Master Degree Project

UNIVERSITY OF SKÖVDE

Merging brain-computer interfaces and virtual reality

A neuroscientific exploration

Master Degree Project in Cognitive Neuroscience
One year Advanced level 30 ECTS
Spring term 2018

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Abstract

Brain-computer interfaces (BCIs) blend methods and concepts researched by cognitive neuroscience, electrophysiology, computer science and engineering, resulting in systems of bi-directional information exchange directly between brain and computer. BCIs contribute to medical applications that restore communication and mobility for disabled patients and provide new forms of sending information to devices for enhancement and entertainment. Virtual reality (VR) introduces humans into a computer-generated world, tackling immersion and involvement. VR technology extends the classical multimedia experience, as the user is able to move within the environment, interact with other virtual participants, and manipulate objects, in order to generate the feeling of presence. This essay presents the possibilities of merging BCI with VR and the challenges to be tackled in the future. Current attempts to combine BCI and VR technology have shown that VR is a useful tool to test the functioning of BCIs, with safe, controlled and realistic experiments; there are better outcomes for VR and BCI combinations used for medical purposes compared to solely BCI training; and, enhancement systems for healthy users seem promising with VR-BCIs designed for home users. Future trends include brain-to-brain communication, sharing of several users' brain signals within the virtual environment, and better and more efficient interfaces.

Keywords: Brain-computer interface (BCI), Brain-machine interface (BMI), Virtual reality (VR), Motor imagery, Visual evoked potentials, Brain-to-brain communication

Some day, for better or for worse … a human being could be wired directly to an advanced computer (not through spoken language or an interface like a console), and by means of that computer to one or more other human beings. Thoughts and feelings would be completely shared, with none of the selectivity or deception that language permits… I am not sure that I would recommend such a procedure at all (although if everything went well it might alleviate some of our most intractable human problems). But it would certainly create a new form of complex adaptive system, a true composite of many human beings. "

– Murray Gell-Mann, Nobel Prize-winning physicist, The Quark and the Jaguar (1994)

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1. Introduction

Brain-computer interfaces (BCIs) are devices that measure and translate brain activity into controlling signals for an external device (Tan & Nijholt, 2010). There are nowadays robotic technologies used for wearable exoskeletons that assist disabled people to stand and walk (Nicolelis, 2012), or help patients in a locked-in state to communicate by spelling words (Donchin & Arbel, 2009; Kübler et al., 2009). This interaction technology is nevertheless progressing from therapeutical purposes to enhancements (Attiah & Farah, 2014).

Moreover, the field of virtual reality (VR) is also expanding and we are currently more bound to technology than ever before. Computer-generated virtual worlds aim to completely immerse the user in a virtual environment (Milgram, Takemura, Utsumi, & Kishino, 1995; Zyda, 2005). VR technology uses either internal or external tracking methods to deliver the feeling of real experiences. Internal tracking methods are components present within the device, such as a camera within a head-mounted display that records the direction of the gaze, while external systems are placed in the nearby physical space.

During the past few decades, researchers have been trying to connect BCIs with VR (Lécuyer et al., 2008). The possibilities are endless: enabling players of video games to manipulate objects in a virtual scene (Lalor et al., 2005), providing interaction with objects in the Internet of Things through smart glasses (Kim, Kaongoen, & Jo, 2015), or allowing researchers to collect information directly from the brains of participants who virtually test marketing or entertainment environments (Pradeep, Knight, Gurumoorthy, & Ratnakar, 2013). By decoding brain activity and implementing the knowledge from neuroscience and technology, the availability of systems combining BCI and VR seems uprising. These technologies are motivating, relatively safe to use and can provide means to analyse the brain mechanisms involved in the processing of virtual realities (Lécuyer et al., 2008). Nevertheless, the development progress comes with its own scientific and technological challenges.

1.1. Research question

The fields of BCI and VR have been researched extensively in various settings, however, a thorough inquiry of the emerging possibilities of combining these two techniques has not been compiled so far. The relation between BCI and VR has been lacking an extensive interdisciplinary perspective.

From the literature reviewed, it became obvious that VR has added value in BCI research and that the integration of these fields has been acknowledged, however, the underlying cognitive neuroscience aspects are not fully explored. Applications of BCI and VR have been recently tackled by various companies which are bringing new products on the market, however, the current knowledge of scientific developments should be extended.

Therefore, the main research question this essay is tackling is:

What is the neuroscientific basis for combining BCI and VR?

To address the research question in this essay, an exploratory perspective has been taken. This project is based on literature study conducted for an issue that has not been studied sufficiently in-depth yet.

In order to delineate the scope of the research, operational definitions of the main concepts, namely BCI and VR, are provided in the following chapters. This exploratory research was further designed in order to study the relation between BCI and VR. The overall strategy was to first study the concepts of BCI and VR in-depth and from a neuroscientific perspective. Following, the study aimed to present a broad range of published research that tackles applications resulting from advances within these fields and to provide a categorization of these developments.

The studies presented in this essay have been selected based on one main method. First of all, the first technique implied web search using Google Scholar as the primary search engine. Various keywords, such as *brain-computer interface, brain-machine interface, virtual reality, BCI, EEG,* etc. have been introduced as search terms. Further, the articles found were screened for relevance and prioritized into three main categories: either fundamental for understanding BCI (such as the brain signals acquired with BCI), or related to cognitive concepts addressed within VR (such as the feeling of presence), or studies that presented an application resulting from merging BCI and VR. For the first two categories of studies, the selection of articles and books was based on reference studies and extended articles, while for the latter category the criteria were more specific. For the papers to be accepted into the third category, the research had to satisfy the main criterion of tackling both BCI and VR within the same study, or more specifically to make use of brain signals in a virtual environment. The number of available studies that fit into this category of papers was much smaller, therefore the increasing need for scientific materials that cover the integration of BCI and VR. Furthermore, the conclusions are drawn with caution, as the current project aims to facilitate and support the research and development of new technologies.

1.2. Research outline

The current project aims to explore the progress and challenges encountered so far within the field of neuroscience of BCI and VR and the interaction possibilities between BCI and VR, as part of the promising future directions of the competition to "merge minds and machines" (Gay, 2015, p. 2).

This essay presents methods that are often used for brain data collection and neuronal signals that are mostly recorded from the brain by a BCI system. Here, the focus is on the noninvasive methods of neural signals acquisition, such as electroencephalography (EEG), a method that has been successfully used in BCI (Marshall, Coyle, Wilson, & Callaghan, 2013).

A selection of the signals used for BCIs is further presented. First, the visual evoked potentials (VEPs), along with the steady-state VEPs, since these are acknowledged as being some of the most useful due to their limited number of electrodes necessary for signal acquisition (Wang, Wang, Gao, Hong, & Gao, 2006). Then, other electrophysiological signals used by BCI are presented, such as the P300, due to the fact that it is one of the first signals to be used in BCIs developed for disabled patients. Motor imagery signals (with a focus on mu and beta rhythms and event-related synchronisation and desynchronization of sensorimotor rhythms) are also summarized in relation to their use for continuous BCIs.

Likewise, the development of VR technologies and the relation to neuroscience is described. The focus of this section is an analysis of the main concepts of immersion and involvement, and the relation with the feeling of presence.

Moreover, the last chapter of this essay presents the exploration of the brain-computer interactions with virtual environments and the resulting applications, challenges, and promises for the future of merging BCI and VR. The scientific literature describing various uses is examined, resulting in three main categories of applications: BCI and VR combinations for improving the training of BCI in the virtual environment, clinical applications for less-able-bodied individuals, and the entertainment and enhancement possibilities for healthy users.

While the technology of these systems is equally important as is the neuroscientific aspect, the decision was to leave out most technical aspects of the equipment, as the field of interest is neuroscience and the more technical aspects did not fit within the scope of this paper. Similarly, while the impacts and the ethics of these techniques are definitely an important matter, this essay does not cover these subjects.

2. Brain-Computer Interfaces

2.1. Developments of a communication system between brain and computer

The first documented attempts to read brain signals using a computer were at the University of California in the 1970s, intent that was sponsored by the Department of Defense of the United States government. In 1973 and 1974, Jaques Vidal, a professor of computer science at the University of California came up with the expression *brain-computer interface* for a pilot project in biocybernetics. Being one of the pioneers of the human and computer communication, Vidal firstly introduced the term *brain-computer interface* in his publications. During this project, he and his colleagues aimed to test direct brain communication, more specifically if "electrical brain signals [can] be put to work as carriers of information in man-computer communication" (Vidal, 1973, p. 157).

One significant result of the biocybernetics project was the success to send brain signals directly to a computer in a so-called human-machine dialogue (Vidal, 1973). However, at that time, the interpretation of the electrical signals generated by the brain and collected by the computer was rather one-directional and progressed into the study of neurophysiological signals by a computer and speculations about future use. Nowadays, the use of the term BCI has a slightly different meaning, requiring some form of command coming from the user and directed to the machine.

The research group of Vidal produced a report describing the development of a methodology for direct discrimination of evoked EEG responses (Vidal, 1973). During their experiments, the group has shown that it is possible to directly detect individual evoked responses and classify them in a reliable manner (Vidal, 1977). The research meant that more subtle information than what can be seen with the naked eye in the EEG (alpha waves, alpha blocking phenomenon, sleep spindles), was made available due to computer analysis (Vidal, 1973).

A few years later, the famous BCI paradigm of the P300-speller has been introduced by Farwell and Donchin (1988). In the paper, they propose a so-called "mental prosthesis" that can be used to spell letters based on the P300 component of the Event-Related Potentials (ERPs), which are changes in the electrophysiological signals triggered by a specific stimulus or event (Farwell & Donchin, 1988, p. 510). This system was aimed towards persons who cannot communicate through the normal motor system and allowed the users to select letters from a computer screen. In the P300-speller, users focus their attention on a letter selected from a grid of 6 by 6 with randomly flashing columns and rows. The user has to, for instance, count the number of times the letter flashes, and this triggers the P300 component in the subject's EEG. Then, the computer processor with real-time detection is able to select the letter. In this pioneering experiment, researchers used healthy volunteers who managed to achieve a spelling rate of 2.3 letters per minute (Farwell & Donchin, 1988). This research paved the way towards BCI developments for motor-impaired users, a motivation that is still one of the main driving forces today (Lotte, Nam, & Nijholt, 2018).

2.2. Defining brain-computer interfaces

For the term that was coined back in the 1970s, the associated definition was rather broad and has changed over the years; nowadays it has a slightly different meaning. While the brain-computer interface back then would be any computer-based system that simply produces information about the brain in general, today the term BCI defines a narrower set of devices, namely those that allow a system to collect information directly from the brain and support communication and control by the user (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002).

Commonly, a BCI is defined as a direct communication system between brain and computer. More specifically, a BCI is regarded as a “system that measures CNS [central nervous system] activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment” (Wolpaw & Wolpaw, 2012, p. 3).

Ron-Angevin, Lopez, and Pelayo (2009) managed to perfectly capture the idea of BCI, stating that:

> The fact that a subject was able to voluntarily modulate his cerebral activity hence generating information, that this information could be registered by means of EEG, processed and translated to statements or commands over a device or computer and, finally, the subject could know the results of those commands by means of biofeedback and hence the loop could be closed; all together sets up the basis of a full-duplex communication system between the man and the machine. (Ron-Angevin et al., 2009, p. 667).

Other definitions have been proposed in the literature, with slightly different terminology.

For instance, Donoghue (2002) emphasizes that a *brain-machine interface* (BMI) has the major goal to “provide a command signal from the cortex. This command serves as a new functional output to control disabled body parts or physical devices” (Donoghue, 2002, p. 1085). Interestingly, Donoghue adds the idea of controlling disabled body parts, with the BMI being a system that surpasses the normal motor output towards a body part via the nervous system.

Levine calls such a system a *direct brain interface* (DBI), mentioning that this gathers voluntary commands directly from the human brain, surpassing the normal motor output and therefore not necessitating physical movement. These signals can be used for operating a computer (Levine et al., 2000). These definitions are more or less similar, with BCI and BMI being the two most common terms and referring to almost identical concepts.

2.3. Mechanisms of BCIs

A BCI is comparable to the communication system of the nervous system: there is an input signal (coming from the brain) and an output signal or command (sent to a device). In between, there is the computer processing that interprets and translates the electrophysiological data into commands for the device.

Different types of BCIs can be characterized based on their signal acquisition method. One category are the BCIs which require users to perform a visual task (e.g. gaze at a blinking object on the screen or imagine movements at predefined moments or when faced with a choice). These systems require a set of stimuli and are therefore, called synchronous or cue-based BCIs because users depend on the predefined signal trigger of the system. They are mostly used in the laboratory conditions as the system is in control of the timing and not the user (Leeb et al., 2007a).

The other category covers the asynchronous BCIs, systems that are mostly based on motor imagery. These are continuous recordings of the EEG oscillatory components and do not require any visual stimuli to be modulated. Instead, users imagine movements of their limbs or tongue (Leeb et al., 2007a). In the case of the self-paced BCI, two states need to be distinguished: the intentional control and the non-control or idle state, therefore making these systems better fit for real-world applications, but also more complex (Leeb et al., 2007a).

This section further focuses on those signals acquired with EEG, such as evoked potentials (e.g. induced by flashing letters) and spontaneous oscillations (e.g. rhythms of the sensorimotor cortex) and briefly mentions one notable method of recording cortical neural activity with ECoG.

Already from the start of the BCI, evoked responses recorded on the scalp with electroencephalographic equipment formed the basis of the signals transmitted to the computer.

2.3.1. Signal acquisition

Most BCIs use input recorded with microelectrodes from the brain of the user, either from the scalp in a non-invasive manner, or invasively, form electrodes placed inside the cortex.

Several technologies are used for measuring brain activity and to collect the brain signals required for the functioning of the BCI. Some of these are electroencephalography (EEG), magnetoencephalography (MEG), electrocorticography (ECoG), subcortical electrode arrays (SEA), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS).

ECoG and SEA are two invasive techniques, meaning that they require sensors implanted under the skull either at the level of the cortex for ECoG or even deeper for SEA. The signals generated on the cortical layers are recorded using ECoG, while subcortically there are local field potentials or single unit microelectrodes that record the firing of individual neurons or small bundles of neurons.

Signals can also be obtained from fMRI or fNIRS, technologies that measure the changes in the hemodynamic responses in the brain. These provide well defined spatial resolution, being able to trace back the location of the changes very accurately, however they are relatively less performant in terms of their temporal resolution (Wolpaw et al., 2006). With MEG, the brain's magnetic activity is measured and this is both spatially and temporally accurate, however, the equipment is very large and demanding, just as with fMRI, creating impractical BCIs.

Resulting from these considerations, it seems that electrical signals collected non-invasively are maintaining the position as the widest spread technique for clinical and non-clinical use of BCIs, while other techniques, most notably fNIRS, come close and deserve further exploration from the researchers within the BCI domain (Wolpaw & Wolpaw, 2012). BCI systems that use data collected non-invasively, directly from the surface of the scalp with external electrodes, are also the only ones likely to be accepted and used by the general population. This section further presents the most widely spread technique of collecting data for a BCI intended for general human use, namely the EEG method.

Electroencephalography

One of the most commonly used methods of signal acquisition is EEG. With this method, electrical signals are recorded from the scalp, in a non-invasive manner, therefore making this technology convenient and safe to use for human research.

Generally, a cap with a certain placement of a number of electrodes is positioned directly on the head of the subject. The location is often determined by the international 10-20 system (Jasper, 1958), although some researchers might develop their own positioning according to the location of interest. The 10-20 system provides a standardized placement of the electrodes used in EEG studies. According to this system, the electrodes are distributed evenly across the scalp and allow for extensions to increase the density of electrodes.

Placing electrodes directly on the scalp is used to measure electrophysiological signals that arise in the underlying brain regions. However, recording electrical activity after it passes the skull results in a relatively low spatial resolution (accuracy of about 1 cm, depending on the number of electrodes attached to the cap). On the other hand, this method detects changes in the electrical fields within milliseconds, giving it a very good temporal resolution (Luck, 2014).

The electrodes that are part of the cap are sensitive to the electrical signals that appear in the postsynaptic phase. These are a result of the exchange of ions between the neurons (Luck, 2014). The EEG device measures differences in potential from the several electrodes placed on the head and digitizes these for analysis. Further along the line of the equipment, there is an amplifier that records these changes and prepares the raw EEG data. This data is an aggregate of all electrical brain activity and not necessarily linked to a specific process (Devlaminck, Wyns, Boullart, Santens, & Otte, 2009). However, BCI system might use different types of signals, either ones that are naturally produced in response to external stimuli (like evoked potentials), or others that need to be trained and self-developed by the user with feedback (sensorimotor rhythms, slow cortical potentials).

Most of the BCIs used for humans are based on non-invasive methods for data collections, such as EEG recorded from the scalp. The EEG recordings generally use either event-related potentials (such as the P300 component of the ERP), and the visual evoked potentials as the basis for natural involuntary responses, or the slow cortical potentials and cortical mu and beta rhythms, which are self-regulatory (Lalor et al., 2005). The first category requires no training since it is based on natural brain responses, while the second necessitates biofeedback training so that subjects learn to regulate and control the neuronal activity (Lalor et al., 2005). These signals are further described in the next sections.

P300

The P300 signal is a positive potential that occurs at approximately 300 ms from the presentation of an infrequent stimulus, with slight variations in latency depending on the subject. Also known under the name P3, it is an evoked potential that represents the cognitive processing associated with certain events. It arises over the parietal cortex when particularly significant or infrequent visual, auditory or somatosensory stimuli are intertwined with frequent or routine stimuli. Typically, the infrequent stimuli account for about 20%, while the frequent stimuli are shown for about 80% of the time. Each possible choice is averaged, with only the chosen character resulting in the prominent P300 potential (Wolpaw et al., 2002).

Donchin and his team are well-known for pioneering the use of P300 response in a BCI communication system (Farwell & Donchin, 1988; Donchin & Arbel, 2009). Back in 1988, they constructed a device aimed at paralyzed individuals who would be able to spell letters based on the P300 potential. The healthy volunteers they tested the device on were able to control the spelling device with just a little calibration time and reaching a quite high accuracy (Farwell & Donchin, 1988).

Today, this system has the advantage that it does not require learning and training because it is based on a naïve response of the brain in relation to the desired choice. However a P300-based BCI might change its performance over time: it might degrade due to the P300 habituation or improve because P300 can becomes larger (Ravden & Polich, 1999). Long-term research on the BCI home use of an ALS patient has shown that it is possible to maintain a stable P300-BCI with bi-weekly calibration for over 2 years and that its performance remained acceptable over time (Sellers, Vaughan, & Wolpaw, 2010).

Visual Evoked Potentials

Visual evoked potentials are a particular type of evoked potentials recorded from the human brain after the presentation of a visual stimulus. These can be elicited by a flashing light or by changes of a checker pattern on a computer screen. The VEPs are generated in the brain as a result of visual stimulation. These potentials are a mark of the mechanisms of visual information processing in the brain, and especially in the visual cortex. For stimuli presented at frequencies higher than 6 Hz, a response is evoked over the visual cortex, with the greatest amplitude at the occipital cortex (Wang et al., 2006).

The steady-state visual evoked potentials (SSVEPs) are natural periodic responses that differ for each frequency of the visual stimuli, with the brain generating the same electrical activity as the one from the stimuli for frequencies higher than a few Hz (between 2 to 6 Hz) and up to 90 Hz (Lalor et al., 2005; Pastor, Artieda, Arbizu, Valencia, & Masdeu, 2003). The flickering stimuli of different frequencies evoke an oscillatory response with the same frequency as the stimulus over the visual cortex. This has been studied on cats and also on humans. With EEG recordings on the human scalp, it has been found that the SSVEP appears in the occipital regions a couple hundred milliseconds after the presentation of a visual stimulus. SSVEPs can be recorded at a wide range of frequencies, however the majority of studies used 8-10 Hz presentation rate because at this rate, the length between two consecutive stimuli is much shorter than the length of the potential that is elicited in response to the individual stimulus presented and thus multiple responses to individual stimuli overlap (Norcia, Appelbaum, Ales, Cottereau, & Rossion, 2015). The amplitude of this response differs, with the largest amplitude at approximately 15 Hz for stimuli illuminated in steps of 1 Hz (Pastor et al., 2003).

At the beginning of BCI research, the systems developed were using dependent VEP that were recorded form the scalp in the area of the visual cortex in order to determine the direction of the gaze (Vidal, 1973; Wolpaw et al., 2002). These dependent signals rely on the visual fixation point changes, therefore allowing the system to determine the direction in which the user wants to move a cursor on a computer screen.

Later on, another type of BCI, called the brain response interface (BRI), was described in 1992 by Sutter. The BRI uses VEPs recorded from the scalp over the visual cortex formed in relation to brief visual stimuli (Sutter, 1992; Wolpaw, 2002). Here, a computer screen displays a matrix of 8 rows and 8 columns (a total of 64 places) filled with letters or other symbols. The user then selects the symbol of interest by looking at it. While the user maintains his focus on the selected symbol, the grid automatically flashes subgroups of these symbols alternatively in red and green at about 40-70 times per second. Any symbol is part of different subgroups, and all subgroups are shown multiple times. Afterward, the amplitude at about 100 ms from the onset of the stimulus is computed for each subgroup and compared to the user's previously defined VEP characteristics. From these computations, the system accurately determines the symbol the user is looking at. Healthy volunteers who have used the system could write about 10-12 words per minute. For users with disabilities that cause uncontrollable neck and head muscle movements, EEG can be problematic and unreliable, however for a patient with ALS this had been solved by using an implant of four epidural electrodes placed on the visual cortex. This intervention allowed the person to communicate at similar speeds with the healthy volunteers (Sutter, 1992; Wolpaw et al., 2002).

Another method of using VEPs to determine the direction of the focal point has been reported by Middendorf, McMillan, Calhoun and Jones (2000). In their study, they report two buttons were shown on a screen, being illuminated at different frequencies. The users were instructed to select one of these buttons by looking at it. When looking at one of these icons, the computer determines the frequency of the user's naturally occurring VEPs and selects the button with the matching frequency. With a maximum of two buttons, users achieved an accuracy of 92% on average after 2 minutes (Middendorf et al., 2000).

The SSVEP is a type of VEP used in BCI due to the high accuracy and low training time. The SSVEP is characterized by higher amplitude at the frequency of the icon the user is looking at. So out of two different buttons flickering at two different frequencies, the SSVEP's amplitude will be higher for the frequency of the button the user is fixating (Middendorf et al., 2000; Devlaminck et al., 2009). SSVEPs have been successfully used as signals for BCI, however, these systems are highly dependent on the movement of the eye.

Since the performance of a BCI is assessed by the achieved information transfer rate (including speed and accuracy), and the SSVEPs are one of the most effective signals used in BCI, the SSVEP-based BCI systems have seen considerable success (Lalor et al., 2005).

According to Lalor and colleagues, the effectiveness of these designs is based on multiple factors. First of all, the measurement is possible in a large population, with only a few not showing this response on the EEG recordings. Then, since there are only a small number of target frequencies (normally, there is one for each button/icon presented on the screen), the feature extraction is cut down to a frequency component extraction. Accuracy is also high for these signals due to the fact that specific frequencies are of interest and only the noise in those bins is considered, therefore reaching a high signal-to-noise ratio at good frequency resolutions. Lastly, normal EEG artifacts, such as blinks, face muscles movement or electrocardiographic noise are either present in the opposite side of the head to the visual cortex or at lower or higher EEG frequencies than the ones where SSVEPs are measured (Lalor et al., 2005).

These systems reported so far used the VEP generated on the basis that users are able to shift their gaze and control their eye movements and attention voluntarily towards the icon or symbol of interest. While independent brain-computer communication based on the SSVEP has been tested as an electrophysiological correlate of visual spatial attention (Kelly, Lalor, Reilly, & Foxe, 2005), most VEP-based BCIs are dependent (Wolpaw et al., 2002).

Independent BCI systems generally use motor imagery, slow cortical potentials or the mu and beta rhythms. These are analysed in the following paragraphs.

Slow Cortical Potentials

Slow cortical potentials (SCP) are one of the lowest frequency signals that can be recorded with scalp based EEG, typically ranging from 0.5 to 10 seconds (Birbaumer, 1999; Wolpaw et al., 2002). These are voltage changes that occur slowly over the cortex and can be either negative or positive. The negative shifts are usually associated with the activation of the cortex, which is often the case for the implementation of movement or during the performance of a mental task. Positive changes indicate cortical relaxation (Birbaumer, 1999).

The voltages originate in the apical dendrites present in the upper cortical layers and are caused by synchronous firing. Their function is to act as a threshold for the local excitation (in case of the negative slow potential) or as inhibition (for the positive potentials) (Birbaumer, 1999).

Studies have shown that people can learn to control these potentials, and this has been exploited in applications that are being used to move a cursor on the screen. The first BCI used here was the Thought Translation Device (TTD) (Kübler et al., 1999). SCP control was used in the TTD to manage movements of an object that was shown on a computer screen. The first 2 seconds determined the user's initial voltage, with the following 2 seconds being the action period in which the user tried to increase or decrease the SCP and chose one of the two options.

Mu and beta rhythms

An EEG-based BCI can also use the 8-12 Hz mu rhythm recorded over the sensorimotor cortex and the related beta rhythm of 18-26 Hz (McFarland, Miner, Vaughan, & Wolpaw, 2000; Wolpaw et al., 2002). Mu rhythms are produced in the cortical areas concerned with movement and motor control. These are traditionally defined as rhythms between 8 and 12 Hz over the sensorimotor cortex that decrease either with actual movement or motor imagery (McFarland et al., 2000).

Associated with the mu rhythms are the beta rhythms, with activity occurring between 18 and 25 or 26 Hz. As the mu is typically non-sinusoidal, and the "modelling of non-sinusoidal waveforms by classical Fourier analysis requires the use of higher frequency harmonic components in addition to a fundamental frequency" (McFarland et al., 2000, p. 178), beta rhythms are thought to result from this transformation and not represent an underlying independent physiological process (Jürgens, Rösler, Hennighausen, & Heil, 1995). However, the investigation of the behaviour of short-lasting beta bursts generated by foot and hand movements showed significant beta-power increase after the termination of movement imagery for both feet, at frequencies between 23-29 Hz (Pfurtscheller, Neuper, Brunner, & da Silva, 2005). More recently, Kilavik and colleagues have reviewed the beta oscillations and suggest that a given component could be resulting from a multitude of processes which, when overlapping in time, might affect the power of the oscillations (Kilavik, Zaepffel, Brovelli, MacKay, & Riehle, 2013).

It is generally accepted that beta power is low during motor action or movement, it temporarily increases once the movement has ended (denoted "beta rebound") and strengthens during object grasping (Kilavik et al., 2013). Movement or preparation for motor action is normally followed by a decrease in mu and beta rhythms, especially contralateral to the movement side. This decrease is named 'event-related desynchronization' (ERD) (Wolpaw et al., 2002). Its reversed phenomenon, the increase of the rhythms, is called 'event-related synchronization' (ERS) and it occurs once the movement is finished and there is relaxation (Pfurtscheller & da Silva, 1999; Wolpaw et al., 2002).

ERD and ERS have been shown to occur also with motor imagery, therefore not requiring actual movement (Pfurtscheller & Neuper, 1997; Wolpaw et al., 2002). This finding has had an impact on the brain-computer systems that have been developed, the independent BCIs, starting around the mid-1980s (Wolpaw et al., 2002). Generally, people can learn to control either the mu rhythm or the beta rhythm that is recorded from the sensorimotor cortex and can use it to control BCIs, like, for instance a cursor on a computer screen (McFarland et al., 2000).

Some of the most common BCI systems that have used motor imagery are the Wadsworth BCI and the Graz BCI (Wolpaw et al., 2002).

Cortical neurons

Recording the signals directly from the neurons require electrodes implanted in the brain at the level of the cortex, epidural, subdural, or intracortical. The technique used, called electrocorticography (ECoG), is similar to the EEG, thus also detecting the firing rates and the electrical signals generated by the activation of neurons. Using implantable neural electrodes, signals acquired by ECoG have higher signal-to-noise ratio, as they are closer to the source, but the threshold for their use is higher than for the scalp electrodes since this method requires a cortical implant (Wolpaw et al., 2002).

Metal microelectrodes have often been used in awake animals to collect data from the firing of single neurons. Evarts (1966) has reported the accomplishment to record the activity of individual cerebral neurons in moving animals, namely the activity of pyramidal tract neurons of the monkey in relation to hand movement. Most studies, back then, focused on the neuronal activity and the resulting sensorimotor performance, and not so much on the capacity of the subject to learn how to control the firing of the studied neurons (Wolpaw et al., 2002).

In the past, researchers also encountered physical limitations for the use of electrodes, as they were either not suitable for human use or did not have a long and stable communication. Traditional electrodes that are implanted in an area of the brain induce a scar in the tissue and cause neurons to move, therefore deteriorating the signal (Wolpaw et al., 2002). The use of modern electrodes, such as an intracortical electrode made of a hollow glass cone where the sensors are contained, provided a longer term stable recording for more than a year (Kennedy, Bakay, Moore, Adams, & Goldwaithe, 2000).

Multielectrode arrays are also used for collecting brain signals that are transmitted towards a machine, such as a robotic arm. Lebedev and his laboratory have trained rhesus monkeys to learn the control of reaching and grasping hand movements of a robotic arm controlled only by producing electrical activity from cortical neurons. The recordings were performed by a multielectrode array, constructed from flexible Teflon-coated microwires, implanted in several cortical areas covering the frontoparietal cortical circuitry (such as the primary motor, somatosensory, or supplementary motor areas), known to control goal-directed arm and hand movements (Carmena et al., 2003; Lebedev & Nicolelis, 2017).

The BrainGate neural interface, an interface that has been tested in humans, makes use of small-scale intracortically implanted microelectrode array that acquires the control signals for a neural prosthesis system (Simeral, Kim, Black, Donoghue, & Hochberg, 2011). The group of researchers has examined the reliability of the interface over the long term, and after about three years they have found that the system remains reliable, with spiking signals recorded from about the half of the originally implanted electrodes (41 out of 96 electrodes were successfully decoded), and the command to the neural cursor point-to-click reached a mean task performance of 91% (Simeral et al., 2011).

2.3.2. Signal processing

The pre-elected signals collected by the electrodes are processed. They are amplified and then digitized (Wolpaw et al., 2002). Further, they are subjected to different extraction procedures, and after the signal has been extracted, it is translated into the commands to a device that performs the order of the user.

BCIs extract either the time-domain signal features for the evoked potential amplitudes or neuronal firing rates, or use frequency-domain signals in the case of mu and beta rhythm amplitudes (Wolpaw et al., 2002). A hybrid-BCI that uses both signal types has also been conceived (Pfurtscheller et al., 2010). In this example, Pfurtscheller el al. propose a hybrid BCI which classified two EEG patterns, one being the event-related (de) synchronisation of sensorimotor rhythms and the other being steady-state visual evoked potentials (Pfurtscheller et al., 2010).

The next step is the removal of the artifacts. As it is happening almost always that signal features are contaminated, it is definitely important to minimize the artifacts occurring from electrooculography, muscle movements or other non-CNS related artifacts. The signal undergoes the processing to extract the features of interest. The following translation algorithm modifies these signal features into commands for the actuator device. Here, the algorithm can be linear (such as the classical statistical analyses), or might involve non-linear methods (neural networks and machine learning) in order to fasten the translation (Wolpaw et al., 2002). After this step, the independent variables (the signal features) have been changed into dependent variables (output commands for the device).

Central to an effective BCI communication is the algorithm's adaptation to the user. This requires three levels, as described by Wolpaw and colleagues (2002): first, the system needs to initially adjust to the user's signal feature (be it P300, SSVEP, or the firing rates of cortical neurons). While this step is satisfactory at some level, given the user's performance being stable, it is often not sufficient as the electrophysiological signals show long- and short-term variation. Therefore, a second level of adaptation is required, namely the periodic online adjustments designed to reduce the influence of spontaneous variation. Variation in a user's signal might occur due to recent events, fatigue, illness and other reasons, and an effective BCI needs to adapt to the user's range of signals. Lastly, effective BCI operation depends on the interaction of two adaptive controllers, namely the BCI and the user's brain. At this level of adaptation, the system employs the capacity of adaptation of the brain. This is a result of the transition of a brain signal's that is normally just a reflection of brain function towards the purpose of being the output and, therefore, the end product. The likely (and desired) outcome is that the brain will modify the signals into making them more effective for the BCI operation, however, inappropriate adaptation from either side could result in damaging the communication.

The actuator, or the output device, which most often is a computer, a projection in a room, or a prosthesis, executes these commands. This allows users to select targets or letters presented on a screen, move cursors towards an item, manipulate objects in VR or guide a prosthesis. Moreover, besides performing the action commanded by the user, the output also acts as feedback for the user.

Each BCI is guided by a protocol, an agreement that guides the operation of the system. This operating protocol is needed in order to define how a system is turned on and off, whether communication happens continuously or not, and whether message transmission is triggered by the user or by the system (e.g. generating stimuli that evoke the P300 or measuring continuously the signals in order to find a trigger signal generated by the user), the speed and sequence of the interactions, and, finally, the feedback provided to the user (Wolpaw et al., 2002).

Still, after these steps, a performant BCI cannot compete with a healthy user's full muscular control, however are valuable for less-able bodied individuals (van Erp, Lotte, & Tangermann, 2012). Healthy users could benefit from additional communication pathways and hands-free control, which might be proven handy for demanding occupations when users' hand are already busy and might use an extra navigation method (e.g. drivers or astronauts) (van Erp et al., 2012).

3. Virtual Reality

3.1. First attempts to generate virtual worlds

Attempts to develop projections of a simulated environment are traceable back to 1957, when in the USA, movie maker Morton Heilig invented a machine aimed to replicate real-world experiences by combining video with sound, odour, wind and vibrations. This device, called Sensorama, could display images stereoscopically and at a wide-angle, therefore creating the illusion of being immersed in the video presented (Heilig, 1962). Even though this machine was very impressive for the technology of the 1960s, it did not receive the necessary funding that would have allowed it to become widespread. However, the setup paved the way for a multitude of ideas that were to be discovered both for computing and computers (Tate, 1996).

A couple of years later, a graduate student, Ivan Sutherland, picked up Heilig's ideas and added a Cathode Ray Tube (CRT) for the display. Sutherland's idea to create a head-mounted three-dimensional display started with the aim to fundamentally improve the user's experience by providing a perspective that changes as the user moves. The military department and NASA noticed a huge potential for the training of pilots, (e.g. flight simulations, moon landings) and in the 1970s, they began supporting the development of helmets that could simulate the perspective of flight (Tate, 1996). These were the first attempts to create virtual environments that could be used with for research or for training.

3.2. Defining virtual reality

Virtual reality denotes the computer-generated 3D environment that is immersive and interactive, and targets a multi-sensorial experience (Burdea & Coiffet, 1994; Vora et al., 2002). The generation of these environments requires the usage of performant hardware and software, including computers, head-mounted displays, and motion detecting sensors to create an environment in which a user can be engaged. VR has been defined as "a simulation in which computer graphics is used to create a realistic-looking world" (Burdea & Coiffet, 2003).

VR "forms a special class of applications where the human-machine interaction is a specific perceptual world designed to create a compelling illusion into which the user can become immersed" (Gigante, 1993; Pimentel & Teixeira, 1993; Vidal, 1999 as cited in Marsh, Gorayska, & Mey, 1999).

As the definitions imply, creating such an environment requires building a human-centric experience, with the user becoming a real participant in the projected world and interacting with the world by manipulating virtual objects. Therefore, user performance is the key consideration in delimitating the requirements for VR (Vora et al., 2002).

The aim is to create an environment in which the user's senses and body movements are involved in the task, thus improving user performance and creating the feeling of immersion.

Creating the impression of a realistic simulation of an environment completely generated by a computer is the basic idea of VR technology. In order to provide this, VR is based on hardware and software which have been increasingly performant over the past years, providing means for the image display and incorporating sensors for recording the movements of the user in order to change the perspectives accordingly to increase the illusion of reality.

While for other human-computer interactions, values such as the ease of use and learning, or user comfort are important concepts (Kalawsky, 1993), for VR the critical aspects are the subjective experiences (e.g the feeling of presence and immersion) (Singer & Witmer, 1996). Moreover, it has been argued that VR has been often portrayed as a technological medium (such as a telephone or television), while it should not exclude the experiential focus of VR. Such an approach fails to provide insight into processes of using such systems or an understanding of the effects of VR (Steuer, 1992).

Some systems that employ VR are divided according to their means of display, resulting in four main categories. These are the cathode ray tube (CRT), the head-mounted display (HDM), the binocular omni-oriented monitor (BOOM) and the audio-visual experience automatic virtual environment (CAVE) (Cruz-Neira, Sandin, DeFanti, Kenyon, & Hart, 1992).

The system with the best user feedback is the CAVE, a room in which three of the walls and the floor receive projections of the environment, with the user seated in the middle of the room. In other words, the CAVE is similar to a cube in which screens surround the user and create a feeling of immersion in the displayed environment, with correct perspective and stereo projections adapting as the user moves within the boundaries (Cruz-Neira et al., 1992). The CAVE-like applications are still up to date one of the most common VR research laboratory facilities.

One aspect of the VR technology that is very important in relation to the communication between the VR and the BCI is a system called Virtual Reality Peripheral Network (VRPN). Once the brain signals have been acquired and received by the computer, the VRPN comes into action by providing the synchronisation and logging of several data channels, with support for the VR devices (Friedman et al., 2007). Friedman and his team wrote about this system, stating that in their experiment, the VRPN communicated with the BCI software that was based on Matlab using a rendering program called DIVE on a Unix machine to control the VR. The established communication received about 20 updates per second, with a slight delay time in order to assure the BCI decisions as smooth as possible (Friedman et al., 2007).

3.3. Subjective experience of virtual reality

In the field of neuroscience, virtual reality is used because of its advantage on two important components, namely the subjective experiences of immersion and presence. The degree to which these factors are felt by the users reflects the systems' performance and affects the usefulness of the machines.

3.3.1. Immersion and involvement

Immersion is the capacity of an environment to allow "oneself to be enveloped by, included in, and interacting with an environment that provides a continuous stream of stimuli and experiences" (Witmer & Singer, 1998, p. 227). It is therefore assumed that when one feels more immersed, one will also feel more present (Wiederhold, Davis, & Wiederhold, 1998).

Devices, such as the head-mounted display target exactly these feelings. It has been shown that HDMs are better at enveloping the user, when compared to a computer display, simply because of the visual and audio fields. These fields are both directly connected and inescapable for the first, while the latter allows user's attention to move towards the real environment due to the distance between the visualisation of the environment and the user (Witmer & Singer, 1998).

Involvement is another concept used in VR, denoting the focusing of attention on a set of stimuli, resulting in chain-like events increasing immersion and presence (Witmer & Singer, 1998; Wiederhold et al., 1998). When users focus their attention on the virtual world, they increasingly feel subjectively present in that environment. This does not necessitate the exclusion of the real world and can be achieved simply with a shift in the focus of the attention (Fontaine, 1992).

3.3.2. Presence and telepresence

The main goal of creating a 3D virtual environment is to immerse a human in a medium completely generated by a computer, in which the user becomes a participant. The user must be able to interact with and therefore, manipulate virtual objects. From this point of view, the human ability to participate is one of the greatest requirements of VR developers and one of the most important considerations when defining a virtual system (Burdea & Coiffet, 1994; Vora et al., 2002). The concept of *presence* is what separates the experience of a virtual environment from other multimedia experiences, and, even though the users know that they are not physically in that environment, they report that they feel like they are there (Steuer, 1992). Achieving a maximum level of presence requires not only that the user feels present in the environment, but also that he is capable of interacting with it and has an interest in the task that needs to be performed (Stark, 1993). In fact, for the feeling of presence to be real, one must even feel more a part of the computer-generated environment and less a part of the real physical world in which the person is actually located (Witmer & Singer, 1998). VR works by creating a visual illusion (Stark, 1995).

Measuring presence requires mostly self-reports, although physiological measures have also been used in military training experiments. Self-reports of presence are questionnaires in which users assign scores to indicate the degree of presence (Witmer & Singer, 1998). Questions like "How well could you move or manipulate objects in the virtual environment?" with answers on a Likert scale with values between e.g. 1-7 or 0-100% provide reliable and valid measures of presence (Witmer & Singer, 1998, p. 232). Physiological measures, for instance, on the behavioural level, might encompass subjects looking away or closing their eyes when presented with images provoking anxiety. On the physiological level, an increased heart rate or sweat glands activity would reflect the presentation of anxiety-provoking scenes (Wiederhold et al., 1998).

Different typologies of presence have been proposed by Heeter (1992), who separates presence into individual, social, and environmental. Individual presence refers to the assumptions one may bring into the experience, the time duration one spends in the virtual environment, and familiarity with that environment. Socially, the presence of other virtual people and their interaction with other participants in the virtual world are some of the factors. Environmental factors refer to, for instance, the range of senses that are stimulated by the environment, resolution of the displays, and quality of the graphics to make the projected world look more or less real (Heeter, 1992; Wiederhold et al., 1998).

Moreover, in an aircraft inspection simulation study, researchers compared whether the VR training platform differs from the PC-based simulation in terms of engagement and presence and whether these impact users' performance; their results showed that the VR system was preferred by the users and training in a virtual environment resulted in much better outcomes than training with sectional 2D images as a training tool (Vora et al., 2002).

4. Brain-computer interactions with virtual environments

When looking at the evolution of BCI, we see that it intertwines with the VR developments (Lotte et al., 2018). The timeline in Figure 1 presents a few key events in the history of these techniques. As described earlier, the idea of VR emerged in the 1950s, when a movie director wanted to present a more realistic looking movie and created a 3D stereoscopic machine. From the 1980s the BCI research has exploded with more and more brain signals that were tested as control signals (Lotte et al., 2018).

From the 2000s we notice also the first applications of BCI controlled in a virtual environment, or an experiment testing whether users could control the directions of a camera in a VR. And just a couple of year ago a hybrid BCI has been proposed for home users to control devices at home.

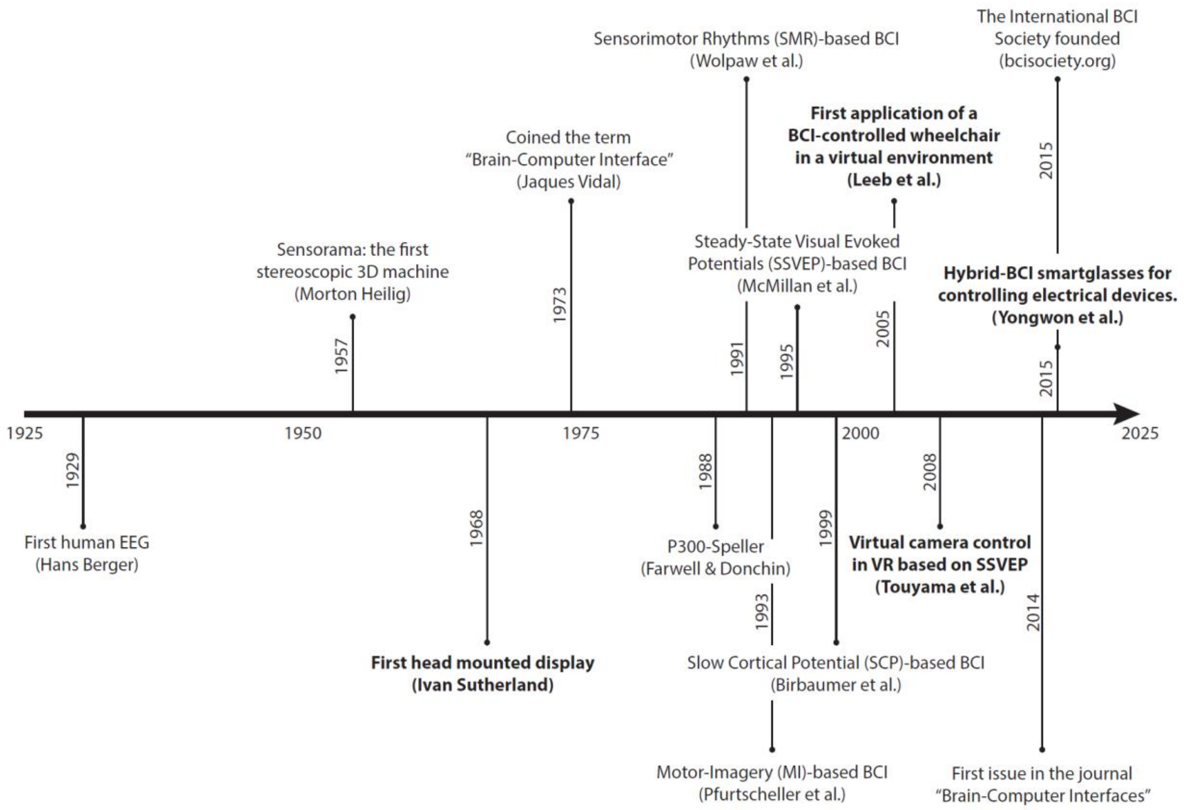

Figure 1. Evolution of BCI intertwines with key events of VR.

Virtual reality applications in cognitive neuroscience have only opened up possibilities since around the year 2000 (Tarr & Warren, 2002). Until then, technological aspects were limited, manufacturers were rare and the market was absent. Improvements quickly began to tackle computer speed, the quality for head-mounted displays and tracking systems. These developments made VR attractive for researchers, who could use this quickly maturing technology to exploit three-dimensional environments. As the performance further improves, potential began to emerge for researchers to perform realistic looking experiments, studying the human organism under ecological conditions (Tarr & Warren, 2002).

4.1. Applications of merging BCI with VR

Attempts to combine brain-computer interfaces with virtual reality technology have only recently started to interest research groups worldwide. Going beyond the classic aim, namely the improvement of motor physiology, the evolution of brain-computer interfaces is integrating the technological developments of mixed realities, especially virtual reality.

Besides the known individual applications of BCI and VR, the integration of these fields has been used by both researchers and commercial organizations. The aim of researching the combination of BCI and VR is to study the neuroscientific aspects related to both fields. By closely looking at the applications resulting from merging these technologies, the neuroscientific basis of these studies is explored.

On one hand, research has shown that VR is a useful tool to test the functioning of BCIs (Velasco-Alvarez, Ron-Angevin, & Lopez-Gordo, 2013). Nowadays, the BCI researchers can perform safe and controlled experiments in the lab, while allowing the users the feeling of real-life control of the device (Leeb et al., 2007a; Leeb et al., 2007b). During the training phase, it is important that the performance of the BCI can be tested and the users can be provided with feedback to allow them to realize their progress (McFarland, McCane, & Wolpaw, 1998). These days, importance is placed on biofeedback and the development of training methods that aim to improve human performance (Ron-Angevin et al., 2009).

On the other hand, there are the applications merging BCI with virtual environments for regular use, either for medical purposes to help patients, or for enhancement purposes for healthy users. Benefits from merging virtual environments with BCIs are the ability to "navigate by thought" (Friedman et al., 2007), as in using brain waves to steer a virtual car (Ron-Angevin, Diaz-Estrella, & Reyes-Lecuona, 2005), delve into a virtual bar room (Leeb et al., 2007b), explore an apartment (Leeb et al., 2007b), or even move in one dimension on a street in a virtual environment (Leeb et al., 2007a).

4.1.1. Virtual reality used for training and testing BCIs

A virtual environment is often used as a testbed for the mobile devices that assist the less mobile or paralyzed users (such as people with ALS, tetraplegia, etc.) (Bayliss & Ballard, 2000). VR is a powerful tool that makes use of graphical possibilities to improve the feedback (Ron-Angevin & Diaz-Estrella, 2009), and also to motivate users to further train their skills.

VR is also used a medium to test the efficacy of electrophysiological signals used in the EEG-based BCI systems. While most tests for the feasibility of brain signals have been concentrated on static environments, a better task is to involve the user in the interaction with the environment.

For example, Bayliss and Ballard (2000) describe an experiment in which they tested whether the P3 evoked potential could also be used in BCI when subjects are physically moving in an environment. In a static setting, the P3 would arise when, given images of red and yellow stoplights, the subject is instructed to select a key or count the number of occurrences of a rare stimulus when it appears on the screen. This framework served for an adapted experiment in which researchers used a virtual environment. In order to test whether the P3 can also be recognized in an online setting and if it is also reliable as a control output for the BCI in a dynamic environment, they created a virtual town.

In this study, a dynamic virtual environment in which subjects were allowed to drive using a modified go-kart with brakes and steering output connected with the control a virtual car was used to test the feasibility of the P3 signal. The go-kart was the most natural-feeling driving method compared to the unrealistic driving of a virtual car on a computer screen by using the mouse and the keyboard. Participants were told to use their go-kart brakes and stop at red lights, but to continue driving and completely ignore the other green and yellow lights, just like in the natural surroundings. The yellow lights were the most common ones, preceding both green and red lights, and were used as the frequent stimulus. The NeuroScan method was used to track the neural response whenever a traffic light changed colors, from 8 electrode locations (Fz, Cz, CPz, Pz, P3, P4 and two vertical EOG). The digitized EEG signals were then analyzed and had artifacts removed.

The researchers first averaged the trials over the yellow lights and the red lights when the driver stopped, excluding just a couple of trials when the user ran a red light, and as expected the P3 was indeed occurring only at the red lights. Secondly, based on this post analysis of the averages, Bayliss and Ballard (2000) determined whether data from single trials was sufficient for real-time BCI control, as the output needed by the BCI depends on quick analysis and recognition. Different classification methods (correlation, independent component analysis (ICA) and a robust Kalman filter) showed different results. The P3 potential was then classified as the “stop” signal, and its absence at the yellow lights meant no action to be performed. Based on the classification of approximately 135 epochs, they found out the percentage of red light P3 (true positives) classified correctly slightly declines from the correlation to the Kalman filter, while the percentage of correctly recognized yellow lights constantly improves. This is a trade-off, because “if an individual uses the P3 to control a TV, it would be acceptable to have to try twice to turn on the TV, but it would be unacceptable to have the TV turn on and off randomly because of falsely recognized P3s” (Bayliss & Ballard, 2000, p. 189). After training the BCI to obtain the P3 for each subject, they performed another driving session on two previous subjects and achieved a relatively high correlation for red lights, but a low one for the recognition of yellow lights between the two sessions. Finally, Bayliss & Ballard (2000) study showed that the P3 is a practical signal for BCI interfaces and can be used to control devices such as TVs and other home appliances, pointing out that a useful BCI might, however, have to rely on a multitude of brain signals, “for example, if a patient can develop mu-rhythm control, they might want to use it to control the volume on a TV with a P3 being used to control the on-off functions” (Bayliss & Ballard, 2000, p. 190).

Virtual reality aids the learning to control BCI providing feedback in an immersive way rather than the traditional 2D method and provides a testing environment that is safe for the rehearsal of scenarios that would otherwise be too dangerous, pricey, or impossible in reality (Leeb et al., 2007a). The safety of VR as a real-looking environment provides a great opportunity for the training of BCIs for patients that are unable to walk in an interesting and motivating environment (Bayliss & Ballard, 2000).

A considerable finding in the field of wheelchair mobility is that individuals with disabilities can actually learn motor training in VR and are able to transfer it into reality once the training period is completed (Kenyon & Afenya, 1995; Rose, Attree, Brooks, Parslow, & Penn, 2000). Moreover, training of a simple sensorimotor task showed not only that training is transferable, but that it was actually equivalent to real training performance and that interfering tasks affected the real performance of real training slightly more than for those trained in VR (Rose et al., 2000). This was assumed to depend on the cognitive load aspects of the virtual training (Rose et al., 2000).

For disabled persons, learning how to control a wheelchair by thinking can be a tough challenge in a real environment, however in a virtual environment this can be safely and realistically performed and the BCI system can be tested and improved (Leeb et al., 2007a). Thus, the system can be learned and the mastered knowledge is applicable in the real world. Leeb and colleagues performed an experiment in which a patient with tetraplegia learned how to control his wheelchair-BCI system in a virtual environment. The group demonstrated for the first time that brain waves can be used as commands for a wheelchair control in VR. In this case study, the subject was a person with spinal cord injury who could generate beta oscillations when imagining movements of his feet. These bursts of brain waves were successfully picked up by the EEG and were used for a self-paced asynchronous BCI. The tetraplegic subject was in control of the speed and the timing of the system, as the idea behind this BCI was to transfer its use from the laboratory to the real-world applications, where the computer would no longer be in charge of sending external stimuli and triggering brain recording movements (as in the cue-based or synchronous BCIs). This asynchronous BCI recorded EEG at all times and therefore it was necessary for the distinction between the ongoing brain activity of the user when in a non-control (idle) state and the actual commands, or intentional control states (Leeb et al., 2007a).

To distinguish between these two states is difficult in reality, as it is in this situation unfortunately not possible to assess the user's actual intent. In the experiment they performed, researchers overcame this struggle by designing the experiment in such a way that the subject is placed inside the virtual reality, on a virtual street populated with different avatars, and is asked to control the wheelchair and stop at each avatar, then move forward, all by imagining movements of his feet. As Leeb et al. acknowledge, "the reason for the VR-setup is that the visual-rich virtual street with the avatars ensured that the experiment is diversified and engaging but contains enough distraction as it would be in a real street" (Leeb et al., 2007a, p. 2).

4.1.2. Brain-computer interfaces and virtual reality in healthcare

Traditionally, mobile devices assisted through voluntarily generated brain signals have been the core of BCI research. Starting with the P300-based spelling devices for the individuals with speech and muscular impairments (such as the locked-in syndrome of ALS patients) (Sellers, Kübler, & Donchin, 2006) and moving to the prostheses for people who have lost a limb (Muller-Putz & Pfurtscheller, 2008).

However, bringing projections of the virtual environments in a research setting have also been done, probably inspired by the idea of the ecological approach of psychologist J. Gibson. "It is not true that the laboratory can never be like life. The laboratory *must* be like life!" stated Gibson in 1979 (Gibson, 1979, p. 3). From this philosophy and the coming technological developments, researchers have tried to stage a real-life situation for experiments. In his approach, Gibson "argues that the process of perception emerges from an organism embedded in and interacting with its environment" (Tarr & Warren, 2002, p. 1089). Tarr and Warren and other researchers have created virtual reality-based laboratories in which they aim to explore how humans interact in a realistic looking environment (Tarr & Warren, 2002). One example is the VEN Lab (Virtual Environment Navigation Laboratory) at the Brown University, where BCI-VR experiments use

Oculus Rift Head Mounted Display and MSI VR One, setup that is wearable and requires no wrangling of cords. This system provides users with a real immersive experience. Wearable EEG has also been shown to recognize the mental state of the user, possibly widening the scope of the applications (Bashivan, Rish, & Heisig, 2016).

It has been shown that primates trained to use prostheses are inclined to recognize the artificial limb as their own after continuous use, as artificial tools can be assimilated by the brain's body schema (Lebedev & Nicolelis, 2017). Users of prostheses might find it easier to cope with artificial limbs when immersive VR would compel them into thinking that the prosthetics are actually their own limbs (Lécuyer et al., 2008).

Moreover, virtual projections of the artificial body member (prosthesis) aid users in training the manipulation of such a device without actually being connected to it (Lamounier, Lopes, Cardoso, Andrade, & Soares, 2010). The use of virtual reality for upper limb training has been proven more effective than traditional situations because it reduces the great mental effort required in the first stages of training (Kuttuva, Burdea, Flint & Craelius, 2005; Lamounier et al., 2010). In such a training environment, problems such as the weight of the device and the pain of the initial training are minimized, since VR can mimic the use of a prosthesis and facilitates a smoother transition for these individuals who are already unfortunate of a missing limb (Lamounier et al., 2010). Also training the use of a wheelchair in a simulated environment helps its user gradually learn the brain actions required for mobility in a safe and controlled life-like environment, which can later be transferred to outdoor use (Leeb et al., 2007a).

4.1.3. Applications for entertainment and beyond

Besides the clinical implications of the VR and BCI connection, several other prototypes allow their users to navigate and move objects into virtual environments by decoding their brain activity (Pfurtscheller et al., 2006; Lécuyer et al., 2008).

Video games are one domain that, besides healthcare, received, so far, much interest for the applications of BCI and VR technologies to provide video game players new means of control and immersive experiences (Lécuyer et al., 2008).

Lalor and colleagues used a SSVEP-based BCI as the controlling device in a 3D video game (Lalor et al., 2005). Players of this game controlled a virtual character who was walking on a thin rope and lost its balance by looking at either the left or the right side checkerboard images to bring it back in a balanced position. On either side of the screen, the checkerboards flashed at certain frequencies, therefore generating the SSVEP. Even though the researchers do not explicitly name the use of VR, a large screen instead of a monitor was used which gave a feeling of immersion to some degree and resulted in an accuracy of about 89%, partially attributed to the motivation of the players (Lalor et al., 2005; Friedman et al., 2007).

The BCI conjunction with multimedia has been studied in Berlin, where the Berlin BCI (BBCI) system has been created specifically for users who are provided with intuitive brain control strategies for gaming applications that use biofeedback (Krepki, Blankertz, Curio, & Muller, 2007) or for other VR multimedia applications (Krepki, 2004) The BCI, therefore, adds an extra dimension to the multimedia experience and offers its users a supplementary independent communication channel based on brain activity (Krepki et al., 2007).

Games played in the virtual world influence the perception of presence and the course of actions. It is even claimed that the chain of actions establishes the feeling of presence, rather than the performance of the technology and visuals (Riva, 2006; Riva, 2009). Riva stated that "the user is more present in a perceptually poor virtual environment (…) where he/she can act in many different ways than in a real-like virtual environment where he/she cannot do anything." (Riva, 2009, p. 161). Thus, being able to interact with the environment is more important, as actions from the player need to directly correspond with those generated in the game world (Gürkök, Nijholt & Poel, 2012).

Walking by thinking is also possible, as demonstrated by Pfurtscheller and colleagues in 2006, when they have shown that single EEG trials from recordings of motor imagery can be used by the participant to virtually move in a computer-generated environment. By imagining the movement of their feet (similar to actual walking), users were moving forward with constant speed in the projected virtual street (Pfurtscheller et al., 2006).

In a home-like setting, BCIs can be used to control and manipulate virtual objects, such as a switch to turn devices on and off. Researchers have managed to help users turn a lamp or a TV on and off using the P300 (Bayliss, 2003), to control a virtual avatar by means of the SSVEP (Lalor et al., 2005), and to control electrical devices by using smart glasses (Kim, Kaongoen, & Jo, 2015).

Bayliss has introduced the use of P3 component in a virtual apartment, where users could control objects presented either in a virtual environment of an apartment or by looking at a computer monitor (Bayliss, 2003). Interestingly, Bayliss found the P3 components of the subjects who performed the experiment while looking at the computer screen were not significantly different from the ones of the participants immersed in the VR, suggesting that the P3 signal is robust over multiple environments (Bayliss, 2003).

Other tests have studied the brain used to control a car in the 3D VR environment. Using an EEG-based asynchronous BCI, Zhao, Zhang, and Cichocki developed a system in which the car could be controlled only with motor imagery tasks without actual muscular movements (Zhao, Zhang, & Cichocki, 2009). The complex system described used the types of motor imagery (either hand or foot movement) to determine the rotation of the car's steering wheel, while adding the extra level of control generated by the duration of the signals as the amplitude of its corresponding command, namely the angle of the steering wheel. This system demonstrated that, contrasting with most BCIs that focus on just two or three distinct commands, "elaborated and smooth control functions, such as car speed and steering wheel angle, can be achieved in real time by modulating duration time of ERD/ERS corresponding to the specific MI tasks" (Zhao et al., 2009, p. 79).

Applications of VR and BCI in a non-medical setting and not for entertainment purposes are also used, mainly for the so-called *serious games.* These cover simulators, such as flight or space simulators. Previous research in VR has explored brain-body actuated control (Nelson et al., 1997) in order to provide alternative control strategies. For example, VR and BCI can potentially be used as interfaces that exploit the human operator's natural cognitive capabilities in non-manual control devices, which might offer a more intuitive way of system control (Nelson et al., 1997). Such hands-off control mechanism is desirable for tasks that require continuous control or some form of toggling between different flight or view modes. Nelson and colleagues tested various participants who have never used BCI and showed that navigating along a predetermined flight path projected on a dome-like display, or a simple task of continuous control on one axis, is easy to learn and use and can be based only on brain signals, therefore providing an alternative control interface (Nelson et al., 1997).

Continuous control of a virtual helicopter by means of EEG-based BCI has also been achieved using motor imagery (Doud, Lucas, Pisansky, & He, 2011). Sensorimotor rhythms induced by motor imagination were decoded and provided a stable and consistent control signal. The method was fast and accurate, allowing the participants to move the helicopter forward and backward and to control its elevation in order to pass through virtual rings on the flight path. The participants used different motor imagery (both arms – rest, tongue – foot, left hand versus right hand), and reached approximately 85% of the targets on average (Doud et al., 2011) .

Moreover, assigning intelligent control strategies to the controlled flight in 3D indicated that it was possible to achieve the mastery of a virtual helicopter by using subject-specific brain signals to the same level as by using a keyboard (Royer, Doud, Rose, & He, 2010).

Overall, VR promises to be an extension of the BCI possibilities, with multiple applications for different research projects. Work using EEG for brain signal acquisition and VR to create an interactive environment has focused on brain and body control which is better and improved when users are immersed in a virtual environment where they are allowed to act as in reality. This also guarantees the research design and control since the research would still happen in a laboratory.

Researchers used VR and BCI systems also to carry out experiments. Friedman and his team performed two navigation studies using the set-up of a BCI and a highly immersive CAVE-like VR system (Friedman et al., 2007). They studied the navigation in a virtual bar room or street, where participants had to rotate in the bar using just the imagination of left or right hand movements, or walk on a single axis on a virtual street on the basis of their imagined foot and hand movements. The researchers were interested in the concept of presence and interviewed subjects after the experiments. Subjects reported that as the control of the BCI increasingly became more and more automatic, so did they feel more present in the virtual world and were more absorbed by their task. Moreover, Friedman et al. (2007) report that this finding was contradictory to earlier research using virtual environments without the BCI component, as users first feel a great sense of presence that gradually decreases when the subjects learn the limitations of the VR (Garau et al., 2004).

4.2. Research challenges

Before there will be a wide development of virtual reality actions guided by users connected to BCIs, neuroscience and technology will have to tackle some challenges. Developing elements with the highest performance is a challenge for the technicians, while finding the most efficient signals from the brain holds neuroscientists responsible. Nevertheless, an interdisciplinary perspective and development methodology is necessary for overcoming these challenges in the most optimal way.

Although there are numerous technical challenges to be faced by this field, this section further presents research challenges faced in the area of neuroscience, as this thesis aims to mainly cover the neuroscientific aspects. The scientific basis for systems using BCI and VR has to be further developed and emphasized in the commercial devices, while researchers could study whether brain signals could replace other communication methods in VR.

All electrophysiological signals identified so far are similarly used. While some of the signals definitely offer a better communication path with devices, none of them is dominant, as they often come with trade-offs.

On one hand, the BCIs using P300 or SSVEP in their systems are not so immersive and are used to only point to the target, while on the other hand, the motor-imagery based systems are somewhat slow to be used in action control (Lécuyer et al., 2008). Furthermore, EEG-based BCI systems have a low signal-to-noise ratio and express a drop in the accuracy of the classification when more than two or three mental states are required for distinct control classification (Pfurtscheller, Neuper, & Birbaumer, 2005b; Wolpaw et al., 2002). In this regard, Nicolelis (2001) proposed a solution in the form of direct implants to be used for computer control (e.g. the Utah Array), which are already being used by completely paralyzed patients (Friehs, Zerris, Ojakangas, Fellows, & Donoghue, 2004). In the case of implants, more than two mental states can be classified with relatively high accuracy, however this highly invasive system faces stricter requirements (Pfurtscheller et al., 2005b).

For the home user of BCI and VR systems, the picking up of the electrophysiological signals requires the precision and accuracy of electrodes, while maintaining the flexibility and user-friendliness of caps. Bulky components could provide a cheaper device, resulting in increased weight, while more compact and performant components would increase the wearing comfort (Kim et al., 2015). Devices tested in the lab when researchers require participants to stay still might not be feasible for home environments, where the users would most likely not be able to stay still while using the device. Adapting the hardware to the user's environment is possible, probably by researching high-performance electrodes. Recently, dry electrodes have been developed and are used for the acquisitions of brain signals simply by being attached to the subject's scalp with an elastic strap (Lécuyer et al., 2008).

Moreover, transmission of the EEG recordings towards the computer interface necessitates a larger bandwidth than the used transfer rates of up to 60 bits per minute (Lécuyer et al., 2008). Innovative signals processing methods, as well as filters and feature extraction, must be developed to overcome the likely challenging muscle artifacts recorded by the EEG when users are not in the typical laboratory sitting position, and the interface must be easy to calibrate, offer different sizes to fit different users, and easy to use without requiring additional help. Ambulatory EEG data collection for BCI systems designed for the use in the outdoor have been prototyped (Touyama & Maeda, 2011; Touyama & Maeda, 2013). Bypassing the limited conditions in the lab, Touyama and Maeda have recorded EEG from subjects equipped with the system while they were walking outside. The experiment used the oddball paradigm with auditory stimuli and showed promising results for recording brain signals in real-time (Touyama & Maeda, 2013).

Learning how to use brain signals to control devices requires extensive training in the case of some BCIs. For patients, training might not always be feasible due to their condition. VR has been shown to help to learn how to control a BCI by providing realistic goal and feedback. However, for some subjects, even after numerous extensive sessions, the use of a BCI is not possible, this phenomenon being called "BCI illiteracy" (Vidaurre & Blankertz, 2010). It is estimated that up to 20% of the users never achieve effective BCI control, while about another 30% are only poorly able to generate controlling signals (Allison et al., 2010). The inter-subject variability is accountable for these differences and researchers are exploring the BCI users' demographics in order to find answers (Allison et al., 2010).

4.3. Promises for the future

Research in the neuroscience field that covers BCI is increasingly growing, with scientists interested in new topics and bringing the BCI paradigm known so far up to a new level.

The expanding research of BCIs has given rise to a multitude of spin-offs (Lebedev & Nicolelis, 2017). One of the most common variations enhances the classical BCI to a modified double BCI system, where multiple brains can be connected to each other establishing a direct brain-to-brain communication link. The brain-to-brain interface (BTBI) "allows multiple animals to exchange information using a protocol that incorporates both neural recording and simulation" (Lebedev & Nicolelis, p. 811). Starting from this idea, scientists have, on one hand, managed to record information from one subject's brain, and, on the other hand, have managed to stimulate another participant's neurons in order to produce sensations.

The first BTBI has been implemented in rats (Pais-Vieira, Lebedev, Kunicki, Wang, & Nicolelis, 2013). A basic binary brain-to-brain interface has been created to allow the real-time sharing of sensorimotor information in rats. In this system, the first rat, the encoder, performed a two-choice behavioural task while neuronal firing rates were measured from either the primary motor cortex or the primary somatosensory cortex are (depending on whether the task performed was a tactile discrimination task or a visuomotor task). Following a transformation, the signals were converted into patterns of intracortical stimulations applied to the decoder rat in the same brain regions, which in turn had to perform the same task as the encoder rat. The experiment reached a success in about 70% of the trials (Lebedev & Nicolelis, 2017; Pais-Vieira et al., 2013).

Since the 2010s, researchers have been studying whether brain to brain communication is possible also in humans, with signals generated by one person's brain, transmitted to a computer, and then sent further as input signals for another person's brain, in a system called brain-machine-brain interface (BMBI). O'Doherty and colleagues are among the first to demonstrate the operation of such a system that "both controls the exploratory reaching movements of an actuator and enables the signalling of artificial tactile feedback through intracortical microstimulation of the primary somatosensory cortex” (O’Doherty et al., 2011, p. 228). The research here was carried out with rhesus monkeys, which performed an exploratory task (using either a cursor or a VR monkey arm) commanded with neuronal activity generated in one of the monkey’s primary motor cortex. Intracortical microstimulation of the other monkey’s primary somatosensory cortex occurred each time one of the virtual objects were touched. The monkeys were rewarded when a unique artificial texture was identified. The results offer the first account that clinical motor neuroprostheses could have an advantage when intracortical microstimulation is added to develop somatic perceptions arising from the use of mechanical or virtual prostheses (O’Doherty et al., 2011).

Non-invasive brain-to-brain communication has been achieved in human subjects, starting with 2013-2014, when a combination of EEG and transcranial magnetic stimulation (TMS) has been employed by two groups of researchers (Grau et al., 2014; Rao et al., 2014). The task described by Rao et al. involved a visual and motor action for which two humans must communicate directly through the brain-to-brain system to achieve the goal of the computer game. The interface detects the EEG signals from one subject, called the sender, processes this information, and sends it via the internet towards the second participant, the receiver, who receives the signals through the TMS connection. This method facilitates the transmission of the signals which, when received, cause the desired motor action of the receiver (e.g. a press on a touchpad). This system provided first rudimentary results of non-invasive direct brain-to-brain communication via a computer and the internet, paving the way for communication systems that are “bypassing language altogether” (Rao et al., 2014, para. 2; Dingemanse, 2017).

Grau and colleagues describe another experiment in which conscious brain-to-brain communication has been achieved in humans using non-invasive methods (Grau et al., 2014). One human subject performed the role of the emitter, operating a motor-imagery based BCI, while the other human subject, the receiver, acquired the information through TMS pulses applied to the visual cortex. Counting on whether the transmitted binary signal was a 1 or a 0, the TMS coil produced an impulse that resulted (or did not result, respectively) in the conscious perception of phosphenes.

Similar systems have been developed to include numerous other brains in one communication, so-called Brainet, where rats, monkey, and humans generated neural control commands towards achieving a common goal (Nicolelis, 2011; Lebedev & Nicolelis, 2017). Noteworthy cooperative systems designed for several humans have been developed using EEG-based control. A cooperative BCI for spatial navigation was used for the control of a virtual spacecraft (Poli, Cinel, Matran-Fernandez, Sepulveda, & Stoica, 2013). The spacecraft simulator relied on an active display that produces ERPs in the user’s brain, which were directly analysed, resulting in the control vectors for the interface. The researchers also tested the potential of the collaborative approach, in which the ERPs of two users were integrated, and demonstrated that "collaborative BCIs produce trajectories that are statistically significantly superior to those obtained by single users" (Poli et al., 2013, p. 149). A handful other paradigms involving the simultaneous communication of more than two users have also been proposed for decision-making (Poli, Valeriani, & Cinel, 2014; Yuan, Wang, Gao, Jung, & Gao, 2013) and for movement planning (Wang & Jung, 2011).

5. Conclusion

The connection between BCI and VR provides a promising interdisciplinary research area. Up to now, multiple prototypes have combined different electrophysiological signals that are processed into commands for machines. Virtual environments display these outputs and provide users with a new feeling of presence by immersing them in a computer-generated world in which they can act solely by means of their brain activity. However, the neuroscientific basis for combining BCI and VR has been lacking a systematic presentation. This essay presents a comprehensive study of the applications and challenges of combining these techniques from a neuroscientific perspective. While there is not just one answer to the research question stated in the introduction, namely "What is the neuroscientific basis for combining BCI and VR?", this essay constitutes the first step in researching a newly emerging interdisciplinary field. Moreover, the essay provides a categorization of the applications, which could be treated as a structural foundation for further research.

Traditionally, BCIs have been used by disabled patients as a means to communicate with the outer world when their normal motor output does not function properly, but nowadays the up-and-coming applications also include devices built for simulations and entertainment. Motor imagery-based BCIs have been shown to facilitate smooth navigation of virtual worlds, as the signals generated with imagined movement are continuous and self-paced. Selecting icons on a computer screen or objects from the VR is also possible for users of evoked potentials BCIs (either P300 or SSVEP). For the use of simulators, BCIs provide extra control possibilities or hands-free operation of vehicles, skills that are transferable to the real world situations.

Overall, the neuroscience and technology of BCI and VR receive a lot of attention, not only from researchers, but also from healthcare and multimedia fields. Developments that allow the control of computers and other devices solely by means of willingly produced brain signals have been researched for more than half a century, with VR technology being developed for just about as long, yet only recently the virtual environments have been merging with BCI. The trends for the future seem to grow exponentially, while public concerns about unethical uses also arise. However, over the long term, the innovations arising from combining BCI with VR will pave the way for new applications and push the limits of the human understanding, increasing the knowledge about the functional properties of electrophysiological signals generated in brain and the relation between the human mind and virtual environments.

6. References

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Word count (excluding References): 14488