Université de Montréal

Study and experimentation of cognitive decline measurements in a virtual reality environment

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Résumé

À l’heure où le numérique s’est totalement imposé dans notre quotidien, nous pouvons nous demander comment évolue notre bien-être. La réalité virtuelle hautement immersive permet de développer des environnements propices à la relaxation qui peuvent améliorer les capacités cognitives et la qualité de vie de nombreuses personnes.

Le premier objectif de cette étude est de réduire les émotions négatives et améliorer les capacités cognitives des personnes souffrant de déclin cognitif subjectif (DCS). À cette fin, nous avons développé un environnement de réalité virtuelle appelé Savannah VR, où les participants ont suivi un avatar à travers une savane. Nous avons recruté dix-neuf personnes atteintes de DCS pour participer à l’expérience virtuelle de la savane. Le casque Emotiv Epoc a capturé les émotions des participants pendant toute l’expérience virtuelle. Les résultats montrent que l’immersion dans la savane virtuelle a réduit les émotions négatives des participants et que les effets positifs ont continué par la suite. Les participants ont également amélioré leur performance cognitive.

La confusion se manifeste souvent au cours de l’apprentissage lorsque les élèves ne comprennent pas de nouvelles connaissances. C’est un état qui est également très présent chez les personnes atteintes de démence à cause du déclin de leurs capacités cognitives. Détecter et surmonter la confusion pourrait ainsi améliorer le bien-être et les performances cognitives des personnes atteintes de troubles cognitifs.

Le deuxième objectif de ce mémoire est donc de développer un outil pour détecter la confusion. Nous avons mené deux expérimentations et obtenu un modèle d’apprentissage automatique basé sur les signaux du cerveau pour reconnaître quatre niveaux de confusion (90% de précision). De plus, nous avons créé un autre modèle pour reconnaître la fonction cognitive liée à la confusion (82 % de précision).

Mots-clés : Démence, IA, Apprentissage Automatique, Maladie d’Alzheimer, Thérapie par réalité virtuelle, Émotions, signaux EEG, Déclin cognitif subjectif, Relaxation, Confusion.

Abstract

At a time when digital technology has become an integral part of our daily lives, we can ask ourselves how our well-being is evolving. Highly immersive virtual reality allows the development of environments that promote relaxation and can improve the cognitive abilities and quality of life of many people.

The first aim of this study is to reduce the negative emotions and improve the cognitive abilities of people suffering from subjective cognitive decline (SCD). To this end, we have developed a virtual reality environment called Savannah VR, where participants followed an avatar across a savannah. We recruited nineteen people with SCD to participate in the virtual savannah experience. The Emotiv Epoc headset captured their emotions for the entire virtual experience. The results show that immersion in the virtual savannah reduced the negative emotions of the participants and that the positive effects continued afterward. Participants also improved their cognitive performance.

Confusion often occurs during learning when students do not understand new knowledge. It is a state that is also very present in people with dementia because of the decline in their cognitive abilities. Detecting and overcoming confusion could thus improve the well-being and cognitive performance of people with cognitive impairment.

The second objective of this paper is, therefore, to develop a tool to detect confusion. We conducted two experiments and obtained a machine learning model based on brain signals to recognize four levels of confusion (90% accuracy). In addition, we created another model to recognize the cognitive function related to the confusion (82% accuracy).

Keywords: Dementia, AI, Machine Learning, Alzheimer's Disease, Virtual Reality Therapy, Emotions, EEG Signals, Subjective Cognitive Decline, Relaxation, Confusion.

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List of acronyms

AD: Alzheimer's disease

AI: Artificial Intelligence

Bi-LSTM: Bidirectional long short-term memory

EEG: Electroencephalography

GUI: Graphic user interface

IUGM: Institut universitaire de gériatrie de Montréal

KNN: K-nearest neighbors

LSTM: Long short-term memory

MAI: Metacognitive awareness inventory

SCD: Subjective cognitive decline

SDK: Sofware Development KIT

SVM: Support Vector Machine

VR: Virtual Reality

WMS: Wechsler Memory Scale

To my great-grandmother, Jeannine Mazurek, who stood up for me without me noticing

To Madame Guay, without whom none of this would have been possible. This thesis should be cherished, as you have told me so often. I have no words to express my gratitude

To my father, who always watched from a distance

To my little old man and to my little old lady who brought me love and security

And mum...

And me

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Chapter 1. Introduction

1.1 General context and motivations

Over the years, technology has made its way into people's daily lives. The global race for technological development that began after the Second World War has led to today's world [1].

The arrival of the Internet has changed the daily lives of many people and especially the way they communicate. Postcards have been replaced by messages on social networks. The access and publication of new information are easier, which accelerates the development of innovations. Internet-connected smartphones have become an integral part of people's lives. They allow constant communication, and their numerous applications make many tasks easier [2]. It is possible to pay bills, check the bank account, check bus and train timetables, reads the news, order food, buy items online, and more.

Technology has helped to save time in the organization of work through collaborative tools. Employees can work on projects at home (telecommuting) using software such as Slack, Microsoft Teams, or Zoom.

In education, distance learning and the emergence of virtual learning environments make educational resources accessible to learners who would not usually benefit from them [3].

Medical practice is also changing; there is a new relationship between individuals and care. With the many connected objects, individuals can become an actor in their health [4]. They can monitor their physiological data (e.g., mobile cardiac monitors). Artificial intelligence (AI) helps speed up diagnosis by analyzing medical images. The use of robots and computer-assisted procedures also reduces the risks associated with surgical operations. The evolution of technology is improving care.

Now is the age of Big Data. There are more and more objects connected (Internet of Things), and a tremendous amount of data is generated, collected, and processed, often using AI. Cities are becoming "smart". It is not uncommon for bus services to offer real-time bus tracking. The interest in autonomous vehicles is growing. There is a move towards smart buildings that allow controlling temperature, controlling cooling, controlling lights to save energy [5].

While they have brought significant benefits, technologies also have a detrimental side for the individuals. They have accelerated the pace of the activity of people and created much stress. Communication in front of a screen creates a kind of detachment. People gradually lose contact with the outside world, which leads to social individualism [6].

Social media is addictive; some people no longer take breaks and are dependent on the approval of others, which functions as a kind of reward. Users perceive the number of "like" mentions, the number of comments, the number of views as the amount of social approval (reward) they receive. The "more than perfect" self-image and life of people on social networks does not reflect reality. Nevertheless, the lack of social approval creates anxiety or even depression in some users [7].

Modern technologies may, in some cases, increase people's negative emotions and thus diminish their health and well-being [8]. Emotions have a broader scope than the well-being of the individual alone. They provide information about who individuals are, how they relate to others, and how they should act socially. Emotions influence thoughts and behaviors. An individual's emotions will tell those around him or her about his or her thoughts and intentions. Finally, emotions play an essential role in keeping human societies together [9].

The importance of emotions has led to the emergence of a particular field: **Affective Computing**. "Affective Computing is computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" [10]. It is a multidisciplinary field that encompasses computer science, psychology, and cognitive science. A key area of affective computing is the design of agents capable of simulating emotions. One example is the simulation of conversational agent emotions in dialogue systems for better human-computer interaction [11]. Another popular area is the detection of user emotions to adjust the behavior of an application [12].

There is a close link between emotion and cognition. Reducing negative emotions can improve people's cognitive performance [13]. For this, the first thing to do is to detect emotions.

New technologies have emerged to access users' emotions in real-time, such as facial expressions, speech and physiological signals [14]. Applications that use voice are limited to environmental noise and the ability to speak intelligibly. Also, speech includes more complex aspects such as sarcasm.

It is also possible to use facial expressions to detect emotions. However, individuals can voluntarily control their facial expressions. Besides, people who are poorly expressive, have a disability, or wear glasses make facial detection difficult [14], [15].

Emotion detection techniques based on brain activity are becoming increasingly popular. Electroencephalography (EEG), for example, allows the detection of emotions through electrodes placed on the scalp. An individual's hair or skull shape can make EEG detection difficult. Movement is also a limitation to detection. If the electrodes are too far apart, there is also a higher risk of noise in the data.

From the elements introduced above, therefore, one of the challenges of modern society seems to be the preservation of human health on an emotional level. Virtual reality (VR), which seems to be a useful relaxation tool, could resolve this challenge. It offers an immersive experience that helps to arouse or regulate emotions [16], [17]. VR can also contribute to more effective learning [18].

1.2. Research aim and objectives

The aim of this thesis is twofold. Our thesis is part of a broader study aimed at reducing negative emotions to improve cognitive abilities for people with cognitive impairment. Our participation in the study concerns the development of a non-pharmaceutical tool to reduce negative emotions.

We believe that people with Alzheimer's disease are more likely to experience negative emotions, like frustration, because of their declining quality of life and loss of control over their emotions [19]. Subjective cognitive decline (SCD) may be the first symptomatic manifestation of Alzheimer's disease. Individuals with SCD are, therefore, more likely to experience negative emotions. We also believe that because of their cognitive decline, it will be easier to observe any improvement in cognitive performance. Thus, we will conduct experiments on individuals suffering from SCD as part of the NSERC-CRD project.

As VR has proved to be efficient for calming anxiety, we intend to develop a virtual reality environment for the relaxation and improvement of the well-being of people suffering from SCD. We will analyze the evolution of one of their negative emotions, namely frustration during the virtual experience with a neurofeedback device.

In the course of our research, we noticed that people with dementia were often confused. The early detection of confusion, can, for example, help to adapt and improve learning. It may also help better to understand a person's behavior in a given situation and thus to treat or help them more effectively. So, the second objective is to develop a tool to detect confusion.

We will conduct experiments to achieve the objectives, and the respective work will be submitted to two international conferences.

Ultimately, we can summarize our two objectives as:

- to develop a relaxing virtual reality environment that helps reduce the frustration and improve cognitive functions of individuals suffering from SCD
- to develop an efficient tool for recognizing confusion

1.3. Thesis organization

In Chapter 2, we explain the characteristics of Alzheimer's disease, its detrimental effect on cognition, and the impact of virtual environments on cognitive impairment. Chapter 3 introduces the research that led to the creation of a virtual environment and provide an overview of the environment. Chapter 4 is a description of the experiment conducted on our virtual environment and the results found. We outline the confusion recognition tool that we developed in Chapter 5. Finally, Chapter 6 concludes the set of findings and opens the way for future work.

Chapter 2. Virtual environments for cognitive impairments

Before we begin, we need to give some definitions of the terms we are going to use.

Emotions and feelings: These two terms are often used interchangeably, although there are differences. Emotions are neurophysiological reactions triggered by an external or internal stimulus. They are physical, while feelings are the mental experience of emotions. It is possible to measure emotions through brain activity, while self-assessment tools measure feelings [20].

Cognitive functions refer "to the mental functions involved in attention, thinking, understanding, learning, remembering, solving problems, and making decisions" [21]. In the book L'erreur de Descartes, António Damásio discusses the role of emotions and feelings in decision making. According to him, reasoning and decision making cannot take place without emotions. Emotions would, therefore, be part of cognitive functions [22].

Affective state refers to emotions.

Dementia "is the umbrella term for many neurological conditions, of which the major symptom is the decline in brain function due to physical changes in the brain" [23].

In the next subsection, we will introduce Alzheimer's disease and its effect on the brain.

2.1. Alzheimer and well-being

2.1.1. Alzheimer's disease

Doctor Alois Alzheimer first described Alzheimer's disease (AD) in 1906 as "a peculiar severe disease process of the cerebral cortex" [24]. Today it is considered an incurable disease that kills brain cells and the neurons that connect brain cells together. It causes mental and memory disorders. Amyloids are protein fragments that are naturally produced by the body. Such protein fragments are decomposed and eliminated in a healthy brain. In the case of AD, amyloid-beta proteins stick together and form plaques that prevent signals from being transferred between neurons, resulting in cell death. Tau proteins (in a healthy brain allow the nutrients to reach their destination) roll up and form tangles that prevent nutrients from reaching neurons, resulting in cell death [25], [26]. Figure 1 below shows the differences between a healthy and a diseased cell.

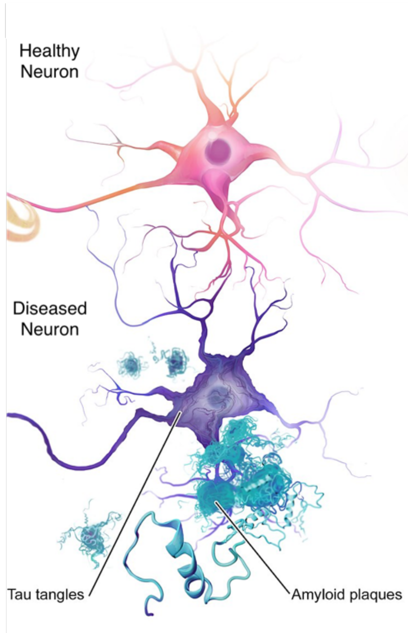


Figure 1. – Alzheimer's disease: healthy and diseased neuron [27]

Before symptoms can even be observed, in the earliest stages of the disease, plaques, and tangles, start to form in brain areas related to learning, memory, thinking, and planning. Brain regions that are critical in memory, thinking, and planning develop more plaques and tangles in mild to moderate stages than they were present in early stages. As a consequence, individuals experience memory or thinking difficulties that are sufficiently serious to interfere with work or social life. They may also get confused and find it difficult to handle money, express themselves, and organize their thoughts. When the disease progresses, individuals can undergo personality and behavioral changes and have difficulty remembering friends and family members. Most of the cortex is seriously damaged in advanced AD. Figure 2 shows that various areas of the brains of individuals with AD respond less due to brain damage. Because of cell death, the brain shrinks considerably. Individuals lose their ability to communicate, recognize people, and take care of themselves [28].

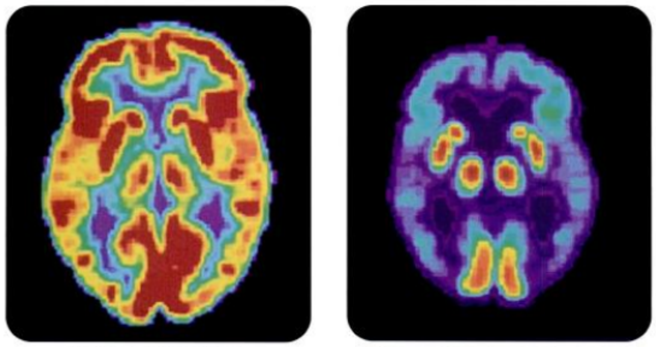


Figure 2. – Activity of a healthy older adult's brain and the brain of an older adult who has Alzheimer's disease [29].

2.1.2. Impact on quality of life

The fact that individuals lose their cognitive ability is likely to **diminish their quality of life**. They will no longer be able to do the things they enjoy or maintain the same lifestyle as before cognitive decline. In the early stages of the disease, anxiety or depression are often felt as individuals are aware of the decline in their cognitive abilities. In later stages, they may also feel anxious because they find themselves in situations they do not understand. They may not recognize places or people and suffer from memory distortion. The majority of people with dementia often experience mood changes, become increasingly dependent on others, and feel helpless as they lose control over their bodies and their reactions. They may be treated differently by people (i.e., devalued) since their diagnosis. Dementia can also affect other areas of an individual, such as finances, employment status, and close relationships. All of these can affect self-esteem and may cause irritation and isolation [30], [31]. In addition, at a later stage, the memory is more affected. People with dementia no longer know how to take care of themselves. They may no longer want to go out or to get up in the middle of the night, thinking it is daytime, or not understanding why they need to eat healthily [32].

2.1.3. **Importance of the external environment**

Since the disease is very likely to diminish an individual's quality of life, the individual must be in a positive environment that is adapted to their condition. They must also have access to positive landscapes, such as natural ones.

> Horticultural therapy describes a process, either active or passive, of purposefully using […] gardens […] to positively affect a set of defined health outcomes for individuals (e.g., improved mood, improved self-esteem, enhanced social interaction) [33].

Therapeutic horticulture may contribute to the **reduction of symptoms** associated with dementia:

– reducing pain perception
– improving attention
– lowering stress
– modulating agitation

Stress accompanied by neurobiological changes may accelerate the loss of cognitive function. Reducing stress is, therefore, an essential step in avoiding the risk of faster cognitive decline [34].

In this subsection, we studied Alzheimer's disease and the importance of having a **favorable external environment** that improves cognition and promotes well-being. We will examine in the following subsection the impact of virtual environments (easier to set up than real ones) on emotions and cognition.

2.2. Literature review on virtual reality

Virtual reality environments offer sensory stimulation in an immersive environment. The head-mounted display immerses the user in the virtual experience.

It is challenging to choose from the long list of virtual environments that had positive effects on the users.

We will, therefore, begin our non-exhaustive review with some popular studies that have been successful in **stimulating and improving cognitive skills**. Table 1 shows three virtual reality environments that made daily tasks less painful and **relaxed** people with various cognitive impairments, including Alzheimer's disease.

Table 1. – Three virtual reality environments that improved cognition in people with cognitive decline.

Health condition	Study	Experimental description	Results
Older people with memory deficits	Optale et al., 2010 [35]	Training of the memory of participants through VR auditory stimulation (stories told with music) and VR orientation experiences (e.g., path memorization).	General improvements in cognitive and memory abilities
Alzheimer	Yamaguchi et al., 2012 [36]	Patients had to make two toasts for breakfast and prepare a cup of coffee in the virtual environment.	Promising results for improving the performance of daily actions in both healthy older adults and patients with Alzheimer's disease
Alzheimer, Huntington, and other dementias	Tabbaa et al., 2019 [37]	Patients used VR headsets to explore one of five virtual environments. They could explore a cathedral, a forest, a sandy beach, a rocky beach, and a country scene.	VR served as cognitive stimulation. It helped patients to recall old memories that provided positive mental stimulation and helped them to relax. The caregiver also had a better understanding of the patient

The treatment of phobias is an area where virtual reality is very effective. VR helps to alleviate social phobia, arachnophobia, agoraphobia, acrophobia, aviophobia, and more [38].

Virtual reality is not limited to healthcare; one of its most popular applications is video games. In the virtual reality game DEEP, the slow and deep breathing of the participants, provided by a stretching sensor, allowed them to better move in the environment [39]. DEEP relied on biofeedback, that is, a set of techniques used to learn how to control the physiological activity of a human being [40]. Physiological activity is measured using instruments. Biofeedback combines well with virtual reality as it improves the regulation of emotions.

Another popular area of VR is the simulation of phenomena (like physics, biology, reasoning). VR allows, for example, to simulate crowds for emergency interventions [41] or to simulate in real-time virtual pipes for future pipe constructions [42].

As well as simulating construction, another promising area of virtual reality is marketing. In tourism, it could be used to market tourist destinations to participants effectively [43].

Virtual reality showed encouraging results in the field of education as well. It has improved the learning of students of different grades in different disciplines [44]. It also helped to improve the skills of industrialists through specific learning tasks in assembly [45]. The army also uses VR for training through flight simulation [46].

We showed in this subsection that virtual environments appear to be highly adapted to improve the well-being and the cognition of people suffering from cognitive impairment. It is furthermore appropriate to present some VR headsets.

In the next subsection, we will briefly introduce some PC-based VR headsets with advanced tracking systems, including the one that we used in the experiment described in Chapter 4.

2.3. Overview of some PC-based virtual reality headsets

There are many virtual reality headsets on the market today.

In VR, **presence** is the feeling of being present and connected to the virtual world. Presence is, therefore, essential to ensure a good **immersion** in the environment. Here are some elements for having a sense of presence [47]:

- Wide field of view of 80 degrees or more
- High resolution of 1080p or better
- A sufficiently high refresh rate of at least 60 Hz
- A fast and accurate tracking system

Table 2 shows some PC-based virtual reality headsets with advanced tracking systems and some of their essential features for having a sense of presence.

Table 2. – Presentation of some PC-based virtual reality headsets with advanced tracking systems. Head tracking lets the user look up or down, to either side or tilt their head. Position tracking allows the user to move around in the virtual environment.

Name	Release date	Tracking sensor	Display	Refresh rate	Field of view
HTC Vive	April 5, 2016	Head tracking, positional tracking	2160x1200	90 Hz	110°
Oculus Quest	May 21, 2019	Hand tracking, head tracking, positional tracking	2880x1600	72 Hz	100° (estimate)
Oculus Rift S	May 21, 2019	Head tracking, positional tracking	2560x1440	80 Hz	110° (estimate)
Fove 0	**November 2, 2016**	**Eyes tracking, head tracking, positional tracking**	**2560x1440**	**70 Hz**	**90° - 100°**

We found that immersive virtual reality environments evoke emotions. The following subsection will introduce a **way to measure an individual's emotion**. One way to measure emotions is to use the method of electroencephalography. It allows access to a person's emotional states in real-time by providing an objective measure of the impact of an environment.

2.4. Measuring affective states

2.4.1. Quick overview of the part of the brains

We will introduce where and how emotions appear in the brain.

The brain is composed of two hemispheres (right and left) which can be divided into six parts (new approach) for each hemisphere:

– the frontal lobe
– the parietal lobe
– the temporal lobe
– the occipital lobe
– the limbic lobe
– the insular cortex

Figure 3 provides a view of the brain and the different lobes.

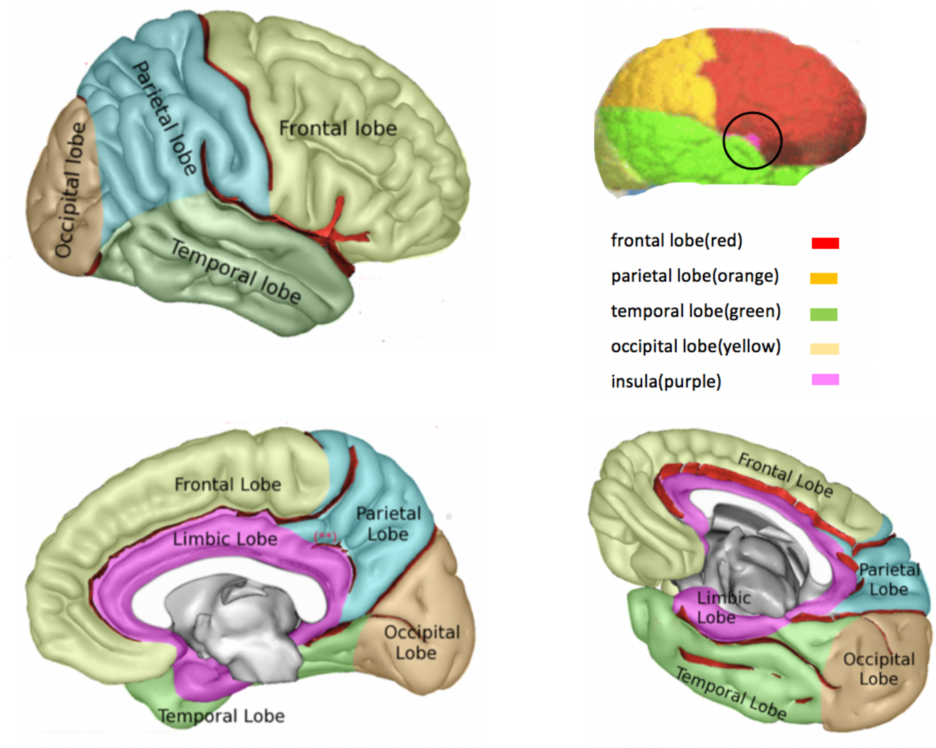


Figure 3. – Different views of the brain to visualize different lobes [48]. The insular cortex is visible in the image where it is circled [49].

In the past, the scientific community associated emotions only with the limbic lobe and associated cognition with the prefrontal cortex (front part of the frontal lobe). New studies now suggest that although the limbic system is heavily involved in experiencing and processing emotions, brain function depends on many different regions of the entire brain working together [50], [51].

Here is a non-exhaustive list of the major functions of each lobe (i.e. brain functions) [52], [53]:

- Frontal lobe: speech and language, reasoning, memory, decision-making, personality, judgment, movement
- Parietal lobe: reading, spatial location, sensitivity
- Occipital lobe: vision
- Temporal lobe: language, memory, emotions
- Limbic lobe: memory, learning, emotions

– Insular cortex: sensory and affective processing, emotions

2.4.2. Electroencephalography and Emotiv EPOC headset

Electroencephalography (EEG) is a method for recording **electrical activity** of the brain by using electrodes positioned on the scalp. The electrical activity of the brain comes from the excitation of neurons that receive and transmit information. EEG makes it possible to see which brain lobes are most active.

To record brain activity, a device widely used and validated in academia is the Emotiv EPOC headset [54].

EEG headsets have **two types of electrodes**: the EEG channels that measure the electrical voltage between two points and the references that serve as a basis for measuring voltages. The channels therefore measure the electrical voltage between themselves and the references.

The international 10-20 system allows electrode placement with **standardized electrode positioning** for test reproducibility. It uses numbers and letters to describe the electrode placement. Odd numbers represent electrodes placed on the left hemisphere and even numbers represent electrodes placed on the right hemisphere. The letters identify the location of the electrodes according to the lobes of the brain. The letters F, T, C, P and O respectively stand for frontal, temporal, central, parietal and occipital. The letter C is used for identification purposes [55].

Figure 4 is a picture of the Emotiv EPOC headset and the location of its electrodes.

Figure 4. – Emotiv EPOC headset and electrodes location.

Reprinted by permission from Springer Nature Customer Service Centre GmbH: Springer virtual, augmented and mixed reality: applications of virtual and augmented reality attention training with an easy–to–use brain computer interface [56].

The Emotiv Epoc has useful software such as Emotiv Testbench, which gives the EEG signals in microvolts in real-time (Fig. 5). One of its other software is the Emotiv Software Development KIT (SDK) which provides measurements (intensity between 0 and 1) for the following affective states in real-time:

- engagement
- excitement (short and long term)
- frustration
- meditation

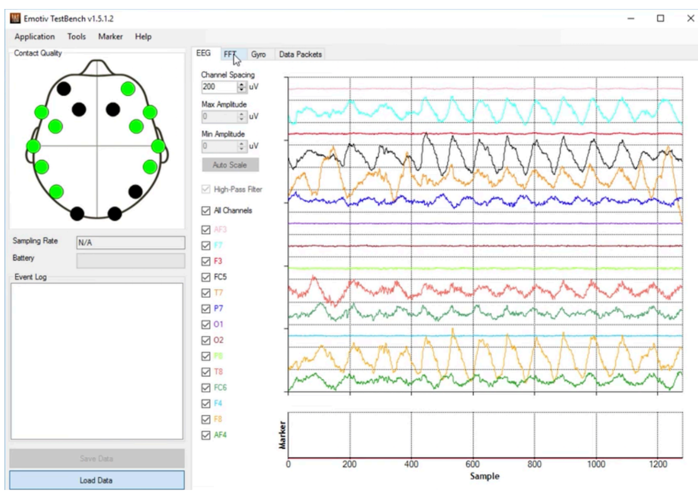


Figure 5. – A screenshot of the Emotiv TestBench software and raw EEG signals. Not all the electrodes are connected yet, which is why the circles are black.

Table 3 shows some of the most commonly used EEG headsets in research. The advantage of having more electrodes is to avoid loss of data (because the distances between the electrodes get longer when there are fewer of them). One disadvantage of having many electrodes is that it requires more time to put the gel that improves the quality of the signals. Having more channels leads to more detailed brain activity. However, it increases the size of the collected data, the preprocessing of the data, and the training time of the learning models.

The Emotiv Epoc headset, which has 14 channels and two reference electrodes, offers a good compromise between installation time and the detail of the brain information collected.

Table 3. – Comparison of some of the most used EEG headsets in research. The presence of an accelerometer reduces the noise generated by sudden movements.

	NeuroSky Mindwave Mobile (first version)	Muse headband (first version)	**Emotiv Epoc (first version)**	OpenBCI Ultracortex Mark IV
Number of electrodes	1	5	**16**	35
Number of channels	1	2	**14**	16
Maximal sampling rate	512 Hz	500 Hz	**128 Hz**	250 Hz
Presence of an accelerometer	No	No	**Yes**	Yes

In light of the elements presented in this subsection, the Emotiv EPOC, therefore, appears to be a useful tool for assessing the impact of an environment on a person's emotions and well-being.

In this chapter, we have seen how virtual reality environments could improve the well-being of people suffering from cognitive decline. The next chapter introduces Savannah VR. It is a virtual reality environment developed to improve the well-being of individuals suffering from SCD. We will first describe in a subsection the research done for the design of the environment and then give an overview of the developed environment.

Chapter 3. Design and overview of the developed environment

The work of some sections of Chapter 3 and Chapter 4 comes mainly from a submitted paper (see Appendix A). The authors of this paper submitted in April 2020 to the International Conference on Brain Function Assessment in Learning are Dakoure, Abdessalem, Boukadida, Cuesta, Bruneau, Belleville and Frasson.

In this paper, my main contribution has been to design and develop Savannah VR. I also explained the potential of virtual reality tools.

Boukadida and Abdessalem conducted experiment with Savannah VR.

Abdessalem extracted the results and highlighted the positive effect of the virtual environment, which reduced the frustration of the participants and improved their memory and attention.

Frasson reviewed the paper, checked the results, and provided financial support for the research.

Belleville reviewed the paper.

All of this is covered in more detail in Chapter 3 and Chapter 4.

3.1. Design of the Savannah VR environment

3.1.1. Literature review of savannah preference

In 1984, Wilson introduced the word biophilia, referring to an innate affinity that people have with nature [57]. Since the first humans lived for thousands of years in the African savannah, modern humans would have a **preference for savannah** landscapes [58]. Ancient threats to survival have led to a connection between natural environments and positive feelings. As a natural setting, the savannah provides a sense of tranquility and harmony [59]. Providing to early humans a place to watch or hide from predators, spreading trees in savannah brings a feeling of security.

Some studies, however, support the idea that humans prefer landscapes that resemble their everyday environment [60]. The preference for a landscape may not only be based on the time when humans lived in the savannah, but also on different moments in evolutionary history [61].

However, in general, savannah is still very much appreciated. We believe that with its diverse and pleasant scenery, it may be an attractive place to travel and explore since it draws curiosity and may help to relax in security. It is, therefore, conceivable that for people with cognitive impairment, this could be a beneficial virtual world.

3.1.2. **Choice of components**

After a considered selection of the setting, we have carefully chosen the elements of the virtual environment to minimize stress. We undertook the audiovisual work before the development of the environment to create concept art that would serve as a source of inspiration for the design of the environment. We watched video footage taken by drones because they offer distant views and provide a useful global perspective to create a virtual environment. Such videos taken from afar served as a basis for imagining the environment with varied landscapes, sunrises and sunsets, water, and various kinds of grass. Relaxing piano music under the Creative Commons license was chosen as background music with 94% positive feedback from about 1500 voters on Youtube [62].

When selecting animals, the key concern was to find animals viewed as harmless. We have chosen to include the following animals in Savannah VR: hornbills, starlings, giraffes, antelopes, gazelles, small elephants, and zebras.

Clarity and readability were crucial factors in the choice of the graphic user interface (GUI). The game Wii Sports has become very popular with the elderly [63]. It has a simple and easy GUI, so a similar interface for text and explanations was adopted.

3.1.3. **Contribution of this study**

One of the considerations was how to make this study stand out from the others. We thought that a system that responds to the user’s emotions could better reduce negative emotions and thus potentially improve cognitive performance. Therefore, one of the objectives was to **make Savannah VR an intelligent environment**. We wanted it to adapt its components according to the user’s emotions measured by EEG.

3.2. Overview of Savannah VR

3.2.1. Summary

Savannah VR was developed in C# with the Unity3D 2017.1.4 game engine. It is a **virtual environment** intended to induce relaxation. Participants follow an avatar, speaking in a soft and reassuring voice, across a savannah. In a way to attract and reassure the participants, the avatar asks users how they feel. It offers succinct and straightforward explanations, both in writing and speaking, to ease the processing of information. We built this Windows-based environment with cognitively impaired people in mind. It requires only a virtual reality headset and a mouse. The dominant colors are warm, the animals are peaceful, and their movement is slow. In the background, users can hear a soothing piano track at a volume low enough to appreciate the sound of each animal. Figure 6 shows the visual aspect of part of the environment.

Figure 6. – Screenshot of Savannah VR

3.2.2. **Navigating in the environment**

Participants automatically follow a gazelle that moves along a specific path. They can only look around without controlling their movements. The users follow the gazelle at low speed to prevent discomfort induced by movement in virtual reality. The animal stands before them to mimic a view of a third person that is less likely to cause motion sickness [64].

Figure 7 gives an overview of the walk-in Savannah VR. At point 0, the gazelle introduces itself and explains that the participant is going to follow it on its walk. The gazelle will then walk and quickly stop at points 1, 2, and 3. The virtual experience will end at point 4.

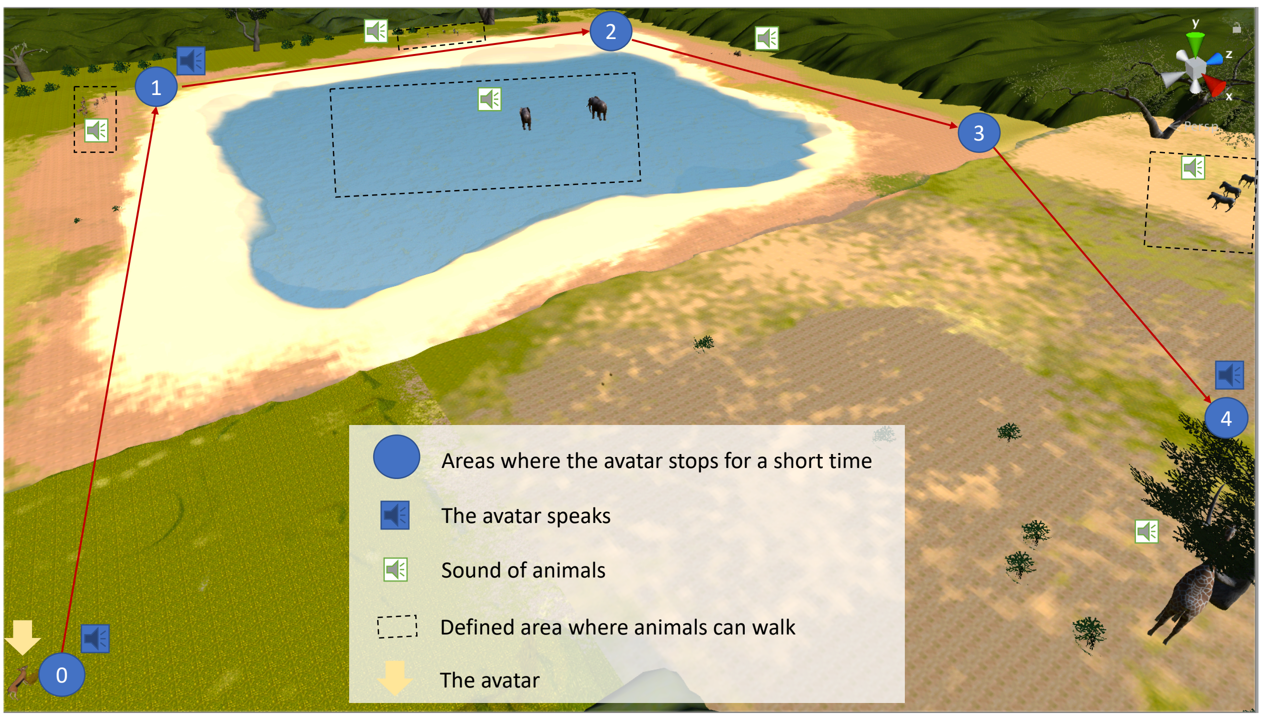


Figure 7. – Diagram of the walk in Savannah VR

During the virtual walk, the animals of the savannah move around. Appendix B presents the animal movement algorithm on which we spent much time to ensure that the animals move smoothly and naturally.

3.2.3. **Real-time environment modifications**

We wanted Savannah VR to be an intelligent environment that adapts in real-time according to the participant's emotions. For this, we first integrated rules of logic that allow the change of the environment parameters. One of the implemented rules is, for example, if the user presses the J key, then Savannah VR displays a sunset. The testing and the more complex development of this adaptation system was part of the research of Hamdi Ben Abdessalem, who is a Ph.D. student in our laboratory. As a result, from our first rules of logic and Hamdi Ben Abdessalem's more complex enhancement, Savannah VR is an intelligent environment. It dynamically modifies its components according to the user's emotions measured by the EEG.

Color and light intensity are among the adjustable parameters, as light affects perception and decision making. The color of light can also stimulate learning [65] and reduce stress faster [66]. It is also necessary to choose the volume carefully; too high a volume can cause noise pollution. The sound level can, therefore, be adjusted [67]. A setting with more trees can also reduce stress more quickly and effectively, so we made an option to increase the number of trees in the area [68]. It is also possible to reduce the number of animals and change the sky and colors to provide a soothing sunset as shown in Figure 8.

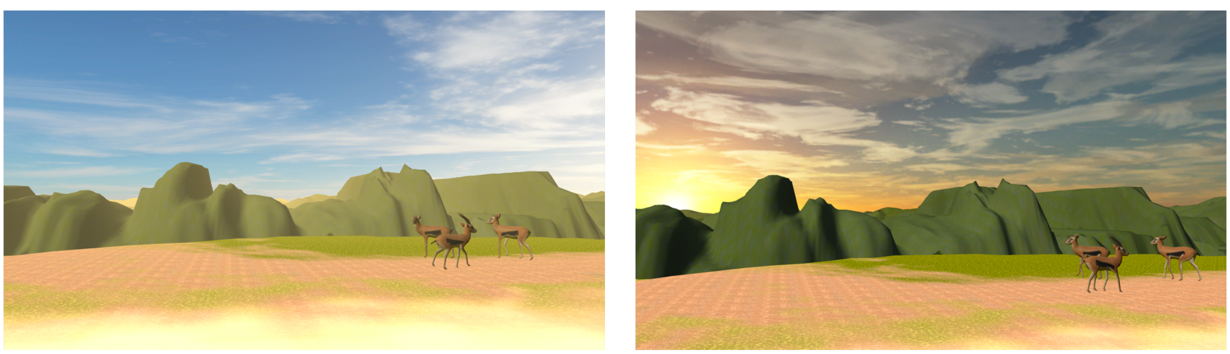


Figure 8. – Screenshots of real-time changes in Savannah VR

After developing our first environment, Savannah VR, we developed a second environment, Underwater VR, to measure the impact of the landscape on the participant's emotions. Although there was no experimentation related to this environment, we will present it briefly in the next subsection starting with the literary review that led to the choice of this environment.

3.3. Going further: another developed environment

3.3.1. Literature review of blue space theory

The term blue planet comes from the fact that the earth is mainly composed of water, with oceans covering 70% of its surface. Water plays a vital role in human beings even before they are born. The embryo and fetus bathe in the amniotic fluid, which is a mixture of water and other substances. "This biological connection triggers an immediate reaction in our brains when we are near water" [69].

Water provides a unique sensory experience and induces powerful emotional responses that can lead to a meditative or hypnotic state. It is also associated with an auditory stimulus that can be revitalizing and relaxing [70].

In 2011, M White et al. questioned the benefits of blue space or aquatic environments in urban and natural environments. Half of the participants indicated that they would prefer to live in an aquatic environment (urban or natural) [71].

A concrete example that demonstrates the benefits of aquatic environments is the game Abzu, which has been a worldwide success [72]. In Abzu, the player navigates underwater in an open environment that is known to be soothing.

In light of the above elements, it is therefore entirely conceivable that aquatic environments could be beneficial virtual environments for people with cognitive impairment.

3.3.2. Summary

Underwater VR is a diverse environment that we created for the relaxation based on the theory mentioned above. It has different colors of corals, rocks, sand, plants, minerals, and different kinds of fish. The amount of fish, the intensity and color of the light are elements of the environment that can be changed. There has not yet been any experimentation with Underwater VR, but our laboratory will do experiments with it later on. Figure 9 provides an overview of the developed environment.

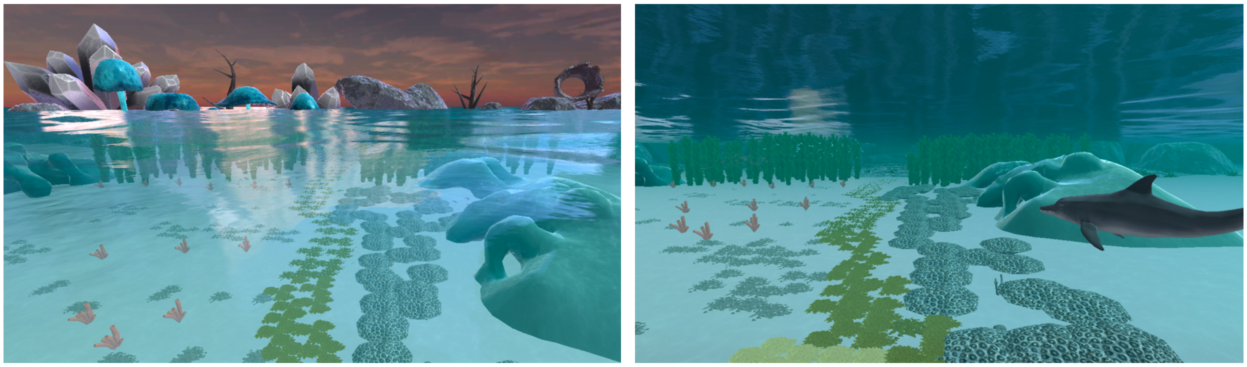


Figure 9. – Screenshot of Underwater VR

We presented the research that led to the development of Savannah VR, whose goal is to improve the well-being of individuals suffering from SCD. In the next chapter, we will detail the experiment we conducted with this virtual environment on people suffering from SCD. We will also present the results to verify that Savannah VR contributes to reduce frustration and improve cognitive abilities, thus validating our first research objective.

Chapter 4. Savannah VR experiment, results and discussion

Important note: This experiment is a team effort with Hamdi Ben Abdessalem and Marwa Boukadida. I will clarify my contribution and that of other team members.

I designed and developed two virtual reality environments whose purpose is relaxation. In the Savannah VR environment, I created a simple agent that allows modifications in the environment in real-time by applying simple rules (section 3). I gave Savannah VR to Hamdi Ben Abdessalem so that he could conduct experiments because I did not have the necessary authorizations. I received and analyzed the graphs of participants' frustration when they were immersed in Savannah VR and the results of their attention and memory exercises (section 4.3).

Hamdi Ben Abdessalem improved the agent so that the Savannah VR environment changes according to the emotions of the participants. He also conducted the experiments on people with SCD at the Institut universitaire de gériatrie de Montréal (IUGM). He put the participants in the Savannah VR and gave them attention and memory tests, which he had previously developed (section 4.2). He provided me with graphs of participants' frustration and the results of their attention and memory exercises.

Marwa Boukadida helped Hamdi Ben Abdessalem to conduct the experiments (section 4.2).

Now that we have clarified everyone's contributions, we will define SCD before presenting the experiments conducted.

Subjective cognitive decline is a self-perceived decline in any cognitive domain over time. It may correspond to the first phase of AD [73].

4.1. Subjects and criteria for participation

4.1.1. Study population

We conducted the experiments on 19 participants (12 women) with SCD and an average age = 71 years (SD = 8.39).

4.1.2. Eligibility criteria

The criteria for eligibility were as follows [74]:

– be over 60 years old
– French-speaking
– normal or corrected vision
– normal hearing
– the participant's memory is not as good as it used to be, and this worries them (self-assessment)
– MoCA score 20-30
– no deficits in logical memory based on Wechsler Memory Scale (WMS) [75]

4.1.3. Subject recruitment

IUGM staff recruited participants who had previously registered in the IUGM participant bank. They contacted them by telephone.

4.2. Course of the experiment

4.2.1. Equipment

For this experiment, we used the Emotiv Epoc EEG headset to track the frustration of the participant (see section 2.4.2 for more information about this device).

In addition to having an EEG device recording their brain activity, participants were also equipped with Fove 0 VR headset (see section 2.3 for more information about this device).

4.2.2. Experimental procedure

Participants attended two sessions. The first was the pre-experimental session, where we invited them to sign a consent form and verified that they were eligible for the study.

In the second session, which was the experimental session, we asked participants to fill out pre-session forms. They were then equipped with an EEG headset and invited to solve attention and memory exercises.

After these tests, we set up the Fove 0 headset, and Savannah VR began. The exploration of the savannah lasted approximately 10 minutes. Following this, the participants again performed different examples of the same attention and memory tests. Lastly, they completed post-session forms.

4.2.3. Memory and attention exercises

We used six exercises of attention and memory [76]. For the attention exercises, the participants had to:

- repeat in order and reverse order a series of numbers
- press a key in less than a second when hearing a letter
- select the first letter of an object they have just seen

For the memorization exercises, the participants had to:

- determine if they have just seen or heard an object
- memorize and reproduce a specific circle sequence
- memorize a set of images and identify it among other sets of images

4.3. Results

One of the objectives of this experiment was to analyze the effect of Savannah VR on the emotions of the participants and to check whether the environment reduces frustration, which is a negative emotion that reduces well-being. To this end, we analyzed participant frustration given by Emotiv SDK, during, and after Savannah VR. As a reminder, Emotiv SDK gave frustration intensity values between 0 and 1 using EEG signals recorded from the Emotiv Epoc headset (see section 2.4.2 for more information about this software).

Figure 10 shows that the mean frustration before Savannah VR was 0.68 (0.24 min and 0.98 max). The mean frustration during Savannah VR was 0.57 (0.31 min and 0.88 max). After Savannah, the average level of frustration was 0.55 (0.28 min and 0.91 max).

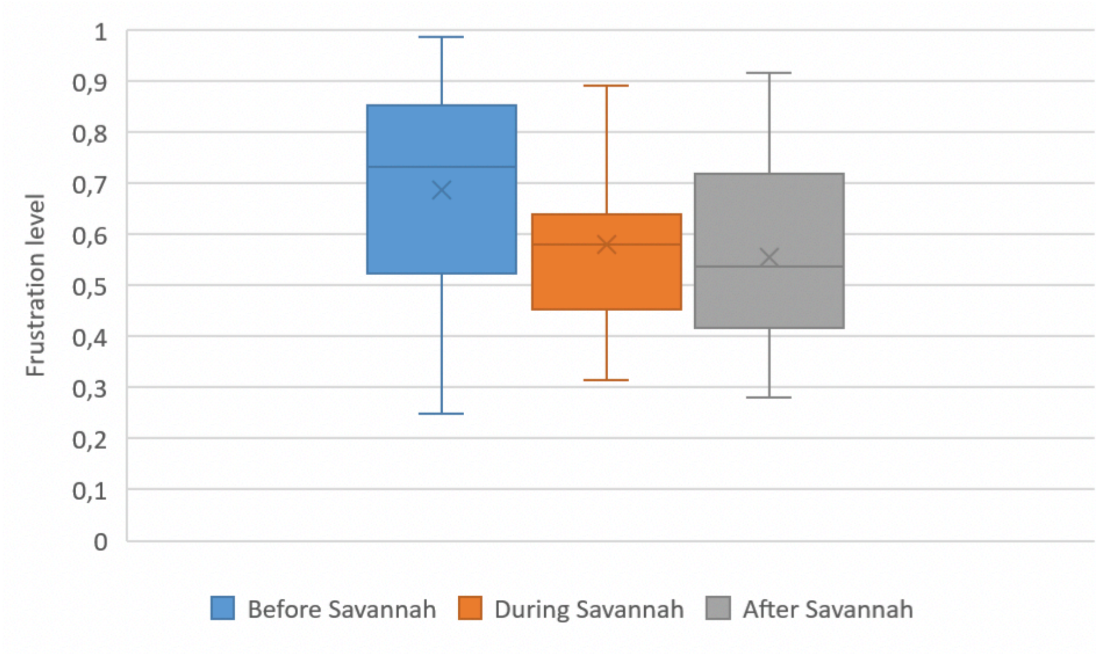


Figure 10. – Boxplot of general mean frustration

Figure 11 indicates that approximately **68% of the participants saw their level of frustration decrease during Savannah VR**. The frustration level of 58% of the participants was lower after the savannah than before the savannah.

Combining the information in figures 11 and 12, we see that about 89% of the participants improved their results in memory tests. Of this 89 %, 41% had a level of frustration that increased during the savannah. Approximately 42% of the participants scored better on the attention exercises after the savannah, and 37% scored similarly on the attention exercises.

Four of the five participants with a higher level of frustration after the savannah than before the savannah (see participants 5,6,8,16), scored lower on attention or memory exercises.

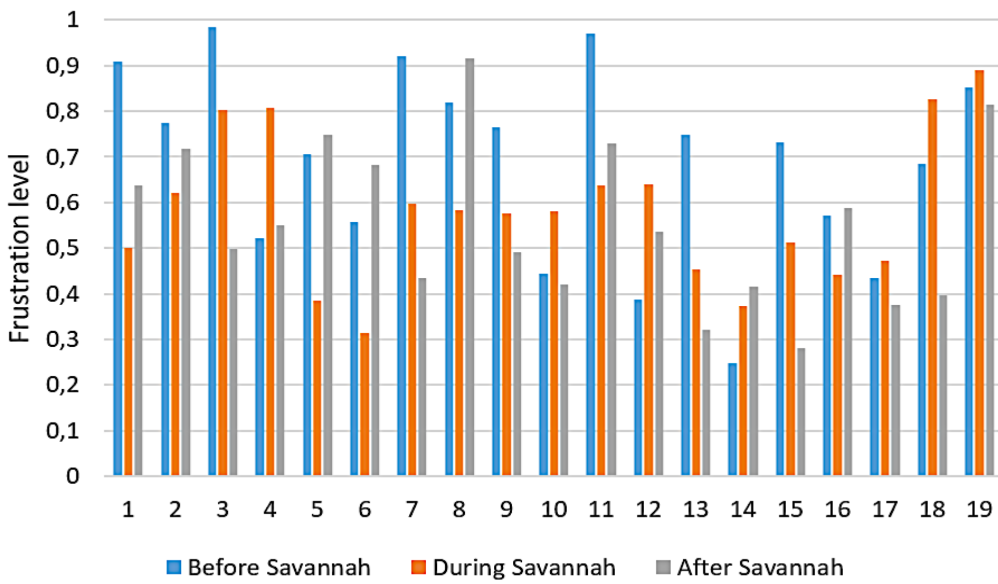


Figure 11. – Individual level of frustration before, during, and after the savannah

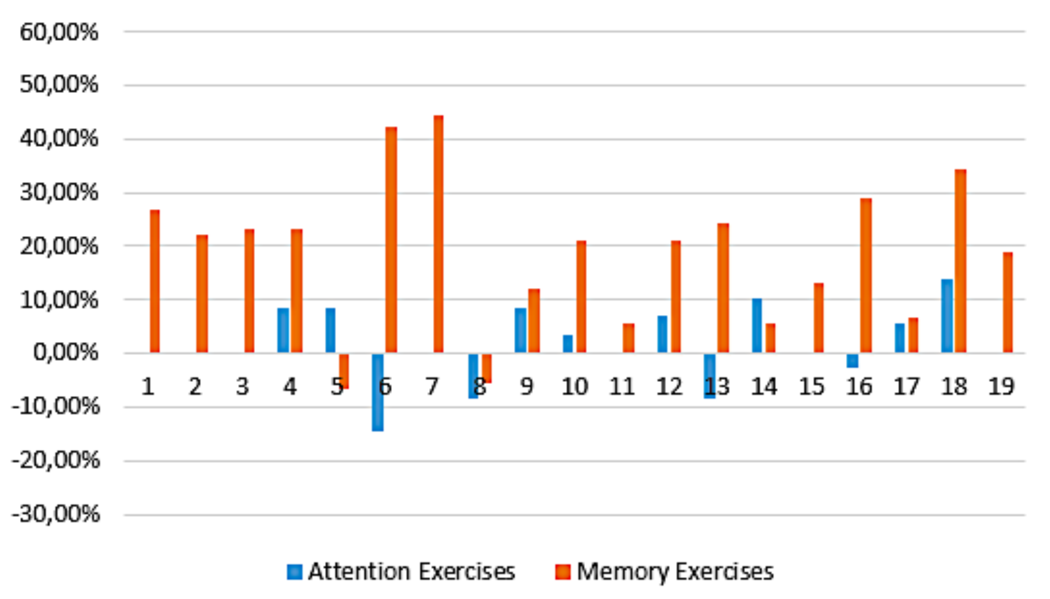


Figure 12. – Percentage of individual improvement in exercises. Some participants had the same scores on the attention exercises before and after Savannah VR. Therefore, they do not have a blue bar.

4.4. **Discussion**

Overall, when participants immersed themselves in Savannah VR, their frustration decreased, and the positive effect remained after the virtual environment. We can, therefore, say that **the virtual environment helps to reduce negative emotions**, especially frustration, thus verifying the first part of our initial objective.

Given the results obtained, we can say that the **majority of the participants improved their results** in the attention and memory exercises, but the reason for this remains unclear. We did not find a clear correlation between the level of frustration during the virtual savannah and the results of cognitive exercises. Indeed, individuals whose frustration increased during the savannah also improved exercise results (see, e.g., participants 4, 10, 12, and 18). The improvement in the results of the attention and memory exercises for most participants may be due to several factors, including:

- learning by repetition of the same type of exercise
- the second set of attention and memory exercises was easier than the first one
- a more attentive and concentrated state (this could be due to Savannah VR, but more measures would be needed to validate this idea)

We noted that frustration increased during the Savannah VR among some participants. This increase may be because they could not move freely in the environment but had to follow a defined path. It may also be due to personal preferences (like the visual aspect of the environment or sounds).

This experimentation also has some limitations. We did not have access to people diagnosed with Alzheimer's disease because it requires many resources. It is necessary to obtain the approval of several committees through ethics certificates and protocols, which takes much time. The size of our sample is also a limitation of our study. Although the experiments lasted for weeks, it was difficult to conduct them regularly because it was difficult to get an appointment with participants with SCD. We, therefore, have a sample size of 19 people, which means that our results are not quantifiable, but are still a considerable basis for future research. It would also have been interesting to have access to other affective states given by Emotiv SDK. We might have been able to find correlations between these affective states and the results of cognitive exercises.

We confirmed that Savannah VR helps reduce the frustration of participants with SCD and helps improve cognitive performance. We are now going to describe in detail our second experiment aiming to create a tool for measuring confusion because people who have dementia are often confused. Detecting confusion quickly and precisely can lead to a better understanding of a person's behavior in a given situation. It is also useful for adapting a system such as adapting learning and adapting care.

Chapter 5. Confusion recognition and measurement tool

Some parts of this chapter are taken from a submitted paper (see Appendix C). The authors of this paper submitted in April 2020 to the IEEE International Conference on Systems, Man, and Cybernetics are Dakoure, Benlamine, and Frasson.

In this paper, my contribution has been to create the machine learning models to detect four levels of confusion (from not confused to highly) efficiently via EEG signals. I also predicted efficiently what activity (e.g., memorization) the participant was doing when they were confused. I developed cognitive exercises to generate confusion in participants. I conducted experiments with these cognitive tests. I used the data from Benlamine's experiment to create other machine learning models and compared the results with those of my experiment. I also did the processing of the data.

Benlamine conducted an experiment and extracted data from it. He also described the equipment used in his experiment.

Frasson reviewed the paper, checked the results, and provided financial support for the research.

All of this is covered in more detail in this chapter.

5.1. Introduction

Before we begin, we should give a clear definition of confusion. **Confusion** is a state in which people do not understand what is happening, what they should do, what something means, who someone or something is [77]. In medicine, one of the causes of confusion is **delirium**, which refers to a sudden, fluctuating, and generally reversible disorder of cognitive function. People suffering from delirium cannot pay attention and think clearly, are disoriented and experiment fluctuations in the level of alertness (consciousness). Delirium can be confused with dementia, which is a slowly developing confusion that is not reversible [78].

Confusion may arise in a wide diversity of situations, for example, during reasoning, learning, memorization, or orientation.

If we focus on learning, confusion is a state that can be either beneficial or negative. It can lead to increased engagement and more profound knowledge, or frustration, and boredom when there is no understanding after a while. Both the intensity and duration of confusion seem to be a factor in frustration or boredom [79].

In the health field, confusion is associated with dementia and is one of the symptoms of Alzheimer's disease. It is, therefore, essential to detect confusion to **adapt the system** to the user's mental condition effectively.

5.2. Confusion recognition

Having explained the importance of detecting confusion, we will now review the literature on previous studies that have detected confusion using EEG devices.

5.2.1. Literature review

Several studies have been conducted to detect binary confusion using EEG signals.

In 2001, confusion was associated with electroencephalography in the medical field in an attempt to identify fluctuating confusions in dementia [80].

Confusion did not only concern the medical field. In 2011, Walker et al. proposed a model to detect academic emotions (boredom, confusion, engagement, and frustration) during a session of a modified version of the Wisconsin Card Sorting Test. The accuracy of the developed model was less than 50% [81].

In 2013, Wang et al. detected confusion in ten adults watching massively open online course videos. Their model achieved an accuracy of 57% [82]. They improved their results with different models over the following years. In 2017, their bidirectional long-short term memory (Bi-LSTM) model achieved an accuracy of 73.3%, and in 2018 their improved LSTM model achieved an accuracy of 75% [83].

A few studies have attempted to combine EEG signals with other data. Yang et al. created the Sedmid model in 2016 to detect confusion with EEG signals and video elements. The Sedmid model obtained an accuracy of 87.8% [84].

5.2.2. **Contribution of this study**

In an attempt to **differentiate this study** from others, we aimed to combine EEG signals with facial expressions to detect confusion objectively. Although there are already studies that combine EEG signals with facial expressions to detect emotions, there are not yet any studies that do so to detect confusion. We aimed at developing a model, unlike other similar work, that does not predict two states of confusion (i.e., confused/not confused) but confusion with four levels of intensity.

Finally, we also wanted to propose an innovative model to identify cognitive skills related to confusion.

5.3. **Experiments**

The work presented in this subsection is the result of a collaboration with Mohamed Sahbi Benlamine. I will clarify my contribution and that of Mohamed Sahbi Benlamine.

I created a set of cognitive exercises in Javascript designed to generate confusion. I then conducted experiments where participants had to do these cognitive exercises (section 5.3.3). I extracted, processed the data collected during this experiment, and trained machine learning models to detect the confusion (sections 5.4. and 5.5). In one of Mohamed Sahbi Benlamine's old experiments, the participants had to orient themselves in a virtual reality game. He felt that participants might have been confused and that the resulting data could be promising. I wanted to know, between the data of his experiment and the data of my experiment, which one would give the best results to predict confusion. So, I waited for him to prepare the data. Once in my possession, I processed it and used it to train machine learning models. I then analyzed the results of the two experiments (sections 5.4. and 5.5).

Mohamed Sahbi Benlamine helped me install the equipment and monitor the participants for my experiment (section 5.3.3). On his side, he extracted and prepared data from one of his previous experiments using FaceReader 7.1 software (sections 5.3.2 and 5.4.1). He provided me with his data.

Now that we have clarified everyone's contributions, we will discuss the two experiments to measure confusion.

The first experiment is an old experiment done in 2015 by Mohamed Sahbi Benlamine [85]. We used his old data with new tools to check if we could measure confusion.

The second experiment that we conducted aimed to measure confusion but also to detect the cognitive processes that the brain goes through during confusion. The purpose was to find out which activity (memorization, reasoning, etc.) led the participant to be confused.

The advantage of having two experiments is that we can compare them afterward.

5.3.1. **Equipment**

Both experiments were conducted with the iMotions tool. This platform allows the synchronization of various equipment such as facial expressions and EEG signals. The Emotiv Epoc headset with Emotiv TestBench software enabled the recording of brain activity in microvolts (see 2.4.2). FaceReader 7.1 software allows the analysis of the participants' facial expressions to extract objective values of the intensity of their emotions. Figure 13 provides an overview of the software.

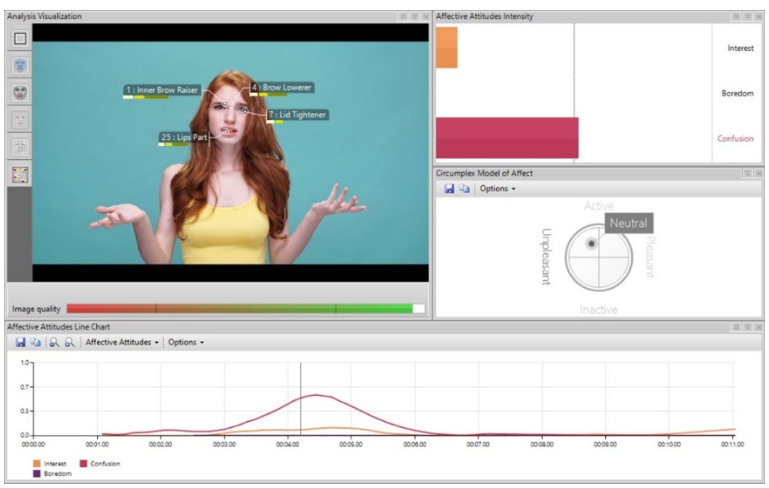


Figure 13. – Overview of FaceReader software [86]. This image is courtesy of Noldus Information Technology

We also gave the Big Five personality traits [87] to the participants of both experiments. It classifies the learner's personality into five dimensions:

- openness
- neuroticism
- extraversion

- agreeableness
- conscientiousness

We chose the Big Five because it is commonly used in our laboratory. Using the same test ensures that the experiments in our laboratory are comparable with each other.

We also relied on the expertise of IUGM psychologists who advised us to use it because:

- it is quick to complete
- it has been developed over several decades by several researchers [88]
- it is one of the most scientifically evaluated personality tests and is considered to be accurate [89]

In future work it would be interesting to study more recent personality tests.

After presenting the equipment used in the experiments, we are now going to explain the experiments conducted to collect the data (Step 1 in Figure 17).

5.3.2. **First experiment**

We will briefly present Mohamed Sahbi Benlamine's previous experiment [85].

Twenty undergraduate students (7 women, 13 men) with ages ranged from 24 to 35 years old from the Computer Science department of the University of Montreal were involved in this experiment. They were recruited via a departmental list serve from the Computer Science department with the following eligibility criteria: to have normal or corrected vision, normal hearing, and be over 18 years of age. Among them, 20% declared themselves to be "gamers".

After recruitment, participants were invited to the experimentation. At the beginning of the session, they signed a consent form. The experimenter checked that the position of the chair was correct and that the computer screen was visible. On the computer, the participants then had to complete the Big Five personality traits.

The experimenter set up the Emotiv Epoc headset. Users then started to play The Danger Island, a game previously developed by Mohamed Sahbi Benlamine et al [85].

The Danger Island is an action-adventure game where the player fought various enemies (like zombies or wild animals). The player's mission was to find fuel cans and return to a helicopter to escape from the island. They had to orient themselves in the game and may experience confusion and frustration in finding their way. The level of difficulty of the game depended on the category of the player (gamer/non-gamer) selected in the game start menu.

5.3.3. **Second experiment**

Ten students from the University of Montreal participated (five women, five men) in the second experiment. This number may seem small, however, this experiment lasted one hour during which we recorded the data continuously, resulting in a considerable dataset. In the end, we had a large enough dataset to get good results. We also saw that Wang et al. conducted an experiment with ten people to detect confusion and achieved good results [82] (see the literature review in section 5.2.1). Twenty participants took part in the first experiment. If the number of participants in the second experiment was insufficient, we had the option of using only the data from the first experiment. So, we preferred to restrict the number of participants to ten and concentrate on processing the data and create the models for both experiments.

The majority of the participants were between 25 and 34 years of age and had at least an undergraduate degree. We recruited them through posters posted in various buildings of the university. Eligibility criteria were as follows: to have a normal or corrected vision and be over 18 years of age.

At the beginning of the experiment, participants signed a consent form (see Appendices D and E). They then completed a demographic questionnaire, Big Five personality traits, and a Metacognitive Awareness Inventory (MAI) [90]. MAI has 52 questions with true or false answers. It helps to determine what the user knows about how they learn, their learning strengths, and how they regulate their cognition for better learning. Once the experimenter set up the Emotiv Epoc headset, the users then began **cognitive ability tests**, that we describe below. They received $20 compensation for participating and were debriefed at the end.

We implemented five sets of cognitive ability exercises using JavaScript. They are varied and designed to involve several cognitive skills:

– abstract and spatial reasoning

– logical argument analysis
– spatial orientation
– spatial memorization
– short-term memory

We took inspiration from Raven's progressive matrices to design the first set of exercises. Participants should find rules and patterns to identify the missing figure among a set of figures [91]. They then read a short text and chose the statement that best completed the text. This set of exercises was based on Gmat critical reasoning test [92]. Next, participants had to complete 2D mazes. For the fourth series based on the WMS-IV [75], the participants had to memorize the position of the items on a grid. Finally, participants had to pass a digit span test and memorize a sequence of digits for the last set of exercises.

Figure 14 shows an example of each set of exercises.

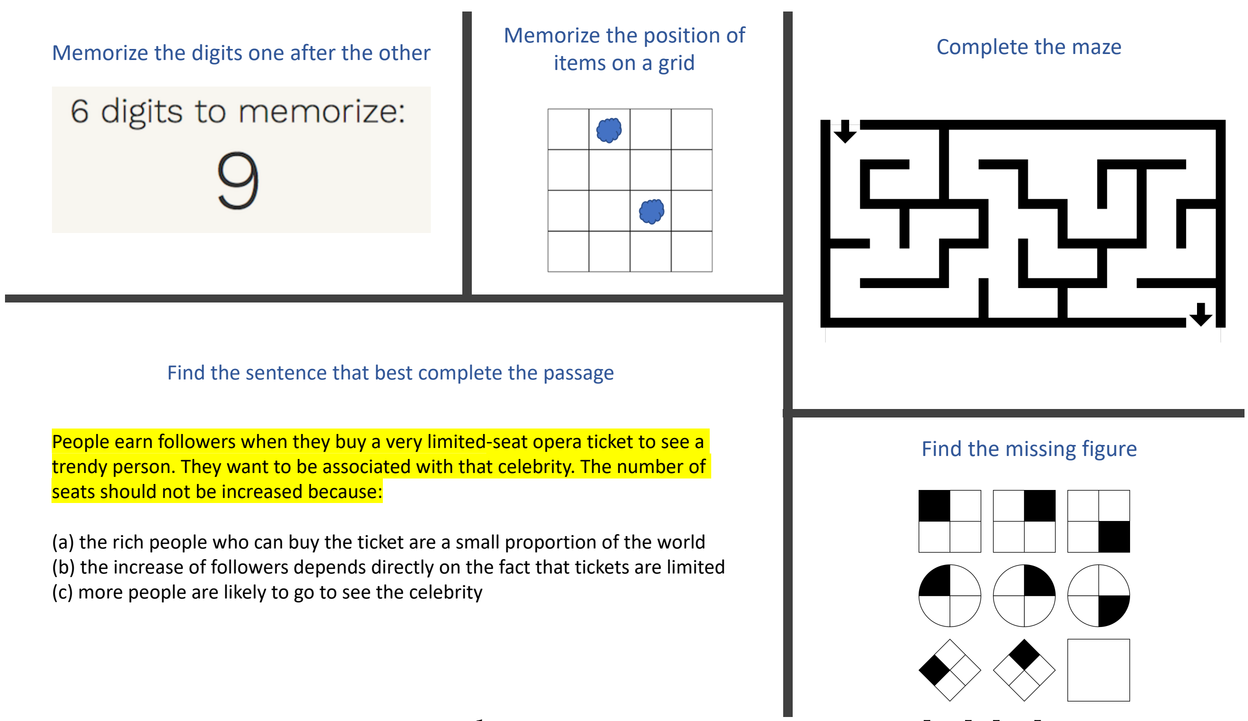


Figure 14. – Second experiment: the different cognitive exercises [93], [94].

The passage is underlined at the bottom because we took the screenshot directly from the exercise we created. In this exercise, we wanted to differentiate the passage that needs to be read carefully from the answer elements.

Each set of cognitive exercises contained one example and four exercises of increasing difficulty.

At the end of each exercise, participants indicated their level of confusion (no confusion, slightly confused, moderately confused, very confused).

In this subsection, we detailed the data collection. We will now talk about the methods we used to extract and transform our data to obtain an accurate model for measuring confusion (Step 2 in Fig. 17).

5.4. Preprocessing and feature extraction methods

Before starting, it is worth recalling the general principle of machine learning and the importance of data preprocessing.

Machine learning is the study of computer algorithms that learn from their experiences. Algorithms go through many data and find patterns between the data that allow them to perform various tasks (e.g., prediction, identification).

In this thesis, we used supervised learning, which, from a set of input variables X and a set of output variables Y, **learn the mapping function** from the inputs to the outputs.

$$Y = f(X)$$

The goal is to approximate the function so that when we have new input examples X, we can predict the output variables Y of these new examples [95].

Data preprocessing in machine learning is a step where the collected raw data is converted into a much more useful or desired form. The learning algorithm can better find patterns between the data and thus obtain better predictions. It is, therefore, an important step.

We will explain the methods for transforming the data we used.

5.4.1. Creation of dataset of EEG signals

In both experiments, we created our dataset differently.

From the videos of the participants of the first experiment, we used FaceReader to obtain confusion values for the whole game sessions (6 confusion values per second). We then transformed these six decimal confusion values into a level of confusion for each second of gameplay, as described in Figure 15. Ultimately, we ended up with one second of EEG signals (vector size 14x128) associated with a level of confusion.

---

if *confusion detected by FaceReader is between [0.0, 0.2[* **then**
  Confusion level = 0 ; // no confusion

else if *confusion detected by FaceReader is between [0.2, 0.4[* **then**
  Confusion level = 1 ; // slightly confused

else if *confusion detected by FaceReader is between [0.4, 0.7[* **then**
  Confusion level = 2 ; // moderately confused

else
  Confusion level = 3 ; // highly confused

Figure 15. – Algorithm for obtaining levels of confusion (model output variables) from FaceReader confusion values.

In the second experiment, we first saved the EEG signals of a participant's entire session in a single file. Therefore, the first step was to extract and separate the EEG signals associated with each exercise. Then we realized that instead of having levels of confusion associated with exercises of different duration, it was better to have levels of confusion every second. Thus, we extracted the EEG signals for each second of an exercise. We then assigned them to the self-reported level of confusion of the entire exercise.

After discussing data extraction, we will talk about an **alternative representation** of the data (spectral features) that allowed us to improve the accuracy of our models.

We will introduce this alternative representation in section 5.4.2.

5.4.2. Spectral feature extraction

When we first used the EEG signals from the second experiment to train our models, we got less than 50% accuracy. Thus, we looked at another representation of the data to improve the accuracy. A conventional approach is the analysis of signals as a function of frequency rather than time. This approach was used by Wang et al. to predict whether a student was confused or not confused (see literature review section 5.2.1) [82].

Frequency can be defined as the number of times a phenomenon occurs in a given time. A high frequency will, therefore, indicate a phenomenon that occurs frequently and vice versa. The principle of switching from the time domain to the frequency domain is to decompose the signal into a sum of several periodic signals to get a different view of the signal and see the frequencies. Having access to the frequencies makes it possible to see how many times each amplitude occurred. An amplitude that occurs frequently will have a higher frequency than an amplitude that occurs more rarely. Figure 16 illustrates the domain transition.

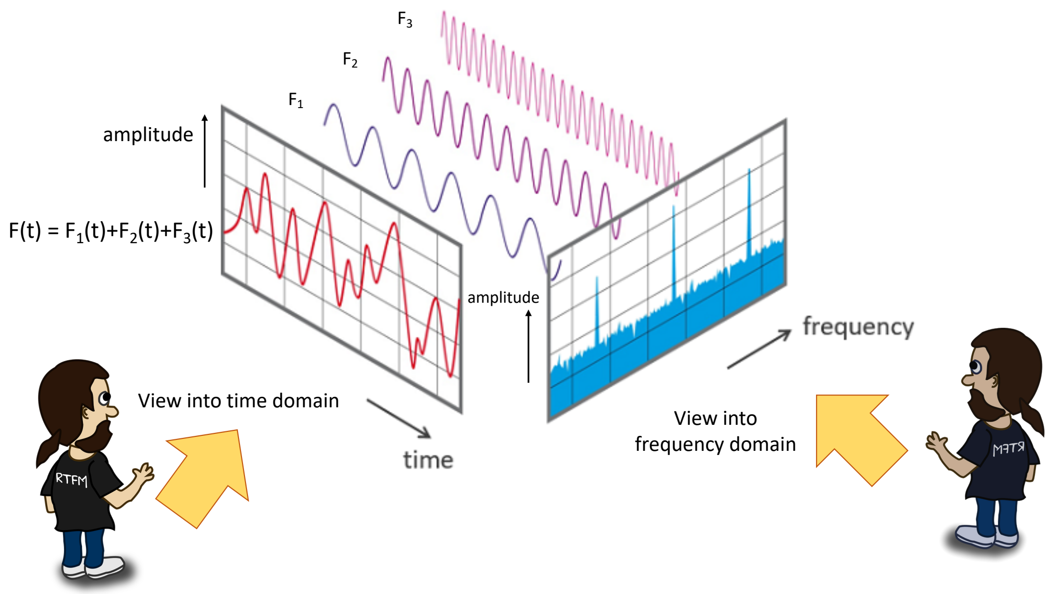


Figure 16. – The transition from the time domain to the frequency domain [96], [97]. A view of the signal in two different ways.

Switching to the frequency domain is supposed to reduce the complexity of the signal representation and, therefore, potentially make it easier for our models to learn. Hence, we converted our EEG signals from the time domain to the frequency domain.

The power spectral density shows the distribution of the strength (amplitude) of a signal in the frequency domain. We calculated an estimate of the power spectral density using Welch's method and the **Fast Fourier Transform** [98]. The estimate gave the average band power, which is a number summarizing the contribution of the frequency band to the total signal power [69]. We used the following bands: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-100 Hz).

5.4.3. **Oversampling**

We also performed another transformation of the data. The datasets were **unbalanced** and had a very different number of inputs for each class (class 0 = not confused up to class

3 = very confused). This imbalance could lead to differences in prediction between classes. The model could, for example, have accurately predicted when individuals were highly confused, but not effectively predicted when individuals were moderately confused. To avoid this situation, we, therefore, applied an oversampling technique. New data in the minority classes was generated by randomly selecting samples with replacement until the classes had the same number of inputs as the majority class.

Figure 17 summarizes the different steps we have taken so far to obtain our models for measuring confusion. After transforming our data to improve the accuracy of our models, we will now present the results obtained.

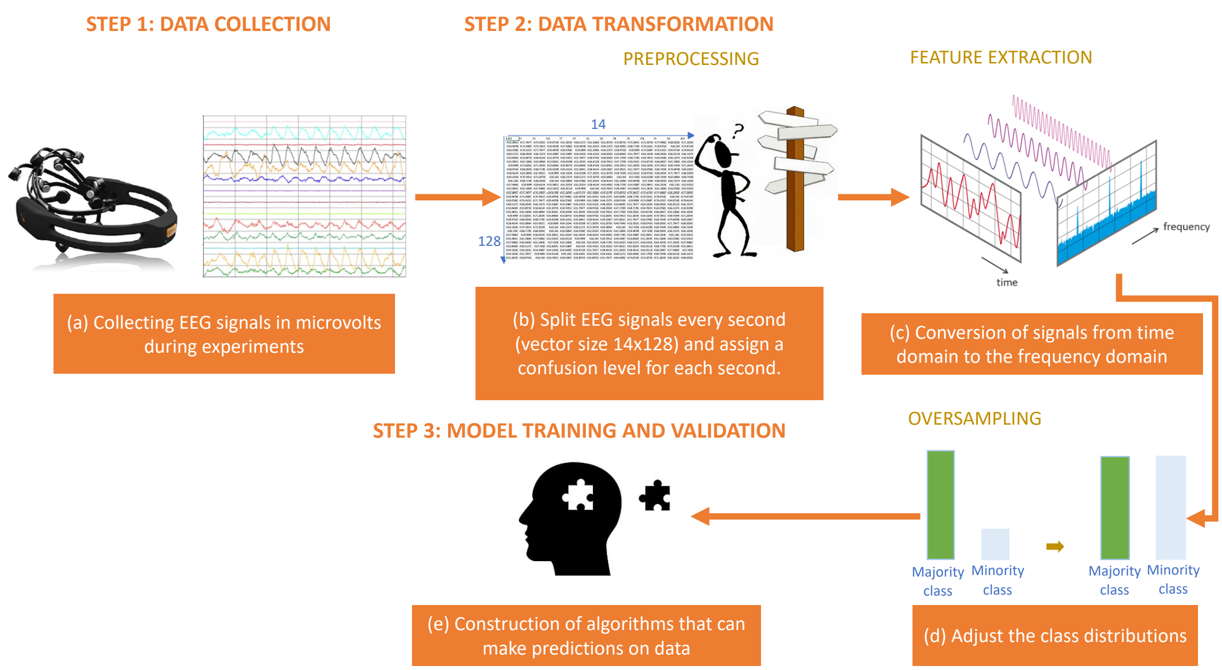


Figure 17. – Machine Learning Process [99], [100]

5.5. Results

First of all, we would like to mention that no model in machine learning outperforms all others for all learning tasks because each learning task is different. Determining which model will give the best performance for a given task is not yet an exact science but more of an intuition or a trial-and-error process.

We wanted to obtain first results with a simple model, quick to implement and easy to parameterize before moving on to more complex models. K-nearest neighbors (KNN) model met all these conditions, plus had the advantage of being very intuitive, which would make it easier to understand the results. Therefore, it was used as a baseline to predict confusion.

The Long short-term memory model (LSTM) is capable of learning over long sequences to predict the next one. It thus seems to be particularly suitable for time series (including EEG signals), we chose it as a second model to improve the results of our baseline.

The Support Vector Machine (SVM) is one of the most popular models for classifying EEG signals. It provides good prediction results on large datasets by transforming the input data. SVM is supposed to be an algorithm that performs well with EEG data (even though, as mentioned above, it is difficult to generalize) [101]. It was the third model used to try to predict confusion.

We chose the Scikit-learn and Keras libraries to run the models in python. For the KNN, we used the class sklearn.neighbors.KNeighborsClassifier with as hyperparameter n_neighbors (better known as k). For the LSTM, we used the classes tf.keras.layers.LSTM and tf.keras.Sequential with the following hyperparameters: batch_size, units, epochs. Finally, for the SVM, we used the class sklearn.svm.SVC with the following hyperparameters: C, gamma, kernel.

We chose the hyperparameters and their values with an exhaustive search. We used sklearn.model_selection.GridSearchCV class from the Scikit-learn library. For selected parameters, the Grid Search tests a series of values and gives the model's accuracy at each test. In summary, with the GridSearch, we could find which hyperparameters significantly improved the accuracy of the models, but also tune them to get the best results.

The metric we chose to evaluate the performance of the models is the **subset accuracy**. The subset accuracy indicates the percentage of inputs (e.g., our EEG signals), in a subset, that exactly match the labels (e.g., our levels of confusion). For example, among the signals that the model associates with an unconfused state, it is the percentage of signals that are truly unconfused. Here is the formula for subset accuracy:

$$SubsetAccuracy = \frac{1}{n}\sum_{i=1}^{n} I(Y_i = Z_i)$$

n is the number of inputs of the class, e.g. the total number of unconfused signals. Y_i is the true level of confusion associated with the signal of index i. Z_i is the predicted level of confusion for the signal of index i. I is the indicator function which returns 1 if $Y_i = Z_i$ and 0 otherwise.

We chose this standard metric because it is a strict metric that does not only take into account correct predictions. It penalizes incorrect predictions as well. It is also a widely used metric as it is one of the standard metrics of the Scikit-learn library. In the following paragraphs, we used the word "precision" instead of "precision subset" for reasons of visibility.

5.5.1. **Spectral features vs. EEG signals**

First of all, we wanted to know when EEG signals were preferable to spectral features to train our models and vice versa. Thus, we decided to use a KNN model that we trained with the EEG signals and then with the spectral features. The plan was then to use the data that would give the best results to train the LSTM and SVM models.

With the KNN model, EEG signals from the first experiment gave much better results (78.7% accuracy) than spectral features (38.2% accuracy). Figure 18 shows these results in the form of a matrix of confusion. Using Scikit-Learn's confusion_matrix function, we normalized our confusion matrix. We normalized it to display results based on correctly predicted data among all predicted data. We are going to detail the first column of Figure 18 so that the reading of all the confusion matrices is clear.

Among the EEG signals associated with a not confused state:

- the model predicted 81.3% of them correctly (i.e., as not confused)
- the model predicted 13.2% of them as not confused while they were actually slightly confused
- the model predicted 3.4% of them as not confused while they were actually moderately confused

– the model predicted 2.1% of them as not confused when they were actually highly confused

The size of the dataset of EEG signals was 28057x14x128 versus 28057x14x5 with spectral features. From KNN, we learned that the EEG signals from the first experiment gave better results than the spectral features. Therefore, we used the EEG signals from the first experiment to train the LSTM and SVM models. The best model was the LSTM, with an accuracy of 84.6% on the test set.

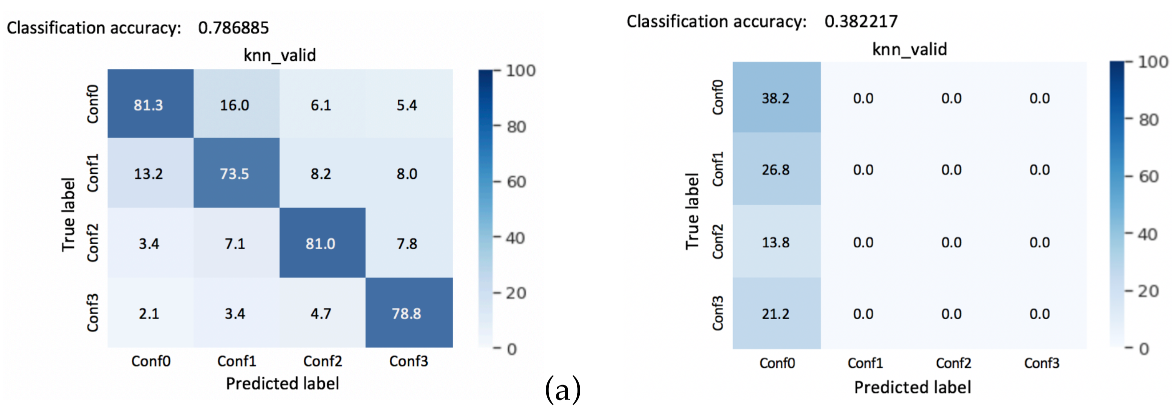
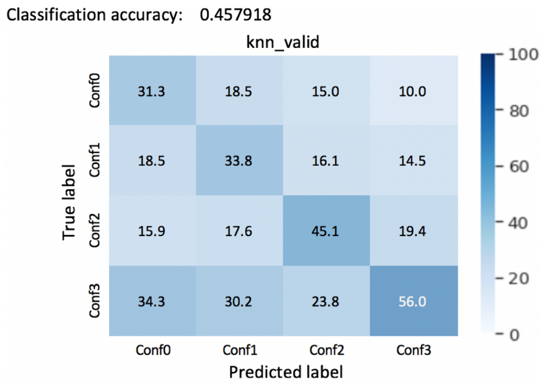
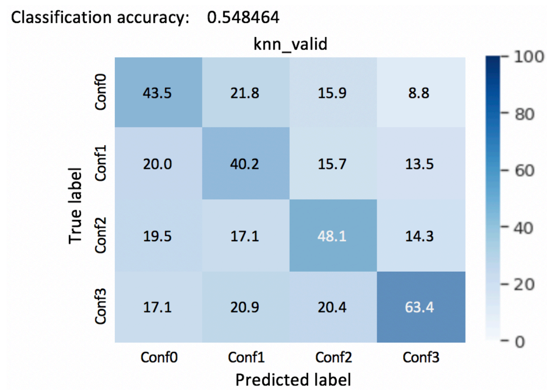


Figure 18. – Predicting the level of confusion with data from the first experiment: Confusion matrix of a KNN with EEG signals (a) vs. spectral features (b). Conf0 stands for no confusion and Conf3 for high confusion.

For the second experiment, the size of the dataset of EEG signals was 12533x14x128 versus 12533x14x5 with spectral features. The spectral features of the second experiment gave better results than the EEG signals of the second experiment (respectively, 54.8% and 45.8%). Figure 19 shows these results. Therefore, we used spectral features of the second experiment to train the LSTM and SVM models. The SVM achieved the best accuracy of 65.5%, while the LSTM achieved an accuracy of 58.3%.



(a)



(b)

Figure 19. – Predicting the level of confusion with data from the second experiment: Confusion matrix of a KNN with EEG signals (a) vs. spectral features (b).

With the data from the second experiment, we also predicted cognitive abilities related to confusion. As a reminder, we wanted to find out what cognitive ability was solicited when confusion occurred. We wanted to know, for example, if the user tried to remember a series of numbers when they were confused. For this, we developed cognitive exercises that involve different types of cognitive skills (see section 5.3.3). We recorded EEG signals for five sets of cognitive exercises. Then we labeled the data for each set of exercises with the cognitive skill involved. We then trained the KNN, LSTM, and SVM models. The principle was the same as for the prediction of confusion.

The SVM model achieved the best accuracy of 70.4%, while the KNN and the LSTM achieved an accuracy of 50.9% and 54.9%, respectively (see Table 5).

5.5.2. **Oversampling**

We oversampled only the most accurate models because a larger sample size increases the required training time. Figures 20 and 21 show that increasing the amount of data improved the accuracy of all models and reduced overfitting.

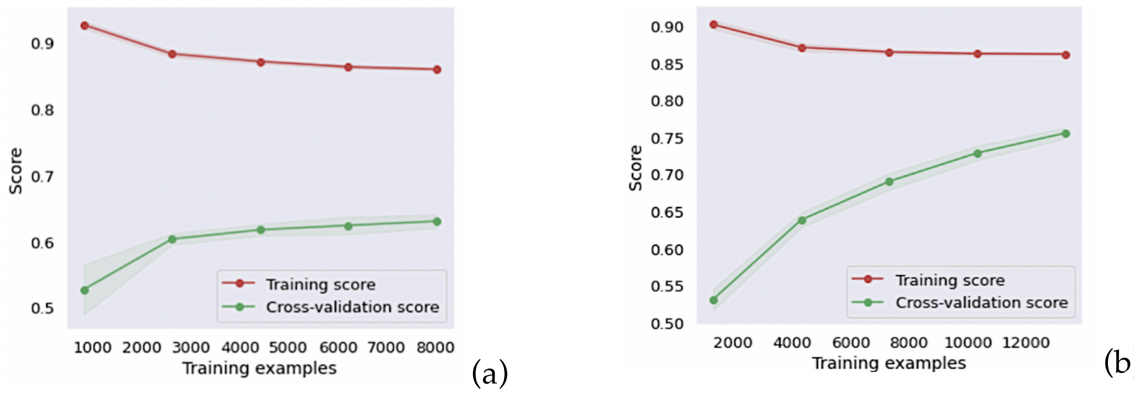


Figure 20. – Improving the prediction of the level of confusion with data from the second experiment: The learning curve of the unsampled dataset (a) vs. the oversampled dataset (b) using SVM.

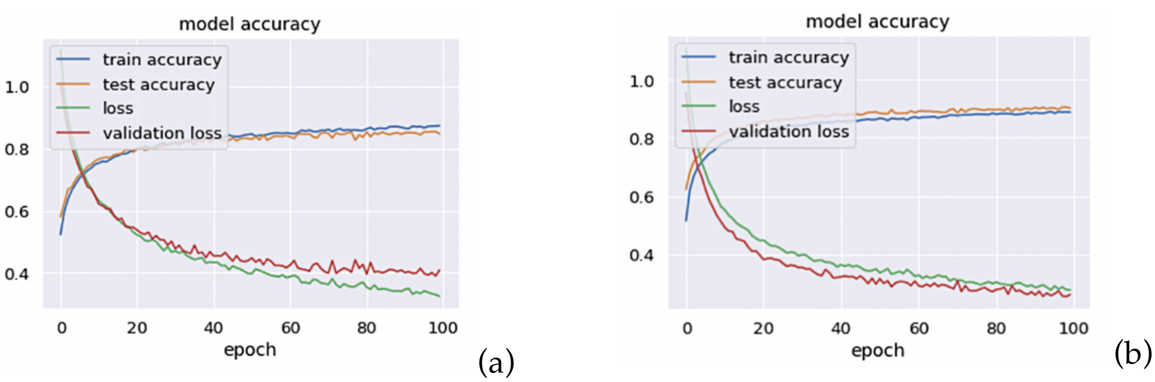


Figure 21. – Improving the prediction of the level of confusion with data from the first experiment: The learning curve of the unsampled dataset (a) vs. the oversampled dataset (b) using LSTM.

After oversampling the data from the first experiment, we obtained a dataset of size 43484x14x128. The precision for predicting the level of confusion went from 84.6 to **90.2%**. The oversampling of the data from the second experiment increased the size of the dataset to 20870x14x5. The accuracy of the prediction of the level of confusion went from 65.5% to 77.3%. The prediction of cognitive skills related to confusion improved from 70.4% to 81.8%. Figure 22 highlights these results.

We are going to detail the first column of Figure 22 b) so that the reading of the confusion matrices with the different series of cognitive exercises is clear.

As a reminder, for the second experiment, we developed cognitive exercises that involve different cognitive skills. We recorded EEG signals when participants performed these exercises (see section 5.3.3). For each second of EEG signals (of size 14x128), we assigned a level of confusion but also another number. This number corresponded to the task involved in the exercise. It varied from 0 to 4 where:

- 0 was an exercise requiring abstract and spatial reasoning
- 1 was an exercise requiring a logical argument analysis
- 2 was an exercise requiring spatial orientation
- 3 was an exercise requiring spatial memorization
- 4 was an exercise requiring short-term memory

Figure 22 b) thus indicates that among the EEG signals associated with abstract and spatial reasoning (series 0):

- the model predicted 87.5% of them correctly (i.e., as signals corresponding to abstract and spatial reasoning)
- the model predicted 8.0% of them as signals corresponding to logical argument analysis when they were actually signals corresponding to abstract and spatial reasoning
- the model predicted 4.0% of them as signals corresponding to spatial orientation when they were actually signals corresponding to abstract and spatial reasoning
- the model predicted 0.3% of them as signals corresponding to spatial memorization when they were actually signals corresponding to abstract and spatial reasoning
- the model predicted 0.3% of them as signals corresponding to short-term memorization when they were actually signals corresponding to abstract and spatial reasoning

The purpose of this model (different from the model for measuring confusion) is to detect cognitive abilities that are currently in use. For example, in an environment with multiple stimuli, we might want to know what exactly confuses people (being disoriented, trying to remember something, etc.). It is particularly relevant if confused people are not aware of themselves and has difficulty communicating like with dementia.

Currently, the model detects five cognitive abilities. In future work, it would be necessary to add more detectable cognitive abilities.

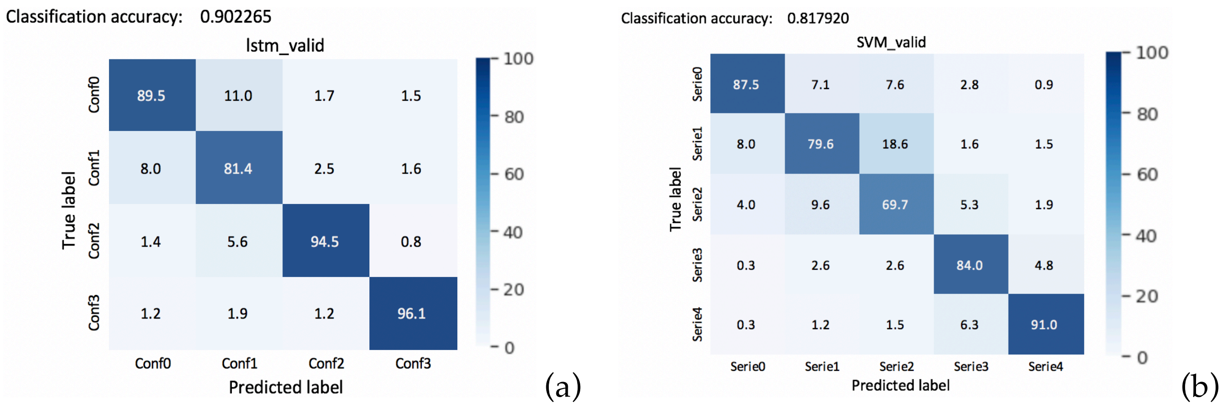


Figure 22. – Models with the best accuracy in predicting the level of confusion (a) and the cognitive skills related to confusion (b). Series from 0 to 4 correspond to the exercises described in section 5.3.3, ranging from abstract reasoning to short-term memory.

5.5.3. **Classification overview**

By using preprocessing methods, we achieved an accuracy of **90.2%** in predicting the level of confusion with the data from the first experiment. Table 4 provides an overview of the results to predict the level of confusion.

It was also possible to predict the cognitive skills related to confusion with **81.8%** accuracy using the data from the second experiment. Table 5 provides an overview of the results to predict the cognitive skills involved in the confusion.

Table 4. – Predicting the level of confusion: an overview of best classifiers accuracy

First experiment		**Second experiment**	
Method	***Accuracy (%)***	***Method***	***Accuracy (%)***
KNN (k=25)	78.7	KNN (k=25)	54.8
LSTM	84.6	LSTM	58.4
LSTM and oversampling	**90.2**	LSTM and oversampling	65.5
SVM (kernel=linear)	55.0	SVM (kernel=linear)	**77.3**

Table 5. – Predicting cognitive skills related to confusion with data from the second experiment: an overview of classifiers accuracy

Method	Accuracy (%)
KNN (k=25)	50.9
LSTM	54.9
SVM (kernel=rbf)	70.4
SVM and oversampling	**81.8**

5.6. Discussion

The use of spectral features from the first experiment led to a significant loss of information. One plausible reason is that the frequencies may have changed over time. The LSTM model performed very well with the EEG signals from the first experiment because it takes advantage of the time domain.

We observed the opposite effect with the data from the second experiment. The models had better results with the spectral features. It is likely that the EEG signals had noise and that switching from the time domain to the frequency domain reduced the noise.

It is also important to remember that in the second experiment, the users reported themselves the levels of confusion for a whole exercise and that we split the inputs for each second of the exercise. So, we had the same level of confusion for every second of the exercise.

This rough assignment of the level of confusion undoubtedly had a considerable effect on the temporal data (EEG signals). The switch to the frequency domain (spectral features), which highlights frequency amplitudes, made it possible to find patterns.

On the whole, the models from the first experiment gave more accurate results because we obtained the levels of confusion using FaceReader. It gave accurate values at a high sampling rate by analyzing facial expressions. We obtained very accurate models, and thus achieved our second objective.

In addition to developing a multiclass classification of confusion for four levels of intensity, we also developed a model to detect cognitive skills related to confusion.

One of the key points of this study is the use of FaceReader software to extract confusion values and assign them to EEG signals. It is also one of its limitations. FaceReader has proven its effectiveness in measuring certain emotions [102]. However, no studies have yet been conducted to validate its measurement of confusion. In short, our models are only relevant if the way FaceReader detects confusion is good.

Chapter 6. Conclusions and future works

In this thesis, we developed a virtual reality environment called Savannah VR for the relaxation of people suffering from subjective cognitive decline. We sought to differentiate our study from others by:

- analyzing the impact of our virtual environment on the cognitive functions of the participants
- making Savannah VR an intelligent environment that adapts to the emotions of the participants

The environment proved to be effective, as 68% of the participants saw their level of frustration decrease during the virtual experience. Savannah VR is also promising for improving cognitive performance. About 89% of participants improved their scores on memory exercises. Approximately 79% of participants scored at or above on attention exercises.

We also wanted to detect confusion using EEG signals. To this end, we designed a web application based on a set of popular cognitive ability tests. We recorded the brain activity of the participants when they were doing the cognitive exercises. Then we considered a different representation of the collected data so that the learning models would give better results. We switched from the time domain (EEG signals) to the frequency domain and thus computed some spectral features.

Our results stood out from the others by their novelty:

- recognition of four levels of intensity of confusion (multiclass classification) with 90.2% accuracy
- recognition of cognitive skills related to confusion with 81.8% accuracy

Following this thesis, two papers have been submitted and will be evaluated in the coming months (see Appendices A and C).

In the future, it would be interesting to regularly immerse the same participants in Savannah VR to analyze the evolution of the participants' affective states and cognitive states over a more extended time (one month, for example). In this way, we could see whether the benefits of virtual savannah apply in the long term.

One promising approach to relieving patients is Reminiscence Therapy, which uses memories of the past to soothe people with dementia. This approach could lead to the development of personalized virtual worlds that would remind patients of their childhood. It would be interesting to see the improvement of cognitive functions in such virtual worlds.

Nowadays, the Alzheimer community is just beginning to benefit from virtual reality. Our study focused on the reduction of negative emotions and the improvement of cognitive functions. However, there is also a need to use VR to reduce the risk of getting AD. It is necessary to develop more cognitive training exercises and more relaxation tools.

Some current research focuses on identifying individuals at risk of getting AD. The game Sea Hero Quest analyzes how at-risk players (with the APOE4 gene) navigate differently in the virtual environment [103]. Developing such games is an essential step because it has the potential to reach many people and identify those at risk quickly and inexpensively.

Although we focused on the well-being of people with cognitive impairment, virtual reality can also benefit healthy individuals. The relaxation environments we mentioned above have benefits for everyone. With today's global lockdown, virtual reality is becoming a popular topic as it can allow users to relax in a safe place or work together. Immersion, which is an attribute of VR, should also be a concern because the limits with reality can become blurred. More VR solutions need to be developed and explored while maintaining a balance with the real world so as not to lose touch with reality.

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Appendix A: First paper

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Virtual Savannah: an Effective Therapeutic and Relaxing Treatment for People with Subjective Cognitive Decline

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Abstract. In an attempt to make the therapeutic aspect less aversive, more attractive and engaging, virtual reality, an increasingly popular application in healthcare, offers an interesting alternative to pharmacological treatments. Positive emotions may improve the cognitive abilities of people suffering from cognitive impairment. Virtual reality can provide immersive and efficient relaxation tool. This paper presents an experiment where 19 people with Subjective Cognitive Decline (SCD) were immersed in a virtual environment representing a savannah. The hypothesis is that the environment may help them reducing their frustration by relaxing. Participants' brain activity was recorded using the Emotiv Epoc headset and the virtual savannah experience lasted 10 minutes. Results suggest that frustration decreased when participants were surrounded by the virtual savannah and that the positive effects continued afterwards.

Keywords: Cognitive Impairment, Virtual Reality Therapy, Emotions, EEG, Savannah, Cognitive Decline, Healthcare Application, Brain activity, Relaxation, Frustration

1 Introduction

As the global proportion of older people is increasing rapidly, attention should be paid to cognitive impairment, as it particularly affects older people. According to the World Health Organization, the world population aged 65 or older was 703 million in 2019 [1]. This number is expected to double to 1.5 billion by 2050. Worldwide, approximately 50 million people (91% over 65 years of age) suffer from dementia causing cognitive decline. By 2050, this number is estimated to triple [2].

New forms of non-drug treatments are in great demand to relieve patients, this study will focus on one of them: Virtual reality therapy is the use of virtual environments for health applications. Virtual reality (VR) environments have the advantage that they can be designed, controlled and configured more easily than real environments. With their immersive experience, they are proven to be effective in treating psychiatric disorders by inducing relaxation [3]. Reducing stress by reducing negative emotions not only can reduce cognitive decline and increases memory performance, but also improves mood and quality of life, thus reducing treatments related to anxiety and agitation [4], [5].

The aim of this study is to assess the impact on frustration of the developed VR environment (Savannah VR) for people with Subjective Cognitive Decline (SCD). The paper is organized as follows. First section introduces research that led to the design of Savannah VR. Savannah VR is presented in the second section. A third section describes the experiments conducted and the results are reported and discussed in the last section.

2 Design of the virtual environment: Conducted research

2.1 From savannah preference to a soothing virtual reality environment

Wilson introduced the word biophilia in 1984, that is an innate affinity people have with nature [6]. Savannah preference is a tendency to prefer savannah landscapes because early humans lived for thousands of years in the African savannahs [7]. The term savannah refers here to open environments where the grass is short, with deciduous green trees, water and animal life. Ancient survival challenges led to a correlation between natural landscapes and positive feelings. Savannah as a natural environment brings back the feeling of tranquility and peace [8]. Spreading trees in savannah give a feeling of security because they provide to early humans a place to observe or hide from predators. Savannah is an ideal place to travel and explore, it attracts attention and relaxes thanks to its varied and pleasant landscapes. Therefore, it is assumed that it can be a beneficial virtual environment for people with cognitive impairment.

2.2 Audiovisual research: Concept art based on drone videos

Prior to creating the environment, audiovisual research was conducted to establish concept art to be used as a source of inspiration for the appearance of the environment. Videos captured by drones provide far-away views that give a useful overall perspective for creating a virtual environment. These videos taken from afar with varied landscapes, sunrises, sunsets, water and different types of grass were taken as the basis for creation.

Relaxing piano music under Creative Commons (CC) license with 94% positive feedback from about 1500 voters on Youtube was chosen as background music.

2.3 Choice of components

The components of the environment were chosen to minimize stress. The main consideration in the choice of animals was to find animals perceived as harmless. Following animals have been chosen to be part of Savannah VR: hornbills, starlings, giraffes, antelopes, gazelles, small elephants and zebras. The key factors in the choice of the graphical user interface were clarity and readability. The Wii Sports game was very popular with the elderly [9]. It has a clear and simple interface, so a similar interface for text and explanations was adopted.

3 Savannah VR: A soothing environment

3.1 Overview

Savannah VR was developed in C# with Unity3D 2017.1.4 engine. It is a therapeutic virtual experience designed to relax and unwind. Participants follow an avatar walking through a savannah speaking in a soft and reassuring voice. As a way of attracting participants' attention and reassuring them, the avatar asks users how they feel and gives clear and concise indications, both in writing and speaking, to ease information processing. The Windows-based environment that requires only a virtual reality headset and a mouse has been designed with cognitively impaired people in mind. The dominant colors are warm, the animals are calm, their movement is slow. A soothing piano tune is played in the background at a volume low enough to appreciate the sound of each animal. Fig. 1 below illustrates the visual aspect of a part of the environment.

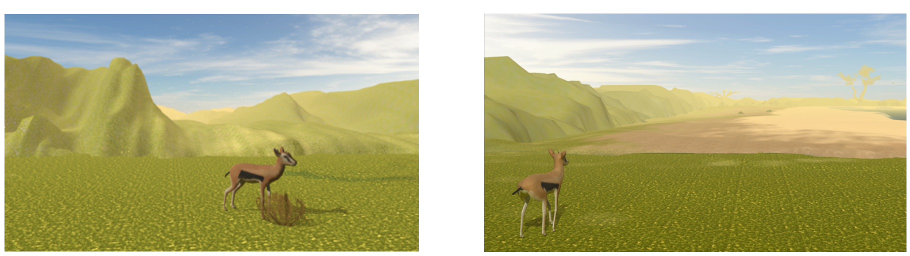

Fig. 1. Screenshots of Savannah VR

3.2 Navigating in the environment

Participants automatically follow a gazelle that moves along a precise path with breaking points. They can only look around them without controlling movements. To avoid nausea caused by movement in virtual reality, users follow the gazelle at low speed. The animal is in front of them to imitate a third person view that is less likely to cause motion sickness [10]. The participant's vision has been adjusted to be more pleasant.

3.3 Real-time environment modifications

Real-time changes of the environment are possible with a view to future research. Functions have been implemented that enable environment parameters to be modified by pressing a key. One of the adjustable parameters is the color and intensity of the light because light influences perception and decision-making [11]. Its color can also improve learning [12] and relieve stress more quickly [13]. Also, it is important to choose the volume carefully; too high volume can cause noise pollution [14] so sound volumes can be changed. An environment with more trees can also relieve stress more quickly and effectively [15], it is therefore possible to increase the number of trees in the environment. The number of animals can also be decreased, and the sky and colors can be changed to have a soothing sunset (Fig. 2).

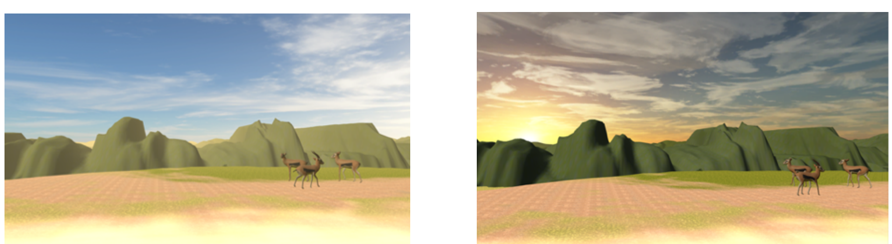

Fig. 2. Screenshots of real-time changes in Savannah VR

4 Experiments

To test whether the virtual environment may reduce frustration, we conducted experiments on 19 participants (12 females) with SCD and a mean age = 71 (SD = 8,39). The participants went through two sessions. The first session was the pre-experimental session in which we made sure that they were eligible for the study. Participants with SCD were eligible to the study and were invited to take part of the experiment.

In the second session which is the experimental session, the participants were first invited to fill out pre-session forms. They were then equipped with an EEG headset and asked to solve attention and memory exercises. Following these tests, a FOVE VR headset was installed and the Savannah VR began. The savannah exploration lasted about 10 minutes. Afterwards, the participants completed again different examples of the same attention and memory tests. Lastly, they were asked to fill out post-session forms.

5 Results

The objective of this study was to analyze the effect of Savannah VR on the emotions of the participants and check whether the environment decreases the negative emotions. To this end, we started by analyzing the emotions of the participants before, during and after the Savannah VR. We analyzed the frustration extracted from Emotiv EEG. The preliminary results show that the mean frustration before Savannah was *0.68* (*0.24* min and *0.98* max). The mean frustration during the Savannah was *0.57* (*0.31* min and *0.88* max). After the Savannah, the mean frustration level was *0.55* (*0.28* min and *0.91* max). Figure 3 shows a boxplot of the mean frustration before, during and after the Savannah.

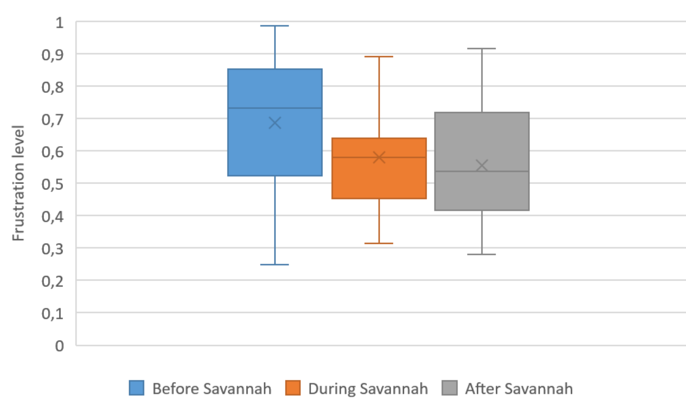

Fig. 3. Boxplot of general mean frustration

Overall, the frustration decreased when the participants were immersed in Savannah VR and the positive effect was still observed after Savannah VR. As mentioned in the introduction [4], by decreasing stress and negative emotions, memory performance could increase. It is therefore likely that Savannah VR, which decreased frustration, could also improve cognitive performance.

6 Conclusion

In this paper, we introduced Savannah VR, a virtual reality therapeutic environment whose purpose is to relax the user. Experiments were conducted during which the participants were first asked to perform attention and memory exercises, then immersed in Savannah VR to reduce their negative emotions. Results showed that the virtual environment helped reducing negative emotions most notably frustration. As it is mentioned by reducing negative emotions memory performance may be improved, so it is likely that Savannah VR may help in reducing cognitive decline. Future work should benefit from an analysis of the results of the attention and memory tests carried out by the participants.

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Appendix B: Animal movement algorithms in Savannah

Algorithm 1: A function that manages the movements of an animal. The animal can be stationary or walking. When the animal is walking, it avoids obstacles.

```
function AnimalMovement;
isStationary ← true ;                    // at the beginning, the animal is stationary
walkingTime ← 0.0 ;                      // the animal does not walk yet

while true do                            // as long as the virtual environment is running
    if walkingTime ≤ 0 then              // if the animal has exceeded its maximum walking time
        Wandering() ;                    // random choice:  the animal will be stationary or walking

    if !isStationary then                // if the animal is walking, check and avoid obstacles
        AvoidObstacles() ;
```

Algorithm 2: A function that chooses whether the animal will be stationary or walking.

```
function Wandering;
rand ← RandomDecimal(0.0, 1.0) ;  // generate a random decimal number between [0.0 and 1.0]
if rand < 0.1 then    // here, the animal will walk to a random destination in a defined area
 for 30s max
    WalkToARandomDestination();
    isStationary ← false ;
    walkingTime ← 30.0 ;
rand ← RandomDecimal(0.0, 2.0) ;
if (destinationIsReached or walkingTime ≤ 0) and (rand < 0.5) then    // if the animal reached
 the destination or ran out of time, here, it stops walking
    StationaryState() ;
    isStationary ← true ;
    walkingTime ← 0.0 ;
else if (destinationIsReached or walkingTime ≤ 0) and (rand ≥ 0.5) then // if the animal reached
 the destination or ran out of time, here, it keeps walking
    WalkToARandomDestination();
    isStationary ← false ;
    walkingTime ← 30.0 ;
```

Algorithm 3: A function that allows the animal to avoid obstacles, especially other animals.

```
function AvoidObstacles;
ScanTheEnvironment();            // scan the environment to find out where the obstacles are
if obstacleIsOnTheRight then
    PerformLeftRotation(distanceFromObstacle,animalSpeed) ; // left rotation whose speed and angle
     depend on the proximity of the obstacle and the current speed of the animal

if obstacleIsOnTheLeft then
    PerformRightRotation(distanceFromObstacle,animalSpeed) ;    // right rotation whose speed and
     angle depend on the proximity of the obstacle and the current speed of the animal

if obstacleIsOnTheTopLeft then
    PerformRightRotation(distanceFromObstacle) ;    // right rotation whose speed and angle depend
     on the proximity of the obstacle

if obstacleIsOnTheTopRight then
    PerformLeftRotation(distanceFromObstacle) ;  // left rotation whose speed and angle depend on
     the proximity of the obstacle

if distanceFromObstacle < 2 then      // If the animal is too close to avoid the obstacle, it
 stops.  This situation can sometimes occur when there is a group of animals that are close
 together
    StationaryState() ;
    isStationary ← true ;
    walkingTime ← 0.0 ;
```

Appendix C: Second paper

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Confusion's level recognition and its related cognitive ability

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***Abstract*— Confusion can occur in a variety of situations such as when reasoning, learning, memorizing or orienting. It affects our ability to make decisions and can lower our cognitive abilities. This study examined whether a confusion recognition model based on EEG features can be used to detect different levels of confusion in tasks related to reasoning, memorizing and orientating. In addition, we tried to classify the confusion related situation such as reasoning, orienting or memorization situation. This study also addresses the improvement of the accuracy of confusion's models through the extraction of additional features relevant to classification. Results suggest that the level of confusion can be efficiently recognized (90% accuracy for four confusion levels) and that the confusion related situation can be classified as reasoning, orientation or memorization situation (82% accuracy). Implications for educational situations are discussed.**

Keywords—confusion recognition, emotion recognition, machine learning, games, physiological data, memorization, reasoning, orientation, cognitive ability tests, eeg signals, emotiv epoc, lstm

I. INTRODUCTION

People may experience confusion in various contexts, notably in learning. There is a wide variety of educational games ranging from immersive, 3D virtual worlds [1] to puzzle games [2] that generate confusion.

Learners' emotions influence their learning experience, for example when they are confused it can lead to erroneous decision-making and influence their performance, engagement, and cognitive load. Confusion is a state that can be both beneficial, since it helps to increase engagement and allows for deeper knowledge or negative because it may lead to frustration and boredom if there is no understanding after a certain amount of time. Intensity and duration of the confusion appear to be a factor of frustration or boredom [3]. Detecting confusion in health, learning environments and games is critical to adapt the system efficiently to the user's state.

Two experiments were conducted to detect confusion. The first machine learning model was constructed from the facial expressions data and the EEG signals of 20 participants. The participants were playing an adventure open space 3D game where they could get lost easily. FaceReader 7.1 software was used to extract precise levels of confusion during playing time.

Two other models were trained with the data of ten participants that self-assessed their levels of confusion (no confusion, low, medium, high) while performing different cognitive exercises related to orientation, reasoning, and memorization.

The first hypothesis is that we can create an effective model to detect four levels of confusion (from not confused to very confused). The second hypothesis is that subcategories of confusion in relation to cognitive skills can be identified: abstract reasoning related confusion, confusion related to the analysis of logical arguments, spatial orientation related confusion, spatial memory related confusion, and short-term memory related confusion.

The paper is organized as follows. Section 2 introduces the state of the art of confusion recognition.

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Conducted experiments are described in a third section. A fourth section indicates used preprocessing methods. The results are presented in the fifth section and discussed in the sixth section. The conclusion aimed at validating our hypotheses can be found in the seventh section.

II. Confusion recognition

A. Related work

Several studies have been conducted to detect binary confusion using EEG signals. In 2001, confusion was associated with electroencephalography in the medical field. The purpose was to identify fluctuating confusion in dementia [4].

In 2011, a model of academic emotions (boredom, confusion, engagement and frustration) was created recording EEG signals during a session of a modified version of the Wisconsin Card Sorting Test [5]. The accuracy of the confusion classifier was less than 50%.

In 2013, Wang et al. used a one-channel MindSet EEG headset to detect confusion in ten adults watching videos of Massive Open Online Courses [6]. The best classifier achieved 57% accuracy. Wang et al. have used this dataset in more recent articles such as in 2017 with a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network that obtained 73.3% accuracy and in 2018 with an improved Bi-LSTM model that achieved 75% accuracy [7].

Other studies have been conducted to detect confusion by combining EEG signals with audiovisual sources. In 2016, Yang et al. created the Sedmid model to detect confusion [8]. They extracted EEG signals but also video features and obtained an accuracy of 87.8%.

B. Highlights of this study

In this study, EEG signals are combined with facial expressions to detect confusion objectively. Although there are already studies that combine EEG signals with facial expressions, this has not yet been done to detect confusion. Moreover, the confusion obtained unlike similar work is not binary but has four levels of intensity. Finally, an innovative model to differentiate subcategories of confusion related to cognitive skills is proposed in this paper.

III. Experiments

A. Equipment

Experiments were conducted with iMotions tool, a platform for multi-modal studies and equipment synchronization (eye tracking, facial expression, EEG, GSR, EMG, ECG). Facial expressions data and EEG were recorded. After each session, data from a log file, Emotiv TestBench and FaceReader were collected.

a) Emotiv TestBench: Emotiv TestBench is a tool that helps the experimenter verify the quality of signal during the Emotiv Epoc headset setup on the participant's head. This program also records the EEG signals from the 14 electrodes of the headset. The Emotiv electrodes are AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 with 2 references behind the ears. The EEG signals are in μVolt with a sampling rate of 128 Samples/sec and frequencies' range between 0.2 and 60 Hz.

b) FaceReader 7.1: FaceReader 7.1 program recognizes besides the seven facial expressions of primary emotion, three secondary emotions (confusion, boredom and interest) using real-time frame-by-frame analysis of user's face via a webcam. Facereader's resulted file includes the following emotion categories with values between 0 and 1: neutral, happy, anger, sadness, surprise, fear, disgust, arousal, confusion, boredom and interest. FaceReader also provides the valence, which indicates whether the person is in a negative or positive emotional state. The valence values are between -1 and 1. In this study, we are interested only about the confusion emotion data.

B. First experiment

1) *Subjects:* Twenty undergraduate students were involved (7 women, 13 men) from the Computer Science department of a North American University. Participants' ages ranged from 24 to 35 years. Twenty percent of the participants reported themselves as "gamers".

2) *Experimental procedure:* The experiment session took approximately one hour and involved participants interacting with Danger Island, a game developed in our lab. At the session's beginning, participants filled out a consent form. The experimenter checked the chair to maintain a good view on the computer screen. Participants had to complete on the computer the Big Five personality traits which classifies the learner's personality into five dimensions: openness, neuroticism, extraversion, agreeableness and conscientiousness. The experimenter set up the Emotiv Epoc headset, users then started to play The Danger Island. They were compensated $20 for participating and debriefed at the end.

3) *The Danger Island game:* The Danger Island (Fig. 1) is an adventure game where the player encounters a lot of enemies (zombies, wild animals and machine guns). The player's mission is to find fuel cans and go back to a helicopter in order to escape the island. Player has to find orientation within the game and may experience confusion and frustration to find their way. The game's difficulty level depends on the player's category (gamer/non gamer) selected in the game's start menu.

Fig. 1. Danger Island environment

C. Second experiment

1) *Subjects:* For the second experiment, ten students from a North American University have participated (five women, five men). Majority of participants were between 25 and 34 years old and had at least an undergraduate degree.

2) *Experimental procedure:* The experimentation session lasted about an hour. At the session's beginning, participants filled out a consent form. They were then asked to fill out the Big Five personality traits, a demographic questionnaire and Metacognitive Awareness Inventory (MAI) [9]. The MAI consists of 52 questions with true or false answers. It evaluates whether the user is aware of how they learn, what their strengths are, and how they regulate their cognition to learn better. The experimenter set up the Emotiv Epoc headset, users then started the cognitive ability tests.
They were compensated $20 for participating and debriefed at the end.

3) Cognitive ability tests: Five sets of cognitive ability exercises have been implemented.

a) Abstract and spatial reasoning: Based on Raven's progressive matrices, a set of geometric figures are displayed, participants have to find rules and patterns to find the missing figure [10].

b) Logical argument analysis: Participants read a short text and choose the statement that best completes the text. It is based on the Gmat critical reasoning test that measures the "ability to make arguments, evaluate arguments, and formulate or evaluate a plan of action" [11].

c) Spatial orientation: Participants have to complete 2d mazes.

d) Spatial memorization: Participants have to memorize the position of items on a grid (Fig. 2). It is based on the WMS-IV [12].

e) Short-term memory: Participants have to take a digit span test and memorize a sequence of numbers.

Each set of exercises contained an example and four exercises with different levels of increasing difficulty. At the end of each exercise, participants had to indicate their level of confusion (no confusion, slightly confused, moderately confused, very confused).

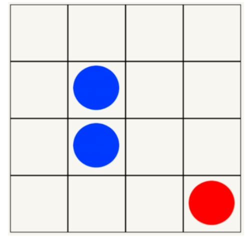


Fig. 2. Second experiment: example of a spatial memorization exercise

IV. Preprocessing and Feature Extraction Methods

We wanted to extract and transform the data so that they can be easily interpreted by the classifier and thus have better classification results.

A. Creation of dataset of EEG signals

1) *Use of FaceReader 7.1 for accurate confusion labels in first experiment:* The videos of the participants of the first experiment playing the game was combined with FaceReader (which analyzed their facial expression), to obtain confusion values for the whole game sessions (6 confusion values per second). We then transformed these 6 decimal confusion values into 1 level of confusion for each second of gameplay (Fig. 3). At the end we obtained one second of EEG signals (vector of size 14x128) associated to one level of confusion.

if *confusion detected by FaceReader is between [0.0, 0.2[* **then**
  Confusion level = 0 ;   `// no confusion`

else if *confusion detected by FaceReader is between [0.2, 0.4[* **then**
  Confusion level = 1 ;   `// slightly confused`

else if *confusion detected by FaceReader is between [0.4, 0.7[* **then**
  Confusion level = 2 ;   `// moderately confused`

else
  Confusion level = 3 ;   `// highly confused`

Fig. 3. Algorithm for obtaining levels of confusion (model output variables) from facereader confusion data.

2) *Getting levels of confusion in the second experiment:* In the second experiment, we recorded the EEG signals of a participant's entire session in a single file. The first step was to extract and separate the EEG signals that corresponded to each exercise. Then we realized that instead of having levels of confusion associated with exercises of different duration, it was advantageous to have confusion every second. So, EEG signals from each second of an exercise were extracted and assigned to the self-reported confusion level of the entire exercise.

B. Feature extraction: Average bandpower of an EEG signal

The raw signals of the Emotiv Epoc are given as a function of time, an alternative representation of the data (spectral features) was investigated to see if it would affect the results of the classifier.

A conversion from time domain signal to frequency domain signal has been performed. The frequency signal domain allows the analysis of signals with respect to frequency rather than time. There is less complexity in the signal representation. Power Spectral Density indicates how the strength (amplitude) of a signal is distributed in the frequency domain. An estimate of power spectral density using Welch's method and Fast Fourier Transform was computed [13]. Getting the estimate resulted in obtaining the average bandpower which is a number summarizing the frequency band's contribution to total signal power [14]. Following bands were used: delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz), and gamma (30-100 Hz).

C. Oversampling

Datasets were imbalanced with an unbalanced number of examples between the different classes. This may lead to differences in prediction between classes, so oversampling was done; new data was generated in the minority classes by randomly selecting samples with replacement until having the same number of examples as the majority class.

V. Results

K-nearest neighbors (KNN) was used as a baseline and then two models were trained: A Long short-term memory (LSTM) and a Support Vector Machine (SVM).

A. Spectral features vs EEG signals:

1) *First experiment:* The use of EEG signals from first experiment aschieved 78.7% accuracy on the test set in predicting the levels of confusion with the KNN model (Fig. 4). On the contrary, spectral features did not give good results in predicting the levels of confusion with the KNN model. The model classified all examples as unconfused. The size of the dataset of EEG signals was 28057x14x128 compared to 28057x14x5 with spectral features.

Therefore, the EEG signals were used to train the other models. The best model was the LSTM, achieving 84.6% accuracy on the test set.

2) *Second experiment:* A KNN model was first trained using a GridSearch on dataset of EEG signals from the second experiment to predict levels of confusion. The size of the dataset was 12533x14x128. The results were not very good with about 45.8% accuracy on the test set. Extracting the spectral features for different frequency bands reduced the dataset size to 12533x14x5 and improved the accuracy of the KNN to 54.8% (Fig. 5). So we used spectral features to train the other models. The SVM had the best accuracy (65.5% accuracy). Cognitive skills related to confusion were also predicted with an accuracy of 70.4%.

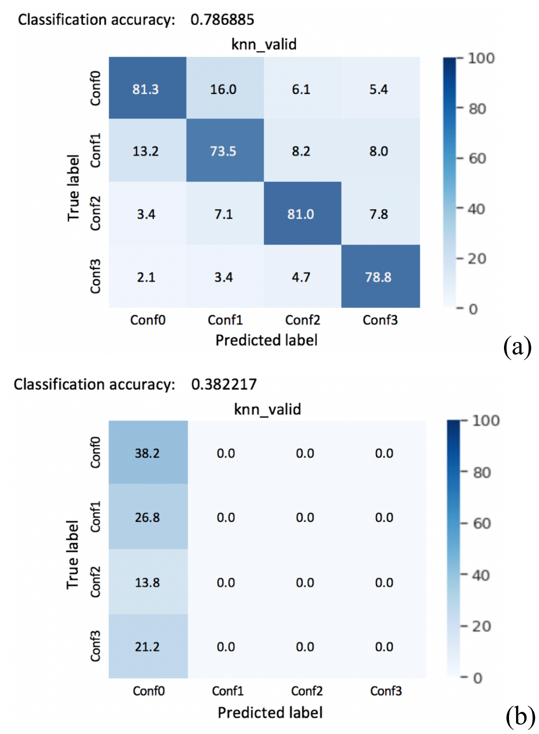
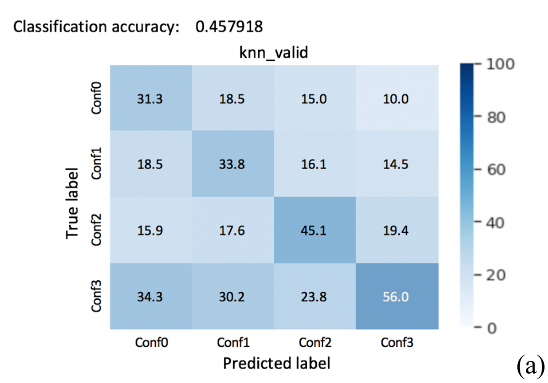
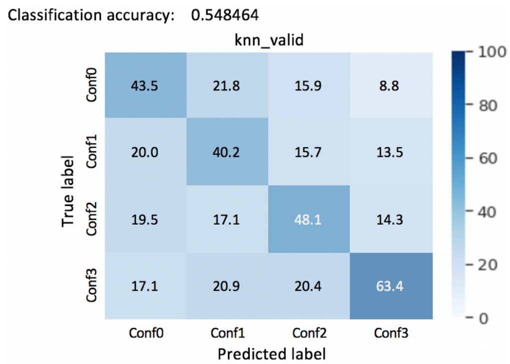


Fig. 4. Predicting level of confusion with data from first experiment: Confusion matrix of a KNN with EEG signals (a) vs spectral features (b). Conf0 stands for no confusion and Conf3 for high confusion.



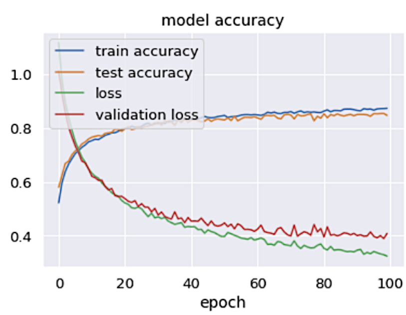


(b)

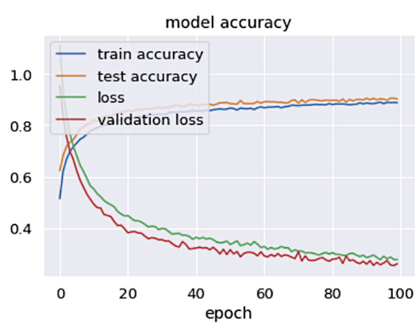
Fig. 5. Predicting level of confusion with data from second experiment: Confusion matrix of a KNN with EEG signals (a) vs spectral features (b).

B. Oversampling

Only the most accurate models were oversampled because increasing the sample size also increased the training time. Increasing the amount of data has improved the accuracy of all models (Fig. 6, Fig. 7).

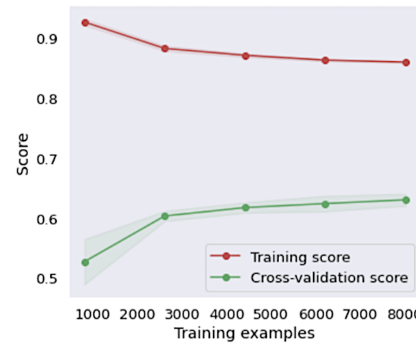


(a)

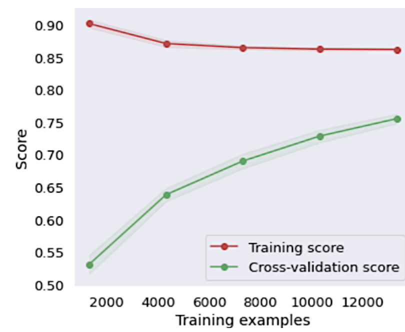


(b)

Fig. 6. Predicting level of confusion with data from first experiment: Learning curve of the unsampled dataset (a) vs the oversampled dataset (b) with an LSTM model. Dropout has been used that is why the test set is more accurate than the training set for the oversampled dataset.



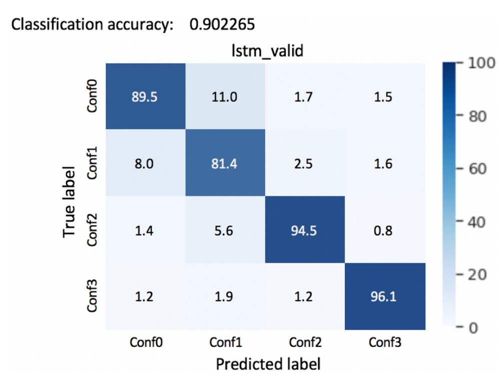
(a)



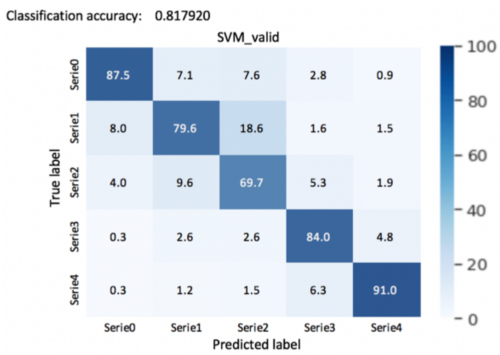
(b)

Fig. 7. Predicting level of confusion with data from second experiment: Learning curve of the unsampled dataset (a) and the oversampled dataset (b) with an SVM model

After oversampling and obtaining a dataset of size 43484x14x128, the accuracy of predicting the level of confusion with the data from the first experiment went from 84.6 to **90.2%** (Fig. 8). Using the oversampled dataset of size 20870x14x5 of the second experiment, the accuracy of predicting the level of confusion increased from 65.5% to **77.3%** and from 70.4% to **81.8%** for predicting cognitive skills related to confusion (Fig. 8). The learning curves show that the amount of data could even be further increased.



(a)



(b)

Fig. 8. Models with best accuracy in predicting the level of confusion (a) and the cognitive skills related to confusion (b). Series from 0 to 4 correspond to the exercises described in section 3C ranging from abstract reasoning to short-term memory.

C. Classification overview

By selecting efficient features and oversampling, **90.2%** accuracy in predicting the level of confusion was achieved with the data from the first experiment (Table 1) and **77.3%** with the data from the second experiment (Table 1). With the data from the second experiment, it was also possible to predict with **81.8%** accuracy the cognitive skills related to confusion (Table 2).

TABLE I. PREDICTING LEVEL OF CONFUSION: OVERVIEW OF BEST CLASSIFIERS ACCURACY FOR THE TWO EXPERIMENTS

First experiment		**Second experiment**	
Method	***Accuracy (%)***	***Method***	***Accuracy (%)***
KNN (k=25)	78.7	KNN (k=25)	54.8
LSTM	84.6	LSTM	58.4
LSTM and oversampling	**90.2**	LSTM and oversampling	65.5
SVM (linear kernel)	55.0	SVM (linear kernel)	**77.3**

TABLE II. PREDICTING COGNITIVE SKILLS RELATED TO CONFUSION WITH DATA FROM SECOND EXPERIMENT: OVERVIEW OF CLASSIFIERS ACCURACY

Method	Accuracy (%)
KNN (k=25)	50.9
LSTM	54.9
SVM (kernel=rbf)	70.4
SVM and oversampling	**81.8**

VI. DISCUSSION

Getting the spectral features with the data from the first experiment led to significant loss of information. One explanation is that the frequencies may have changed over the time. The LSTM model had very good results with the EEG signals from the first experiment because it takes advantage of the time-domain. The extraction of spectral features is more efficient with the data from the second experiment, because it is likely that the EEG signals from this experiment had more noise and that the change of domain reduced the noise. It should also be considered that the EEG signals of the second experiment did not give good results because users self-reported the levels of confusion for an entire exercise while the inputs were split per second. Spectral features show at which frequencies the amplitude variations are high or low, which may have resulted in finding patterns between the different data for each second of the exercise.

Overall, the models from the first experiment gave more accurate results because the intensity of the confusion was obtained using FaceReader software which, by analyzing facial expressions, gave accurate values at a high sample rate.

These models can be used in learning environments, games or in the health field since confusion recognition is very important especially to efficiently adapt the system to the user's confusion state or the type of cognitive situation.

VII. CONCLUSION

This innovative study demonstrates not only the feasibility of decomposing confusion into subcategories related to cognitive skills, but also the possibility of multiclass classification of confusion for four levels of intensity. In addition, our best model for classifying levels of confusion reached 90.2% accuracy and our best model for classifying subcategories of confusion related to cognitive skills achieved 81.8% accuracy. The results exceed those of the state of the art. It would be interesting for a future study to analyze whether confusion led to engagement or frustration and find a way to predict if confusion is likely to have a positive or negative outcome.

ACKNOWLEDGMENT

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Appendix D: Experimental protocol

The protocol was written in French.

Protocole Expérimental
Caroline Dakouré, Sahbi Benlamine, Claude Frasson (30 Janvier 2020)

Installation :
1. Utiliser des chaises sans roues.
2. Préparer le test cognitif en ligne
3. Mettre en ligne les formulaires Google de pré-session : démographique et MAI

Installation matérielle (~10-15 min)
1. **Formulaire de consentement** : faire lire et signer le formulaire de consentement aux participants.
2. **Formulaire démographique** : faire remplir le formulaire démographique aux participants
3. **Formulaire Big Five personality traits** : faire remplir le big 5 aux participants
4. **Formulaire 'Metacognitive Awareness Inventory (MAI)** : faire remplir le formulaire 'Metacognitive Awareness Inventory' aux participants.
5. Demander aux participants d'éteindre leurs téléphones.
6. **EEG**: Placer et calibrer le casque Emotiv Epoch EEG et le récepteur USB.
7. **iMotions**: Démarrer le logiciel iMotions.
8. **Vérifier la caméra** : Vérifier l'enregistrement caméra sous iMotions
9. **Emotiv TestBench** : Démarrer le logiciel Emotiv TestBench
10. **Vérifier les EEG** : Vérifier la réception des données EEG sous Emotiv TestBench
11. **Démarrer l'enregistrement EEG :** Démarrer l'enregistrement des données EEG
12. **Enregistrer iMotions :** Démarrer l'expérience via iMotions
13. Démarrer les tests d'aptitude cognitive sur l'écran du participant.

Début de l'expérience. (~1-3mins)
Explications : Maintenant que nous avons terminé l'installation matérielle nous allons commencer le jeu. Mais avant de commencer nous allons ensemble voir l'interface. Vous allez faire 5 séries de 4 exercices d'aptitude cognitive. Au début de chaque exercice, un exemple vous sera montré avec des explications. Vous serez ensuite invité à indiquer la confusion que vous avez ressenti durant l'exercice. Je n'interviendrai que pour des questions ou explications techniques. Si vous êtes prêts, cliquez sur démarrer l'expérience.

EXPERIENCE : **Pendant l'expérience. (~30 mins)**

Série 1 : Raisonnement abstrait et spatial. Le participant doit déduire des relations entre les figures géométriques.

- Prenez soin de bien lire
- Appuyez sur Question Suivante lorsque vous êtes prêts
- Cliquez sur le numéro que vous pensez être la bonne réponse
- Validez en appuyant sur Question Suivante

Série 2 : Raisonnement critique. Le participant doit trouver l'énoncé qui répond le mieux à un passage.

- Prenez soin de bien lire
- Appuyez sur Question Suivante lorsque vous êtes prêts
- Cliquez sur le numéro que vous pensez être la bonne réponse
- Validez en appuyant sur Question Suivante

Série 3 : Orientation Spatiale. Le participant doit tracer une ligne qui relie l'entrée d'un labyrinthe 2D à sa sortie.

- Prenez soin de bien lire
- Appuyez sur Question Suivante lorsque vous êtes prêts
- Vous devez tracer une ligne en maintenant le clic gauche de la souris enfoncé. Vous avez la possibilité d'effacer en cliquant sur « effacer le trait »
- Validez en appuyant sur Question Suivante

Série 4 : Mémorisation Spatiale. Le participant doit mémoriser l'emplacement de certains cercles sur une grille et en ignorer d'autres.

- Prenez soin de bien lire
- Appuyez sur Question Suivante lorsque vous êtes prêts (3 fois)
- Vous devez dessiner des cercles en choisissant la couleur à l'aide du menu déroulant et en maintenant le clic gauche de la souris enfoncé. Vous avez la possibilité d'effacer en cliquant sur « effacer le trait »
- Validez en appuyant sur Question Suivante

Série 5 : Mémoire de travail. Le participant doit mémoriser une série de nombres.

- Prenez soin de bien lire
- Appuyez sur Voir la séquence de nombre à mémoriser lorsque vous êtes prêts

En cas de difficultés techniques vous pouvez toujours me poser des questions.

Après les tests d'aptitude cognitive (~10-15 min)

14. Arrêter les captures de données.
15. Retirer tous les senseurs.
16. Donner au participant les réponses des questions.
17. Faire remplir le Questionnaire d'utilisabilité par le participant.
18. Faire remplir le formulaire de paiement par le participant.
19. Payer le participant.
20. Expliquer l'objectif de l'expérience.
21. Demander de ne pas parler aux probables futurs participants du déroulement de l'expérience.

Appendix E: Consent form

Université de Montréal

FORMULAIRE D'INFORMATION ET DE CONSENTEMENT

Titre de la recherche : Negative Emotions

Chercheurs : Sahbi Benlamine, Caroline Dakoure, *étudiants MSc*

Directeur du Laboratoire et responsable du projet : Claude Frasson, *Professeur Associé, DIRO, Université de Montreal*

Cette recherche est financée par le Conseil de recherche en Science naturelles et génie du Canada (CRSNG)

Vous êtes invité à participer à un projet de recherche. Avant d'accepter, veuillez prendre le temps de lire ce document présentant les conditions de participation au projet.

A) RENSEIGNEMENTS AUX PARTICIPANTS

1. Objectifs de la recherche.
Ce projet de recherche vise à identifier quelles émotions (joie, peur, stress, désengagement, excitation, etc.) peuvent intervenir dans un environnement virtuel interactif et peuvent générer une réduction de l'attention et des capacités cognitives. Nous utiliserons des dispositifs VR et AR ainsi que des équipements EEG et mettrons en place des outils spécifiques pour l'évaluation des émotions négatives. Nous identifierons également les conditions émotionnelles possibles pouvant conduire à des émotions négatives (succession d'états émotionnels par exemple). Le participant pourra interagir avec le jeu au moyen de manettes ou de gants permettant de déclencher des actions dans l'environnement virtuel.

2. Participation à la recherche
Votre participation à cette recherche consiste tout d'abord à passer un test permettant de connaitre votre niveau de connaissance et émotion initiale. On procédera à l'installation des casques EEG et RV. Ensuite, nous commençons par projeter pendant 5 minutes des séquences vidéos qui vont générer des émotions et après chaque vidéo, vous allez indiquer votre niveau d'émotions négatives. Par la suite, vous allez répondre à des exercices cognitifs durant 5-10 minutes. Après, nous allons projeter des environnements qui ont pour but de vous relaxer durant 5-10 minutes. Ensuite, vous allez répondre encore une fois à des exercices cognitifs. Pendant cette expérience on enregistrera votre *activité cérébrale* (EEG) et votre *suivi visuel* (oculométrie de suivi du regard)

ainsi que vos résultats des tests. L'environnement virtuel pourra inclure de la musique, des images suscitant diverses émotions et des exercices cognitifs à réaliser. Enfin vous répondrez à un test final des connaissances. L'expérience se déroulera dans un local du département d'informatique de l'Université de Montréal et durera environ 1h.

3. Compensation

Pour vous remercier de votre participation, 20$ vous seront remis à la fin de l'expérience.

4. Risques et inconvénients

L'utilisation des capteurs physiologiques est indolore et sans risque. Il est possible que l'utilisation du casque occasionne un peu de fatigue visuelle de la même manière que pour les films en 3D. Vous pouvez à tout moment interrompre l'expérience.

5. Avantages et bénéfices du projet

Il n'y a pas d'avantage particulier à participer à ce projet. En participant à cette recherche, vous pourrez contribuer à l'avancement des connaissances sur l'apprentissage par les environnements de réalité virtuelle et leurs potentiels. Vous bénéficierez d'un montant de 20$ qui vous seront remis à la fin de l'expérience.

6. Confidentialité

Les renseignements que vous nous donnerez demeureront confidentiels. Chaque participant de l'étude se verra attribuer un numéro d'identification. Aucune information permettant de vous identifier d'une façon ou d'une autre ne sera publiée. Ces données seront conservées durant sept ans, conformément à la politique habituelle de l'Université de Montréal. Après ce délai, elles seront totalement détruites.

7. Droit de retrait

Votre participation est entièrement volontaire. Vous êtes libre de vous retirer en tout temps par avis verbal, sans préjudice et sans devoir justifier votre décision. Si vous décidez de vous retirer de la recherche, vous pouvez communiquer avec l'assistant de recherche, au numéro de téléphone indiqué à la page suivante du formulaire. À votre demande, tous les renseignements qui vous concernent pourront aussi être détruits. Cependant, après le déclenchement du processus de publication, il sera impossible de détruire les analyses et les résultats portant sur vos données.

B) CONSENTEMENT

Déclaration du participant

Je déclare avoir pris connaissance des informations ci-dessus, avoir obtenu les réponses à mes questions sur ma participation à la recherche et comprendre le but, la nature, les avantages, les risques et les inconvénients de cette recherche. Je reconnais avoir reçu des informations complémentaires de façon orale sur l'environnement expérimental choisi. Je déclare aussi ne pas porter de pacemaker, être sujet à l'épilepsie ou aux vertiges.

Conservation de vos coordonnées pour des projets futurs
Acceptez-vous que nous conservions vos coordonnées pendant un (1) an pour des participations à des expériences et projets futurs ? Oui ☐ Non ☐

Après réflexion et un délai raisonnable, je consens librement à prendre part à cette recherche. Je sais que je peux me retirer en tout temps sans préjudice et sans devoir justifier ma décision.

Signature du participant : ___________________________ Date : __ / /2020__________

Nom : _______________________________ Prénom : ______________________

Engagement du chercheur
Je déclare avoir expliqué le but, la nature, les avantages, les risques et les inconvénients de l'étude et avoir répondu au meilleur de ma connaissance aux questions posées. Je leur ai indiqué que la participation au projet de recherche est libre et volontaire et que leur participation peut être cessée en tout temps.

Signature du chercheur___________________ Date : __ / /2020______________
(ou de son représentant)

Nom : Prénom :

Pour toute question relative à la recherche, ou pour vous retirer de la recherche, vous pouvez communiquer avec Caroline Dakoure [redacted] ou Sahbi Benlamine à l'adresse courriel suivante : [redacted]

Pour toute préoccupation sur vos droits ou sur les responsabilités des chercheurs concernant votre participation à ce projet, vous pouvez contacter le Comité d'éthique de la recherche en arts et en sciences par courriel à l'adress[redacted]ou par téléphone au[redacted]ou encore consulter le site Web http://recherche.umontreal.ca/participants.
Toute plainte relative à votre participation à cette recherche peut être adressée à l'ombudsman de l'Université de Montréal, au numéro de téléphone [redacted]u à l'adresse courriel [redacted]**L'ombudsman accepte les appels à frais virés).**

Un exemplaire du formulaire de consentement signé doit être remis au participant