Université de Montréal

Detection, Recuperation and Cross-subject Classification of Mental fatigue

In Virtual Simulated Environment

Par

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Résumé

La fatigue mentale est un état complexe qui résulte d'une activité cognitive prolongée. Les symptômes de la fatigue mentale inclus des changements d'humeur, de motivation et une détérioration temporaire de diverses fonctions cognitives. Plusieurs recherches approfondies ont été menées pour développer des méthodes de reconnaissance des signes physiologiques et psychophysiologiques de la fatigue mentale. Les signes psychophysiologiques concernent principalement signaux d'activité cérébrale et leur relation avec la psychologie et la cognition. Celles-ci ont permise le développement de nombreux modèles basés sur l'IA pour classer différents niveaux de fatigue, en utilisant des données extraites d'un appareil *eye-tracking*, d'un électroencéphalogramme (EEG) pour mesurer l’activité cérébrale ou d'un électrocardiogramme (ECG) pour mesurer l’activité cérébrale. Dans cette mémoire, nous présentons le protocole expérimental et développé par mes directeurs de recherche et moi-même, qui vise à la fois à générer et mesurer la fatigue mentale, et à proposer des stratégies efficaces de récupération via des séances de réalité virtuelle couplées à des dispositifs EEG et *eye tracking*. Réussir à générer de la fatigue mentale est nécessaire pour générer un ensemble de données suivant l’évolution de la fatigue et de la récupération au cours de l’expérience, et sera également utilisé pour classer différents niveaux de fatigue à l’aide de l’apprentissage automatique. Cette mémoire fournit d'abord un état de l'art complet des facteurs prédictifs de la fatigue mentale, des méthodes de mesure et des stratégies de récupération. Ensuite, l'article présente un protocole expérimental résultant de l'état de l'art pour (1) générer et mesurer la fatigue mentale et (2) évaluer l'efficacité de la thérapie virtuelle pour la récupération de la fatigue, (3) entrainer un algorithme d'apprentissage automatique sur les données EEG pour classer 3 niveaux de fatigue différents en utilisant un environnement simulé de réalité virtuelle (VR). La thérapie virtuelle est une technique favorisant la relaxation dans un environnement simulé virtuel et interactif qui vise à réduire le stress. Dans notre travail, nous avons réussi à générer de la fatigue mentale en accomplissant des tâches cognitives dans un environnement virtuel. Les participants ont montré une diminution significative du diamètre de la pupille et du score thêta/alpha au cours des différentes tâches cognitives. Le score alpha/thêta est un indice EEG qui suit les fluctuations de la charge cognitive et de la fatigue mentale. Divers algorithmes d'apprentissage automatique ont été formés et testés sur des segments de données EEG afin de sélectionner le modèle qui s'ajuste le mieux à ces données en ce qui concerne la métrique d'évaluation "précision équilibrée" et "f1". Parmi les 8 différents classificateurs, le SVM RBF a montré les meilleures performances avec une précision équilibrée de 95 % et une valeur de mesure f de 0,82. La précision équilibrée fournit une mesure précise de la performance dans le cas de jeu de données déséquilibrées, en tenant compte de la sensibilité et de la spécificité, et le f-score est une mesure d'évaluation qui combine les scores de précision et de rappel. Finalement, nos résultats montrent que le temps alloué à la thérapie virtuelle n'a pas amélioré le diamètre pupillaire en période post-relaxation. D'autres recherches sur l'impact de la thérapie devraient consacrer un temps plus proche du temps de récupération standard de 60 min.

Mots-clés : Fatigue Mentale, Récupération, Apprentissage Machine, Charge Mentale, Engagement, Réalité Virtuelle, Diamètre pupillaire, EEG.

Abstract

Mental fatigue is a complex state that results from prolonged cognitive activity. Symptoms of mental fatigue can include change in mood, motivation, and temporary deterioration of various cognitive functions involved in goal-directed behavior. Extensive research has been done to develop methods for recognizing physiological and psychophysiological signs of mental fatigue. Psychophysiological signs are mostly concern with patterns of brain activity and their relation to psychology and cognition. This has allowed the development of many AI-based models to classify different levels of fatigue, using data extracted from eye-tracking devices, electroencephalogram (EEG) measuring brain activity, or electrocardiogram (ECG) measuring cardiac activity. In this thesis, we present the experimental protocol developed by my research directors and I, which aims to both generate/measure mental fatigue and provide effective strategies for recuperation via VR sessions paired with EEG and eye-tracking devices. Successfully generating mental fatigue is crucial to generate a time-series dataset tracking the evolution of fatigue and recuperation during the experiment and will also be used to classify different levels of fatigue using machine learning. This thesis first provides a state-of-the-art of mental fatigue predictive factors, measurement methods, and recuperation strategies. The goal of this protocol is to (1) generate and measure mental fatigue, (2) evaluate the effectiveness of virtual therapy for fatigue recuperation, using a virtual reality (VR) simulated environment and (3) train a machine learning algorithm on EEG data to classify 3 different levels of fatigue. Virtual therapy is relaxation promoting technique in a virtual and interactive simulated environment which aims to reduce stress. In our work, we successfully generated mental fatigue through completion of cognitive tasks in a virtual simulated environment. Participants showed significant decline in pupil diameter and theta/alpha score during the various cognitive tasks. The alpha/theta score is an EEG index tracking fluctuations in cognitive load and mental fatigue. Various machine learning algorithm candidates were trained and tested on EEG data segments in order to select the classifier that best fits EEG data with respect to evaluation metric 'balanced accuracy' and 'f1-measures'. Among the 8 different classifier candidates, RBF SVM showed the best performance with 95% balanced accuracy 0.82 f-score value and on the validation set, and 92% accuracy and 0.90 f-score on test set. Balanced accuracy provides an accurate measure of performance in the case of imbalanced data, considering sensitivity and specificity and f-score is an evaluation metric which combines precision and recall scores. Finally, our results show that the time allocated for virtual therapy did not improve pupil diameter in the post-relaxation period. Further research on the impact of relaxation therapy should allocate time closer to the standard recovery time of 60 min.

Keywords : Mental fatigue, Recovery, Machine Learning, Mental Workload, Task-engagement, Virtual Reality, EEG, Eye-Tracking, Pupil Diameter.

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List of acronyms

AI : Artificial Intelligence

BD: Blinking duration

BR : Blinking rate

CNN: Convolution Neural Network

ECG: Electrocardiogram

EEG: Electroencephalogram

EOG: Electrooculogram

HRV: Heart Rate Variability

KNN : k-nearest neighbors

ML : Machine Learning

PD: Pupil diameter

RBF: Radical Basis Function

SVM : Support Vector Machine

TE : Task Engagement

TOT : Time on Task

VR : Virtual Reality

WL : Mental Workload

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Chapter 1 – Introduction

Mental fatigue is a complex state that mainly manifests as change of mood, motivation, and a decline in cognitive functions (Hopstaken, Linden, Bakker, & Kompier, 2015) (Ishii, Tanaka, & Watanabe, Neural mechanisms of mental fatigue., 2014) Although our knowledge about the neurocognitive process underlying mental fatigue is not fully understood, the consequences of such state can negatively impact workplace performance and, sometimes, be a potential danger for oneself or/and others. For instance, we know that one of the main characteristics of mental fatigue is that it reduces one's ability to maintain engagement when performing a task (Wang, Chang, Schmeichel, & Garcia, 2022). Thus, this poses a serious problem in the context of driving, for example, where sustained attention is required to adapt to various changes in environment and avoid deadly accidents. The consequences of mental fatigue on individuals have been documented extensively in the literature. In general, mental fatigue results in a deterioration of various cognitive functions, mainly the ones that are involved in goal-directed behavior (Corbetta & Shulman, 2002) (Boksem, Meijman, & Lorist, Effects of mental fatigue on attention: An ERP study, 2005). One approach to this problem is to develop a system that is able to recognize signs of mental fatigues and procure adapted techniques to recover cognitive functions.

Psychophysiological measures are mostly concern with assessing the relation between physical states and psychology/cognition. For mental fatigue, this means associating brain, visual or cardiovascular response to symptoms of mental fatigue. In recent years, many intelligent systems have been developed to detect mental fatigue, using various physiological and psychophysiological features (Parekh, Shah, & Shah, 2020). However, most work published on mental fatigue and intelligent systems is limited to the detection without addressing options to alleviate symptoms. In theory, sleep or sufficient resting time are essential to recover cognitive functions affected by prolonged hours of work (Torbjörn, Peter, & Göran, 2009). However, daily responsibilities and duties do not always allow enough time to rest and fully recover attentional resources. Thus, more attention should be paid to the development of recuperation strategies after inducing fatigue. Such strategies can be used to temporarily alleviate some symptoms of mental fatigue, until proper resting time is possible for a more complete recovery.

Thus, detecting early or late signs of mental fatigue is the first step for preventing accidents in situations where few seconds of inattention can turn into potential danger for our well-being and for others'. Once fatigue is detected, access to efficient recuperation techniques are important to temporarily restore cognitive functions and prevent exhaustion. This thesis will present the work of my colleagues and I on the supervised cross-subject classification of mental fatigue and recuperation technique for symptoms alleviation in a virtual simulated environment. The objectives of this study were to (1) **induce** mental fatigue in a pool of participants, (2) collect EEG and eye-tracking data to train multiple supervised machine learning models to **detect** mental fatigue and (3) attempting to **alleviate** symptoms of mental fatigue with a virtual relaxation technique. In our work, we generate and measure mental using an office-like interactive virtual environment as a way to accentuate symptoms of fatigue (Shen, Weng, Chen, Guo, & Fang, 2019). We to use relaxation therapy in our protocol for fatigue recuperation since its effect of mental fatigue specifically has not been explored and since we can also include natural landscapes in the immersive environments. The labeling methodology and measurement for fatigue segments used for our protocol were inspired by the methodology used by Ren Ziwu and colleagues for their Radical Basis Function (RBF) Neural Network to detect fatigue in driving simulation using EEG signals (will be presented in 2.1). Hence, our approach to mental fatigue measurements is to use EEG power spectral density segments for classification. However, we use pupil dilatation instead of eye closure (PERCLOS) to label EEG segments due to the sensibility of pupil dilatation to both fatigue and workload. Additionally, this labeling methodology will allow for real time detection and labeling of mental fatigue instead of relying on subjective questionnaires.

We hypothesize that (H1) we can generate fatigue in a limited amount of time (approx 25 min) through completion of cognitively demanding exercises, (H2) detect mental fatigue from EEG and eye tracking patterns and (H3) bring fatigue indicators to baseline levels with 10-15 min of virtual relaxation therapy.

This thesis is composed of 6 chapters. In Chapter 2, I will present previous work in the generation/detection of mental fatigue and introduce key concepts which will shape our understanding of the protocol chosen to generate and detect mental fatigue. The first section of this chapter will present factors which influence the rise mental fatigue, and the second part will present multiple ways to measure mental fatigue through physiological and psychophysiological measurements. In Chapter 3, I will present information related to the recuperation of mental fatigue. Hence, it will present the progression of mental fatigue measures during resting periods along with several techniques that have been shown to accelerate the recovery of mental fatigue symptoms. In Chapter 4, I will present the methods and materials of the experiments along with measures chosen to generate mental fatigue among participants and the recovery techniques. In this chapter, I will also present the protocol developed to generate, measure and recover mental fatigue based on the literature introduced in chapters 2 and 3. In chapter 5, I will present the results of the experiments which will be structured as follows: (1) Presents the distribution and the progression of the set of mental fatigue factors chosen to show that exercises presented have successfully generated mental fatigue among participants, (2) Compare various machine learning (ML) models for the classification of mental fatigue and (3) Analyze the effects of the recuperation technique chosen on mental fatigue measures. This chapter will discuss the results and limitations of the experimental protocol along with further improvements that can be realized. Finally, I will summarize the highlights and important findings of our work and provide insights about future work on the topic in Chapter 6.

Contribution

I have contributed to developing the protocol for generating, detecting and recover mental fatigue by choosing the set of exercises to generate mental fatigue and the types of fatigue measures to be collected. I have chosen the set of physiological measure and EEG indices to measure levels of mental fatigue. The protocol developed by Claude Frasson, Hamdi Ben Abdesslem, Mahdi Zarour and I for the generation and detection of mental fatigue and distraction is presented in Chapter 4. I have chosen the labeling methodology, cleaned, selected, transformed and analyzed the data collected to extract and monitor fatigue progression and recuperation throughout the experiment. I have selected, trained, optimized and evaluated different set of machine learning algorithm which is detailed in Chapter 5. Finally, I have written a scientific article on this research which has been published in the Journal of Behavioral and Brain Science[1] and in the conference of Augmented Intelligence and Intelligent Tutoring Systems 2023. [2]

Chapter 2 –Mental fatigue: State of the Art and Main Factors

In this chapter, we will cover the set of concepts needed to understand how to generate and measure mental fatigue. The first section of this chapter will present related studies in the field of mental fatigue generation and detection. The second chapter is concerned with the different tasks demands that can push an individual to mental fatigue. For instance, the numbers of minutes/hours spent to complete a task will highly influence the level of mental energy remaining at the end of it. However, the time on task alone is not sufficient – we can also ask ourselves: how hard is it to complete the task? Is this a task we enjoy doing? In reality, there is a myriad of factors which can influence the occurrence and the severity of mental fatigue at the individual level: time of the day, hours of sleep from the previous night, physical exercise, food intake, daily screen time, etc. (Baumann, Mentzoni, Erevik, & Pallesen, 2022). However, factors that are concerned with daily habits (individually or paired) can be challenging to control in a laboratory setting. Thus, the first section of this chapter will focus on task-related factors, predictive factors, which can be controlled with more ease in order to generate mental fatigue. The second part of the chapter will be concerned with measuring mental fatigue with physiological and psychophysiological

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[1] Assaf, A. , Abdessalem, H. and Frasson, C. (2023) Detection and Recuperation of Mental Fatigue. Journal of Behavioral and Brain Science, 13, 15-31. doi: 10.4236/jbbs.2023.132002.

[2] Assaf, A.H., Ben Abdessalem, H., Frasson, C. (2023). Detecting Mental Fatigue in Intelligent Tutoring Systems. In: Frasson, C., Mylonas, P., Troussas, C. (eds) Augmented Intelligence and Intelligent Tutoring Systems. ITS 2023. Lecture Notes in Computer Science, vol 13891. Springer, Cham. https://doi.org/10.1007/978-3-031-32883-1_6

measures. There are 3 main approaches to detect and measure fatigue in laboratory settings: psychology-based approach, video-based approach and physiological approach (Ziwu, et al., 2021). Psychology-based approach mainly relies on psychometric questionnaires to evaluate subjective evaluation of mental fatigue symptoms. Some drawbacks of self-reported measurements include the difficulty in measuring symptoms in real time, as well as the time cost associated with questionnaire filling (Ziwu, et al., 2021). Video-based approach is mostly concerned in capturing behavioral and physical response to mental fatigue such as facial features, head position and reaction time. Finally, physiological approaches are mostly concerned with measuring physiological features of the body that are influenced during mental fatigue with EOG (or eye tracking), EEG and ECG devices (Ziwu, et al., 2021). Finally, the third section of this chapter will exclusively present physiological approaches to measure mental fatigue due to its promising modality in detecting fatigue. Thus, this section will present various effects of mental fatigue on human body features such as eye features, heart and brain waves and the patterns associated with their respective mental fatigue symptoms.

2.1 Related Work

Generating and detecting mental fatigue in laboratory settings is not a trivial task. This is mainly because it is hard to reproduce settings in which mental fatigue can occur in a limited time and environment, while mental fatigue can arise in various places (eg., workplace, transport hubs, school, home, etc) where workload condition and exposure time to factors or tasks that may lead to fatigue varies. In that effect, many different protocols have been proposed across the literature to generate fatigue in laboratory settings to generate fatigue, as well as different ways to label levels of fatigue. Among the different protocols proposed to generate fatigue, simulations and isolated mental tasks are the most popular. Simulation usually targets a specific environment where mental fatigue symptoms are caused from tasks specific to this environment: driving simulation, flight simulation, surgery simulations, etc. The goal here is to best reproduce the specific environmental condition and the associated set of tasks to generate and detect symptoms of mental fatigue specific to this environment. In isolated mental tasks, participants subject to different mentally demanding tasks during a prolonged period. The nature of the tasks varies from solving arithmetic questions, remembering seen or not seen elements finding objects that don't belong in the presented set. The goal here is to generate mental fatigue by depleting the cognitive resources of participants through mentally demanding tasks.

Machine learning systems are widely used tools used to monitor and detect mental fatigue. In a review written by Vidhi Parekh and colleagues (2020), many different AI-based models of mental fatigue detection developed and published in the last decade were analyzed and compared (Table 1).

Tableau 1 *Summary table of various AI algorithms to detect fatigue, from Vidhi Parekh and colleagues (2020)*

Device	Fatigue Measure	Algorithm and techniques	Feature extraction	Classification Algorithm	Accuracy (%)
EEG (electroencephalography)	Electrical brain activities	Back-propagation algorithm	Discrete wavelet transform (DWT)	Neural classifier	95 +- 4
Neuroscan 32 channel system	Visual display terminal (VDT)	Kernel learning algorithm	Wavelet packet decomposition (WPD)	Kernel principal component analysis (KPCA), support vector machine (SVM)	87
Camera and infrared illuminator	PERCLOS, eye closure, duration, blink, frequency	Two Kalman filters for people detection	Modification of the algebraic distance algorithm for conic approximation and finite state machine	Fuzzy classifier	Close to 100
HRV (heart rate variability	Variation in heart rate	Butterworth's filter	Fast Fourier transforms	Neural classifier	90
CCD camera	Yawning	Gravity center template and gray projection	Gabor Wavelets	LDA	91.97
Digital video camera	Facial action	Gabor filter	Wavelet decomposition	Support vector machine (SVM)	96
Logger application	Analysis of user interaction patterns	Mann-Whitney test	Mouse acceleration, mouse velocity, key down time, time between	K-NN (k-neasrest neighhbor)	95 +- 3

			keys and error per key		
Fire wire camera and webcams	Eye closure, duration and frequency of eye closure	Hough transform	Discrete wavelet transform (DWT)	Neural classifier	95
CCD camera, piezo-film sensors	Image analysis	Fuzzy logic model	Blink measurement, eyelid closure time	Neural classifier	96 +- 2.5
Simple camera	Eye blink	Cascade classifier algorithm	Duration of eyelid closure, number of continuous blinks, frequency of eye blink	Region mark algorithm	98
EEG (electroencephalography)	Electrical brain activities	Widrow-Hoff rule and Levenberg-Marquardt learning rule	Wavelet prepossession	Neural classifier	97.6 +- 4.3
Camera with IR illuminator	PERCLOS	Harr algorithm to detect face	Unscented Kalman filter algorithm	Support vector machine (SVM)	99

These models capture behavioral, physiological, and/or psychophysiological measures of fatigue, transform these measures for suitability and classify the input measure of the user into different levels of fatigue. Vidhi Parekh and colleagues provide an in-depth analysis of these different models in terms of ML algorithms and feature performance and limitations. Generally speaking, model incorporating electrical brain activity or eye measurements as fatigue measure performed best, which motived the interest of combining both measurements for our model.

Laurent and co-workers. (Laurent, et al., 2012) investigated the use of different physiological and psychophysiological measures to detect mental fatigue. Participants required to perform six blocks of a switch task to induce mental fatigue, while electroencephalogram (EEG), electromyogram (EOG) and electrocardiogram (ECG) signals were continuously monitored during the experiments. Laurent and colleagues used support vector machine (SVM) to classify mental fatigue under different feature combination conditions: EEG, EOG and ECG separately and together. Their results showed that EEG was the best single mode of detection for mental fatigue classification and when combined with EOG and ECG features, classification accuracy was significantly increased. The authors concluded that multimodal feature combination (EOG+EEG+ECG) improves rapid detection of mental fatigue (Laurent, et al., 2012).

Kamińska and colleagues (Kamińska, Smółka, & Zwoliński, 2021) investigated the use of EEG signals to classify a subject's mental stress level using virtual reality environment. Participants were immersed in two alternating VR interactive simulation: stress inducing and relaxing. The stress-inducing environment consisted of the Stroop test[3], while relaxing environment consisted of interactive relaxing scene based on scenarios created for psychotherapy treatment. During the session, brain wave activity was continuously monitored using EEG and participants were asked to fill out a questionnaire to assess their mood and level of stress, before and after the session. The experimenters used a convolutional neural network (CNN) to classify the level of stress of the participants and matched the subjective stress assessment of the participants with 96.42% accuracy (Kamińska, Smółka, & Zwoliński, 2021).

When training AI models to detect mental fatigue, labels can be obtained from a physiological, and/or psychophysiological measures (different from the ones used as features) that are reliable in predicting fatigue (eg. Using EEG time series as training features and eye-blink rate to label these time series with a level a fatigue (Ziwu, et al., 2021)). Another way to label physiological, and/or psychophysiological time series segments by simply asking the participant the level of fatigue felt (eg. On a scale from 1 to 10) with short questionnaires in between fatiguing exercises. Time series are attributed the label of fatigue indicated by the participant in the questionnaire period which is closest (in time) to the time-series segment. When using subjective questionnaires as label, the precision is by segment: more occurrence of questionnaires periods makes the model more precise. The number of time participants report their level of fatigue is important to take into consideration when making labels from subjective questionnaire since it's not reflected in the overall accuracy value of the model.

Like many other related studies, Kamińska and colleagues established their labels based on subjective assessment of fatigue via questionnaire. However, subjective feedback questionnaires are time-consuming and unreliable for real-time fatigue detection (Ziwu, et al., 2021). Ren Ziwu and colleagues developed a Radical Basis Function (RBF) Neural Network to detect fatigue in

[3] Stroop test: Test in which participants are required to answer the color of a color-word as fast and accurately as possible. For example, if the word 'orange' written in blue appears on the screen, the participant must suppress the 'orange' signal and answer 'blue'.

driving simulation using EEG signals. Instead of using questionnaires, they used eye closure, a well-known fatigue indicator to label fatigue and alert segments. Ren Ziwu and colleagues achieved 92.71% mean accuracy on their RBF neural network.

2.2 Predictive Factors

Predictive factors are the set of task demand exerted on an individual, that might influence whether they become mentally fatigued by the task. For instance, the time spent on a task, the number of cognitive resources required, and the level of engagement are important factors to predict if a task is mentally fatiguing or not. Several factors are identified: (1) time on task, (2) workload and (3) task engagement. Moreover, different levels of predictive factors can lead to different types of fatigue. This section presents the predictive factors (1) (2) (3) of mental fatigue and the different types of fatigue that can result from them.

2.2.1 Time on Task (TOT)

The effect of task duration on mental fatigue and performance is known as the **time-on-task effect** (TOT). In general, mental fatigue increases as the time spent on a task increases (Li, et al., 2020). However, it should be noted that the relation between TOT and performance is not linear: during the first blocks of a task, an improvement in performance can be observed as a result of learning or automation of performance (Csathó, Linden, Hernádi, Buzás, & Kalmár, 2012). Nonetheless, this peak in performance is generally followed by a decrease in performance caused by mental fatigue, which makes task duration an important task-related prediction factor.

2.2.2 Mental Workload (WL)

The mental workload can be defined as the amount of cognitive resources or/and energy required to execute a task, such as attention, memory, alertness or decision-making (Chaouachi, Jraidi, & Frasson, 2011). In general, working under high levels of mental workload over prolonged periods results in an individual's depletion of cognitive resources and energy and, eventually, mental fatigue (Fan & Smith, 2017). Thus, mental workload is also important task-related factor in predicting mental fatigue. Measuring and monitoring workload with EEG spectral feature is more complex than task engagement. Intelligent systems are often used to derive workload index from EEG spectral features. Chaouachi and colleagues (Chaouachi, Jraidi, & Frasson, 2011) monitored EEG extracted features from participants performing various tasks under different workload condition. They used a Gaussian Process Regression model trained on the EEG data of each participant to derive a workload index and reported that their workload index correlated with the subjective workload assessment of the participants (Chaouachi, Jraidi, & Frasson, 2011).

Changes in mental workload can also be tracked via the fluctuation of different brain waves. The ratio of theta power in frontal areas over alpha power in parietal area is a well-known measure of workload variation. Thus, this index is based on the principle that during increases in task demands, theta power increase in frontal regions while alpha power decreases in parietal regions (Raul, et al., Electroencephalographic Workload Indicators During Teleoperation of an Unmanned Aerial Vehicle Shepherding a Swarm of Unmanned Ground Vehicles in Contested Environments, 2020). Thus, increases in the theta frontal to alpha parietal ratio indicate an increase in task load perception. However, from transition states from high mental workload to increasing mental fatigue levels, this ratio decreases as alpha power starts increasing (Cao, Wan, Wong, Cruz, & Hu, 2014). Thus, this ratio can be used to monitor changes in workload and mental fatigue perception.

2.2.3 Task Engagement (TE)

The level of attention, involvement, and interest one dedicates to a particular task is one of the many factors affected by mental fatigue. Hence, mental fatigue can result in unwillingness for further efforts, abandoning behavior, where one becomes disengaged with the current task (Hopstaken, Linden, Bakker, & Kompier, 2015). Consequently, task engagement decreases with

TOT effects (mental fatigue). Pope and colleagues (1995) at the NASA developed an engagement task index based on EEG frequency bands applied in a closed-loop system to modulate task allocation. This index is defined by the ratio of frequency bands Beta/(Alpha+Theta) (Pope, Bogart, & Bartolome, 1995). This ratio reflects allocation of attention, information gathering, and visual processing (Laurent, et al., 2012).

2.2.4 Passive vs. Active Fatigue

An important theory proposed by Desmond and Hancock's (2001) suggested there are two types of fatigue: active and passive. In driving studies, active fatigue is characterized by elevated stress and results from a continuous and prolonged demanding interaction vehicle control requiring constant perceptual and motor adjustments. On the other hand, passive fatigue is characterized by task disengagement and is the result of prolonged hours of little to no perceptual-motor response or interaction with vehicle control (Desmond & Hancock, 2001) (Saxby, et al., 2008). Thus, active fatigue appears to occur in higher workload conditions while **passive fatigue** occurs in lower workload conditions. The distinction between passive and active fatigue is that active fatigue is associated with cognitive overload from high-workload while passive fatigue is associated with boredom from low-workload settings (Saxby D. J., Matthews, Warm, Hitchcock, & Neubauer, 2013). Passive fatigue induced by low workload condition results in a significantly greater task disengagement and performance impairment over time while active fatigue results in a greater emotional distress and less task disengagement overtime (Saxby, et al., 2008) (Hu & Lodewijks, 2021)(Neubauer, Matthews, & Santos, 2023). Thus, the conditions in which fatigue arise (types of fatigue) predicts how it manifests in terms of workload and task engagement.

2.3 Physiological and psychophysiological measures

Signs and symptoms of mental fatigue can be detected and measured via multiple sets of physiological and psychophysiological measures. This section will present 5 different measures of mental fatigue: Eye blink rate (BR), blink duration (BD), pupil diameter, PERCLOS, heart rate variability and power spectral density with electroencephalography.

2.3.1 Eye blinking rate and duration in workload

Increasing frequency of eye blinking rate (BR) with respect to TOT has been identified as a good measure of visual workload (Benedetto, et al., 2011). Hence, during visual attention tasks, the amount of attention required to extract relevant information could lead to blink inhibition and sustained attention on task leading to fatigue would disrupt this inhibition (Recarte, Pérez, Conchillo, & Nunes, 2008) . Along with BR, eye blink duration (BD) was also found to be a good indicator of mental fatigue, with respect to visual workload (Recarte, Pérez, Conchillo, & Nunes, 2008). Simulated flight studies reported a decrease in BD as visual workload increases, suggesting that long-lasting blinks as an indicator of drowsiness while short-lasting blinks are associated with sustained attention (JA & AW, 1996) (Ahlstrom & Friedman-Berg, 2006).

In research conducted by Simone Benedetto and colleagues (2010), the effect of workload on BR and BD were both explored in a driving simulation environment. This study had participants driving an Oktal SCANeR II simulator during a primary (baseline) and secondary (dual) task with an SML iView X HED monocular eye-tracking device. The primary driving task, Lance Change Test (LCT) required the participants to perform at least 18 lane changes on a 3 km three-lane straight road on the driving simulation device. In the secondary driving task, participants were required to drive the simulation device while performing a visual search task (Surrogate Reference Task). Participants had a 2-column SuRT (Surrogate Reference Task) and had to double-click on the portion (left or right) where the target circle was located. There was 2 difficulty levels for the SuRT task: easy (fewer distractors) and hard (more distractors). A subjective measure of workload, BR, BD, average pupil size, reaction time, and IVIS performance was recorded. This study reported that short blinks significantly increase with the visual workload (single task vs. dual task). Unlike Jesper F. Hopstaken and colleagues (2005), this study reported a significant difference in average pupil size between all single vs. dual-task conditions. Once again, these results suggest that pupil size might be related to the visual aspect workload. Finally, no significant result were obtained in the analysis of BR, suggesting that BR is a more complex variable, primarily affected by inter-subject variability.

Thus, the latter results suggest that BD is a more sensible and reliable measure of the visual workload compared to BR, and, thus, a better candidate to measure mental fatigue. BR and BD are non-intrusive measures and ease of use, but this measure can also be sensible to lightning conditions (Parekh, Shah, & Shah, 2020).

2.3.2 Pupil diameter in mental fatigue and workload

Pupil diameter (PD) is another eye measurement which can be used to detect workload and mental fatigue. As mental fatigue increases, the pupil diameter decreases with respect to baseline measurements (Hopstaken, Linden, Bakker, & Kompier, 2015; Körber, Cingel, Zimmermann, & Bengler, 2015; Bafna, Bækgaard, & Hansen, 2021). While pupil diameter is also sensitive to changes in arousal and fatigue, it is also sensitive to changes in mental workload. Gonca Gokce Menekse Dalveren and colleagues conducted a study to measure changes in mental workload in surgical residents during surgery where participants were subjected to a computer-based simulation of surgical task. This study found that pupil diameter grows in direct proportion with mental workload (Dalveren, Cagiltay, Ozcelik, & Maras, 2018). Bastian Pfleging and colleagues also used pupil diameter to develop a model able to predict mental workload under different task load demands. They were able to accurately predict workload under varying mental demands and lightning condition with 75% accuracy (Pfleging, Fekety, Schmidt, & L, 2016).

2.3.3 PERCLOS in mental fatigue

PERCLOS is another eye-related psychophysiological measure that is widely used in driving simulation and aircraft pilot studies as a drowsiness metric. PERCLOS is the ratio of eyelid closure over time (Zhang, Zhou, Yin, & Liu, 2018). This metric is often used in concert with other eye-related measurements to assess mental fatigue. Zhang and colleagues (2018) derived a model for estimation of fatigue value in a simulated flight and visual search task using PERCLOS, blink frequency (BF) measurements, and subjective measures of mental fatigue. This study reported a strong correlation between mental fatigue values and eye movement measurement and used Bayesian algorithm to assess a fatigued and non-fatigued state, treating PERCLOS and BF as independent variables. Their classifier on the cross-validation grouping and initial grouping attained an accuracy rate of 97.4% (Zhang, Zhou, Yin, & Liu, 2018).

2.3.4 Heart rate variability (HRV) in mental workload

The heart rate and respiration variation are known to be linked to the variation of emotional states in humans. Across the literature and aviation studies, HR is used to measure workload, due to its sensibility to task difficulty (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). However, it must be noted that other physiological and environmental factors might influence HR. For this reason, the heart rate *variability* (HRV) is used in mental studies, which can be studied thanks to the Fourier Transform of the HR signal. Thus, it has been reported that the increase of power in the low-frequency bands of the HRV has a strong link to the workload and working time (Gianluca, Astolfi, Vecchiato, Mattia, & Babiloni, 2014).

Therefore, HRV is significantly linked to the occurrence of mental fatigue, due to its high correlation with task demand and mental workload. (Gianluca, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). HRV is a non-invasive and easy-to-use measure. However, it remains sensitive to individual variability and environmental set-up.

2.3.5 Electroencephalogram (EEG) Power Spectral Density

The electroencephalogram is a non-invasive way to measure the electrical activity originating from the brain from a set of electrodes spaced on the scalp. EEG is a common way to assess and monitor mental workload and fatigue because of the fluctuation in EEG waveforms – delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (14-30 Hz) in various cortical areas (Zhao, Zhao, Liu, & Zheng, 2012) (Gianluca, Astolfi, Vecchiato, Mattia, & Babiloni, 2014) (Figure 1). Transition state between increasing workload and mental fatigue generally results in an overall increase in delta, theta and alpha frequency band, and a decrease in beta frequency band (Ismail, 2020) (Qi, et al., 2019) (Gianluca, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). EEG is one of the most promising tools to measure mental fatigue due to its high temporal resolution and sensitivity to brain states, but is also very susceptible to environmental noise which can make the extraction of informative pattern challenging (Ziwu, et al., 2021) (Gao, Wang, Potter, Zhang, & Zhang, 2020).

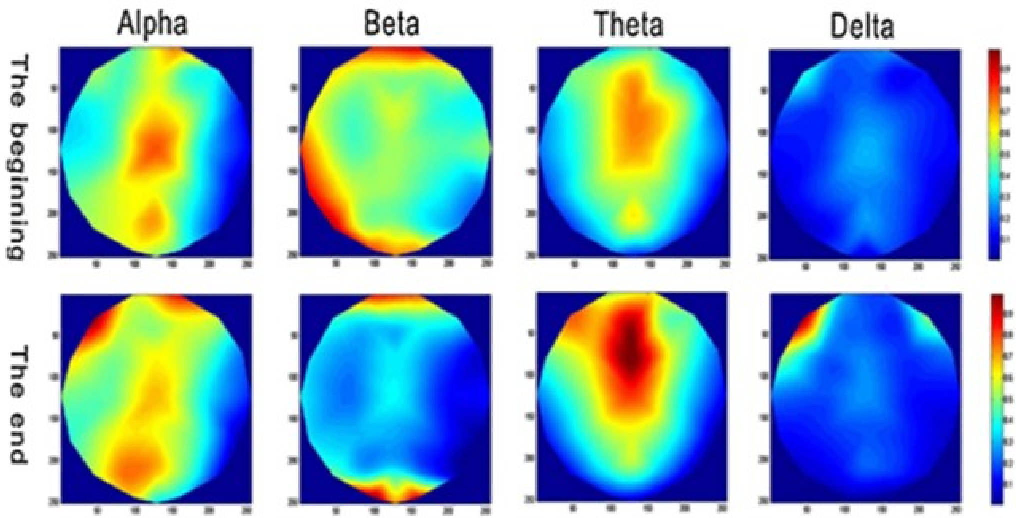


Figure 1 *From Gianluca & al. literature review: ''Scalp topography of electroencephalogram activity before and after driving simulation. Blue indicates a decrease in power spectra and red an increase in power spectra for the specified wave band, from Zhao et al 2012 (Zhao, Zhao, Liu, & Zheng, 2012)''*

2.3.6.1 Decomposing EEG frequency bands in mental fatigue occurrences

The relative power of the delta frequency band (0.5-4 Hz) is known to decrease in the majority of scalp areas as a result of mental fatigue (Li, et al., 2020) (Jap, Lal, Fischer, & Bekiaris, 2009). More precisely, decrease of relative delta rhythms is related to daily levels of fatigue sensations (Ishii, Tanaka, & Watanabe, 2014)

Theta frequency band (4-8 Hz) fluctuation captured by the EEG electrodes due to an increase in task demand and required attention in driving stimulation studies is linked to the emergence of fatigue in various studies (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). More precisely, an increase in EEG power spectra in theta bands over frontal areas is linked to an increase in attention demands, and an increase in theta bands over parietal areas is linked to an increase in task demands (Fairclough, Venables, & Tattersall, 2005).

Alpha frequency bands (8-13 Hz) typically manifest when the eyes are closed, reduces when the eyes are open and severely drops during attention tasks (Gharagozlou, et al., 2015). Alpha band is considered to be one of the most sensitive indicators of brain fatigue (Li, et al., 2020). An increase in alpha power is related to lower mental alertness which can be the result of increasing levels of task difficulty (Raul, et al., 2020).

Beta Frequency Bands (14-30 Hz) have been reported to be sensitive to visual attention and short-term memory (Raul, et al., 2020). A driving simulation conducted by C. Zhao and colleagues (2012) compared relative EEG band frequency at the beginning of the simulation and at the end. The study reported a significant decrease in various scalp areas for the beta frequency band at the end of the simulation, suggesting disengagement and decrease in vigilance (Zhao, Zhao, Liu, & Zheng, 2012).

2.3.6.2 EEG-based indices for mental fatigue

In the previous section, we have seen how mental fatigue translates to changes in multiple EEG frequency bands and cortical sections. To study the fluctuation of these bands with respect to changes in mental fatigue levels, several EEG-based indices and ratio indices have been derived from EEG power spectral density data and subjective assessments.

Looking at individual frequency bands α, θ, Δ, β (alpha, theta, delta beta) power spectral density can convey a lot of information about fatigue. As seen in sections 2.3.6.1 increase in alpha bands are associated with increasing fatigue levels (Cao, Wan, Wong, Cruz, & Hu, 2014). However, this relation is not linear when fatigue is generated from increasing task difficulty and/or memory load. Thus, during rises of mental workload, alpha bands in parietal regions decreases (Gianluca, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). Then, from transition states from high mental workload to mental fatigue, alpha bands increase in frontal, occipital, temporal, parietal and central scalp areas (Lal & Craig, 2002) (Qi, et al., 2019). Rises in theta bands are associated with decreases in task performance, attention, and arousal levels (Cao, Wan, Wong, Cruz, & Hu, 2014). Thus, theta index has been used to capture fluctuations from aroused to mental fatigue state during prolonged mental efforts. Decrease in delta power is associated with increase in fatigue sensation. Finally, lower amplitudes of beta relative powers are monitored to capture changes in active concentration (Cheng & Hsu, 2010). In general, the relative power spectral density of individual bands is preferred over absolute power spectral density as it reduces inter-subject variation of EEG signals (Park, Lee, Jeong, Shin, & Park, 2020).

$$(E1)\ WL = \frac{\theta}{\alpha}$$

E1 is the ratio of theta power in frontal areas over alpha power in parietal area, a well-known measure to track variation in workload. As seen in section 2 of this chapter, changes mental workload is an important indicator of mental fatigue. This index in based on the principle that during increases in task demands, theta power increases in frontal regions while alpha power decreases in parietal regions (Raul, et al., 2020). Thus, increases in the theta frontal to alpha parietal ratio indicates an increase in task load perception. However, from transition states from high mental workload to increasing mental fatigue levels, this ratio decreases as alpha power starts increasing (Cao, Wan, Wong, Cruz, & Hu, 2014).

$$(E2)\ \ TE = \frac{\beta}{\alpha + \theta}$$

E2 is the ratio of beta power over alpha and theta power of parietal areas, an EEG-based index used to measure task engagement. This index was developed by Pope and colleagues in 1995 (Pope, Bogart, & Bartolome, 1995). As seen in section 2 of this chapter, decline in task engagement can be an important precursor of mental fatigue.

Relative power of individual frequency band and/or workload/task engagement ratios are necessary to track changes in fatigue levels using electroencephalography. These indices and ratios will later be used in the protocol to monitor rises in mental fatigue.

In this chapter, we explored the many ways in which mental fatigue can arise and be measured. We have seen that fatigue rises as a function of TOT and can also be impacted by the amount of cognitive resources needed to complete a task (mental workload), which can in turn impact the engagement/motivation to the task (task engagement). The choice of measurements for mental fatigue for the protocol was based on the selection of physiological signs presented and detailed throughout section 2.3. The labeling methodology and measurement for fatigue segments used for our protocol were inspired by the methodology used by Ren Ziwu and colleagues for their Radical Basis Function (RBF) Neural Network to detect fatigue in driving simulation using EEG signals (presented in 2.1). Hence, our approach to mental fatigue measurements is to use EEG power spectral density segments for classification. However, we use pupil dilatation instead of eye closure (PERCLOS) to label EEG segments due to the sensibility of pupil dilatation to both fatigue and workload. Additionally, this labeling methodology will allow for real time detection and labeling of mental fatigue instead of relying on subjective questionnaires. The set of EEG indices presented will also allow for real time monitoring of known mental fatigue wave patterns. Finally, due to the limited amount of time allowed to generate mental fatigue, our protocol aims to generate fatigue under high workload and stress conditions, which will likely result in a less severe decrease of task engagement overtime as can be observed in **active fatigue**. Thus, although passive fatigue results in more severe fatigue symptoms, it requires prolonged hours of task interactions which we will not be able to procure for this experiment. Next chapter will present the set of possible recuperation techniques considered for our protocol in order to alleviate symptoms of mental fatigue.

Chapter 3 – Mental Fatigue Recuperation

There is no miracle solution to fully recover from mentally fatiguing tasks: sleep and an appropriate resting time are essential needs to recover cognitive functions affected by prolonged hours of work (Torbjörn, Peter, & Göran, 2009) (Boksem & Tops, 2008). Justine R. Magnuson and colleagues (2021) investigated the development and recovery of mental fatigue by measuring participants neural activity with EEG and gathering subjective measures of mental fatigue during 60 min cognitive exercises and 60 min post-task resting time. The latter study observed that mental fatigue was induced after 30-45 min of the high mental load task, from both objective and subjective measures. They also observed a 60 min recovery of some alpha and theta levels to baseline levels during the post-task phase (Hopstaken, Linden, Bakker, & Kompier, 2015).

However, daily responsibilities and duties do not always allow enough time to rest and fully recover attentional resources. In this chapter, we will explore several recuperation strategies used to alleviate some symptoms of mental fatigue as temporary solutions until proper resting time is possible for a more complete recovery. This chapter will present 4 different recuperation and relaxation strategies that can aid in reducing mental fatigue symptoms.

3.1 Relaxation Therapy (Sophrology)

Relaxation therapy is a broad term used to describe techniques promoting stress reduction. It includes techniques such as sophrology, a form of directed meditation. Sophrology is a self-help relaxation method that can be used in various ways. One of the ways sophrology can be practiced is through virtual reality technology and EEG feedback. A Virtual Sophrologist System was developed by Guoxin Gu and Claude Frasson based on VR environment, EEG feedback and sophrology instructions. The Virtual Sophrologist system provides one of three relaxing immersive environments while sophrology instruction is displayed and spoken by a virtual speaker. During the session, EEG is used to measure brain activities, processed to calculate a Meditation Score which is then displayed onto the VR environment of user feedback (Guoxin Gu, 2017). The Virtual Sophrologist System was shown effective in helping people to relax and manage their stress, which motivates the interest in exploring its effects on mental fatigue symptoms.

3.2 Natural environment

Exposure to natural environments promotes efficient recovery of cognitive resources, which can be greatly depleted in a mental fatigue. Since it is not always possible for urban workers to benefit from sufficient exposure to natural environments, some research has studied the effects of virtual exposure to natural environment such as videos or photos (Berto, Baroni, Zainaghi, & Bettella, 2010). Kimura Tsukasa and colleagues studied the effect of brief virtual exposure to natural environments on workload, task performance and directed attention. This study found that virtual exposure between tasks did not affect subjective workload and task performance, but did restore directed attention for the following task (Tsukasa, Tatsuya, Yohko, & Kazumitsu, 2021)

3.3 Increase reward

Maarten AS Boksem and Mattie Tops (2008) proposed that the feeling of mental fatigue is the result of a motion to abandon an ongoing behavior when “energical costs continue to exceed rewards of task performance” (Boksem & Tops, 2008). This framework was later investigated by Jesper F. Hopstaken and colleagues who measured the effect of a reward presented at the last task time block of a series of fatiguing tasks on subjective fatigue ratings and pupil measurements. The later studies observed a significant increase in task performance, subjective task engagement rating and stimulus-evoked pupil dilatation on the time block where the reward was presented (Hopstaken, Linden, Bakker, & Kompier, 2015). Thus, these results show that sufficient reward can motivate participants to re-engage on a task they were initially fatigued by.

3.4 Pharmaceutical countermeasures (caffeine)

Caffeine is an adenosine receptor antagonist drug which improves alertness, attention, wakefulness, and mood. Although caffeine effects on mental workload and task engagement is unclear, the effects of caffeine intake related to time-on-task (TOT) improve performance vigilance in fatigued subjects (Lorist & Tops, 2003). The caffeine intake promotes better performance on cognitive and psychomotor vigilance task, as well as general, positive effect on the attentional system. However, there is no clear understanding about the exact interaction between caffeine and these systems as EEG, ERP and behavioral studies differ in their conclusion with regards to exact nature of caffeine's effects on various systems (Lorist & Tops, 2003). It should be noted that the stimulant effects of caffeine are various to different arousal levels of the consumer and the nature of the task. Moreover, the effects of caffeine largely depend on the consumer's daily exposure to caffeine. Thus, frequent consumption of caffeine fails to enhance mental alertness and performance and increase anxiety (Rogers, Heatherley, Mullings, & Smith, 2013). Finally, caffeine withdraws effects include lower mental alertness, greater sleepiness and poorer task performance (Rogers, Heatherley, Mullings, & Smith, 2013).

In this chapter we explored different methods that can be used to temporarily alleviate symptoms of mental fatigue. We have seen that brief exposure to natural environment and caffeine can temporarily restore attention, increasing the reward expected can temporarily restore engagement and relaxation therapy can reduce stress following a high demand task. These are the 4 recuperation techniques candidates that were considered for our research. Ideally, the recuperation technique chosen would temporarily reduce some fatigue symptoms but would also need to be easy to reproduce without having potential withdraw effects. This means that exposure to natural environment and relaxation therapy would be ideal for this study. Finally, we decided to include relaxation therapy in our protocol since its effect of mental fatigue specifically has not been explored and since we can also include natural landscapes in the immersive environments which provides a practical in between for the 2 ideal candidates.

Chapitre 4 – Materials and Methods

This chapter presents the details of the protocol as well as the measures chosen from the previous chapters. The goal is to generate mental fatigue and collect fatigue measures to produce a dataset which will be suitable for machine learning analysis and test the effects of relaxation therapy on fatigue measures. We believe that finding adequate techniques to temporarily restore cognitive function is as important as the detection of mental fatigue. We hope that our work will motivate others to explore efficient and adequate mechanisms for recuperation. This chapter will first present the measures chosen for the generation and recuperation of mental fatigue followed by the details of the study design. Finally, this chapter will present the methodology for participants and EEG/Eye tracking data acquisition and data pre-processing/segmentation.

4.1 Measures Chosen: Generation and Recuperation

The experimental protocol has two parts: the first is the generation of mental fatigue and the second is the recuperation of mental fatigue. We aim to successfully generate mental fatigue in the first part through the means of cognitively demanding exercises displayed in an immersive virtual environment, which is presented in more details in section 4.2. Thus, this fatigue scenario corresponds to the environment suitable for the development of active fatigue, which is the result of a high-load cognitive environment. **EEG** and **eye-tracking** data are the psychophysiological and physiological measurement types chosen for this experiment to monitor **relative brain power spectral density** and **pupil diameter**, respectively. **Mental workload** and **task engagement** were computed throughout the experiment (EEG indices presented in 2.2.6.2). Mental workload and task engagement indices are derived from EEG data to provide further evidence of the presence of mental fatigue symptoms. Then, EEG data and pupil diameter are used as a feature matrix and label vector, respectively, and fed to a subset of supervised machine learning algorithms and different parameters to obtain the optimal classifier to fit the data. Using EEG data and eye-tracking data as a feature matrix and labels were used by Ren Ziwu and colleagues developed a Radical Basis Function (RBF) Neural Network to detect fatigue in driving simulation (Ziwu, et al., 2021).

Additionally, we aim to alleviate symptoms of mental fatigue in the second part of the experiment, following the generation of mental fatigue. Among the fatigue recuperation methods presented in Chapter 3, a **virtual relaxation therapy** detailed in section 4.2 was chosen to study its effect on mental fatigue symptoms. The effects of virtual relaxation therapy will be analyzed by comparing pupil dilatation and brain power spectral density before and after the relaxation.

The objectives of this study were to (1) **induce** mental fatigue in a pool of participants, (2) collect EEG and eye-tracking data to train multiple supervised machine learning models to **detect** mental fatigue and (3) attempting to **alleviate** symptoms of mental fatigue with a virtual relaxation technique.

Mental workload and task engagement indices are derived from EEG data to provide further evidence of the presence of mental fatigue symptoms. Then, EEG data and pupil diameter are used as a feature matrix and label vector, respectively, and fed to a subset of supervised machine learning algorithms and different parameters to obtain the optimal classifier to fit the data. Using EEG data and eye-tracking data as a feature matrix and labels were used by Ren Ziwu and colleagues developed a Radical Basis Function (RBF) Neural Network to detect fatigue in driving simulation (Ziwu, et al., 2021).

4.2 Study Design

Participants were invited to a room at Beam Me Up, partner of the project, 5925 Monkland Ave, H4A1G7, Montréal, to complete the different steps of the experiment and a few real time and offline outcome measures. My colleague Mahdi Zarour set up the system worn by the participants including an Emotiv Epoc+ EEG Headset and Vive eye VR headset which has a built-in eye-tracking module (Figure 2). We generated mental fatigue among participants through a simulated environment of a work office where participants are prompted to perform various sets of cognitive tasks (Figure 3).

Figure 2 *Apparatus of the Emotiv Epoc EEG headset with control remote and VR headsets*

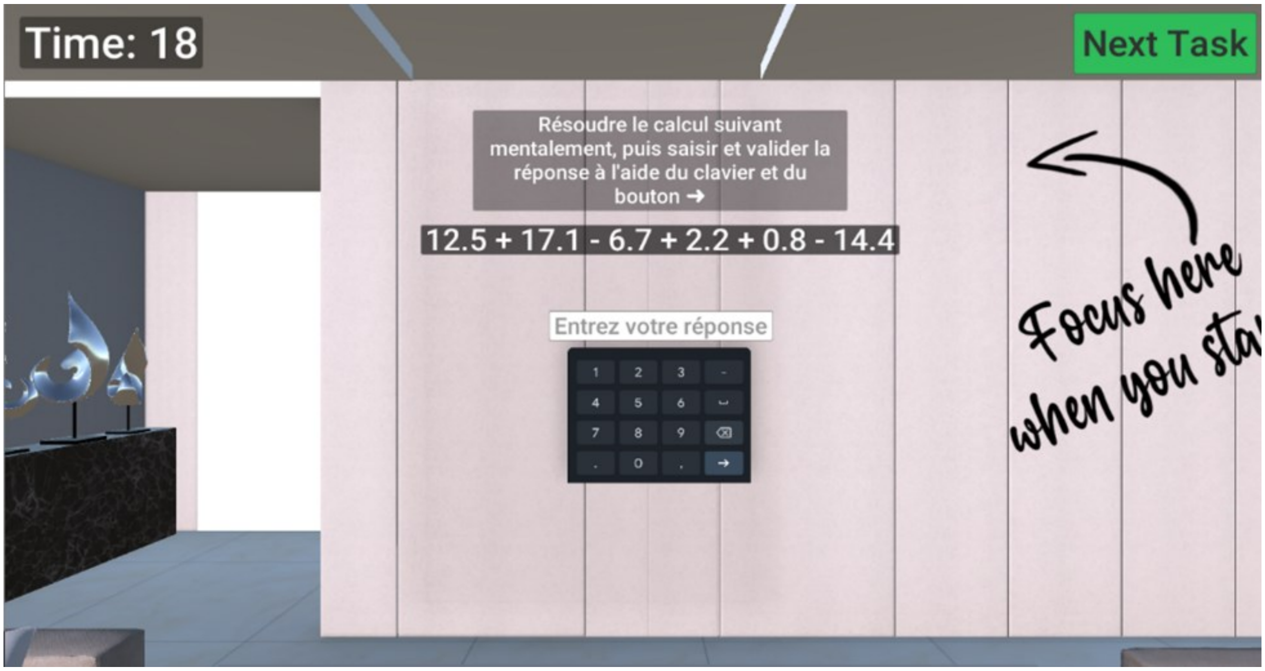


Figure 3 *Mental arithmetic tasks (first task of the cognitive task with distractors) before the appearance of distractor answers on the screen.*

There are two types of cognitive tasks set: one **with distractors** and one **without distractors** Distractors in the form of fake 'hints' are meant to increase the difficulty of the task by misguiding participants and increase frustration. During these tasks, fatigue is measured by 3 indicators: pupil dilation, workload, and task engagement. The exercises chosen to generate mental fatigue are aligned with the **active fatigue** framework discussed in section 3: we generate mental fatigue through cognitive tasks which aim to exert a high cognitive load on the participants.

First, participants will perform both set of tasks consecutively (25 min). They are asked to answer questions from the task as fast as possible without scarifying accuracy. Then the relaxation period will begin (10 min). Finally, the participant will answer different questions from the set of cognitive tasks without distractors (10 min).

The set of cognitive tasks **with distractors** consists of mental arithmetic tasks, anagram tasks and backward digit span (BDS) tasks. For each cognitive task, fake answers in the form of “hints” will be displayed in the user’s virtual visual field to distract them. The goal of the distractors is to add difficulty by generating negative emotions: participants are distracted by unhelpful information which causes frustration and learn to ignore them as they realize they are affecting their performance. The user must perform these tasks within the time allocated for each. The arithmetic tasks (Figure 3) consist of a series of addition and subtraction of decimal numbers presented in the virtual environment that must be solved by the user. An example of a mental arithmetic task is an equation of the form “24.54 – 12.89 + 2.13 +11.72 – 7.08 - 3.23” in which the user must use the virtual keyboard to summit the correct answer to this equation, 15.19 in this example. In the anagram task, the user is presented with a set of letters, and must rearrange these letters to form the appropriate dictionary word. For example, a user is presented with the letters “R”, “E”, “D”, “R”, “U”, “M”, and must use his virtual keyboard to type the correct word “MURDER”. In the backward-digit span, the user is presented with an ordered sequence of numbers that appear on the user’s virtual environment for a short period of time. The user is asked to memorize the sequence during that period. A few moments after the sequence is removed from the user’s screen, the participant is asked to recall the sequence in the reverse order of presentation using their virtual keyboard. For instance, if the user is presented with the sequence “9742593”, he must memorize the sequence during the allowed time window and enter the reverse sequence order, “3952479”.

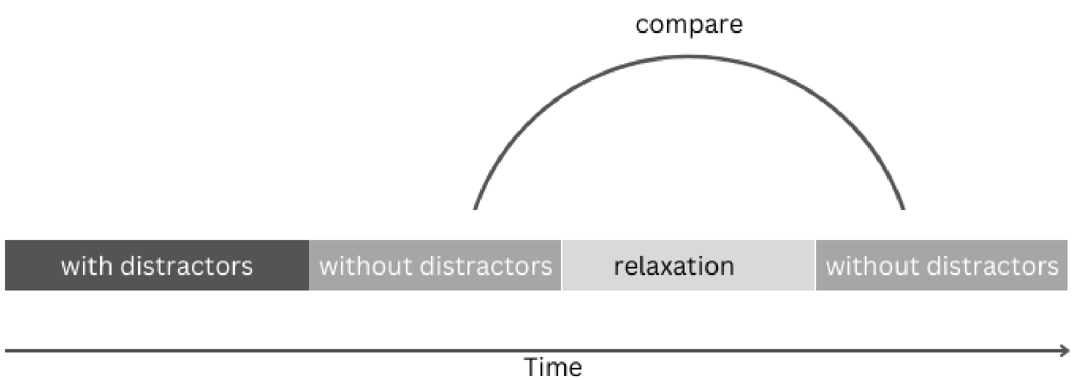
Then another set of cognitive tasks **without distractors** is presented to the participant. This set has different types of exercises of a 5 min duration to measure cognitive and memory performance. These tests continue to generate mental fatigue as they require concentration, attention, memory, and other cognitive resources. This set is composed of attention, a naming exercise and three different memory tests to evaluate contextual/visual memory, working memory and short-term memory. These exercises will allow cognitive performance comparison between post-fatigue and post-recuperation states.

After the mental fatigue generation events, participants are exposed to the “Traveling Therapy” VR environment (Figure 4) for 10-15 minutes to reduce their negative emotions and increase their concentration (Abdessalem, et al., 2020). This environment projects the users into a virtual train (360-degree environment), where they are sitting and can turn their head to look through the windows or observe events inside the train. The windows reveal a natural/relaxing landscape which can consist of forests with animals, mountains, snow mountains, simple roads, lakes, etc. (Figure 4). In the train, the user can also see persons and/or pets interacting. It is known that exposure to natural elements and landscape aid in the recovery of attentional fatigue (Sullivan & Li, 2021) and experiments realized with this virtual train has proved a reduction of negative emotion and an increase in memory and cognitive function. We aim to analyze if exposure to this virtual natural landscape can produce similar effects on mental fatigue recovery.

Figure 4 *The virtual train (relaxing environment).*

In summary, participants will first complete the set of cognitive tasks with distractors followed by the set of cognitive tasks without distractors. Then, participants will participate in a 10-15 min traveling train therapy session, followed by a second completion of the cognitive tasks without distractors to allow comparison between post-fatigue and post-recuperation states (Figure 5). We chose to compare results by only retesting cognitive task without distractor to avoid possible scenarios where the participants realize that the distractors are not helpful hints by the end of the first session and learn to completely ignore them during retesting.

Figure 5 *Timeline of the experiment. Participants will complete the set of cognitive tasks with distractors and without distractors, followed by a relaxation period and another set of cognitive tasks without distractors. Fatigue indices collected from the sets of cognitive tasks without distractors during the pre-and post relaxation period will be compared to analyze the effect of relaxation.*



4.3 Participants and EEG/Eye Tracking Data Acquisition

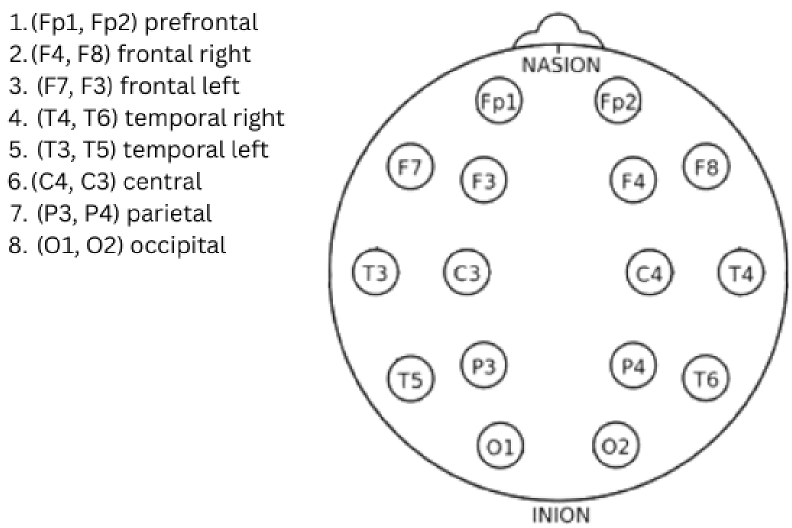
The VIVE Pro-Eye Specs is a VR headset with an integrated eye tracking device. The VIVE Pro will be used to display the virtual environment created in Unity and collect eye tracking data throughout the mental fatigue generation and recuperation steps of this experiment. The integrated tracking device allows continuous measurements of gaze origin, gaze direction, pupil position, pupil size, and eye openness.

OpenBCI (brain-computer interface) headset and platforms will be used for continuous monitoring of real-time EEG data during mental fatigue generation and recuperation. The

OpenBCI cap allows measurements of EEG brain waves from 16 electrodes placed on the scalp. Alpha, theta, and beta brain frequencies from the 16 electrodes were extracted for analysis of fatigue and recuperation.

Thirty-one participants (15 women and 16 men) aged between 19 and 29 years old were invited to a room at Beam Me Up to complete the different steps of the experiment. There are 8 regions derived from the 16-scalp electrode detailed in Figure 6.

Figure 6 EEG Headset electrode topography and associated cortical areas.



4.3.1 Selection of participants and EEG channels

During the course of the experiment, some electrodes lost the different cognitive tasks their signal due to displacement caused movement of the head and/or weak signal caused by hair density and movement on the scalp. EEG channels selected for analysis were chosen to ensure that for the majority of participants, at least 1 of 2 electrodes defining a scalp region remained intact while conserving an equal proportion of males and females. Thus, the central electrodes (c4, c3) were discarded from the dataset for all participants due to failure of both electrodes for a large portion of females. Participants missing 2 electrodes forming any of the 7 remaining scalp regions were removed from the dataset for analysis. Thus, 7 participants (4 females and 3 males) were removed from the data analysis due to one or more scalp region measurement failure. Finally, 3 more participants (1 female, 2 male) were additionally discarded from the dataset due to failure of the EEG headset during the experiment or because they were unable to finish the experiment due to discomfort/headaches.

The final sample was thus composed of **12398** EEG power spectral density segments of prefrontal, frontal right, frontal left, right temporal, temporal left, parietal and occipital electrodes from 21 participants (10 female and 11 male). Due to outliers removal and electrode failure, the sample size per participant is not exactly 12398/21.

4.4 Data Pre-processing and Segmentation

The EEG signal was band-pass filtered with a fourth-order Butterworth filter (high-pass filter cut-off frequency: 1 Hz, low-pass filter cut-off frequency: 30 Hz). The signal was then passed onto a wavelet denoising filter to remove signal noise, then the power spectral density was computed from the result using the Welch method. Outliers were removed using the interquartile range[4] independently for each participant dataset. From the result of the Welch calculation to retrieve power spectral density, the relative power of theta (1), alpha (2), beta (3) and delta (4) was calculated and normalized by subtracting the minimum value of the feature and dividing by the range.

$$(E3)\ \theta_{relative} = \frac{\theta}{\theta + \alpha + \beta + \delta}$$

$$(E4)\ \alpha_{relative} = \frac{\alpha}{\theta + \alpha + \beta + \delta}$$

$$(E5)\ \beta_{relative} = \frac{\beta}{\theta + \alpha + \beta + \delta}$$

$$(E6)\ \delta_{relative} = \frac{\delta}{\theta + \alpha + \beta + \delta}$$

[4] Interquartile range is a measure of statistical dispersion, which is the spread of the data set.

Band powers of 2 electrodes elements of the same region were averaged when both electrodes' data was available. If one of the 2 electrodes was identified as 'railed', only the available electrode from the pair was taken to describe the target region.

Labels have been established based on variation of the pupil diameter, which is a well-known physiological indicator of mental fatigue and mental workload: pupil diameter increases with respect to the baseline when subjects are under high mental charge and decreases when fatigue rises as seen in sections 2.3.2. This labeling methodology enables us to identify 3 types of fatigue segments throughout this experiment:

- **Label 0: No change in mental fatigue**. Condition: When the mean pupil diameter of the segment is between the baseline range.
- **Label 1: Slow increase in mental fatigue.** Condition: When the mean pupil diameter rises above baseline range (which indicates an increasing workload, early stage of fatigue).
- **Label 2: Important increase in mental fatigue**. Condition: the mean pupil diameter falls below the baseline range (fatigue).

Baseline range is calculated at the first 60 epoch for each participant (1 epoch = 2 seconds). Then 10 epoch moving segments by 1 epoch increments are assigned to the label falling into one of the 3 levels from the baseline.

Chapitre 5 – Results and Discussion

The first section of this chapter will be concerned with analysis of the pupil size with respect to the method chosen to classify mental fatigue. The second part will be concerned with the fatigue indicators, workload and task engagement and progression throughout the experiment. The third part will address selection of the best machine learning model to classify mental fatigue. The fourth section will be concerned with the analysis of fatigue indicators following the relaxation period. Finally, the last section will be concerned with further discussion about the experimental results and limitations of the experiment. In some of the sections, the before/after mean of fatigue indicators will be compared to show light on the progression of mental fatigue. For example, in sections 5.1 and 5.2, the EEG and eye data segments of cognitive task period have been separated between the first half and the second half of the cognitive task period, in order to perform a Wilcoxon test on before/after distribution of fatigue indicators' means. The goal of this timeline separation is not to compare the effects of the different cognitive tasks, but just to show that fatigue was successfully generated by the TOT (time-on-task) factor.

5.1 Pupil Size Analysis

Labels were assigned with respect to pupil size variation with respect to baseline, to identify segments with levels of increasing workload and fatigue. Assigning fatigue labels according to eye measurements is a methodology that was employed by Ren Ziwu and colleagues to classify mental fatigue using an RBF neural network (Ziwu, et al., 2021).

The mean distribution of the labels during the first half and the second half of the cognitive tasks part of the experiment shows a significant decrease in absence of fatigue segments and slow fatigue progression proportion. Moreover, we noted a significant increase in high fatigue increase label proportion during the second half of cognitive tasks (with and without distractors) compared to the first half and a significant decrease in the no and slow increase labels (Table 2, Figure 7). The Wilcoxon nonparametric test was chosen to compare different fatigue segments as their distribution did not follow the normality assumption from parametric tests.

Recall of labels and their meaning:

- **Label 0: No change in mental fatigue**. Condition: When the mean pupil diameter of the segment is between the baseline range.
- **Label 1: Slow increase in mental fatigue.** Condition: When the mean pupil diameter rises above baseline range (which indicates an increasing workload, early stage of fatigue).
- **Label 2: Important increase in mental fatigue**. Condition: the mean pupil diameter falls below the baseline range (fatigue).

Tableau 2 *Wilcoxon test of the proportion of mental fatigue signs comparing the first half of the experiment and the second half. Results show a significant decrease in non-fatigue and slow fatigue signs, and significant increase in rapid fatigue progression signs.*

label number	Median first half	Median second half	Alternate hypothesis	Residual statistic.	P value
0	0.888	0.607	$\mu0 > \mu1$	168	0.00002
1	0.025	0.001	$\mu0 > \mu1$	5	0.005
2	0.041	0.393	$\mu0 < \mu1$	0	0.000004

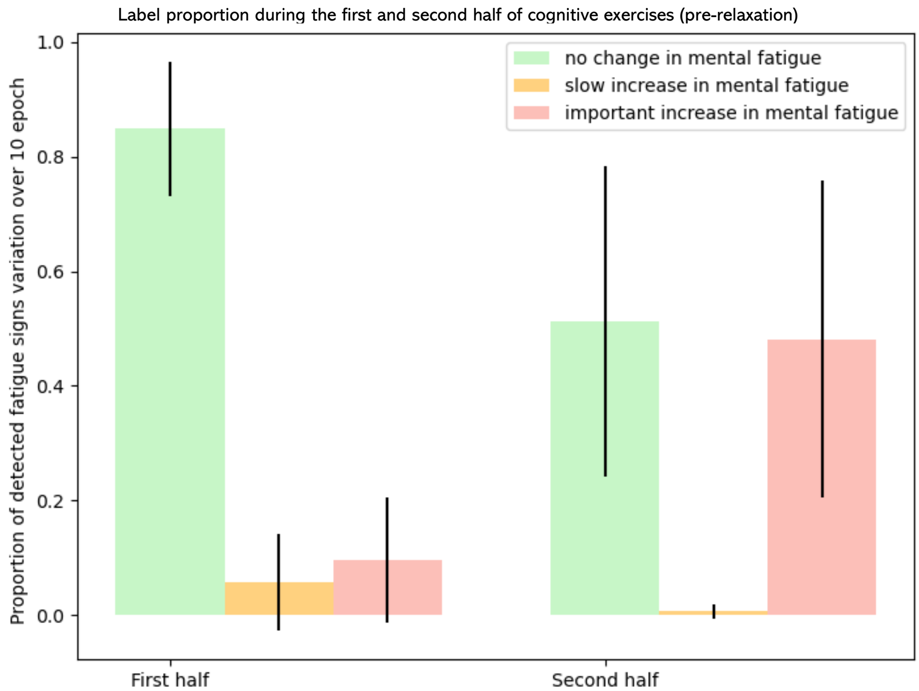


Figure 7 *Proportion of labels during the first half and second half of the fatigue generation tasks.*

We can observe that the proportion of time series labeled as no change and slow increase is higher in the first half the experiment, while the proportion time series labeled as important increase is higher in the second half of the experiment, suggesting a shift in the general fatigue state from the end to beginning.

All 21 participants displayed an increase in pupil diameter followed by a continuous decrease during the execution of cognitive tasks (Figure 8). Thus, increase in pupil diameter in simulation environment is known to grow proportional to mental workload (Dalveren, Cagiltay, Ozcelik, & Maras, 2018). Additionally, baseline-related pupil diameter is expected to reduce as mental fatigue increases (Bafna, Bækgaard, & Hansen, 2021).

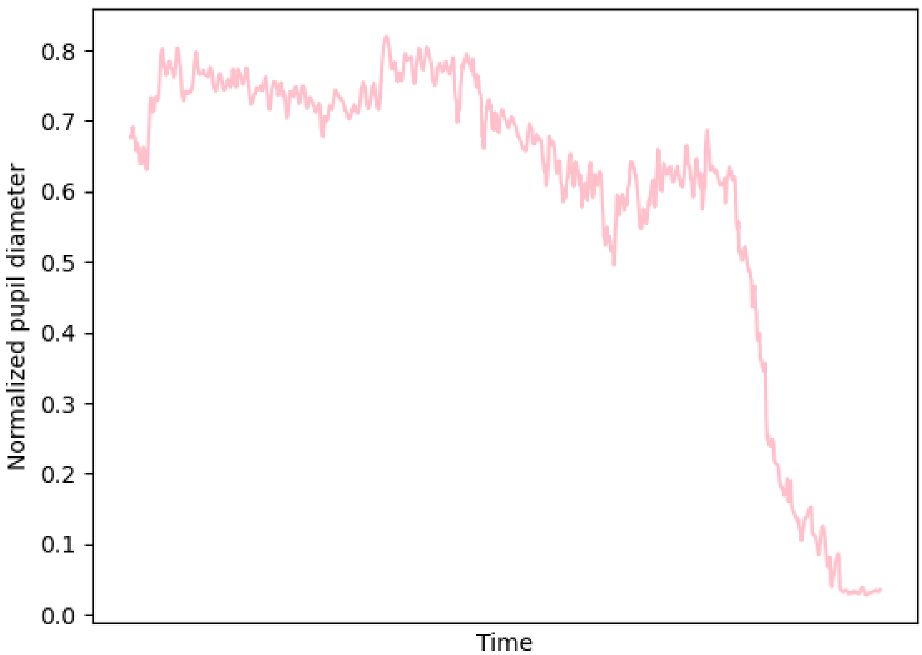


Figure 8 *Average pupil diameter progression across task state before relaxation period (cognitive exercises with distractors and without distractors)*

We can observe that pupil diameter first increase, indicating an increase in workload, followed by decrease indicating an increase in mental fatigue.

5.2 Workload, Task Engagement and Fatigue analysis

The mean workload and task engagement EEG score of all participants were computed from the EEG-based index formulas presented in sections 2.3.5.2. during task state. For analysis purposes, we have separated the task state timeline into 5 time period (T0, T1, T2, T3, T4). Here again, the

Wilcoxon nonparametric test was chosen to compare fatigue indicators at different time periods as their distribution did not follow the normality assumption from other parametric tests. Hence, we observed a significant increase in mean workload score across all participants between T0 (baseline) and T1, as well as a decrease in workload between T0 and T4 in workload score during task state ($p < 0.05$) (Figure 9). However, we did not observe a significant change in mean task engagement across all participants between time period T0 and T4.

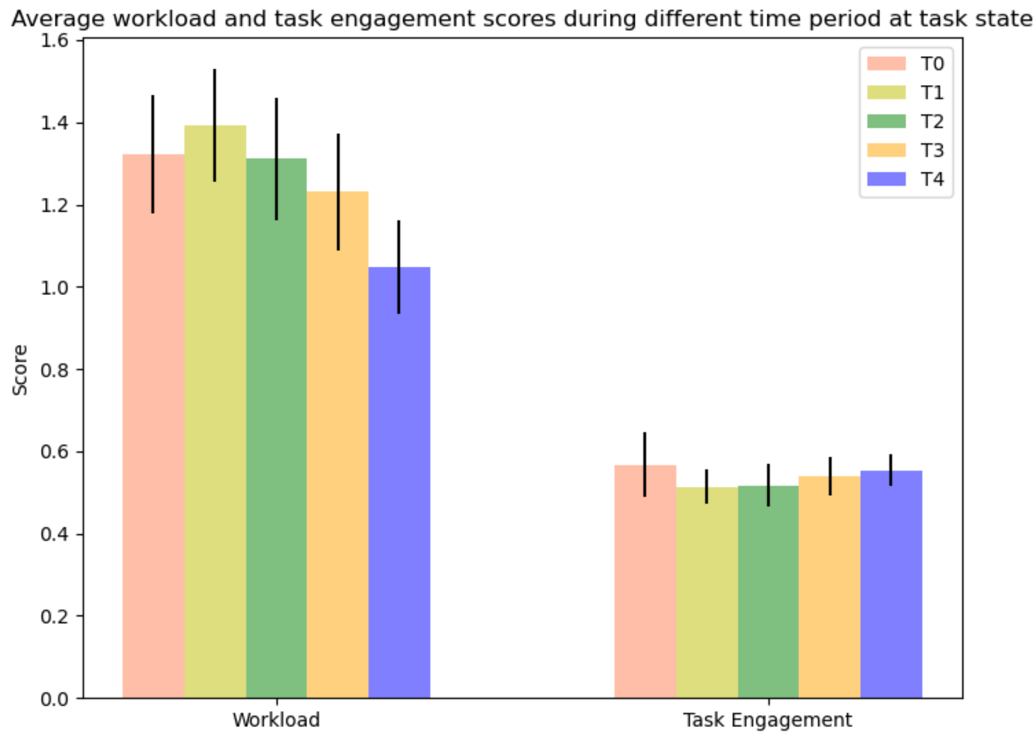


Figure 9 *The average workload and task-engagement index score at different time periods during task state*

Figure 10 shows the mean relative power of all four bands of all participants across all brain regions from the period T0 to T4 of the task period. Relative band powers were computed from the EEG-based formulas presented in sections 2.3.5.2. during task state. We can observe that alpha band power at T3 and T4 increases significantly, indicating a increase in mental fatigue.

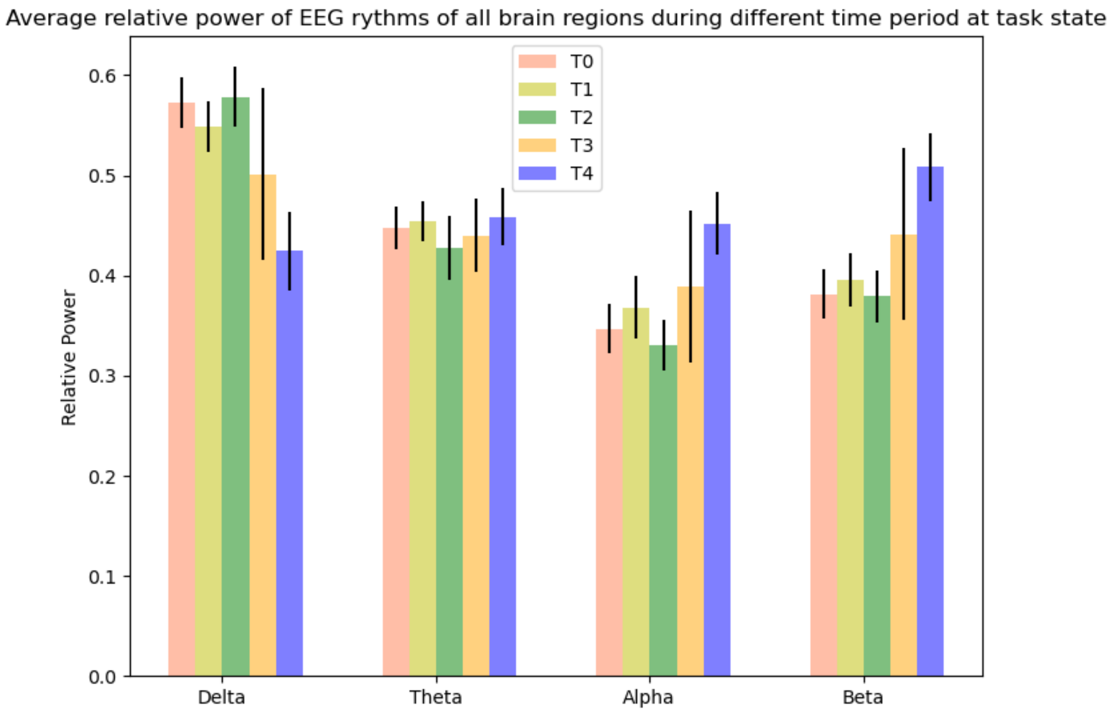


Figure 10 *The average relative power of EEG rhythms over all the brain regions at different time periods during task state*

A significant decrease ($p<0.05$) in the relative power of delta was observed between T0 and T4 at task state. Moreover, a significant increase in the relative power of alpha and beta was observed between T0 and T4 and task state ($p<0.05$). Finally, a smaller, nonetheless significant, increase in the relative power of theta was observed between T0 and T4 at task state ($p<0.05$). The mean for T0[delta, theta, alpha, beta] = [0.573, 0.441, 0.341, 0.381] and T4[delta, theta, alpha, beta] = [0.437, 0.459, 0.452, 0.516]

5.3 Mental Fatigue Classification

12398 samples delta: 26% decease of EEG relative power spectral density data at task state are represented by a 28-feature vector scalp region *S* and band *B*.

The feature matrix is as follows : M = S x B

$$S = \{prefrontal, frontal\ right, frontal\ left, temporal\ right, temporal\ left, parietal, occipital\}$$

$$B = \{delta, theta, alpha, beta\}$$

Features uniquely represent one of the 7 cerebral areas and one of the 4-frequency bands. EEG channels were normalized using a stratified normalization[5] method, in which the data from the feature matrix is normalized per feature, participant and session. This method is commonly used in cross-subject classification from EEG signals to subtract inter-subject variability and improve model performance (Javier, Nicholas, Olaf, & Antoine, 2021).

The proportion of each label group derived from the pupil diameter was highly unbalanced across the dataset (Table 3). This unbalance in the proportion of labels is consistent with the analysis of other fatigue indicators presented in 5.4, as the slow increase in mental fatigue (aka increase in workload) mainly occurs at T1 and important increases in mental fatigue are greater at T4. Thus, the balanced accuracy, the weighted f1-measure and the confusion matrix were the evaluation metrics chosen to evaluate model performance. Moreover, the class weight of the Nearest Neighbor, SVM RBF and Random Forest classifier was adjusted to reflect the class proportions.

Label number	Definition	Proportion
0	No change in mental fatigue	0.701226
1	Slow increase in mental fatigue	0.030286
2	Important increase in mental fatigue	0.268489

[5] In stratified normalization, the data from the feature matrix is normalized per feature, participant and session.

Tableau 3 Proportion of eye-derived labels across the dataset

Table 4 summarizes the cross-subject classification performance during task segments achieved by 8 different machine learning classifiers using 5-fold cross-validation, with Scikit-learn default model's parameter configuration and class weight set to balance when applicable. The best average balanced accuracy was achieved by RBF SVM with 87.0% and best average f1 measure was achieved by Random Forest with 90.5%. Overall, RBF SVM performed best out of the 8 different classifiers, obtaining balanced accuracy and f1 score over 80%. Nearest Neighbors and Random Forest were the second and third-best classifiers in terms of balanced accuracy and f1 measure.

Classifier	Average balanced accuracy	Average f1 measure
Nearest Neighbors	*0.785653*	*0.901256*
RBF SVM	*0.869718*	*0.820500*
Decision Tree	0.721963	0.823052
Random Forest	*0.734867*	*0.905245*
Neural Net	0.425775	0.691259

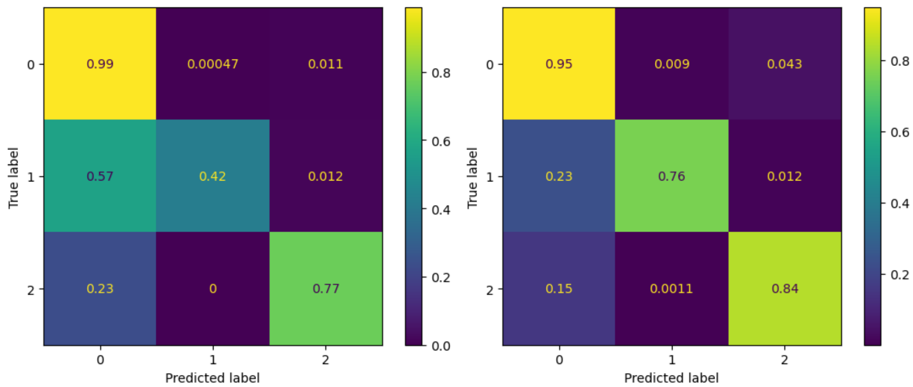
Classifier	Average balanced accuracy	Average f1 measure
AdaBoost	0.426200	0.667939
Naïve Bayes	0.511668	0.503480
QDA	0.734363	0.762419

Tableau 4 *Average balance accuracy and f1 measure of 5-fold cross-validation for 8 different ML classifiers*

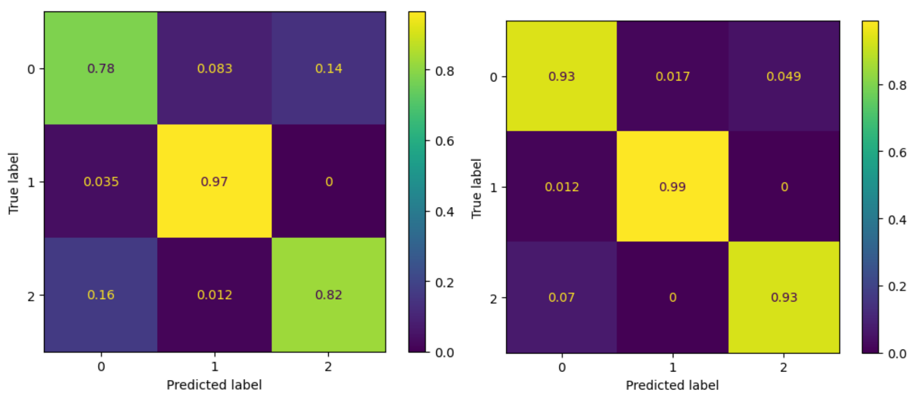
Figure 11 shows the confusion matrices for the 3 best performing algorithms before and after parameter tuning using randomized grid search algorithms. Matrices on the same row (A, B or C) represent results from the same learning algorithm: Random Forest (A), SVM (B) and KNN (C). For a row representing a learning algorithm, the matrix on the **left** is the confusion matrix of the validation set prior to parameter tuning and the matrix on the **right** is after parameter tuning. Random forest achieved. The balanced accuracy for Random Forest, SVM and KNN following parameter tuning on the validation set was 0.85, 0.95 and 0.94.

Random Forest, SVM and KNN with optimized parameter tuning were also fed to a permutation feature importance technique to inspect the relationship learned between features and targets. Figure 12 shows the bar plots of the permutation results scores for Random Forest (A), SVM (B) and KNN (C) indicating the most important feature in decreasing order.

Random Forest (A)



SVM (B)



KNN (C)

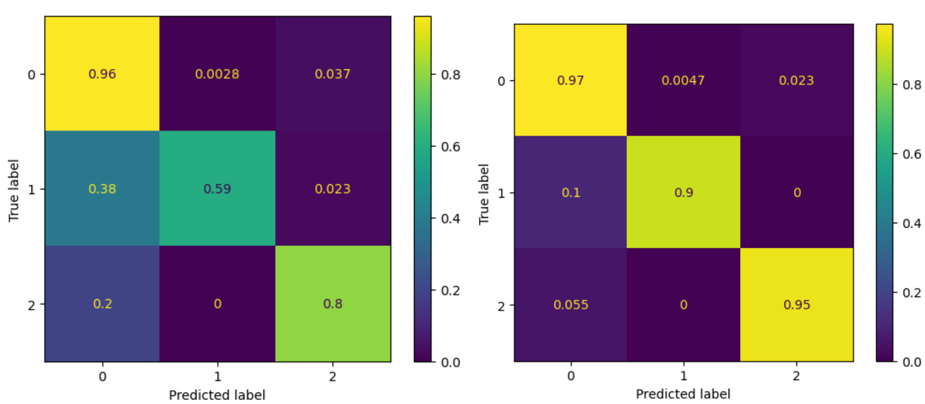


Figure 11 *Confusion matrices of Random Forest (A), RBF SVM (B) and KNN (C), before (right) and after (left) parameter tuning using randomized grid search algorithms.*

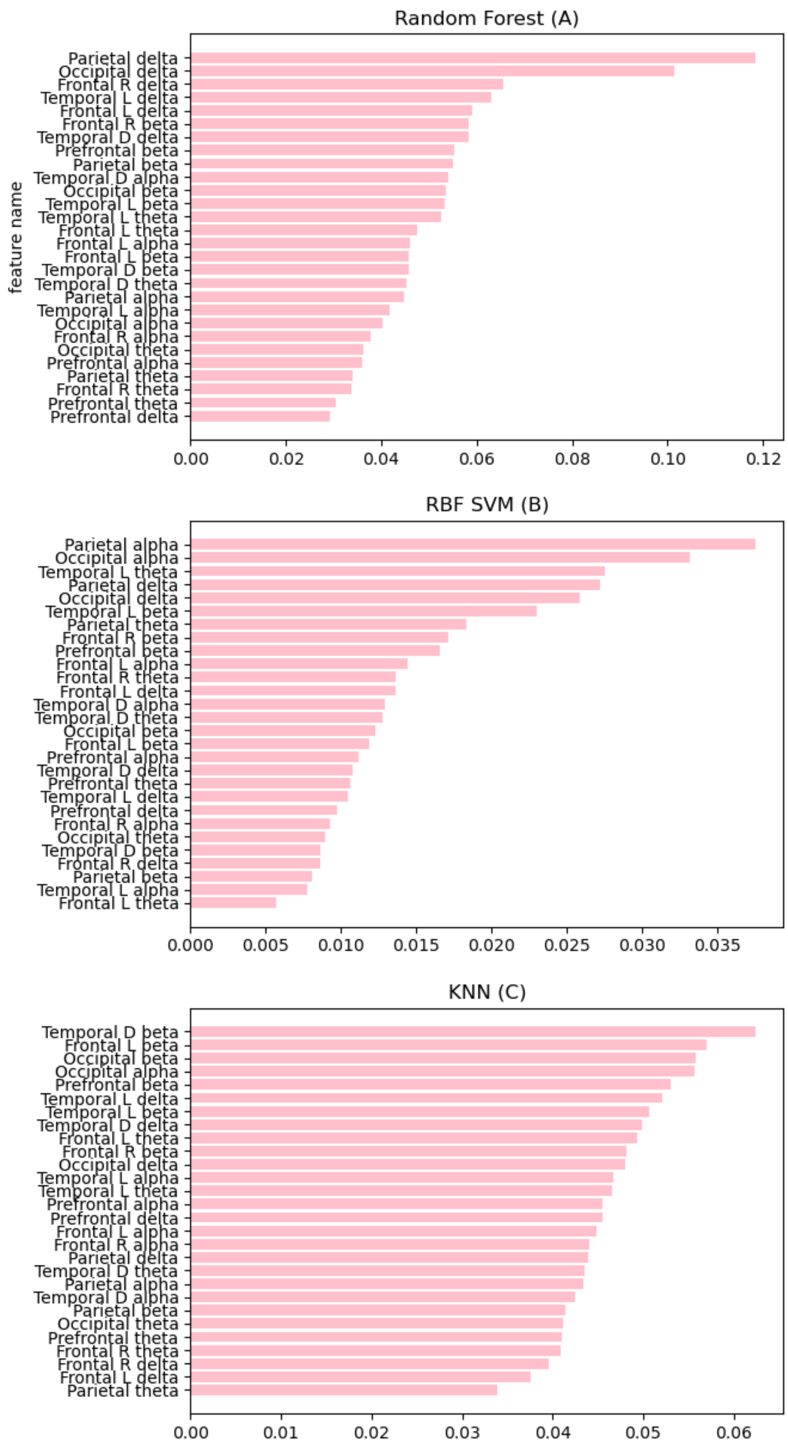


Figure 12 *Permutation features importance score bar plot for Random Forest (A), RBF SVM (B) and KNN (C) after parameter tuning.*

5.5 Relaxation period

This section compares fatigue parameters 10 min before and after the relaxation period. The set of cognitive tasks without distractors was presented before and after the relaxation therapy to compare fatigue levels through brain frequencies and pupil dilation. Figure 13 presents the results of the average relative power of EEG rhythm for all participants during periods prior to relaxation (T0 to T4) and following relaxation (T5). Here again, the Wilcoxon nonparametric test was chosen to compare fatigue indicators for periods T4 and T5 period as their distribution did not follow the normality assumption from other parametric tests. T5 period will be compared both to T4 and T0 period in order to analyze the effects of the 10-15 min relaxation therapy with respect band relative power at the end of the task session and baseline. There was a significant decrease in relative power of alpha, theta and beta at T5 with respect to T4. No significant difference between delta band was found between T4 and T5. Alpha, delta and beta relative power at T5 did not score below baseline levels (T0), while theta relative power did. T5[delta, theta, alpha, beta] = [0.455, 0.393, 0.377, 0.379].

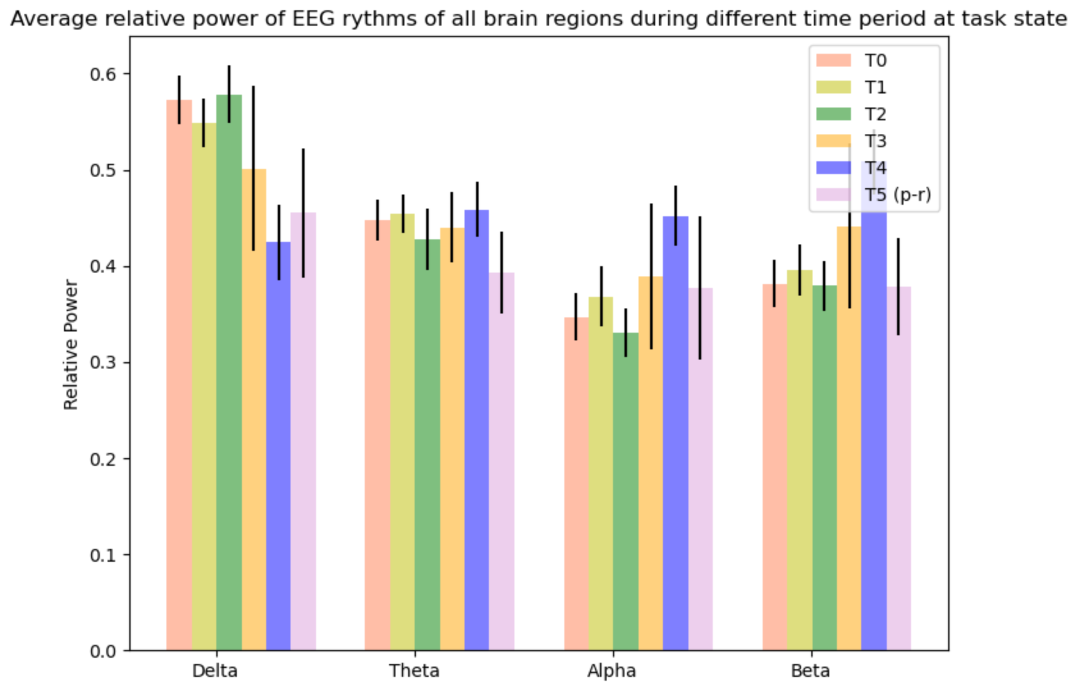


Figure 13 *The average relative power of EEG rhythms over all the brain regions at different time periods during task state (T0-T4) + post relaxation (T5).*

Figure 14 shows the mean theta relative power across all participants and brain region during task-state post-relaxation period. We can observe that theta relative power starts increasing immediately after the relaxation period, and that this trend is consistent across brain regions.

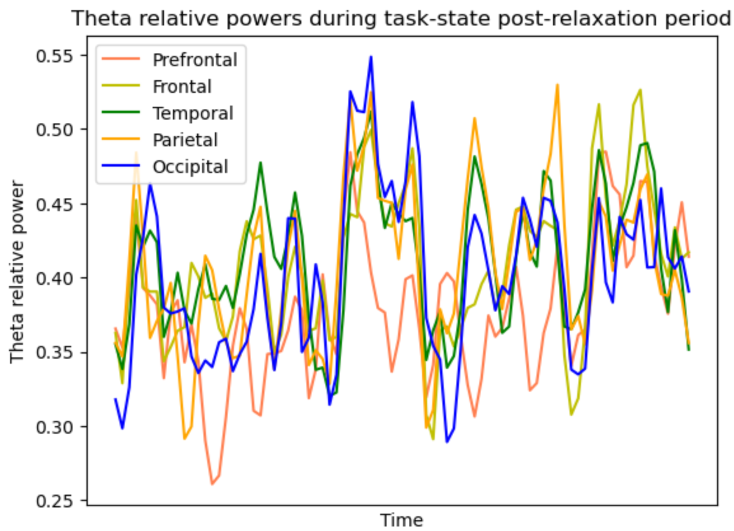


Figure 14 *Mean theta relative power across all participants and brain region during task-state post-relaxation period.*

Figure 15 shows the mean alpha relative power across all participants and brain region during task-state post-relaxation period. Here, we can observe a short burst of alpha levels shortly after the end of the relaxation followed by stabilized alpha levels around 0.377. This trend for alpha levels is consistent across all brain regions.

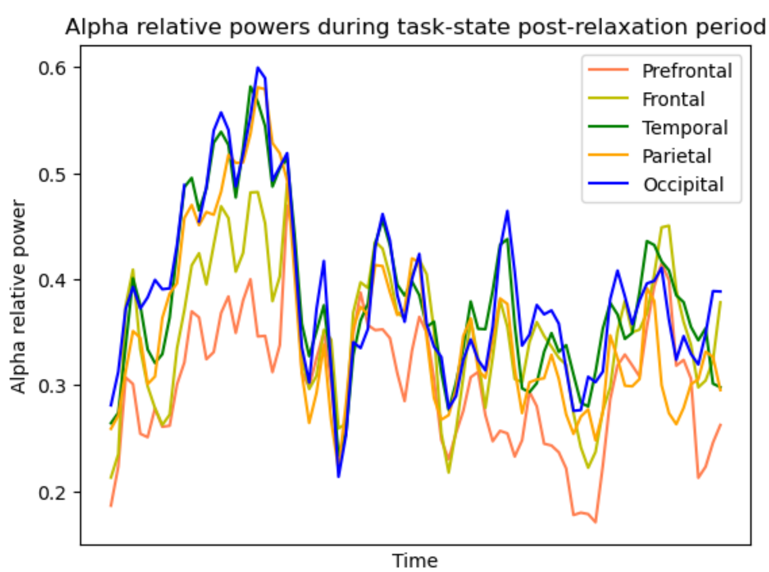


Figure 15 Mean alpha relative power across all participants and brain region during task-state post-relaxation period.

Lastly, pupil diameter comparison before and after relaxation period was tested to measure the impact of the relaxation therapy on fatigue indicators. A Wilcoxon test performed on mean pupil diameter across participants for pre-and post relaxation period (10 min) favored rejection of the alternative hypothesis: difference in mean pupil diameter across participants eye segments for pre-and post relaxation period (Figure 16).

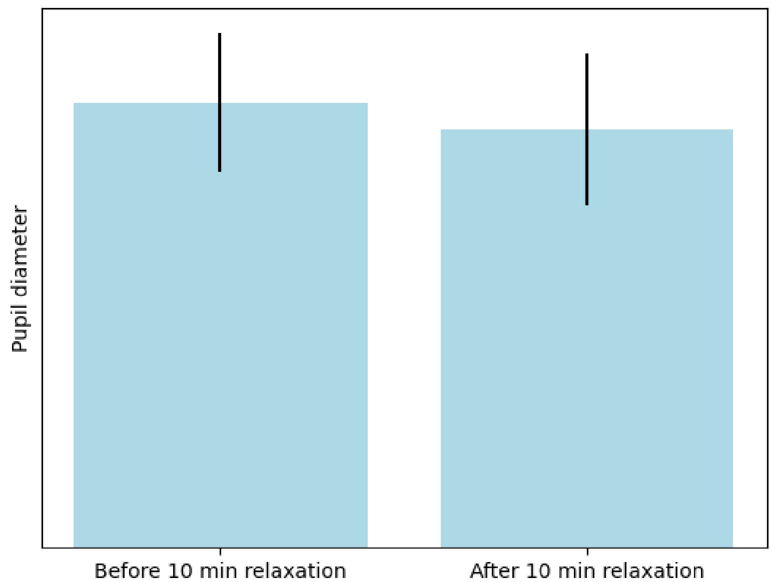


Figure 16 *Mean pupil diameter across all participants during the pre-relaxation period and post-relaxation period.*

5.6 Discussion and limitations

The variation of the pupil diameter is categorized into 3 distinct events: no change, increase from baseline, decrease from baseline. Thus, these 3 events allow us to extract information about workload and mental fatigue, as an increase in pupil diameter indicates an increase in workload perception and a decrease indicate an increase in fatigue perception (Bafna, Bækgaard, & Hansen, 2021 ; Dalveren, Cagiltay, Ozcelik, & Maras, 2018). Our result shows that pupil increase events were mostly occurring during the first half of the task period while pupils decrease events were mostly occurring during the second half (Table 2, Figure 7). In figure 8, showing the average normalized pupil diameter across all participants, we can observe that pupil diameter increases from baseline shortly after the start of the cognitive tasks is followed by a decrease in pupil diameter until the end of the cognitive tasks. The pupil size variation in our results is consistent with the relation between high mental load (workload) and mental fatigue (Díaz-García, et al., 2021). However, it should be noted that the causes of mental fatigue might not always be related to the level of mental load cause by a task, as several covariables like engagement, enjoyment/aversion, the period of the day, the amount of sleep and many others highly influence mental fatigue. Finally, the overall decrease in pupil diameter as a function of TOT during fatigue generation is consistent with the majority of literature reporting a similar trend (Körber, Cingel, Zimmermann, & Bengler, 2015; Hopstaken, Linden, Bakker, & Kompier, 2015). About light intensity: pupil size was not adjusted to the light intensity of the environment because the light intensity barely differs from an exercise to another: it is always the same virtual environment. The only thing that changes from a cognitive exercise to another are the exercises questions written in the virtual panel in front of the participant which produces minimal changes on the light intensity.

Our results show that relative power of delta across brain region decreases significantly as function of time on task (TOT) before relaxation period (Figure 10) which is consistent with the tendency reported by many fatigue studies (Jap, Lal, Fischer, & Bekiaris, 2009) (Li, et al., 2020). However, blink and eye movement artifacts highly coincide with the delta frequency band (Li, et al., 2020), which might have induced bias in delta frequency result before relaxation period because of the distractor component of the first set of cognitive exercises. Thus, the set of cognitive exercises with distractors is likely to produce more eye movement than the set without distractors. Since the distractors are only presented in tasks before the relaxation period, there is a possibility that results for delta were influenced by the nature of the cognitive exercises.

Alpha rhythm reflects the state of wakefulness and relaxation and is the most sensitive brain rhythm of mental fatigue (Li, et al., 2020). Our results show an increase in relative alpha power as a function of TOT during cognitive exercises (Figure 10) which is consistent with what has been reported by many studies: alpha activity increases as mental fatigue increases (Raul, et al., 2020)

(Cao, Wan, Wong, Cruz, & Hu, 2014) (Zhao, Zhao, Liu, & Zheng, 2012). In the analysis of relative alpha powers in mental fatigue and resting state, many studies further divide alpha powers into 2 sub-bands: alpha1 and alpha2 (Li, et al., 2020). Narrower band frequency division of alpha band allows for better physiological analysis of fatigue vs. resting state as alpha1 and alpha2 display different trends between opposite states with different statistical meaning. Thus, alpha1 is related to attention while alpha2 is positively correlated with long-term memory function (Li, et al., 2020). This alpha band subdivision was not exploited in this study as we do not compare alpha bands during tasks vs. resting state but rather during task state before vs. after relaxation period, and since alpha1 and alpha2 both increase during task state as a function of TOT (Li, et al., 2020).

Our results show that theta rhythm significantly increased as a function of TOT (Figure 10) which is consistent with the results reported by most studies on brain rhythm and mental fatigue (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014; Li, et al., 2020). However, theta rhythm's change % from T0 to T4 (4% increase) was the smallest % change across all bands from T0 to T4 (delta: 26% decrease, alpha: 30% increase, beta: 33% increase). This lower variation change in theta rhythm is unusual considering that theta in cortical areas is an important brain indicator of mental fatigue and attention (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). It is possible that theta rhythms as well as beta rhythms were highly influenced by the effect of a virtual environment on focus. In their review on **attention detection** in virtual environment, Rhaíra Helena Caetano e Souza and Eduardo Lázaro Martins Naves highlight that many studies exploring EEG variables in virtual environment have reported lower powers of theta bands compared to real-world setting (Souza & Naves, 2021). This improvement in attention in simulated environment was reflected through theta/beta band EEG ratio. This means that lower variation in theta power in our results might be the result of high engagement towards the virtual simulated environment. This factor might have also highly influenced beta rhythms in our results.

Thus, beta rhythm increasing trend as a function of TOT in our result (Figure 10) was not aligned with most of the literature reporting a decreasing tendency for the beta band with increasing mental fatigue (Zhao, Zhao, Liu, & Zheng, 2012) (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014) (Li, et al., 2020). Since beta rhythm is highly related to visual attention (Raul, et al., 2020), the virtual environment's influence on participants' attentional demands was more impacted then for the theta rhythms. Benjamin Schöne and colleagues explored the emotional arousal and vigilance with EEG and HRV in height exposure for 3 different experimental set-up condition: PC (computer interface), VR (virtual reality) and RL (real life). The results of this experiment indicated a higher beta power in the VR condition compared to both RL and PC. The authors stated that beta power difference between the 3 conditions is associated with a memory-promoting state modulated by the different attention, emotional and somatosensory implications of the different states (Benjamin, et al., 2023). While changes in attention and engagement are highly impacted by mental fatigue, more studies exploring the impact of virtual simulated environment on EEG features **during mental fatigue** would be needed to investigate the latter statement about theta and beta rhythms.

EEG indices presented for mental workload and task engagement in sections 2.3.5.2. allowed us to compute the value of these fatigue indicators in real time for all participants. The ratio of theta bands in frontal areas over alpha bands in parietal areas was chosen to capture workload and mental fatigue, as an increase in this ratio indicates an increase in mental workload and a decrease in this ratio indicates an increase in mental fatigue (Cao, Wan, Wong, Cruz, & Hu, 2014) (Gianluca, et al., 2018). Figure 9 shows that there was a significant increase in average mental workload from T0 to T1 followed by a significant decrease in mental workload from T1 to T4. These results show that on average, participant experience a high mental load at the beginning of the task period followed by an increase in mental fatigue. This is consistent with the literature as well as trends reported earlier on pupil diameter. Thus, workload (calculated from ThetaF/AlphaP increase as a result of higher theta frontal at the beginning of the experiment indicating an increase in task load perception. Then, from transition states from high mental workload to increasing mental fatigue levels, workload index decreases as alpha power starts increasing (Cao, Wan, Wong, Cruz, & Hu, 2014). Thus, both EEG index and pupil diameter measurement show that on average, participant experienced an increase in mental workload followed by an increase in mental fatigue perception, which is consistent with the relation between mental workload and fatigue reported in the literature (Bafna, Bækgaard, & Hansen, 2021) (Díaz-García, et al., 2021) (Cao, Wan, Wong, Cruz, & Hu, 2014). Additionally, results in figure 9 show that there was no significant change in task engagement from T0 to T4. Those results are not aligned with the majority of the literature, reporting a decrease in task engagement as mental fatigue increases (Hopstaken, Linden, Bakker, & Kompier, 2015) (Cao, Wan, Wong, Cruz, & Hu, 2014). This gap can be partly explained by the virtual simulated environment itself. Most of the work on mental fatigue generation published as of now used traditional computer interfaces to interact with the participants to either engage in a simulation (e.g. Driving simulation) or cognitive tasks of exercise sets. However, ecological studies comparing traditional real-world laboratory settings and virtual simulated environments showed that engagement and negative emotions were higher in VR settings (Jennifer, et al., 2017). Thus, participants interacting with an immersive VR environment might have played an important role in participants' motivation without necessarily preventing fatigue. The motivational influence on task engagement and mental fatigue was studied by Jesper F. Hopstaken and colleagues in 2016. In their work, the authors introduced a reward to the participants at the end of a prolonged cognitive task meant to induce mental fatigue. Jesper F. Hopstaken and colleagues observed that: task engagement decreased as a function of TOT before reward, and task engagement and performance increase after introducing a reward **but** participants still reported to be highly fatigue (Hopstaken, van der Linden, Bakker, Kompier, & Leung, 2016). The results of this study imply that change in task engagement is likely to be influenced by a complex relation of the trade-off/reward system rather than depletion of a finite reserve of cognitive resources. Finally, another reason to explain this gap is that most of the literature available and compiled for comparison of task engagement generated fatigue for a much longer time: 40 min and above. Thus, considering that high-workload fatigue (**active fatigue**) results in a lower task-disengagement overtime (Saxby, et al., 2008) (Hu & Lodewijks, 2021)(Neubauer, Matthews, & Santos, 2023) and that we generated fatigue among participants in 25 min, it is possible that the time allowed for fatigue exercises was not sufficient to observe the expected trend for task engagement. The stability of the task engagement index Beta/(Alpha+Theta) in our results is also reflected in our previous results regarding the beta band component which was expected to decrease as a function of TOT but increased our results. Finally, we believe that the stability of the task engagement observed might be due to the time allocated and type for/of fatigue generation combined with the motivational aspects of VR settings. More research controlling the latter variables in the context of fatigue generations needs to be done.

After generating mental fatigue, our goal was to classify 3 different states of fatigue segments during the period where participants were asked to perform in various cognitive tasks. The final data set was composed of 12398 EEG segments represented by 28 features, each feature element of the pair of cortex region identified in section 4.3 (except central) and frequency band. The balanced accuracy as opposed to standard accuracy was chosen as one of the parameters to evaluate model performance, as the proportion of labels across the dataset was unbalanced (Table 3). Various machine learning (ML) algorithm candidates (Nearest Neighbors, RBF SVM, Decision Tree, Random Forest, Neural Net, AdaBoost, Naïve Bayes, Q.D.A.) were trained and evaluated with a 5-fold cross validation in order to select the 3 ML algorithm best fitting our data with respect to evaluation metric 'balanced accuracy' and 'f1' measures. Among the 8 different classifier candidates, Random Forest, RBF SVM and KNN showed a better performance with respect to balance accuracy and f1 evaluation metrics (Table 4). The grid search algorithm was applied with a 5-fold cross validation on these 3 models in order to find the best set of parameters with respect to balanced accuracy. After parameter tuning achieved through grid search algorithm, the balanced accuracy of the RBF SVM and KNN were very similar (0.95 vs. 0.94 5-fold cross-val) and much higher than Random Forest (0.85) (Figure 11). However, between these two models, RBF SVM was much more promising in terms of feature importance. As we can observe in Figure 12, the feature of most importance for RBF SVM was parietal alpha, which is a very important region-band feature for mental fatigue, present in workload and task engagement index. Additionally, occipital alpha and temporal theta were the second and third most important features for RBF SVM which are also strong fatigue indicators (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014). Our results on feature importance (Figure 12) shows that KNN classifier mostly picked up on beta band fluctuations to classify mental fatigue, which is not ideal in this present study given that beta band variation followed a trend inconsistent with previous mental fatigue studies as discussed earlier. In Random Forest classifier, a lot of the weight was picked up by features targeting delta frequency bands which does not reflect the variety of frequency bands influenced during mental fatigue. In consequence, RBF SVM classifier was the preferred choice in terms of performance metrics and feature importance with a final balanced accuracy of 0.92 on the test set.

After a 10-15 min session of the Traveling Train, participants were prompt to participate in another session of cognitive exercises without distractors to compare fatigue indicators pre-and post relaxation. Figure 13 shows there was a significant decrease in relative powers of alpha, theta and beta bands following relaxation period during task-state T5 compared to task state prior to the relaxation period T4. Most of the literature available on recuperation after mental fatigue inducing exercises targets the fluctuation of alpha and theta bands. For this reason, alpha and theta relative powers will be exclusively discussed for comparison and assessment of the effectiveness of the traveling train therapy. Although we suggest in the future that more in-dept analysis on beta and delta band fluctuations post mental fatigue generation and recuperation. As shown in figure 15, alpha levels displayed short burst at the beginning of task-state post-relaxation before stabilizing around 0.38. This short burst is likely the result of the continuous effects of the relaxation therapy, as relaxation methods such as meditation and yoga are known to alpha band amplitude during sessions (Gaur, Panjwani, & Kumar, 2020) (Morais, Quaresma, Vigário, & Quintão, 2021). However, this short burst is followed by stable alpha levels around 0.377 which is 11% higher than baseline at T0 but 20% lower than alpha levels right before relaxation at T4. Thus, it shows that although alpha levels reduced during the second task state compared to pre-relaxation T4 but did not return to baseline levels T0. This is consistent with the study conducted by Justine R. Magnuson and colleagues (2021), who investigated the development and recovery of mental fatigue by measuring participants neural activity with EEG and gathering subjective measures of mental fatigue during a 60 min N-back test and 60 min post-task resting time. The latter study observed that mental fatigue was induced after 30-45 min of the N-back test, from both objective and subjective measures. They observed a 60 min recovery of some alpha levels to baseline levels during the post-task phase (R.Magnuson, M.Doesburg, & J.McNeil, 2021). Theta relative power sample mean during the first 7 min of the 2 task-state post relaxation was 12% lower than baseline levels at T0. However, a closer view of theta powers fluctuations shown in figure 14 reveal that theta levels continuously increase during task-state post relaxation with final relative power levels similar to T4. This suggests that although theta levels were reduced following relaxation therapy, they quickly returned to fatigue indicating levels during the second task state. Finally, we found that there was no significant difference between mean pupil dilation between 10 min during pre-and post relaxation (Figure 16). These results suggest that relaxation therapy might have aided in reducing alpha levels during the second cognitive task period but did not have a long-lasting effect on theta levels and no effect on pupil dilatation. Overall, pre-and post relaxation comparison of average relative power of alpha and theta, and pupil dilation were not sufficient to validate the effects of virtual therapy on mental fatigue symptoms when returning to task state. It is possible that the time allocated for relaxation in this experiment might have not been sufficient to observe significant benefits in this recuperation technique, given that the standard recovery time found by Justine R. Magnuson and colleagues was 60 min (without relaxation aid). Additionally, our results are aligned with recent findings on regular short-break effects on mental fatigue. Hence, in an EEG study published in the International Journal of Psychophysiology in 2023, Marius Brazaitis and Andrius Satas concluded 10 min breaks every 50 min during a 7h office workday did not prevent mental fatigue or impairments in cognitive functions (Marius & Andrius, 2023). In the future, a comparative study between virtual therapy and standard rest time with more allocated time would be needed to quantify the aid that virtual therapy can provide in alleviating mental fatigue symptoms in healthy young adults.

One of the main limitations of this study was the important amount of electrode which has failed during the experiment, which has led to the exclusion of data from 10 participants. While we were still able to generate a sample size of 12398 EEG segments from the remaining 21 participants, more EEG samples from a larger pool of people (ideally 30 and above) would have been preferred to acquire a larger confidence in our analysis. We suspect that the large frequency of electrode failure during this experiment was due to the displacement of electrodes during head movements, more specifically caused by participants moving their head to see distractors appearing in the VR environment during the cognitive tasks. In the future, an apparatus of the EEG headset more adapted to VR head movement would be needed to ensure electrode stability.

Another limitation of this study is the time limit to generate fatigue among participants. Although we were able to generate fatigue for the majority of participants, most signs of fatigue were present at the very end of cognitive tasks without distractors. Thus, this is likely one of the reasons why we did not observe change in task engagement in the majority of participants, since fatigue generated in high workload conditions (active fatigue) results in a less greater impairment of task engagement over time than in low workload conditions (passive fatigue). Another time related limitation is the absence of control variables to quantify the effect of the virtual reality environment and exercises with distractors on fatigue. Thus, since we had limited time (1 hour) to generate both fatigue and recuperation as well as limited number of participants, the protocol focuses mainly on mental fatigue measurements and evolution from beginning to end of the experiment and was inspired on how other previous studies collected fatigue data for machine learning purposes. The goal of the experiment was to generate fatigue from beginning to end to collect data for machine learning and evaluate the impact of virtual sophrology. Having more time and resources, we would've included 2 control groups:

- One with a grey screen projection during the entire exercises period (with and without distractors)
- A second with grey screen projection only during the exercises period with distractors

Which would allow comparison between the 2 different task nature (with and without distraction) and quantifying their contribution to the overall fatigue state.

Model limitation in terms of mental fatigue detection includes the limited numbers of labels to describe different levels of fatigue. In this study, we capture 3 different levels of fatigue observed during the experiment which reflected in the label definition. However, fatigue levels in general are not limited to this number. For instance, levels of fatigue greater than the ones observed in the data such as drowsiness displays a different EEG pattern in the transition from mental fatigue to drowsiness (Gianluca, et al., 2018). Thus, more advanced levels of mental fatigue are not guaranteed to be classified in their closest intensity category. Thus, the model is limited in detecting levels of fatigue as high as the ones observed in the experiment. Another model limitation for fatigue detection is the age range of the participants for the experiment. Thus, EEG segments came from young adults aging between 19 and 29 years old and the model performance for classifying EEG segment of individual aging outside this range is not guaranteed as EEG patterns of mental fatigue can vary from an age group to another. For instance, frontal theta power and alpha occipital power modulation as a function of TOT display different patterns in older adults (56-70 years old) than in younger adults (20-30 years old) (Arnau, Möckel, Rinkenauer, & Wascher, 2017).

In summary, the consistent increase of alpha, theta and workload EEG index and the decrease in delta relative power among participants during the execution of cognitive exercises indicates that we have successfully generated mental fatigue during pre-relaxation period. We did not observe a decrease in beta relative power and, consequently, a decrease in task-engagement EEG index during the cognitive exercises during pre-relaxation period. We suspect that this anomaly observed beta relative power in our results might be related to the attentional and somatosensory components influenced in virtual reality set-ups (Benjamin, et al., 2023). However more evidence on the impact of virtual reality set-ups and mental fatigue EEG power bands would be needed to confirm this statement. This anomaly was taken into consideration when comparing different classifier models based on feature importance. Hence, we trained and tuned an RBF SVM classifier capable of classifying (cross-subject) 10 epoch EEG segments into 3 different fatigue levels with 92% accuracy on the test set. Finally, we observed that 10-15 min of the Traveling Train virtual relaxation therapy was not sufficient to restore alpha bands and pupil diameter when immediately returning to task state after relaxation.

Chapitre 6 – Conclusion

Over the course of this thesis, we have seen the fundamental concepts around mental fatigue: factors influencing fatigue, different types of fatigue, physiological symptoms and ways to measure them. We hypothesized that (H1) we can generate fatigue in a limited amount of time (approx 25 min) through completion of cognitively demanding exercises, (H2) detect mental fatigue from EEG and eye tracking patterns and (H3) bring fatigue indicators to baseline levels with 10-15 min of virtual relaxation therapy.

1. We consider that we have successfully induced mental fatigue in a 25-minute period of cognitive exercises in a virtual environment based on the following results obtained:
    a. Observed an increase in the relative power spectral density of alpha and theta and a decrease in delta frequency band across participants
    b. Observed an increase in workload index followed by a decrease consistent with the trend observed in the fatigue literature for this EEG index
    c. Observed an overall decrease in pupil dilation across participants indicating a positive fatigue progression.
    d. Although we did not observe a decline in task engagement EEG index across the majority of participants, it is possible for task engagement to be influenced by the experimental environment which highlights the complex relationship between task engagement and fatigue.
2. We have successfully selected and trained a model for cross-classification of 3 different levels of fatigue observed during the experiment
    a. labels were derived from the pupil diameter due to its relationship with workload and fatigue. Feature matrix was obtained from transformations on EEG electrode signals.
    b. Various machine learning models were trained, optimized and analyzed under different evaluation parameters (balanced accuracy, f1, confusion matrix) and feature importance. Best overall model was RBF SVM 0.92 balanced accuracy on test set.
3. We did not find that a 10-15 min relaxation period had a significant improvement on mental fatigue physiological signs.
    a. Alpha and theta relative power spectral density did not return to baseline levels during task-state following relaxation period.
    b. No significant difference was found between average pupil diameter 10 min before and after relaxation period.

Despite the promising results obtained for the RBF SVM to classify signs of mental fatigue observed in the laboratory, there are many ways improvements that could be made to increase the performance and confidence of the model, and the impact of this experiment. Some are quick wins that have been discussed earlier such as gathering more participants from a larger age range, increase the time allocated to the generation of mental fatigue and reduce EEG noise by improving the EEG headset set-up to prevent displacement of the electrodes on the scalp. Others would require more in-dept analysis which will be discussed in the next sub chapter.

6.1 Future work

The first half of this experiment was dedicated to generation and detection of mental fatigue. Among the fatigue variables monitored and analyzed for the generation and detection of mental fatigue of this experiment, task engagement EEG index did not behave as expected. Thus, the majority of the literature collected on mental fatigue observed a decrease in task engagement as a function of TOT, while our results show that task engagement remained stable during the 25 min task period (pre-relaxation). Our results indicate that the level of engagement of participants remained constant while the variation of all other monitored fatigue variables was consistent with the development of mental fatigue. As mentioned in the discussion, it is possible that this gap between our results and the literature comes differences between our protocol. In fact, there are 2 elements of our methodology for fatigue generation which differs from the majority of the literature collected for result analysis : the use of virtual environment and the time allocated for fatigue generation. Most of the study collected dedicated more time to fatigue generation (ranging from 40 min to 8 hours) and computer/screen interfaces for cognitive or simulation tasks. However, we know that task engagement decreases as a function of time on task and that engagement tends to be higher in VR settings than other standard lab settings (Jennifer, et al., 2017). One interesting future direction is to evaluate the progression of task engagement of time in VR environments vs. computer screen interface for fatigue generation. This would require to allocate a longer period of time to the generation of mental fatigue to ensure maximal TOT effects on fatigue variables. This is useful to assess the ecological validity of virtual environments for mental fatigue generation. In fact, it would allow evaluating the influence of the experimental environments on task engagement and other fatigue variables and orient future experimental set-ups towards ones that best reproduces contexts in which mental fatigue occurs in the real world and thus better transferability of detection models developed in the laboratory.

The second half of the experimental protocol was dedicated to evaluate the impacts of a 10-15 min virtual therapy session on mental fatigue recuperation. There are not as many studies published on the recuperation of mental fatigue as there are for the generation of mental fatigue. Picking an adequate period of time for relaxation therapy was therefore a challenge. The period of time needed to be long enough to maximize the effects of relaxation but much shorter than the standard recovery time of 60 min (no rest aid) in order to be impactful. Although we did not find that 10-15 min of virtual therapy alleviate the impact of mental fatigue on alpha, theta relative power spectral density and pupil diameter, an interesting future direction is to evaluate different time-length period of virtual therapy on mental fatigue recuperation. Thus, this would require to allocate a longer time range to the recuperation technique in order to compare time periods to each other (e.g. [15 min, 30 min, 45 min, 1h]) and to the standard recovery time. This is an important future direction, as it could provide a direct and adequate solution to some cases of mental fatigue once detected. While detection of early to late signs of mental fatigue is the first step in prevention, the reality is that daily responsibilities and duties do not always allow enough time to rest and fully recover attentional resources. Currently, not enough attention and efforts are focused on the development of short term recuperation strategies following fatigue while the precision and accuracy of detection models improve year after year. Focusing research efforts on evaluating different types/conditions of short term recuperation strategies is necessary to tackle the problem as a whole and provide more comprehensive solutions.

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