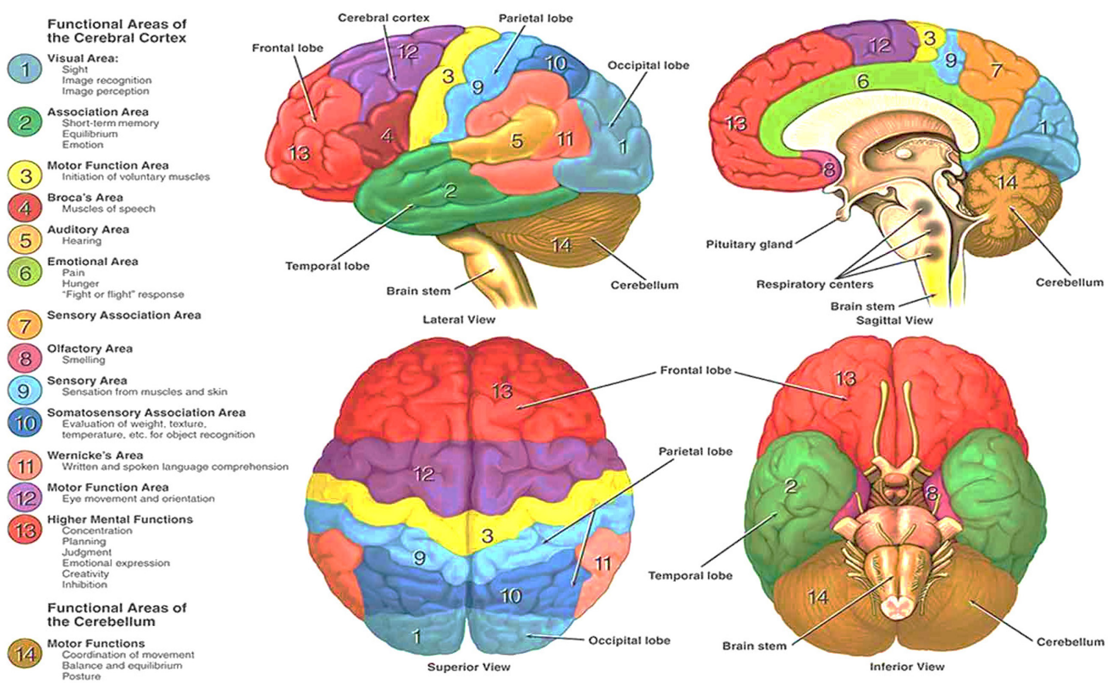


Figure 1.6 Main brain regions and function
https://biofeedback-neurofeedback-therapy.com/neurofeedback-therapy-training/s

1.4.3 Brain areas involved in neural control of gait

Previous studies state that motor centers in the brain play a very big role in human walking [95, 109]. For example, at physical gait initiation and motor imagery of gait initiation, a strong activity was found in the medial frontal cortex (over EEG electrode Cz) [117].

However, during physical walking, a stronger activity was found in dorsal brainstem [118], striatum, cerebellar vermis, visual cortex [119], caudate, medial primary sensorimotor area and SMA [120], while at MI of walking, a stronger pre-SMA activity was found compared to the MI of standing and physical walking.

MI of standing, walking and running was also studied [121]. The findings show an increase in the activation of the cerebellum during MI of running, but not during MI of walking and standing. However, during the physical forward walking, and during the MI of forward walking, and as walking speed increases, a power increase was found in the prefrontal, premotor, vestibular and somatosensory cortices [122]. These results confirm the importance of vestibular and somatosensory feedback during walking. The results also confirm that during walking, the speed of gait is under the control of a cerebellar locomotor center.

Furthermore, during active compared to passive foot movements, an increase in cerebral activity was found in the somatosensory cortex, SMA, cingulate motor area, secondary somatosensory cortex, insular cortices, putamen, thalamus and cerebellum during active movement [123]. Bilateral leg coordination was investigated too, and the results show an increase in cerebral activity bilaterally in primary sensorimotor cortices, SMA and the anterior part of the cerebellum [124]. These findings propose that the motor control of rhythmic foot movements involves both cortical and subcortical structures.

As summarized by La Fougère et al. (2010) [125], during real and imagined walking, activations were found in the occipital gyri, parahippocampal, frontal cortex, fusiform and cerebellum. Deactivations were found in the multisensory vestibular cortices, i.e. in the inferior parietal lobule and superior temporal gyrus. Physical walking appears to select a direct route via the primary motor cortex, whereas MI walking selects an indirect route via the supplementary motor cortex and basal ganglia loop.

1.4.4 Neurons and EEG recordings

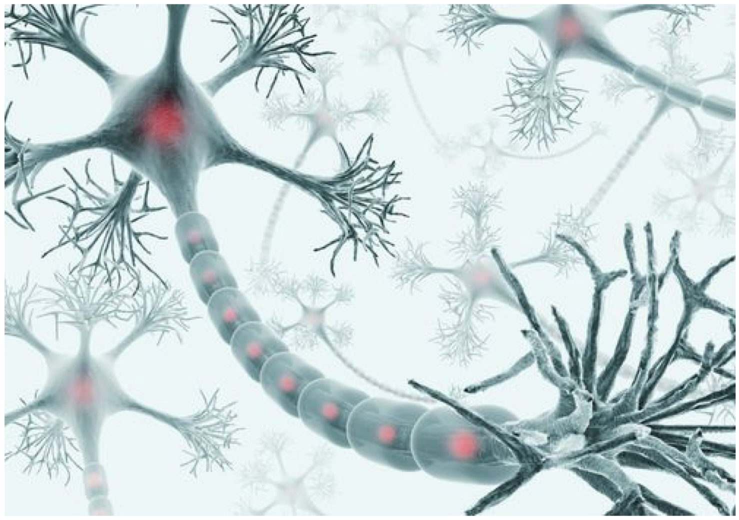


Figure 1.7 Illustration of neuron circuitry in the brain

Cortical neurons are organized in the form of columns, in which the neurons are distributed with the main axes of the dendrite trees parallel to each other and perpendicular to the cortical surface, and are connected via synapses (Figure 1.7) [65]. The electrical activity of the brain is emitted by 10^{14} pyramidal neurons and 10^{20} synapses. Neurons are electrically charged by membrane transport proteins that pump ions across their membranes, where this electrical activity travels through synapses [65]. Thus, a voltmeter can be used to measure the difference of electric voltages between any two electrodes applied to the scalp. Recording these voltages over time gives us the EEG. One single EEG electrode measures the electrical activity lying over a volume that could contain 10^7–10^9 neurons [65].

1.4.5 EEG signals involved in neural control of gait

There is a big challenge that lies in the difficulty of recording the brain signals of walking. This is due to the deep location of the foot's motor area within the interhemispheric fissure over the brain motor cortex [126]. Despite this, brain signals related to walking or imagined walking and stepping have been studied and even classified reliably using machine learning algorithms [127].

Many researchers have used EEG to study walking during different phases [51, 128]. For example, Severens et al. [129] found spectral power increases of μ (8-12 Hz) and β (16-30 Hz). These increases were found to be close to the right/left sensorimotor and dorsal anterior cingulate cortex at the end of each stance phase of walking.

Based on these findings, the power over the right/left sensorimotor cortex was increased during contralateral leg push-off (ipsilateral heel strike), more than for ipsilateral leg push-off (contralateral heel strike). This finding was also supported by many other researchers [130, 131]. Gwin et al. (2011) [128] also found the same patterns of activity right before the heel strike, during the swing phase of the gait cycle. These results confirm that the muscle activity involved in gait is directly controlled by the motor cortex.

1.5 Gait rehabilitation – a glance

1.5.1 Gait impairments

Millions of people worldwide suffer from gait instability after accidental amputation, neuromuscular disorder, traumatic brain injury, spinal cord injury or stroke [24]. In many cases, a loss of the ability to walk independently is very common amongst patients. Moreover, many of those patients can't recover to walk in their normal walking speeds following a stroke [132, 133]. Post-stroke gait is characterized by several sensorimotor deficits such as muscular weakness, lack of coordination, impaired balance, slow gait speed, poor endurance, changes in the quality and adaptability of walking pattern and gait asymmetries in spatial and temporal parameters such as support times and step length. These sensorimotor deficits are variable due to the size and location of the lesion, leaving patients with asymmetric, hemiplegic or paraplegic walking, for example [134].

1.5.2 Gait rehabilitation challenges

Previous studies suggest different strategies to improve walking quality:

1- To use repetitive and intensive training, which is continually incremented in difficulty according to the tolerance of the participant [135].

2- To combine different rehabilitation strategies.
3- To use robotic devices, even though they need further research to show their suitability for walking training and their effects on over-ground gait [25].

When walking to reach a goal, the actual movements are considered, in some control levels, automatic, as opposed to leg movements such as taking a single step or kicking. An additional difference between gait and body-part movements is that gait also triggers internal sensory systems, such as vestibular sensations, as well as a perception of visual changes (optic flow) in the surrounding extra-personal space.

Recent studies have used virtual environments to navigate in while walking [136-138]. The training complexity can be gradually adapted to the user [139] to control an engaging game [140], which promotes neuroplasticity and motor learning [141]. Moreover, treadmills combined with VR scenarios have been shown to be effective for post-stroke gait rehabilitation [139]. These studies have shown that in a VE, the perceptual feeling of walking can be improved by the effects of oscillating the viewpoint of a participant. This would generate an optic flow similar to what would be produced by physically walking [142].

However, the major challenge for gait rehabilitation is that the neural gait control system must dynamically integrate both the stabilization process of static posture at standing, and destabilization processes of dynamic posture representing the dynamic control of the body posture and limbs [109].

This complexity is reflected in the limited performance of existing passive leg protheses and orthoses that cannot replicate such mechanisms. Therefore, gait-impaired users of such devices have to compensate for these limitations, and they are generally faced with non-natural gait patterns and considerable fatigue [143-145].

Given that the brain plays a great role in monitoring and controlling gait patterns and functions, and therefore contains information regarding central pattern generation, the power of brain control can be used to improve gait rehabilitation. This can be done via brain-computer interfaces (BCIs) [39].

1.6 Brain-computer interfaces (BCI)

A BCI is an artificial communication system that bypasses the brain's normal output pathways of peripheral nerves and muscles, measuring brain activity (EEG) associated with the user's intention to do something. It then characterizes these intentions with signal processing algorithms in order to translate them into control signals that replace, restore, enhance, supplement or improve natural brain activity output [4, 5]. The control signals usually command a device to act according to those intentions, without the presence of any muscle activity [146].

EEG signals are complex and weak (μ-volts) and typically have low signal-to-noise ratios (affected by muscular artifacts such as eye and jaw movements). This complicates the processing of these signals, making their use for performing a simple task, such as moving a cursor left or right, very challenging [147]. To operate a BCI, users are trained, as a response to an external stimuli, to produce task-specific brain activity signals that may be separated from ongoing brain activity signals [147]. For such use of these signals, the support comes from powerful computational capabilities represented in recent advances in computer hardware and in signal processing algorithms. This can be very clear if we just compare the first BCI presented by Dr. Grey Walter in 1964, and the BCIs presented by Wolpaw in 2010 [148, 149], for example. With this comparison, we can see how computers have become fast and strong enough to handle the real-time advanced BCI signal processing algorithms.

1.7 BCI framework and design

In order to design a BCI system, the designer needs to go through 5 phases (Figure 1.8).

These phases are:

1- Selection and set-up of the BCI type
2- Selection of features and classifiers
3- Selection of type of feedback
4- BCI Calibration
5- User learning and co-adaptation [148, 150]

Figure 1.8 illustrates the main phases of a BCI design.

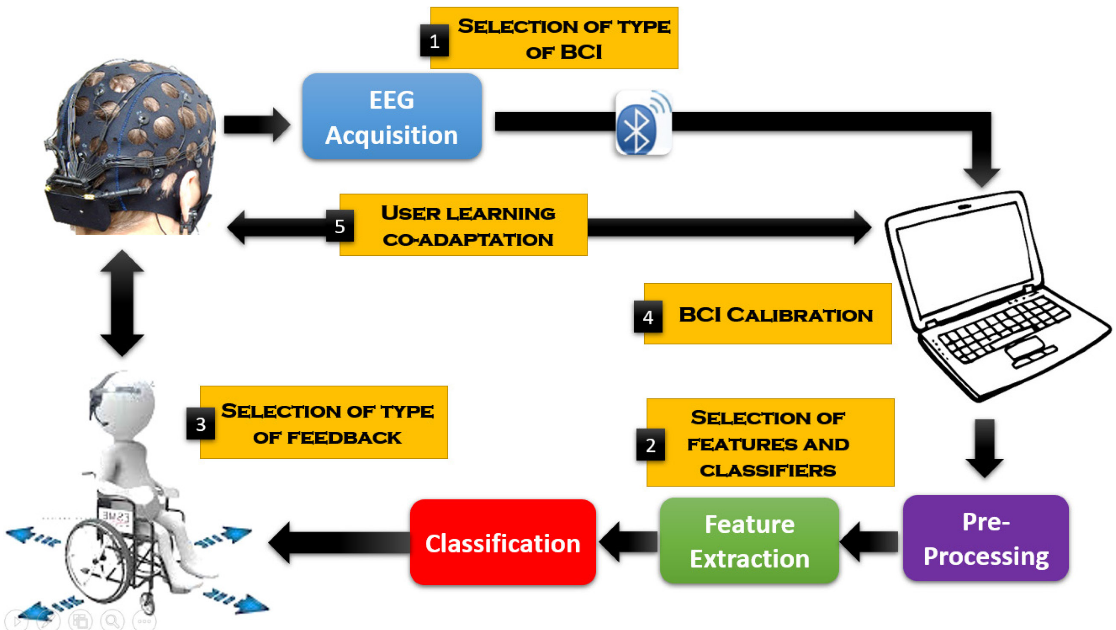


Figure 1.8 BCI framework

1.7.1 Phase 1 – Selection and set-up of the BCI type

1.7.1.1 EEG device

A BCI starts with the acquisition of an EEG with up to 256 electrodes. Each brain activity produces EEG signals specific to the activity in terms of position and rhythm, so numbers and positions of electrodes (according to the 10-20 system) are related to the task the designer wants to achieve with a BCI.

1.7.1.2 EEG source and patterns

Some types of signals used to drive BCIs are P300, Visual Evoked Potentials (VEP) and Steady State Visual Evoked Potentials (SSVEP), which are generated mainly in the occipital area in response to a flashing visual stimulus [150].

However, the two most common EEG patterns used for BCI training are the Bereitschafts potential (BP, slow cortical potential that deepens in negativity about 1.5 s to 1 s before the movement onset) and the event-related synchronization/de-synchronization (ERS/ERD) with short-lasting decrease of power resulting from the motor imagery (MI) paradigm

[150]. To control a BCI, participants imagine the movement of a specific limb of their body. This motor imagery (MI) is detected by BCI and translated into control commands [151]. Do Nascimento et al. [152] studied the BP signal of gait initiation of walking and steps. The results showed that the BP potentials were similar for all tasks, thus a classification between those tasks would be difficult. Therefore, the detection of ERD/ERS is more widely used in gait MI studies.

A physical, observed and imagined movement results in an ERD, a power decrease in the EEG bands μ (8-12 Hz), sensory-motor rhythm SMR (12-15 Hz) and β (16-30 Hz). It begins in the task-specific brain contralateral region, where it starts at the onset of a movement and becomes bilaterally symmetrical immediately after execution of movement. The power increases with an ERS and is dominant ipsilaterally during and contralaterally after the movement and reaches a maximum of around 600 ms after movement offset [148]. At the beginning of the training to control a BCI, activation areas are the regions that are implicated in movement planning and learning, as well as spatial and sensory guidance, which are the motor/pre-motor cortex and SMA [153].

μ-rhythm is also an indirect EEG measure of the activity of the mirror neurons, which are resting motor neurons that are normally active during both the observation and execution of the same action. The strength of activation of those neurons correlates with the amount of μ suppression and desynchronization [154]. It has been also shown that in the earlier stage of pathology, combining virtual feedback with MI of the intended movements can aid patients to gradually recover from impairment [18]. In their study, Soekadar et al. [22] state that MI-BCIs can expedite neuroplasticity, thus enhancing motor learning and motor recovery [155, 156], especially when combined with occupational therapy [38]. MI plays a key role in neuroplasticity and thus, motor learning and recovery. This is because the complex brain neuro-circuitry and operations that control motor and sensorimotor functions can be reorganized and re-wired dynamically through neuroplasticity in response to the task-specific training [157]. In 2014, Rayeghani et al. [158] studied 3 groups with ten patients each. Group 1 received physical therapy, group 2 received BCI training and group 3 received combined BCI and physiotherapy. Although their results showed that all three groups had similar motor improvements, combining MI-BCI mental practice with robotic feedback neurorehabilitation has been also shown in many other studies to be effective in restoring upper limb motor function in stroke patients [20]. Other studies showed that post MI-BCI hand training elicited stronger ERS [23, 26].

1.7.1.3 EEG signals that drive lower-limb BCI

Beneficial effects of MI in the motor control of lower limbs have not been as widely shown as for upper limbs, because of the complexity of gait neural control. The control of human gait is of great interest to the field of lower body BCIs for gait rehabilitation, especially given that more than 50,000 stroke patients per year in Canada suffer from lower-limb sensorimotor deficits [159]. For example, stroke patients present several sensorimotor deficits such as asymmetrical step lengths, that may be indicative of the underlying impairments and compensatory mechanisms used [134, 160] such as gait temporal asymmetries. The foot's motor area representation is located deep within the interhemispheric fissure. Therefore, the detection of gait patterns through the EEG signals is very difficult [126]. Many researchers have studied the EEG signatures of gait, such as left and right foot discrimination [48], gait initiation and termination in order to move forward and stop [50] and normal gait cycles [51]. In all of these studies, it was found that the brain areas that contained the best discriminant information for initiation of walk were: mid-frontal (over EEG electrode FCz), central (over EEG electrode Cz) and central-parietal (over EEG electrode CPz) [50]. Furthermore, the brain areas that contained the best discriminant information for stepping were: central (over EEG electrode Cz), central-parietal (over EEG electrode CPz) [50], right-central for left steps and left-central for right steps (over EEG electrode C4 and C3 respectively) [48]. For example, King et al. in 2013 [161] have shown that paraplegic and tetraplegic patients could trigger a walking simulator by imagining themselves walking or idling. Based on the μ power over the central areas, classification results estimated offline in those studies ranged from about 60% to 90%.

Based on this, researchers were able to deploy BCI systems to control lower-body powered robotic exoskeletons [6]. For example, Donati et al. [55] found that using long-term training of paralyzed patients with a BCI to control the gait of a virtual self-avatar, and later of a lower-limb exoskeleton, lead to partial neurological recovery.

On the other hand, in terms of neurorehabilitation for gait control, the main challenge for BCIs is a correct classification between the MI of a movement and idle (no movement), or the default resting state of the brain, since it involves complex dynamic interchange between conscious and unconscious processes [162]. This default mode of the brain is related to the concept of the “global work space” of consciousness [163] “in which an observing function is exerted by the frontal pole of the brain on its own sensory influx” [164-166].

1.7.1.4 Experimental paradigm

Designing a BCI paradigm is a complex and challenging task which requires multidisciplinary expertise such as programming, signal processing, neurosciences and psychology [146]. The main goal of an experimental paradigm [167] is to guide the user on how to generate the brain activity required for the tasks of the experiment. The experimental paradigm is mainly defined by its duration, repetitiveness, pause between trials and complexity of the mental task [168].

1.7.1.5 Control approaches

1.7.1.5.1 Closed-loop and open-loop modes

In the closed-loop mode, the BCI recognizes the characteristic EEG in response to an external stimulus like a visual or an auditory stimulus, an emotional response, a response to a physical task like bicycling or walking on a treadmill, or a response to an internal stimuli or a cognitive task like arithmetic [111]. It doesn’t require much effort from the user, since it doesn’t imply any type of learning, and it is mainly used in SSEVP-BCI.

However, in the open-loop mode, the BCI requires the user to perform specific mental tasks described in the instructions given by the experimenter. The feedback of those mental tasks is usually in the form of an output signal that controls an external device or software. So, the better the mental task is achieved, the better the feedback control will be. In this type of BCI, the user has to learn to master the skill of being able to self-regulate his EEG signal in order to accomplish those tasks and receive the targeted feedback. The learning process depends on the error-correction learning scheme, which requires repetitions of the tasks in lengthy training sessions within a biofeedback environment [169]. This type of BCI is mainly used for MI-BCIs.

1.7.1.5.2 Cue-paced and self-paced modes

In this phase, designers choose between a cue-paced or self-paced BCI. In a cue-paced BCI, the user is cued as to when to start producing the MI. Then, the EEG is processed in predefined time windows, where the user is allowed to control the targeted application only during these predefined specific time periods. Usually, these time periods are triggered by an external audio/visual stimulus, where they are imposed by the computer system. However, self-paced BCIs continuously analyze EEG data, so the user can choose to perform the specific mental pattern whenever he wishes. This is a computationally demanding process, even much more so than cue-paced BCIs. It leads to a high amount of data being processed and makes designing a self-paced BCI much harder than designing a cue-paced BCI [148].

1.7.1.5.3 Switch (on/off) and continuous (linear) control modes

Self-paced BCIs can work in two modes, either in switch control mode or in a continuous control mode [58]. In a BCI-based switch control, once the classifier output forms a control signal to select a specific command, the feedback is provided only once. For example, Leeb et al. [57] developed a BCI system working in switch mode that allowed a tetraplegic patient to navigate forward in a virtual environment. When the participant performs MI of the right hand, the VR wheelchair navigates to the right and for a certain distance. However, in a BCI with continuous mode, the control and feedback are maintained as long as the MI is maintained by the participant. Once the participant stops the MI task, the control and feedback stops as well [58]. For example, Galan et al. [170] developed a BCI system that allowed participants to navigate forward in a virtual environment using continuous control mode. When the participant performed MI of the right hand, the VR wheelchair navigated to the right and continued navigating forward as long as the motor imagery was maintained by the participant.

1.7.1.5.4 BCI control modes in neurorehabilitation

The key to selecting the right BCI control mode is the design of the type and complexity of the rehabilitation training program. Thus, it is very important to study how the previously mentioned modes can be used most effectively in a training program and schedule adapted to facilitate learning and produce beneficial changes.

Each of these control modes contribute specific benefits to the neurorehabilitation process, depending on the training program of the rehabilitation process, the current phase within the training program of the rehabilitation process, the level of pathology and the progress of the user within his training program of the rehabilitation process.

For example, the SSVEP-BCI works in the closed-loop control mode. This type of BCI can be used in a training program that only requires a 3D presentation of the correct gait patterns to the user, and there is no need for the user to produce mental efforts to control the BCI. Selecting this mode also saves the user from the burden of the lengthy training required to control an open-loop BCI. However, this mode can't be used in a training program that requires the integration of the MI benefits of cortical reorganization in the training. In this case, the open-loop control must be used instead.

On the other hand, one of the rehabilitation goals is to let the pathological user be independent in his locomotor tasks, in a gradual, adaptive and progressive sequence of training that is shaped according to the user's performance and progress throughout the training. Thus, when the training to control an open-loop BCI is needed, the ability to control a self-paced BCI is the final aim of the training. However, for a successful BCI control of gait, the user needs first to be trained to control the cue-paced BCI. Once the user starts mastering this control, he can be transferred to the training of controlling the self-paced BCI. Once there, and at the very beginning of the neurorehabilitation process, the switch control mode is most suitable to control initiation of individual steps, which requires an on/off control strategy. However, with the progression of the neurorehabilitation process, the continuous control mode becomes essential to be able to control the gait as a succession of left and right step motor commands at same time. However, the switch control mode, which is intermittent, does not allow for the use of the MI of walking to produce normal gait cycles. This would require the use of the continuous control mode instead.

To summarize, every control mode contributes its specific benefits to the neurorehabilitation process and should be selected depending on the user's training program.

1.7.1.6 Cleaning and pre-processing methods

After EEG acquisition, the signals are amplified and cleaned [111]. The main goal of this process is to clean the EEG data by eliminating all non-pertinent information, such as the electrical activity of the eyes and the muscles, and the power line network. This process is very important, because keeping the noise in the data could lead to false analysis of the EEG signals or make it harder to work with [111]. Many algorithms have been used by different BCI studies, such as Common Average Reference (CAR) and Principal Components Analysis (PCA) [150]. The details of the algorithms used in this project will be presented in Chapter 3.

1.7.2 Phase 2 – Selection of features and classifiers

1.7.2.1 Feature extraction

'In phase 2, and in order to design an effective BCI training protocol, it is important to select the brain signal features that are best suited for the selected type and purpose of BCI, and to select as well the type of classifier that distinguish between the different signal features provided by the user' [171]. What helps in this phase is that, in the world of BCI research, many powerful machine-learning algorithms have been developed as well as feature selection and spatial filtering algorithms [150]. After cleaning the signals of non-pertinent information, the residual information is known as features. This information needs to be extracted and gathered into a feature vector [150]. The resultant feature vector has the signal values that reflect the underlying brain mechanism generated by the user's intentions for control [148, 150]. Different types of features have been used by different BCI studies. There are temporal methods such as band power (BPr) and their auto regression models (AR) or the common spatial patterns (CSP), and spectral methods such as power spectral density (PSD). In contrast to temporal methods, which are not always reliable due to noise and instability, spectral methods use the frequency domain of the signal. The details of the simplest, most computationally efficient and widely used features for MI-BCIs [150] and those used in this project will be presented next.

1.7.2.1.1 Power spectral density

PSD have been widely used for BCI [148, 150] and are sometimes called spectrum. PSD inform on the distribution of the power of a signal between the different frequencies [148].

PSD features were computed by the Welch method as follows [172]:

1- Breaking the series of the time signal (or its autocorrelation) into successive segments by multiplying it by a Hamming time window, to reduce the variance.
2- Computing the periodogram for each segment using the FFT.
3- Computing PSD for each segment by squaring its periodogram

$$\boldsymbol{P}(\boldsymbol{f}) = \frac{\Delta t}{N}\left|\sum_{n=0}^{N-1} h_n x_n e^{-j2\pi f n}\right|^2$$

Where x_n is the signal, f is the sampling frequency, h_n is the time window, Δt is the sampling interval.

4- Reassigning each PSD segment to the center of energy of its bin to provide exact localization for chirps and impulses [173].
5- Averaging the squared reassigned PSD segments to produce the estimate of PSD

$$PSD_f = \frac{1}{k}\sum_{k=0}^{k-1} P(f)$$

Given that the segments usually overlap, data values at the beginning and end of the segment, tapered by the window in one segment, occur away from the ends of adjacent segments. This guards against the loss of information caused by windowing.

1.7.2.1.2 Power asymmetry ratio

The power asymmetry ratio is used in studies that involve interhemispheric tasks and is defined as:

$$Ra = \frac{R - L}{R + L}$$

Where R is the PSD of a specific frequency band in the right electrode and L is the PSD of a specific band in the left electrode [148].

1.7.2.2 Feature selection

Since the number of features in the feature datasets is usually too high compared to the number of samples, this can cause two problems:

1- A high chance of having redundant and noisy features in the feature set and
2- Longer computation time, and thus less BCI efficiency.

That is why a feature selection method is necessary. The Wilcoxon test and cross-correlation methods are usually used to remove features that are highly correlated and keep only the features that are distinctive and informative. This process over the feature datasets results in a smaller dataset with a more distinctive set of features for successful classification.

1.7.2.3 Features classification

The most important step in a BCI design involves tuning the central part of the BCI system: the classifier [62]. In this step, the classifier is fed with different MI patterns produced by the user, and "learns" to discriminate these distinct patterns. Then, the classifier translates the extracted signal features in the feature vector into control commands related to the underlying brain pattern. Thus, with these control commands, the device will act according to the identified user's intention.

The classifier is a set of decoding weights that map brain activity to a control signal. For an effective BCI design and good control performance, the right classifier and tuning parameters must be chosen very carefully. Powerful algorithms have been used to counteract the problems and limitations of some of the classification algorithms, such as using regularization parameters to counteract overfitting problems and generalize the classification models [148, 150].

The main characteristics that determine BCI performance are complexity [111], classification accuracy [146] and computational efficiency.

1.7.2.3.1 Linear Discriminant Analysis (LDA)

LDAs are the most common classification methods used in BCI designs (27%) [150]. LDAs are more robust compared to non-linear classification methods, and require less training and computation compared with neural networks-based classifiers and K-nearest neighbour (KNN), thus they are faster in training and predicting. They are also easier to implement, use and interpret. This is also why 75% of the BCI designs use classification algorithms that are not based on neural networks (NN) [150]. LDAs also require fewer tuning parameters compared with support vector machines (SVM) for example. However, LDAs require more discriminatory feature vectors to successfully distinguish between the classes, but even when this is applied, they outperform many other algorithms such as decision trees and KNN. Using an ensemble of classifiers rather than using a single classifier has been investigated but didn't always yield better performances of BCI systems [174].

LDA is a classification method that categorizes observations to the corresponding class, based on a set of linear combinations of predictors, by finding an optimal linear transformation of weights that maximizes the class separability into classes with k n-space hyperplanes [24]. This is how LDA functions:

1- It assumes a normal data distribution with a common covariance matrix.
2- It computes the within-class variance. This is the distance between the mean and the sample of every class
3- It computes the separability between different classes, which is the distance between the mean of different classes (between-class and within-class scatter matrices).
4- It computes the eigenvectors and corresponding eigenvalues for the scatter matrices.
5- It sorts the eigenvectors by decreasing eigenvalues and chooses eigenvectors with the largest eigenvalues to form a new weighting matrix.

6- It uses this matrix to construct the lower-dimensional space that maximizes the between-class variance and minimizes the within-class variance.
7- It predicts the output class with the highest probability based on Bayes method.
8- Each transformation is given a score to determine how well it predicts group placement.

However, LDAs can suffer from overfitting [175]. Overfitting is when the classification model is too closely fit to a limited set of data points and can't be generalized to complete new data points. To counteract overfitting, for this research LDA was used with an integrated algorithm called the regularization technique.

1.7.2.3.2 Regularized Linear Discriminant Analysis (RLDA)

RLDA is a classification algorithm that has been used in many MI-BCI studies [176]. RLDA is a regularization technique and is particularly useful to find an optimal and sparse combination of prediction weights when there is a large varying set of features. The regularization amount hyperparameters λ and γ are used to make a more generalized, robust and simpler model by trying to remove predictors without diminishing the performance of the model.

In order to assign x_i, based on d measurements x_i=(x_{i1},,.. x_{id}) to one of k a priori defined classes, the classification score is defined as:

$$cf(x_i) = (x_i - \mu_k)^T \sum\nolimits_k^{-1} (x_i - \mu_k) + ln \left| \sum\nolimits_k cov \right| - 2ln(\pi_k)$$

where $\sum_k$ is the class covariance matrix of class k, μ_k is the mean vector of class k, and (π_k) is the prior probability of class k. They are estimated by:

$$\mu_k = {}^1/_{n_k} \sum_{i=1}^{n_k} x_i$$

$$\hat{\sum} = {}^1/_{n_k} \sum_{i=1}^{n_k} (x_i - \mu_k)(x_i - \mu_k)^T$$

$$\pi_k = {}^{n_k}/_{n}$$

where n_k is the number of objects in class k, and n is the total number of objects in the training set. Object x_i is assigned to the class for which it has the lowest classification score.

In the case of LDA, the class covariance matrices are assumed to be equal and the constants are ignored so that a pooled covariance matrix is substituted for the class covariance matrix. Thus, the following classification rule for LDA is derived:

$$cf(x_i) = (x_i - \mu_k)^T \sum\nolimits_{pooled}^{-1} (x_i - \mu_k) - 2ln(\pi_k)$$

The regularization technique replaces the within-group sample covariance by the average of the whole sample covariance and can be applied as follows:

$$\Sigma_k(\gamma, \lambda) = (1-\gamma)[(1-\lambda)\Sigma + \lambda \Sigma pooled] + \gamma diag\,[(1-\lambda)\Sigma + \lambda\Sigma\ pooled]$$

The parameter λ controls the degree to which the pooled class covariance matrix should be used, while the parameter γ controls the degree of shrinking to the average eigenvalue. Technically, these parameters increase larger eigenvalues of the covariance matrix while decreasing smaller ones, therefore creating a pooled-covariance matrix that is corrected for the bias when estimating sample-based eigenvalues [177, 178].

Thus, the regularization improves the classification performance by:

1) stabilizing the variance,
2) reducing the bias of the discriminant function,
3) providing high robustness with accommodating outliers,
4) providing generalization,
5) preventing overfit, and
6) decreasing calculation time compared to other classification methods [179].

The regularization parameter λ is usually optimized by setting different values of λ over the range of [0, 1.0] in 0.1 increments, and then validated by cross-validation [177]. Setting λ=1 yields to LDA, while setting λ=0 yields to quadratic LDA (a form of LDA).

A third regularization hyperparameter is usually used, which is the linear coefficient threshold (δ): if a coefficient in the model has a magnitude smaller than (δ), the algorithm sets this coefficient to 0, and the corresponding predictor can be eliminated from the model.

1.7.2.3.3 Linear Regression Models (LRM)

Linear regression models (LRM) have been used in many BCI studies to model the relationship between the datasets and their class labels. LRM uses the standard ordinary least squares (OLS) approach to minimize the Loss function (L_{OLS}), which can be described as:

$$L_{OLS}(\hat{\beta}) = \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2$$

(for n observations of the response variable Y, with a linear combination of m predictor variables, X). The OLS parameter estimates $\hat{\beta}_{OLS}$ can be obtained by:

$$\hat{\beta}_{OLS} = (X'X)^{-1}(X'Y)$$

The threshold assigned for classes are set in the optimization steps. Linear regression models (LRM) are usually varied by using two choices of penalty hyperparameters:

1- Regularization Weight (α) which varies between Lasso (L1), Ridge (L2) and Elastic Net (L3) [180] and
2- Regularization amount (λ).

When the linear regression model contains many predictor variables or if these variables are correlated, the standard ordinary least squares (OLS) parameter estimates have large variance, thus making the model unreliable. To counter this, we regularize by penalizing the predictors that are too far from zero and force them to be small. Thus, we decrease the model complexity, that is the number of predictors, in order to lower the variance at the cost of some bias. This can be done by one of three different types of regularization and weighting techniques using the penalty parameters λ and α :

a) Ridge Regression, which penalizes the sum of squared coefficients (L2 penalty).

   $L_{ridge}(\hat{\beta}) = \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2 + \lambda\sum_{j=1}^{m}\widehat{\beta^2}$ with

   $\hat{\beta}_{ridge} = (X'X + \lambda I)^{-1}(X'Y)$ where I is the identity matrix

b) Lasso Regression, which penalizes the sum of absolute values of the coefficients (L1 penalty).

$L_{Lasso}(\hat{\beta}) = \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2 + \lambda \sum_{j=1}^{m}\left|\widehat{\beta_j}\right|$ with

$\hat{\beta}_{Lasso} = (X'X + \lambda I)^{-1}(X'Y)$ where I is the identity matrix

c) Elastic Net, a convex combination of Ridge and Lasso (L3 penalty).

$$L_{enet}(\hat{\beta}) = 1/2n \sum_{i=1}^{n}(y_i - x_i'\hat{\beta})^2 + \lambda \left(\frac{1-\alpha}{2} \sum_{j=1}^{m} \widehat{\beta^2} + \alpha \sum_{j=1}^{m} \left|\widehat{\beta_j}\right| \right)$$

Where is (α) the regularization weight.

1.7.2.3.4 Tuning hyperparameters: Grid search

As stated earlier, RLDA models are usually varied by the choice of two hyperparameters, which would be reliable in terms of generalization error: 1-regularization amount (λ) and 2-linear coefficient threshold (δ). LRM models are varied by the choice of two hyperparameters: 1- regularization amount (λ) and 2- regularization weight (α).

Grid search is an exhaustive search approach that is used for selecting a model (such as in RLDA or LRM models) by hyperparameter tuning. It methodically builds and evaluates a model for every possible combination of hyperparameters specified in a grid.

1.7.2.3.5 Cross-Validation

In order to validate the performance of the classification models, a 10-fold cross-validation algorithm is usually used. This algorithm divides data (n) into 10 parts of datasets of size n/10, trains on 9 datasets and tests on 1, repeats this 10 times and finally takes an average accuracy. The main advantage of this method is that all observations in the data are used for both training and validation, and each observation is used for validation exactly once [148, 150].

1.7.3 Phase 3 – Selection of type and feedback

Phase 3 is where the user controls the BCI through the feedback of the application. The key of this phase is the design of the type and complexity of the feedback to be controlled. Some studies showed that feedback in form of a virtual street or a realistic moving hand resulted in a greater effect on μ and β ERS and a heart rate acceleration, than watching abstract feedback in the form of a moving bar [181].

For example, a tetraplegic participant mastered 3D cursor control after 6 days of BCI training, with long training sessions lasting between 4–6h [182]. In an other study, users mastered cursor control BCI after 10 sessions over 3 days, with a training that lasted an hour and half per session [183]. MI-BCI users were also trained over a 3 days sequential paradigm to control navigation in virtual reality [16]. They were trained in phase 1 without feedback, where signals of imagined foot/right/left movements were used to control walk/turn-left/turn-right of a switch control BCI. Then in phase 2 they were trained to use the continuous control BCI, where classification data of Phase 1 were used to tune and recalibrate the classifier for this phase. Classifiers were tuned again to control a self-paced BCI in phase 3. Thus, in BCI training, the feedback of the performance the users receive, leads to co-adapt with the BCI system. Hence, feedback design has powerful effects in the process of MI learning and performance improvement [42].

1.7.4 Phase 4 – BCI calibration to enhance performance

Controlling a BCI is a skill that must be learnt, and in order to shorten the BCI training time and overcome the limitations of performance in multi-modal lower-limb MI-BCIs, Tillery et al. [184] indicated that computer-assisted BCI learning approaches, that could be added to every phase, led to enhanced performance and greater learning rates.

1.7.4.1 Retraining the classifier

As the classifier needs to be tuned for a specific user, a large amount of data from each must be fed to the classifier, requiring a long calibration period. This is a major limitation of BCIs. To counteract this limitation, a new computer-assisted approach has been used, which implements algorithms to retrain the classifier after every session [185, 186]. For example, Sun et al. [187] trained users to control BCI over multiple sessions, and adaptively updated the classifier based on new data from each session. Shenoy et al. [188]

explored several methods of re-biasing and retraining classifiers in real time after every trial. The same algorithms were used to update an LDA classifier by Acqualagna et al. [189]. Llera et al. [190] applied similar algorithms to multi-class/tasks BCIs. Other groups, like Li et al. [191], tested an algorithm to compensate for drifts and changes in the feature distributions between training and testing data. Arvaneh et al. [192] used data space adaptation to transform EEG data from the testing session space to the training session space. Xu et al. [19] trained participants on a generic BCI (calibrated with the data from multiple other participants), then on a participant-optimized BCI, where good performance was obtained after 3–6 min of adaptation.

1.7.4.2 Generic classifier

Since the classifier needs to be tuned for a specific user, a large amount of data from each user must be fed to the classifier [182]. Therefore, a long calibration period is needed, which is a major limitation of BCIs. To counter this limitation, many studies have suggested eliminating offline calibration using a generic classifier that is pre-trained over many participants, using many trials [193, 194]. This generic classifier is used to train participants to control a participant-optimized BCI [194]. For example, Lotte et al. [195] proposed using a participant-independent P300 BCI, previously trained from the data of many other participants. Their BCI resulted in a better performance, and with a reduced training time from 40 minutes to 2 minutes. Similar results were found in other studies running a generic LDA classifier in a MI-BCI [196, 197]. Their findings state that, even though the inter-participant variability poses a challenge, all participants scored high performance [196]. Generic classifiers based on the data of 80 participants have also been used by Vidaurre et al. [198], who showed that the performance is significantly better (an increase of 13%) than the state-of-the-art classical classification approach.

1.7.5 Phase 5 – User learning and co-adaptation to enhance performance

1.7.5.1 Co-adaptive training

In this approach, the user adapts to the machine and the machine adapts to the user.
The BCI user learns to generate specific EEG patterns to form a control signal output with

the given decoding weights. Then, it is the user's turn to try to recognize the meaning of the feedback generated by the computer, which illustrates how well the computer understood the command that it had received from the user, and this practice often requires significant effort and time. The key to this phase is the design of the type and complexity of the training paradigm. Thus, it is very important to study how the previously selected features, algorithms and feedback can be used most effectively in a training type and schedule, adapted to facilitate learning by producing beneficial changes in brain signals without causing fatigue to the participant due to the complexity and length of the training. One computer-assisted approach that was developed to enhance the outcome of this phase was the adaptive progressive sequence of tasks. With this approach, the main BCI task is regulated gradually as the task difficulty increases, in order to help the user adapt to the process and tune his performance. It is a powerful approach to handle task complexity and keep the participant engaged with the learning process while shaping brain control performance [62, 63]. Using this approach, the brain also adapts to the classifier periodically, thus getting the maximum benefits of the neural changes induced all along the BCI training phases. For example, McFarland et al. [149] started training the BCI users to control a cursor in 1D over three different dimensions separately, then in 2D (for each pair of dimensions), and finally in 3D. Allison et al. [9] trained participants with severe impairments to use a cursor-control BCI. Sequential training was implemented to shape the training gradually from switch control mode to continuous control mode. Participants were also trained to control a BCI with a generic classifier that was calibrated with the data from many other participants, then progressively adapted the classifier inputs and outputs from the new user specific brain activity [197, 199].

1.7.5.2 Modified feedback

Another computer-assisted approach that was developed to enhance the control of a BCI is delivering feedback that is either positively or negatively modified. With positive modified feedback (MDF), it is the user that adapts to the machine. The BCI user is provided with a number of successful trials (correct control results and feedback), regardless of his real performance. The user then becomes more motivated and has to mentally adapt to the tasks. This is a promising technique since it involves minimal effort and mental workload from the user. On the other hand, with negative MDF, the BCI user is provided with a number of unsuccessful trials (incorrect control results and feedback), representing the augmentation of error, regardless of his real performance. The user must then become more focused and modulate his brain activity to produce the correct brain patterns in order to compensate for the error. Even though this technique requires an elevated level of focus and an additive mental workload from the user, it yields better control of BCIs. One group that studied the effects the MDF and visual-motor adaptation tasks had on the control of a BCI was Barbero et al. [64]. The main advantage shown in their results, was that positive biasing improved for participants with poor performance, while the inaccurate feedback negatively affected those with better performance. Luu et al. [200] used a BCI that decodes lower limb joint angles from the EEG delta band (0.1-3 Hz) during treadmill walking to control a walking avatar in a VE. Then, asymmetric walking gait patterns of the avatar were provided over 8 days, resulting in the participant's neural and gait adaptation. In a similar study [201], authors provided participants fake negative and positive feedback of their performance and reported that positive feedback had a greater learning effect on MI-BCIs. In yet another study [202], researchers developed a BCI to control VR human-like robotic hands in 1PP. Participants were provided with positive or negative MDF in 90% of the session trials. Results revealed that positive MDF optimized and improved the participants' MI learning skills, motor learning and ownership illusion. This is also consistent with what Lotte et al. [203] found in their study.

Eventually, the ability and time for a BCI user to reach a high performance depends on all of the previous phases, in addition to a user's cognitive functions and performance.

1.8 BCI applications for gait rehabilitation and ambulatory assistive technologies

1.8.1 Introduction

Several MI-BCI systems have been proposed in the fields of gait rehabilitation and ambulatory assistive technologies. Some do not use imagined movements that are congruent with the produced actions. Many of these allow user to simple navigate (move in different directions), either using physical devices or within VEs. Others allow users to control the gait of an avatar, with or without the imagined movements being those made by the avatar (taking a step, for example). This section presents an overview of these different BCIs that have been proposed in these fields.

1.8.2 BCI to control wheelchairs

Gait replacement technologies, such as wheelchairs controlled via BCI, have been extensively researched. For example, it was shown that participants controlled the movements of a wheelchair as forward movement and turn left/right [204]. In other studies, participants followed left/right wall and stop [205] with the motor imagery of left/right hand, cube rotation imagery, subtraction and word association [206].

Moreover, BCI users were able to use the continuous control mode to control the start/stop of the navigation of a wheelchair [2, 170]. To allow the user to control the navigation of a wheelchair with more options, like accelerate, decelerate, turn left, right, etc., the alternative strategy they used was a P300 BCI [207-209] (Figure 1.9) or even an SSVEP-BCI [210, 211].

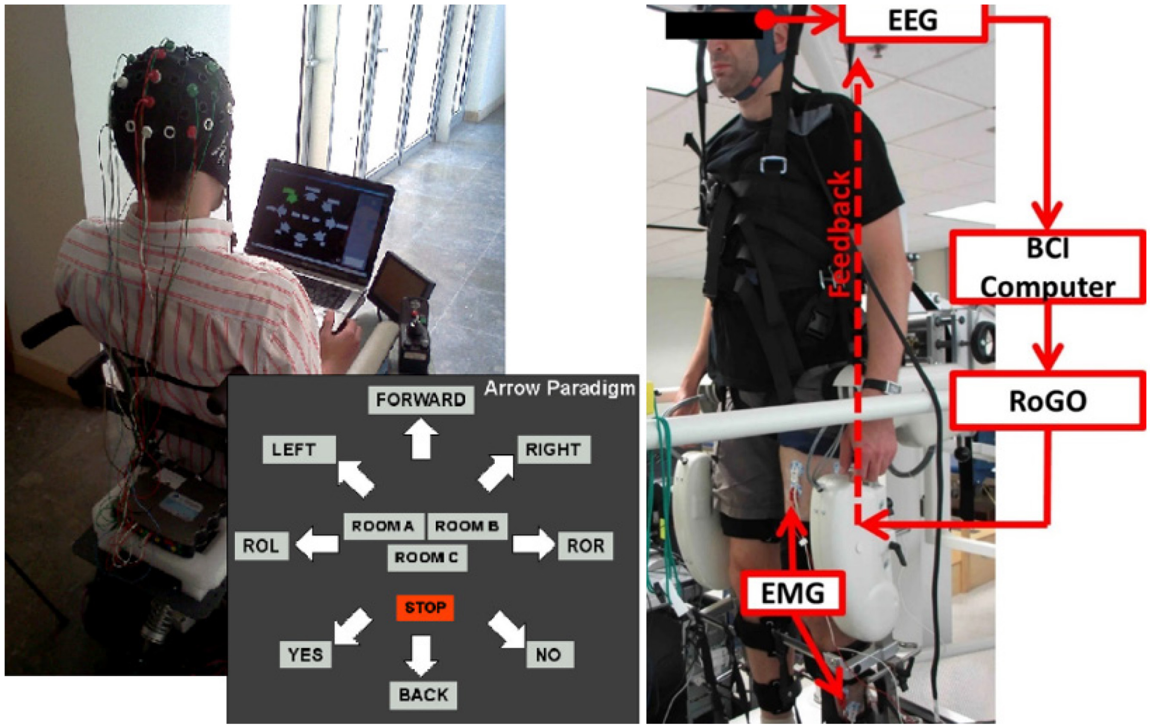


Figure 1.9 BCI to control wheelchairs:
A wheelchair controlled by P300 BCI (left) [206], and gait orthosis RoGo controlled by a BCI (right) [212]

1.8.3 BCI to control robotic and prosthetic devices

Gait assistive technologies controlled via BCI have also been extensively researched and many BCI-controlled gait orthoses have been investigated. For example, Xu et al. [213] presented closed-loop BCI driven motorized ankle-foot orthoses (known as BCI-MAFO), intended for stroke rehabilitation. Their system was able to detect slow cortical waves of intended dorsiflexion movements (for walking) with a short latency. In a similar work, Do et al. [212] introduced the gait orthosis system, RoGo (Figure 1.9). It suspends participants over a treadmill and initiates a gait cycle after classifying the user's intention between idling and walking. Similar work was introduced in many other studies, where researchers were able to control neurorehabilitation orthoses via BCI systems that used the PSD features of participant's MI commands of idle state (no movement) and initiation of gait, in order to classify these two conditions using LDA [161, 204, 212, 214].

Kilicarslan et al. pioneered the deployment of BCI systems to control lower-body powered robotic exoskeletons by participants with a spinal cord injury using MI of the hands [215].

Gordleeva et al. [216] developed a BCI to control an exoskeleton. After 3 sessions of training to modulate their hands with MI over the μ and SMR bands, participants achieved an accuracy of 70%.

1.8.4 BCI to control navigation in VEs

VR-based rehabilitation has seen an important gain in recent years, fueled by the availability of affordable mass-market VR devices and several advantages such technology offers for patients and researchers [217, 218]. One such advantage is the high level of control that can be exerted on all aspects of a participant's VE, such as the full control of navigation in a motivating VE scenario.

For example, it was shown in BCI studies that it was possible to control a virtual wheelchair using a 2-channel BCI with both switch and continuous control mode [58, 219]. Participants had to follow a 38-meter path (Figure 1.10) to reach, as fast as they could, an avatar placed at the end of it. If the movement led the participants off of this path, the wheelchair collided with an invisible wall, so the movement ended. The performance feedback was a bar placed in the centre of a circle that was continuously rotating clockwise. The circle had the commands for controlling the navigation of the wheelchair, which were: move forward, turn right and turn left. If the LDA classified a movement versus an idle state (no movement) when the participant produced hand MI, accumulating more than a "selection time", the bar extended over the "selection threshold". Then the participant could extend the bar carrying out the MI task to select a command when the bar was pointing at it, and the wheelchair would move in the direction selected by the user, at a fixed speed, and the bar changed its color to red. When compared to other BCI paradigms and feedback types, researchers found that BCI performance can be modified via feedback presentation [220].

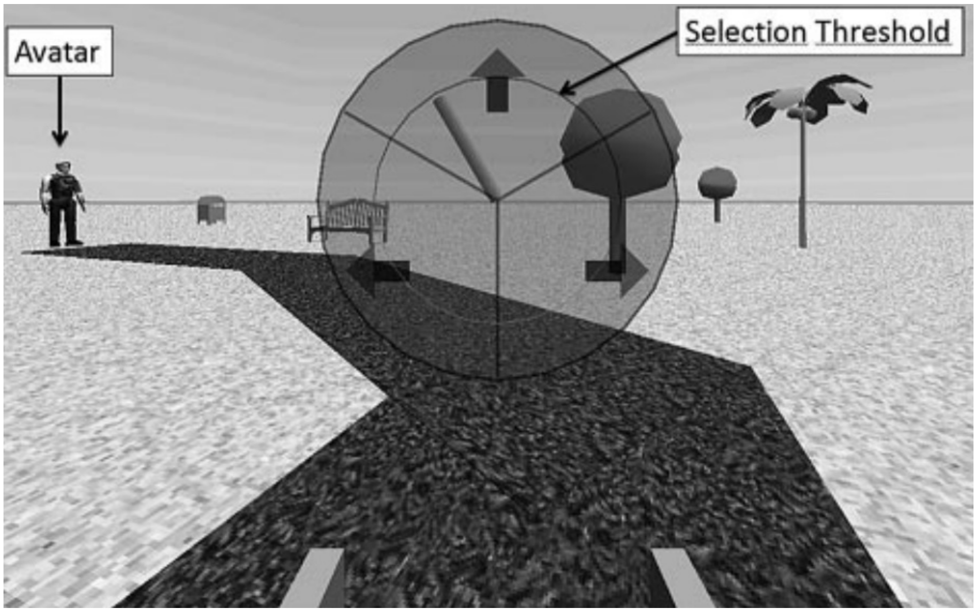


Figure 1.10 A virtual wheelchair controlled by a 2-channel BCI [219]

On the other hand, the goal of the study conducted by Leeb et al. [41] (Figure 1.11) was to move forward to the end of a virtual street by imaging right hand/foot movements, recorded with a 3-channel cue-paced BCI with an LDA classifier. At MI of "right hand movement" the participant stopped, whereas at MI of "foot movement" the participant began walking with constant speed. For motivation purposes, if the classifier's output and the cue did not match, a backward movement followed. The same BCI paradigm was also used by a hemiplegic participant to navigate in a VE replica of the National Austrian Library (Figure 1.11). The goal was to move until the end of the main hall of the library along a predefined pathway where the participant had to stop at five specific points [221]. The participants had to perform the motor imagery over 10.5 and 25.6 seconds, which is a very long period, and considered to be a disadvantage of the experimental protocol. The VE was designed to mimic a photo-realistic model of the 80-meter-long and 14-meter-wide main hall.

Figure 1.11 BCI to control navigation in VEs:
Exploration of the National Austrian Library through thoughts (left) [221] and walking in a virtual city using BCI (right) [41]

The results of these two studies suggested that the more the MI-BCI visual display is enhanced, the better it gets in terms of the performance of the user in controlling this BCI. In a similar work [57], the same BCI paradigm was used to allow a tetraplegic patient to navigate his wheelchair's simulated movements along an immersive virtual street populated with 15 avatars (Figure 1.12). While navigating forward in the VE, the participant used foot-MI to move from avatar to avatar. The participant was instructed to stop as close to an avatar as possible, where the avatar started talking to the participant if he was standing still for one second. The avatar would speak short sentences like "Hi", "My name is Ted", "The weather is nice today". After that, the avatar walked away [222]. This tetraplegic participant was trained in two days and was able to stop at 90 percent of the displayed avatars.

Figure 1.12 BCI-based VR applications for disabled participants
(adapted from Leeb et al. (2007)[56]). While navigating forward in the VE, the participant used foot-MI to move from avatar to avatar. The participant was instructed to stop as close to an avatar as possible, where the avatar started talking to the participant if he was standing still for one second. After that, the avatar walked away.

After the experiment, the participant mentioned that "*It has never happened before, in the sense of success and interaction. I thought that I was on the street and I had the chance to* *walk up to the people. I just imagined the movement and walked up to them"[222].* This answer suggests that the user felt very immersed in the VE [222].

A main advantage of using VEs is that it allows such patients to be exposed to experiences they may have long forgotten or never had. This participant had a feet impairment for years but because of the plasticity of the human brain, he was still able to perform foot-MI in a VE [148].

1.8.5 BCI to control a VR avatar

Using a VR head-mounted display (HMD) can immerse the user in the VE. This feeling could help control his body self-representation in the form of a self-avatar. It was shown in previous studies that mimicking the movements of a self-avatar or even the observation of a movement performed by an avatar led to motor improvements [223, 224]. In 2014, Caudron et al. [225] showed that an avatar that replicates real-time anteroposterior trunk position and orientation of the head improved the postural balance of patients with Parkinson's disease.

It was mentioned earlier in the literature review that combining virtual visual feedback with MI of the intended movements, can help patients gradually recover from impairment through neuroplasticity [18], when combined with physiotherapy [18, 38, 139, 226]. The beneficial effects of MI in motor control of lower limbs have not been as widely shown as for upper limbs because of the complexity of gait neural control [39]. There are few studies that have developed a lower-limb MI-BCI to control the gait of an immersive virtual avatar. However, all of these studies reported that controlling an avatar's gait in VR physically and mentally (through a BCI) could be beneficial for gait rehabilitation [18, 54, 139, 215, 226-231] and for improving balance in chronic stroke patients [228].

For example, Wang et al. [3] developed a self-paced BCI where participants were trained over 5 sessions of 10-min each to control the gait and linear ambulation of an avatar and make ten sequential stops at designated points within the VE. They were able to do that by alternating between the MI of only two commands: idling and walking.

Figure 1.13 BCI systems to control an avatar:
An avatar controlled by a self-paced BCI (left) [3], a female participant controlling the gait of her avatar in the virtual room (middle) [40], control of the right/left steps of an avatar, then of an exoskeleton with a BCI (right) [55]

In a similar work, Friedman et al. [40] used the LDA output of MI of hands and feet in a 3-channel Graz BCI with a highly immersive cave-like system for the navigation of a sex-matched avatar (Figure 1.13). When the participants imagined moving their right arm the avatar would wave its right arm, and when they imagined moving their legs the avatar would start walking forward slowly. In a similar work, Nicolelis et al. [55] used the LDA output of MI of right and left foot to control the right and left steps of an avatar displayed from a first person perspective (1PP). They later used the same BCI to control the right and left steps of an exoskeleton (Figure 1.13).

An SSVEP-BCI was also used to control the navigation of an avatar in different VEs such as a virtual apartment or even a World of Warcraft game scene [232, 233] (Figure 1.14). In a similar work [43], the LDA output of MI of a cube manipulation was used in a BCI to control the navigation of an avatar in a rehabilitation room (Figure 1.14). An et al. [234] also developed a self-paced BCI to control an avatar in a computer game. However, in their design, they used the output of an RLDA classifier to classify MI of right/left hands and foot, in order to control the SPEED, JUMP, and ROLL actions of the avatar.

Figure 1.14 BCI-based games to control an avatar:
Controlling an avatar in a virtual apartment using a SSVEP BCI (left), controlling the navigation of an avatar in the World of Warcraft game (middle) [232, 233], controlling the navigation of an avatar in a rehabilitation room using BCI (right) [43]

In a similar work, Hazrati et al. [45] used the same classifier and control commands as in the previous study, but mapped them to control the right/left/forward navigation of an avatar in the Second Life's VE (Figure 1.15). The same BCI with the same classification paradigm and mapping was used by Cohen et al. [235], but this time with the additional option of self-paced navigation of the avatar. The participants were asked to fill 10-step Likert scale questionnaires, with questions about the degree of feeling embodied in the avatar and sense of control. Their analysis revealed that participants felt a higher sense of being embodied in the avatar.

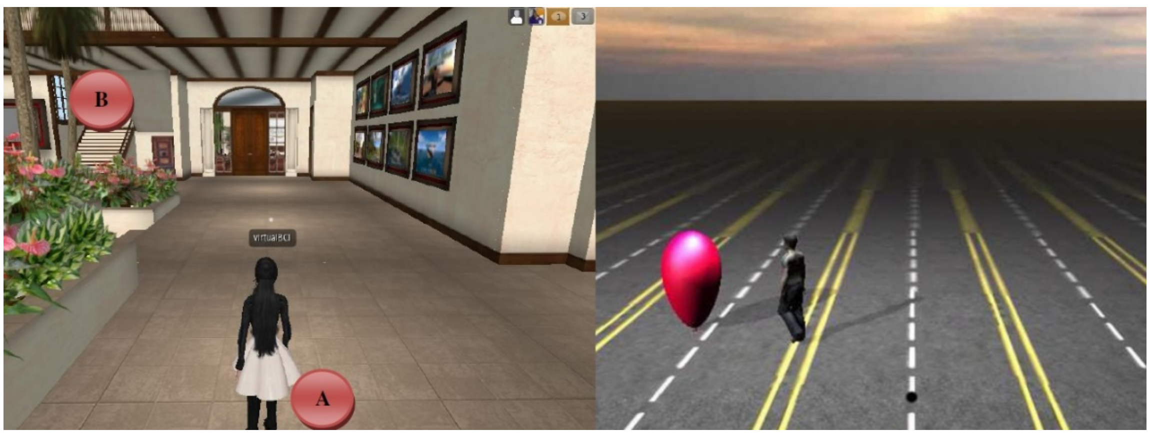


Figure 1.15 BCI systems to control the navigation of avatars:
Control the right/left/forward navigation of an avatar in Second Life's VE using a MI-BCI (left) [45], control the right/left/forward navigation of an avatar with a self-paced BCI (right) [235]

The group of Lulu et al. [236] developed a closed-loop BCI to allow users to control an avatar's walk (Figure 1.16). They were able to decode the user's idle state (no movement), intent to initiate gait and continuous kinematics, and found cortical adaptation following the control of the avatar gait as follows [237]:

1- parietal μ suppression due to presence walking with BCI control;
2- increased activity of the anterior cingulate cortex involving error monitoring and motor learning;
3- increased activity of the superior temporal gyrus due to the control of gait.

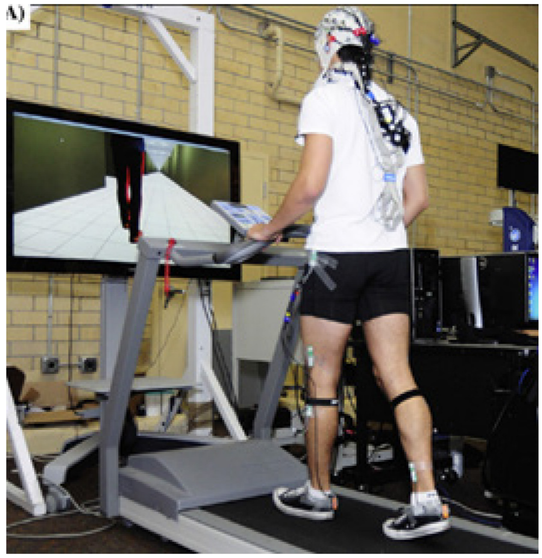


Figure 1.16 A closed-loop BCI to control a modulated avatar's walk [236]

The same group used the same system to investigate gait adaptation over the slow cortical waves (0.1-3 Hz). When training participants to use their BCI, they introduced virtual kinematic perturbations over a period of eight days, resulting in asymmetric walking gait patterns of the avatar. The results of this study have shown the possibility of controlling a walking avatar with a BCI under normal and altered visual-motor perturbations, which involved cortical adaptations as well. The modulation of the asymmetry in the avatar could lead to a modulation of the asymmetry in the participant.

1.9 Embodiment

1.9.1 Introduction

Embodiment is the gradual process of the perceptual illusion that artificial body parts or full bodies can be perceived by people as their own [30]. The generation of such an illusion is based on providing synchronous multisensory or sensorimotor correlations coherent with the ownership of the fake body part [238] (Figure 1.18). On the other hand, this understanding should also be accompanied by the understanding of the action being embodied.

In the studies mentioned in section 1.8.5, participants reported a high feeling of being embodied in the avatar while controlling its gait.

It has been shown that participants can have the illusion of agency over the walking of a virtual body even though in reality they are seated and only allowed head movements [239]. Kokkinara et al. [142] showed that a first person perspective of a life-sized virtual human female body that appears to substitute the male participants' own bodies was sufficient to generate a body transfer illusion. This was found by the answers to questions such as "How much did you feel that the seated girl's body was your body?" and "How strong was the feeling that the woman you saw was directly touching you on the shoulder?". It was also shown that the uncomfortable body posture of an avatar seen from 1PP influenced stress over participants' performance in VE [240] (Figure 1.17).

Leeb et al. [57] reported the results of a 35 year-old male tetraplegic participant, who learned to control a BCI where signals of imagined foot/right/left movements were used to control walk/turn-left/turn-right. He navigated in a VR scene, in order to move from avatar to avatar by the imagination of movement of his paralyzed feet. Concerning the experience, he mentioned that "I thought that I was on the street, and I had the chance to walk up to the people", "I forgot the surrounding environment of the lab. Every time I moved forward, I felt the environment being an extension of myself", "I felt like I was located in a street in America".

The feelings described by the participants in all of these different studies demonstrate that humans can feel successfully embodied in an immersive VE or in a surrogate body, either that of an avatar [27, 241] or a robot [242].

Figure 1.17 Uncomfortable body posture of an avatar seen from 1PP.
The experimental scenario. (A) The actual posture of the participant. (B) The posture in the Discomfort position seen from a third person perspective. (C) The posture in the Comfort condition seen from third person perspective. (D) First person perspective view of the male virtual body in the Comfort condition. Note that the head was never visible in the mirror [240]

Figure 1.18 Person-to-person haptic interaction with force feedback in VR.
The remote doctor explores patient's arm mobility. The patient sees a virtual representation of the real doctor, which gives the hand to him (left). The ring task. A virtual ring is passed along a virtual wire without touching it. Whenever the wire is touched, force-feedback is enabled. Camera view is from 1PP(right) [238]

1.9.2 Embodiment components

Embodiment has three main components: the sense of agency, the sense of presence and localization and the sense of body ownership [243].

The first embodiment component is the sense of agency. The sense of agency is the feeling of authorship that we experience when initiating and controlling an action and distinguishes our own self-generated actions from those actions generated by others [243]. Agency requires the intention to carry out the action, and subsequently a match between its predicted and actual sensory consequence [35, 243]. The sense of agency has two aspects: the feeling of agency and the judgement of agency. The first aspect, the feeling of agency, occurs at the very early stages of the action. Then, once the feedback has been perceived and processed, the judgment of agency results from the computation of the comparison between the predicted and actual outcomes of the action [243].

The second embodiment component is the sense of presence and localization. Sense of presence is the psychophysiological state which reproduces realistic behaviors and physiological responses as if the participant was experiencing a real-life situation [244].

The third embodiment component is the sense of body ownership and mineness over a static manikin body that substitutes for the real body, which was first shown by Petkova and Ehrsson [245]. It is the feeling that is described in statements such as "This is 'my' hand," and occurs when the visual and tactile information coming from this object spatiotemporally correlates [243]. Evidence suggests that the first person perspective over the virtual body can be a sufficient condition to create the sense of body ownership and presence [246], but that synchronous movement between the real and virtual body can also contribute strongly to the sense of embodiment by inducing a strong sense of agency and control in the virtual reality environment [241, 247, 248].

Is there a way to determine if someone has reached the sense of embodiment in the context of these three components? And to what degree?

1.9.3 Measurement of embodiment

Questionnaires are currently the method most commonly used to assess the different dimensions of embodiment [28, 33]. This method of assessment has the obvious disadvantage of being a subjective evaluation that is dependent on a participant's interpretation of the different questions. Moreover, questionnaires do not enable real-time/in-task recordings of the level of embodiment [28].

Therefore, researchers have combined neurophysiological measurements [34, 35]. Some of these studies used positron emission tomography (PET) or fMRI but these methods are not suitable for everyday monitoring of embodiment in VR experiments because they are not portable and expensive. Leonardis et al. [249] used sensors over the left hand and chest to measure skin conductance, plethysmography, heart rate and respiration rate to measure embodiment over a walking avatar. However, these methods are not very reliable, because they give an indirect measure.

This is why recently, some researchers have started to use electroencephalography (EEG) and near-infrared spectroscopy (NIRS) instead.

1.9.4 Neural signatures of embodiment

Sanchez-Vives and colleagues [250] found that participants retrieved their physical hands when their virtual hand were threatened with a knife, resulting in a brain activation of μ-ERD (8-12 Hz) over the motor cortex and central-parietal areas of the brain, which suggests a potentially new measure of virtual embodiment. Clemente et al. [34] compared EEG presence during observation and control of navigation VE. They found an increase of frontal theta and alpha activity during the perception of presence. In normal circumstances, when our occurring behavior and the predicted sensory results of this behavior (feedback) is consistent, we experience the sensation of agency regarding this behavior or action ("this action is mine"), which usually happens unconsciously [251, 252]. However, when there is a mismatch between the expected results of someone's own behavior and its actual results [253, 254], this person might sense an agency violation through an error detection mechanism. This mechanism of sensory comparison verifies continuously if a final behavior sensory feedback is consistent with this predicted behavior sensory feedback, generated by an internal process of motor commands. These sensory feedback predictions throughout the behavior might depend on previous postures of the body in terms of limb position and movement, which generates the natural sense of being the agent of his own actions for someone [255-257]. Padrao and colleagues [36] investigated the neurophysiological correlates of modified feedback and found a parietal N400 elicited by error monitoring loops after such violation, which typically characterizes semantic or conceptual violations. They also found that the amplitude of the N400 correlated with the subjective feeling of body-ownership. When the same participants merely observed the avatar correct and error movements, no parietal N400 was elicited. This is what Llobera et al. confirmed [258]; that when participants looked at pictures representing themselves or others, the parietal positive ERP component P200 was less in the self-pictures.

Another explanation of this activity is the mirror neurons system that lies in the parietal and pre-motor cortex [259]. Mirror neurons fire when someone acts or observes the same action performed by another [260, 261]. Thus, the neuron "mirrors" the action of the other, as if it was the observer who was performing this action himself. This process aids in comprehending the behaviors of others, and for learning new skills by imitation. Thus, researchers could measure the embodiment of an avatar's hand during the control of BCI. However, is there a way to measure the embodiment of human gait during the control of a BCI?

1.9.5 BCI control, performance and embodiment

In the case of amputees with a neuro-prosthetic limb, the long term and efficient usage of the limb depends on how well the patient accepts the limb as an integrated part of their own body rather than a tool attached to them. This impact can extend on the BCI control and practicality; thus, it becomes very important to measure embodiment online and in real time. But is there any real relationship between the effectiveness of any BCI training using VR and the level of embodiment in the VR?

It was shown, in the case of BCI-control for a moving avatar or robot, that the incitation of embodiment for the user boosts up his involvement in the MI task and enhances his skills in navigation and operation [47, 262]. Hence, controlling a VR using BCI, such as controlling the gait of an immersive self-avatar, is linked to the degree of embodiment [31]. Reaching a high level of both BCI performance and embodiment are inter-connected. To reach one of them, the second must be reached as well, so the more the participant feels ownership, the more effective the results will be [47, 263].

1.10 Summary of literature review

Gait is one of the most important body functions and is divided into many phases and forms. The control of gait in each phase and form is assured by a very complex integration, interaction and harmonization of many internal systems, such as the musculoskeletal system, the nervous system, the visual system and vestibular system.

Unfortunately, millions of people worldwide suffer from gait instability after accidental amputation, neuromuscular disorder, traumatic brain injury, spinal cord injury or stroke. Furthermore, gait rehabilitation techniques face many challenges and limitations. To counter some of these limitations, two recent technologies have been used and later integrated together, to be a part of the rehabilitation program. This has been part of the goals of gait-enhancement or gait-assistance to the impaired user in his rehabilitation process.

The first of these technologies is VR. Due to recent advances in the head-mounted devices and the design of virtual environments, VR now has the power to immerse the user in environments that are: very similar to physical walking, (especially when using avatars), more engaging, adaptable to the user's level of advancement and able to create high levels of embodiment. The second of these technologies is the BCI, which allows for the transfer of the user's intent (when using motor imagery of a movement for example) into an external control command. Due to the recent advances in computer hardware, signal processing and machine learning algorithms, BCIs can use the power of brain control and plasticity, over the brain motor cortex area, to control external devices and software for gait rehabilitation purposes.

Recently, the advantages (and disadvantages) of each technology have been brought together to form what is called BCI-based VR gait rehabilitation systems.

Table 1.1 summarizes the most important studies that used MI-BCIs to control the gait of an avatar.

Table 1.1 Summary of the most important studies that used BCIs to control the gait of an avatar

Group	PP	BCI type	classifier	Training	MI	control	Perf
Wang et al	3PP	Self-paced	LDA	50 min	Forward walking/idling	Forward walking /idling	77 %
Friedman et al.	3PP	Cue-paced	LDA	~ 70 hours	Moving legs	Forward walking	85 %
Nicolelis et al.	1PP	Cue-paced - self-paced	LDA	244 hours	Right/left foot	Right/left steps	82 %
Longo et al.	3PP	Cue-paced	LDA	25 min	Cube manipulation	Navigation	83 %
An et al.	3PP	Self-paced	RLDA	40 min	Right/left hand + foot	SPEED, JUMP, and ROLL	NA
Hazrati et al.	3PP	Cue-paced	RLDA	30 min	Right/left hand + foot	Right/left/ forward navigation	70 %
Cohen et al.	3PP	Self-paced	RLDA	30 min	Right/left hand + foot	Right/left/ forward navigation	75%
Lulu et al	3PP	closed-loop	CLDA	144 min	Left foot	Left steps	85 %

Despite their low performance and lengthy training, these systems allow the user to feel a high level of embodiment in an avatar's body, while controlling this avatar's gait with the power of the his/her brain. Furthermore, it is know that when the embodiment increases, the performance increases too, and vice versa [262]. However, existing methods for measuring the level of embodiment are generally subjective (questionnaires) and only allow for the measure to be obtained after the experiment (or session) is over. Therefore, there is a need to develop an objective on-line measure of the level of embodiment over a walking avatar which would allow strategies to maintain and maximize embodiment throughout the experiment or training session. Previous studies have found correlations between subjective embodiment levels and EEE measures, in upper-limb BCIs. Table 1.2 summarizes the most important studies that have used EEG to measure embodiment (Ul = Upper-limb, MDF =Modified Feedback).

Table 1.2 Summary of the most important studies that used EEG to measure embodiment

Group	PP	System	Control	Finding	Correlation with
Jeunet et al.	1PP	MI-BCI	Ul	parietal μ-ERD	BCI performance
Alimardani et al.	1PP	MI-BCI	Ul	μ-ERD over motor cortex	BCI performance
Sanchez-Vives et al.	1PP	MI-BCI	Ul	Central parietal and motor μ-ERD	feeling of danger
Clemente et al.	1PP	EEG	Ul	frontal theta and alpha ERD	Sense of presence
Padrao et al.	3PP	EEG	Ul (MDF)	parietal N400	subjective feeling of body-ownership
Jeunet et al.	1PP	EEG	Ul (MDF)	Fronto-central and parietal μ-ERD	Sense of agency - Questionnaire

The literature review also revealed that existing MI-BCIs have many limitations. Thus many techniques have been used to overcome those limitations and enhance the results of these BCI systems. Table 1.3 summarizes the most important BCI studies that have implemented some of the proposed enhancement techniques.

Table 1.3 Summary of the most important BCI studies that implemented performance enhancement techniques

Technique	Control	Group	Improvement
Retraining the classifier	MI-BCI for upper-limbs MI-BCI for cursor control MI-BCI for neuroprothesis for upper-limbs	Shenoy et al. Acqualagna et al. Llera et al. Vidaurre et al. Taylor et al. Sanchez et al.	10-15 %
Positive modified feedback	MI-BCI for upper-limbs MI-BCI for cursor control	Alimardani et al. Gonzalez-Franco et al. Barbero et al.	3-10%
Negative modified feedback	MI-BCI for upper-limbs MI-BCI for cursor control	Alimardani et al. Gonzalez-Franco et al. Barbero et al.	-11 – 13%
Generic Classifier	MI-BCI of upper-limbs MI-BCI for cursor control P300 BCI	Fazli et al (45 participants) Arvaneh et al (80 participants) Lotte and Guan (10 participants) Vidaurre et al (11 participants)	10- 25%
Co-adaptive sequential training	MI-BCI of upper-limbs MI-BCI for cursor control MI-BCI for lower-limbs rehabilitation	Alison et al. Wang et al.(2012, 2013) Meng et al. Donati et al.	Few sessions in 1 day to many sessions over many days

To summarize, there is a great need for a gait-enhancement tool, that contributes to the patient's rehabilitation process, and at the same time, saves him from the burden of lengthy physical training. Since the brain is already involved in gait control, a prominent solution might be the use of a technology that would "train the brain", and at the same time uses scenarios that mimics real world's scenarios. This sparked the idea to use BCI-based VR gait rehabilitation systems.

Although those systems show promising results, they still need many improvements to overcome their limitations. This will be discussed in detail in next chapters.

Chapter 2: Problem statement, objectives and hypotheses

2.1 Problem statement

BCI-based VR gait rehabilitation systems have shown promising results, but they still lack many functionalities and have many limitations, diminishing their clinical potential.

First, there are no previous studies that have investigated the objective measure of embodiment during the control of gait of an avatar (through physical movements or imagined movements via BCI). Moreover, existing methods mostly rely on subjective questionnaires which only allows a survey after the user experience. Therefore, there currently is no reliable method to establish whether a participant feels embodied in his self-avatar and perceives the movements of the avatar as being his own.

Hence, there is no way of confirming, at a specific moment (online), to what degree the participant is embodied in the avatar, and thus in the VR rehabilitation training, in order for the system to reinforce the embodiment when needed to maximize the benefits.

Second, from what was covered in the literature review, the vast majority of the BCIs to control an avatar's gait or navigation, the avatar is displayed to the participant from a 3PP, which reduces embodiment and thus, the performance level of controlling the BCI and ultimately the effects of gait rehabilitation as well.

Third, existing gait MI-BCIs mostly work in a single BCI mode or single type of walking. No previous gait rehabilitation BCI allows the users to choose between cue-paced or self-paced control, and between switch and continuous control mode. Each BCI control mode contributes its specific benefits to the rehabilitation process, and the current gait MI-BCIs lack the possibility to enable the user to control BCIs in different modes simultaneously in the same session [39, 59]. This is a very critical limitation, since one of the rehabilitation goals is to let the pathological user be independent in his locomotor tasks, in a gradual, adaptive and progressive sequence of training that is shaped according to the user's performance and progress throughout the training. Thus, the lack of such feature prevents the user, within his same rehabilitation program or same training session, to progress to another type of training that is needed to take him to the next level.

Fourth, previous studies limit patients to only one type of command for walking and do not allow the user to control the BCI with different gait strategies; for example, individual left and right steps without allowing patients to progress using the imagination of walking in normal gait cycles, or the other way around [8]. This is a limitation of such BCIs that makes them not ideal for generalized gait rehabilitation, because they cannot accommodate different rehabilitation programs and patient progression within them.

Fifth, most of the studies presented mapped the MI of upper limb movements in a BCI to control the feedback of navigation or lower limb movements of an avatar. MI of both feet was also used to control the navigation direction of the avatar. These studies didn't use the MI of gait to control the gait of an avatar, or MI of steps to control the steps of an avatar. The fact that the imagined movement is different from the produced movement of the avatar prevents its use in gait rehabilitation. Indeed, such a BCI would not allow the user to benefit from the neural plasticity properties of MI training, which is a crucial part in rehabilitation for restoring or enhancing motor functions. Moreover, performing MI of one movement and receiving visual feedback of another movement, sometimes from a different limb, would not be conducive to the feeling of embodiment over the virtual avatar. This would therefore have a detrimental effect on BCI performance.

Sixth, lower limb MI-BCIs still have limitations in terms of performance and accuracy. The literature review covered the three most widespread BCI enhancement techniques used to overcome these limitations. Each technique has been used separately in different studies, but no previous study has integrated these techniques to combine the accuracy gains they afford. By integrating the different techniques, each of them will play its role in enhancing the performance. This could shorten the training time to control the BCI and increase performance, which would result in more effective, multi-purpose and goal-directed training.

Seventh, these BCIs have limitations in terms of training time in the initial data acquisition stage, which can last for a few weeks. To overcome this limitation, the literature review refers to the solution of using a generic classifier and then adapting to the user's specific patterns. There exist databases of upper-limb MI EEG that have been used to test different machine learning algorithms or even to control BCIs [264]. However, there is no such database or generic classifier that can be used for lower-limb MI-BCIs.

2.2 Objectives

2.2.1 Main objectives

Generally, this thesis aims to develop a generic multi-modal MI-based BCI to control the gait of a highly immersive self-avatar.
The main objectives were threefold, with each objective addressed in a separate study that built upon the previous one. These objectives were:
Objective 1: To develop and investigate the possibility of using an EEG-based objective measure of the feeling of embodiment over a walking self-avatar (study 1).

Objective 2: To develop and validate a multi-modal MI-based BCI for controlling left and right steps as well as forward walking of an immersive virtual self-avatar (study 2). The secondary objective of this study was to investigate the increased performance of the BCI by integrating the three enhancement techniques.

Objective 3: To construct generic classifiers of EEG signals, using a large database of features extracted from the MI of lower limbs that can be used in different studies to reduce training time. These generic classifiers are to be used to control a MI-based BCI for controlling left and right steps as well as forward walking of an immersive virtual self-avatar (study 3).

2.2.2 Specific objectives

Each of the main objectives, addressed in separate studies has a number of different specific objectives. These are:

<u>*Study 1:*</u>

1) Specific objective 1: To identify EEG signatures of the intention of observing, imagining and performing real steps of an immersive VR self-avatar using left/right steps and forward walking.
2) Specific objective 2: To identify the EEG signatures of embodiment by comparing the observing condition with the performing condition, to find any difference between embodiment control and observer.
3) Specific objective 3: To identify the EEG signatures of embodiment by introducing an incongruent feedback.
4) Specific objective 4: To verify if there is a correlation between the EEG signature and subjective questionnaires.

<u>*Study 2:*</u>

1) Specific objective 5: To map the gait MI signals to control the gait of a highly immersive self-avatar with a cue-paced MI-BCI.
2) Specific objective 6: To quantify the effect on BCI accuracy when employing positive modified feedback, co-adaptative training and classifier retraining.
3) Specific objective 7: To verify the performance of a co-adaptive self-paced BCI to control the avatar's gait in different self-paced modes (switch and continuous).
4) Specific objective 8: To quantify changes in brain activity induced by BCI control of the avatar's gait.

<u>*Study 3:*</u>

1) Specific objective 9: To quantify the accuracy of a generic classifier, trained for right/left steps and forward walking from previously acquired data.
2) Specific objective 10: To compare the performance of models with regularization to models with regression.

2.3 Hypotheses

Study 1:

(H1) The differences in EEG signals correlate to subjective questionnaires of embodiment.

(H2) It is possible to distinguish between embodiment and observant control of gait using EEG.

(H3) There are brain activity differences between right and left doing/observing and imagining movement using EEG.

(H4) The observing condition will have lower embodiment levels than the other conditions.

Study 2:

(H5) It is possible to control the gait of an avatar with MI-BCI.

(H6) Participants will perform better in cue-paced rather than in self-paced BCI.

(H7) It will require less training to control the cue-paced BCI with MI of forward navigation.

(H8) Participants will perform better in switch mode than continuous mode.

(H9) Each of the enhancement techniques will increase the performance of the BCI.

Study 3:

(H10) It is feasible to construct generic machine learning models for right/left steps and forward walking that can be used on different participants.

(H11) The models with regularization will have higher performance.

Chapter 3: Materials and methods

3.1 General overview

These next chapters of this thesis present three scientific articles that each present the findings of a separate study. The data contained in these three studies were obtained from two separate experiments involving human participants. There are several similarities between these studies with regards to the material and the collected objective and subjective data.

In study one, participants were standing on a treadmill while viewing the self-avatars, in a virtual corridor, through an HMD. They wore an EEG cap with electrodes to record brain signals. During this experiment, they were asked to imagine, watch or perform steps and forward walking of this avatar, while their EEG signals were recorded. The main goal was to use EEG to measure the feeling of embodiment over a walking self-avatar.

In the second study, participants wore the same equipment (HMD and EEG cap) but they were standing on the floor, rather than on the treadmill. During this experiment, they were asked, in a first training session, to only imagine the steps and forward walking of this avatar. Then, they were asked in the following training sessions to control the gait of this avatar with MI. Study three used EEG data from study one and study two, in order to construct two generic classifiers for lower-limbs BCI.

This chapter presents an overview of the different studies and presents some methodological details that were not included in the submitted manuscripts. . The following chapters will detail each of the studies and their findings.

3.2 Participants

Twenty neurologically healthy naive participants volunteered to take part in each of the two studies. More details are mentioned in the chapters of each study.

3.3 Experimental setup

3.3.1 Experimental setup of study 1

The experimental setup of study 1 is shown in Figure 3.1. In the figure, the top images represent the VR setup, the motion tracker system and the treadmill. Then, the flow in the figure points to the EEG system, the wireless transmitting via Bluetooth, the laptop used to run the study protocol, and the PC that plays the VE.

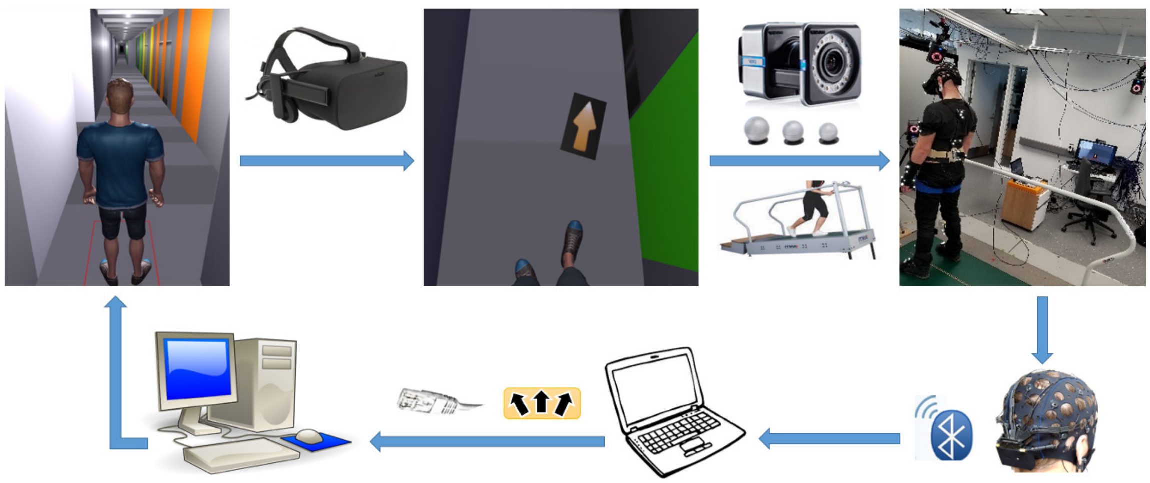


Figure 3.1 Experiment design of study 1
with the flow between different components and equipment

3.3.2 Experimental setup of study 2

The experimental setup is shown in Figure 3.2. In the figure, the top images represent the VR setup. Then, the flow in the figure points to the EEG system, the wireless transmitting via Bluetooth, the laptop used to run the study protocol, and the PC that plays the VE.

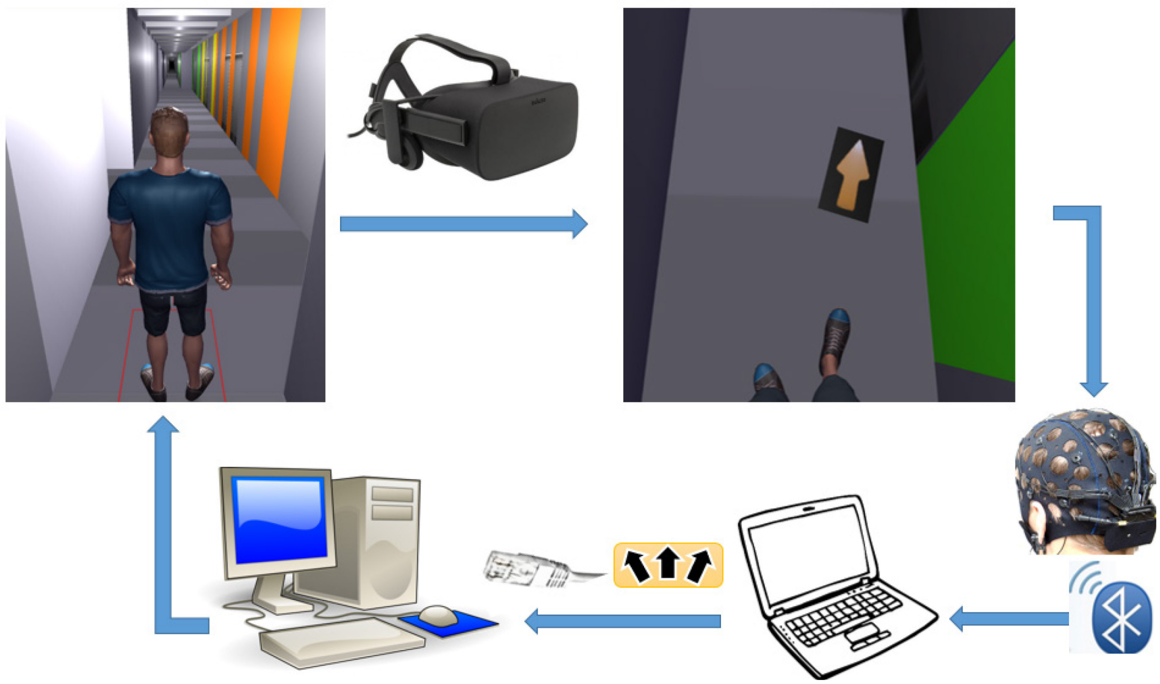


Figure 3.2 Experimental setup of study 2
with the flow between different components and equipment.

3.4 Experimental setup (used in both studies)

3.4.1 VR setup: Oculus Rift 1

An Oculus Rift HMD (consumer version 1) was used in these experiments in order to immerse participants in a VE. The Oculus Rift is a VR headset that consists of a stereoscopic head-mounted display (providing separate images for each eye), head motion tracking sensors and headphones, and it is aimed to provide an immersive virtual reality experience (Figure 3.3). It has a resolution of 1080×1200 per eye, a 90 Hz refresh rate, and a diagonal field of view of 110 degrees. The rotational tracking of the HMD was accomplished using its internal inertial sensors (1000 Hz) and positional tracking was accomplished using the system's stationary IR sensor (study 2) or a Vicon motion capture system (study 1).

Figure 3.3 Oculus Rift HMD and IR positional sensor.

3.4.2 VR environment: 3D corridor and avatar

The VE was developed using the Unity 3D game engine and consisted of an infinite virtual hallway (Figure 3.4), which was a replica of the hallway in our research center. Horizontal lines were added to the floor design in order for forward movement to be more easily perceived while looking at one's feet.

Figure 3.4 The virtual environment used in our studies.

A 3PP view of the virtual avatar standing in the middle of the VE (left); a 1PP view of what the participants saw in the HMD, showing the cue for a step with the right foot (right).

A generic virtual self-avatar was created using MakeHuman and displayed from a 1stperson perspective with respect to the participant. The size of the avatar was set to be proportional to the size of the VE, and the height of the camera was calibrated according to the height of the participant in order to align the visual perspective with the positions of the avatar's eyes. The gait movements were applied to the avatar using a generic human walking animation obtained from Mixamo (Adobe, USA).

The stimuli action cues that were presented in front of the virtual feet consisted of a yellow arrow pointing left, right or straight ahead. When the avatar took a step or started walking, he moved forward in the virtual hallway, thus resulting in a realistic optical flow of the VE. In the cases where the avatar was moving without being physically controlled by the participant, each step of the avatar was coded to be 0.75 m in length, resulting in a speed of 0.7 m/s.

3.4.3 Wireless EEG system: Smart BCI

The EEG was recorded using the Smart BCI system (Figure 3.5), which is a device designed for BCI applications. It consists of a cap with 19 Ag/Cl cup electrodes set according to the 10-20 system and could be fixed to the scalp with conductive gel (SignaGel). The electrode positions were re-configured to accommodate this study, covering the whole scalp with a higher density above the pre-motor, motor and parietal areas, which were the main regions of interest (Figure 3.5). These electrodes were grounded to AFz and referenced to both ears using an ear clip on each ear. The system also consists of a built-in accelerometer (for movements noise compensation), sensor-signals which are digitized with 24-bit resolution and a sampling rate of 250 Hz, a memory card to save EEG data and a PC Bluetooth adapter to receive EEG data wirelessly from the AD-box. The EEG device sends EEG data via Bluetooth to the EEGStudio software, which in turn streams them in real time via API to MATLAB.

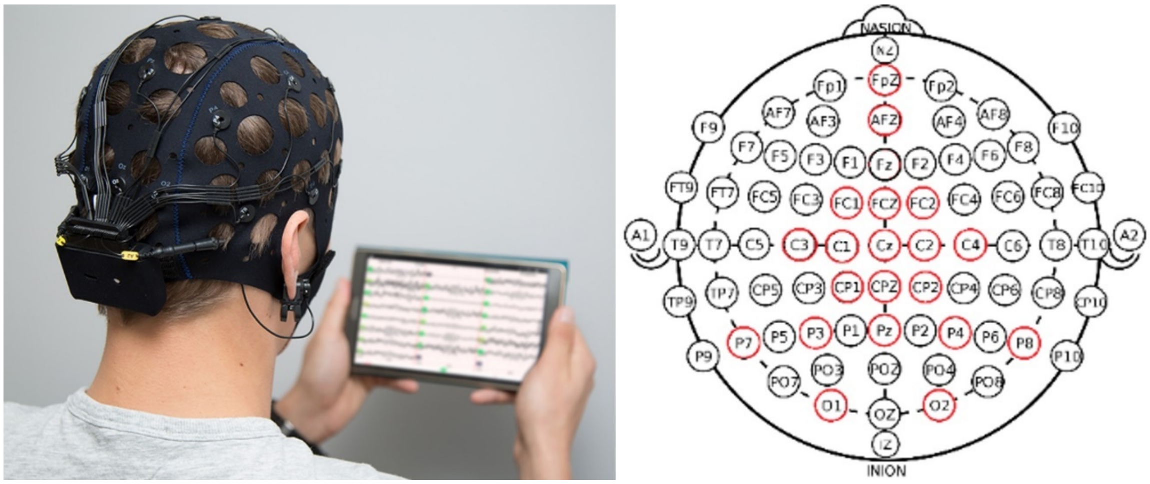


Figure 3.5 The Smart BCI system (left) EEG-electrode configuration used for this project (right).

The electrodes cover the central area (electrodes Cz, C1,C2,C3 and C4), the central frontal area (electrodes FCz, FC1 and FC2), the frontal area (FPz), the central-parietal area (electrodes CPz, CP1, and CP2), the parietal area (Pz, P3, P4, P7 and P8) and the occipital area (O1 and O2)

3.5 Experimental setup (used only in study 1)

3.5.1 Treadmill

Participants walked on an instrumented, self-paced and split-belt treadmill (AMTI). They were asked to take single steps, and then to initiate forward walking. Then the participant's specific output for both commands were used to trigger the treadmill via an API when needed during the experiment. The average speeds that were used were 0.07 km/hr for steps and 0.2 km/hr for forward walking. This treadmill and its particular speeds were used for one single specific purpose: to bring back the participant to the same starting point after making forward movement in every trial, within the trial time window, and in an extremely slow movement that would not be felt by the participant. However, these treadmill specific speeds were sometimes adjusted according to the user's specific gait speed and step length.

3.5.2 Motion capture system

When physically controlling the gait of the immersive virtual reality avatar, participant's movements were transmitted to the avatar in real time via a motion capture system. Motion capture (mocap) is the process of recording the movement of objects or people.

When using this system, the movements of the avatar must have no noticeable delays when compared to the participant's real movements, and this strong visual-motor synchrony between avatar and participant's movements creates a strong feeling of ownership.

For such requirements, we used the Vicon Vantage tracking system. A set of 15 rigid bodies containing reflective motion-capture markers were placed on the participants' segments (Figure 3.6) using Velcro and custom-made attachments. A 12-camera Vicon optoelectronic motion-capture system (sampling rate of 120 Hz), mounted on tripods and wall rails, with Vicon Tracker software, was used to track the participants' movements. Movements were then applied to the virtual avatar in real-time, via TCI-IP protocol. To control for non-body movement made by the attachments, visual attention was carried out on two levels: attention to the markers' positions within Tracker, and to the avatar's projection as well. During a short calibration phase, the participant performed a series of squats, hip circumduction movements and upper limb rotations in order to identify the position of their joint centers so as to align them with those of the virtual avatar's rig (obtained from MakeHuman).

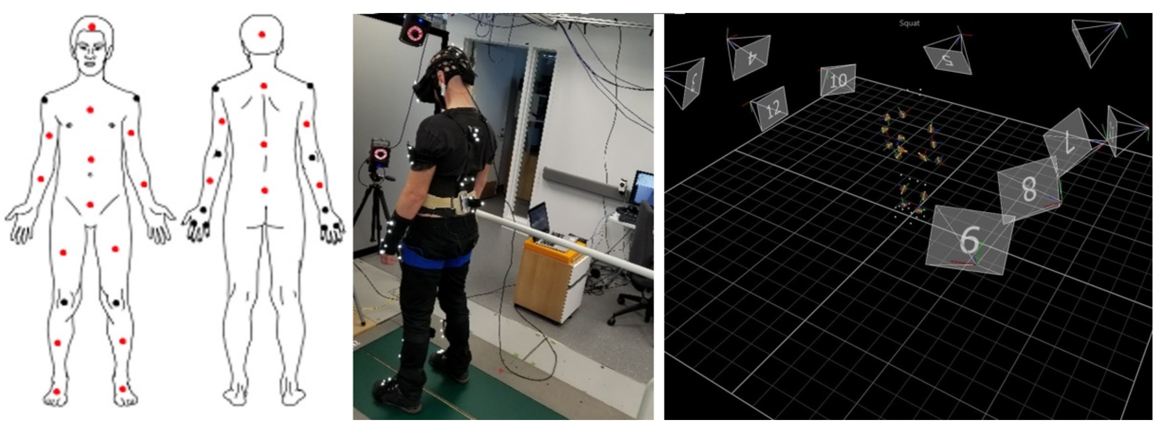


Figure 3.6 Using VICON system in the setup.

The positions of the mocap markers (left), a participant takes a step on the treadmill while wearing the mocap markers, HMD and EEG cap (middle), a screen shot of Tracker showing VICON cameras tracking real-time positions of markers over a participant's body movements (right)

3.6 Software

3.6.1 Online control

In addition to the equipment's built-in software, a MATLAB custom-made script was coded, using some functions from the MATLAB toolbox BCILAB. The script was used to:

1) receive the real-time EEG data stream via an API;
2) run and control the experiment protocol;
3) send triggers directly over TCP-IP to control the synchrony, activation and activation parameters of the treadmill at every trial of the experiment.

A software interface application was used to:

1) send the MATLAB script experiment control parameters and triggers over TCP-IP to the Unity game developed to control avatar movements;
2) receive real-time data from the motion tracker system;
3) send real-time data from the motion tracker system over TCP-IP to the Unity game developed to control the movements of the avatar.

3.6.2 Offline analysis

Two MATLAB toolboxes were used for EEG offline analysis and BCI offline training. These were EEGLAB and BCILAB. These libraries have been used for EEG dataset analysis, as well as the design, prototyping, testing, experimentation and evaluation of BCIs. They provide an interactive graphic user interface (GUI) or command line scripts allowing users to flexibly and interactively process EEG data.

3.7 EEG data pre-processing

Next is a short description of the methods and steps of EEG data offline analysis used for cleaning and pre-processing, after EEG acquisition by the EEG device.

3.7.1 Temporal filters

In the two studies, as in all MI-BCIs, EEG signals were band-pass filtered to the 8-30Hz frequency band, as this band contains both the µ and ß rhythms. This type of filter eliminated many undesired effects such as heart rate signals, or even power-line interference (60 Hz in Quebec). Such a filtering was achieved in this project using an 18th order Butterworth Infinite Impulse Response (IIR) filter [148].

3.7.2 Primary artifacts removal

Primary artifact removal was performed using

1- a semi-automatic method that is explained in the next chapters.

2- Independent Component Analysis (ICA)

ICA was then used to separate the EEG signal into a set of other sub signals [148, 265] like eye blinks and electrocardiogram signals and to isolate and remove electro-ocular components and all forms of noise from the EEG data [266]. An example of ICA is the "cocktail party problem" [267], where a specific speech signal is separated from a large dataset composed of the speech signals of people talking simultaneously in a room [268].

An automatic ICA and noise rejection algorithm (MARA, a plugin of EEGLAB [269]) was used in our studies. This algorithm has trained classifiers that were optimized and trained on expert ratings of large datasets with frequency features, spatial features and temporal features, to identify both artifact components and relevant components.

3.7.3 Secondary artifacts removal

Secondary artifact removal was then performed using common average referencing (CAR), baseline removal and visual inspection. The details of how these algorithms were used in each study will be explained in the chapters of each study.

3.8 EEG data processing

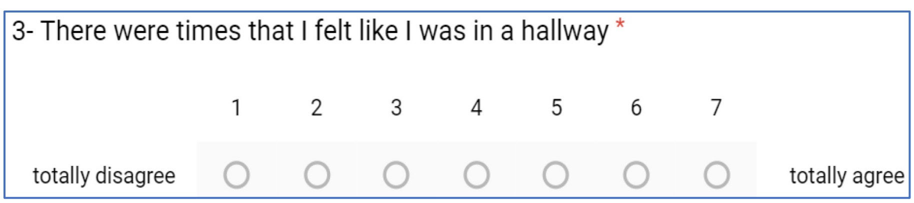
This phase includes data epoching and segmenting, spectral analysis, features extraction, features selection and features classification.

All algorithms used in this phase were explained in chapter 1 of this thesis. The details of how these algorithms were used in each study will be explained in the next chapters.

3.9 Questionnaires

3.9.1 Type of questionnaire

In study 1 and 2, participants were asked to answer a subjective questionnaire, presented to them as a Google form, on a computer. The questionnaire consisted of 18 questions on a 7-point Likert scale (Figure 3.7) with: strongly disagree (1), disagree (2), somewhat disagree (3), neither agree nor disagree (4), somewhat agree (5), agree (6), strongly agree (7).


3- There were times that I felt like I was in a hallway *

1 2 3 4 5 6 7

totally disagree ○ ○ ○ ○ ○ ○ ○ totally agree

Figure 3.7 Sample question from the questionnaire used in both studies

The questions were related to the sense of presence (1-3), body ownership (4-6), sense of agency (7-9) [33, 270], BCI performance (10-12), BCI tasks and design (13-15) and BCI environment feedback (16-18) [203, 271]. The questions used in our questionnaire were adjusted to accommodate the experiment context and environment and were presented to participants in French.

For participants of study 1, they were asked, after each condition, to answer only the first half of the questionnaire, which were embodiment-related questions. Participants of study 2 were asked, after each day of training, to answer the full questionnaire. In general, it took approximately 1-2 minutes to complete the full questionnaire.

The English (original) version of these questions, and the details about the analysis of the scores, are all mentioned in chapter 5 of this thesis.

3.10 Introduction to next chapters

Chapter 4 (EEG Can Be Used to Measure Embodiment When Controlling a Walking Self-Avatar) addresses main objective 1 of this thesis: to develop and investigate the possibility of using an EEG-based objective measure of the feeling of embodiment over a walking self-avatar. This chapter includes a slightly modified version of the article that was published by Alchalabi et al. in the proceedings of the IEEE Conference on Virtual Reality and 3D User Interfaces [272]. The original article is included in Annex 1.

The Institute of Electrical and Electronics Engineers (IEEE) is the world's largest and most important professional organization dedicated to advancing technologies in the domain of engineering [273]. IEEE publishes more than 1,700 leading-edge conference proceedings every year, which are recognized by academia and industry worldwide as the most vital collection of consolidated published papers in electrical engineering, computer science, and related fields. In computer science and engineering, a vast majority of the peer-reviewed publications are in the form of conference proceedings, which have become the primary channel of research communication in these domains [274].

Since 1993, the IEEE Virtual Reality Conference has been the premier international forum for the presentation of research results in the broad field of virtual reality (VR). The acceptance rate for papers and oral presentations in this conference is under 20% year after year. The article in this chapter was accepted for publication and oral presentation at the conference, and was also nominated for best conference paper.

Chapter 5 (Multi-Modal Modified-Feedback Self-Paced BCI To Control The Gait of An Avatar) addresses main objective 2 of this thesis, and its secondary objective: to develop and validate a multi-modal MI-based BCI for controlling left and right steps as well as forward walking of an immersive virtual self-avatar; to investigate the increased performance of the BCI by integrating the three enhancement techniques that were presented in Chapter 1 of this thesis. The chapter presents an article accepted in the Journal of Neural Engineering, which is ranked 23rd out of 324 in the field of neural engineering (according to Scimago Ranking), with an impact factor of 4.8. The original article is included in Annex 2.

Chapter 6 (Generic BCI classifiers for MI of left/right steps and forward walking) addresses main objective 3 of this thesis: to construct generic classifiers of EEG signals, using a large database of features extracted from the MI of lower limbs that can be used in different studies to reduce training time. These generic classifiers are to be used to control a MI-based BCI for controlling left and right steps as well as forward walking of an immersive virtual self-avatar. This chapter includes a slightly modified version of a conference paper that was published in the IEEE BCI 2021: the 9th International Winter Conference on Brain-Computer Interfaces. This Conference has been one of the top international forums for the presentation of research results in the broad field of brain-computer interfaces (BCI) (according to guide2research rankings). The original article is included in Annex 3.

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Chapter 4: EEG Can Be Used to Measure Embodiment When Controlling a Walking Self-Avatar

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4.1 Abstract

It has recently been shown that inducing the ownership illusion and then manipulating the movements of one's self-avatar can lead to compensatory motor control strategies in gait rehabilitation. In order to maximize this effect, there is a need for a method that measures, and monitors embodiment levels of participants immersed in VR to induce and maintain a strong ownership illusion. The objective of this study was to propose a novel approach to measuring embodiment by presenting visual feedback that conflicts with motor control to embodied participants. Twenty healthy participants were recruited. During experimentations, participants wore an EEG cap and motion capture markers, with an avatar displayed in an HMD from a first-person perspective. They were cued to either perform, watch or imagine a single step forward or to initiate walking on the treadmill. For some of the trials, the avatar took a step with the contralateral limb or stopped walking before the participant stopped (modified feedback). Results show that subjective levels of embodiment correlate strongly with the difference in μ-ERS power over the motor and pre-motor cortex between the modified and non-modified feedback trials.

Keywords: Virtual reality, μ-rhythm EEG, event-related-potentials, gait rehabilitation, mirror neuron system.

4.2 Introduction

Virtual reality (VR) -based rehabilitation has seen an important gain in recent years, fueled by the availability of affordable mass-market VR devices and the several advantages such technology offers for patients and researchers [217, 218]. One such advantage is the high level of control that can be exerted on all aspects of a participant's virtual environment (VE). When a participant is immersed in VR through the use of a head-mounted device (HMD), there is the added possibility of controlling his body self-representation in the form of a self-avatar.

There are examples in the literature where imitation of the movements of a simulated avatar or representation of movement by an avatar led to motor improvements [223, 224]. In 2014, Caudron and colleagues [275] showed that a simple avatar that replicates real-time anteroposterior trunk position and orientation of the head of patients with Parkinson's disease improved their postural balance. There are also randomized controlled trial studies that reported that controlling an avatar's gait in VR physically and mentally (through a BCI) could be beneficial for gait rehabilitation [18, 54, 139, 226-231, 263, 276] and for improving balance in chronic stroke patients [230]. Moreover, treadmills combined with VR scenarios have proved to be effective for post-stroke gait rehabilitation [54, 139, 263]. In their study, Rizo et al. [263] showed the advantages of using VR in gait rehabilitation by creating an obstacle avoidance VE system during walking in chronic post-stroke patients.

It has also been shown that in the earlier stage of pathology, motor imagery of the intended movements, combined with virtual feedback, can aid patients to gradually recover from impairment [18, 226]. This technique was then applied for gait rehabilitation in stroke. For example, Kilicarslan and colleagues [276] pioneered the deployment of BCI systems to control lower-body powered robotic exoskeletons by participants with a spinal cord injury. Leeb and colleagues [57] reported on a 35 year old male tetraplegic participant, who learned to control a BCI where signals of imagined foot/right/left movements were used to control walk/turn-left/turn-right. He navigated in a VR scene, in order to move from avatar to avatar by movement imagination of his paralyzed feet. Concerning the experience with the interaction, he mentioned that "I thought that I was on the street, and I had the chance to walk up to the people".

These feelings described by the participant in such studies demonstrate that humans can be successfully embodied in a surrogate body, either of an avatar [27, 241] or a robot [30]. Embodiment is the gradual process of the perceptual illusion that artificial body parts or full bodies can be perceived by people as their own [243]. Embodiment has three main components: body ownership, sense of localization and presence, and sense of agency and control. Agency is the feeling of authorship that we experience when initiating and controlling an action and distinguishes our own self-generated actions from those actions generated by others [243]. Agency requires the intention to carry out the action, and subsequently a match between its predicted and actual sensory consequence [35, 243]. The sense of agency starts with the feeling of agency, which is triggered at the very early stages of the action. Then, once the feedback has been perceived and processed, the judgment of agency results from the computation of the comparison between the predicted and actual outcomes of the action [243]. The second embodiment component is the sense of presence and localization. Sense of presence is the psychophysiological state which reproduces realistic behaviors and physiological responses as if the participant was experiencing a real-life situation [244]. The third embodiment component is the sense of body ownership and mineness over a static manikin body that substitutes for the real body, which was first shown by Petkova and Ehrsson [245]. It is the feeling that is described in statements such as "This is 'my' hand," and occurs when the visual and tactile information coming from this object spatiotemporally correlates [243]. Evidence suggests that first person perspective over the virtual body can be a sufficient condition to create the sense of body ownership and presence [246], but that synchronous movement between the real and virtual body can also contribute strongly to the sense of embodiment by inducing a strong sense of agency and control in the virtual reality environment [241, 248, 277].

However, is there a way to determine if someone has reached the sense of embodiment in the context of its three components? And to what degree? Questionnaires are currently the most used method to assess the different dimensions of embodiment [28, 33]. This method of assessment has the obvious disadvantage of being a subjective evaluation that is dependent on a participant's interpretation of the different questions. Moreover, questionnaires do not enable real-time/in-task recordings of the level of embodiment [28]. Therefore, researchers have combined neurophysiological measurements [34, 35]. Most of these studies used positron emission tomography (PET) or functional magnetic resonance imaging (fMRI) but these methods are not suitable for everyday monitoring of embodiment in VR experiments because they are neither portable nor inexpensive. This is why recently some researchers have started to use electroencephalography (EEG) and near-infrared spectroscopy (NIRS) instead.

For example, Sanchez-Vives and colleagues [250] found that participants pulled back their physical hands when their virtual hands were threatened with a knife, resulting in a brain activation of μ-ERD (8-12 Hz) over the motor cortex and central-parietal areas of the brain, which suggests a potentially new measure of virtual embodiment. Clemente et al. [34] compared presence during observation and control of navigation VE, using EEG. They found an increase of frontal theta and alpha activity during the perception of presence. In normal circumstances, when our ongoing actions and the predicted sensory consequences of these actions (feedback) are coherent, we experience the sensation of agency with respect to our actions ("this action is mine"), and we are typically not even aware of such considerations [251, 252]. However, in the case where there is a conflict between the predicted consequences of our actions and their actual consequences [253, 254], we might detect an agency violation through an error detection mechanism. This mechanism might be constantly checking whether the final sensory feedback is coherent with expected sensory consequences of our actions, created using an internal copy of our motor commands. These sensory feedback estimations during movement may rely strongly on previous representations of the body in terms of limb position, movement, or posture which normally give us a natural sense of being the agents of our actions [255-257]. Padrao and colleagues [36] investigated the neurophysiological correlates of modified feedback and found a parietal N400 elicited by error monitoring loops after such violation, which typically characterizes semantic or conceptual violations. They also found that the amplitude of the N400 correlated with the subjective feeling of body-ownership. When the same participants merely observed the avatar's correct and erroneous movements, no parietal N400 was elicited. This is what [258] confirmed, when participants looked at pictures representing themselves or others, and found that parietal positive ERP component P200 was lesser for self-pictures.

Another explanation of this activity is the mirror neurons system that lies in the parietal and pre-motor cortex [259]. A mirror neuron is a neuron that fires both when someone acts or observes the same action performed by another [260, 261]. Thus, the neuron "mirrors" the behavior of the other, as though the observer were itself acting, which helps in understanding the actions of other people, and for learning new skills by imitation.

However, is there any relationship between the effectiveness of any training using the VR, and the level of embodiment in the VR? Alimardani and colleagues [47] showed in the case of BCI-control for a moving avatar or robot, the arousal of embodiment for the user is assumed to promote his involvement in the motor imagery task and enhance his skills in the navigation and operation. The effectiveness of controlling a VR is linked to the degree of embodiment, so the more the participant feels ownership, the more effective the results are [263]. For instance, in the case of amputees with a neuro-prosthetic limb, the long term and efficient usage of the limb depends on how well the patients accept the limb as an integrated part of their own body rather than a tool attached to them. Thus, there is a need for a way of confirming, at a specific moment (online), to what degree the participant is embodied in the avatar, and thus in the VR rehabilitation training, in order for the system to reinforce the embodiment when needed to maximize the benefits and enhance the BCI performance. The main objective of this study was to propose a novel approach to measure virtual embodiment during gait using EEG.

4.3 Materials and Methods

4.3.1 Participants

Twenty neurologically healthy naive participants (13 women, 7 men; aged 23.3±3.93 years old) volunteered to take part in this study. They were recruited through University electronic message boards and signed a consent form. The inclusion criteria were that participants be 18-35 years old, in good general health, with good vision (with or without glasses), not taking any medication that acted on the central nervous system and not suffer from motion sickness.

4.3.2 Protocol and experiment design

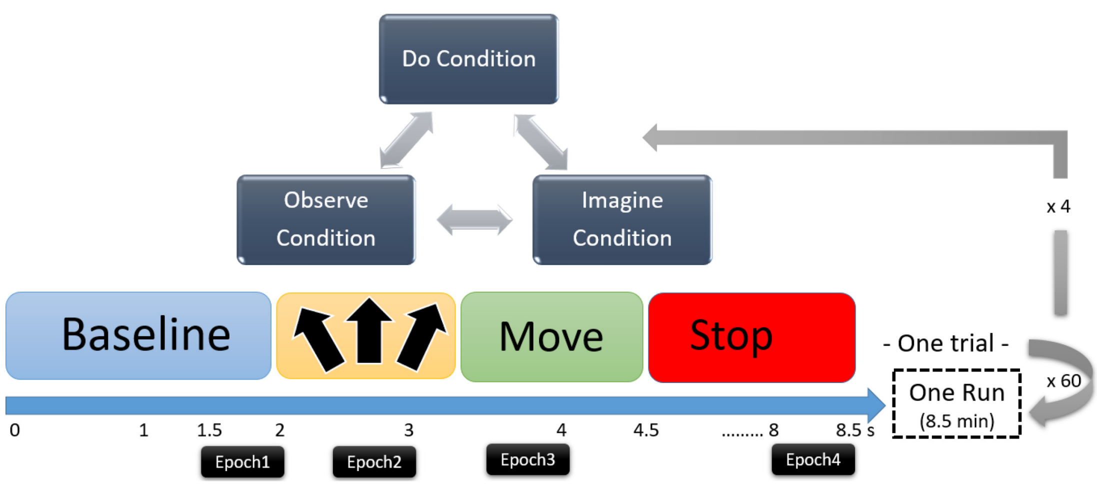

Figure 4.1 Experimental design of the study.

Above are the 3 conditions of the experiment, within each condition there are 4 blocks, and within each block there are 60 trials. In the middle, there is the design of one trial. Below are the epochs (time slots) used in the analysis.

This experimental protocol was inspired from the protocol that was developed by the BCI pioneers, the Graz University Group, who developed the Graz BCI protocol design [278, 279] and illustrated in figure 4.1.

It consisted of 3 randomly-presented conditions where the participants were asked to “do”, “imagine” or “observe” three different tasks while looking at the lower limbs of their self-avatar through a head-mounted display (HMD). The duration was approximately 3 hours, including preparation time and regular breaks. The experiment was approved by the Research Ethics Committees of the University of Montreal Hospital Center (CHUM) and of Ecole de technologie superieure (ETS), project ID number 16.170.

In the “do” condition, brain activity was recorded while the participants were physically controlling the movements of the avatar in real time. The main goal for this condition was to measure embodiment during the physical gait control in an immersive virtual reality environment. In the “imagine” condition, brain activity was recorded while the participants were imagining the avatar moving, without the physically moving. The main goal of this condition was to measure embodiment during motor imagery of moving in an immersive virtual reality environment.

In the “observe” condition 3, brain activity was recorded while the participants were only observing an avatar moving, without physically moving. This condition was to measure embodiment during observing the gait of an avatar, and to rule out the possibility that any brain activity occurring during the “do” or “imagine” conditions was due to mere observation.

The experimental design is shown in Figure 4.1. Each condition consisted of 240 trials. Each trial was 8.5 seconds long and started with a two-second pause in order to acquire a baseline EEG recording. An arrow was then presented on the virtual floor in front of the participant for a period of 1.25 seconds [278, 279]. This arrow either pointed to the left, cueing a step with the left foot; to the right, cueing a step with the right foot; or forward, cueing to start walking. Upon receiving the cue, participants either performed, imagined or observed the appropriate action, depending on the condition they were in. They did this while standing on an instrumented treadmill.

For the first 60 trials of each condition, participants received concurring visual feedback in the form of the avatar performing the cued action (non-modified feedback - NMF). The avatar performed the action in real time for the "do" condition or 1.25 seconds after the cue onset for the "imagine" and "observe" conditions. These first 60 trials were to engage the participant in the experiment and to create the sense of embodiment.

In trials 61 to 240, for one out of every 5 trials, the avatar provided conflicting visual feedback (modified feedback - MF). For these trials, when the cue was for a single step, the avatar took that step with the contralateral limb. When the cue was to start walking, the avatar started walking but stopped walking before the end of the trial, while the participant was still walking or imagining himself walking. This movement violation was implemented to create a mismatch between the intended and resulting movement and measure for an EEG-response to the modified feedback that is dependent on being embodied.

EEG data were only analyzed offline. The feedback provided to the participants was therefore not dependant on their brain activity.

4.3.3 Experimental Setup

Participants were immersed in a VE using an Oculus Rift (Consumer Version 1) HMD. The VE was developed in Unity 3D game engine and consisted of a virtual hallway (figure 4.2), which was a replica of the hallway in our research center, although the virtual hallway was designed to be infinite. Horizontal lines were added to the floor design in order to for forward movement to be more easily perceived while looking at one's feet.

A virtual self-avatar was displayed from a 1st person perspective with respect to the participant. The action cues that were presented in front of the virtual feet consisted of a yellow arrow pointing left, right or straight ahead. When the avatar took a step or started walking, he moved forward in the virtual hallway, thus resulting in a realistic optical flow of the VE.

Figure 4.2 A 3PP view of the virtual avatar standing in the middle of the VE (left image); a 1PP view of what the participants saw in the HMD, showing the cue for a step with the right foot (right image).

For the "do" condition, a set of 15 rigid bodies containing reflective motion-capture markers were placed on the participants' bodies (figure 4.3). A 12-camera Vicon optoelectronic motion-capture system (sampling rate of 120 Hz) with Vicon Tracker software was used to track the participants' movements. During a short calibration phase, the participant performed a series of squats, hip circumduction movements and upper limb rotations in order to identify the position of their joint centers to align them with those of the virtual avatar's rig.

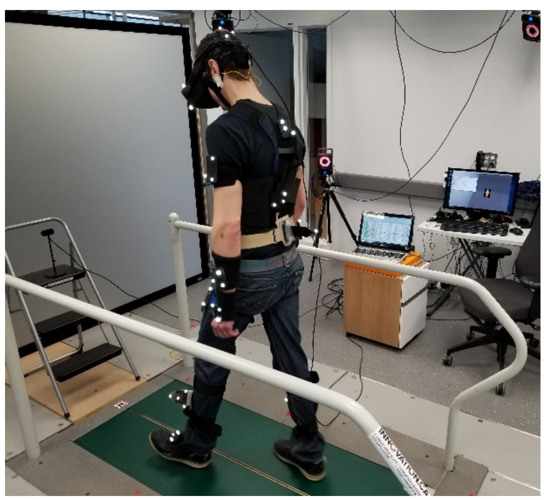

Figure 4.3 The experimental set-up.

A participant takes a step on the treadmill while wearing the mocap markers, HMD and EEG cap

Movements were then applied to the virtual avatar in real-time, via TCI-IP protocol. The movements of the avatar had no noticeable delays when compared to the participant's real movements.

For this condition, participants walked on an instrumented, self-paced and split-belt treadmill (AMTI). They were asked to take single steps, and then to initiate forward walking. Then the participant's specific output for both commands were used to trigger the treadmill via an API when needed during the experiment. The average speeds that were used were 0.07 km/hr for steps and 0.2 km/hr for forward walking. This treadmill and its particular speeds were used for one single specific purpose: to bring back the participant to the same starting point after making forward movement in every trial, within the trial time window, and in an extremely slow movement that would not be felt by the participant. However, these treadmill specific speeds were sometimes adjusted according to the user's specific gait speed and step length.

The EEG was recorded using a Smart BCI system consisting of a cap with 19 Ag/Cl cup electrodes set according to the 10-20 system and fixed to the scalp with conductive gel (SignaGel). These electrodes were grounded to AFz and referenced to both ears using an ear clip on each ear. The electrode positions were configured to accommodate this study (figure 4.4), covering the whole scalp with a higher density above the pre-motor, motor and parietal areas, which were the main regions of interest. The EEG device sends EEG data via Bluetooth to the EEGStudio software, which in turn streams them in real time via API to MATLAB.

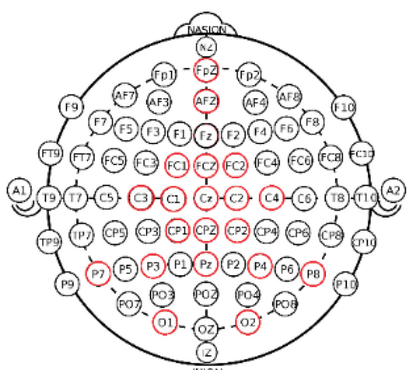

Figure 4.4 The EEG-electrode configuration for the current study.

Red circles indicate the positions of electrodes

4.3.4 EEG data pre-processing

The data were recorded using EEGStudio, pre-processed and processed using MATLAB/EEGLab. EEG signals were band-pass filtered in 4-30Hz, then artefact removal was performed using 4 methods:

1- a semi-automatic method, where epochs containing abnormal values (inferior to -200µV or superior to 200µV) or abnormal trends (maximal slope superior to 200µV with a R-squared limit fixed to 0.3) were rejected;
2- an approach based on blind source separation (BSS) algorithms was used, which includes an automated independent component analysis (ICA) to isolate and remove electro-ocular components from the EEG data [266].
3- With visual inspection, artifacted epochs were also rejected. This was done by a visual identification and recognition of the waveforms and patterns of the remaining artefacts, such as eye movements, eye blinks, cardiac and muscle movement [280].
4- data were then re-referenced using Common average referencing (CAR): This is a common and basic EEG filtering method, where the average of the signal at all EEG electrodes is computed and subtracted from the EEG signal at every electrode for every time point.
5- a baseline removal algorithm was applied, using the 200 ms preceding the cueing (apparition of the arrow) as the baseline.

Data were then epoched into 4 main 500 ms epochs: preceding the cueing, following the cueing, during the movement and after the end of the movement. The rationale behind this epoching was that the feeling of agency is supposed to occur during the trial beginning period while the judgment of agency should occur during the feedback processing period. Finally, each epoch was filtered into 2 bands: alpha band (8-12 Hz) and SMR (12-15 Hz).

4.3.5 EEG data offline analysis

In the above-mentioned epochs and frequency bands, spectral power analyses were performed. Statistical analysis (paired t-test) was then performed in order to determine if the recorded signal power was significantly different over all of the above-mentioned cases. These analyses were also performed using permutation statistics. A permutation test is a type of statistical significance test in which the distribution of the test statistic under the null hypothesis is obtained by calculating all possible values of the test statistic under all possible rearrangements of the observed data points.
In this statistical analysis, the threshold p-value was fixed at 0.05, completed by a false discovery rate (FDR) correction for multiple comparisons.

4.3.6 Questionnaires

After each condition, participants were asked to answer a questionnaire consisting of 9 questions with 7-point Likert scales. These questions were related to the sense of presence (1-3), body ownership (4-6) and sense of agency and control (7-9) [30, 36, 270]. It took approximately one minute to complete the questionnaire. Wilcoxon test was used to perform correlation analysis between the embodiment questionnaire results and the brain activity data.

4.4 Results

4.4.1 Neurophysiological results

Data analysis revealed significant differences between trials with modified and non-modified visual feedback only in μ frequency band. All results presented in this section are therefore within this frequency band. Brain activity related to the left- and right-footed steps was found to be laterally inverted, so the results were mirrored and combined in one plot in order to facilitate the analyses. These results are depicted in figure 4.5.

In the "do" and "imagine" conditions, the spectral power peaks were over the central-motor and central-parietal areas of the brain, with a stronger activation of the central-frontal areas in the walk stimuli in epoch 2 (500 – 1000 ms after the cueing appeared). These brain activations are a representation of a larger event-related synchronisation (ERS - i.e. increase of the signal power compared to baseline) and they may be specific to the higher feeling of agency. These spectral power increases occurred with no significant difference between the “do” and “imagine” conditions ($p=0.2$) but were significantly weaker in the “observe” condition, for both central-parietal ($p=0.04$ and $p=0.001$) and central-frontal areas ($p=0.04$ and $p=0.001$).

For NMF trials of the “do” and “imagine” conditions, the high central-parietal and central ERS seen in epoch 2 remained in epoch 3 (250 – 750 ms after the visual feedback started) on the central-parietal ($p=0.3$) but spanned to left-parietal areas of the brain ($p<0.05$). Moreover, there was no significant difference in central-parietal area between the “do” and “imagine” conditions ($p=0.3$). In the “observe” condition, the analysis of NMF trials did not show the left-parietal ERS component observed during the “do” and “imagine” conditions ($p<0.001$).

In contrast, for MF trials (i.e. in low agency) the “do” and “imagine” conditions show that the high ERS was diminished or disappeared from the central-parietal region ($p<0.001$) and became more central-frontal after a walk stimulus ($p<0.05$) and left-central after the step stimuli ($p<0.001$). Moreover, there was significant difference in the epoch 3 central-parietal ERS between the MF and NMF for the “do” ($p<0.05$) and “imagine” ($p<0.001$) conditions

Pairwise comparisons showed that the central-frontal ERS amplitude was significantly increased for the “do” ($p<0.05$) and “imagine” ($p<0.001$) conditions, when compared to the “observe” condition. No significant differences were found between MF and NMF trials for the “observe” condition.

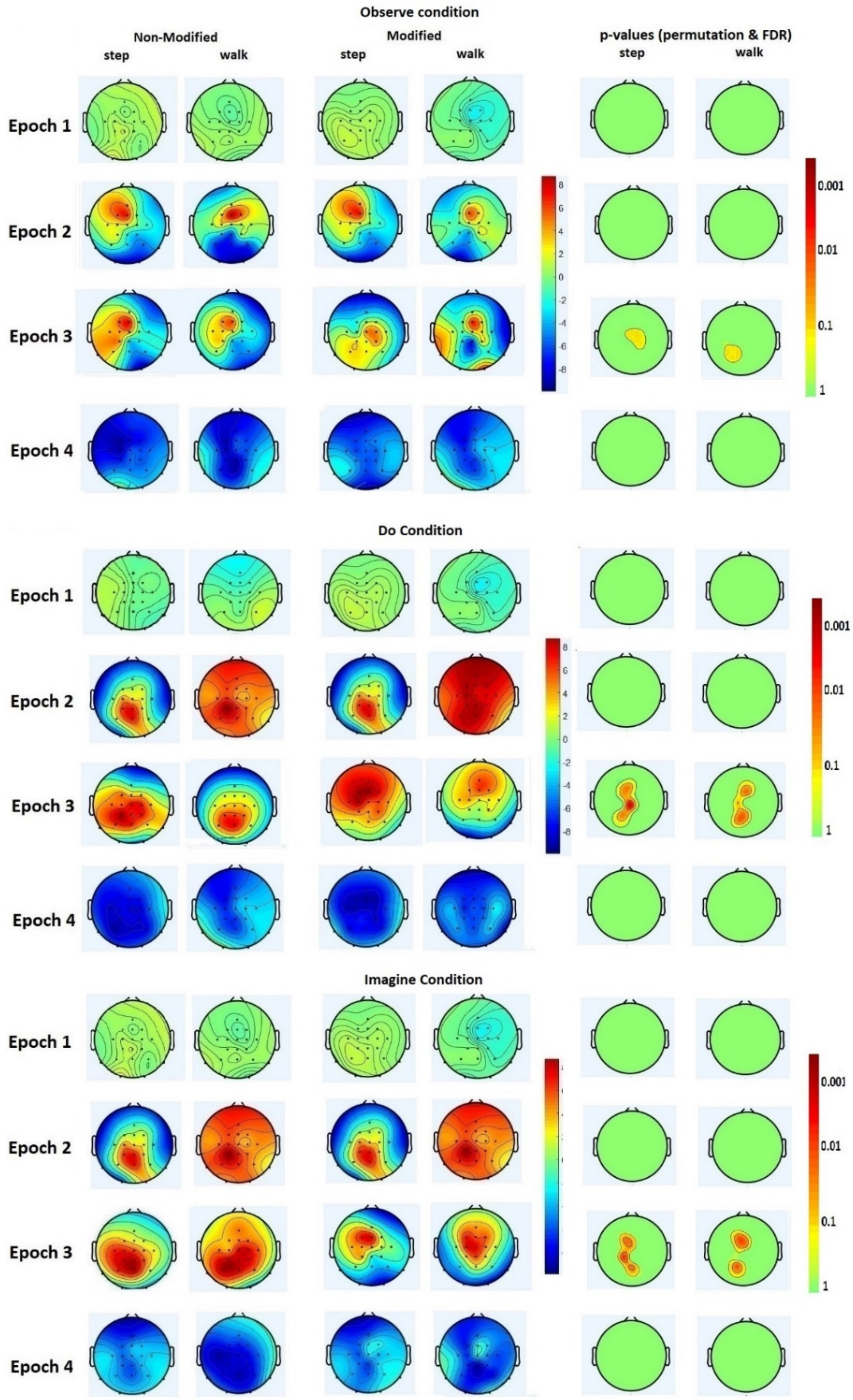

Figure 4.5 Spectral power maps of the μ frequency band (8-12 Hz)

for the different epochs (time slots), conditions and cases. The analysis shows when controlling the avatar's gait, a strong central and parietal ERS in the case of non-modified feedback, versus a stronger frontal ERS in the case of modified feedback.

4.4.2 Behavioral results

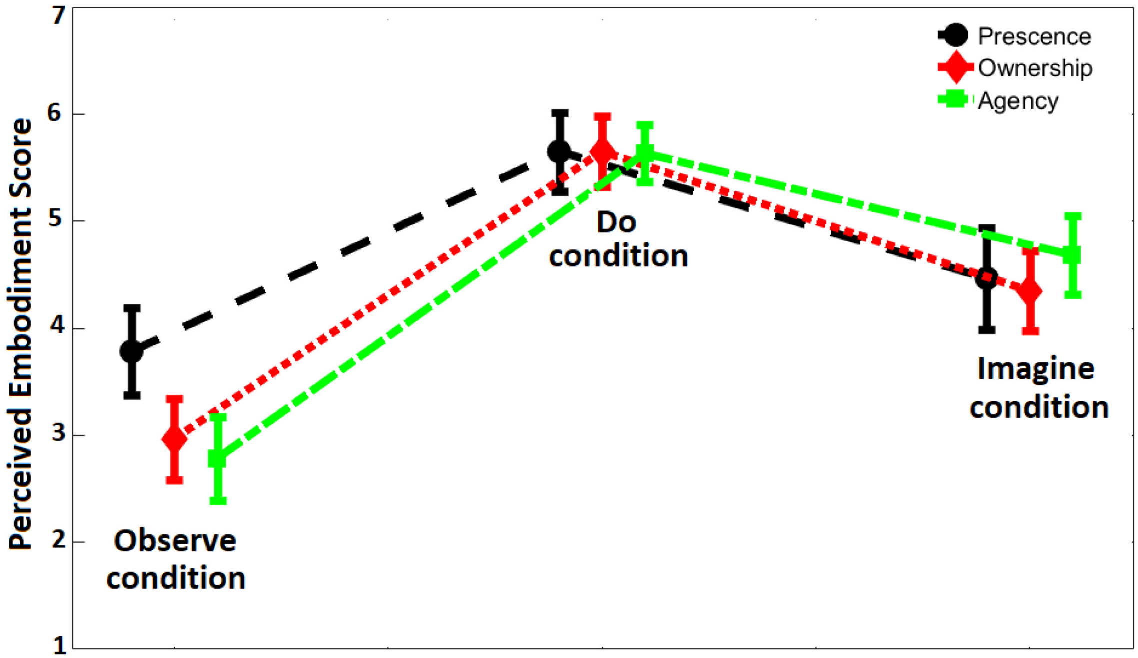

Figure 4.6 Behavioral results based on the questionnaire answers obtained after every block and decomposed into the 3 embodiment components. The score for each component was computed by averaging the three questions related to this component

Overall, these results (figure 4.6) are consistent with our expectations and show that in general, when physically controlling the avatar ("do" condition), the perceived embodiment is higher than when mentally controlling the avatar ("imagine" condition), which is in turn higher than when observing the gait of an avatar.

Within the "do" condition, the three embodiment components had almost the same perceived levels (at ~5.7/7), with no significant differences. This suggests that the modified feedback influenced the embodiment components altogether. However, in "imagine" and "observe" conditions, we can see a relatively higher score of sense of presence, compared to the two other components of embodiment. In the "observe" condition, the score for the sense of presence was significantly higher than the scores for agency ($Z= -2.3532$, $p=0.018$) and ownership ($Z= 1.8716$, $p= 0.06$) but also significantly lower than the presence score for the "do" condition ($Z= -3.8701$, $p<0.001$).

In the “imagine” condition, the sense of agency score was significantly higher than in the “observe” condition ($Z= -4.0860$, $p<0.001$) and significantly lower than in the “do” condition ($Z= 2.8801$, $p=0.004$).

A correlation analysis (Wilcoxon rank sum test correlation) was performed between the embodiment questionnaire results and the brain activity of the central-frontal (electrodes FCz, FC1 and FC2) and parietal areas (electrodes CPz, CP1, CP2, Pz, P3 and P4). This brain activity was represented as the difference in mean amplitude of the ERS between MF and NMF trials, elicited at epoch 3.

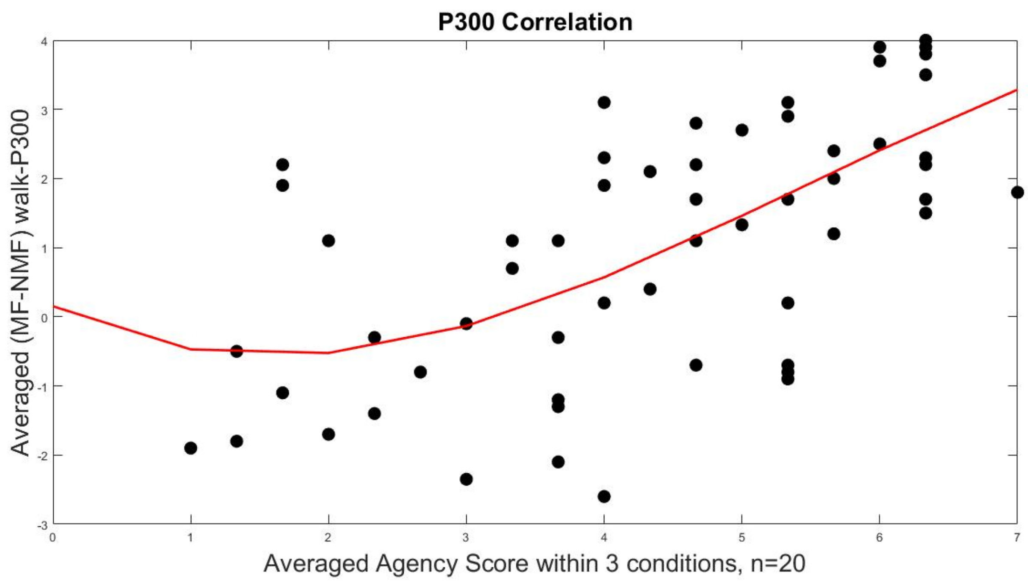

Figure 4.7 A correlation analysis over the subjective strength of agency, and the mean amplitude of the epoch 3 ERS over the 3 different conditions. This amplitude was computed subtracting the steps/walk NMF-ERS from the steps/walk MF-ERS over the parietal and central frontal electrodes

In other words, it is a correlation between the subjective evaluation of embodiment and the mean effect of the MF over the central-frontal and parietal areas. This was done for each of the 3 conditions. Results show a positive correlation between these measures ($r_{step}= 0.69$, $r_{walk}=0.61$). When using only the scores of the sense of agency, the correlation is stronger ($r_{step}= 0.73$, $r_{walk}=0.61$). This result, shown in figure 4.7, suggests that participants who experienced stronger embodiment, elicited stronger ERS modulations in response to agency violations.

4.5 Discussion

This study focused on the possibility of measuring the perceived feeling of embodiment using EEG, when a user controls an avatar that represents his body and mimics his movements, or his imagined movements, in real time. To do so, an experiment investigated the effect of providing modified visual feedback to embodied participants, in the form of a self-avatar whose movements were incongruent with those performed or imagined by the participant (modified feedback).

When delivering modified feedback (low agency), a strong and long central-frontal ERS was found in the "do" and "imagine". This ERS might be due to the judgment of agency, where it might be generated by the error-monitoring cycles and the complex compensatory cognitive control mechanisms that were triggered after the avatar error, where the user intends to stop the motion on reaching the goal position. This activity was found to be much lower in the absence of modified feedback, and this is may be due to the normal activity of the error-monitoring neuronal circuits in the brain area.

The way someone perceives himself as a controller of his own behavior depends on the continuous monitoring of the sensory output of his ongoing actions. When a discrepancy is found between any of these internal predictions and reafferent signals, a disruption of the sense of agency might be triggered. Thus, the output of this comparison process might be generating such frontal-central ERS. This comparison process might be situated as a principal component of the movements monitoring cycles. This pattern of greater MF ERS over the central-frontal areas may be specific to the judgment of agency, where the user intends to stop the motion in order to reach the target position [36]. This is due to the mirror neurons system in the frontal lobe, firing neuronal activity in order to understand and manage this erroneous action of the avatar. Moreover, the ERS over the parietal areas may be due to the role of this part the brain in spatial navigation when the feeling of agency occurs.

These neurophysiological measures revealed the same patterns as the ones described in the literature:

1- A strong central-frontal and central-parietal μ-ERS was revealed in the non-modified feedback epochs (high sense of agency).

2- This parietal μ-ERS was due to role of the angular gyrus in the inferior parietal cortex to the feeling of agency [281] and the comparison processes between predicted and actual consequences of ongoing actions [275, 282].

3- A strong central-frontal and left-frontal μ-ERS was revealed in the modified feedback epochs (low sense of agency).

Remarkably, the step MF-ERS over the left central area was higher than the walk MF-ERS for the "do" and "imagine" conditions. This may be due to the complex compensatory cognitive control mechanisms that were triggered after the avatar moved incongruently with regards to the participant. When physically or mentally controlling the gait of an avatar, the movement violation of the walk (walk MF) was presented by delivering an absence of feedback. However, the movement violation of the steps (steps MF) was presented by delivering an incongruent feedback, and the latter seems to be more power-consuming by the brain than the former. This is aligned with previous findings, that the cognitive return of an anti-saccadic movement is stronger than the cognitive return of a movement inhibition.

In contrast, when observing the gait of an avatar in that immersive virtual reality environment, no central-frontal or parietal μ-ERS changes occurred after delivering modified feedback, but only few parietal and frontal ERS traces were found. This was confirmed by the scores in response to questions such as 'It felt as if I was in a corridor' or 'There were times when, I forgot my presence in the real world, believing that the avatar was me', where we can see a relatively high score of sense of presence and localization,

This may be due to the immersive virtual reality environment, and the avatar that was displayed in 1PP. This result is consistent with previous findings, that watching an avatar's gait in a 3D immersive virtual environment is good enough to create the sense of embodiment. On the other hand, could the modified feedback influence the low scores of the two other components in the watching block? Actually, and as stated above, the modified feedback influences all the embodiment components, thus the high score of the sense of presence rules out the possibility of effect of modified feedback over the watching condition.

In this study, the results show a significant correlation between the amplitude of the frontal-central and parietal ERS component and the subjective feeling of body ownership. The results show that bigger the subjective feeling of body ownership, the stronger the agency disruption occurs, which is represented by ERS amplitude. More importantly, this activity was not found when observing the modified feedback of an avatar's gait. In this condition, the participants' questionnaire scores showed a high feeling of immersivity in the VE, but at the same time they felt significantly less in control. These results supports the idea that the strength of frontal-central ERS can be used to measure the sense of agency over the gait of a virtual avatar when delivering modified feedback.

Overall, the "imagine" condition induced a high level of embodiment toward the self-represented avatar (as measured by body ownership, localization, and agency) [243, 248, 253]. Even though participants did notice that they could not always control the avatar movements, as reflected by the scores in response to questions such as 'The movements of the avatar corresponded to my movements / imagined movement in real time' or 'There were times when I felt that I was walking with my walk and not with someone else's walk', their sense of agency score was higher than in the "observe" condition and lower than the "do" condition.

To summarise, these analyses support the aforementioned hypothesis, which stated that with EEG measures, it is possible to distinguish between embodiment and observant control of gait, with lower embodiment levels of observant than the other conditions. They suggest that when physically or mentally controlling the gait of an avatar, the three embodiment components can be measured by neuro-markers represented by the central-frontal and central-parietal μ-ERS changes after modified feedback, potentially reflecting the sense of presence, the sense of agency with its two c (the feeling and the judgment of agency) and the sense of ownership.

These analyses also support the hypothesis of EEG differences between right and left doing/observing and imagining movement.

4.6 Conclusion

This study showed that it is possible to use EEG to measure the level of embodiment when physically or mentally controlling the gait of an avatar, through the neuro-markers elicited after providing modified feedback of the avatar’s gait. To our knowledge, this is the first study to show an EEG response to incongruent visual feedback of a self-avatar during gait. It is also the first the show a correlation between this EEG response and subjective questionnaires of embodiment of an avatar, in the context of lower limb-movements.

To conclude, our results have important implications for the development of a more objective method of assessing the sense of embodiment, based on physiological data. Most importantly, the approach used in this study could eventually be used for online real-time monitoring of the sense of embodiment. This could ensure embodiment is maintained in order to maximize the benefits of rehabilitation protocols in embodied immersive VR.

Chapter 5: A Multi-Modal Modified-Feedback Self-Paced BCI To Control The Gait of An Avatar

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5.1 Abstract

Brain-computer interfaces (BCI) have been used to control the gait of a virtual self-avatar with a proposed application in the field of gait rehabilitation. Some limitations of existing systems are: 1- some systems use motor imagery (MI) of movements other than gait; 2- most systems allow the user to take single steps or to walk but do not allow both; 3- most function in a single BCI mode (cue-paced or self-paced). The objective of this study was to develop a BCI to control single steps and forward walking of a self-avatar in immersive virtual reality, using MI of these actions, in cue-paced and self-paced modes. Different performance enhancement strategies were implemented to increase BCI performance. Twenty healthy participants participated in this study, which was comprised of 4 sessions across 4 different days. They were cued to imagine a single step forward with their right or left foot, or to imagine walking forward. They were instructed to reach a target by using the MI of multiple steps (self-paced switch control mode) or by maintaining MI of forward walking (continuous control mode). The movement of the avatar was controlled by two calibrated RLDA classifiers that used the μ power spectral density (PSD) over the foot area of the motor cortex feature. The classifiers were retrained after every session. For a subset of the trials, positive modified feedback was presented to half of the participants, where the avatar moved correctly regardless of the classification of the participants' MI. The performance of the BCI was computed on each day, using different control modes. All participants were able to operate the BCI. Their average offline performance, after retraining the classifiers was 86.0±6.1%, showing that the recalibration of the classifiers enhanced the offline performance of the BCI ($p < 0.01$). The average online performance was 85.9±8.4% showing that modified feedback enhanced BCI performance ($p = 0.001$). The average performance was 83% at self-paced switch control and 92% at continuous control mode.

Keywords: Brain-computer interface, Virtual reality, EEG, Classification, Avatar, Gait rehabilitation.

5.2 Introduction

A brain-computer interface (BCI) is a system that measures brain activity of an intention to do something and converts it into a control command that replaces, restores, enhances, supplements or improves natural brain activity output [4, 5]. This control command has been used to control external devices such as robotic and prosthetic devices [6], software [7], the movements of a cursor on a computer screen [8, 9] or even a virtual keyboard [10]. BCI systems appear to be a particularly promising communication channel for individuals suffering from motor impairment [3] or severe paralysis [11], such as those suffering from amyotrophic lateral sclerosis (ALS) [12] or spinal cord injury (SCI) [13]. In these populations, BCIs can be used to control: assistive exoskeletons [13], self-navigation in virtual reality (VR) [14, 15] or the movements of a virtual self-avatar [3, 16, 17]. Such uses of BCI technology have found increasingly widespread applications in the field of neurorehabilitation [18, 19] where it has been used to control the ambulation of a virtual self-avatar in VR in a SCI patient [3] and in post-stroke individuals [20-23]. In this type of BCI, users imagine the movement of a specific limb of their body and this motor imagery (MI) is detected by the BCI and translated into control commands that result in an action in VR or in movements of their avatar [26].

When the movement of the avatar is the same as the movement that was imagined and the feedback is provided with sufficiently short latency, this results in visuomotor synchronicity between the user and his/her avatar [27, 28]. When this occurs, an illusion of embodiment of the virtual body can be induced [27, 29]. Embodiment is the perceptual illusion whereby one perceives a virtual body, in part or in whole, as being their own [30]. The induction of such an illusion is important in MI-BCIs, where reaching a high level of both BCI performance and embodiment are inter-connected. To reach a high level in one, the other must also be reached to a high level [31, 32].

In addition to its role in inducing embodiment, MI of an intended limb movement also induces changes in μ (8-12 Hz) and β (16-30 Hz) rhythms over the corresponding sub-region of the sensorimotor cortex [37]. Previous studies have shown that providing virtual visual feedback corresponding to the MI of intended movements can help patients gradually recover from impairment through neuroplasticity [18, 283, 284].

However, the benefits of using MI of the lower limbs during gait have not been as widely shown as they have been for upper limb movements, partly because of the complexity of the neural control of gait [39]. Walking to reach a goal is considered to be, on some control levels, automatic. Gait can be described as a process of rhythmic and consecutively repeated symmetric movements. These movements are generated by a precise and complex series of neuromuscular interactions that are based on a very complex hierarchical system. This includes several control networks located both at the spinal and supra-spinal levels, making the study and understanding of these signals very difficult [39].

Because of this complexity, several studies have used MI of upper limb movements in a BCI to control the feedback of the navigation or lower limbs of an avatar [40-45] or of an exoskeleton [44]. For example, Hazrati and Hofmann [45] used the signals of MI of right/left hand movements to control the left/right navigation of an avatar. The same BCI with the same classification paradigm and mapping was used in [235], but this time with the additional possibility of self-paced navigation of the avatar.

In similar work, the linear discriminant analysis (LDA) classifier output of MI of the manipulation of a cube was used in a BCI to control the navigation of an avatar in a rehabilitation room [43]. Such methods have been shown to allow a user to control the gait of an avatar but the fact that the imagined movement is different than the produced movement of the avatar prevents its use in gait rehabilitation. Indeed, such a BCI would not allow the user to benefit from the neural plasticity properties of MI training, which is a crucial part in rehabilitation and restoring or enhancing motor functions [23, 46]. Moreover, performing MI of one movement and receiving visual feedback of another movement, sometimes even from a different limb, would not be conducive to the feeling of embodiment over the virtual avatar. This would therefore have a detrimental effect on BCI performance [28, 47].

To overcome this limitation, many studies have focused on the EEG signatures of gait, such as left and right foot discrimination [48, 49], gait initiation and termination in order to move forward and stop [50] and normal gait cycles [51]. They found that brain areas employed by these controls are lateralized (for steps) [48, 52, 53] and centralized (for walking) [50]. However, few studies have used MI of the lower limbs in a BCI system that controls walking feedback [3, 6, 54].

To our knowledge, only two studies have used MI of the lower limbs in a BCI system to control the feedback of taking steps [55]. For example, Donati et al. [55] found that using long-term training of paralyzed patients with a lower-limb MI-BCI to control the left and right steps of a virtual self-avatar, and later of a lower-limb exoskeleton, lead to partial neurological recovery. Such studies show promising results but they limit patients to only one type of command for walking (individual left and right steps) without allowing patients to progress to using imagination of walking in normal gait cycles [3]. This is a limitation of these BCIs since normal gait is not controlled as a succession of left- and right-step motor commands [39].

Another limitation of existing gait MI-BCIs is that they generally function in a single BCI mode. Usually, a user can control BCIs in different modes. In cue-paced BCIs, the user is cued as to when to start producing the MI and the EEG signal has to be analyzed in predefined time windows. In contrast, self-paced BCIs continuously analyze EEG data, allowing the user to produce the specific mental pattern whenever he/she wishes. These self-paced BCIs can be further categorized in two modes. The first uses a brain switch control where the feedback is provided only once after the classification (switch control mode) [57]. The second uses a continuous control [58], where the feedback is provided continuously for as long as the MI is maintained by the user (continuous control mode) [58].

Each BCI control mode contributes its specific benefits to the rehabilitation process, depending on the training program of the rehabilitation process, the current phase within the training program of the rehabilitation process, the level of pathology and the progress of the user within his training program of the rehabilitation process. For example, the switch control mode is most suitable to control initiation of individual steps, which requires an on/off control strategy. But with the progression of the neurorehabilitation process, the continuous control mode becomes essential to be able to control the gait as a succession of left- and right-step motor commands at the same time. Furthermore, the current gait MI-BCIs lack the possibility to enable the user to control BCIs in different modes at the same time [59].

Therefore, when designing a BCI for gait rehabilitation, a proposed way to overcome the aforementioned limitations is to allow the use of MI of left/right steps and of forward walking at the same time, and to map these signals to control the gait of an avatar in different modes (cue-paced, self-paced switch, self-paced continuous). Given the advantages of the different BCI-control modes for neurorehabilitation [60], the concurrent implementation of all of them would allow to accommodate different rehabilitation programs and patient progression within them.

However, the combination of more control options and several modes in a single system would result in diminished performance, which is already low in lower-limb MI-BCIs, in comparison to upper-limb MI-BCIs [59]. This lower performance is particularly problematic for rehabilitation applications because receiving feedback that is incongruent with the imagined movement would diminish embodiment [61] and be detrimental to achieving neural plasticity benefits [23].

To overcome performance limitations, three enhancement techniques have been used in previous studies. The first consists of using a co-adaptive sequential experimental protocol to train users over different control modes. Experimenters gradually increase the task difficulty in order to help the user stay engaged in the learning process, adapt to this process and tune his/her performance [62, 63]. They take into account the performance of the user at every stage of the training, using the method described by Tariq et al. [59]. Using this approach, the brain also adapts to the classifier periodically, thus getting the maximum benefits of the neural changes induced throughout the BCI training phases. For example, Allison et al. [9] successfully trained impaired participants to use a cursor-control BCI using sequential training that was implemented to shape the training gradually from switch control mode to continuous control mode. In two different studies, a tetraplegic participant mastered 3D cursor control after co-adaptive sequential training that lasted 6 days in the first study [182] or 10 sessions in the other study [183]. Scherer et al. [16] trained users over a period of 3 days to control navigation in VR through a MI-BCI.

The second enhancement technique is the use of modified feedback. Feedback that is either positively or negatively modified has been shown to result in an adaptation on the part of participants, with performance enhanced up to 10% [64]. Luu et al. [200] used a BCI that decoded the EEG of left ankle joint angles while the participant was walking on a treadmill. Their BCI was used to control the gait of a virtual avatar. After an initial training period, asymmetric gait patterns of the avatar were introduced over 8 days, resulting in neural and gait adaptation in participants. Similarly, Gonzalez-Franco et al. provided participants with feedback of their BCI performance, that was negatively and positively modified. They reported that positive feedback had a greater learning effect on MI-BCIs [201]. Alimardani et al. [202] developed a cue-based BCI to control human-like robotic hands in 1PP VR. Participants were provided with modified positive and negative feedback in up to 90% of the session trials. The results revealed that positive modified feedback improved performance and the ownership illusion. This is also consistent with the results of Lotte et al. [203].

The third enhancement technique is used when we have a BCI training of multiple sessions, in order to retrain the classifier after every session [185, 186]. This technique reduces the problem of the long calibration time that is required for BCIs, due to the large amount of calibration data that is required. For example, Sun and Zhang [187] trained users to control a cue-based BCI over 3 sessions, and adaptively updated the classifier based on new data from each session. The classification results of their adaptive classifiers were significantly better than the classification results of the classifiers without retraining. With the adaptive classifiers, the classification results were improved by an average of 10% between session 1 and session 3, versus a 2% improvement when using non-retrained classifiers. Shenoy et al. [188] and Acqualagna et al. [189] explored several methods of re-biasing and retraining classifiers in real-time after every trial. Llera et al. [190] applied similar algorithms to multi-class/task BCIs. In all of these studies, retraining led to significant improvements in BCI performance, as high as 12%.

The main objective of this study was to design and evaluate a BCI for gait rehabilitation that integrates MI of left/right steps and forward walking at the same time, mapping these MI signals to control the gait of an avatar in immersive VR. This BCI had to allow control in cue-based mode and in the different self-paced modes (switch and continuous). We hypothesized that participants would be able to operate this BCI in all modes, with a better performance in cue-paced mode than in self-paced mode. We further hypothesized that performance in switch control mode would be higher than in continuous control mode. The secondary objective of this study was to investigate the increased performance of the BCI by integrating the three aforementioned performance enhancement techniques. We hypothesized that each of these techniques would contribute to increasing the overall performance of the BCI.

5.3 Materials and methods

5.3.1 Experimental design

Twenty participants participated in this experiment (12 women, 8 men; aged 26.7±6.1 years old). They were recruited through our lab's newsletter emails. Participants were only recruited if they were 18-45 years old, in good general health, not taking any medication that acted on the central nervous system, with good vision (with or without glasses), and not suffering from motion sickness. This was verified by the verbal confirmation of the participants, and by signing the consent form. The experiments were approved by the Research Ethics Committees of the University of Montreal Hospital Center (CHUM) and of École de technologie supérieure (ETS), project ID number 16.170.

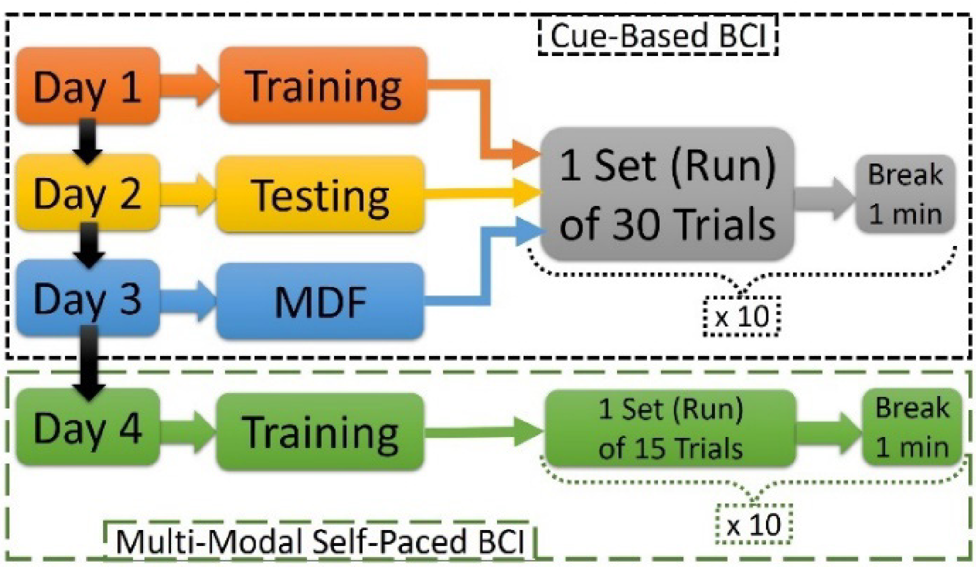

Figure 5.1 Experimental design of the study over the 4 days of training

This study was conducted over 4 consecutive days, in a co-adaptive sequential training setting, in order to control a BCI in a self-paced paradigm (Figure 5.1). During the experiment, participants were instructed to wear a head-mounted display (HMD) and to always focus on the lower limbs of their self-avatar displayed to them in this device. Meanwhile, they were instructed to “imagine” three different types of movements. The experiment lasted approximately 1.5 hours per day, including equipment set-up time and regular breaks.

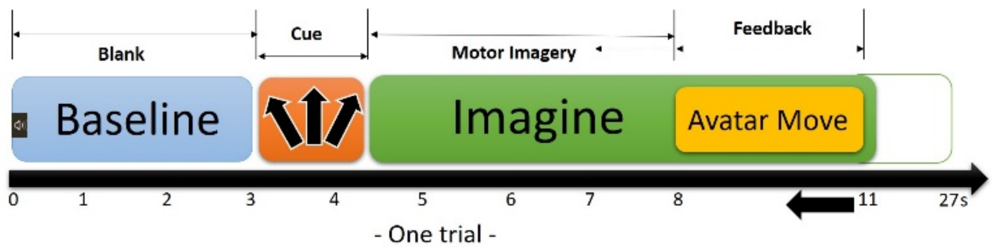

Figure 5.2 Experimental design of one trial
showing the total one-trial duration of 11 seconds for trials on days 1 to 3, and the total one-trial duration of 27 seconds for trials on day 4

Training on days 1 through 3 included 10 runs, with 30 trials each, for a total of 300 trials. The training on day 4 included 10 runs of 15 trials, for a total of 150 (Figure 5.2). Each trial lasted approximatively 11 seconds and started with an auditory cue (a beep) to indicate the beginning of a trial. It was followed by a baseline EEG acquisition that lasted three-seconds. Then, and for a period of 1.25 seconds, the participant was able to see, 152 cm in front of his feet, a yellow arrow over the virtual floor. This arrow was used to cue the three different types of movements the participant had to imagine during the experiment. Thus, if the arrow was pointing to the left, the participant had to imagine a step with the left foot. If the arrow was pointing to the right, the participant had to imagine a step with the right foot, and if the arrow was pointing forward, the participant had to imagine walking forward. The participant would then receive feedback in the form of an action from their self-avatar (Figure 5.2).

5.3.2 Experimental setup

Figure 5.3 The VE that was used in this study.
The left image shows the virtual avatar displayed from a 3PP; the right image shows the avatar displayed to the participant from 1PP in their HMD. It also shows the arrow cue for a right step

An Oculus Rift HMD was used in this experiment in order to immerse the participant in a VE. This VE, developed in Unity 3D, was an infinite virtual corridor (Figure 5.3) that mimicked the hallway in our research center. To perceive forward movements within this corridor, horizontal lines were added to the floor design. A generic virtual self-avatar was created using MakeHuman and displayed from a 1st person perspective with respect to the participant. The size of the avatar was set to be proportional to the size of the VE, and the height of the camera was calibrated according to the height of the participant in order to align the visual perspective with the positions of the avatar's eyes. The gait kinematic segments were applied to the avatar using a generic human walking animation obtained from Mixamo.

When the avatar initiated a forward step or forward walking within the virtual corridor, a realistic optical flow of the VE occurred.

EEG recording was done with a Smart BCI system (Mitsar, Russia). This system consisted of an EEG cap with 19 Ag/Cl cup electrodes. The electrode positions were set to cover the main regions of interest (Figure 5.4) in this study. Thus, most of the electrodes were sitting over the pre-motor, motor and parietal areas. The EEG electrodes were placed as stated by the 10-20 system and applied to the head with conductive gel. AFz was used as ground, and an ear clip on each ear was used for reference. Since the HMD was positioned right over the EEG cap, special care had to be taken when installing it in order not to displace the electrodes.

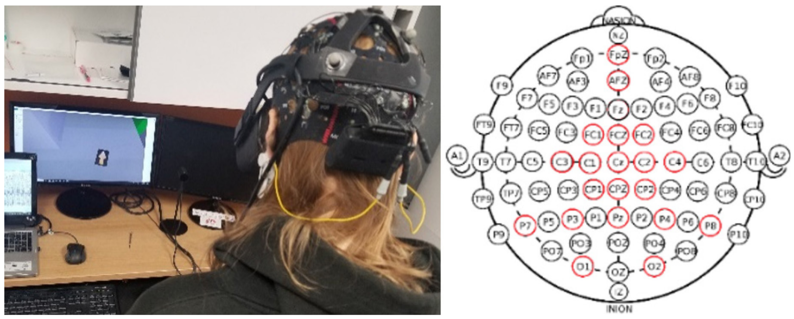

Figure 5.4 The BCI setup:

The image on the left shows when a participant controls the BCI by imagining a right step while wearing the HMD and EEG cap. The image on the right shows EEG-electrode placement design for this study. The positions of the electrodes are indicated by red circles.

When controlling the avatar via the EEG-based BCI, Smart BCI sent raw EEG to EEGStudio software via Bluetooth, which in turn streamed them in real-time via an API to MATLAB. These signals were analyzed online, then control signals were formed. The TCI-IP protocol was then used to send these control commands in real-time to the virtual avatar.

5.3.3 Study protocol

5.3.3.1 Cue-paced BCI design

On day 1, EEG was acquired during the cued foot MI performed by the participants, without physically moving. The avatar performed the cued movements after the cue disappeared, but they were independent of the recorded brain activity. The main goal for this part was to acquire the signals related to the motor imagery of the participants and train two classifiers. At the end of this day, signals were analyzed, and the two classifiers were trained: a classifier with two possible classes, walking forward or no movement (Cl1), and another classifier with three possible classes, right step, left step or no movement (Cl2).

On day 2, the previously trained classifiers were used in the same paradigm as day 1, but this time the avatar performed the movement according to the classification of the brain activity signal. The classifier output was updated every 200 ms. In order to change from the no-movement to the movement state, and to prevent rapid changes, the participant had to accumulate more than a "selection time" with the correct movement selected [58, 285]. The selection time is the number of successive correct classifier outputs resulting from motor imagery of a movement. The selection time was set to three consecutive outputs, i.e. 600 ms.

If the motor imagery was held for less than this selection time, the state remained in no-movement. Similarly, if the motor imagery output classification was for the incorrect class, the state remained in no-movement.

5.3.3.2 Modified feedback cue-paced BCI design

On day 3, in order to enhance the BCI performance, two techniques were used: 1- the two classifiers were updated and retrained using the data from both day 1 and day 2; 2- modified feedback was provided.

The same paradigm as days 1 and 2 was used but 10 participants were provided with modified feedback (MDF) of their performance, whereas 10 participants were provided with their real performance (regular feedback, RGF). Participants were randomly assigned to one of the two groups and were not informed of the possibility of altered feedback. In the MDF condition, the participants first performed two runs where the feedback of the BCI (the avatar's movements) was congruent with the classification of the participant's brain activity. This was followed by six runs of positive modified feedback, wherein the feedback of the BCI was set to reflect the cued movement, regardless of the participant's brain activity, in 70% of the trials. In the remaining trials of runs 3 to 8 and in all trials of runs 9 and 10, the feedback of the BCI reflected the classification of brain activity.

5.3.3.3 Multi-modal self-paced BCI design

The main goal of day 4 was to control a self-paced BCI in two randomly presented modalities: continuous and switch modes. Before this session, the two classifiers were updated and retrained again using the data from days 1, 2 and 3. Participants completed 10 sets of 15 trials and were presented with one of the three action cues, in randomized order.

They were informed that when they received a forward walking cue, their avatar would move forward as long as they maintained the imagination of this movement (continuous mode). When they received right and left step cues, their avatar would take a single step forward after each correct motor imagery task (switch mode).

There were 3 requirements that had to be met for a trial to be considered successful. First, the participant's avatar had to reach a target arrow by either sustaining motor imagery of walking forward or by imaging multiple successive steps (starting with a left or right step, depending on the received cue). The second requirement was for the target arrow to be reached within a time frame of 24 seconds. In the continuous control mode, it took 12 seconds of sustained motor imagery to reach the arrow, starting from the time the avatar began moving. In the switch mode, six steps were necessary to complete the whole trajectory. The third requirement was for the participant to initiate movement within 5 seconds of the presentation of the cue and to continue forward progression for more than 5 seconds. In other words, if the classifier was classifying no-movement for 5 consecutive seconds, that trial was ended, and the next trial started.

For forward walking trials, the participants were instructed to maintain the imagination of forward walking as long as possible or until the avatar had reached the arrow. If the participant stopped maintaining the imagination at any time during the trial, the movement of the avatar stopped. The system allowed the participant to restart the same movement if he again produced the correct imagination signals, as long he/she was within the 5- and 24-second time frames.

For switch mode trials, the participants were instructed that they were free to control the avatar the way they wanted but that the best strategy was to alternate between left and right steps. So, for example, if they received a right cue, the best strategy to move was to imagine a right step (according to the cue) then a left step, then a right one, and so on until they reached the arrow.

5.3.4 Data acquisition and analysis

5.3.4.1 EEG data pre-processing

The EEG was processed using MATLAB/EEGLAB. The signals were amplified, band-pass filtered (18th order butterworth IIR filter) between 8 and 30 Hz and sampled at 256 Hz. Artifacts and noise were auto-rejected using an automatic ICA and noise rejection algorithm (MARA, a plugin of EEGLAB [269]) and the signals were then detrended, where an automatic baseline removal algorithm was applied. The referenced baseline that was used was the 200 ms segment preceding the apparition of the arrow.

5.3.4.2 EEG data processing and feature extraction

When using MI of the feet, it is very important to select the most informative features that could be used to determine the specific brain areas and activity that differentiate idling, right steps, left steps and forward navigation. In this study, power spectral density (PSD) of every channel, and 5 PSD asymmetrical ratios (1-sec hanning) were chosen for the feature sets. From the data of day 1, these features were segmented between 4 to 8 seconds using 200ms epochs with no overlap, resulting in 20 different epochs. This was done in order to identify the optimum time slot (and thus feature points) where the imagery signal achieved the best classification accuracy [39]. Data were also segmented over the 8-30 Hz frequency range using 3 Hz bins with 2 Hz overlap, in order to investigate the optimum frequency range where the MI signal performed the best classification performance [39]. This resulted in a total of 10 frequency bins and, thus, in 200 feature sets. The PSDs in each specific segment and frequency range were all concatenated together to form the feature set.

5.3.4.3 EEG data processing and feature selection

The number of features was too high compared to the number of samples. This can cause the existence of noisy features in the feature set and longer processing time, and thus less BCI efficiency. The Wilcoxon test was used to select the most useful features, and then cross-correlation was applied to take out features that were highly correlated. The result of this processing stage was a smaller dataset with a further distinguished set of features for better classification.

5.3.4.4 EEG data processing and spectral maps analysis

Spectral power analyses were performed over only the segments and frequency bands that yielded the best classification accuracy. To verify the significant difference of EEG spectra over pair-wise comparisons, the two-sample unpaired t-test was performed. Permutation statistics was used as well, and the p-value threshold was set to be 0.05. Then, for multiple comparisons, a false discovery rate (FDR) was applied.

5.3.4.5 EEG data processing and feature classification

The selected features were fed into 2 regularized linear discriminate analysis (RLDA) classifiers where a 10-fold cross-validation was used. Classifier 1 (Cl1) was trained to distinguish between forward walking and no movement. Classifier 2 (Cl2) was trained to distinguish right step, left step and no movement. On day 4, the two classifiers were employed together. The brain signal was first classified by Cl1. If it was classified as no movement, the signal was then classified by Cl2.

RLDA is a classification method that has been used in many motor imagery BCI studies [176]. Since RLDA is a regularization technique, it is particularly useful when there is a large set of features. The regularization amount hyperparameter λ is used to enhance the model by omitting predictors without decreasing the predictive power of the model. Thus, the regularization improves the classification performance by:

1) stabilizing the variance,
2) reducing the bias of the discriminant function,
3) providing generalization,
4) preventing overfit,
5) providing high robustness with respect to outliers, and
6) decreasing calculation time compared to other classification methods [179].

The regularization amount hyperparameter λ was optimized by incrementing λ by 0.1 over the range of [0, 1.0] in a random search. It was validated by using cross-validation. The 2 RLDA classifiers were trained using the optimal λ.

5.3.5 Questionnaires

After each day of training, participants were asked to answer a questionnaire on a computer. The questionnaire consisted of 18 questions on a 7-point Likert scale with: strongly disagree (1), disagree (2), somewhat disagree (3), neither agree nor disagree (4), somewhat agree (5), agree (6), strongly agree (7). The questions were an evaluation of the sense of presence (1-3), body ownership (4-6), sense of agency (7-9) [33, 270], BCI performance (10-12), BCI tasks and design (13-15) and BCI environment feedback (16-18) [33]. Participants were able to complete the questionnaire in one minute. Each embodiment component was rated with 3 questions, and each of the aspects of the BCI system was also rated with 3 questions. The score for each component was calculated as the average of the three questions [28]. A stronger sensation for an aspect/component would be indicated by a high average component score.

The questions were:

Presence

1. I had the feeling that the projection of the avatar was of my body
2. I felt like I was in a hallway
3. I forgot my presence in the real world, believing that I was in the virtual corridor, and that the avatar was me

Ownership

4. I felt like the virtual leg was my own leg
5. I felt like the avatar was me and not just a picture
6. When the virtual leg was moved, I felt that my own leg was moving, as if I was walking

Agency

7. The movements of the avatar corresponded to my thoughts/movements

8. The movements of the avatar were caused by my thoughts/movements
9. I felt that I was walking with my step and not with someone else's step

<u>BCI Performance</u>

10. My performance in controlling the walk of the avatar was mostly good
11. I felt disappointed with the avatar following my orders
12. I felt confident with the imaginative strategy of my feet

<u>BCI Tasks</u>

13. Controlling the movement of the left foot was easy
14. Controlling the movement of the right foot was easy
15. Controlling the forward walking movement was easy

<u>BCI Feedback</u>

16. I was comfortable with the starting arrows
17. I was comfortable with the avatar during the control of his walk
18. I was comfortable with the virtual corridor during control of the avatar's walk

5.3.6 BCI performance analysis

The performance of the cue-paced BCI (days 2 and 3) was evaluated by the number of correctly classified trials. The performance of the self-paced BCI (day 4) was evaluated using the following parameters:

1. BCI performance accuracy: for each trial, if the participant met all 3 requirements, it was considered successful.

2. Trajectory completion time: the average time it took to complete the trial.

3. Average Number of stops: during forward walking, the number of times a participant stopped before reaching the target.

4. Average Stop times: between steps, the mean time elapsed between each step, in switch mode.

5. Steps alternation performance: the number of times a participant was able to alternate between left and right steps, in switch mode.

6. Maximum walk-maintain time: maximum control time, the longest amount of time the participant was able to maintain the motor imagery of forward walking, without any stops or interruptions.

All parameters were averaged over the last two runs.

5.3.7 Statistical Analysis

The Shapiro-Wilk test was performed to verify normality of all the collected data.

For all statistical analysis over multiple days, or over more than two groups in the same condition (online and offline classifier performance with different retraining; subjective questionnaires) the Shapiro-Wilk test revealed that the normality assumption was not rejected. Thus, two-way repeated measures ANOVAs were used. Pairwise comparisons were performed using the Tukey HSD post-hoc test.

For statistical analysis between two groups, the Wilcoxon rank sum test was performed when the normality assumption was rejected for at least one of the two groups (this was the case for the success rate and the performance parameters of the self-paced BCI). When the normality assumption was not rejected (this was the case for spectral power comparisons), parametric unpaired t-tests were used.

In all cases, the threshold significance level was set to 0.05. Statistical significance is indicated in the figures by: * when $p < 0.05$, ** when $p < 0.01$ and *** when $p < 0.001$.

5.4 Results

For all results presented, the classification was performed over the features that yielded the best classification results. For frequency bands, these were sensorimotor rhythms (SMR) (12-15 Hz) for 2 participants and upper μ (10-13 Hz) for the other participants. For the segments, these were the 5th epoch for 3 participants, and the 3rd epoch for the rest of the participants.

5.4.1 Retraining of the classifiers – Cue-paced BCI

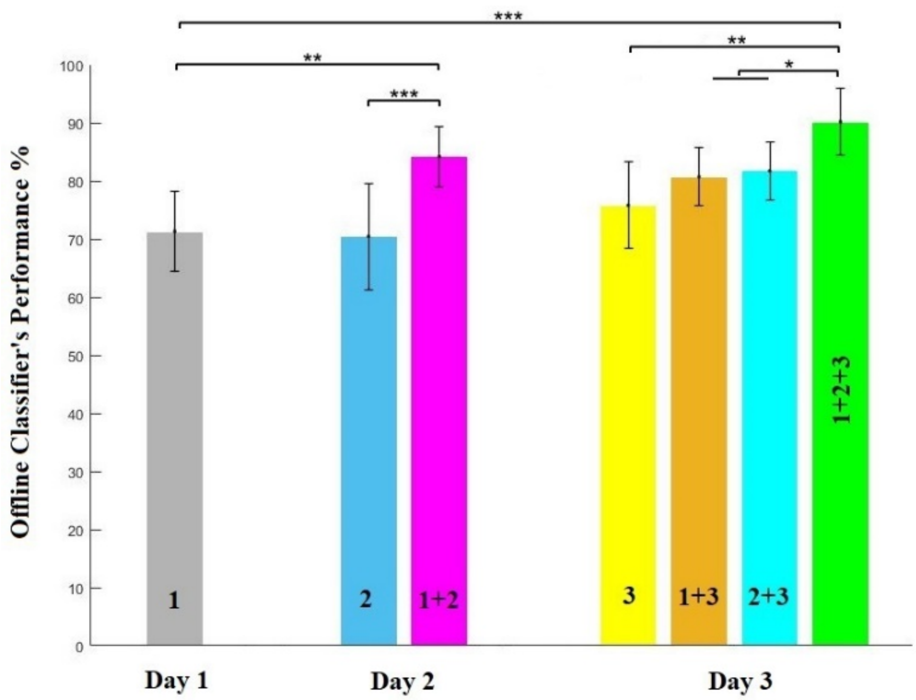

Figure 5.5 Offline Classification results averaged over the 2 classifiers for the first 3 days of training. It shows the mean offline classifiers accuracy on each day, when trained using data from that day only and when trained using data from different combinations of days (the numbers on the columns indicate which days were used for training classification results averaged over the 2 classifiers, for the first days of training

The first technique implemented to enhance the BCI results was to retrain the classifier after every session. The results (Figure 5.5) show a mean classification accuracy of 71% on day 1 that is increased to a mean classification accuracy of 90% on day 3, when retraining was done using days 1 through 3. Repeated measures ANOVA over retraining through days 1 to 3 yielded a statistically significant effect of "Retraining" on performance on the first 2 days of training (F=18.26, $p < 0.001$) and a significant effect of "Days" x "Retraining" interaction (F=9.02, $p < 0.05$). The results of pairwise comparisons over retraining revealed that the classification performance was significantly increased on: day 2 when training classifiers with data from days 1 + 2 versus data from day 2 only (diff = 13.77, p < 0.01); day 3 when training classifiers with data from days 1 + 2 + 3 versus data from days 1 + 3 (diff = 8.38, p < 0.05) or days 2 + 3 (diff = 8.45, p < 0.05); day 3 when training classifiers with data from days 1+ 2 + 3 versus data from day 3 only (diff = 14.83, p < 0.01). No significant differences were found between training with day 3 only and training with days 1 + 2. The results of pairwise comparisons over retraining and days revealed that the classification performance was significantly increased on day 2 when training classifiers with data from days 1 + 2 versus data from day 1 only (diff = 12.9, $p < 0.01$) and on day 3 when training classifiers with data from days 1 + 2 + 3 versus data from day 1 only (diff = 18.84, $p < 0.001$). No significant differences were found between day 1 only and day 3 only, nor between day 2 only and day 3 only. Figure 5.5 shows the BCI performance of the offline classifiers, trained with the data from different combinations of days.

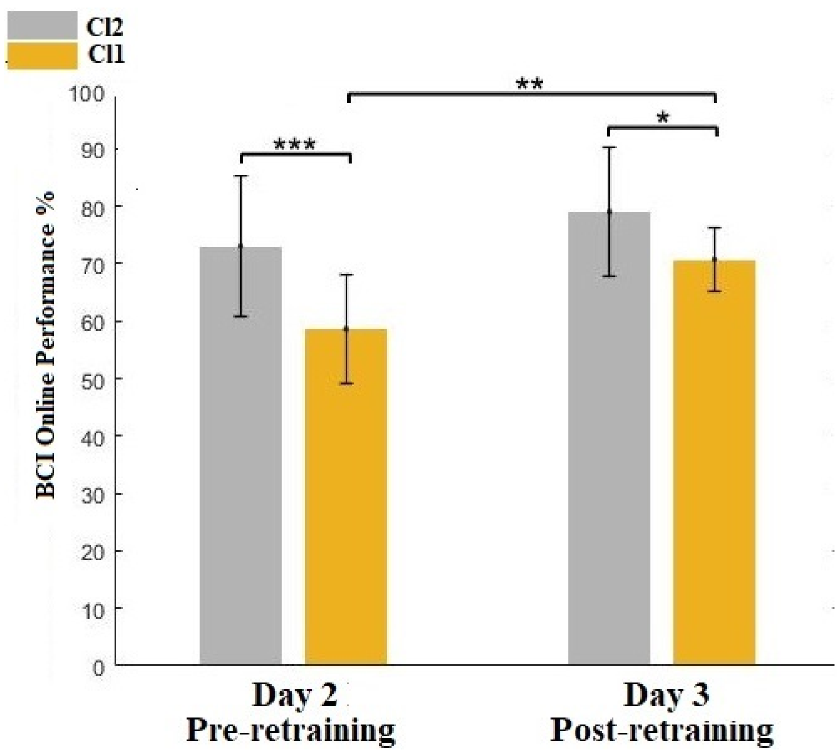

Figure 5.6 Online performance results at the end of day 2 and the online performance results at the beginning of day 3, for each of the 2 classifiers

Figure 5.6 illustrates the effects of the retraining technique over online performance of the cue-paced BCI. It shows the online performance at the end of day 2 and the online performance at the beginning of day 3, i.e. after retraining the classifiers with the data from day 1 and day 2. The average online performance of the two classifiers at the end of day 2 (pre-retraining) was 65.8%, which was increased to 74.7% at the beginning of day 3 (post-retraining). Repeated measures ANOVA over retraining and classifiers through days 1 to 3 yielded a statistically significant effect of “Retraining” ($F=19.32$, $p < 0.05$) and a significant effect of "Classifiers" (F=24.64, p < 0.001). No significant effect of "Classifiers" x "Retraining" interaction was found. The results of pairwise comparisons over "Retraining" revealed that, for Cl1, performance was increased significantly from 58.6±9.5% (pre-retraining) to 70.7±5.5% (post-retraining) with a difference of 12.10, p < 0.05. For Cl2, performance was increased from 73.0±12.2% (pre-retraining) to 79.01±11.15% (post-retraining), which was not statistically significant. In pairwise cross-comparisons between classifiers within the group, a significant difference was obtained between Cl1 and Cl2 in pre-retraining (diff = 14.43, p < 0.001) and post-retraining (diff = 8.30, p < 0.05).

5.4.2 Modified feedback – Cue-paced BCI

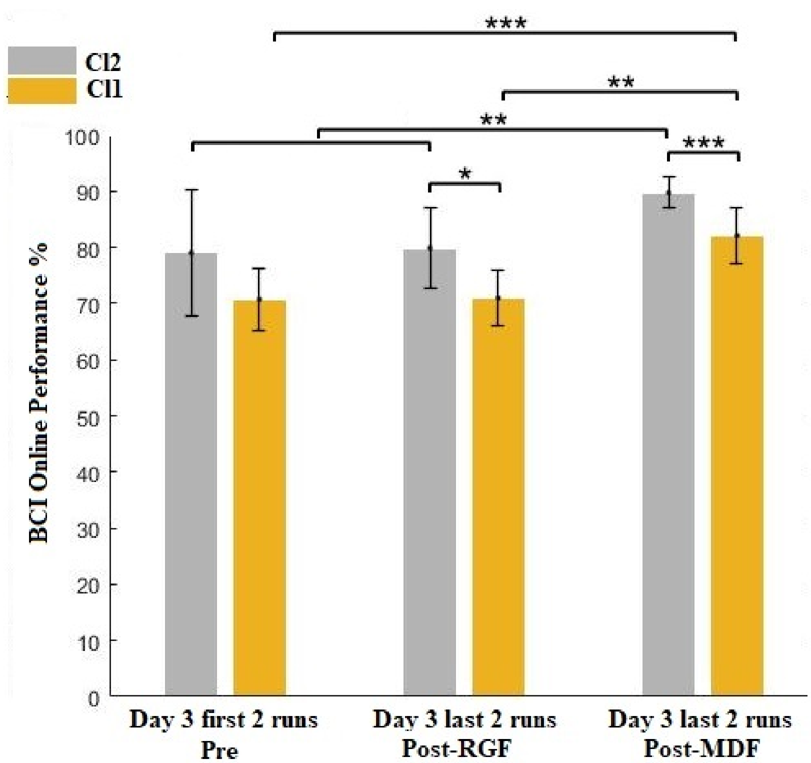

Figure 5.7 Online classification of the 2 classifiers, averaged over the first 2 runs of day 3 and the last 2 runs of day 3, with and without modified feedback (MDF).

The average online performance (across both classifiers) at the beginning of the training on day 3 was 74.7% (pre). At the end of the training day, it reached 75.5% for the group who received regular feedback (post-RGF) and 85.9% for the group who received modified feedback (post-MDF). Figure 5.7 shows the online BCI performance for each of the 2 classifiers in the first two and last two runs of day 3. The performances for the last 2 runs are separated by group (RGF vs MDF).

Repeated measures ANOVA over Feedback and Classifiers for performance on day 3, yielded a statistically significant intra-participant main effect of "Feedback" ($F=37.04$, $p < 0.001$) and a significant effect of "Classifiers" ($F=17.22$, $p<0.001$). The effect of "Feedback" x "Classifiers" interaction was not significant. The results of pairwise comparisons over feedback revealed that for the MDF group, Cl1 performance increased significantly from 70.7±5.5% at the beginning of the training on day 3 (pre), to 82.1±4.9% in post-MDF (diff = 11.39, $p < 0.001$). There was a significant difference of Cl1 between post-MDF and post-RGF (diff = 11.12, $p < 0.01$). Cl2 performance increased significantly from 79.0±11.2% in the first runs of day 3 (pre) to 89.7±2.9% in post-MDF (diff = 10.68, $p < 0.01$). There was a significant difference of Cl2 between post-MDF and post-RGF (diff = 9.28, $p < 0.01$). In pairwise cross-comparisons between classifiers within the same group, a significant difference was obtained between Cl1 and Cl2 in post-MDF (diff = 7.59, $p < 0.001$) and post-RGF (diff = 8.87, $p < 0.05$). No significant difference between classifiers was found in the first 2 runs. Overall, providing 6 sets of positive modified feedback enhanced the BCI online performance significantly.

5.4.3 Modified feedback – Cue-paced BCI - Neurophysiological results

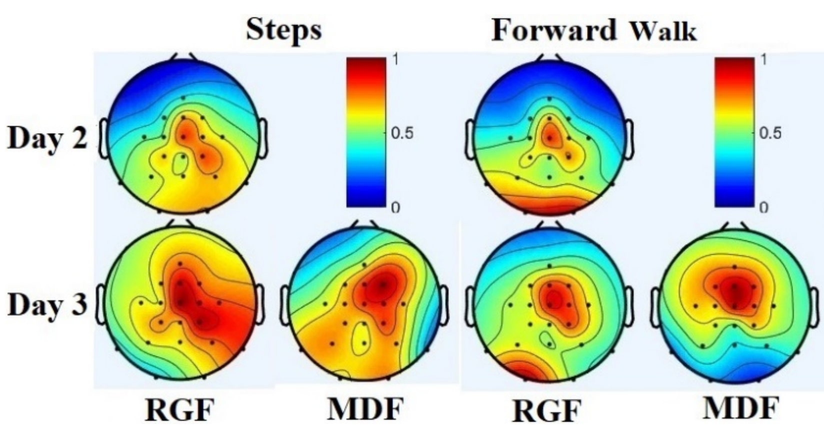

*Figure 5.8 Spectral power maps (10*log $\mu v^2/Hz$) of the upper μ frequency band (10-13 Hz) over the epoch that yielded the best classification accuracy, over Day 2 and Day 3, and for the MDF and No-MDF condition for the Cue-Paced BCI. The analysis shows when controlling the avatar's gait, a strong central and parietal ERS in the case of non-modified feedback, versus a stronger frontal ERS in the case of modified feedback.*

Using the segments and frequency bands that yielded the best classification accuracy, spectral power maps were plotted (Figure 5.8). Brain activity related to the left- and right-footed steps was found to be laterally inverted, so the results were mirrored and combined in one plot in order to facilitate the analyses.

Data analysis revealed significant differences between trials with modified and non-modified visual feedback. When controlling the steps of the avatar, one can observe the spectral power peaks over the central and parietal areas of the brain, with a stronger activation at the end of the training. When MDF is provided, these spectral power peaks increase over the frontal areas, with a significant difference ($p < 0.05$). When controlling the forward walking of the avatar, central power peaks are also observed, spanning more to frontal and parietal areas at the end of the training. However, when MDF is provided, these spectral power peaks increase over the frontal areas, with a significant difference ($p < 0.05$).

5.4.4 Self-paced BCI

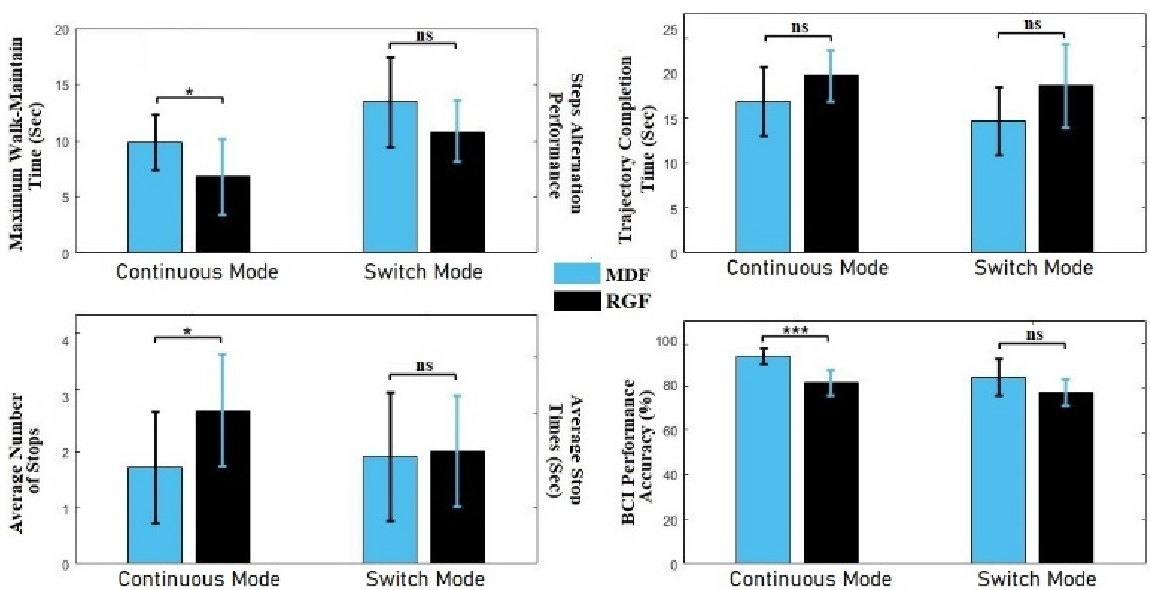

Figure 5.9 Online classification results for both self-paced BCI modes

for participants who received regular feedback (RGF, in blue) and modified feedback (MDF, in black). Each of the 4 plots depicts a parameter of evaluation of the performance of this BCI, which are in order: Maximum walk-maintain time/ Steps alternation performance, Trajectory completion time, Average Number of stops/ Average Stop times and BCI performance accuracy

Figure 5.9 shows the results of the self-paced BCI. In continuous mode, BCI performance accuracy was significantly increased ($Z=3.4395$, $p < 0.001$) in the MDF group (92.5±3.5% success rate) compared to the RGF group (80.8±5.6% success rate). Maximum walk-maintain time was also increased significantly to 9.6±2.4 s with MDF versus 6.8±3.3 s with RGF ($Z=2.0301$, $p < 0.05$). The Average Number of stops was significantly decreased from 2.7±1 stops with RGF to 1.0±0.9 stops with MDF ($Z=-2.0062$, $p < 0.05$). Trajectory completion time was decreased from 19.7±2.8 s with RGF to 16.8±3.8 s with MDF. Trajectory completion time was not significantly different between groups.

In switch mode, results show a tendency towards improved BCI performance accuracy with modified feedback but differences between groups were not statistically significant. BCI performance accuracy was greater in the MDF group (82.9±8.1% success rate) compared to the RGF group (76.5±5.8% success rate). Steps alternation performance was increased to 67.1±20.0% success rate with MDF, from 53.9 ±13.0% success rate with RGF. The average stop times between steps was decreased from 2.0±1.9 s with RGF to 1.9±1.1 s with MDF. Trajectory completion time was decreased from 18.6±4.7 s with RGF to 14.6±3.7 s with MDF.

5.4.5 Behavioral results

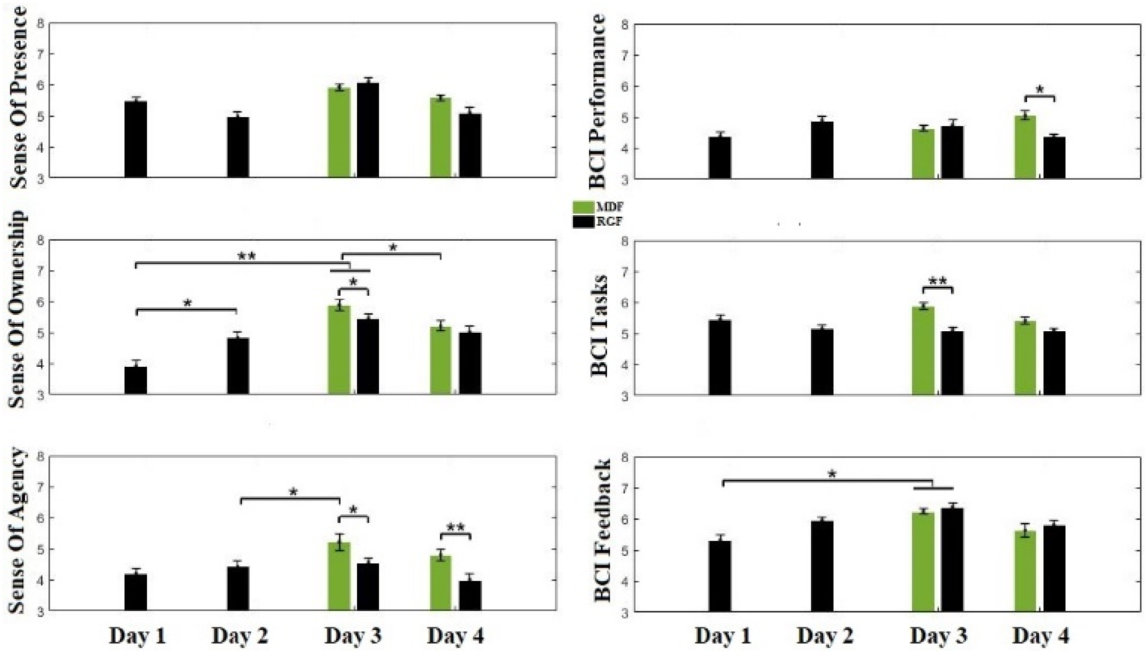

Figure 5.10 Behavioral results based on the questionnaire answers obtained after each day and decomposed into the 3 embodiment components and 3 BCI aspects, as well as a decomposition of the BCI tasks

Figure 5.10 shows the behavioral results of this study. Repeated measures ANOVA were run over the 3 embodiment components and 3 BCI design aspects. It revealed a significant intra-participant main effect of “Training”, and a significant effect of “Feedback”.

Pairwise comparisons revealed that when operating a BCI to control the gait of an avatar, the sense of presence, which starts at 5.4/7 on day 1, does not significantly change through the days, with no significant effect of MDF.

The perceived body ownership, which starts at 3.9/7 on day 1, increased significantly to 4.8/7 on day 2 (diff = 0.93, $p < 0.05$). Ownership also increased significantly from day 2 to day 3 for both the MDF (diff = 1.96, $p < 0.01$) and RGF (diff = 1.53, $p < 0.01$) groups. For group RGF, it decreased significantly from day 3 to day 4 (diff = -0.92, $p < 0.05$). The MDF group had no significant difference between days 3 and 4. On day 3, ownership was significantly higher in the MDF group than in the RGF group (diff = 0.42, $p < 0.05$).

The perceived sense of agency, which starts at 4.2/7 on day 1, does not significantly change through the days for the RGF group. In the MDF group, it increased significantly from 4.4/7 on day 2 to 5.2/7 on day 3 (diff = 0.78, $p < 0.05$). The sense of agency was significantly higher in the MDF group (vs RGF group) on day 3 (diff = 0.74, $p < 0.05$) and day 4 (diff = 1.01, $p < 0.01$).

As for BCI design, pairwise comparisons show that the perceived feedback of the cue-paced BCI was increased significantly from day 1 to day 2 in the MDF group (diff = 1.06, $p < 0.05$) and in the RGF group (diff = 0.93, $p < 0.05$). Compared to the RGF group, the MDF group had significantly higher perceived performance with the self-paced BCI ($p < 0.05$) and significantly higher perceived easiness of tasks with the cue-paced BCI ($p < 0.01$). There was no significant difference between groups in BCI environment feedback questions.

5.5 Discussion

This study aimed to develop a gait rehabilitation BCI, integrating MI of lower limbs to control the gait of a virtual avatar in different control modes, such as cue-based and self-paced. This approach was used in order to overcome the design limitations of the currently used gait rehabilitation BCIs. This study also investigated the implementation and combination of different BCI performance enhancement techniques such as the co-adaptive sequential training paradigm, modified feedback and classifier retraining. This was a novel approach for lower-limb MI-BCIs, because, as far as we know, there is no previous study that has integrated all of these techniques in one single BCI system that uses MI of lower limbs. It was used in order to overcome the performance limitations of such BCIs that would hinder embodiment and limit use in gait rehabilitation. The results confirm our hypotheses that participants were able to operate the BCI in all modes, and that the three enhancement techniques increased BCI performance. However, the hypothesis that participants would perform better when using the continuous self-paced control than when using switch-based self-paced mode is rejected.

5.5.1 Retraining of the classifiers – Cue-paced BCI

The offline classification results show that on day 1 of the training, the classifiers reached a performance that was at least 10% higher than the chance level, in their worst case. This classification accuracy was enhanced significantly after using the recalibration technique. When the trained classifiers were used online, they were able to perform with a strong generalization. This was clear from the online results of day 2. The recalibration technique was shown to perform well, not only for offline classification, but also for online classification. This is shown by comparing the online performance at the end of day 2, when the classifiers were trained on data from day 1 only, with the online performance at the beginning of training on day 3, where the recalibration technique enhanced the BCI performance by 10%. This is similar to the range of enhancement (10-15%) found by other studies [188-190, 197]. The classification accuracy was significantly enhanced for Cl2 and for the combination of both classifiers. It is worth noting that the results always show a higher classification accuracy for Cl1 versus Cl2. This lower performance and higher enhancement for Cl2 may be due to the complexity of this MI tasks (left step, right step or no movement) and the fact that there are 3 classes, compared to the two tasks classified by Cl1 (walking forward or no movement). Nevertheless, the classifiers reached high classification performance for many participants. After retraining, they achieved offline classification accuracies on day 3 between 70% and 95% (mean: 86%), which were significantly superior to chance.

In the field of BCI, the offline classification accuracy for a MI-BCI is considered to be good if it reaches more than 70% [286], which is the case in this study, even before retraining the classifiers. Furthermore, the findings after retraining were consistent with what other BCI studies have previously found [185, 186], in that, at the stage of classifier design, using an ensemble of LDA with regularization and retraining of classifiers after every session provided high classification accuracy and performance [197]. The results of the classifications of forward walking in this study were better than the performances that were reported in studies that used the RLDA algorithm to classify walk versus no movement, which were between 70% and 80% [287, 288]. This could be due to the technique of retraining the classifiers used in this study. To our knowledge, this is the first study that has used RLDA classification for discrimination of right step, left step and no movement. This is also the first study to integrate RLDA with the classifier retraining enhancement technique for a lower-limb MI-BCI. Our findings demonstrate the feasibility of using these methods for such BCIs.

The high classification performances presented in this study also support the feasibility of using the features of PSD and PSD asymmetrical ratios between the two brain hemispheres for encoding the differences between the main control commands of gait. This is in accordance with what was found in previous studies that investigated EEG signatures of gait [48, 50, 52]. On the other hand, the optimized feature sets had data only from the frontal, prefrontal and central areas of the brain. Since those channels are localized over the foot representation areas of the brain, it would be possible to further lower the number of electrodes from 19 to 10 or less.

5.5.2 Modified feedback – Cue-paced BCI

The results show that providing 6 runs of positive MDF enhanced the cue-paced BCI performance significantly when compared to the group that did not receive MDF. With MDF, the average general performance reached ~83%, an accuracy that is considered to be very good in the field of MI-BCIs [286].

The positive MDF used in this study enhanced the mean performance over both classifiers by at least 10%, with a 12% enhancement for Cl2 specifically. When previous studies compared the effects of providing positive and negative MDF, some found that it was negative MDF that had the larger enhancing effect on BCI performance. This was the case in studies that trained users to control a bar on the screen [64, 201]. Others found that positive MDF had a larger effect on enhancing BCI performance which was the case, for example, of a study that trained users to control the hand of a human-like robot [202]. The results found by the latter study are consistent with the findings of our study.

The different findings with regards to the superiority of positive or negative MDF may be due to the nature of the study and, specifically, to the nature of the feedback to be controlled. Since this is, based on what we know, the first study to use MDF to enhance the performance of a multi-command lower-limb MI-BCI, the results show the feasibility of using this method to enhance such BCIs.

MDF also contributed to the reorganization of cortical activation after participants trained to control the BCI. Spectral power maps show that when controlling the forward walk of the avatar, a stronger activation is observed over the central areas. However, when controlling steps, a stronger activation is observed over central and parietal areas of the brain. One can also observe a stronger activation at the end of the training, especially at the right-central regions.

These brain activations can be described as large event-related synchronisations (ERS). ERS occur usually as signal rebounds after a mental activity, and they are characterized as an increase of the signal power, compared to baseline. In this study, and after MDF over gait control, those ERS peaks could be due to the higher feeling of agency [28].

The central and right-central μ-ERS may have been due to the role of MI mechanisms over the brain areas of the feet. This implies an elevated degree of the sense of ownership when controlling the limb by MI. The parietal μ-ERS could be explained by 2 factors. First, this is the region of the brain implicated in dimensional navigation, and thus, this is the region that is activated when the feeling of presence takes place. Second, the angular gyrus is situated in this region and in the inferior parietal cortex in particular. This region is involved in the feeling of agency and the operation of comparison between the anticipated and real outcomes of one’s actions [281, 282].

When MDF was provided, these spectral powers increased significantly to a strong parietal, central-frontal and frontal μ-ERS. The frontal activation represents the judgement of agency, which suggests that the perceived feeling of agency was significantly higher in the group that received MDF [289]. The stronger frontal central sensorimotor rhythm (SMR) and μ-ERS may be explained by one of the following:

1- When the participant wants to either hold or end the movement upon reaching the target position, the elevated process of the mismatch-surveillance circuits of the brain and the compensatory neural control mechanisms emulate this type of brain activation [36]. It was found that for the group that didn’t receive MDF, this specific activation was much lower, and it could be a consequence of the regular process of the mismatch surveillance circuits of the brain.

2- The mirror neurons system (MNS) situated in the frontal cortex. This system exhibits specific brain activation that tunes and modulates μ-ERS to the goal-directed motor experiences in movement imitation of the avatar (frontal). This activity follows movement observation of the avatar (central). These activations are necessary for the brain to comprehend and handle actions of the avatar [290].

3- The working memory consolidation [291]. Because the sequential training to control the BCI presented in this study lasts four days, the working memory could have been consolidated over these days. This means that the skills that the participants have acquired during the training have accumulated during these days. Thus, an enhanced MI performance could be obtained.

Remarkably, when MDF was not provided, the frontal-central and parietal μ-ERS were higher for the control of steps than for the control of forward walking. This difference can be explained by the different complex compensatory neuronal control circuits that were triggered right after a movement of the avatar that conflicts with the participant's MI, in both conditions.

In this study, and in the case of MI command of forward walking, the misclassification of that command resulted in a movement violation. This particular movement violation was delivered to the participant as an absence of feedback. In the case of individual steps, it was an absence of feedback or a contradictory feedback. The results show that the second demands more power from the brain because it has to suppress the anti-saccadic effects.

Thus, when MDF was not presented, this triggered a stronger central frontal activation in the individual steps condition. This finding is consistent with the results of previous studies that showed that for an anti-saccadic movement, the neural and perceptual consequences are stronger than for those of a movement inhibition [292, 293]. This also explains the apparition of significant post-MDF changes over the parietal μ-ERS.

The power spectral map findings on the effects of MDF on MI are consistent with the results of previous studies [28].

In summary, the results show that when mentally controlling the gait of an avatar, MDF enhances cue-paced BCI performance, especially when controlling harder tasks, such as right and left steps. This performance can be measured by the classification rate and by the μ-ERS power spectral changes over the central-frontal and the central-parietal areas.

5.5.3 Co-adaptive sequential training – Self-paced BCI

To reach high performance in controlling the self-paced BCI in its two modes, an effective, goal directed and short-time sequential training for operating a cue-based BCI is needed. Participants gained good control of the self-paced BCI after being trained for 3 days to control the cue-paced BCI and having completed only a few runs of controlling the self-paced BCI. They were able to control the steps and forward walking of their self-avatar after only 4 days of training, in total. Other studies have used the co-adaptive sequential training paradigm to train users to control a cue-paced followed by a self-paced BCI for cursor control [9], avatar control [3] or navigation in VR [16]. The required time for this training varied between a few sessions in one day [183] and many sessions over several days [182]. For gait rehabilitation MI-BCIs, sometimes it would take weeks before participants mastered the control of their self-paced BCI [55].

The short amount of training time that was sufficient in this study may be due to the three BCI enhancement techniques that were combined and implemented throughout the training. To our knowledge, this is the first study that investigated the feasibility of using a combination of all of these enhancement techniques, in the same training paradigm, in order to control a lower-limb MI-BCI. Our results suggest that such a method could potentially shorten the training time required to reach a high performance in controlling the cue-paced, and later the self-paced BCI.

The general BCI performance accuracy performance scores in both modes of our self-paced BCI were above 70%. This is equal to or higher than what was found in BCI-VR studies to control a cursor [294], upper limbs [295] or even gait [13]. Considering the complexity of the tasks being carried out in the current study, the performance is satisfactory.

Some of the other parameters used to evaluate performance of the self-paced BCI, such as steps alternation performance, were specific to our study and therefore cannot be directly compared to existing literature. Other parameters, such as 'Maximum walk-maintain time' and 'Average Stop times / Average Number of stops' are at the core of self-paced BCIs and have been reported in previous studies. In the self-pace continuous control mode, participants were able to maintain the MI for a long enough time to reach the target with minimal or no interruptions (mean of 1.0 stops for MDF group and 2.7 stops for RGF group). As for the self-paced switch control mode, participants were able to alternate their steps, and reach the arrow target with short times between steps (mean of 2.0 s between steps for the MDF group, 1.9 s for the RGF group). This is consistent with the findings of previous studies, which found that users were able to reach a high level of performance in evaluation parameters when using different control modes of a self-paced BCI [16, 58, 294].

Scores were generally high for the difference performance parameters in both modes. However, it was surprising to observe that the effects of the positive modified feedback, provided for the cue-paced BCI on day 3, had spanned to significantly increase the score of most of the parameters that were used to evaluate the performance of the continuous self-paced BCI on day 4. Participants from the MDF group may have been more confident in their results and performance, more concentrated and more motivated to control the avatar and finish the training successfully. In comparison, participants in the RGF, may have felt more discouragement or frustration with the BCI after non-successful trials. Other hypotheses are that differences could be related to memory consolidation or that they were due to cortical activation re-organization and the MNS modulation that followed MDF training. A combination of these factors may be in play. To our knowledge, this is the first study to show that MDF could improve BCI performance in successive training sessions, on subsequent days. Alimardani et al. [202], using an upper limb MI-BCI, found that the improvement in participant's performance following MDF carried over to subsequent training sessions of a same task. The effect on sessions that occurred on different days was not investigated. Overall, our results and those of Alimardani et al. show that modified feedback can be used in sequential training of MI-BCIs for the objective of increasing the performance of a participant's ability in controlling the BCI.

On the other hand, MDF did not have the same beneficial effect on performance in the switch control mode. Scores in the different performance parameters where improved but not significantly. In the continuous control mode, the participant had to hold the MI for a relatively longer period compared to the switch mode. Although the switch control mode is considered to require less concentration, it consumes more brain-power due to the anti-saccadic mechanisms, since the brain tries to supress the effects of those mechanisms. Thus, participants performed better using the continuous control mode. These differences in performance might also be due to the use of different mental strategies for control by the participants. Given the complexity of the biomechanics nature of forward walking, represented by the very complex series of upper and lower limb movements, for which there may not be a universal MI strategy. This is consistent with what Valesco-Alvarez et al. [58] found in their study when they compared the two self-paced BCI modes in order to control navigation in VR. In their study, the success rates were similar to ours for both control modes, although the times needed to complete a path were notably lower in the continuous control mode.

To summarize, these analyses suggest that a sequential co-adaptive training to control a cue-paced, followed by a self-paced MI-BCI is very successful. The implementation of an ensemble of the previously mentioned enhancement techniques may shorten the training time. The implementation of the MDF technique in specific trials also enhanced the performance, especially for harder tasks.

5.5.4 Behavioral measures of embodiment and performance

In order to operate a BCI that controls the gait of an avatar, there is a very strong link between the degree of embodiment over that avatar, and the level of performance to control that avatar. To reach one of them, the second must be reached as well [31]. In this study the feedback of MI to control the gait of an avatar resulted in elevated levels of embodiment of the 1PP avatar, which is consistent with previous literature [243, 253].

In a previous study, the effect of MDF over the central-frontal and the parietal areas correlated with the subjective evaluation of embodiment [272]. That means that the ERS modulations following agency violations were stronger with participants who experienced stronger embodiment, which justifies the use of questionnaires in this experiment.

The scores from the questionnaires revealed that the sense of presence was generally high (> 4.9/7), especially on day 3 when participants were mastering the control of the cue-paced BCI, whether they received MDF or not. This is also consistent with what was shown in the spectral power maps, regarding the parietal μ-ERS that peaks when there is a high sense of presence. The perceived sense of ownership was low at the beginning of the training but was increased significantly at the end of the training to control the cue-paced BCI (day 3). This is consistent with the finding that the right-central peaks were stronger at the end of the training.

MDF significantly increased the sense of ownership on day 3 but not when controlling the self-paced BCI (day 4). Again, this may be due to the avatar's behavioral differences between a cue-paced control and a self-paced control BCI. The sense of agency was low at the beginning of the training but MDF participants felt significantly more in control (agency) on day 3 and on day 4. This is consistent with what was found in the neurophysiological results: when producing MDF to the gait of a virtual avatar, the sense of agency can be measured using the strength of the elicited frontal central ERS.

The embodiment question scores showed that participants felt immersed, which was confirmed and supported by the results of previous studies. Thus, when an avatar's gait is presented to the user from 1PP in an immersive VE, the feedback of MI, in the form of the avatar walking, is sufficient to produce the sense of embodiment [272]. This was confirmed as well by the high scores that were observed in the answers of the participants to the questions related to the BCI feedback, which reached 5.3/7 on day 1 and increased to 6.3/7 on day 3.

The BCI question scores showed a high perceived performance and easiness of tasks for the MDF group when controlling the self-paced BCI, with a higher score for easiness of tasks for the MDF groups when controlling cue-paced BCI. MDF probably played a strong role on perceived performance, which increased agency and embodiment given that the feedback is more often consistent with what the participants are trying to imagine. Consequently, their performance perception and agency perception were increased.

To summarize, these analyses suggest that when using a lower-limb multi-modal MI-BCI to control the gait of an immersive avatar, the questionnaire score results are in accordance with neurophysiological and performance measures and can be used as an assistive measure to monitor embodiment and performance.

5.5.5 General discussion

In general, when compared to related cue-paced or self-paced BCI-VR studies that control gait, the current study shows similar or better performances, despite variations in experimental designs. Our results show that the developed BCI could meet the requirements of an ideal BCI to control the gait of an avatar. The key factors that make BCIs a real alternative communication channel are: fast setup, short training time, effective control and artifacts processing [296]. In this study, some of these factors, such as short training time were used, and high performance results were attained.

This study had some limitations. For one, many MI-BCI studies include a classifier progress bar added to the VE, either separately on the screen, or super-imposed over the cue. This usually helps the user, in real time, to be aware of his performance in controlling the BCI and to try to adjust accordingly. The absence of such an aspect left the participants sometimes unaware of the best mental strategy to use, especially when there were multiple mental commands at a time, such as in the switch control mode. Therefore, the absence this bar may have diminished the BCI performance achieved in this study, especially in the self-paced switch mode.

An important limitation of the setup was the use of generic animations of the avatar's gait. Several participants noticed and commented that the avatar's gait looked different from their own gait. Since this study is a first step towards a BCI that could be used for gait rehabilitation, it is very important to have calibrated participant-specific avatar gait animations for future work.

Interestingly, the scores obtained in the subjective questionnaires may reflect another limitation of this study. This experiment did not use a sex-matched avatar contrary to what other studies have done. Non sex-matched avatars have been shown to decrease embodiment [40]. This could partly explain the low scores associated with the ownership questions on the first days of training, when the feeling of agency is less established.

5.6 Conclusion

This study reports on the feasibility and successful design and development of a BCI system that uses lower-limb MI to control the steps and forward walking of a self-avatar in immersive VR.

Twenty participants were able to operate the BCI after 4 sessions of co-adaptive sequential training of 1 hour per session, with a general performance of 70-94%. To our knowledge, this study represents the first demonstration of integrating all of these design approaches and enhancement techniques in parallel in one single multi-modal BCI system. This BCI could be used for gait rehabilitation by imagining real steps, and progressing to imagining forward walking, while receiving the matching visual feedback from an embodied virtual avatar over which we feel agency.

Future work will incorporate proprioceptive feedback that is congruent with the movements of the avatar.

5.7 Acknowledgements

This work was supported by a research grant of NSERC and FQRNT. The authors would like to thank Philippe Charbonneau for his help in developing the virtual environment.

Chapter 6: Generic BCI classifiers for MI of left/right steps and forward walking

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6.1 Abstract

Brain-computer interfaces (BCI) have been used to control the gait of a virtual self-avatar, using motor imagery of the feet, in order to restore motor control in gait rehabilitation. The considerable training time required to use such a BCI is an obstacle to their adoption in a clinical setting. One technique used to enhance BCI control and to shorten training time is to eliminate offline calibration using a generic classifier that is pre-trained over many participants, each performing many trials.

This paper investigates the performance of generic models that were derived from 2 datasets, each containing the data of 20 participants. They participated in a sequential training to control the gait of an avatar when cued to imagine a single step forward using their left or right foot, or to start walking forward. The avatar moved in response to two calibrated RLDA classifiers that used the μ PSD over the foot area of the motor cortex as features. The generic models were tested on the offline and online data of the participants. The models performed as well as models obtained from participant-specific offline data with a mean performance of 87%. The results show the possibility of designing a participant-independent, zero-training lower-limb MI-BCI.

Keywords—Brain-computer interface, Virtual reality, EEG, Classification, Avatar, Gait

6.2 Introduction

A BCI is a system that measures brain activity of an intention to do something and converts it into a control command that replaces, restores, enhances, supplements or improves natural brain activity output [4, 5]. In the field of rehabilitation, this control command has been used to control external devices such as robotic and prosthetic devices [6] and a lower limbs exoskeleton [13] as well as to control the gait of a virtual self-avatar [55]. When such systems are controlled through motor imagery (MI) of the desired actions (e.g. individual left and right steps as well as walking forward), this can trigger neural circuitry reorganization [297] and restore motor control during gait rehabilitation [3].

When designing a BCI, the most important step is tuning the classifier [62]. When fed with different MI patterns produced by the user, the classifier "learns" to discriminate these distinct patterns and translate the extracted signal features into control commands. For an effective BCI design and control performance, the right classifier and tuning parameters must be chosen very carefully [62]. Powerful algorithms have been used to counter-act the problems and limitations of some of classification algorithms, such as using regularization parameters [298] to counter-act overfitting [175]. Overfitting is when the classification model is too closely fit to a limited set of data points and can't be generalized to complete new data points.

Since the classifier needs to be tuned for a specific user, a large amount of data from each user must be fed to the classifier. To counter this limitation, many studies have suggested to eliminate offline calibration using a generic classifier that is pre-trained over many participants, using many trials [193, 194]. This generic classifier is used to train participants to control a participant-optimized BCI [194].

For example, Lotte et al. [195] proposed to use a participant-independent P300 BCI, previously learnt from the data of many other participants. Their BCI resulted in a better performance, and with a reduced training time from 40 minutes to 2 minutes of training. Similar results were found by other studies by running a generic LDA classifier in a MI-BCI [196, 197]. Their findings state that, even though the inter-participant variability poses a challenge, all participants scored high performance [196]. Generic classifiers based on the data of 80 participants have been used also by Vidaurre et al. [198], who showed that its performance is significantly better (an increase of 13%) than the state-of-the-art classical classification approach. However, these previous studies used generic classifiers for an upper-limbs MI-BCI. To our knowledge, there are no generic classifiers that have been used for lower-limbs MI-BCIs.

The objective of this study was to investigate the possibility of using generic classifiers to shorten the time required to learn to operate a BCI that controls the gait of an avatar and enhance the performance of this BCI. Different sparse-data algorithms were investigated in order to select the algorithm that would yield the highest classification accuracy. The training and test datasets were derived from the two previous studies. The generic models were tested only offline, on different tests.

6.3 Materials and methods

6.3.1 Experiment design and datasets

The datasets used for this study were derived from the two previous studies that recruited 20 participants each, resulting in 40 participants in total. In both studies, the participants performed the same MI tasks.

Participants produced MI of right/left steps and of forward walking, and the same protocol and experimental design for producing MI was used. In both studies, the same VE was used, which consisted of a virtual self-avatar, presented in 1PP. In both studies, this avatar provided the same form of visual feedback to the participants, which is the right/left steps or forward walking of the avatar. The same proportion and randomized order of trials of left steps, right steps and forward walking was used in both studies.

In study 1, the feedback was independent of the participant's MI, while in the study 2, the feedback was the result of two calibrated RLDA classifiers responding to the participant's MI. From each participant in each study, the dataset of that participant was constructed from the features of μ PSD over the foot area of the motor cortex, over all trials.

Study 1 consisted of a single session with 240 trials of lower-limb MI per participant, resulting in a dataset of 4513 trials, after excluding the trials that were too noisy to be included and processed in the study. Study 2 was composed of 3 sessions with 300 trials of lower-limb MI, where session 1 collected offline data, and sessions 2 and 3 collected online data. This resulted in almost 900 trials per participant for study 2, and a dataset of 17456 trials in total, after excluding the trials that were too noisy to be included and processed.

Two groups of datasets were formed: the first group contained data of right steps, left steps and idle (no movement). The second group contained data of forward walking and idle (no movement).

6.3.2 EEG data recording and pre-processing

EEG was recorded using the 19-electrodes Smart BCI system. These electrodes were grounded to AFz and referenced to both ears using an ear clip on each ear. The electrode positions were covering the whole scalp with a higher density above the pre-motor, motor and parietal areas. The signals were band-pass filtered (18th order butterworth IIR filter) into 10-13Hz (higher μ band). Artifacts and noise were auto rejected using MARA, an automatic ICA and noise rejection algorithm [269]. Signals were then detrended, where a baseline removal algorithm was applied, using the 200ms preceding the apparition of the arrow.

6.3.3 EEG features extraction and selection

μ PSD of every channel, and 5 PSD asymmetrical Ratios (1-sec hanning) were chosen, over 20 different 200ms-time epochs to form the features sets. To reduce number of features, the Wilcoxon test and cross-correlations were chosen to be the criterion to select distinctive and informative features.

6.3.4 EEG features classification

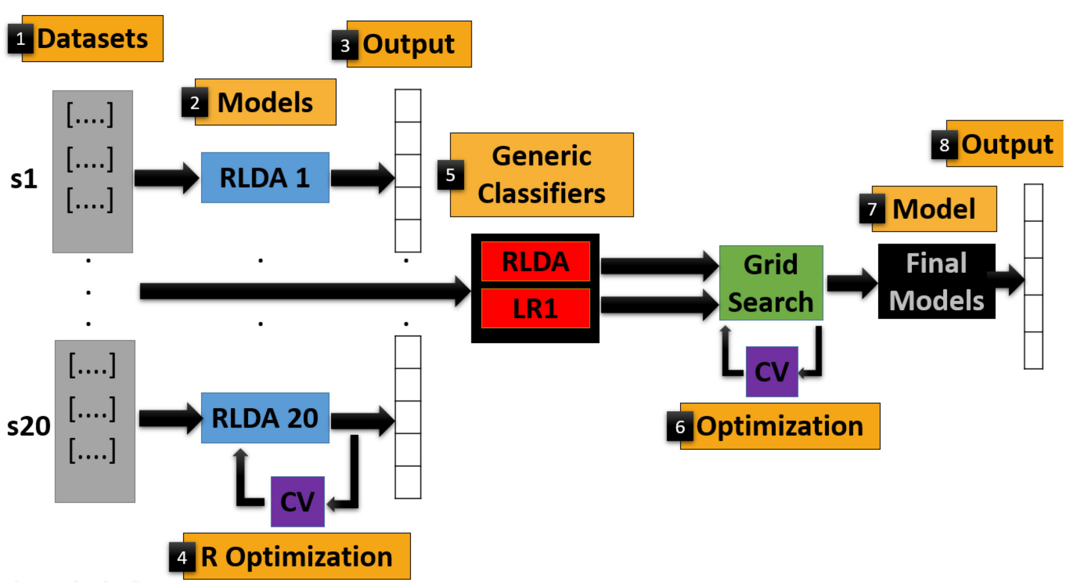

Figure 6.1 The flow of the study

The datasets were used to train two classifiers: classifier 1 (Cl1) was trained to distinguish between forward walking and idle (no movement) classifier 2 (Cl2) was trained to distinguish right step, left step and idle (no movement).

In order to construct the generic classifiers, the datasets were first normalized (Z-Scored). Then, two types of classifiers were investigated and were used to train the data and form the generic classification models (Figure 6.1).
The first classification algorithm that was used was RLDA. This is the same classification method that was previously used in study 2. Since this method has a regularization parameter and it showed good performance in study 2, it is ideal to be used in a generalization study.

Used in many motor imagery BCI studies [176], the regularization amount (λ) increases larger eigenvalues of the covariance matrix while decreasing smaller ones, therefore creating a pooled-covariance matrix that is corrected for the bias when estimating sample-based eigenvalues [177].

Thus, regularization improves classification performance by:

1) providing generalization and preventing overfit
2) decreasing calculation time compared to other classification methods [179].

LDA Models were varied by using: 1-Regularization amount (λ) and 2-Linear Coefficient threshold (δ). The regularization amount parameter λ was optimized by setting different values of λ over the range of [0, 1.0] in 0.1 increments in a random search and validated by a 10-fold Cross-Validation. [148, 150, 177].

The second classification algorithm that was used in this study was linear regression modelling (LRM). The linear regression models were varied by using two choices of penalty hyperparameters: 1-regularization weight (α) and 2-regularization amount (λ), which vary between Lasso (L1), Ridge (L2) and Elastic Net (L3) [115].

6.3.5 Generic Classification Models

Then final Classification Models were built from training Generic RLDA Models and training Generic Linear Regression Models.

For both classification algorithms, and when training the classifiers, an optimization step was performed to select the hyperparameters that would yield the best classification model. For this purpose, grid search was used to select the best model by hyperparameter tuning [299].

6.3.6 Protocol of testing the generic classification models

Seven different tests were run over both classifiers (Cl1 and Cl2) using the best models of each of the classifiers' types (RLDA and LRM). The performance of these best models of generic classifiers was compared between classifiers and between classifier types. The performance of the generic classifiers was compared to the average performance of the participant-specific classifiers (referred to as Average S-S), when they were run online. The seven tests that were run are the following:

Test #1 Initial performance: Data from study 2 - session 1 were used as a training and testing dataset, and cross-validation was used to estimate the performance of the classifiers. This test was performed to investigate the initial performance of the classification models. For this purpose, the classifiers should train and test on the same data. Since the cross-validation result represents an average performance of the classifiers when tested on different subsets, and in order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 1, which was an offline session, when using the participant's specific dataset-RLDA combinations.

Test #2 Initial generalization performance: This test used the classifiers constructed in Test 1, where data from study 2 - session 1 were used as a training dataset, but data from study

2 - session 2 were used as a testing dataset. Model classification was used to estimate the classifiers performance. This test was performed to investigate the initial generalization performance of the classifiers, so the datasets were chosen in a way that the testing datasets come from the same participants as those of the training datasets, but from another session. The test was performed over each participant's data separately, then averaged over all participants. In order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 2, which was an online session, when using the participant's specific dataset-RLDA combinations.

Test #3 Validation of initial generalization performance: Data from study 2 - session 1 were used as a training dataset, and data from study 2 - session 3 were used as a testing dataset. Model classification was used to estimate the classifiers performance. This test was performed to validate the initial generalization performance of the classifiers, so the datasets were chosen in a way that the testing datasets come from the same participants as those of the training datasets, but from another session. The test was performed over each participant's data separately, then averaged over all participants. In order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 3, which was an online session, when using the participant's specific dataset-RLDA combinations.

Test #4 Primary generalization performance: Data from study 2 - session 1 were used as a training dataset, and data from study 1 were used as a testing dataset. Model classification was used to estimate the classifiers performance. This test was performed to investigate the generalization performance of the classifiers, so the datasets were chosen in a way that the testing datasets come from completely different participants. The test was performed over each participant's data separately, then averaged over all participants. In order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 1, calculated offline when using the participant's specific dataset-RLDA combinations.

Test #5 Initial performance with larger dataset: Data from study 2 - sessions 1 to 3 were used as a training and testing dataset at the same time, and cross-validation was used to estimate the classifiers performance. This test was performed to investigate the initial performance of the classification models, but this time for a larger amount of data. For this purpose, the classifiers should train and test on the same data. Since the cross-validation result represents an average performance of the classifiers when tested on different subsets, and in order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 2 – sessions 1 to 3, when using the participant's specific dataset-RLDA combinations.

Test #6 Initial generalization performance with larger dataset: Data from study 2 - session 1 to 3 were used as a training dataset, and data from study 1 were used as a testing dataset. Model classification was used to estimate the classifiers performance. This test was performed to investigate the generalization performance of the classifiers when using a larger training dataset, so the datasets were chosen in a way that the training dataset come from 3 sessions instead of 1, and that the testing dataset come from completely different participants. The test was performed over each participant's data separately, then averaged over all participants. In order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 1, calculated offline when using the participant's specific dataset-RLDA combinations.

Test #7 Final generalization performance: Data from study 2 - sessions 1 to 3 and data from study 2 were used as a training and testing dataset at the same time, and cross-validation was used to estimate the classifiers performance This test was performed to investigate the performance of the final classification models, but this time for a much larger amount of data. For this purpose, the classifiers should train and test on the same data. Since the cross-validation result represents an average performance of the classifiers when tested on different subsets, and in order to investigate the feasibility of performance of these generic classifiers, a comparison was made with another Average S-S performance. This Average S-S was calculated as the mean classification performance cross-participants of study 2 – sessions 1 to 3 and study 1, when using the participant's specific dataset-RLDA combinations.

These seven tests are summarized in the Table 6.1

Table 6.1 The training and testing details of the performed tests

Test	Training dataset	Testing dataset	Estimating classifiers performance	Average S-S	Nature of data
1 Initial performance	study 2 - session 1	study 2 - session 1	Cross-validation	study 2 – session 1	offline
2 initial generalization performance	study 2 - session 1	study 2 - session 2 (same participants-different session)	Model classification	study 2 – session 2	online
3 Validation of initial generalization performance	study 2 - session 1	study 2 - session 3 (same participants-different session)	Model classification	study 2 – session 3	online
4 Primary generalization performance	study 2 - session 1	study 1 (completely new participants)	Model classification	study 1	offline
5 Initial performance with larger dataset	study 2	study 2	Cross-validation	study 2	Online + offline
6 Initial generalization performance with larger dataset	study 2	study 1 (completely new participants)	Model classification	study 1	offline
7 Final generalization performance	study 2 + study 1	study 2 + study 1	Model classification	study 2 + study 1	Online + offline

6.4 Statistical analysis

The Shapiro-Wilk test was performed to verify normality of all the collected data. For all statistical analysis over multiple days, or over more than two groups in the same condition, the Shapiro-Wilk test revealed that the normality assumption was not rejected.

Therefore, two-way repeated measures ANOVAs were used. Pairwise comparisons were performed using the Tukey HSD post-hoc test.

In all cases, the threshold significance level was set to 0.05. Statistical significance is indicated in the Figures 6.3 to 6.8 by: * when $p < 0.05$, ** when $p < 0.01$ and *** when $p < 0.001$.

6.5 Results

6.5.1 Test #1 Initial performance

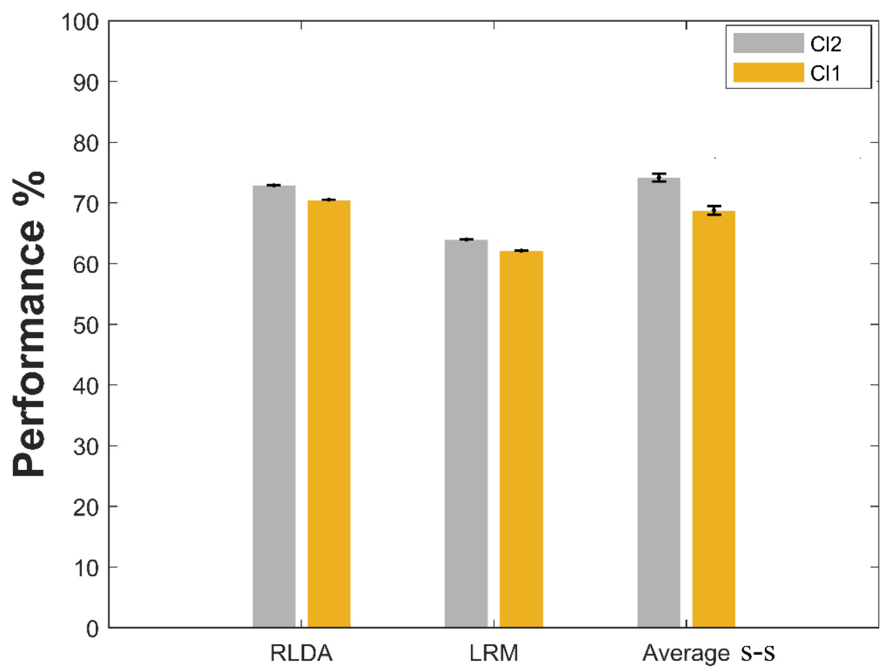

Figure 6.2 Results of Test #1 Initial performance
Data from study 2 - session 1 were used as a training and testing dataset, using RLDA and LRM algorithms. Cross-validation was used to estimate the classifiers performance. Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 1, when using the participant's specific dataset-RLDA combinations

Test #1 Initial performance: (Figure 6.2) demonstrates that when trained and tested on the same lower-limb MI data, the performance of the RLDA classification models reached 70.5% for Cl1 and 72.9% for Cl2. This performance was around 9% higher than LRM classification models (averaged over the two classifiers), which reached 62.1% for Cl1 and 64.0% for Cl2. However, RLDA performance was almost equal to the performance of the cross-participants Average S-S, which reached 68.8% for Cl1 and 74.2% for Cl2. Repeated measures ANOVA over "Algorithm" and "Type" for performance in test #1, didn't show any significant differences of algorithm performance between RLDA, LRM and Average S-S.

6.5.2 Test #2 Initial generalization performance

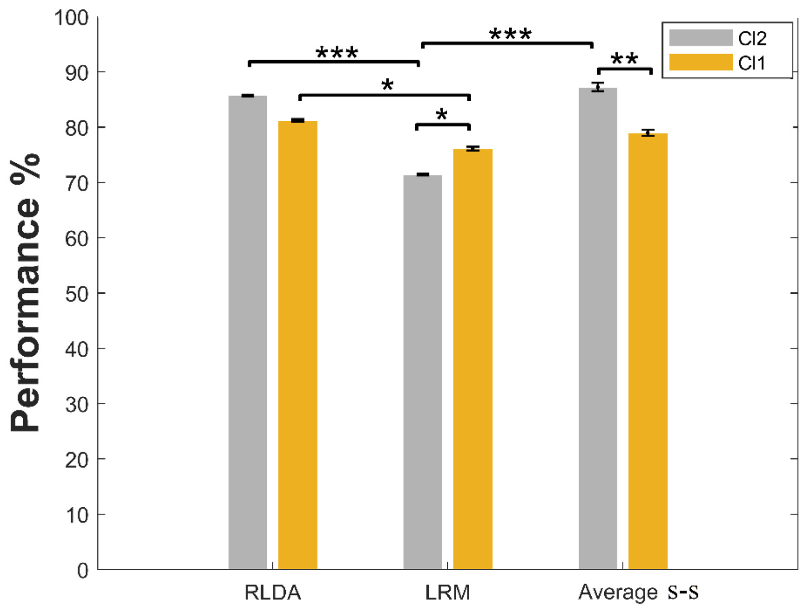

Figure 6.3 Results of Test #2 Initial generalization performance
Data from study 2 - session 1 were used as a training dataset, but then data from study 2 - session 2 were used as a testing dataset. RLDA and LRM classification algorithms were used. Model classification was used to estimate the classifiers performance. Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 2, when using the participant's specific dataset-RLDA combinations.

Test #2 Initial generalization performance (Figure 6.3) demonstrates that when tested on the same participants but in a different session, the cross-participants average performance of the RLDA classification models reached 81.2% for Cl1 and 85.7% for Cl2. The cross-participants average performance of the LRM classification models reached 76.1% for Cl1 and 71.4% for Cl2. The Average S-S was 78.9% for Cl1 and 87.2% for Cl2.

Repeated measures ANOVA over "Algorithm" and "Type" for performance in test #2, yielded a statistically significant intra-participant main effect of "Algorithm" ($F=12.5$, $p < 0.05$) and a significant effect of "Type" ($F=21$, $p<0.05$). The effect of "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly higher than LRM over Cl1 (diff = 76.1, $p < 0.05$) and Cl2 (diff = 14.2, $p < 0.001$). There was no significant difference of algorithm performance between RLDA and Average S-S.

In pairwise cross-comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 in LRM (diff = 4.6, $p < 0.05$) and Average S-S (diff = 8.2, $p < 0.01$).

6.5.3 Test #3 Validation of initial generalization performance

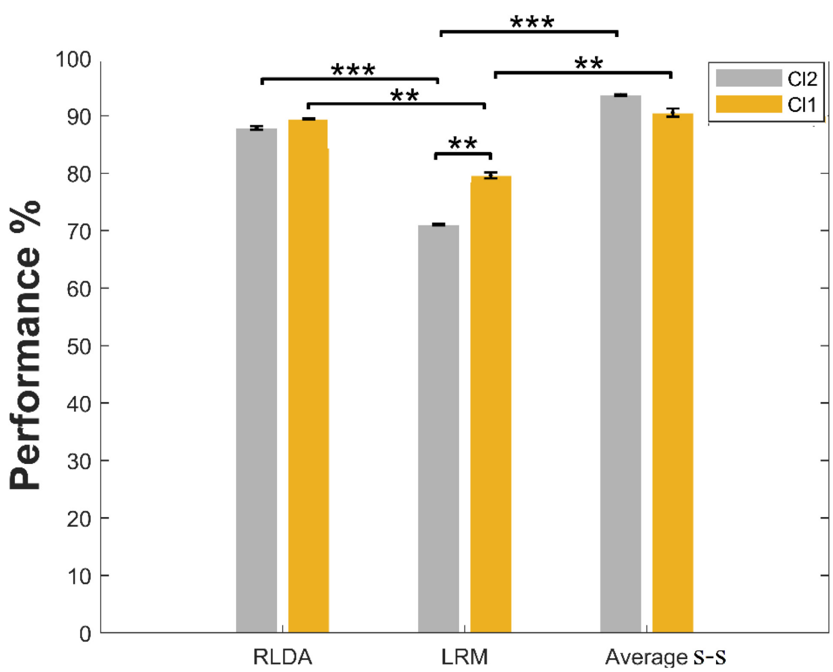

Figure 6.4 Results of Test #3 Validation of initial generalization performance
Data from study 2 - session 1 were used as a training dataset, and data from study 2 - session 3 were used as a testing dataset. RLDA and LRM classification algorithms were used. Model classification was used to estimate the classifiers performance. Average S-S was calculated as the mean classification performance cross-participants of study 2 – session 3, when using the participant's specific dataset-RLDA combinations.

Test #3 Validation of initial generalization performance (Figure 6.4) demonstrates that when tested on the same participants but in a different session, the cross-participant average performance of the RLDA classification models reached 89.4% for Cl1 and 87.8% for Cl2. The cross-participants average performance of the LRM classification models reached 79.6% for Cl1 and 71% for Cl2. The Average S-S was 90.5% for Cl1 and 93.5% for Cl2.

Repeated measures ANOVA over "Algorithm" and "Type" for performance in test #3, yielded a statistically significant intra-participant main effect of "Algorithm" ($F=17$, $p < 0.01$) and a significant effect of "Type" ($F=13$, $p<0.05$). The effect of "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly higher than LRM over Cl1 (diff = 9.83, $p < 0.01$) and Cl2 (diff = 16.8, $p < 0.001$). There was no significant difference of algorithm performance between RLDA and Average S-S.

In pairwise cross-comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 only in LRM (diff = 8.5, $p < 0.01$).

6.5.4 Test #4 Primary generalization performance

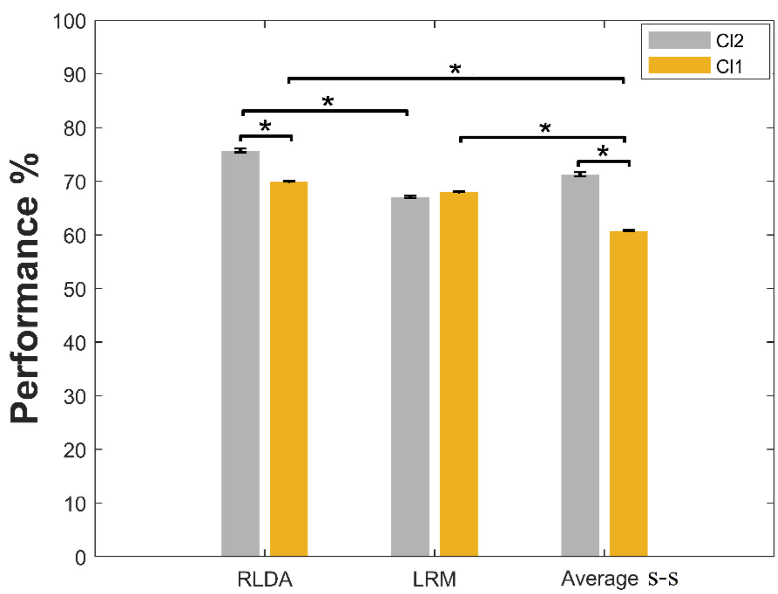

Figure 6.5 Results of Test #4 Primary generalization performance
Data from study 2 - session 1 were used as a training dataset, and data from study 1 were used as a testing dataset. RLDA and LRM classification algorithms were used. Model classification was used to estimate the classifiers performance. Average S-S was calculated as the mean classification performance cross-participants of study 1, when using the participant's specific dataset-RLDA combinations

Test #4 Primary generalization performance (Figure 6.5) demonstrates that when tested on different participants, the cross-participant average performance of the RLDA classification models reached 69.9% for Cl1 and 75.7% for Cl2. The cross-participants average performance of the LRM classification models reached 68% for Cl1 and 67.07% for Cl2. The Average S-S was 60.8% for Cl1 and 71.3% for Cl2.

Repeated measures ANOVA over "Algorithm" and "Type" for performance in test #4, yielded a statistically significant intra-participant main effect of "Algorithm" ($F=11.3$, $p < 0.05$) and a significant effect of "Type" ($F=19$, $p<0.05$). The effect of "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly higher than LRM only over Cl2 (diff = 8.6, $p < 0.05$). There was a significant difference of algorithm performance between RLDA and Average S-S only over Cl1 (diff = 9.1, $p < 0.05$).

In pairwise cross-comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 in RLDA (diff = 5.7, $p < 0.05$) and Average S-S (diff = 10.4, $p < 0.05$).

6.5.5 Test #5 Initial performance with larger dataset

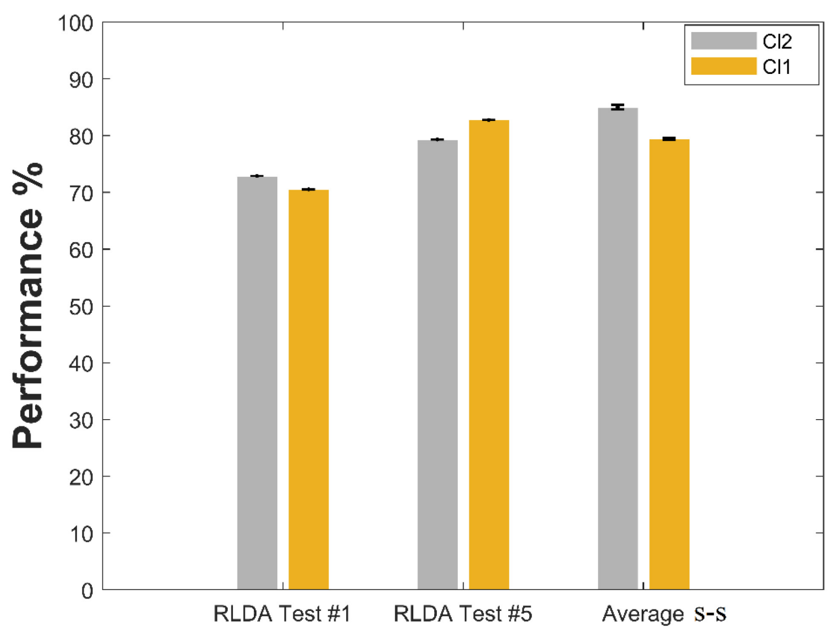

Figure 6.6 Results of Test #5 Initial performance with larger dataset
Data from study 2 - sessions 1 to 3 were used as a training and testing dataset at the same time, and cross-validation was used to estimate the classifiers performance. The Average S-S was calculated as the mean classification performance cross-participants of study 2 – sessions 1 to 3, when using the participant's specific dataset-RLDA combinations

Test #5 Initial performance with larger dataset (Figure 6.6) demonstrates that when trained and tested on the same lower-limb MI data, using the data of 3 sessions from the same participants, the performance of the RLDA classification models reached 82.7% for Cl1 and 79.3% for Cl2. This performance was a bit lower (3%) than the performance of the cross-participants Average S-S, which reached 79.4% for Cl1 and 85% for Cl2.

6.5.6 Test #6 Initial generalization performance with larger dataset

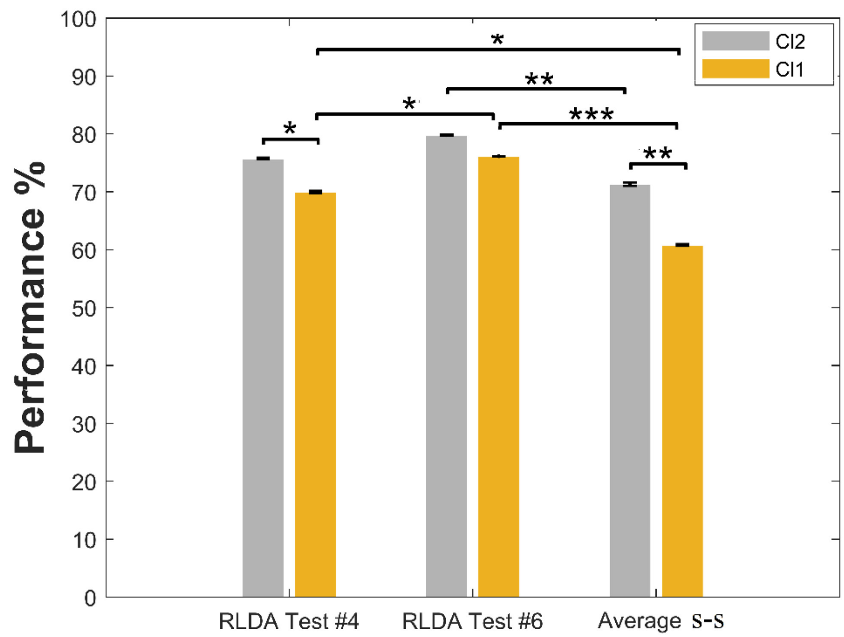

Figure 6.7 Results of Test #6 Initial generalization performance with larger dataset
Data from study 2 – session 1 to 3 were used as a training dataset, and data from study 1 were used as a testing dataset. RLDA and LRM classification algorithms were used. Model classification was used to estimate the classifiers performance. Average S-S was calculated as the mean classification performance cross-participants of study 1, when using the participant's specific dataset-RLDA combinations

Test #6 Initial generalization performance with larger dataset (Figure 6.7) demonstrates that when tested on completely different participants using a larger dataset to train the classifiers, the cross-participants average performance of the RLDA classification models reached 79.3% for Cl1 and 82.7% for Cl2. The cross-participants Average S-S was 60.8% for Cl1 and 71.3% for Cl2.

Repeated measures ANOVA over "Algorithm" and "Type" for performance in test #6, yielded a statistically significant intra-participant main effect of "Algorithm" (F=29.1, p <

0.01) and a significant effect of "Type" ($F=35.1$, $p<0.05$). The effect of "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly higher than Average S-S over Cl1 (diff = 9.3, $p < 0.001$) and Cl2 (diff = 7., $p < 0.01$). There was a significant difference of algorithm performance between RLDA test #4 and RLDA test #6 only over Cl1 (diff = 9.3, $p < 0.05$).

In pairwise cross-comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 only in Average S-S (diff = 10.4, $p < 0.01$).

6.5.7 Test #7 Final generalization performance

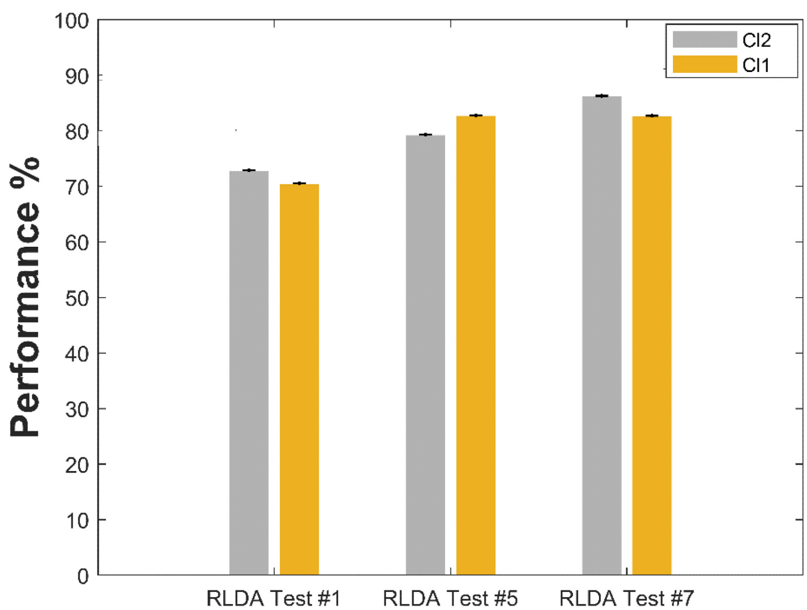

Figure 6.8 Results of Test #7 Final generalization performance
Data from study 2 - sessions 1 to 3 and data from study 2 were used as a training and testing dataset at the same time, and cross-validation was used to estimate the classifiers performance. RLDA and LRM classification algorithms were used. Average S-S was calculated as the mean classification performance cross-participants of study 2 – sessions 1 to 3 and study 1, when using the participant's specific dataset-RLDA combinations

Test #7 Final generalization performance (Figure 6.8) demonstrates the results of the classifiers when trained and tested on lower-limb MI data, using the data of 3 sessions from the same participants (study 2) and the data from completely different participants (study 1). The performance of the RLDA classification models reached 82.7% for Cl1 and 86.2

% for Cl2. This performance was a bit higher (3%) than the performance of the classifiers when trained on data from only study 1.

6.6 Discussion

Since the classifier is the heart and brain of the BCI system [62], developing and tuning the classifier used in a BCI study is a very important factor that affects the co-adaptive learning process to control the BCI.

This study focused on the possibility of implementing a technique to reduce the training time required to learn to control a lower-limb MI-BCI, and at the same time provide high performance. The proposed technique was to use two large datasets in order to construct a novel generic classifier that can classify the MI of left steps, right steps and idle (no movement), and to construct another novel generic classifier that can classify forward walking and idle (no movement). This was a novel approach for lower-limb BCIs since, to our knowledge, there is no study that has done this before.

The factors that characterized the nature of the datasets are: large number of participants, training on different sessions and the complexity of the MI tasks being conducted due to the complexity of the neural control of gait [39]. The classification methods were used over seven tests to build the models that would achieve the best classification performances.

6.6.1 Test #1 Initial performance

The results of this test show that when trained and tested on the same lower-limb MI data, the cross-validation performance of the RLDA classification models reached around 71% averaged over the two classifiers, which was not different from when using the participant-specific classifiers.

In the machine learning world, when trained on a dataset and then tested on completely new data, the performance should be lower than when trained and tested on the same data. Since these classifiers were intended to be later used as generic classifiers, this means that when tested on the same training data, the performance should be high enough so that when completely new data is fed into these classifiers, good classification performance is obtained. As stated by Kübler et al. [286], in the field of BCI, the offline classification accuracy for a MI-BCI is considered to be good if it reaches more than 70%. This, however, is in the context where this classifier is used only as a participant-specific classifier, and not as a generic classifier. For a generic classifier, the offline performance that was obtained in other studies was greater than 80% [198, 300]. A direct comparison cannot be made, since, to our knowledge, this is the first study that uses generic classifiers for lower-limb MI. It is also the first that specifically uses RLDA classification for discrimination of right step versus left step versus no movement. The results of this test mean that the classification models obtained would not be suitable as generic classifiers.

Taken alone, this result would suggest that the reasons behind the low performance obtained in this test could either be due to the small amount of data (only 20 participants), the sparsity of the data (20 participants with one session only), the complexity of the data (gait data) or the offline nature of the data (no-self-regulation of the brain activity to produce better control commands due to the absence of training). The results of test #2 Initial generalization performance supported this statement.

6.6.2 Test #2 Initial generalization performance

The high performance of the RLDA classifiers in the results of this test explained an important fact which is the importance of the nature of data. In this test, the classifiers were tested on new data, which should have led to a decrease in performance compared to cross-validation. This was not the case as the performance increased from approximately 71% to approximately 83% (averaged over the two classifiers).

This unexpected result could be explained by the fact that although the testing data was new, it comes from the same participants. Moreover, they not only come from another session, these data come from an online session. In this session, participants received visual feedback, so they could improve the MI signals (datasets) they were trying to produce. Session 1, on the other hand, lacked feedback and participants didn’t know how well they were doing in terms of MI performance. Therefore, the main reasons behind the low performance obtained in test #1 Initial generalization performance, could be the small amount of data and the nature of this data. The results of test #3 Validation of initial generalization performance can validate this finding since this test was conducted on the data of the same participants, but from the following session, when participants should have had more training and learned to better control the BCI.

On the other hand, although the performance of the classifiers in this test were considered good, this performance was no different from what was obtained when using the participant-specific classifiers. Generic classifiers are supposed to shorten the training time to control a BCI, but in this test they were also found to increase the performance compared to participant-specific classifiers [195].

6.6.3 Test #3 Validation of initial generalization performance

In this test, the performance of the classifiers was increased from 83% to 88% (averaged over the two classifiers). This validates what was found in test #2 Initial generalization performance.

On the other hand, even though the performance of the classifiers in this test were considered good, this performance was again no different from what was obtained when using the participant-specific classifiers. This confirms that the nature of the data plays a role in increasing the generic classifier's performance for lower-limb BCI, but not to the extent of reaching higher performance than participant-specific classifiers. The results of test #4 Primary generalization performance supported this idea of how to increase the performance.

6.6.4 Test #4 Primary generalization performance

This is the first test in this study where completely new data from new participants were used as testing data. The performance of the generic RLDA classification models were significantly better than when using the participant-specific classifiers but the increase in the performance was only 7%, which is considered poor when compared to other studies [195, 198]. Thus, neither the 72% of performance (averaged over the two classifiers), nor the 7% increase are considered to be good for a generic classifier.

From previous tests, the findings indicate that the nature of the data plays a role in increasing the generic classifier's performance for lower-limb BCI. In this test, the testing data come from a session which lacked feedback, and participants didn't know how they were doing in terms of MI performance. They therefore had no way to improve their MI and BCI control skills. This problem extends to the training data as well. This could explain the low performance results obtained in this test. Tests #2 Initial generalization performance, and Test #3 Validation of initial generalization performance, used better datasets in an attempt to increase performance.

6.6.5 Test #5 Initial performance with larger dataset

After including the datasets of the two sessions where participants received feedback and improved their MI skills to control the BCI, the performance of cross-validation of RLDA classification models were increased by 10% (to 81%), compared to the use of a dataset from only one session. This increase in performance might be due to the use of a larger dataset to train the classifiers.

Compared to the results of other studies, such as that of Vidaurre et al. in 2011 [196], and considering the complexity of the MI tasks being carried out in this study, the performance is satisfactory. Although the performance of these classification models was a bit lower than what was obtained when using the participant-specific classifiers, these new RLDA classification models were tested on completely new data, as lower-limb MI generic classifiers.

6.6.6 Test #6 Initial generalization performance with larger dataset

The results of this test revealed that the new generic RLDA classification models had significantly increased performance, by 10%, compared to when using the participant-specific classifiers. This amount of increase in performance was consistent with what other studies have found [195, 198].

As far as we know, this is the first study that uses generic classifiers for lower-limb MI, so results can not be directly compared to other studies. With that being said, the performance of 81% of these new RLDA classification models was a little bit lower than what was found by other groups such as Lotte and Guan in 2009 [195] and this might be due to the complexity of the MI tasks.

In order to construct generic classifiers with a satisfactory performance, a large amount of data is required. For example, Fazli et al. [174] used a large database of EEG recordings from 45 participants. Also, Arvaneh et al. [198] recruited 80 participants and used their data to train the generic classifier. These number of participants are more than double and quadruple of the number of participants recruited for study 2. Even though the data in our datasets come from 3 sessions of testing, they come from the same participants. Thus, the data that were used to train the classifiers were less sparse. The greater the number of participants is and the sparser the data fed to the classifiers are, the better the classifier can perform when the data come from completely new participants. So, the fact that the new RLDA classifiers of this study resulted in performance that was a little lower than what was found by other groups might also be due to the small amount of data used to train the classifiers, which is a main limitation for this test. We think that if there were more participants in study 2, and more sessions from study 2, the performance would have increased further.

6.6.7 Test #7 Final generalization performance

This test was conducted to investigate the effect of including a large number of participants in the training dataset, in contrast to the low number of participants that was used in other tests. This number was doubled by including the datasets from 20 more participants that were recruited in study 1.

The results revealed that including the datasets of those participants significantly increased the performance, but the increase was modest and for only one classifier (Cl2). As with previous tests, this may be due the fact that the added dataset was from a session which lacked feedback. We believe that if there were feedback sessions in study 1, the performance would have increased further.

The datasets that were fed to the classifiers, from studies 1 and 2, come from all the participants of those studies, even those with lower performance. This may have contributed to decrease the performance, not only in this test but in all previous tests as well. We think that the training datasets should only include the data of the participants who had the best performance, which would consequently require more participants.

6.6.8 General discussion

Even though the tests were conducted only offline, the results confirm our first hypothesis, which is the possibility and feasibility of constructing such generic classifiers, while keeping the performance high enough to be tested on completely novice participants. The results also confirm our second hypothesis, that Cl2 would have a higher performance than Cl1 due to the complexity of the tasks. The performance increase was modest, however.

It should be noted that the performance of RLDA to classify lower-limb MI was significantly better than LRM. Moreover, in five tests out of seven, the performance of Cl2 was better than the performance of Cl1. This may be due to the fact that classification of only two MI commands that are easy to categorize, such as walking versus no movement, is easier than the classification between the MI of three motor commands such as right step, left step and no movement. However, it may be that the complexity of the neural control of walking versus taking normal steps makes this task harder to categorize.

In summary, these analyses suggest that it is possible to shorten the training time to control a lower-limb BCI by eliminating the BCI calibration session for all participants, even those with lower performance in controlling a BCI. This novel approach can be employed by taking advantage of a large dataset from a high number of participants, trials, and sessions as well as by selecting datasets where participants learned to control BCI and by applying the appropriate machine learning algorithms. All of these selections can be used to construct novel participant-independent generic classifiers that can classify lower-limb MI data from completely new participants. This lower-limb MI generic classifier technique can also provide comparable accuracy to techniques such as classifier re-calibration, which are dependent on participant-specific data.

However, further work needs to be done to validate what type of lower-limb generic classifiers can be used for pathological participants. More specifically, to validate whether the pathological participants can use the generic classifiers that were trained with the data of healthy participants, or whether they will have to use generic classifiers that were trained with the data from other pathological participants with the same pathology, or a mix of both.

6.7 Conclusion

This study reports on the first successful development of two novel generic classifiers that can classify between 4 Motor Imagery commands: Left step versus Right step versus No Movement and Walk versus No Movement. The generic classifiers were constructed and tested using a large dataset of 40 participants from two different studies and different sessions, who performed MI tasks in an immersive virtual reality environment, with a performance of 87%, similar to when using participant-specific data. These results indicate that these generic classifiers reported here, will be able to eliminate the calibration phase of a lower-limbs motor imagery BCI, and thus shorten the time to learn to control this type of BCIs. Thus, for a future work, these classifiers can be implemented on-line with an adaptive RLDA, in order to be used later in a BCI to control the gait of an avatar using different modalities of control.

Chapter 7: General Conclusions

7.1 General conclusions and novel contributions

The main goals for gait rehabilitation are to either restore, enhance or assist walking ability for patients with gait instability.

Despite the complex mechanisms of gait generation and control, gait rehabilitation techniques face many challenges and limitations. For example, robotic devices, assistive technologies, active leg protheses and treadmills, all still need further research to show their effectiveness for walking training and their effects on real gait. Previous studies suggest that the optimal program to improve walking ability involves repetitive and intensive practice which is gradually incremented in difficulty according to the advancement of the user within his rehabilitation program, which at the same time, can cause fatigue to the user [135].

Also, previous studies show that a combination of different rehabilitation systems seems to be more effective than a single gait training program alone [135] .

All these rehabilitation methods provide the user with gait re-education, considering the advantage of the plasticity of the brain in motor learning of new tasks. Furthermore, the brain has a great role in monitoring and controlling gait patterns and functions. This sparked the idea to directly “train the brain”, by using the power of the brain to control gait, in a BCI, as an additive tool to improve gait rehabilitation. This technology was combined with VR, in order to create realistic visual scenes that are: very similar to physical walking, very powerful alternative platforms, and are adapted to the user’s level of advancement. These combined systems show promising results, however they still need many improvements to overcome their limitations.

To counteract these limitations, this project firstly used an avatar displayed to the user from 1PP. Then, it showed through a novel approach that it is possible to use the BCI source signals, EEG, to measure the level of embodiment when physically or mentally controlling the gait of an avatar. This was done through the neuro-markers elicited after providing modified feedback of the avatar’s gait. This is consistent with what other studies found, such as that of Lee et al. (2015), Padrao et al. (2016) and Jeunet et al. (2018), in the context of upper-limb movements. Based on our information, this is the first study to show an EEG response to incongruent visual feedback of a self-avatar during gait.

Padrao et al. (2016) [36] also found that the amplitude of a specific EEG response to modified feedback correlated with the subjective feeling of body-ownership over upper limb movements. Our study is the first to show a correlation between this EEG response and subjective questionnaires of embodiment of an avatar, but in the context of lower limb movements. These results have important implications for the development of a more objective method of assessing, in real time, the sense of embodiment, over a walking avatar, based on physiological data. Then, the sense of embodiment can be monitored and increased when needed.

This will be reflected on the performance of the BCI, since reaching a high level of both BCI performance and embodiment are inter-connected. To reach one of them, the second must be reached as well, so the more the participant feels ownership, the more effective the results will be [47, 263].

Although the literature review revealed that rehabilitation MI-BCIs have mostly been developed for the rehabilitation of upper limbs [25], many researchers have developed BCI-based VR gait rehabilitation systems. However, most of those studies mapped the MI of upper limb movements in a BCI to control the feedback of navigation or lower limb movements of an avatar, which would not allow the user to benefit from the neural plasticity properties of MI training, and at the same time deteriorate embodiment. For example, Hazrati et al. [45] mapped MI of right/left hand and foot to control the right/left/forward navigation of an avatar in the Second Life's VE. On the other hand, BCI-based VR gait rehabilitation systems work in a single BCI mode or single type of walking. For example, Nicolelis et al. [55], whose study is the closest to the studies of this thesis, used the LDA output of the MI of right and left foot to control the right and left steps of an avatar displayed from a first person perspective (1PP). However, their BCI can not control forward walking, and does not allow for different modes of self-paced control. With such limitations, these types of BCI cannot accommodate different rehabilitation programs and patient progression within them.

To overcome these mapping and single-modality control limitations, this project reports on the feasibility and successful design and development of a BCI system that uses lower-limb MI in a multi-modal control paradigm to control the steps and forward walking of a self-avatar in immersive VR.

To our knowledge, this study represents the first demonstration of integrating all these design approaches in parallel in one single multi-modal BCI system. This BCI could be used for gait rehabilitation by imagining real steps, and progressing to imagining forward walking, while receiving the matching visual feedback from an embodied virtual avatar over which we feel agency.

However, the existing lower-limb MI-BCIs still have more limitations in terms of long overall training time, low performance and long data acquisition training time.

In previous studies, the required time for the overall training varied between a few sessions in one day [183] and many sessions over several days [182]. For gait rehabilitation MI-BCIs, sometimes it would take weeks before participants mastered the control of their self-paced BCI [55]. In this project, the twenty recruited participants were able to control the steps and forward walking of their self-avatar after only 4 days of training compared to these previous studies.

Our results suggest that such a method could potentially shorten the training time required to reach a high performance in controlling the cue-paced, and later the self-paced BCI.

As for performance, the literature review covered the three most widespread BCI enhancement techniques used to overcome these limitations: retraining of the classifiers, modified feedback (MDF) and co-adaptive training. Each technique has been used separately in different studies, but no previous study has integrated these techniques to combine the accuracy gains they afford.

To overcome the low-performance limitation of the existing lower-limb MI-BCIs, this project implemented and integrated these three different techniques, where each of them played its role in decreasing the training time and increasing the performance.

The results of this project revealed that each technique increased the performance of the BCI. For example, retraining the classifiers increased the performance by 10%, compared to (10-15%) found by other studies [188-190, 197]. MDF also increased the mean performance (10-12%) and the increase in performance spanned to later sessions. This aligns with what other groups found. For example, Alimardani et al. [202] used an upper-limb MI-BCI, and also found that the improvement in participant's performance following MDF carried over to subsequent training sessions.

As for the general BCI performance accuracy performance scores in both modes of our self-paced BCI with a general performance of 70-94%, this is equal to or higher than what was found in BCI-VR studies to control a cursor [294], upper limbs [295] or even gait [13]. Considering the complexity of the tasks being carried out in the current study, the performance is satisfactory.

As far as we know, this study represents the first demonstration of integrating all these enhancement techniques in parallel in one single multi-modal BCI system with such short training time and satisfactory performance.

Finally, to overcome the limitation of long data acquisition training time, the literature review refers to the solution of using a generic classifier and then adapting to the user's specific patterns. There exist databases of upper-limb MI EEG that have been used to test different machine learning algorithms or even to control BCIs [260]. However, there is no such database or generic classifier that can be used for lower-limb MI-BCIs.

Based on our information, this is the first study that uses generic classifiers for lower-limb MI, so results can not be directly compared to other studies. With that being said, the performance was significantly increased by 10% compared to when using the participant-specific classifiers. This amount of increase in performance was consistent with what other studies have found [195, 198]. However, this average performance was a little bit lower than what was found by other groups such as Lotte and Guan in 2009 [195]. This might be due to the complexity of MI tasks, or the low number of participants compared to other studies, such as that of Fazli et al. [174] who used a large database of EEG recordings from 45 participants. Also, Arvaneh et al. [192] recruited 80 participants and used their data to train the generic classifier.

In any case, study 3 of this project describes the first successful development of two novel generic classifiers that can classify between 4 MI commands: left step versus right step versus no movement, and walk versus no movement. The generic classifiers were constructed and tested using a large dataset of 40 participants from two different studies who performed MI tasks in an immersive VR environment. Their performance varied from good to high. This study also investigated the performance of different sparse-data classification methods that used a variety of sparse-data control algorithms such as regularization and regression hyperparameters and found that the best classification method to use was the RLDA, with a performance of 87%.

These results indicate that the generic classifiers reported here will be able to eliminate the calibration phase of a lower-limb MI-BCI, and thus shorten the time to learn to control this type of BCI. This shortened learning time is critical for it to be used in a clinical setting.

In future work, these two classifiers can be implemented online with an adaptive RLDA, in order to be used later in a BCI context to control the gait of an avatar using different modalities of control and reducing training time.

To summarize, this project reports on the novel successful development of a multi-modal and multi-control self-paced lower-limb MI-BCI to control the gait of an avatar that is displayed from 1PP. Compared to the study of Nicolelis et al., and in addition to these features, this project implemented gradual training of BCI to reach high control performance, while at the same time counteracting some limitations of such existing systems. Furthermore, this BCI used modified feedback of gait as a novel approach. Modified feedback was introduced: negatively as an online EEG-based measure of embodiment, and positively to enhance the performance of the BCI. Finally, this project counteracted the limitation of lower-limb MI lengthy training by developing novel user-independent generic classifiers for lower-limb MI of forward walking and stepping.

This BCI could be used for gait rehabilitation, where the user needs first to be trained to control the cue-paced BCI by imagining either real steps, or progressing to imagining forward walking, or both. At the same time, he will be receiving the matching visual feedback from an embodied virtual avatar over which we feel agency. The use of the generic classifier would decrease the training time at this phase. During the training to control this BCI, the experimenter can adjust the control mode to when needed, in order to follow the progress of the participant within the training program. For example, once the user starts mastering the control of the cue-paced BCI for the desired commands, he can move towards training to control the self-paced BCI. Once there, and at the very beginning of the neurorehabilitation process, the switch control mode is most suitable to control initiation of individual steps, which requires an on/off control strategy. But with the progression of the neurorehabilitation process, the continuous control mode becomes essential to be able to control the gait as a succession of left and right step motor commands at same time. However, the switch control mode, which is intermittent, does not allow for the use of the MI of walking to produce normal gait cycles. This would require the use of the continuous control mode instead. Thus, during the training, and at any time, the experimenter can choose the control mode and control command, according to the progress of the rehabilitation program.

Also, during the training to control this BCI, the experimenter can apply positive modified feedback to enhance the control of the BCI, and apply, from time to time, negative modified feedback to measure embodiment. When the level of embodiment dips, modified feedback can be limited to increase it again. To this end, a protocol of visuo-tactile synchronicity can be applied, whereby the participants is touched by an object and simultaneously sees his avatar touched in the same location.

In the longer term, the approaches developed in these studies could be used not only for regaining the ability to walk but also to reduce step length asymmetry for hemiparetic stroke patients, in combination with split-belt treadmill training.

7.2 Limitations and recommendations

The studies presented in this thesis had some limitations. Thus, many improvements will be considered for future work in different parts of the experiments:

1- In order to shorten the preparation time, dry EEG electrodes could be used instead of the active electrodes which are currently used. The performance of such electrodes has been proven to be high and effective.

2- To shorten the preparation time, fewer EEG electrodes could be used. According to the results of the two experiments presented in this thesis, the number of electrodes can be reduced by 50%, without any loss of relevant information, thus providing the same accuracy and performance.
3- In order to shorten the BCI training phase, the generic classifier developed in study 3 could be tested online in a co-adaptive paradigm, where the classifier inputs and outputs are progressively adapted to the new user's specific brain activity. This step could shorten the BCI sequential training from four to three or even two days.
4- In order to improve the training to control the BCI, many BCI studies use MI and a classifier's progress bar. It is a performance bar that can be added to the VE, either separately on the screen or super-imposed over the cue. This usually helps the user to know, in real-time, the state of his performance in controlling the BCI and to try to adjust accordingly. The absence of such a visual indication left the participants sometimes unaware of the best mental strategy to use, especially when there were multiple mental commands at a time, such as in the switch control mode. Therefore, the absence of this bar may have diminished the BCI performance achieved in this study, especially in self-paced switch mode.
5- Interestingly, the scores obtained in the subjective questionnaires reflected another of the limitations of this study. Our studies did not use a sex-matched avatar, contrary to what some previous studies have done. Non sex-matched avatars have been shown to decrease embodiment in some contexts [40], even though other studies suggest that sex-matching the self-avatars does not significantly improve embodiment [27, 301]. Across both of our studies, most of our female participants commented that they felt uncomfortable when they were embodied in a male avatar, and more specifically when they had to control the gait of this male avatar. One of those participants commented that it felt bizarre to be controlling the gait of a male avatar, looking at his feet, while wearing a skirt and an anklet. Those female participants commented that they would have felt more comfortable, and that it would have felt more realistic, to control a female avatar instead. Therefore, it is possible that the use of a sex-matched avatar could have improved and augmented the feeling of embodiment.

6- In order to accommodate different gait asymmetries and impairments, an improvement could be added to the BCI by augmenting the number of controls, such as adding step length and speed. Then, MDF could be performed over these new controls in a way that would either reduce or enlarge the error. This could be done by implementing the closed-loop feature in the BCI system.
7- An important limitation of the setup was the use of generic animations of the avatar's gait. Several participants noticed and commented that the avatar's gait looked different from their own gait. User-matched gait kinematics would therefore be an important improvement in augmenting embodiment and perhaps performance. However, since this study is a first step towards a BCI that could be used for gait rehabilitation, this may not be possible in the case of users with important impairments, some preventing them from walking at all.
8- In order to increase the performance of the generic classifiers, a larger database of right/left and forward walking MI-EEG can be used. Thus, more participants, trials and sessions would be required to build this larger database.
9- The last thing to do, as part of future work and recommendations, is to test the developed system with all these improvements on the target population for such systems such as SCI patients and post-stroke patients with different gait asymmetry problems.

7.3 Final reflection

The human brain is a world of magic and wonders. This small organ that represents three percent of the body's weight and uses 20 percent of the body's energy, not only can generate approximately 23 watts of power when awake, but also has a magnificent power of control. The brain not only controls the functions of our body on different levels, but also has the power to control external devices and software, even following the partial or complete loss of some of the body’s functions. Thousands of research groups around the globe are trying to decipher how the brain works, how we think, how we learn, how we control our bodies, and our life and, moreover, how this immense power can be used to enhance people’s lives. More is coming!

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EEG Can Be Used to Measure Embodiment When Controlling a Walking Self-Avatar

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Abstract

It has recently been shown that inducing the ownership illusion and then manipulating the movements of one's self-avatar can lead to compensatory motor control strategies in gait rehabilitation. In order to maximize this effect, there is a need for a method that measures, and monitors embodiment levels of participants immersed in VR to induce and maintain a strong ownership illusion. The objective of this study was to propose a novel approach to measuring embodiment by presenting visual feedback that conflicts with motor control to embodied subjects. Twenty healthy participants were recruited. During experimentations, participants wore an EEG cap and motion capture markers, with an avatar displayed in a HMD from a first-person perspective. They were cued to either perform, watch or imagine a single step forward or to initiate walking on the treadmill. For some of the trials, the avatar took a step with the contralateral limb or stopped walking before the participant stopped (modified feedback). Results show that subjective levels of embodiment correlate strongly with the difference in μ-ERS power over the motor and pre-motor cortex between the modified and non-modified feedback trials.

Keywords: Virtual reality, μ-rhythm EEG, event-related-potentials, gait rehabilitation, mirror neuron system.

1 Introduction

Virtual reality (VR) -based rehabilitation has seen an important gain in recent years, fueled by the availability of affordable mass-market VR devices and the several advantages such technology offers for patients and researchers [1, 2]. One such advantage is the high level of control that can be exerted on all aspects of a participant's virtual environment (VE). When a participant is immersed in VR through the use of a head-mounted device (HMD), there is the added possibility of controlling his body self-representation in the form of a self-avatar.

There are examples in the literature where imitation of the movements of a simulated avatar or representation of movement by an avatar led to motor improvements [3, 4]. In 2014, Caudron and colleagues [5] showed that a simple avatar that replicates real-time anteroposterior trunk position and orientation of the head of patients with Parkinson's disease improved their postural balance. There are also randomized controlled trial studies that reported that controlling an avatar's gait in VR physically and mentally (through a BCI) could be beneficial for gait rehabilitation [6-16] and for improving balance in chronic stroke patients [16]. Moreover, treadmills combined with VR scenarios have proved to be effective for post-stroke gait rehabilitation [7, 14, 15]. In their study, Rizo et al. [15] showed the advantages of using VR in gait rehabilitation by creating an obstacle avoidance VE system during walking in chronic post-stroke patients.

It has also been shown that in the earlier stage of pathology, motor imagery of the intended movements, combined with virtual feedback, can aid patients to gradually recover from impairment [6, 9]. This technique was then applied for gait rehabilitation in stroke. For example, Kilicarslan and colleagues [10] pioneered the deployment of BCI systems to control lower-body powered robotic exoskeletons by subjects with a spinal cord injury.

Leeb and colleagues [17] reported on a 35 year old male tetraplegic subject, who learned to control a BCI where signals of imagined foot/right/left movements were used to control walk/turn-left/turn-right. He navigated in a VR scene, in order to move from avatar to avatar by movement imagination of his paralyzed feet. Concerning the experience with the interaction, he mentioned that "I thought that I was on the street, and I had the chance to walk up to the people".

These feelings described by the participant in such studies demonstrate that humans can be successfully embodied in a surrogate body, either of an avatar [18, 19] or a robot [20]. Embodiment is the gradual process of the perceptual illusion that artificial body parts or full bodies can be perceived by people as their own [21]. Embodiment has three main components: body ownership, sense of localization and presence, and sense of agency and control. Agency is the feeling of authorship that we experience when initiating and controlling an action and distinguishes our own self-generated actions from those actions generated by others [21]. Agency requires the intention to carry out the action, and subsequently a match between its predicted and actual sensory consequence [21, 22]. The sense of agency starts with the feeling of agency, which is triggered at the very early stages of the action. Then, once the feedback has been perceived and processed, the judgment of agency results from the computation of the comparison between the predicted and actual outcomes of the

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action [21]. The second embodiment component is the sense of presence and localization. Sense of presence is the psychophysiological state which reproduces realistic behaviors and physiological responses as if the subject was experiencing a real-life situation [23]. The third embodiment component is the sense of body ownership and mineness over a static manikin body that substitutes for the real body, which was first shown by Petkova and Ehrsson [24]. It is the feeling that is described in statements such as “This is ‘my’ hand,” and occurs when the visual and tactile information coming from this object spatiotemporally correlates [21]. Evidence suggests that first person perspective over the virtual body can be a sufficient condition to create the sense of body ownership and presence [25], but that synchronous movement between the real and virtual body can also contribute strongly to the sense of embodiment by inducing a strong sense of agency and control in the virtual reality environment [18, 26, 27].

However, is there a way to determine if someone has reached the sense of embodiment in the context of its three components? And to what degree? Questionnaires are currently the most used method to assess the different dimensions of embodiment [28, 29]. This method of assessment has the obvious disadvantage of being a subjective evaluation that is dependent on a participant’s interpretation of the different questions. Moreover, questionnaires do not enable real-time/in-task recordings of the level of embodiment [29]. Therefore, researchers have combined neurophysiological measurements [22, 30]. Most of these studies used positron emission tomography (PET) or fMRI but these methods are not suitable for everyday monitoring of embodiment in VR experiments because they are neither portable nor inexpensive. This is why recently some researchers have started to use electroencephalography (EEG) and near-infrared spectroscopy (NIRS) instead.

For example, Sanchez-Vives and colleagues [31] found that participants retrieved their physical hands when their virtual hand were threatened with a knife, resulting of a brain activation of μ-ERD (8-12 Hz) over the motor cortex and central-parietal areas of the brain, which suggests a potentially new measure of virtual embodiment. Clemente et al. [30] compared EEG presence during observation and control of navigation VE. They found an increase of frontal theta and alpha activity during the perception of presence. In normal circumstances, when our ongoing actions and the predicted sensory consequences of these actions (feedback) are coherent, we experience the sensation of agency with respect to our actions (“this action is mine”), and we are typically not even aware of such considerations [32, 33]. However, in the case where there is a conflict between the predicted consequences of our actions and their actual consequences [34, 35], we might detect an agency violation through an error detection mechanism. This mechanism might be constantly checking whether the final sensory feedback is coherent with expected sensory consequences of our actions, created using an internal copy of our motor commands. These sensory feedback estimations during movement may rely strongly on previous representations of the body in terms of limb position, movement, or posture which normally give us a natural sense of being the agents of our actions [36-38]. Padrao and colleagues [39] investigated the neurophysiological correlates of modified feedback and found a parietal N400 elicited by error monitoring loops after such violation, which typically characterizes semantic or conceptual violations. They also found that the amplitude of the N400 correlated with the subjective feeling of body-ownership. When the same participants merely observed the avatar correct and error movements, no parietal N400 was elicited. This is what [40] confirmed, when participants looked at pictures representing themselves or other, and found that parietal positive ERP component P200 was less in the self-pictures.

Another explanation of this activity is the mirror neurons system that lies in the parietal and pre-motor cortex [41]. A mirror neuron is a neuron that fires both when someone acts or observes the same action performed by another [42, 43]. Thus, the neuron "mirrors" the behavior of the other, as though the observer were itself acting, which helps in understanding the actions of other people, and for learning new skills by imitation.

But is there any relationship between the effectiveness of any training using the VR, and the level of embodiment in the VR? Alimardani and colleagues [44] showed in the case of BCI-control for a moving avatar or robot, the arousal of embodiment for the user is assumed to promote his involvement in the motor imagery task and enhance his skills in the navigation and operation. The effectiveness of controlling a VR is linked to the degree of embodiment, so the more the participant feels ownership, the more effective the results are [15]. For instance, in the case of amputees with a neuro-prosthetic limb, the long term and efficient usage of the limb depends on how well the patients accept the limb as an integrated part of their own body rather than a tool attached to them. The main objective of this study was to propose a novel approach to measure virtual embodiment during gait using EEG.

2 MATERIALS AND METHODS

2.1 Participants

Twenty neurologically healthy naive participants (13 women, 7 men; aged 23.3 ± 3.93 years old) volunteered to take part in this study. They were recruited through University electronic message boards. The inclusion criteria were that participants be 18-35 years old, in good general health, with good vision (with or without glasses), not taking any medication that acted on the central nervous system and not suffer from motion sickness.

2.2 Protocol and Experiment Design

This experiment consisted of 3 conditions where the participants were asked to “do”, “imagine” or “observe” three different tasks while looking at the lower limbs of their self-avatar through a head-mounted display (HMD). The duration was approximately 3 hours, including preparation time and regular breaks. The experiment was approved by the Research Ethics Committees of the University of Montreal Hospital Center (CHUM) and of Ecole de technologie superieure (ETS), project ID number 16.170.

In the “do” condition, brain activity was recorded while the participants were physically controlling the movements of the avatar in real time. The main goal for this condition was to measure embodiment during the physical gait control in an immersive virtual reality environment. In the “imagine” condition, brain activity was recorded while the participants were imagining the avatar moving, without the physically moving. The main goal of this condition was to measure embodiment during motor imagery of moving in an immersive virtual reality environment.

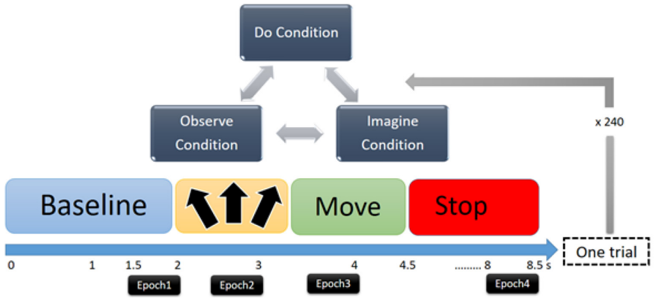

Figure 1: Experimental design of the study. Above are the conditions of the experiment, in the middle is the design of one trial. Below are the epochs (time slots) used in the analysis.

In the "observe" condition 3, brain activity was recorded while the participants were only observing an avatar moving, without physically moving. This condition was to measure embodiment during observing the gait of an avatar, and to rule out the possibility that any brain activity occurring during the "do" or "imagine" conditions was due to mere observation.

The experimental design is shown in Figure 1. Each condition consisted of 240 trials. Each trial was 8.5 seconds long and started with a two-second pause in order to acquire a baseline EEG recording. An arrow was then presented on the virtual floor in front of the participant for a period of 1.25 seconds. This arrow either pointed to the left, cueing a step with the left foot; to the right, cueing a step with the right foot; or forward, cueing to start walking. Upon receiving the cue, participants either performed, imagined or observed the appropriate action, depending on the condition they were in. They did this while standing on an instrumented treadmill.

For the first 60 trials of each condition, participants received concurring visual feedback in the form of the avatar performing the cued action (non-modified feedback - NMF). The avatar performed the action in real time for the "do" condition or 1.25 seconds after the cue onset for the "imagine" and "observe" conditions. These first 60 trials were to engage the participant in the experiment and to create the sense of embodiment. In trials 61 to 240, for one out of every 5 trials, the avatar provided conflicting visual feedback (modified feedback - MF). For these trials, when the cue was for a single step, the avatar took that step with the contralateral limb. When the cue was to start walking, the avatar started walking but stopped walking before the end of the trial, while the participant was still walking or imagining himself walking. This movement violation was implemented to create a mismatch between the intended and resulting movement and measure for an EEG-response to the modified feedback that is dependent on being embodied.

EEG data was only analyzed offline. The feedback provided to the participants was therefore not dependant on their brain activity.

2.3 Experimental Setup

Participants were immersed in a VE using an Oculus Rift (Consumer Version 1) HMD. The VE was developed in Unity 3D game engine and consisted of a virtual hallway (Figure 2), which was a replica of the hallway in our research center, although the virtual hallway was designed to be infinite. Horizontal lines were added to the floor design in order to for forward movement to be more easily perceived while looking at one's feet. A virtual self-avatar was displayed from a 1st person perspective with respect to the participant. The action cues that were presented in front of the virtual feet consisted of a yellow arrow pointing left, right or straight ahead. When the avatar took a step or started walking, he moved forward in the virtual hallway, thus resulting in a realistic optical flow of the VE.

Figure 2: A 3PP view of the virtual avatar standing in the middle of the VE (left image); a 1PP view of what the participants saw in the HMD, showing the cue for a step with the right foot (right image).

For the "do" condition, a set of 15 rigid bodies containing reflective motion-capture markers were placed on the participants' bodies (Figure 3). A 12-camera Vicon optoelectronic motion-capture system with Vicon Tracker software was used to track the participants' movements. During a short calibration phase, the participant performed a series of squats, hip circumduction movements and upper limb rotations in order to identify the position of their joint centers to align them with those of the virtual avatar's rig.

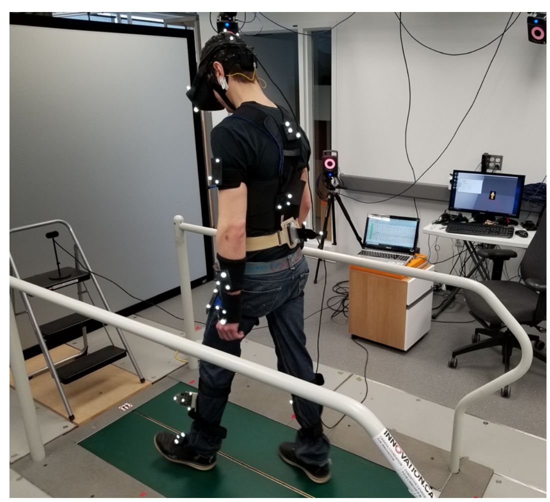

Figure 3: The experimental set-up. A participant takes a step on the treadmill while wearing the mocap markers, HMD and EEG cap

Movements were then applied to the virtual avatar in real-time, via TCI-IP protocol. The movements of the avatar had no noticeable delays when compared to the participant's real movements.

The EEG was recorded using a Smart BCI system consisting of a cap with 19 Ag/Cl cup electrodes set according to the 10-20 system and fixed to the scalp with conductive gel (SignaGel). These electrodes were grounded to AFz and referenced to both ears using an ear clip on each ear. The electrode positions were configured to accommodate this study (Figure 4), covering the whole scalp with a higher density above the pre-motor, motor and parietal areas, which were the main regions of interest. The EEG device sends EEG data via Bluetooth to the EEGStudio software, which in turn streams them in real time via API to Matlab.

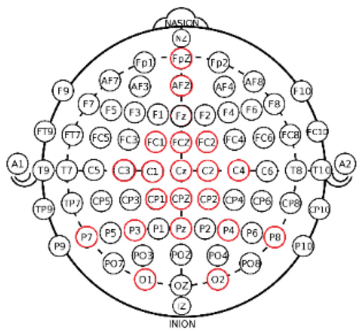

Figure 4: The EEG-electrode configuration for the current study. Red circles indicate the positions of electrodes.

2.4 EEG Data Pre-Processing

The data were recorded using EEGStudio, pre-processed and processed using Matlab/EEGLab. EEG signals were band-pass filtered in 4-30Hz, then artefact removal was performed using 3 methods: 1- a semi-automatic method, where epochs containing abnormal values (inferior to -200µV or superior to 200µV) or abnormal trends (maximal slope superior to 200µV with a R-squared limit fixed to 0.3) were rejected; 2- an approach based on blind source separation (BSS) algorithms was used, which includes an automated independent component analysis (ICA) to isolate and remove electro-ocular components from the EEG data [45]; 3- with visual inspection, artefacted epochs were also rejected. Data were then re-referenced using Common average referencing (CAR). A baseline removal algorithm was applied, using the 200ms preceding the cueing (apparition of the arrow) as the baseline. Data were then epoched into 4 main 500ms epochs: preceding the cueing, following the cueing, during the movement and after the end of the movement. The rationale behind this epoching was that the feeling of agency is supposed to occur during the trial beginning period while the judgment of agency should occur during the feedback processing period. Finally, each epoch was filtered into 2 bands: alpha band (8-12 Hz) and SMR (12-15 Hz).

2.5 EEG Data Offline Analysis

In the above-mentioned epochs and frequency bands, spectral power analyses were performed. A statistical analysis (paired t-test) was then performed in order to determine if the recorded signal power was significantly different over all of the above-mentioned cases. These analyses were performed using permutation statistics, with a threshold p-value fixed at 0.05, completed by a false discovery rate (FDR) correction for multiple comparisons.

2.6 Questionnaires

After each condition, participants were asked to answer a questionnaire consisting of 9 questions with 7-point Likert scales. These questions were related to the sense of presence (1-3), body ownership (4-6) and sense of agency and control (7-9) [20, 39, 46]. It took approximately one minute to complete the questionnaire.

3 Results

3.1 Neurophysiological Results

Data analysis revealed significant differences between trials with modified and non-modified visual feedback only in µ frequency band. All results presented in this section are therefore within this frequency band. Brain activity related to the left- and right-footed steps was found to be laterally inverted, so the results were mirrored and combined in one plot in order to facilitate the analyses. These results are depicted in Figure 5.

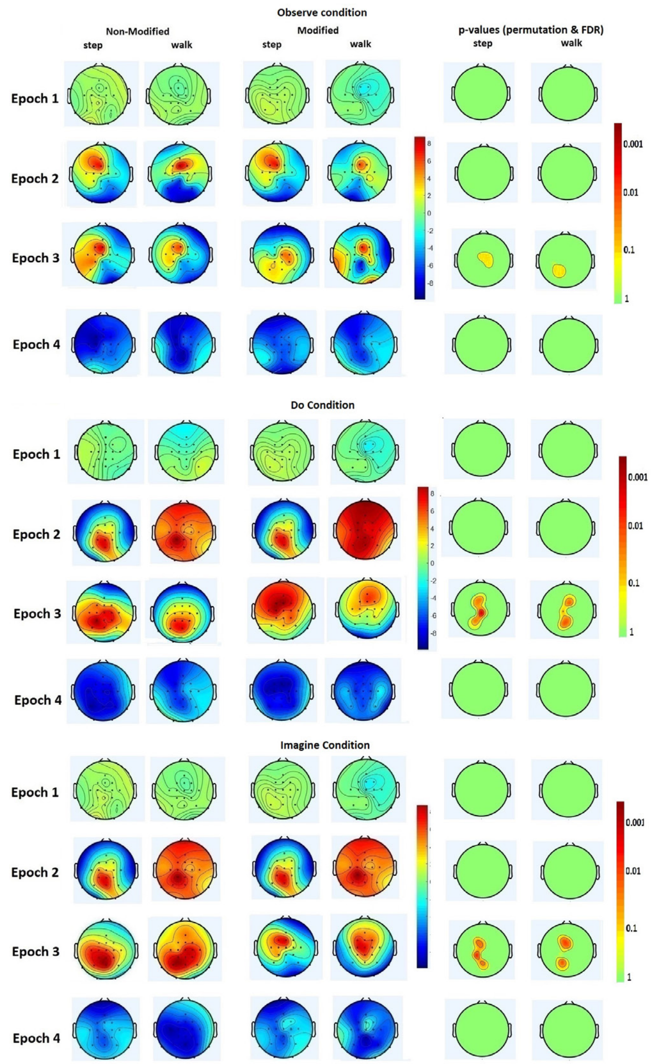

Figure 5: Spectral power maps of the µ frequency band (8-12 Hz) for the different epochs (time slots), conditions and cases. The analysis shows when controlling the avatar's gait, a strong central and parietal ERS in the case of non-modified feedback, versus a stronger frontal ERS in the case of modified feedback.

In the "do" and "imagine" conditions, the spectral power peaks over the central and central-parietal areas of the brain, with a stronger activation of the central-frontal areas in the walk stimuli in epoch 2 (500 – 1000 ms after the cueing appeared). These brain activations are a representation of a larger event-related synchronisation (ERS - i.e., increase of the signal power compared to baseline) and they may be specific to the higher feeling of agency. These spectral power increases occurred with no significant difference between the "do" and "imagine" conditions ($p=0.2$) but were significantly weaker in the "observe" condition, for both central-parietal ($p=0.04$ and $p=0.001$) and central-frontal ($p=0.04$ and $p=0.001$).

For NMF trials of the "do" and "imagine" conditions, the high central-parietal and central ERS seen in epoch 2 remained in epoch 3 (250 – 750 ms after the visual feedback started) on the central-parietal ($p=0.3$) but spanned to left-parietal areas of the brain ($p<0.05$). Moreover, the was no significant difference in central-parietal area between the "do" and "imagine" conditions ($p=0.3$). In the "observe" condition, the analysis of NMF trials did not show the left-parietal ERS component observed during the "do" and "imagine" conditions ($p<0.001$).

In contrast, for MF trials (i.e. in low agency) the "do" and "imagine" conditions show that the high ERS was diminished or disappeared from the central-parietal region ($p<0.001$) and became more central-frontal after a walk stimulus ($p<0.05$) and left-central after the step stimuli ($p<0.001$). Moreover, there was significant difference in the epoch 3 central-parietal ERS between the MF and NMF for the "do" ($p<0.05$) and "imagine" ($p<0.001$) conditions

Pairwise comparisons showed that the central-frontal ERS amplitude was significantly increased for the "do" ($p<0.05$) and "imagine" ($p<0.001$) conditions, when compared to the "observe" condition. No significant differences were found between MF and NMF trials for the "observe" condition.

3.2 Behavioral Results

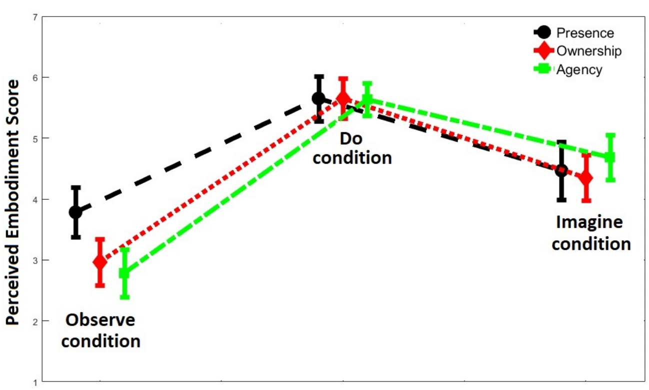

Figure 6 Behavioral results based on the questionnaire answers obtained after every block and decomposed into the 3 embodiment components. The score for each component was computed by averaging the three questions related to this component

In the questionnaires, there were 3 questions to rate each of the components of embodiment. The score for each component was computed by averaging the three questions. A high score on the component average indicates a stronger sensation for this embodiment component (Figure 6). The Shapiro-Wilk test revealed that the normality assumption is rejected, so the Wilcoxon test was performed over all paired samples of the questionnaire responses.

Overall, these results are consistent with our expectations and show that in general, when physically controlling the avatar ("do" condition), the perceived embodiment is higher than when mentally controlling the avatar ("imagine" condition), which is in turn higher than when observing the gait of an avatar.

Within the "do" condition, the three embodiment components had almost the same perceived levels (at 80%), with no significant differences. This suggests that the modified feedback influenced the embodiment components altogether. However, in "imagine" and "observe" conditions, we can see a relatively higher score of sense of presence, compared to the two other components of embodiment. In the "observe" condition, the score for the sense of presence was significantly higher than the scores for agency ($Z= -2.3532$, $p=0.018$) and ownership ($Z= 1.8716$, $p= 0.06$) but also significantly lower than the presence score for the "do" condition ($Z= -3.8701$, $p<0.001$).

In the "imagine" condition, the sense of agency score was significantly higher than in the "observe" condition ($Z= -4.0860$, $p<0.001$) and significantly lower than in the "do" condition ($Z= 2.8801$, $p=0.004$).

A correlation analysis (Wilcoxon rank sum test correlation) was performed between the embodiment questionnaire results and the brain activity of the central-frontal (electrodes FCz, FC1 and FC2) and parietal areas (electrodes CPz, CP1, CP2, Pz, P3 and P4). This brain activity was represented as the difference in mean amplitude of the ERS between MF and NMF trials, elicited at epoch 3.

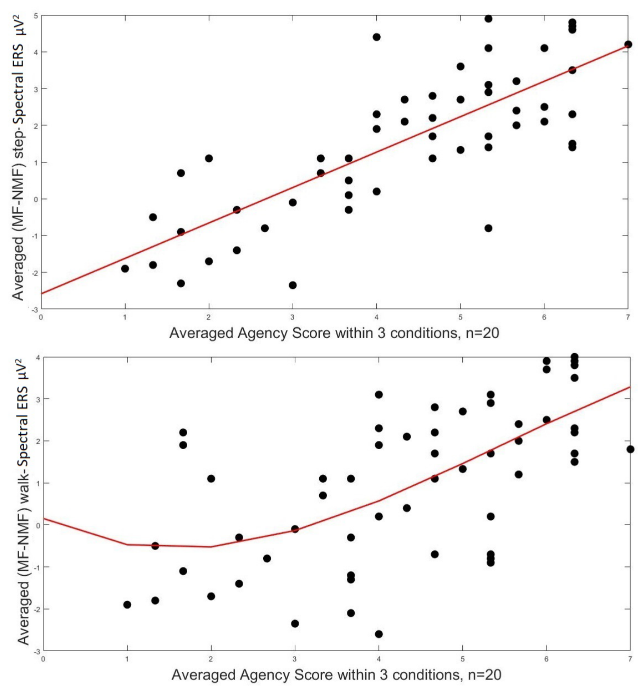

Figure 7 A correlation analysis over the subjective strength of agency, and the mean amplitude of the epoch 3 ERS over the 3 different conditions. This amplitude was computed subtracting the steps/walk NMF-ERS from the steps/walk MF-ERS over the parietal and central frontal electrodes

In other words, it is a correlation between the subjective evaluation of embodiment and the mean effect of the MF over the central-frontal and parietal areas. This was done for each of the 3 conditions. Results show a positive correlation between these measures ($r_{step}= 0.69$, $r_{walk}=0.61$). When using only the scores of the sense of agency, the correlation is stronger ($r_{step}= 0.73$, $r_{walk}=0.61$). This result, shown in Figure 7, suggests that participants who experienced stronger embodiment, elicited stronger ERS modulations in response to agency violations.

4 Discussion

This study focused on the possibility of measuring the perceived feeling of embodiment using EEG, when a user controls an avatar that represents his body and mimics his movements, or his imagined movements, in real time. To do so, an experiment investigated the effect of providing modified visual feedback to embodied participants, in the form of a self-avatar whose movements were incongruent with those performed or imagined by the participant (modified feedback).

When delivering modified feedback (low agency), a strong and long central-frontal ERS was found in the "do" and "imagine", representing the judgment of agency and resulting from the error-monitoring loops and the complex compensatory cognitive control mechanisms that were triggered after the avatar error, where the user intends to stop the motion on reaching the goal position. This activity was found to be much lower in the absence of modified feedback, and this is may be due to the normal activity of the error-monitoring neuronal circuits in the brain area.

Our ability to recognize ourselves as agents of our own behavior depends on constantly monitoring the sensory consequences of our ongoing actions. When a mismatch is detected between any of these internal predictions and reafferent signals, a violation of the sense of agency might be triggered. Thus, this frontal-central ERS could be reflecting the output of this comparison process, which might lie at the core of the movements monitoring loop. This pattern of greater MF ERS over the central-frontal areas may be specific to the judgment of agency, where the user intends to stop the motion of the in order to reach the target position [41]. This is due to the mirror neurons system in the frontal lobe, firing neuronal activity in order to understand and manage this erroneous action of the avatar. Moreover, the ERS over the parietal areas may be due to the role of this part the brain in spatial navigation when the feeling of agency occurs.

These neurophysiological measures revealed the same patterns as the ones described in the literature:

1- A strong central-frontal and central-parietal μ-ERS was revealed in the non-modified feedback epochs (high sense of agency).
2- This parietal μ-ERS was due to role of the angular gyrus in the inferior parietal cortex to the feeling of agency [47] and the comparison processes between predicted and actual consequences of ongoing actions [5, 48].
3- A strong central-frontal and left-frontal μ-ERS was revealed in the modified feedback epochs (low sense of agency).

Remarkably, the step MF-ERS over the left central area was higher than the walk MF-ERS for the "do" and "imagine" conditions. This may be due to the complex compensatory cognitive control mechanisms that were triggered after the avatar moved incongruently with regards to the participant. When physically or mentally controlling the gait of an avatar, the movement violation of the walk (walk MF) was presented by delivering an absence of feedback. However, the movement violation of the steps (steps MF) was presented by delivering an incongruent feedback, and the latter seems to be more power-consuming by the brain than the former. This is aligned with previous findings, that the cognitive return of an anti-saccadic movement is stronger than the cognitive return of a movement inhibition.

In contrast, when observing the gait of an avatar in that immersive virtual reality environment, no central-frontal or parietal μ-ERS changes occurred after delivering modified feedback, but only few parietal and frontal ERS traces were found. This was confirmed by the scores in response to questions such as 'It felt as if I was in a corridor' or 'There were times when, I forgot my presence in the real world, believing that the avatar was me', where we can see a relatively high score of sense of presence and localization,

This may be due to the immersive virtual reality environment, and the avatar that was displayed in 1PP. This result is consistent with previous findings, that watching an avatar's gait in a 3D immersive virtual environment is good enough to create the sense of embodiment. On the other hand, could the modified feedback influence the low scores of the two other components in the watching block? Actually, and as stated above, the modified feedback influences all the embodiment components, thus the high score of the sense of presence rules out the possibility of effect of modified feedback over the watching condition.

In this study, a significant correlation was observed between the amplitude of the frontal-central and parietal ERS component and the subjective feeling of body ownership. The greater the subjective feeling of body ownership, the stronger the ERS amplitude or the electrophysiological signature of agency violation. More importantly, this activity was not found when observing the modified feedback of an avatar's gait. In this condition, the participants' questionnaire scores showed that they felt immersed but felt significantly less in control, which supports the theory that the strength of frontal-central ERS can be used to measure the sense of agency over the gait of a virtual avatar when delivering modified feedback.

Overall, the "imagine" condition induced a high level of embodiment toward the self-represented avatar (as measured by body ownership, localization, and agency) [4,20,39]. Even though participants did notice that they could not always control the avatar movements, as reflected by the scores in response to questions such as 'The movements of the avatar corresponded to my movements / imagined movement in real time' or 'There were times when I felt that I was walking with my walk and not with someone else's walk', their sense of agency score was higher than in the "observe" condition and lower than the "do" condition. To summarise, these analyses suggest that when physically or mentally controlling the gait of an avatar, the three embodiment components can be measured by neuro-markers represented by the central-frontal and central-parietal μ-ERS changes after modified feedback, potentially reflecting the sense of presence, the sense of agency with its two components (the feeling and the judgment of agency) and the sense of ownership.

5 Conclusions

This study showed that it is possible to use EEG to measure the level of embodiment when physically or mentally controlling the gait of an avatar, through the neuro-markers elicited after providing modified feedback of the avatar's gait. To our knowledge, this is the first study to show an EEG response to incongruent visual feedback of a self-avatar during gait. It is also the first the show a correlation between this EEG response and subjective questionnaires of embodiment of an avatar, in the context of lower limb-movements.

To conclude, our results have important implications for the development of a more objective method of assessing the sense of embodiment, based on physiological data. Most importantly, the approach used in this study could eventually be used for online real-time monitoring of the sense of embodiment. This could ensure embodiment is maintained in order to maximize the benefits of rehabilitation protocols in embodied immersive VR.

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Journal **XX** (XXXX) XXXXXX https://doi.org/XXXX/XXXX

A Multi-Modal Modified-Feedback Self-Paced BCI To Control the Gait of an Avatar

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Abstract

Brain-computer interfaces (BCI) have been used to control the gait of a virtual self-avatar with a proposed application in the field of gait rehabilitation. Some limitations of existing systems are: 1- some systems use mental imagery (MI) of movements other than gait; 2- most systems allow the user to take single steps or to walk but do not allow both; 3- most function in a single BCI mode (cue-paced or self-paced). **Objective**: The objective of this study was to develop a high performance multi-modal BCI to control single steps and forward walking of an immersive virtual reality avatar. **Approach**:This system used MI of these actions, in cue-paced and self-paced modes. Twenty healthy participants participated in this study, which was comprised of 4 sessions across 4 different days. They were cued to imagine a single step forward with their right or left foot, or to imagine walking forward. They were instructed to reach a target by using the MI of multiple steps (self-paced switch-control mode) or by maintaining MI of forward walking (continuous-control mode). The movement of the avatar was controlled by two calibrated RLDA classifiers that used the μ power spectral density (PSD) over the foot area of the motor cortex as a feature. The classifiers were retrained after every session. For a subset of the trials, positive modified feedback was presented to half of the participants, where the avatar moved correctly regardless of the classification of the participants' MI. The performance of the BCI was computed on each day, using different control modes**. Main results:** All participants were able to operate the BCI. Their average offline performance, after retraining the classifiers was 86.0 ± 6.1%, showing that the recalibration of the classifiers enhanced the offline performance of the BCI ($p < 0.01$). The average online performance was 85.9 ± 8.4% showing that modified feedback enhanced BCI performance ($p = 0.001$). The average performance was 83% at self-paced switch control and 92% at continuous control mode. **Significance**: This study reports on a first BCI to use motor imagery of the lower limbs in order to control the gait of an avatar with different control modes and different control commands (single steps or forward walking). BCI performance is increased in a novel way by cmobining three different performance enhancement techniques, resulting in a single high performance and multi-modal BCI system. This study also showed that the improvements due to the effects of mofified feedback lasted for more than one sesson.

Keywords: Brain-computer interface, Virtual reality, EEG, Classification, Avatar, Gait Rehabilitation

1. Introduction

A brain-computer interface (BCI) is a system that measures brain activity of an intention to do something and converts it into a control command that replaces, restores, enhances, supplements or improves natural brain activity output [1-3]. This control command has been used to control: assistive exoskeletons [4], self-navigation in virtual reality (VR) [5, 6] or the movements of a virtual self-avatar [7-9]. Such uses of BCI technology have found increasingly widespread applications in the field of neurorehabilitation [10-12] where it has been used to control the ambulation of a virtual self-avatar in VR in a Spinal Cord Injury (SCI) patient [7] and in post-stroke individuals [13-17]. In this type of BCI, users imagine the movement of a specific limb of their body and this motor imagery (MI) is detected by the BCI and translated into control commands that result in an action in VR or in movements of their avatar [18].

When this occurs, an illusion of embodiment of the virtual body can be induced [19-21]. Embodiment is the perceptual illusion whereby one perceives a virtual body, in part or in whole, as being their own [22]. The induction of such an illusion is important in MI-BCIs, where reaching a high level of both BCI performance and embodiment are inter-connected. To reach a high level in one of them, the second must also be reached to a high level [23, 24].

In addition to its role in inducing embodiment, MI of an intended limb movement also induces changes in μ (8–12 Hz) and β (16-30 Hz) rhythms over the corresponding sub-region of the sensorimotor cortex [25, 26]. Previous studies have shown that providing virtual visual feedback corresponding to the MI of intended movements can help patients can gradually recover from impairment through neuroplasticity [10, 26-31].

However, the benefits of using MI of the lower limbs during gait have not been as widely shown as they have been for upper limb movements, partly because of the complexity of the neural and biomechanical control of gait [32]. Hence, several studies have used MI of upper limb movements in a BCI to control the feedback of the navigation or lower limbs of an avatar [33-38] or of an exoskeleton [37]. For example, Hazrati and Hofmann [38] used the signals of MI of right/left hand movements to control the left/right navigation of an avatar. The same BCI with the same classification paradigm and mapping was used in [39], but this time with the additional possibility of self-paced navigation of the avatar. In similar work, the Linear Discriminant analysis (LDA) classifier output of IM of the manipulation of a cube was used in a BCI to control the navigation of an avatar in a rehabilitation room [36]. Such methods have been shown to allow a user to control the gait of an avatar but the fact that the imagined movement is different than the produced movement of the avatar prevents it's use in gait rehabilitation. Indeed, such a BCI would not allow the user to benefit from the neural plasticity properties of MI training, which is a crucial part in rehabilitation and restoring or enhancing motor functions [16, 40]. Moreover, performing MI of one movement and receiving visual feedback of another movement, sometimes even from a different limb, would not be conducive to the feeling of embodiment over the virtual avatar. This would therefore have a detrimental effect on BCI performance [41, 42].

To overcome this limitation, many studies have focused on the EEG signatures of gait, such as left and right foot discrimination [43, 44], gait initiation and termination in order to move forward and stop [45] and normal gait cycles [46]. They found that brain areas employed by these controls are lateralized (for steps) [43, 47, 48] and centralized (for walking) [45]. However, few studies have used MI of the lower-limbs in a BCI system that controls walking feedback [7, 49, 50]. To our knowledge, only two studies have used MI of the lower-limbs in a BCI system to control the feedback of taking steps [51]. For example, Donati et al. [51] found that using long-term training of paralyzed patients with a lower-limb MI-BCI to control the left and right steps of a virtual self-avatar, and later of a lower-limb exoskeleton, lead to partial neurological recovery. Such studies show promising results but they limit patients to only one type of command for walking (individual left and right steps) without allowing patients to progress to using the imagination of walking in normal gait cycles [7, 52].

On the other hand, a user can control BCIs in different modes. In cue-paced BCIs, the user is cued as to when to start producing the MI and the EEG signal has to be analyzed in predefined time windows. In contrast, self-paced BCIs continuously analyze EEG data, allowing the user to produce the specific mental pattern whenever he/she wishes. These self-paced BCIs can be further categorized in two modes. The first uses a brain switch control where the feedback is provided only once after the classification (switch-control mode) [53]. The second uses a continuous control , where the feedback is provided continuously for as long as the MI is maintained by the user (continuous-control mode) [54]. Each BCI control mode has its specific benefits to the rehabilitation process, depending on the training program of the rehabilitation process, the current phase within the training program of the rehabilitation process, the level of pathology and the progress of the user within his training program of the rehabilitation process. For example, the switch control mode is most suitable to control initiation of individual steps, which requires an on/off control strategy. But with the progression of the neurorehabilitation process, the continuous control mode becomes essential to be able to control the gait as a succession of left and right step motor commands at same time. Furthermore, the current gait MI-BCIs lack the possibility to enable the user to control BCIs in different modes at the same time [55].

Therefore, when designing a BCI for gait rehabilitation, a proposed way to overcome the aforementioned limitations is to allow the use of MI of left/right steps and of forward walking at the same time, and to map these signals to control the gait of an avatar in different modes (cue-pace, self-paced switch, self-paced continuous). Given the advantages of the different BCI-control modes for neurorehabilitation [56], the concurrent implementation of all of them would allow to accommodate different rehabilitation programs and patient progression within them. However, the combination of more control options and several modes in a single system would result in diminished performance, which is already low in lower-limb MI-BCIs, in comparison to upper-limb MI-BCIs [3, 55]. This lower performance is particularly problematic for rehabilitation applications because receiving feedback that is incongruent with the imagined movement would diminish embodiment and be detrimental to achieving neural plasticity benefits [16].

To overcome performance limitations, three enhancement techniques have been used in previous studies. The first consists of using a co-adaptive sequential experimental protocol to train users over different control modes [57]. Experimenters gradually increase the task difficulty in order to help the user stay engaged in the learning process, adapt to this process and tune his/her performance [58, 59]. They take into account the performance of the user at every stage of the training, using the method described by Tariq et al. [55]. Using this approach, the brain also adapts to the classifier periodically, thus getting the maximum benefits of the neural changes induced throughout the BCI training phases. For example, Allison et al. [60] shaped the cursor-control BCI training gradually from switch-control mode to continuous-control mode. In two different studies, it took 6 – 10 days [61] to master the control of the BCI [62]. Scherer et al. [8] trained users over a period of 3 days to control navigation in VR through a MI-BCI.

The second enhancement technique is the use of modified feedback. Feedback that is either positively or negatively modified has been shown to result in an adaptation on the part of participants, with performance enhanced up to 10% [63]. The BCI of Luu et al. [64] was used to control the gait of the left foot of a virtual avatar. After and initial training period, asymmetric gait patterns of the avatar were introduced over 8 days, resulting in neural and gait adaptation in participants. Similarly, Gonzalez-Franco et al. [65] and Alimardani et al. [66] reported that positive feedback had a greater learning effect on MI-BCI performance and the ownership illusion. This is also consistent with the results of Lotte et al. [67].

The third enhancement technique is used when we have a BCI training of multiple sessions, and it is to retrain the classifier after every session [68, 69]. This technique reduces the problem of the long calibration time that is required for BCIs, due to the large amount of calibration data that is required. For example, Sun and Zhang [70] trained users to control a cue-based BCI over 3 sessions, and adaptively updated the classifier based on new data from each session. The classification results were improved by an average of 10% between session 1 and session 3, versus a 2% improvement when using non-retrained classifiers. The same improvements were reported by Shenoy et al. [71] , Acqualagna et al. [72] and Llera et al. [73].

The main objective of this study was to design and evaluate a BCI for gait rehabilitation that integrates MI of left/right steps and forward walking at the same time, mapping these MI signals to control the gait of an avatar in immersive VR. This BCI had to allow control in cue-based mode and in the different self-paced modes (switch and continuous). We hypothesized that participants would be able to operate this BCI in all modes, with a better performance in cue-paced mode than in self-paced

and for self-paced more. We further hypothesized that performance in switch-control mode would be higher than in continuous-control mode. The secondary objective of this study was to investigate the increased performance of the BCI by integrating the three aforementioned performance enhancement techniques. We hypothesized that each of these techniques would contribute to increasing the overall performance of the BCI.

2. Materials and Methods

2.1 Data acquisition and recording

EEG signals were recorded with a Smart BCI system (Mitsar, Russia). This system consists of an EEG cap with 19 Ag/Cl cup

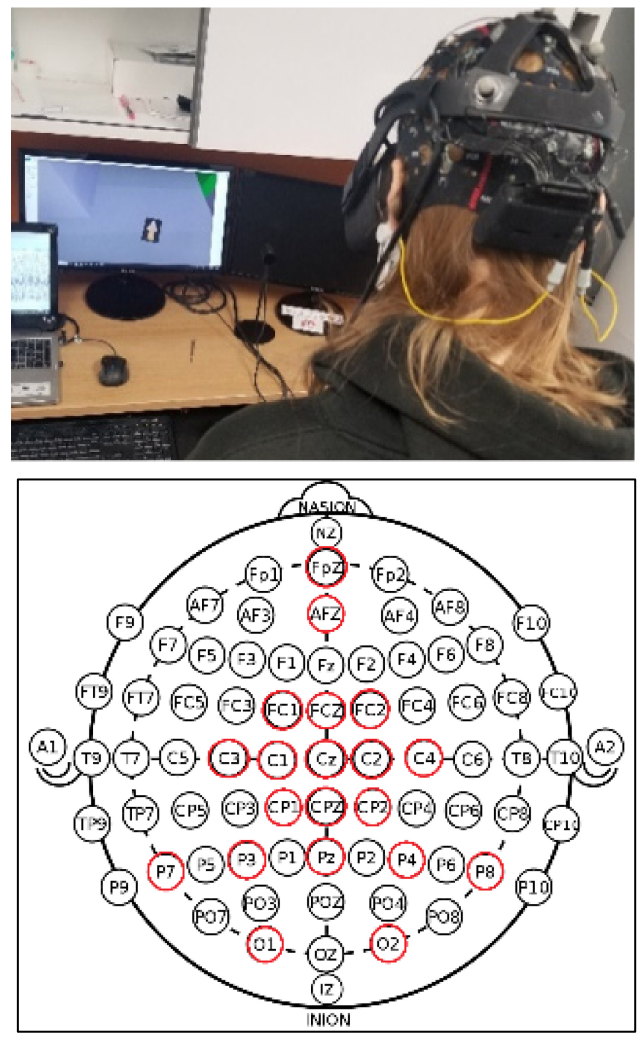

Figure 1: Top: a participant controls the BCI by imagining a right step while wearing the HMD and EEG cap. Bottom: EEG-electrode placement design for this study. The positions of the electrodes are identified by red circles.

electrodes. The electrode positions were set to cover the main regions of interest (Figure 1) in this study. Thus, most of the electrodes were sitting over the pre-motor, motor and parietal areas. The EEG electrodes were placed as stated by the 10-20 system and applied to the participant's scalp with conductive gel. The electrodes cover the central area under electrodes C1, C2, C3, C4 (lateralised feet control) [43, 47, 48] and Cz (forward walk control) [45], the central frontal area under electrodes FCz, FC1 and FC2 (movement planning) [45], the frontal area (FPz) [74] the central-parietal area under electrodes CPz, CP1, and CP2 (spatial navigation and feet control) [45], the parietal area under electrodes Pz, P3, P4, P7 and P8 (spatial navigation and sense of presence) [43, 44] and the occipital area (O1 and O2). The AFz electrode was used as ground, and an ear clips on each ear were used for reference. Since the HMD was positioned right over the EEG cap, special care was taken when installing it, in order to not displace the electrodes.

When controlling the avatar via the EEG-based BCI, the EEG signals where streamed to EEGStudio software (Mitsar, Russia) via Bluetooth, which in turn streamed them in real-time via an API to MATLAB. These signals were analyzed online, then control signals were formed. The TCI-IP protocol was used to send these control commands to the virtual avatar, in real-time.

An Oculus Rift HMD was used in this experiment in order to immerse the participant in a VE. This VE, developed in Unity 3D (Unity Technologies, USA), was an infinite virtual corridor that was a replica of the hallway in our research center (Figure 2). To increase the perception of forward progress within the corridor, horizontal lines were added to the floor texture, increasing the optical flow. A generic virtual self-avatar was created using MakeHuman. The size of the avatar was set to be proportional to the size of the VE. The height of the camera was calibrated according to the height of the participant in order to align the visual perspective with the positions of the avatar's eyes. The avatar was animated using a generic human walking animation obtained from Mixamo (Adobe, USA).
When the avatar initiated a forward step or forward walking within the virtual corridor, a realistic optical flow of the VE was produced.

Figure 2: The VE that was used in this study. The left image shows the virtual avatar displayed from a 3PP; the right image shows the avatar displayed to the participant from 1PP in their HMD. It also shows the arrow cue for a right step.

2.2 Experimental Protocol

Twenty participants that fit the following inclusion criteria were recruited for this study: aged between 18 and 45 years old, in good general health, not taking any medication that acts on the central nervous system, with good vision (with or without glasses), and not suffering from motion sickness. These participants (12 women, 8 men; aged 26.7 ± 6.1 years old) were recruited through our research laboratory's newsletter emails. The experiment was approved by the Research Ethics Committees of the University of Montreal Hospital Center (CHUM) and of Ecole de technologie superieure (ETS), project ID number 16.170. All recruited participants signed an informed consent form prior to their participation in the study.

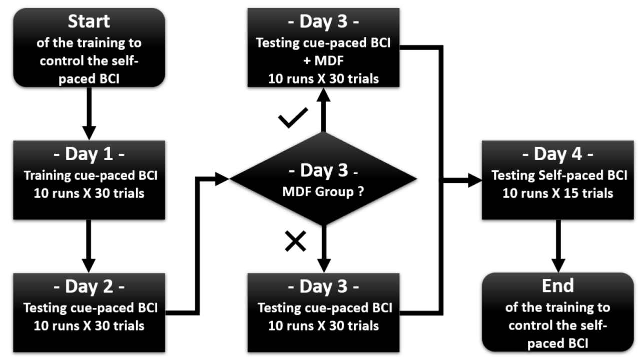

Figure 3: General experimental design of the study

The study was conducted over 4 consecutive days (1 session per day), in a co-adaptive sequential training, in order to control a BCI in a self-paced paradigm (Figure 3). During the experiment, participants were instructed to wear a head-mounted display (HMD) and to always focus on the lower limbs of their self-avatar, displayed in this device from a first-person perspective (1PP). They were instructed to "imagine" three different types of movements. The experiment lasted approximately 1.5 hours per session, including setup time and regular breaks.

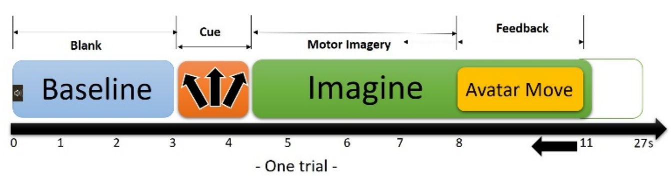

Figure 4: Experimental design of one trial, showing the total duration of 11 s for each trial of days 1 to 3, and the total duration of 27 s for each trial of day 4

Training in days 1 through 3 included 10 runs, with 30 trials each, for a total of 300 trials. The training in day 4 included 10 runs of 15 trials, for a total of 150 trials (Figure 2). Each trial lasted approximatively 11 seconds and started with an auditory cue (a beep) to indicate the beginning of a trial. It was followed by a baseline EEG acquisition that lasted three-seconds. Then, for a period of 1.25 s, the participant was shown a yellow arrow on the virtual floor, 152 cm in front of his feet. This arrow was used to cue the three different types of movements the participant had to imagine during the experiment. When the arrow was pointing to the left, the participant had to imagine a step with the left foot, when the arrow was pointing to the right, the participant had to imagine a step with the right foot and when the arrow was pointing straight forward, the participant had to imagine walking forward. Following MI of the action, the participant received feedback in the form of an action from his/her self-avatar (Figure 4).

2.2.1 Cue-Paced BCI design

On day 1, EEG was acquired during the MI the participants performed of the cued actions, without them physically moving. The avatar performed the cued movements after the cue disappeared, but the actions of the avatar were independent of the recorded brain activity. The main goal of this session was to acquire the signals related to the MI of the participants and train two classifiers. At the end of this session, signals were analyzed, and the two classifiers were trained: a classifier with two possible classes: walking forward or no movement (Cl1), and a classifier with three possible classes: right step, left step or no movement (Cl2).

On day 2, the previously trained classifiers were used in the same paradigm as on day 1, but this time the avatar performed the movements according to the classification of the brain activity signal. The classifier output was updated every 200ms. In order to change from the no-movement to the movement state, and to prevent rapid changes, the subject had to accumulate more than a “selection time” with the correct movement selected [54, 75]. The selection time is the number of successive correct classifier outputs resulting from MI of a movement. The selection time was set to three consecutive outputs, i.e. 600 ms.

If the MI was held for less than this selection time, the state remained in no-movement. Similarly, if the MI output classification was for the incorrect class, the state remained in no-movement.

2.2.2 Modified Feedback Cue-Paced BCI design

On day 3, in order to enhance the BCI performance, two techniques were used: 1- the two classifiers were updated and retrained using the data from both day 1 and day 2; 2- modified feedback was provided.

The same paradigm as on days 1 and 2 was used but 10 participants were provided with modified feedback (MDF) of their performance, whereas 10 participants were provided with feedback reflecting their actual performance (regular feedback, RGF). Participants were randomly assigned to one of the two groups and were not informed of the possibility of altered feedback. In the MDF condition, the participants first performed two sets where the feedback of the BCI (the avatar’s movements) was congruent with the classification of the participant’s brain activity. This was followed by six sets of positive MDF, wherein the feedback of the BCI was set to reflect the cued movement, regardless of the participant’s brain activity, in 70% of the trials. In the remaining 30% of trials in sets 3 through 8, and in all trials of sets 9 and 10, the feedback of the BCI reflected the classification of brain activity.

2.2.3 Multi-Modal Self-Paced BCI design

The main goal of day 4 was to control a self-paced BCI in two randomly presented modalities: continuous and switch modes. Before this session, the two classifiers were updated and retrained again using the data from days 1, 2 and 3. Participants completed 10 sets of 15 trials where they were presented one of the three action cues, in randomized order. They were informed that when they received a forward walking cue, their avatar would move forward as long as they maintained the imagination of this movement (continuous mode). When they received right and left step cues, their avatar would take a single step forward after each correct MI task (switch mode).

There were 3 requirements that had to be met for a trial to be considered successful. First, the participant’s avatar had to reach a target arrow by either sustaining MI of walking forward or by imagining multiple successive steps (starting with a left or right step, depending on the received cue). The second requirement was for the target arrow to be reached within a time frame of 24 s. In the continuous control mode, it took 12 seconds of sustained MI to reach the arrow, starting from the time the avatar started moving. In the switch mode, six steps were necessary to complete the entire trajectory. The third requirement was for the participant to initiate movement within 5 s of the presentation of the cue and to not stop forward progression for more than 5 s. In other words, if the classifier was classifying no-movement for 5 consecutive s, that trial was ended, and the next trial started.

For forward walking trials, the participants were instructed to maintain the imagination of forward walking as long as possible or until the avatar had reached the arrow. If the participant stopped maintaining the imagination at any time during the trial, the movement of the avatar stopped. The system allowed the participant to restart the same movement if he again produced the correct imagination signals, as long he/she was within the 5- and 24-s timeframes.

For switch mode trials, the participants were instructed that they were free to control the avatar any way they wanted but that the best strategy was to alternate between left and right steps. For example, if the they received a right cue, the best strategy to move forward was to imagine a right step (according to the cue), then a left step, then a right one, and so on until they reached the arrow.

2.3 EEG Signal Pre-processing

The EEG was processed using Matlab/EEGLab. The signals were amplified, band-pass filtered (18th order butterworth IIR filter) between 8 and 30 Hz and sampled at 256 Hz. Artifacts and noise were automatically rejected using an automatic independent component analysis (ICA) and noise-rejection algorithm (MARA, a plugin of EEGLAB) and the signals were then detrended, where an automatic baseline removal algorithm was applied. The referenced baseline that was used was the

200ms segment right before preceding the apparition of the arrow.

2.4 Feature Extraction

When using MI of the feet, it is very important to select the most informative features that can be used to determine the specific brain areas and activity that differentiate idling (no movement), right steps, left steps and forward navigation. In this study, power spectral density (PSD) of every channel, and 5 PSD asymmetrical ratios (1 s hanning) were chosen as the feature sets. From the data of day 1, these features were segmented between 4 – 8 s using 200-ms epochs with no overlap, resulting in 20 different epochs. This was done in order to identify the optimum time slot (and thus feature points) where the imagery signal achieved the best classification accuracy [39]. Data were also segmented over the 8-30 Hz frequency range using 3 Hz bins with 2 Hz overlap, in order to investigate the optimum frequency range where the MI signal resulted in the best classification performance [39]. This resulted in a total of 10 frequency bins and, thus, in 200 feature sets. The PSDs in each specific segment and frequency range were all concatenated together to form the feature set.

2.5 Feature Selection

The number of features was too high compared to the number of samples, which is known to lead to the existence of noisy features in the feature set and to longer processing time, reducing BCI efficiency. Wilcoxon signed rank based feature selection was used to remove redundant features [74]. The mean absolute value of the cross-correlation coefficient was calculated between each feature and all other individual features. The features that were not significantly different ($p<0.05$) from all existing features were removed.The result of this processing stage was a smaller dataset with a further distinguished set of features, for a better classification.

2.6 Classification

The selected features were fed into 2 regularized linear discriminate analysis (RLDA) classifiers where a 10-fold cross-validation was used. Classifier 1 (Cl1) was trained to distinguish between forward walking and no movement. Classifier 2 (Cl2) was trained to distinguish right step, left step and no movement. On day 4, the two classifiers were employed together. The EEG signal was first classified by Cl1. If it was classified as no movement, the signal was then classified by Cl2.

RLDA is a classification method that has been used in many MI-BCI studies [76]. Since RLDA is a regularization technique, it is particularly useful when there is a large set of features. The regularization amount hyperparameter λ is used to enhance the model by omitting predictors without decreasing the predictive power of the model. Thus, the regularization improves the classification performance by:

1) stabilizing the variance
2) reducing the bias of the discriminant function
3) providing generalization
4) and thus, preventing overfit
5) providing high robustness with respect to outliers
6) decreasing calculation time compared to other classification methods [77].

The amount of regularization was optimized by incrementing hyperparameter λ by 0.1 over the range of [0, 1.0] in a random search. It was validated by using cross-validation. The two RLDA classifiers were trained using the optimal λ.

2.7 Performance Evaluation

The performance of the cue paced BCI (days 2 and 3) was evaluated by the number of correctly classified trials. The performance of the self-paced BCI (day 4) was evaluated using the following parameters:

1. BCI performance accuracy: for each trial, if the participant met all 3 requirements, it was considered successful.
2. Trajectory completion time: the average time it took to complete the trial.
3. Average Number of stops: during forward walking, the number of times a participant stopped before reaching the target.
4. Average Stop times: the mean time elapsed between each step, in switch mode.
5. Steps alternation performance: the number of times a participant was able to alternate between left and right steps, in switch mode.
6. Maximum walk-maintain time: the longest amount of time the participant was able to maintain the MI of forward walking, without any stops or interruptions.

All parameters were averaged over the last two runs.

2.8 Spectral Map Analysis

Spectral power analyses were performed over only the segments and frequency bands that yielded the best classification accuracy. To verify the significant difference of EEG spectra over pair-wise comparisons, the paired t-test was performed. Permutation statistics was used as well, and the p-value threshold was set to be 0.05. Then, for multiple comparisons, a false discovery rate (FDR) was applied.

2.9 Questionnaires

After each day of training, participants were asked to answer a questionnaire on a computer. The questionnaire consisted of 18 questions on a 7-point Likert scale with: strongly disagree (1), disagree (2), somewhat disagree (3), neither agree nor disagree (4), somewhat agree (5), agree (6), strongly agree (7). The questions were an evaluation of the sense of presence (1-3), body ownership (4-6), sense of agency (7-9) , BCI performance (10-12), BCI tasks and design (13-15) and BCI environment feedback (16-18) [78]. Participants were able to complete the questionnaire in approximately one minute. Each embodiment component was rated with 3 questions, and each of the aspects of the BCI system was also rated with 3 questions. The score for each component was calculated as the average of the three questions [42]. A stronger sensation for a given aspect or component would be reflected by a higher score (Figure 10).

The questions were:

Presence

1. I had the feeling that the projection of the avatar was of my body
2. I felt like I was in a hallway
3. I forgot my presence in the real world, believing that I was in the virtual corridor, and that the avatar was me

Ownership

4. I felt like the virtual leg was my own leg
5. I felt like the avatar was me and not just a picture
6. When the virtual leg was moved, I felt that my own leg was moving, as if I was walking

Agency

7. The movements of the avatar corresponded to my thoughts/movements
8. The movements of the avatar were caused by my thoughts/movements
9. I felt that I was walking with my step and not with someone else's step

BCI Performance

10. My performance in controlling the walk of the avatar was mostly good
11. I felt disappointed with the avatar following my orders
12. I felt confident with the imaginative strategy of my feet

BCI Tasks

13. Controlling the movement of the left foot was easy
14. Controlling the movement of the right foot was easy
15. Controlling the forward walking movement was easy

BCI Feedback

16. I was comfortable with the starting arrows
17. I was comfortable with the avatar during the control of his walk
18. I was comfortable with the virtual corridor during control of the avatar's walk

2.10 Statistical Analysis

The Shapiro-Wilk test was performed to verify normality of all the collected data. For all statistical analysis over multiple days, or over more than two groups in the same condition (online and offline classifier performance with different retraining; subjective questionnaires) the Shapiro-Wilk test revealed that the normality assumption was not rejected. Thus, two-ways repeated measures ANOVAs were used. Pairwise comparisons were performed using Tukey HSD post-hoc test. For statistical analysis between two groups, the Wilcoxon test was performed over all paired samples when the normality assumption was rejected for at least one of the two groups (this was the case for the success rate and the performance parameters of the self-paced BCI). When the normality assumption was not rejected (this was the case for spectral power comparisons), parametric paired t-tests were used. In all cases, the threshold significance level was set to 0.05. Statistical significance is indicated in the figures by: * when $p < 0.05$, ** when $p < 0.01$ and *** when $p < 0.001$.

3. Results

For all results presented, the classification was performed over the features that yielded the best classification results. For frequency bands, these were sensorimotor rhythms (SMR) (12-15 Hz) for 2 participants and upper μ (10-13 Hz) for the other participants. For the segments, these were the 5th epoch for 3 participants, and the 3rd epoch for the rest of the participants.

3.1 Retraining of the Classifiers – Cue-Paced BCI

The first technique implemented to enhance the BCI results was to retrain the BCI after every session. The results show a mean classification accuracy of 71% on day 1 that is increased to a mean classification accuracy of 90% on day 3, when retraining was done using days 1 through 3. Repeated-measures ANOVA over retraining through days yielded a statistically significant effect of "Retraining" on performance on the 2 days of training (F=18.26, $p < 0.001$) and a significant effect of "Days" x "Retraining" interaction (F=9.02, $p < 0.05$). The results of pairwise comparisons over retraining revealed that the classification performance was significantly increased on: day 2 when training classifiers on data from days 1 + 2 versus data from only day 2 (diff = 13.77, $p < 0.01$); day 3 when training classifiers on data from days 1 + 2 + 3 versus data from days 1 + 3 (diff = 8.38, $p < 0.05$) or days 2 + 3 (diff = 8.45, $p < 0.05$); day 3 when training classifiers on data from days 1+ 2 + 3 versus data from only day 3 (diff = 14.83, $p < 0.01$). No significant differences were found between training with day 3 only and training with days 1 + 2. The results of pairwise comparisons over retraining and days revealed that the classification performance was significantly increased on day 2 when training classifiers on data from days 1 + 2 versus data from only day 1 (diff = 12.9, $p < 0.01$) and on day 3 when training classifiers on data from days 1 + 2 + 3 versus data from day 1 only (diff = 18.84, $p < 0.001$). No significant differences were found between day 1 only and day 3 only, nor between day 2 only and day 3 only. Figure 5 shows the BCI performance of the offline classifiers, trained with the data from different combinations of days.

Figure 6 illustrates the effects of the retraining technique over online performance of the cue-paced BCI. It shows the online performance at the end of day 2 and the online performance at the beginning of day 3, i.e. after retraining the classifiers with the data of day 1 and day 2. The average online performance at the end of day 2 (pre-retraining) was 65.8%, which was increased to 74.7% at the beginning of day 3 (post-retraining). Repeated measures ANOVA over retraining and classifiers through the different days yielded a statistically significant effect of "Retraining" (F=19.32, $p < 0.05$) and a significant effect of "Classifiers" (F=24.64, $p < 0.001$). No significant effect of "Classifiers" x "Retraining" interaction was found. The results of pairwise comparisons over "Retraining" revealed that, for Cl1, performance was increased significantly from 58.6±9.5% (pre-retraining) to 70.7±5.5% (post-retraining) with (diff = 12.10, $p < 0.05$). For Cl2, performance was increased from 73.0±12.2% (pre-retraining) to 79.01±11.15% (post-retraining), which was not statistically significant. In pairwise cross-comparisons between classifiers within the group, a significant difference was obtained between Cl1 and Cl2 in pre-retraining (diff = 14.43, $p < 0.001$) and post-retraining (diff = 8.30, $p < 0.05$).

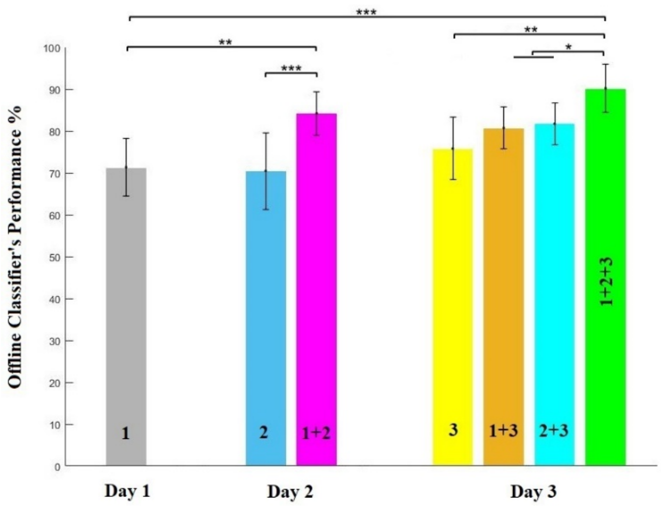

Figure 5: Offline Classification results averaged over the 2 classifiers (Cl1 and Cl2) for the first 3 days of training. It shows the mean accuracy of the offline classifiers on each day, when trained using data from that day only and when trained using data from different combinations of days (the numbers on the columns indicates which days were used for training).

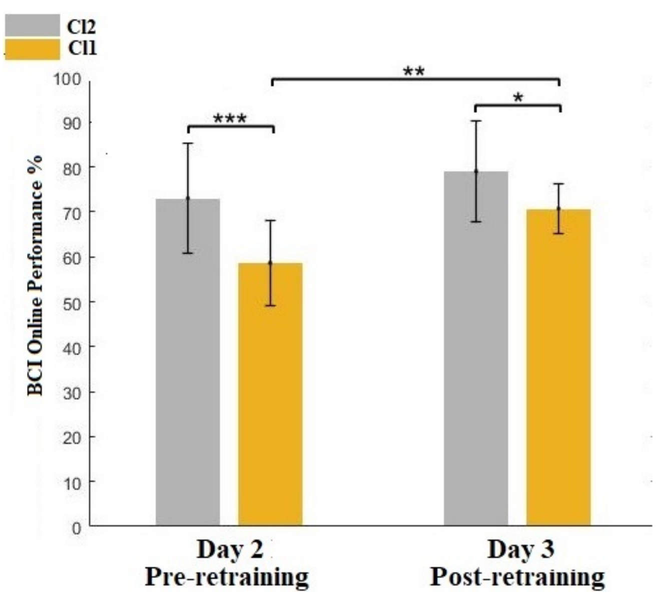

Figure 6 Online performance results at the end of day 2 and at the beginning of day 3, for each of the 2 classifiers.

3.2 Modified feedback – Cue-Paced BCI

The average online performance (across both classifiers) at the beginning of the training on day 3 was 74.7% (pre). At the end of the training day, it reached 75.5% for the group that received regular feedback (post-RGF) and 85.9% for the group that received modified feedback (post-MDF). Figure 7 shows the online BCI performance for each of the 2 classifiers in the first two and last two runs of day 3. The performances for the last 2 runs are separated by group (RGF vs MDF).

Repeated measures ANOVA over Feedback and Classifiers for performance in day 3, yielded a statistically significant intra-subject main effect of "Feedback" ($F=37.04$, $p < 0.001$) and a significant effect of "Classifiers" ($F=17.22$, $p<0.001$). The effect of "Feedback" x "Classifiers" interaction was not significant. The results of pairwise comparisons over feedback revealed that for the MDF group, Cl1 performance increased significantly from 70.7±5.5% at the beginning of the training in day 3 (pre), to 82.1±4.9% in post-MDF (diff = 11.39, $p < 0.001$). There was a significant difference of Cl1 between Post-MDF and post-RGF (diff = 11.12, $p < 0.01$). The performance of Cl2 increased significantly from 79.0±11.2% in the first runs of day 3 (pre) to 89.7±2.9% in post-MDF (diff = 10.68, $p < 0.01$). There was a significant difference of Cl2 between post-MDF and post-RGF (diff = 9.28, $p < 0.01$). In pairwise cross-comparisons between classifiers within the same group, a significant difference was obtained between Cl1 and Cl2 in post-MDF (diff = 7.59, $p < 0.001$) and post-RGF (diff = 8.87, $p < 0.05$). No significant difference between classifiers was found in the first 2 runs. Overall, providing 6 sets of positive MDF enhanced the BCI's online performance significantly.

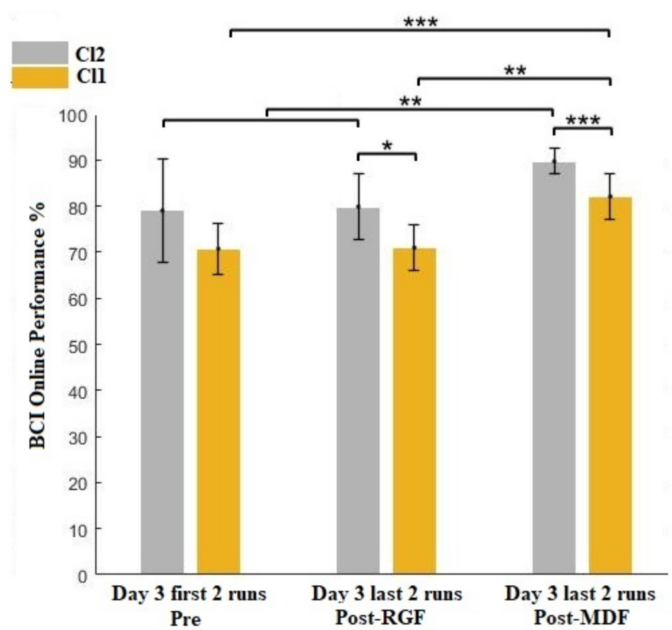

Figure 7: Online Classification of the 2 classifiers, averaged over the first 2 runs of day 3 and the last 2 runs of day 3, with and without modified feedback (MDF).

3.3 Modified feedback- Cue-Paced BCI : Neurophyiological Results

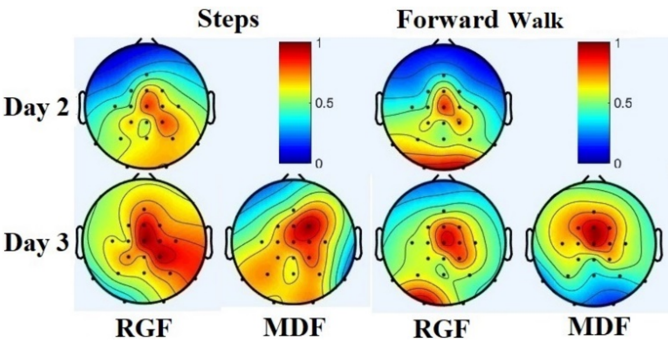

Figure 8: Spectral power maps (10*log μv^2/Hz) of the upper μ frequency band (10-13 Hz) over the epoch that yielded the best classification accuracy, over day 2 and day 3, and for the MDF and RGF condition for the cue-paced BCI. The results revealed a strong central and parietal ERS in the case of RGF, compared to a stronger frontal ERS in the case of MDF.

Using the segments and frequency bands that yielded the best classification accuracy, spectral power maps were plotted (Figure 8). During analysis, the EEG spectral topography revealed a bilateral inversion of the MI left and right steps. Thus, in order to facilitate the analysis, these maps were mirrored and merged into a single map.

The analysis revealed significant differences between trials with RGF and MDF. When controlling the steps of the avatar, one can observe an activation over the central and parietal areas of the brain, which is getting stronger at the end of the training. When MDF is provided, these spectral powers increase over the frontal areas, with a significant difference ($p < 0.05$). When controlling the forward walking of the avatar, central power peaks are observed, spanning more to frontal and parietal areas at the end of the training. However, when MDF is provided, these spectral powers increase over the frontal areas, with a significant difference ($p < 0.05$).

3.4 Self-Paced BCI

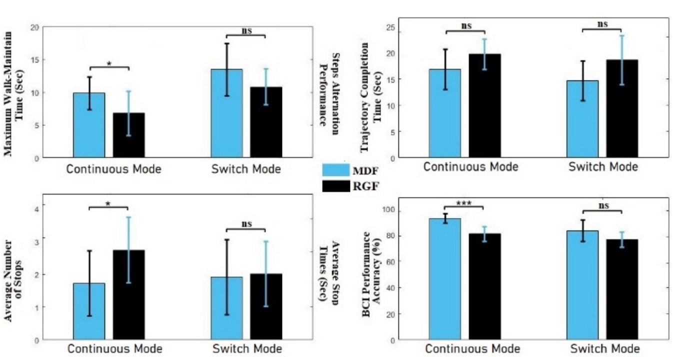

Figure 9: Online classification results for both self-paced BCI modes, for participants who received regular feedback (RGF, in blue) and modified feedback (MDF, in black). Each of the 4 plots depicts a parameter of evaluation of the performance of this BCI, which are in order: Maximum walk-maintain time/ Steps alternation performance, Trajectory completion time, Average Number of stops/ Average Stop times and BCI performance accuracy.

In continuous mode, BCI performance accuracy was significantly increased ($Z=3.4395$, $p < 0.001$) in the MDF group ($92.5 \pm 3.5\%$ success rate) compared to the RGF group ($80.8 \pm 5.6\%$ success rate). Maximum walk-maintain time was also increased significantly to 9.6 ± 2.4 s with MDF versus 6.8 ± 3.3 s with RGF ($Z=2.0301$, $p < 0.05$). The average number of stops was significantly decreased from 2.7 ± 1 stops with RGF to 1.0 ± 0.9 stops with MDF ($Z=-2.0062$, $p < 0.05$). Trajectory completion time was decreased from 19.7 ± 2.8 s with RGF to 16.8 ± 3.8 s with MDF. Trajectory completion time was not significantly different between groups.

In switch mode, results show a tendency towards improved BCI performance accuracy with MDF but differences between groups were not statistically significant. BCI performance accuracy was increased in the MDF group ($82.9 \pm 8.1\%$ success rate) compared to the RGF group ($76.5 \pm 5.8\%$ success rate). Step alternation performance was increased to $67.1 \pm 20.0\%$ success rate with MDF, from $53.9 \pm 13.0\%$ success rate with RGF. The average stop times between steps was decreased from 2.0 ± 1.9 s with RGF to 1.9 ± 1.1 s with MDF. Trajectory completion time was decreased from 18.6 ± 4.7 s with RGF to 14.6 ± 3.7 s with MDF.

3.5 Behavioral Results

Repeated measures ANOVA were run over the 3 embodiment components and 3 BCI design aspects. It revealed a significant intra-subject main effect of 'Training', a significant effect of 'Feedback'. Pairwise comparisons revealed that when operating a BCI to control the gait of an avatar, the sense of presence, which starts at 5.4/7 on day 1, does not significantly change through the days, with no significant effect of MDF.

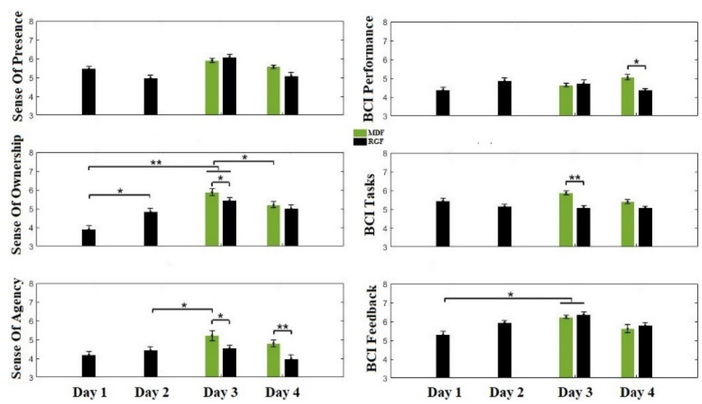

Figure 10: Behavioral results in the form of the participants' answers to the questionnaires. Those questionnaires were answered by the participants after each day of training. The three plots on the left represent the 3 embodiment components, where the three plots on the right represent the 3 BCI aspects and tasks.

The perceived body ownership, which starts at 3.9/7 in day 1, increased significantly to 4.8/7 in day 2 (diff = 0.93, $p < 0.05$). Ownership also increased significantly from day 2 to day 3 for both the MDF (diff = 1.96, $p < 0.01$) and RGF (diff = 1.53,

$p < 0.01$) groups. For group RGF, it decreased significantly from day 3 to day 4 (diff = -0.92, $p < 0.05$). The MDF group had no significant difference between days 3 and 4. In day 3, ownership was significantly higher in the MDF group than in the RGF group (diff = 0.42, $p < 0.05$).

The perceived sense of agency, which starts at 4.2/7 in day 1, doesn't significantly change through the days for the RGF group. In the MDF group, it increased significantly from 4.4/7 in day 2 to 5.2/7 at day 3 (diff = 0.78, $p < 0.05$). The sense of agency was significantly higher in the MDF group (vs RGF group) on day 3 (diff = 0.74, $p < 0.05$) and day 4 (diff = 1.01, $p < 0.01$).

As for BCI design, pairwise comparisons show that the perceived feedback of the cue-paced BCI was increased significantly from day 1 to day 2 in the MDF group (diff = 1.06, $p < 0.05$) and in the RGF group (diff = 0.93, $p < 0.05$). Compared to the RGF group, the MDF group had significantly higher perceived performance with the self-paced BCI ($p < 0.05$) and significantly higher perceived easiness of tasks with the cue-paced BCI ($p < 0.01$). There was no significant difference between groups in BCI environment feedback questions.

4. Discussion

This study aimed to develop a gait rehabilitation BCI, integrating MI of lower limbs to control the gait of a virtual avatar in different control modes, such as cue-based and self-paced. This approach was used in order to overcome the design limitations of the currently used gait rehabilitation BCIs. This study also investigated the implementation and combination of different BCI performance enhancement techniques such as co-adaptive sequential training paradigm, modified feedback and classifier retraining. This was a novel approach for lower-limbs MI-BCIs, because, to our knowledge, there is no previous study that integrated all of these techniques in one single BCI system that use MI of lower limbs. It was used in order to overcome the performance limitations of such BCIs that would hinder embodiment and limit use in gait rehabilitation. The results confirm our hypotheses that participants were able to operate the BCI in all modes, and that the three enhancement techniques increased BCI performance. However, the hypothesis that participants would perform better when using the continuous self-paced control than when using switch-based self-paced mode is rejected.

4.1 Retraining of the Classifiers – Cue-Paced BCI

The offline classification results show that on day 1 of the training, the classifiers reached a performance that was at least 10% higher than the chance level, in their worst case. This classification accuracy was enhanced significantly after using the recalibration technique. When the trained classifiers were used online, they were able to perform with a strong generalization. This was clear from the online results of day 2. The recalibration technique was shown to perform well, not only for offline classification, but also for online classification. This is shown by comparing the online performance at the end of day 2, when the classifiers were trained on data from day 1 only, with the online performance at the beginning of training on day 3, where the recalibration technique enhanced the BCI performance by 10%. This is similar to the range of enhancement (10-15%) found by other studies [71-73, 79]. The classification accuracy was significantly enhanced for Cl2 and for the combination of both classifiers. It is worth noting that the results always show a higher classification accuracy for Cl1 versus Cl2. This lower performance and higher enhancement for Cl2 may be due to the complexity of this MI tasks (left step, right step or no movement) and the fact that there are 3 classes, compared to the two tasks classified by Cl1 (walking forward or no movement). Nevertheless, the classifiers reached high classification performance for many participants. After retraining, they achieved offline classification accuracies at day 3 between 70% and 95% (mean: 86%), which were significantly superior to chance.

In the field of BCI, the offline classification accuracy for a MI-BCI is considered to be good if it reaches more than 70% , which is the case in this study, even before retraining the classifiers. Furthermore, the findings after retraining were consistent with what other BCI studies have previously found [68, 69], e.g. that, at the stage of classifier design, using an ensemble of LDA with regularization and retraining of classifiers after every session provided high classification accuracy and performance [79]. The results of the classifications of forward walking in this study were better than the performances that were reported in studies that used the RLDA algorithm to classify walk vs no_move, which were between 70 and 80% [80, 81]. This could be due to the technique of retraining the classifiers used in this study. To our knowledge, this is the first study that has used RLDA classification for discrimination of right step, left step and no movement. This is also the first study to integrate RLDA with the classifier retraining enhancement technique for a lower-limb MI-BCI. Our findings demonstrate the feasibility of using these methods for such BCIs.

The high classification performances presented in this study also support the feasibility of using the features of PSD and PSD asymmetrical ratios between the two brain hemispheres for encoding the differences between the main control commands of gait. This is in accordance with what was found in previous studies that investigated EEG signatures of gait [43, 45, 47]. On the other hand, the optimized feature sets had data only from the frontal, prefrontal and central areas of the brain. Since those channels are localized over the foot representation areas of the brain, it could be possible to further lower the number of electrodes from 19 to 10 or less.

4.2 Modified feedback – Cue-Paced BCI

The results show that providing 6 runs of positive MDF enhanced the cue-paced BCI performance significantly when compared to the group that didn't receive MDF. The results show that with MDF, the average general performance reached ~83%, an accuracy that is considered to be very good in the field of MI-BCIs [82]. The positive MDF used in this study enhanced the mean performance over both classifiers by 10%, with a 12% enhancement for Cl2 specifically. When previous studies compared the effects of providing positive and negative MDF, some found that it was negative MDF that had the larger enhancing effect on BCI performance. This was the case in studies that trained users to control a bar on the screen [63, 65]. Others found that positive MDF had a larger effect on enhancing BCI performance. This was the case, for example, of a study that trained users to control the hand of human-like robot [66]. The results found by the latter are consistent with the findings of our study. The different findings with regards to the superiority of positive or negative MDF may be due to the nature of the study and, specifically, to the nature of the feedback to be controlled. Since this is, to our knowledge, the first study to use MDF to enhance the performance of a multi-command lower-limb MI-BCI, the results show the feasibility of using this method to enhance such BCIs.

MDF also contributed to the reorganization of cortical activation after participants trained to control the BCI. Spectral power maps show that when controlling the forward walk of the avatar, a stronger activation is observed over the central areas. However, when controlling steps, a stronger activation is observed over central and parietal areas of the brain. One can also observe a stronger activation at the end of the training, especially at the right-central regions. These brain activations can be described as large event-related synchronisations (ERS). ERS usually occur as signal rebounds after a mental activity, and they are characterized as an increase of the signal power, compared to baseline. In this study, after MDF was provided during gait control, these ERS peaks could be due to the higher feeling of agency [42].

The central and right-central μ-ERS may have been due to the role of MI mechanisms over the brain areas of the feet. This implies an elevated degree of the sense of ownership when controlling the limb by IM. The parietal μ-ERS could be explained by 2 factors. First, this is the region of the brain implicated in dimensional navigation, and thus, this is the region that is activated when the feeling of presence takes place. Second, the angular gyrus is situated in this region and in the inferior parietal cortex in particular. This region is involved in the feeling of agency and the operation of comparison between the anticipated and real outcomes of one's actions [83, 84].

When MDF was provided, these spectral powers increased significantly to a strong parietal, central-frontal and frontal μ-ERS. The frontal activation represents the judgement of agency, which suggests that the perceived feeling of agency was significantly higher in the group that received MDF [85]. The stronger frontal central sensorimotor rhythm (SMR) and μ-ERS may explained by one of the following:

1- When the participant wants to either hold or end the movement upon reaching the target position, the elevated process of the mismatch-surveillance circuits of the brain and the compensatory neural control mechanisms emulate this type of brain activation [86]. It was found that for the group that didn't receive MDF, this specific activation was much lower, and it could be a consequence of the regular process of the mismatch surveillance circuits of the brain.
2- The mirror neurons system (MNS) situated in the frontal cortex. This system is exhibits specific brain activation that tunes and modulates μ-ERS to the goal-directed motor experiences in movement imitation of the avatar (frontal). This activity follows movement observation of the avatar (central). These activations are necessary for the brain to comprehend and handle actions of the avatar [87].
3- The working memory consolidation [88]. Because the sequential training to control the BCI presented in this study lasts four days, the working memory could have been consolidated over these days. This means, that the skills that the participants have acquired during the training have accumulated during these days. Thus, an enhanced MI performance could be obtained.

Remarkably, when MDF was not provided, the frontal-central and parietal μ-ERS were higher for the control of steps than for the control of forward walking. This difference can be explained by the different complex compensatory neuronal control circuits that were triggered right after a movement of the avatar that conflicts with the participant's MI, in both conditions. In this study, the movement violation that resulting from a misclassification of that command was delivered as an absence of feedback, in the case of forward walking. In the case of individual steps, it was an absence of feedback or a contradictory feedback. The results show that the second demands more power from the brain because it has to where suppress the anti-saccadic effects. Thus, when MDF was not presented, this triggered a stronger central frontal activation in the individual steps condition. This finding is consistent with the results of previous studies that showed that for an anti-saccadic movement, the neural and perceptual consequences are stronger than those of a movement inhibition [89, 90]. This also explains the apparition of significant post-MDF changes over the parietal μ-ERS.

These power spectral maps findings on the effects of MDF on MI are consistent with the results of previous studies [42]. To summarise, the results show that when mentally controlling the gait of an avatar, MDF enhances cue-paced BCI performance, especially when controlling harder tasks, such as right and left steps. This performance can be measured by the classification rate and by the μ-ERS power spectral changes over the central-frontal and the central-parietal areas.

4.3 Co-adaptive sequential training - Self-paced BCI

To reach high performance in controlling the self-paced BCI in its two modes, an effective, goal directed and short-time sequential training for operating a cue-based BCI is needed. Participants gained good control of the self-paced BCI after being trained for 3 days to control the cue-paced BCI and after having completed only a few runs of controlling the self-paced BCI. They were able to control the steps and forward walking of their self-avatar after only 4 days of training, in total. Other studies have used the co-adaptive sequential training paradigm to train users to control a cue-paced followed by a self-paced

BCI for cursor control , avatar control or navigation in VR [8]. The required time for this training varied between a few sessions in one day and many sessions over several days [61]. For gait rehabilitation MI-BCIs, some participants requires weeks of training to control a self-paced BCI [51].

The short amount of training time that was sufficient in this study may be due to the three BCI enhancement techniques that were combined and implemented throughout the training. To our knowledge, this is the first study that investigated the feasibility of using a combination of all of these enhancement techniques, in the same training paradigm, in order to control a lower-limb MI-BCI. Our results suggest that such a method could potentially shorten the training time required to reach a high performance in controlling the cue-paced, and later the self-paced BCI.

The general performance scores in both modes of our self-paced BCI were 85% in average. This is equal to or higher than what was found in BCI-VR studies to control a cursor , upper limbs or even gait [4]. Considering the complexity of the tasks being carried out in the current study, and compared to other rehabilitation studies, the performance is satisfactory.

Some of the parameters used to evaluate performance of the self-paced BCI, such as step alternation, were specific to our study and therefore cannot be directly compared to existing literature. Other parameters, such as 'Maximum time maintaining the MI' and 'stop times' are at the core of self-paced BCIs and have been reported in previous studies. In the self-paced continuous control mode, participants were able to maintain the MI for a long enough time to reach the target with minimal or no interruptions (mean of 1.0 stops for MDF group and 2.7 stop for RGF group). As for the self-paced switch control mode, participants were able to alternate their steps, and reach the target with short times intervals between steps (mean of 2.0 s between steps for the MDF group, 1.9 s for the RGF group). This is consistent with the findings of previous studies, which found that users were able to reach a high level of performance in evaluation parameters when using different control modes of a self-paced BCI [8, 54, 91].

Scores were generally high for the different performance parameters in both modes. However, it was surprising to observe that the effects of the positive MDF, provided for the cue-paced BCI on day 3, had spanned to significantly increase the score of most of the parameters that were used to evaluate the performance of the continuous self-paced BCI on day 4. Participants from the MDF group may have been more confident in their results and performance, more concentrated and more motivated to control the avatar and finish the training successfully. In comparison, participants in the RGF, may have felt more discouragement or frustration with the BCI after non-successful trials. Other hypotheses are that differences could be related to memory consolidation or that they were due to cortical activation re-organization and the MNS modulation that followed MDF training. A combination of these factors may be in play. To our knowledge, this is the first study to show that MDF can improve BCI performance in following training sessions, on subsequent days. Alimardani et al. , using an upper-limb MI-BCI, found that the improvement in participant's performance following MDF carried over to subsequent training sessions of a same day. The effect on sessions that occurred on different days was not investigated. Overall, our results and those of Alimardani et al. show that MDF can be used in sequential training MI-BCIs for the objective of increasing the performance of participant's in controlling the BCI.

On the other hand, MDF did not have the same beneficial effect on performance in the switch-control mode. The scores in the different performance parameters were improved but not significantly. In the continuous control mode, the participants had to maintain the MI for a longer period of time, compared to the switch mode. Although the switch control mode is considered to require less concentration, it consumes more brain-power due to the anti-saccadic mechanisms. Thus, participants performed better using in continuous control mode. It is well known that walking requires a very complex sequence of upper and lower limbs movements. Consequently, there may not exist a single common mental strategy of gait motor imagery strategy. Thus, participants may have been employing various mental strategies for the same task, which may explain those differences. This is consistent with what Valesco-Alvarez et al. found when comparing the two self-paced BCI modes in order to control navigation in VR. In their study, the success rates were similar to ours for both control modes, although the times needed to complete a path were notably lower in the continuous control mode.

To summarise, these analyses suggest that a sequential co-adaptive training to control a cue-paced, followed by a self-paced MI-BCI is very successful. The implementation of an ensemble of the previously mentioned enhancement techniques may shorten the training time. The implementation of MDF technique specifically also enhanced the performance, especially for more difficult tasks.

4.4 Behavioral measures of embodiment and performance

In order to operate a BCI that controls the gait of an avatar, there is a very strong link between the degree of embodiment over that avatar, and the level of performance to control that avatar. To reach one of them, the second must be reached as well [23]. In this study the feedback of MI to control the gait of an avatar resulted in elevated levels of embodiment of the 1PP avatar, which is consistent with previous literature [92, 93]. In a previous study, the effect of MDF over the central-frontal and the parietal areas correlated with the subjective evaluation of embodiment [94]. That means that the ERS modulations following agency violations were stronger with participants who experienced stronger embodiment, which justifies the use of questionnaires in this experiment.

The scores of the questionnaires revealed that the sense of presence was generally high (> 4.9/7), especially in day 3 when participants were mastering the control of the cue-paced BCI, whether they received MDF or not. This is also consistent with what was shown in the spectral power maps, regarding the parietal μ-ERS that peaks when there is a high sense of presence. The perceived sense of ownership was low at the beginning of the training but was increased significantly at the end of the training to control the cue paced BCI (day 3). This is consistent with the finding that the right-central peaks were stronger at the end of the training. MDF significantly increased the sense of ownership on day 3 but not when controlling the self-paced BCI (day 4). Again, this may be due to the avatar's behavioral differences between a cue-paced control and a self-paced control BCI. The sense of agency was low at the beginning of the training but MDF participants felt significantly more in control (agency) on day 3 and on day 4. This is consistent with what was found in the neurophysiological results: when producing MDF to the gait of a virtual avatar, the sense of agency can be measured using the strength of the elicited frontal central ERS.

The embodiment question scores showed that participants felt immersed, which was confirmed and supported by the results of previous studies. Thus, when an avatar's gait is presented to the user from 1PP in an immersive VE, the feedback of MI, in the form of the avatar walking, is sufficient to produce the sense of embodiment [94]. This was confirmed as well by the high scores that were observed in the answers of the participants to the questions related to the BCI feedback, which reached 5.3/7 in day 1 and got increased to to 6.3/7 in day 3.

The BCI question scores showed a high perceived performance and easiness of tasks for the MDF group, when controlling the self-paced BCI, with a higher score of tasks for the MDF groups when controlling cue-paced BCI. MDF probably played a strong role on perceived performance, which increased agency and embodiment. With positive modified feedback (MDF group), the feedback is more often consistent with what the participants are trying to imagine. Consequently, their performance perception and agency perception were increased.

Since the results of behavioral measures were higher for the MDF group than for the RGF group, the use of MDF during the self-paced BCI could probably improve the behavioral measures of the sense of agency, BCI performance and BCI easiness of tasks.

To summarise, these analyses suggest that when using a lower-limb multi-modal MI-BCI to control the gait of an immersive avatar, the questionnaire score results are in accordance with neurophysiological and performance measures and can be used as an assistive measure to monitor embodiment and performance.

4.5 General discussion and limitations

In general, when compared to related cue-paced or self-paced BCI-VR studies that control gait, the current study shows similar or better performances, despite variations in experimental designs. Our results show that the developed BCI could meet the requirements of an ideal BCI to control the gait of an avatar. The key factors that make BCIs a real alternative communication channel are: fast setup, short training time, effective control and artifacts processing [95]. In this study, some of these factors, such as short training used and the high performance the results have shown, were attained.

This study had some limitations. For one, many MI-BCI studies a classifier progress bar added to the VE, either separately on the screen, or super-imposed over the cue. This usually helps the user, in real time, to be aware of his performance in controlling the BCI and to try to adjust accordingly. The absence of such an aspect, left the participants sometimes unaware of the best mental strategy to use, especially when there were multiple mental commands at a time, such as in the switch control mode. Therefore, the absence this bar may have diminished the BCI performance achieved in this study, especially in self-paced switch mode. Had such a bar been present and improved performance, it could have presumably improved the behavioral measures of BCI performance, BCI tasks and sense of agency.

An important limitation of the setup was the use of generic animations of the avatar's gait. Several participants noticed and commented that the avatar's gait looked different from their own gait. Since this study is a first step towards a BCI that could be used for gait rehabilitation, it would be useful to have calibrated subject-specific avatar gait animations for future work. Such personalised animations could increase the behavioral measures of the sense of ownership and the BCI feedback.

Interestingly, the scores obtained in the subjective questionnaires could have reflected another limitation of this study. This experiment didn't use a gender-matched avatar contrary to what other studies have done. Non gender-matched avatars have been shown to decrease embodiment [33] and some of our female participants did question why they were embodying a male avatar. This could partly explain the low scores in the ownership questions in the first days of training, when the feeling of agency is less established.

5. Conclusion

This study reports on the feasibility and successful design and development of a BCI system that uses lower-limb MI to control the steps and forward walking of a self-avatar in immersive VR. Twenty participants were able to operate the BCI after 4 sessions co-adaptive sequential training of 1 hour per session, with a general performance of 70-94%. To our knowledge, this study represents the first demonstration of integrating all of these design approaches and enhancement techniques in parallel in one single multi-modal BCI system. This BCI could be used for gait rehabilitation by imagining real steps, and progressing to imagining forward walking, while receiving the matching visual feedback from an embodied virtual avatar over which we feel agency. Future work will incorporate proprioceptive feedback that is congruent with the movements of the avatar.

Acknowledgment

This work was supported by a research grant of NSERC and FQRNT. The authors would like to thank Philippe

Charbonneau for his help in developing the virtual environment.

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Generic BCI Classifiers for Discrimination of Motor Imagery of Left/Right Steps and Forward Walking

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***Abstract*—Brain-computer interfaces (BCI) have been used to control the gait of a virtual self-avatar, using motor imagery of the feet, in order to restore motor control in gait rehabilitation. The considerable training time required to use such a BCI is an obstacle to their adoption in a clinical setting. One technique used to enhance BCI control and to shorten training time is to eliminate offline calibration using a generic classifier that is pre-trained over many participants, each performing many trials. This paper investigates the performance of generic models that were derived from 2 datasets, each containing the data of 20 participants. They participated in a sequential training to control the gait of an avatar when cued to imagine a single step forward using their left or right foot, or to start walking forward. The avatar moved in response to two calibrated RLDA classifiers that used the μ PSD over the foot area of the motor cortex as features. The generic models were tested on the offline and online data of the participants. The models performed as well as models obtained from participant-specific offline data with a mean performance of 86%. The results show the possibility of designing a participant-independent, zero-training lower-limb MI-BCI.**

Keywords*—*Brain-computer interface, Virtual reality, EEG, Classification, Avatar, Gait, Generic classifier.

I. Introduction

A BCI is a system that measures brain activity of an intention to do something and converts it into a control command that replaces, restores, enhances, supplements or improves natural brain activity output [1]. In the field of rehabilitation, this control command has been used to control external devices such as robotic and prosthetic devices [2] and a lower limbs exoskeleton [3] as well as to control the gait of a virtual self-avatar [4]. When such systems are controlled through motor imagery (MI) of the desired actions (e.g. individual left and right steps as well as walking forward), this can trigger neural circuitry reorganization [5] and restore motor control during gait rehabilitation [6].

When designing a BCI, the most important step is tuning the classifier [7]. When fed with different MI patterns produced by the user, the classifier "learns" to discriminate these distinct patterns and translate the extracted signal features into control commands. For an effective BCI design and control performance, the right classifier and tuning parameters must be chosen very carefully [7]. Powerful algorithms have been used to counter-act the problems and limitations of some of classification algorithms, such as using regularization parameters to counter-act overfitting [8]. Since the classifier needs to be tuned for a specific user, a large amount of data from each user must be fed to the classifier. To counter this limitation, many studies have suggested to eliminate offline calibration using a generic classifier that is pre-trained over many participants, using many trials [9]. This generic classifier is used to train participants to control a participant-optimized BCI [10].

For example, Lotte et al. [11] proposed to use a participant-independent P300 BCI, previously learnt from the data of many other participants. Their BCI resulted in a better performance, and a shorter training time, reduced from 40 minutes to 2 minutes. Similar results were found by other studies by running a generic LDA classifier in a MI-BCI [12]. Their findings state that, even though the inter-participant variability poses a challenge, all participants scored high performance [12]. Generic classifiers based on the data of 80 participants have also been used by Vidaurre et al. [13], who showed that their performance is significantly better (an increase of 13%) than the state-of-the-art classical classification approach. However, these previous studies used generic classifiers for an upper-limb MI-BCI. To our knowledge, there are no generic classifiers that have been used for lower-limb MI-BCIs.

The objective of this study was to investigate the possibility of using generic classifiers to shorten the time required to learn to operate a BCI that controls the gait of an avatar and to enhance the performance of this BCI. Different sparse-data algorithms were investigated in order to select the algorithm that would yield the highest classification accuracy. The training and test datasets were derived from the two previous studies [14, 15]. The generic models were tested only offline, on different tests.

II. Materials And Methods

A. Experiment Design and Setup

The datasets used for this study were derived from two previous studies that recruited 20 participants each. During both experiments, participants were looking at the lower limbs of their self-avatar through a head-mounted display (HMD). The VE consisted of a virtual hallway with horizontal lines on the

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floor in order to for forward movement to be more easily perceived while looking at one's feet.

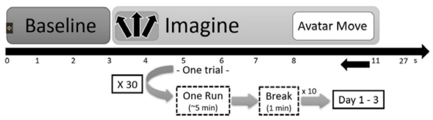

Figure 1: Experimental design of one trial

The VE consisted of a virtual hallway with horizontal lines on the floor in order to for forward movement to be more easily perceived while looking at one's feet. The training of study 1 consisted of a one-day session of 240 trials. The training of study 2 consisted of three sessions on consecutive days with 300 trials on each day (Figure 1). In both studies, each trial lasted approximatively between 7 and 11 s. A trial started with a beep, followed by a three-second pause in order to acquire a baseline EEG recording. An arrow was then presented on the virtual floor in front of the participant for a period of 1.25 s. This arrow either pointed to the left, cueing a step with the left foot; to the right, cueing a step with the right foot; or forward, cueing to imagine walking forward. Upon receiving the cue, participants imagined the appropriate action. On days 2 and 3 of study 2, the avatar was controlled by the participant's brain activity (day 1 was training only). The BCI classifiers were retrained on each day using the data from the previous days. In order to change from the no-movement to the movement state, and to prevent rapid changes, the participant had to accumulate more than a "selection time" (ST) with the correction movement selected [16, 17]. The selection time is the number of successive correct classifier outputs resulting from motor imagery of a movement. ST was set to 3 consecutive outputs, i.e. 600 ms.

B. EEG Data Recording and Pre-Processing

EEG was recorded using the 19-electrode Smart BCI system. These electrodes were grounded to AFz and referenced to both ears using an ear clip on each ear. The electrodes covered the whole scalp with a higher density above the pre-motor, motor and parietal areas. The signals were band-pass filtered (18th order butterworth IIR filter) into 10-13Hz (higher μ band). Artifacts and noise were automatically rejected using MARA, an automatic ICA and noise rejection algorithm [18]. Signals were then detrended with a baseline removal algorithm that used the 200ms preceding the apparition of the arrow.

C. EEG Feature Extraction and Selection

μ PSD of every channel, and 5 PSD asymmetrical ratios (1-sec hanning) were chosen for the feature sets from 20 different 200 ms epochs. To reduce the number of features, the Wilcoxon test and cross-correlation were used to select distinctive features and reduce the dataset by removing features that were highly correlated.

D. Participant-Specific Classification Models

The selected features were normalized [19] and then fed into 2 RDLA classifiers. Classifier 1 (Cl1) was trained to distinguish between right steps, left steps and no movement. Classifier 2 (Cl2) was trained to distinguish forward walking from no movement.

1- Regularized Linear Discriminant Analysis (RLDA)

Used in many MI-BCI studies [20], the regularization amount (λ) increases larger eigenvalues of the covariance matrix while decreasing smaller ones, therefore creating a pooled-covariance matrix that is corrected for the bias when estimating sample-based eigenvalues [21].
Thus, regularization improves classification performance by:

1) providing generalization and preventing overfit
2) decreasing calculation time compared to other classification methods [22].

LDA models were varied by adjusting the regularization amount (λ) which was optimized by setting different values of λ over the range of [0, 1.0] in 0.1 increments [21] in a random search and was validated by a 10-fold cross-validation .

1- Fitting Linear Regression Models (LRM)

The linear regression models were varied by using two choices of penalty hyperparameters: regularization amount (λ) and regularization weight (α), which varied between Lasso (L1), Ridge (L2) and Elastic Net (L3) [23].

E. Generic Classification Models

Final classification models were built by training generic RLDA models and training generic LRMs. Grid search was used for tuning parameters.

F. Protocol for Testing the Generic Classification Models

Six different tests were run over both classifiers (Cl1 and Cl2) using the best models of each of the classifiers' types (RLDA and LRM). The performance of these best models of generic classifiers was compared between classifiers and between classifier types. The performance of the generic classifiers was compared to the average performance of the equivalent participant-specific classifiers (referred to as Average S-S), when they were run online.

<u>Test #1 Initial performance</u>: Data from study 2 - session 1 were used as a training and testing dataset, and cross-validation was used to estimate the performance of the classifiers. For this test, the Average S-S was calculated as the mean cross-participant classification performance of study 2 – session 1 (which was an offline session) using the participant-specific dataset and RLDA.
<u>Test #2 Initial generalization performance</u>: This test used the classifiers constructed in Test 1, but data from study 2 - session 2 were used as a testing dataset. Model classification was used to estimate the performance of the classifiers. This test was performed over each participant's data separately, then averaged across all participants. In order to investigate the performance of these generic classifiers, a comparison was made with Average S-S. For this test, Average S-S was calculated as the mean cross-participant classification performance of study 2 – session 2 (which was an online session) using the participant-specific dataset and RLDA.

Table 1The training and testing details of the performed tests

Test	Training dataset	Testing dataset	Estimating classifiers performance	Average S-S	Nature of data
1 Initial performance	Study 2 - session 1	Study 2 - session 1	Cross-validation	Study 2 – session 1	Offline
2 initial generalization performance	Study 2 - session 1	Study 2 - session 2 (same participants-different session)	Model classification	Study 2 – session 2	Online
3 Primary generalization performance	Study 2 - session 1	Study 1 (completely new participants)	Model classification	Study 1	Offline
4 Initial performance with larger dataset	Study 2	Study 2	Cross-validation	Study 2	Online + offline
5 Initial generalization performance with larger dataset	Study 2	Study 1 (completely new participants)	Model classification	Study 1	Offline
6 Final generalization performance	Study 2 + study 1	Study 2 + study 1	Model classification	Study 2 + study 1	Online + offline

Test #3 Primary generalization performance: Same as Test #2, but data from study 1 were used as a testing dataset, so the datasets were chosen in a way that the testing datasets come from completely different participants. The Average S-S was calculated as the mean cross-participant classification performance of study 1, calculated offline using the participant-specific dataset and RLDA.
Test #4 Initial performance with larger dataset: Same as Test #1, but data from study 2 - sessions 1 to 3 were used as both training and testing datasets. The Average S-S was calculated as the mean cross-participant classification performance of study 2 – sessions 1 to 3, using the participant-specific dataset and RLDA.
Test #5 Initial generalization performance with larger dataset: Same as Test #3, but data from study 2 – sessions 1 to 3 were used as a training dataset. The Average S-S was calculated as the mean cross-participant classification performance of study 1, calculated offline when using the participant-specific dataset-RLDA combinations.
Test #6 Final generalization performance: Data from study 2 - sessions 1 to 3 and data from study 1 were used as both the training and testing datasets. The Average S-S was calculated as the mean cross-participant classification. These six tests are summarized in Table 1.

G. *Statistical analysis*

Two-way repeated measures ANOVA was used. Pairwise comparisons were performed using Tukey HSD post-hoc test. In all cases, the threshold for statistical significance was set to 0.05. Statistical significance is indicated in the figures by: * for $p < 0.05$, ** for $p < 0.01$ and *** for $p < 0.001$.

III. Results

Test #1 Initial performance

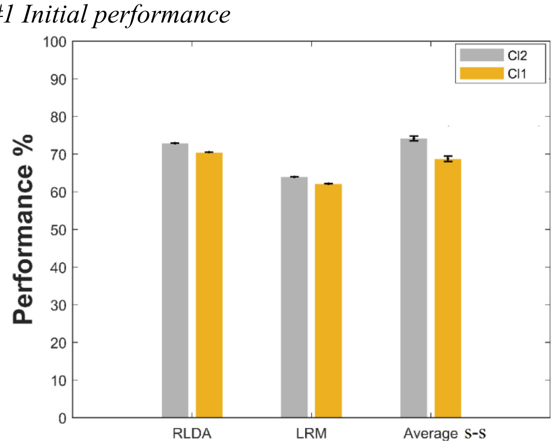

Figure 2: Results of Test #1. Data from study 2 - session 1 were used as a training and testing dataset

Results of test #1 show that when trained and tested on the same lower-limb MI data, the performance of the RLDA classification models reached 70.5% for Cl1 and 72.9% for Cl2 (Figure 2). This performance was around 9% higher than the performance of the LRM classification models (averaged over the two classifiers), which reached 62.1% for Cl1 and 64.0% for Cl2. However, RLDA performance was almost equal to the performance of the cross-participant Average S-S.

Test #2 Initial generalization performance

Test #2 shows that when tested on the same participants but on a different session, the cross-participants average performance of the RLDA classification models reached 81.2% for Cl1 and 85.7% for Cl2 (Figure 3). The cross-participants average performance of the LRM classification models reached 76.1% for Cl1 and 71.4% for Cl2. The Average S-S was 78.9% for Cl1 and 87.2% for Cl2.
Repeated measures ANOVA over 'Algorithm' and 'Type' for performance, yielded a statistically significant intra-participant main effect of "Algorithm" ($F=12.5$, $p < 0.05$) and a significant effect of "Type" ($F=21$, $p<0.05$). The effect of "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly better than LRM for Cl1 (diff = 76.1, $p < 0.05$) and Cl2 (diff = 14.2, $p < 0.001$). There was no significant difference of algorithm performance between RLDA and Average S-S.

In pairwise comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 in LRM (diff = 4.6, p < 0.05) and in Average S-S (diff = 8.2, p < 0.01).

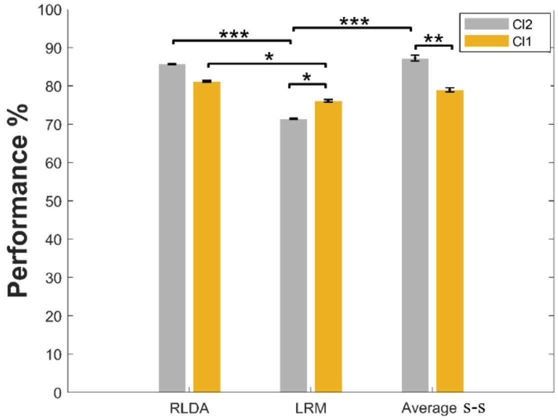

Figure 3: Results of Test #2. Data from study 2 - session 1 were used as a training dataset, but data from study 2 - session 2 were used as a testing dataset.

Test #3 Primary generalization performance

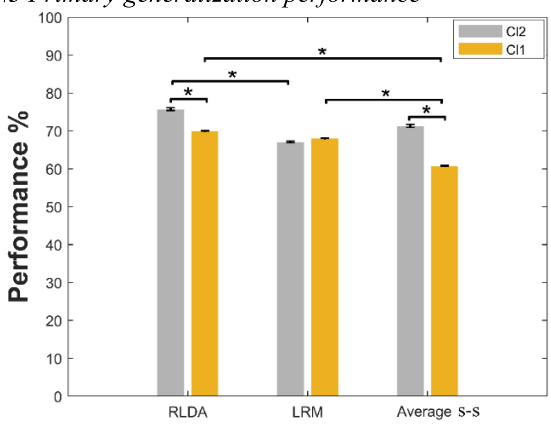

Figure 4: Results of Test #3. Data from study 2 - session 1 were used as a training dataset, and data from study 1 were used as a testing dataset.

The results of Test #3 show that when tested on different participants, the cross-participant average performance of the RLDA classification models reached 69.9% for Cl1 and 75.7% for Cl2 (Figure 4). The cross-participant average performance of the LRM classification models reached 68.0% for Cl1 and 67.1% for Cl2. The Average S-S was 60.8% for Cl1 and 71.3% for Cl2.

Repeated measures ANOVA over 'Algorithm' and 'Type' for performance, yielded a statistically significant intra-participant main effect of "Algorithm" (F=11.3, p < 0.05) and a significant effect of "Type" (F=19, p<0.05). The effect of the "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly better than LRM for Cl2 only (diff = 8.6, p < 0.05). There was a significant difference of algorithm performance between RLDA and Average S-S only for Cl1 (diff = 9.1, p < 0.05).

In pairwise comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 in RLDA (diff = 5.7, p < 0.05) and in Average S-S (diff = 10.4, p < 0.05).

Test #4 Initial performance with larger dataset

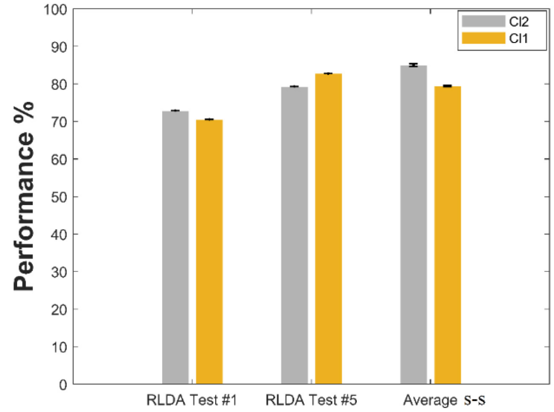

Figure 5: Results of Test #4. Data from study 2 - sessions 1 to 3 were used as both a training and testing dataset. Cross-validation was used to estimate the classifiers' performance.

The results show that when trained and tested on the same lower-limb MI data, using the data of 3 sessions from the same participants, the performance of the RLDA classification models reached 82.7% for Cl1 and 79.3% for Cl2. This performance was a bit lower (3%) than the performance of the cross-participants Average S-S, which reached 79.4% for Cl1 and 85% for Cl2.

Test #5 Initial generalization with larger dataset

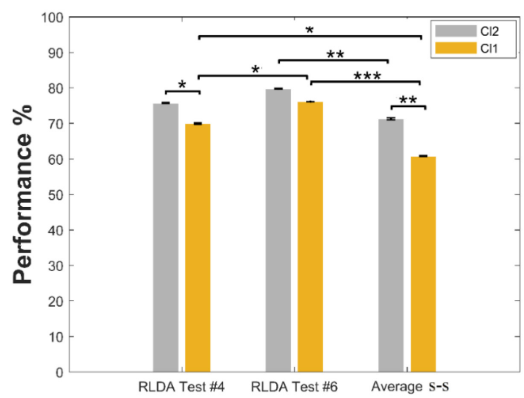

Figure 6: Results of Test#5. Data from study 2 – session 1 to 3 were used as a training dataset and data from study 1 were used as a testing dataset.

The results show that when tested on completely different participants and using a larger dataset to train the classifiers, the cross-participant average performance of the RLDA classification models reached 79.3% for Cl1 and 82.7% for Cl2 (Figure 6). The cross-participants Average S-S was 60.8% for Cl1 and 71.3% for Cl2.

Repeated measures ANOVA over 'Algorithm' and 'Type' for performance, yielded a statistically significant intra-participant main effect of "Algorithm" (F=29.1, p < 0.01) and a significant effect of "Type" (F=35.1, p<0.05). The effect of the "Algorithm" x "Type" interaction was not significant. The results of pairwise comparisons over algorithms revealed that the performance of RLDA was significantly better than Average S-S over Cl1 (diff = 9.3, $p < 0.001$) and Cl2 (diff = 7., $p < 0.01$). There was a significant difference of algorithm performance between RLDA Test #3 and RLDA Test #5 only for Cl1 (diff = 9.3, $p < 0.05$). In pairwise comparisons between classifiers within the same algorithm, a significant difference was obtained between Cl1 and Cl2 only for Average S-S (diff = 10.4, $p < 0.01$).

Test #6 Final generalization performance

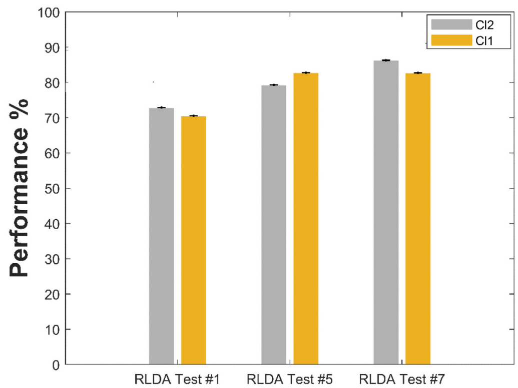

Figure 7: Results of Test #6. Data from study 2 - sessions 1 to 3 and data from study 1 were used as both a training and testing dataset. Cross-validation was used to estimate the classifiers' performance.

The results show that the performance of the RLDA classification models reached 82.7% for Cl1 and 86.2 % for Cl2 (Figure 7). This performance was a bit higher (3%) than the performance of the classifiers when trained on data from only study 1.

IV. DISCUSSION

This study focused on the possibility of using two large datasets in order to construct a novel generic classifier that can classify between MI of left steps, rights steps and idle (no movement), and to construct another novel generic classifier that can classify between forward walking and idle (no movement).

Test #1 Initial performance

The results of this test show that when trained and tested on the same lower-limb MI data, the cross-validation performance of the RLDA classification models reached around 71% averaged over the two classifiers, which was not different from when using the participant-specific classifiers.

As stated by Kübler et al. [24], in the field of BCI, the offline classification accuracy for a MI-BCI is considered to be good if it reaches more than 70%. This, however, is in the context where this classifier is used only as a participant-specific classifier, and not as a generic classifier. For a generic classifier, the offline performance that was obtained in other studies was > 80% [13, 25]. A direct comparison to our results cannot be made since, to our knowledge, this is the first study that uses generic classifiers for lower-limb MI. It is also the first that specifically uses RLDA classification for discrimination of right steps, left steps and no movement. The results of this test mean that the classification models obtained would not be suitable as generic classifiers.

Taken alone, this result would suggest that the reasons behind the low performance obtained in this test could either be due to the small amount of data (only 20 participants), the sparsity of the data (20 participants with only one session), the complexity of the data (gait data) or the offline nature of the data (no self-regulation of the brain activity to produce better control commands due to the absence of training). The results of test #2 support this statement.

Test #2: Initial generalization performance

The performance increased from approximately 71% to approximately 83% (averaged over the two classifiers).

This unexpected behavior of the classifiers between the use of data in test #1 and the use of the data in test #2 could be explained by the fact that, although the testing data were new data, they were from the same participants. Moreover, they were not only from another session, but also from an <u>online</u> session. In this session, participants received visual feedback, so they could improve the MI signals (datasets) they were trying to produce. Session 1, on the other hand, lacked feedback and participants didn't know how well they were doing in terms of MI performance. Therefore, the main reasons behind the low performance obtained in test #1 could be the small amount of data and the nature of this data.

Test #3 Primary generalization performance

This is the first test in this study where completely new data from new participants were used as testing data. The performance of the generic RLDA classification models were significantly better than when using the participant-specific classifiers but the increase in the performance was only 7%, which is considered poor when compared to other studies [11, 13]. Thus, neither the 72% of performance (averaged over the two classifiers), nor the 7% increase are considered to be good for a generic classifier. In this test, the testing data come from a session which lacked feedback, and participants didn't know how they were doing in terms of MI performance. They therefore had no way to improve their MI and BCI control skills. This problem extends to the training data as well. This could explain the low performance results obtained in this test. Test #2 (Initial generalization performance) used better datasets in an attempt to increase performance.

Test #4 Initial performance with larger dataset

In this test, the use of a larger dataset to train the classifiers led to a performance increase of 10% (to 81%), compared to the use of a dataset from only one session.

Compared to the results of other studies, such as the study of Vidaurre et al. in 2011 [12], and considering the complexity of the MI tasks being carried out in this study, the performance is satisfactory. Although the performance of these classification models was a bit lower than what was obtained when using the participant-specific classifiers, these new RLDA classification models were tested on completely new data, as lower-limb MI generic classifiers.

Test #6 Initial generalization with larger dataset

The results of this test revealed that the new generic RLDA classification models had significantly increased performance, by 10%, compared to participant-specific classifiers. This increase in performance was consistent with what other studies have found [11, 13].

The performance of 81% of these new RLDA classification models was a little bit lower than what was found by other groups such as Lotte and Guan in 2009 [11] (upper-limbs BCI) and this might be due to the complexity of MI tasks, or the small amount of data used to train the classifiers, which is a main limitation for this test.

In order to construct generic classifiers with a satisfactory performance, a large amount of data is required. For example, Fazli et al. [19] used a large database of EEG recordings from 45 Participants. Also, Arvaneh et al. [13] recruited 80 participants and used their data to train the generic classifier. These numbers of participants are more than double and quadruple the number of participants recruited for study 2. One can assume that if there were more participants in study 2, and more sessions from study 2, the performance would have increased further.

Test #7 Final generalization performance

The results revealed that including the datasets of all participants significantly increased the performance, but the increase was modest and for only one classifier (Cl2). As with previous tests, this may be due the fact that the added dataset was from a session which lacked feedback. It is probable that if there were feedback sessions in study 1, the performance would have increased further.

The datasets that were fed to the classifiers, from studies 1 and 2, come from all the participants of those studies, even those with lower performance. This may have contributed to a decrease in performance, not only in this test but in all previous tests as well. It is our belief the training datasets should only include the data of the participants who had the best performance, which would consequently require more participants.

V. Conclusion

This study reports on the first successful development of two novel generic classifiers that can classify between 4 MI commands: left step versus right step versus no movement and forward walking versus no movement. The generic classifiers were constructed and tested using a dataset of 40 participants performing MI tasks in an immersive virtual environment, from two different studies and a total of 4 sessions. The generic classifiers reached a performance of 87%, similar to the same classifiers using participant-specific data. These results indicate that these generic classifiers will be able to eliminate the calibration phase of a lower-limbs MI-BCI, and thus shorten the time required to learn to control this type of BCIs. Thus, for future work, these classifiers can be implemented on-line with an adaptive RLDA, in order to be used later in a BCI to control the gait of an avatar.

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