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Brain-controlled virtual environments - an evaluation study of brain-computer interfaces for serious game interaction

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Brain-Controlled Virtual Environments - An evaluation study of Brain-Computer Interfaces for Serious Game Interaction

Athanasios Vourvopoulos

**A thesis submitted in partial fulfilment of the University's requirements
for the Degree of Master of Science by Research**

July 2013

Coventry University

“You can learn more about a man in an hour of play than in a year of conversation.”

- Plato (427-347 BC), from The Republic

Abstract

Brain-Computer Interfaces (BCIs) have been increasingly used the last few years in research as a control input to various BCI games, incorporating different techniques and methodologies. So far all current brain-controlled games and virtual environments are proof-of-concepts, with low information-transfer-rate, lack of 3D graphics or poor game-play resulting to poor immersion. Within the last few years commercial BCI equipment had been introduced as an alternative game controller from various companies like Emotiv and Neurosky, setting a milestone in user experience. Although new games are emerging which make use of these (out-of-the-box) headsets, there is not much knowledge concerning the game design principles that have to be taken into account to create a game or virtual environment that is controlled by a unique device like EEG headsets bearing in mind that even neuroscientists have just started (with modern methodologies and tools) to map the human brain and its functions.

This study presents the background in BCI's and a state-of-the-art from current BCI controlled serious games and Virtual Environments (VEs), investigates the effect on the user experience this kind of brain-to-computer interface has. In addition, it examines whether or not the incorporation of a BCI in Serious Games and VEs can offer similar control and engagement that other Natural User Interfaces (NUIs) can offer. To achieve this, a pilot study of $n=31$ naïve participants (with no previous experience with BCI's) had been conducted, gathering feedback through a presence questionnaire, an unstructured interview and Encephalographic (EEG) data during task performance. For the evaluation process, two serious games were used. The first was designed for controlling a robot in a virtual maze (BrainMaze) in a third person perspective and the second game was "Roma Nova", a high-fidelity serious game created in Coventry University.

Results indicate that users are capable of controlling a virtual avatar followed a training task. User self-report questionnaires indicate enjoyment and acceptance of the proposed system. Finally, the correlation between the user answers based on the gaming experience and the extracted EEG data for engagement and attention is very small

indicating that current BCI technology is not capable to deliver the same qualities of interaction as other Natural User Interaction (NUI) devices that are currently on the market. Furthermore, this study sets the base for the development of future BCI driven serious games.

The objectives of this thesis are threefold. First, to control an avatar of a serious game in real-time performance using only EEG data; secondly, to examine the reaction of users while playing the game and thirdly to test each system in terms of: ‘learnability of the interface using the game’, ‘satisfaction of the player’, ‘performance of the interfaces’ and ‘effort put by the player’. This will help us to build a more generic framework for future brain-controlled games.

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I would like to thank my family for supporting my academic studies, my Director of Studies (DoS) Dr. Fotis Liarokapis and my supervisory team for giving necessary pieces of advice. In addition, the Interactive Worlds Applied Research Group (iWARG) and the Serious Games Institute (SGI) of Coventry University for supporting my research.

Videos of this project can be found online at: <http://www.vourvopoulos.com/> and <http://www.youtube.com/user/vourvopa>

Athanasios Vourvopoulos

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Abbreviations

BCI - Brain Computer Interface

NUI - Natural User Interface

ECG - Electrocardiography, Electric activity in the heart

EEG - Electroencephalography, Electric brain activity

EMG - Electromyography, Electric activity in the muscles

EOG - Electrooculography, Electric activity in the eyes

FFT - Fast Fourier Transform

fMRI - functional Magnetic Resonance Imaging

MEG - Magnetoencephalography

P300 - Event related Potential occurring 300 ms after stimulus

Symbols

α alpha band EEG frequencies

β beta band EEG frequencies

δ delta band EEG frequencies

μ mu band EEG frequencies

θ theta band EEG frequencies

Publications

Publications resulting from this thesis:

Peer-Reviewed Conference Proceedings:

- **Vourvopoulos, A.**, Liarokapis, F., Petridis, P. Brain-Controlled Serious Games for Cultural Heritage, Proc. of the 18th International Conference on Virtual Systems and Multimedia (VSMM2012), IEEE Computer Society, Milan, Italy, 2-5 September, (2012).
- **Vourvopoulos, A.**, Liarokapis, F. Robot Navigation using Brain-Computer Interfaces, Proc. of the 11th International Conference on Ubiquitous Computing and Communications (IUCC-2012), IEEE Computer Society, Liverpool, UK, 25-27 June, (2012).
- Liarokapis, F., **Vourvopoulos, A.**, Ene, A., Petridis, P. Assessing Brain-Computer Interfaces for Controlling Serious Games, 5th International Conference on Games and Virtual Worlds for Serious Applications (VS-GAMES'13), IEEE Computer Society, Bournemouth, UK, 11-13 September, (2013).

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Book Chapter:

- Liarokapis, F., Debattista, K., **Vourvopoulos, A.**, Ene, A., Petridis, P. Comparing Interaction Techniques for Serious Games through Brain-Computer Interfaces, Intelligent Computer Graphics 2013, Springer.

1 Introduction

The first who discovered the electrical nature of the brain is considered to be Richard Caton (1875), a physician from Liverpool, discovering electrical impulses from the surfaces of living brains in animal subjects. The study of the human brain through Electroencephalography (EEG) dates back to 1929 where the German psychiatrist Hans Berger discovers EEG and publishes the first papers (Berger 1933) analysing the interrelation and brain diseases initiating that way a new era in neuroscience by introducing a new tool for medicine and psychology. Berger recognising the importance of R. Caton cites him in his 1929 report on the discovery of Alpha waves. Since then EEG started to be part of computer gaming and Human-Computer Interaction (HCI) through commercial low cost headsets. This giant leap results from many years of medical research and technology advancement, enabling companies to produce user friendly, low cost EEG equipment for commercial use. First developments for using brain waves as inputs started during the 70's with DARPA having a vision of the "enhanced human" initiating the first step in the right direction. The first successful experiments involved electrode arrays implantation to monkeys during the 90's with offline reproducing of movements until the first robot control using brainwaves from a monkey (Wessberg et al. 2000). Only the last decade humans started to benefit from this technology using both invasive and non-invasive approaches for communication and control.

Table 1.1: Disadvantages of current brain sensing Technologies (Lee and Tan 2006)

Computer game interfaces are continuously improving towards a more natural user interaction. Natural User Interfaces (NUI) unlike the use of traditional devices such as standard input/output (I/O) devices (i.e. the keyboard and the mouse) do not require training and familiarisation. Modern interaction devices like MS Kinect (Microsoft Corporation, Washington, USA) and Nintendo Wii (Nintendo Co., Ltd. , Kyoto, Japan) are an example of this transition into a more compelling gaming experience without the use of any mediatory device that the user has to learn to use and operate. Going a step further, direct neural interfaces which connect the human brain to a computer have recently appeared as an alternative gaming controller. This is achieved with the help of commercial BCIs and the use of Electroencephalography by capturing signals from the users scalp. Research into brain-controlled games started within the last few years. Companies have released low cost EEG equipment, Software Development Kits (SDKs) and integration packages for game engines like Unity 3D (Unity Technologies, San Francisco, USA) making this integration easier for developers and researchers.

1.1 Aims and Objectives

A good gaming environment involves an immersive experience to the user, giving the feeling they are inside the virtual world as part of the virtual 'eco-system'. BCIs are a special case of interfaces, introducing to the user a unique experience through neurofeedback (real-time control feedback based on brain activity). This process requires training and familiarisation to 'tame' all the acquired information of the brain into the desirable action within the virtual environment. Compared with traditional input devices such as the mouse, keyboard and joystick, BCI is considered as an unreliable input channel of control. The questions that arise are: Does this way of interaction obstruct immersion and feelings of presence in the game? Can a BCI be of value in future virtual world interaction for serious applications? Is it fun and enjoyable to play with BCI control? This was examined by focusing on two main research objectives: 'evaluation of the system that allows us to quantitative and qualitative capture the effects on the user experience', and 'by collecting extensive synchronized brain activity and behavioural data on user's performance during the testing process.

Overall, this research project explores the use of non-invasive EEG-based technology for VEs and serious games interaction, assessing the overall experience of naïve users. Such methods receive increasing attention in the research community since they may offer a more effective and intuitive way that users interact with games and virtual worlds as other Natural-User Interfaces (NUIs). This can be achieved with the use a low cost neuro-headsets (real-time EEG and EMG recordings) and modern game development platforms that rapidly become part of commercially available systems. Such technological advances have a strong potential towards new interaction techniques in a way that users never experienced before, excluding the traditional use of devices like mouse and keyboard. Serious games development for eHealth applications can make use of such technologies allowing the development of personalized and person-centric care methods and processes.

By analysing the development and implementation of a serious gaming system based on BCIs it is possible to collect valuable data that will allow us to build a general framework based on the quantification of the user experience for future interaction. This

could extend towards a participatory design for BCI games (both for entertainment and serious applications) in which all stakeholders have active role in the design process.

The specific areas of contribution are:

- Evaluation of two Brain-Controlled Serious Games with a sample of 31 users.
- Electrophysiological and statistical data resulting from the game interaction with the BCI interfaces.
- Design and implementation details showing an efficient method of interaction with Brain-Controlled Virtual Environments.

1.2 Thesis Overview

This thesis is divided into three parts. **Part I** gives an overview of Brain-Computer Interfaces and previous research on the subject. **Part II** describes the design, implementation and the results of the system. **Part III** discusses the conclusions drawn from this research project and provides suggestions for future work.

An overview of each chapter is as follows:

Chapter 1 Gives a brief introduction on electroencephalography and the progression towards BCI's and brain-controlled games.

Chapter 2 provides information on how the human brain works, a brief introduction on the Biomedical Signal Processing including the Electroencephalogram and finally BCIs and their connection with serious games.

Chapter 3 gives an overview of the System Architecture, technical details of the neuro-headset, design details of the Brainmaze game including the building elements and further information for the RomaNova game.

In **Chapter 4** the user testing process and the overall evaluation of the system are described in detail. Experimental conditions, protocol and participants feedback.

In **Chapter 5** a brief description of the tools used for the data analysis is provided. That includes SPSS for the statistical analysis and Matlab with the EEGLab toolkit for the EEG analysis.

In **Chapter 6**, the results from the user testing are presented in detail. This includes the statistical analysis and the details from the extracted signals, plotting, data presentation and analysis with the EEGLAB toolkit in Matlab.

Chapter 7 concludes by providing a summary of the contributions made and the research techniques described with this thesis. Possible improvements that could be made along with expansion ideas are also discussed. Also suggestions are made for areas that could benefit from future research and development.

Part I - Research

2 Background

This chapter gives a brief introduction on the basic physiological elements of the human brain with the different areas responsible for different functions. Biomedical signals are explained including different types of signals with the description of electroencephalography and the progression towards BCI's. Moreover, with the progression of technology (both in the hardware and software domain) brain-controlled games are introduced including past and current systems.

2.1 The Human Brain

The brain is the centre of the nervous system weighting on average about 1.5 kg. It's divided into four areas: 'cerebral cortex', 'cerebellum', 'brain stem', 'hypothalamus', 'thalamus' and within each area different functional sub-areas are included as it is illustrated in Figure 2.1. The brain can be divided into two hemispheres. The hemispheres are connected with each other via corpus callosum and each hemisphere can be divided into four lobes: frontal, parietal, occipital and temporal lobes. Each area is responsible for different functions (Chudler 2000). These areas can be seen in Figure 2.1. The functions are described in Table 2.1. This kind of knowledge has been used with BCIs based on the pattern recognition approach. The mental tasks are chosen in such a way that they activate different parts of the brain.

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Figure 2.1: Functional areas of the brain (Chudler 2000)

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Table 2.1: Cortical areas of the brain and their function (Chudler 2000)

2.2 Biomedical Signal Processing

Biomedical signals are produced by living biological systems through their cells, organs or the whole body. Those signals carry important indications of the state of the system that produces them. This relevant information can be used to extract useful information of the systems biological activity for further analysis with the help of Biomedical Signal Processing (BSP). BSP can be used for diagnosis, monitoring, prognosis and research for the effectiveness of treatments and methods.

In the past, BSP focused on filtering signals to remove noise and artefacts (Gholam-Hosseini, Nazeran and Reynolds 1998, Levkov et al. 2005, Thakor and Zhu 1991).

A biological system is a complex system that contains mixed signals of other subsystems. Removing unwanted signal components from the different subsystems is what enables scientists to extract and analyse vital information for further biomedical discoveries. Bio Signals carry different information that has to be dealt by different processing techniques with noise cancelation methods, analysing the signal spectra, suppressing undesired frequencies. Another method derives from statistical signal processing, treating the data as random signals. Filtering like Wiener (Clancy, Morin and Merletti 2002) or Kalman (Bonmassar et al. 2002, Charleston and Azimi-Sadjadi 1996) utilize statistical characteristics of the signals, extracting the desired components.

Variation of Signals: As it is aforementioned, each subsystem produces different kind of signals, waveforms and frequencies for different pathological states. A few examples are the Electrocardiogram (ECG), Electromyogram (EMG) and the Electroencephalogram (EEG).

Differentiating these signals is crucial for the biomedical signal processing and analysis.

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Table 2.2. Frequency and amplitude ranges for ECG, EEG, EOG, and EMG (Parve 2009)

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Figure 2.2: Biomedical Signals example (Parve 2009)

Transmission Problems: In non-invasive measurements the signals are recorded from surface electrodes capturing signals produced from inside the body. This can modify the signal features making more difficult the signal analysis and the possible feature extraction. A good example is the EEG signals that are captured with sensors attached to the scalp, being difficult to identify the position of the EEG inside the brain because of the skins impedance.

Noise and Interference: Different kind of noises is captured inside the signal. They vary from mechanical noise by moving the electrodes, electrical noises from electrical equipment nearby or from additional electric activity produced inside the body like the muscle movement. Although the electric activity produced from the body is what the biomedical signal processing is analysing, when it comes to EEG signal processing for Brain-Computer Interfacing the interfering signals have to be eliminated. EEG data is almost always contaminated by such biological artefacts, including:

- Eye-induced artefacts (includes eye blinks, eye movements and extra-ocular muscle activity)
- ECG (cardiac) artefacts
- EMG (muscle activation)-induced artefacts
- Glossokinetic (tongue movement) artefacts

The main stages of processing a biomedical signal are the same for any other type of signal processing. There are different methods available for identifying and extracting the biomedical signal characteristics depending on the goal of the analysis.

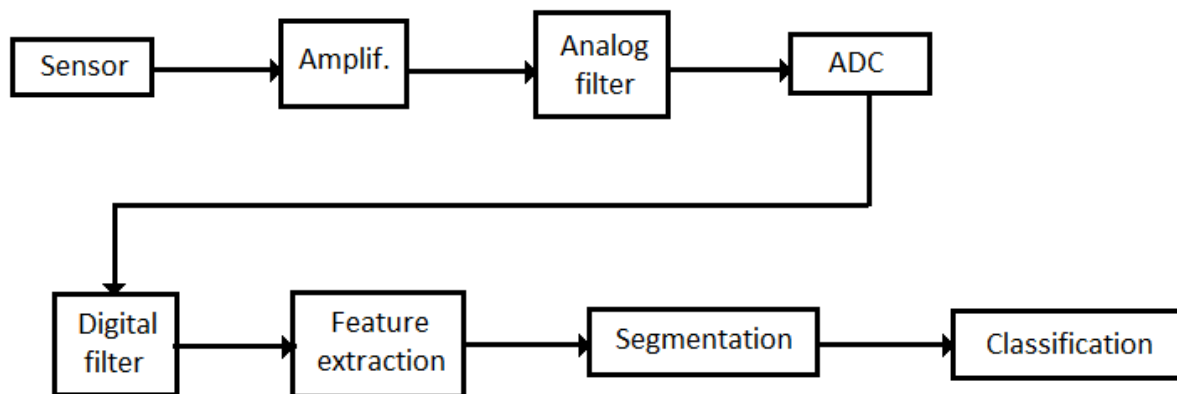


Figure 2.3: Main stages in Biomedical Signal Processing

2.3 Electroencephalography (EEG)

Electroencephalography (EEG) is a method used for measuring the electrical activity of the brain. This activity is generated by billions of nerve cells, called neurons. Each neuron is connected to thousands of other neurons. Some of the connections are excitatory while others are inhibitory. The signals from other neurons sum up in the receiving neuron. When this sum exceeds a certain potential level called a threshold, the neuron fires nerve impulse. The electrical activity of a single neuron cannot be measured with scalp EEG.

However, EEG can measure the combined electrical activity of millions of neurons (Malmivuo and Plonsey 1995) .

2.3.1 Method of measurement

The EEG is recorded with electrodes, which are placed on the scalp. Electrodes are small plates, which conduct electricity. They provide the electrical contact between the skin and the EEG recording apparatus by transforming the ionic current on the skin to the electrical current in the wires. Electrolyte gel is applied between the electrode and the skin in order to provide good electrical contact (Malmivuo and Plonsey 1995). A specific system of electrode placement is used called International 10-20. The distance between the specific anatomic landmarks (nasion and inion, see Figure 2.4) is measured after which the electrodes are placed on the scalp using 10 and 20 % inter-electrode distances (Klem et al. 1999). Each electrode position has a letter (to identify the underlying brain lobe) and a number or another letter to identify the hemisphere location. Odd numbers are on the left side and even on the right side. Z (for zero) refers to electrode placements at midline. The system allows the use of additional electrodes.

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Figure 2.4: The international 10-20 electrode system – Top view (Klem et al. 1999)

2.3.2 Wave Patterns

Overall there are five main wave patterns that are distinguished. In increasing frequency they are: *Delta*, *Theta*, *Alpha*, *Beta* and *Gamma* waves.

Delta (δ) is the frequency range up to 4 Hz. It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow wave sleep. It is also seen normally in babies. It may occur focally with subcortical lesions and in general distribution with diffuse lesions, metabolic encephalopathy hydrocephalus or deep midline lesions.

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Figure 2.5: Delta waves (Davis 2012)

Theta (θ) is the frequency range between 4 Hz to 7 Hz. Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation. Excess theta for age represents abnormal activity. This range also has been associated with reports of relaxed, meditative, and creative states.

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Figure 2.6: Theta waves (Davis 2012)

Alpha (α) is the frequency range between 8 Hz to 12 Hz. Hans Berger named the first rhythmic EEG activity he saw as the "alpha wave". This was the "posterior basic rhythm", seen in the posterior regions of the head on both sides, but higher in amplitude on the dominant side. It emerges with closing of the eyes and with relaxation, and attenuates

with eye opening or mental exertion. In young children, the posterior basic rhythm is actually in the theta range.

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Figure 2.7: Alpha waves (Davis 2012)

Beta (β) is the frequency range between 12 Hz to about 30 Hz. It is seen usually on both sides in symmetrical distribution and is most evident frontally. Beta activity is closely linked to motor behaviour and is generally attenuated during active movements. Low amplitude beta with multiple and varying frequencies, however, is often associated with active, busy or anxious thinking and active concentration. It is the dominant rhythm in patients who are alert or anxious or who have their eyes open.

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Figure 2.8: Beta waves (Davis 2012)

Gamma (γ) is the frequency range approximately 30–100 Hz. Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function. This is the least understood of all.

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Figure 2.9: Gamma waves (Davis 2012)

2.4 Brain-Computer Interface's (BCIs)

Brain-computer interfaces (BCIs) are communication devices which enable users to send commands to a computer by using brain activity only (Wolpaw et al. 2002). In a BCI system, signals from the brain are being analysed to determine the user's state of mind or intentions, which in turn can be translated into actions. A diagram of a BCI system can be seen in Figure 2.10. BCI technology is a rapidly growing field of research and an interdisciplinary endeavour. Research in BCI involves areas of neuroscience, computer science, engineering and clinical rehabilitation. Brain-controlled robots, VEs and serious games can be used for a wide range of applications from modern computer games (Lecuyer et al. 2008) to prosthetics and control systems (Loudin et al. 2007).

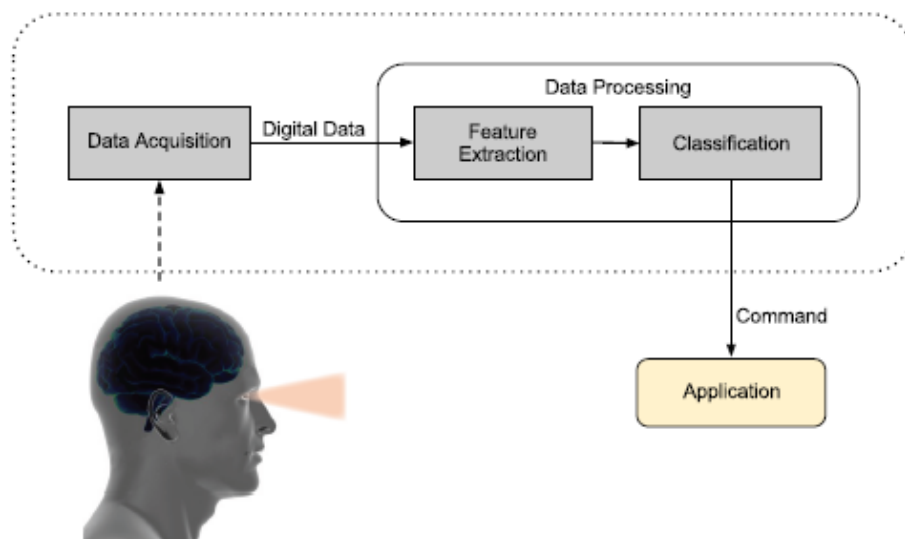


Figure 2.10: Block diagram of a BCI system

Brain-Computer Interfacing (BCI) research was mostly driven for rehabilitation purposes in the medical domain mostly, assisting paralyzed people to communicate and interact with the outside world. During the last five years BCI research has been moving into applications for ‘healthy’ people thanks to commercial BCI headsets from companies like Neurosky and Emotiv. These headsets are primarily designed to be used as an alternative game controller. Comparing professional EEG systems (ranging from £8.000 to £200.000) for medical research, commercial BCI headsets are cheaper to buy, easier to interact and quick to setup.

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Table 2.3: Commercial BCI systems cost. Source (Stamps and Hamam 2010)

A recent study attempts to support further research into the development of practical and inexpensive non-invasive brain-computer interface systems comparing different low-cost EEG systems by price and functionality(see Table 2.3) also rated by usability (see Figure 2.11). In their findings, the Emotiv Epoc headset scored high in terms of usability and was ranged in the middle price segment (Stamps and Hamam 2010).

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Figure 2.11: Usability rating of low cost EEG acquisition devices. Source (Stamps and Hamam 2010)

Lowering the cost of BCI equipment allowed Gamers to focus their interest to BCI headsets as a new game device as they're often the first to adopt any new technology, willing to put the effort into learning and work with it (Nijholt and Tan 2007). Brain-Computer interaction at this stage is slower and less accurate than traditional interfaces that are currently available. This makes healthy users to be more demanding while interacting with the game. In addition, BCI's often require a lot of training for successful interaction which weakens the overall user experience. Current Brain-Controlled games are just proof of concepts with simple BCI paradigms, such moving a paddle left and right in the game Pong with imaginary movement of the hand (Krepki et al. 2007). The Information Transfer Rate (ITR) of this kind of BCIs is still around 25 bits per minute (Wolpaw et al. 2002), which makes it incomparable with the speeds of over 300 characters per minute (roughly 400 bits per minute) of a typical keyboard (Cover and Thomas 2006). Due to these limitations, there is still a big gap between research and entertainment games. Based on that, the question that rises is why would a healthy person want to play BCI games instead of using the current (commercial) controllers? The popularity of motion sensors like Nintendo Wii and Microsoft's Kinect for gesture recognition is example of a trend towards natural interaction. If the user can interact with the virtual world as the real world, then the

learnability and memorability may not be an issue (Witmer and Singer 1998). Based on that, natural interaction can move further with BCIs, connecting directly to the virtual world bypassing any physical mediation limited to bodily actions. Like thoughts, computer games are not constrained, enhancing the possibilities of the human-machine interaction. Therefore, connecting the user directly with the virtual world gives a more natural way of control and communication. Games can respond and adapt based on users' brain activity, that way if the mental state is known the system can "manipulate" it, keeping the user engaged in equilibrium (see Figure 2.12). Alternative, adaptation of non-player characters (NPCs) like A.I. avatars based on user's mood or mental state can be used for a well matched interaction.

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Figure 2.12: Csikszentmihalyi flow diagram (Csikszentmihalyi 1990)

Summarized, BCIs can uniquely provide information to the game environment that no other traditional game controller can provide. This non-physical interaction is based on a neuro-feedback loop between the user and the game, improving user's ability to control brain-generated events. This can result in higher intelligence, even in coping with stress

(Doppelmayr et al. May, Tyson 1987). BCI game development has to move beyond feasibility tests, and focus on the role that BCI can play in improving the gaming experience.

2.4.1 How it started

Although research on BCI started during the 1970's only the last few years we have been able to introduce brain-computer interfaces to simple users mostly through commercial BCI headsets for computer games. Research on BCI began from UCLA in the 1970's marking for the first time the expression Brain-Computer Interface on the papers and journals that have been published (Vidal 1973, Vidal 1977). Early research had to do with neuro-prosthetics that aim at restoring damaged hearing, sight and movement. Over the years several laboratories have managed to create systems that carry out movements of robotic arms handled by monkeys getting biofeedback. That way they were able to map patterns of the neural activity of the brain and develop algorithms. In 1999, researchers at University of California, Berkeley decoded neuronal firings to reproduce images seen by cats. They decoded the signals from the targeted brain cells of the cats' brain, to generate movies of what the cats saw and were able to reconstruct using mathematical models (Stanley, Li and Dan 1999).

In the 1980s, researchers at Johns Hopkins University found and formulated the relationship between the electrical responses of single motor-cortex neurons in rhesus macaque monkeys and the direction that monkeys moved their arms (Georgopoulos et al. 1989). Later experiments using rhesus monkeys researchers reproduced reaching and grasping movements in a robotic arm. By mid-90's invasive BCI's have started applied into humans. One example of invasive BCI is the direct brain implant to treat non-congenital blindness. Sixty-eight electrodes were implanted into the patient's visual cortex and succeeded in producing phosphenes, the sensation of seeing light without light actually entering the eye, through cameras that were mounted on glasses to send signals to the implant (Kotler 2002). In 1998, researchers at Emory University in Atlanta were the first to install a brain implant in a human that produced signals of high enough quality to simulate movement (Kennedy and Bakay 1998). More recently, researchers succeeded in building a

BCI that reproduced owl monkey movements while the monkey operated a joystick or reached for food (Wessberg et al. 2000). In 2004, researchers from Washington University in St Louis enabled a teenage boy to play Space Invaders using his Electrocorticography (ECoG) implant, a partially invasive BCI device (Fitzpatrick 2006).

The last few years' research groups have investigated various ways in controlling robotic platforms mainly electrical wheelchairs or robotic arms for people suffering from a diverse range of impairments. People who are locked-in by brainstem stroke, spinal cord injury or damaged regions of the brain responsible for the body movement like the motor cortex area which generates the neural impulses controlling execution of movement (Neumann and Kubler 2003).

2.4.2 Direct Interface Techniques via EEG

Three main techniques are currently used in BCI systems for user interaction and control. These techniques are also used successfully for locked in patients where haptic and linguistic interfaces fail:

- **Steady State Visual Evoked Potentials (SSVEP)**

SSVEP are caused by visual stimulation by flashing lights to the patient and occur at the primary visual cortex of the brain. This evoked response in EEG signals to repetitive visual stimulations is called SSVEP. In a SSVEP BCI system, specific frequencies are used to the repetitive visual stimuli. For SSVEP detection, analysis on the frequency domain is performed in order to identify the peak on the frequency spectrum based in the frequency of the repetition of stimulus in which the participant had been focused. By detecting this frequency, we can translate it into a control signal for a BCI system. Using this technique can come across to some issues. One is gaze dependence according to Allison et al. (Wolpaw 2012) and another one is that in some users, the flickering stimulus is annoying and produces fatigue. Using higher frequencies for the flickering stimuli can reduce the issue but it makes it harder to detect the SSVEP. On the other hand SSVEP BCI's do not require any significant training and the information transfer rate is high (Wang, Wang and Jung 2010).

- **P300**

P300 BCI is measuring the brain evoked response after stimulus onset, positive and negative deflections in the EEG signal. These deviations are called event-related potential (ERP) and depending on the latency of these deviations, they are clustered as: exogenous and endogenous components (Fazel-Rezai et al. 2012). The exogenous component occurs approximately 150 ms after the evoked stimulus and the endogenous components have a longer latency. The largest positive deflection of the response occurs between 250 to 750 ms after the stimulus. It appears as a positive curve on the EEG after 300ms (hence the name) through relevant and seldom stimulation with the strongest signals captured at the parietal lobe. P300 is the most used ERP component in BCI systems.

- **ERS/ERD**

ERS/ERD stands for event related synchronization/desynchronization through the imaginary limb movement, located at the motor and somatosensory cortex of the brain. This kind of EEG activity has been used as one of the sources in BCI (Wolpaw et al. 2002). Motor imagery is one way to create changes in ERD/ERS and has been used in a plethora of BCI systems (Pfurtscheller and Lopes da Silva 1999). During the imagery movement (e.g. of a limb), ERD occurs predominantly over the contralateral brain motor area and, therefore, can be used as a control signal for a BCI system. ERD/ERS BCIs have been used in different kinds of applications including the two-dimensional cursor control of the first BCI systems.

2.4.3 Brain-Controlled Serious Games and Virtual Worlds

With the launch of low cost commercial BCI headsets in the last few years, Brain-Computer Interfaces were introduced as an alternative gaming controller in the computer games domain. This gave the opportunity to applied research groups to get involved with BCI research for various applications by using relatively low cost non-invasive EEG equipment and SDKs. This technology boosted the BCIs in Games oriented research with main target brain rehabilitation through serious games and VEs. This is also reflected in the

increasingly popular BCI research studies with a large upsurge within the last few years (see Figure 2.13).

Early non-invasive BCI research methods in serious games development were usually oriented in the medical domain rather than entertainment. The first BCI game was created in 1977. In this game, the user could move in four directions in a maze by fixating on one of four diamond-shaped points periodically flashed. The methodology used was far ahead of its time using online artefact rejection and adaptive classification. The information transfer rate (ITR) was remarkable being above 170 bits/min (Vidal 1977). A much simpler example of brainwave integration with games comes from the game Brainball (Hjelm 2003), making use of a broadband use of brain frequencies such as the: alpha, beta, gamma, theta and the mu-rhythm. Using a headband, the EEGs of the player is measured and a relaxation score is derived from the ratio between the alpha and beta activity in the EEG signal.

Another BCI game that measure user's attention level has been developed for training those who suffering from Attention Deficit Hyperactivity Disorder (ADHD). These games are designed in order to control a virtual hand's movement, utilizing 3D animation technique (Lijun et al. 2011) for rehabilitation purposes. A relatively modern study that uses an animal instead of a human brain comes from a team who developed an internet game linked to a BCI system translating real-time brain activities from prefrontal cortex (PFC) or hippocampus (CA1) of a rat. These activities are translated into external device control commands and used them to drive an internet game called RaviDuel (Unjoo et al. 2006). Another medical oriented system was the implementation of a game capable of moving an avatar from a tennis game using only brain activity for assisting people with diseases involving movement difficulties for controlling keyboard and mouse of a computer. To achieve this mu (μ) rhythm of brain activity has been used (Lopetegui, Zapirain and Mendez 2011, Mattiocco et al. 2006). An EEG pattern recognition system to adapt a serious game has been designed comparing recognition rates in order to apply for experimental serious games without any traditional controllers. Their proposed Support

Vector Machine (SVM) algorithm for classification is compared with other algorithms, improving the recognition rate (Jae-Sung and Won-Hyung 2011).

A Quantitative and Qualitative Study in Self-Paced Brain-Computer Interaction with Virtual Worlds showed that, without training, roughly half of the subjects were able to control the application by using real foot movements and a quarter were able to control it by using imagined foot movements. The application consisted of an interaction with a virtual world inspired by the “Star Wars” movie. Users were asked to control the take-off and height of a virtual spaceship by using their motor-related brain activity (Lotte, Renard and Lécuyer 2008). The use of mixed reality systems like Virtual and Augmented Reality (VR and AR respectively) is also a step towards the design of immersive BCI systems in order to enhance the user experience (Faller et al. 2010, Pfurtscheller et al. 2010). A series of BCI games have exploited the last ten year, varying from neuro-feedback based games, the imagination of movement games, and those based on different techniques.

The most common BCI based input devices are using motor-control. An example is the mu (μ) rhythm based first person shooter game from (Pineda et al. 2003) which uses the players brain waves (from the motor cortices) to steer left/right, while forward/backwards movement is controlled from physical buttons. Four participants had been used with 10 hours of training in a range of 5 weeks for them to learn how to control their mu-power. Another similar BCI system by Krepki (Krepki et al. 2007) uses motor-control based on lateralized readiness potential (LRP) - a slow negative shift in the EEG over the activated motor cortex – for controlling the Pacman game. An example of P300 based games are Bayliss virtual driving task and a virtual apartment (Bayliss 2003, Bayliss, Inverso and Tentler 2004) with highlighted red objects evoking a P300 when the uses wanted to make a selection. Another recent P300 game is Finkes (Finke, Lenhardt and Ritter 2009) MindGame where the P300 events are translated into movements of a character on a three-dimensional game board. The classification (score 0.65) during the online run of the game is computed on a single-trial basis without averaging over sub-trials. SSVEP based games have been also designed based on subjects attention to a visual stimulus. In the MindBalance game by (Lalor et al. 2005), a SSVEP is evoked by two different

checkerboards with the participants attention focused in one of the two checkerboards in order to balance an avatar in a piece of a string. An advantage of SSVEP over induced BCI paradigms is the multiple option selection by focussing attention on a stimulus. An example is the (Martinez, Bakardjian and Cichocki 2007) 2D racing game using SSVEP to control four different directional movements in a similar way an FPS game was controlled in (Jackson et al. 2009) SSVEP BCI.

While these kinds of BCI techniques for controlling games are quite interesting, most of the games so far are proofs of concept. The interaction with these games is really slow, often with decreased gameplay speed in order to allow for BCI control feasible as a result reducing fast-paced games into turn-based games. Recent projects move towards to a more stable control in BCI games (Jackson et al. 2009, Zhao, Zhang and Cichocki 2009), focusing on a smooth and more meaningful interpretation of BCI control signals. This is the time where we need to move beyond feasibility tests and proof-of-concepts, and focus on the role that BCI can play in improving the gaming experience and interaction within a virtual-environment.

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Figure 2.13 BCI games papers produced the last decade (Marshall et al. 2013)

2.5 Serious Games

As a serious game is generally referred the category of games that are uniquely differentiated from entertainment games (and their genres) through their purpose of design. Serious games can be applied to a broad spectrum of areas, generally used for education, science, health and military without excluding their property of being entertaining as-well. Although entertainment in these applications is not the primary goal, there is currently no single definition of the concept. As an example, Zyda (2005) defines a serious game as:

“a mental contest, played with a computer in accordance with specific rules, which uses entertainment to further government or corporate training, education, health, public policy, and strategic communication objectives”.

Zyda (Zyda 2005) supports that while pedagogy is the main element of a serious game, entertainment has to come first in order for the serious game to be fun to interact with. A game that is not ‘fun’ to play would be useless, independent of its pedagogical content or value. On the other hand, Michael and Chen (2006) define serious games as *“games that do not have entertainment, enjoyment or fun as their primary purpose”*. Both constituents of the term “Serious” and “Game” seem to be mutually exclusive. The word, “serious”, is according to Ben Sawyer (Michael and Chen 2006) intended to reflect the purpose, why it was created, and not for describing the content of the game itself. Defining the concept of the game can be complicated; already Wittgenstein (Wittgenstein 1953) had showed that half a century ago that there simply are no necessary and sufficient conditions. According to Michael and Chen (Michael and Chen 2006) games are described as:

“...a voluntary activity, obviously separate from real life, creating an imaginary world that may or may not have any relation to real life and that absorbs the player’s full attention. Games are played out within a specific time and place, are played according to established rules, and create social groups out of their players.”

Sawyer and Smith (2007) introduced a Serious Games Taxonomy (see APPENDIX A), providing of a strong definition of the serious games field, but also presenting a platform upon which to drive further activity and understanding of serious games. This serves as a starting point to define serious games and a step towards a unified definition among the research community.

Johnston and Whitehead (Johnston and Whitehead 2009) have created a classification (see Figure 2.14) where they distinguish Games, Serious Games, and Training Simulators based on closeness to reality and basis of intent. For example, using a system that is designed to develop or enhance specific skill then it is considered to be a simulation. If the primary objective is only entertainment, but also through the process the user learns along the way, it could be seen as a serious game. Their approach shows that simulations can be a type or belongs to a subset of a serious game, incorporating elements from the real world in an attempt to mirror realistic behaviours.

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Figure 2.14 Games Classification (Johnston and Whitehead 2009)

To summarise, serious games can be of any genre, use a broad range of game technology, and be multiplatform. They can be entertaining, but also be able to teach the user something or help him to develop and enhance various skills. One definition in which most of the researchers agree upon, is that serious games are designed with the use of tools and technology of current games for non-entertainment purposes. Such purposes as it was

aforementioned include education, training, health, etc. Although fun and entertainment is excluded in many authors others argue that those elements constitute a key component of the design of serious games.

Part II - The System

3 System Architecture

The 3D environment of both games and the training control panel of the headset had been designed using the Unity3D game engine (Unity Technologies, San Francisco, USA) programmed using Unity programming languages including C# and Javascript through Mono¹. Mono is an open-source .NET Framework-compatible set of tools including, among others, a C# compiler and a Common Language Runtime (CLR). Mono supports also CS-Script² and Boo³ scripting languages allowing to be portable and have unlimited access to .NET/CLR functionality. Both the robot of “BrainMaze” and the virtual character navigation of “Roma Nova” consists of the Emotiv EPOC[®] headset and a Unity3D Wrapper for the Emotiv EPOC API using native C calls.

3.1 The Neuro-Headset

The Emotiv EPOC[®] Headset (Emotiv Systems, San Francisco, USA) is a neuro-signal acquisition and processing wireless neuro-headset with 14 wet sensors and 2 reference sensors (see Figure 3.1) being able to detect brain signals and user’s facial expressions, offering optimal positioning for accurate spatial resolution. An integrated gyroscope generates positional information for cursor and camera controls, connected wirelessly through a USB dongle and comes with a lithium battery providing 12 hours of continuous use. The sixteen (14 plus 2 reference) sensors are placed on the international 10-20 system (Klem et al. 1999), an internationally recognized method which describes the electrode placement on the scalp for EEG tests or experiments as illustrated in Figure 3.2.

¹ <http://www.mono-project.com/>

² <http://www.csscript.net/>

³ <http://boo.codehaus.org/>



Figure 3.1: Emotiv Epoc headset

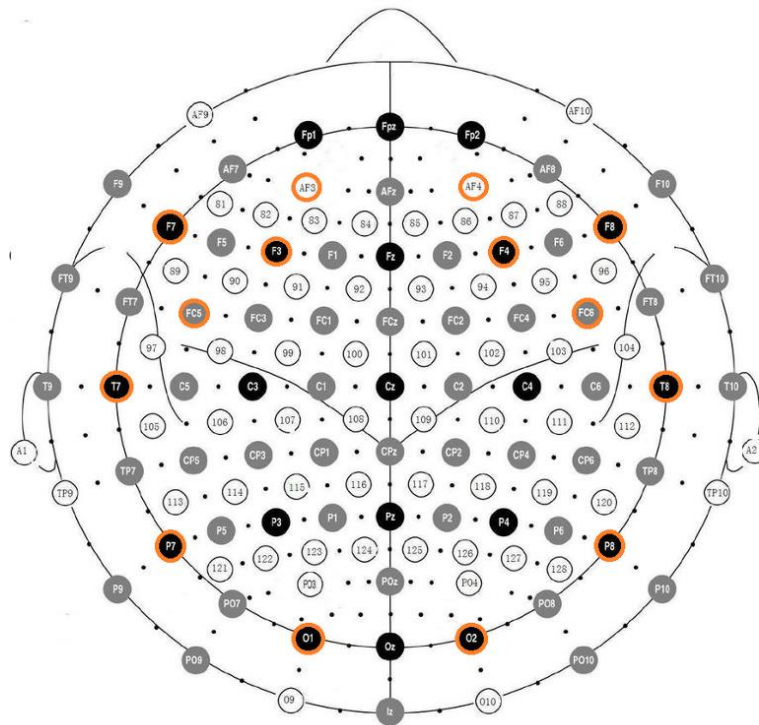


Figure 3.2: International 10-20 system and Electrode locations used by the EPOC (in orange circles)

The EPOC electrodes are modular allowing for easy replacement for alternative or replacement sensor modules. The device is currently using only saline sensor modules with a future plan from Emotiv to introduce dry sensor modules at some point in the future.

Reference electrodes are located at P3 (CMS) and P4(DRL) or at alternative locations behind the ear. All incoming data from the headset is encrypted and must be first decrypted by edk.dll or another Emotiv application. The technical specifications are illustrated on the Appendix.

3.2 System Overview

The system relies in a combination of Cognitiv[®] and Expressiv[®] functions as they translated from the Emotiv library. In terms of the implementation, the Emotiv Development Kit was used connecting the Emotiv Epoc headset to a training control panel made in Unity3d to create and train a new user profile. The Cognitiv[®] functions (brainwaves) are used to move the robot, and the Expressiv[®] functions (facial expression) is used in order to assist the steering of the robot left/right. Emotiv neuro-headset needs a unique user profile in order to train the classifier. In a training session of no more than 5 minutes, user's skills are increased approximately up to 45% for 2 actions (e.g. forward/backwards).An overview of the system is illustrated on Figure 3.3.

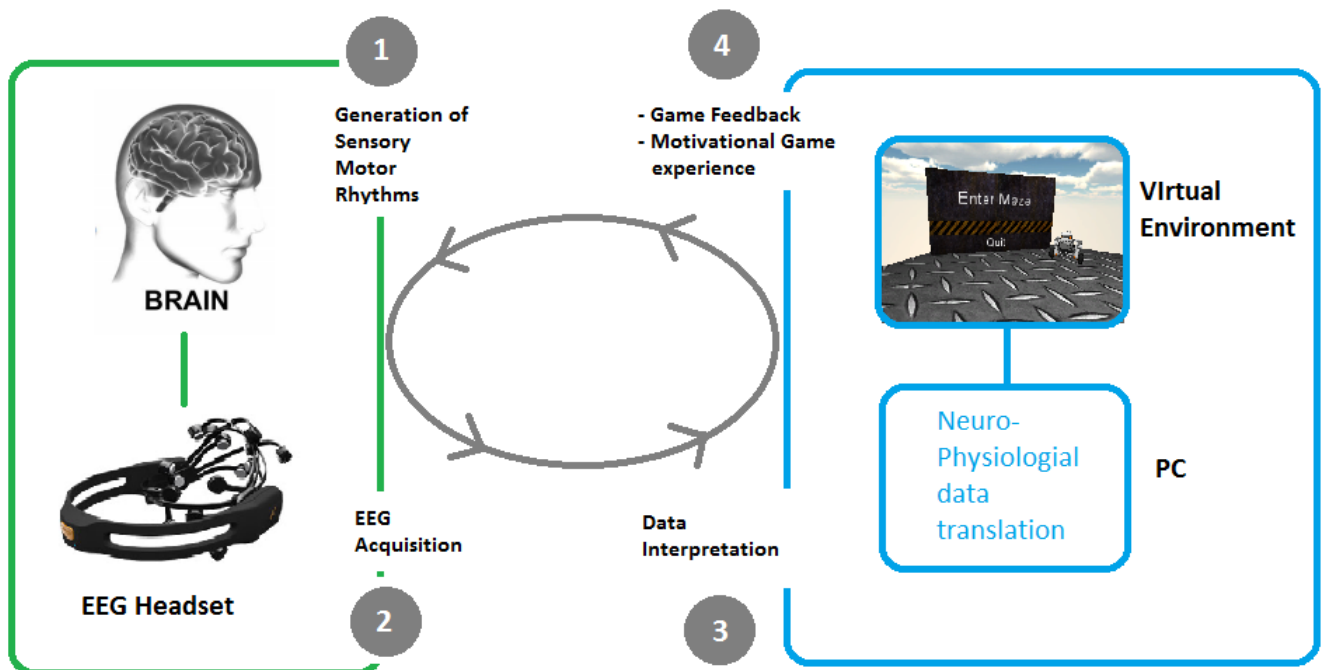


Figure 3.3: Closed feedback loop diagram

Training the profile requires practice and familiarization, especially when the user needs to train more than two actions as it is easy to get distracted from outside stimuli and ‘confuse’ the training process of the users real ‘intentions’. Linear classification of two actions is relatively easy for the classifier to perform successfully. Furthermore, when it is necessary to train 4 actions (for 2 axis movement), it is quite hard for the classifier to perform a good training percentage with low error. Hence, the Expressiv[©] functions had been used for assisting the left/right choice for a smooth interaction. When the trained percentage value reaches a certain level (usually around 80% is an acceptable classification) the user is ready to start playing the game. The training algorithm used by Emotiv[©] is ‘Black boxed’ and it cannot be examined. To take control of the events the EmoKey[©] (see Figure 3.4) application was used connected with the Control Panel to generate keyboard events for each identified and trained thought. After that the EmoKey[©] application is transferring these events to the game as key strokes.

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Figure 3.4: EmoKey[©]

The sensitivity adjustment display on the control panel supports two types of “signatures” that are used to classify input from the neuro-headset as indicating a particular facial expression. Right Wink / Left Wink: these detections share a common graph line as it is illustrated in Figure 3.5. A centre level indicates no wink, low level indicates a left wink and high level indicates a right wink.



Figure 3.5: Sensitivity Adjustment Panel Display

3.3 Training Control Panel

To set up the experiment a Control Panel had been re-designed in order to create a user profile, acquire data, log data to a file for analysis and send trained actions to EmoKey[®] real-time to create key events for the games as inputs. From Unity3D, native C calls had been used from the Emotiv[®] API to access the acquired data from the headset and use the Emotiv[®] training algorithms.

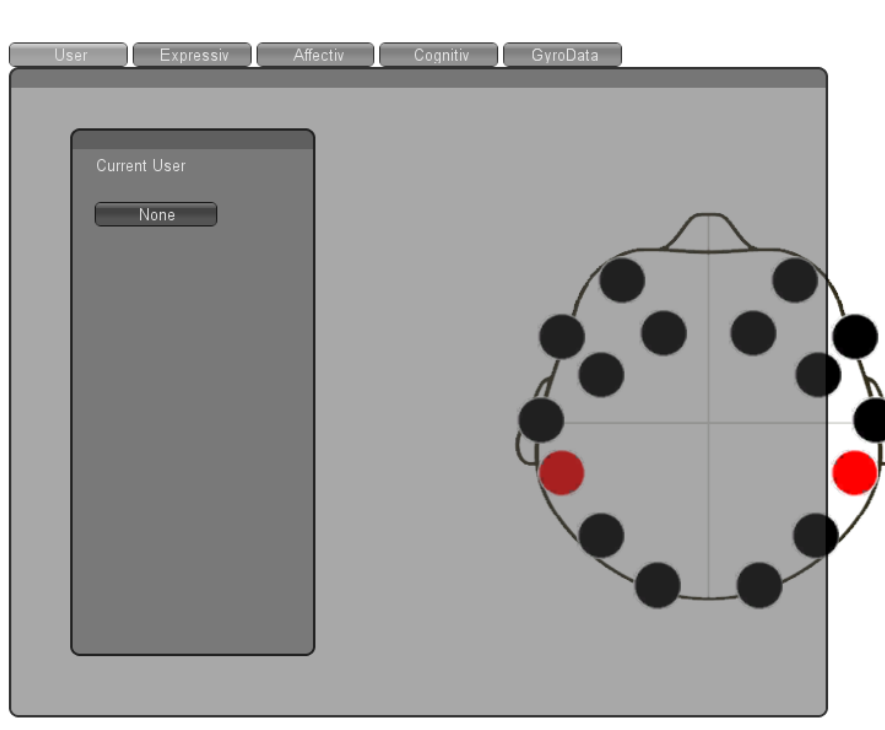


Figure 3.6 Control Panel General Layout

In the main screen of the Control Panel before the new user profile addition is illustrated. All the headset electrodes must be active and appear green on the panel for the training process to be initialised. When a new user is added, the headset must be calibrated for acquiring the user's facial data as it is illustrated in Figure 3.6.

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Figure 3.7 Control Panel - Affectiv[®] Suit

In Figure 3.7 it is illustrated the Affectiv© Suit panel were the frustration and engagement levels are presented through real time graphs as they are calculated through Emotiv's Affectiv© algorithm.

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Figure 3.8 Control Panel – Calibrating the Expressiv© Functions

Finally, users train a Cognitiv© profile by pushing and pulling a virtual cube as it is illustrated in Figure 3.9. When the training and calibration settings are done, then Emokey© connects to the Control Panel to get the trained actions though port: 3008 and parse them to the game as key-stroke inputs.

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Figure 3.9 Training Cognitiv[®] profile by moving a virtual cube with the University logo.

3.4 The “BrainMaze” Game

Brainmaze was designed (in the context of this project) for the user to navigate a 3D version of the LEGO[®] NXT Robot inside a maze with main goal to find the different waypoints that will lead to the finish line. If the robot hits a wall, the position resets and starts again from the beginning. For this, users have to be precise and cautious in order to be able to find the way to the end. The walls are relatively narrow, requiring soft control and not sudden moves that could cause a position reset. This game session follows the first training session of the user in the Control Panel, so the user is familiar with basic brain-control (on a 3D cube) but not in a navigation task. This could trigger frustration but also engage the user to be more occupied on the maze. The navigation within a maze –trying to find the right way- could also increase the workload of the brain (both motor and

cognitive), important for the results of the second training session that follows. Additionally, the NXT navigation was selected in order to assess user performance, complementary to a previous study by using a real world robot (Vourvopoulos and Liarokapis 2011). An example screenshot of the game is illustrated in Figure 3.10.

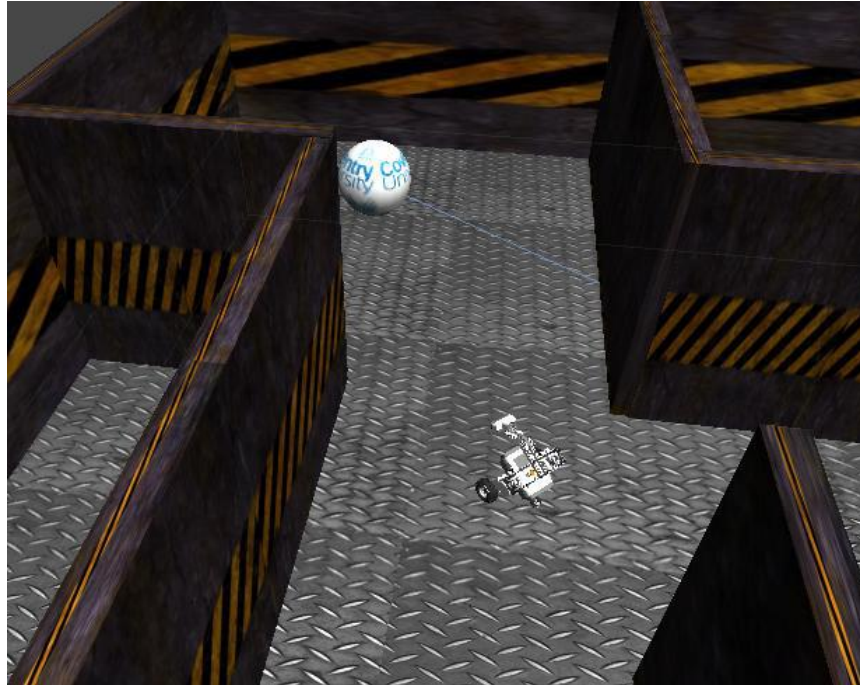


Figure 3.10: Robot approaching a waypoint

As it was aforementioned, the objective for a single player is to try to find the waypoints in the best time possible without getting lost inside the maze. The different levels are statically allocated from pre-defined maze designs. The player is using a personalized trained profile from the Control Panel.

3.4.1 Game Elements and Interface

In this section the main elements of the maze are briefly explained to provide a better understanding of the game design and architecture.

Maze walls: The maze is made by a set of hetero-sized blocks. Each wall block has a cube mesh filter. The Mesh Filter takes a mesh from the game assets and passes it to the

Mesh Renderer for rendering on the screen. The Mesh Renderer takes the geometry from the Mesh Filter and renders it at the position defined by the object's Transform component (see Figure 3.11). As a collider the basic Box Collider Is used. The Box Collider is a basic cube-shaped collision primitive. This Collider can be resized into different shapes of rectangular prisms. It works great for doors, walls, platforms, etc. Finally, a simple material is used as a wall texture. Materials are used in conjunction with Mesh or Particle Renderers attached to the GameObject. They play an essential part in defining how the object is displayed.

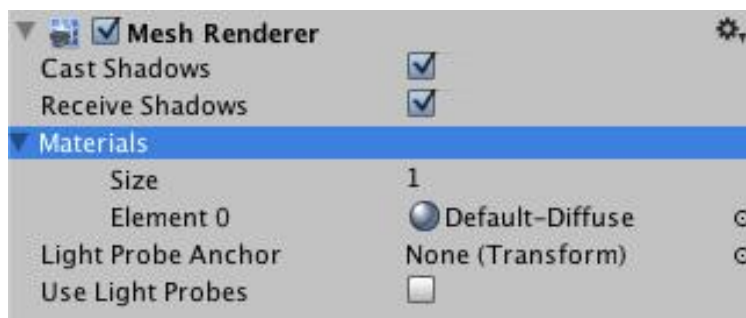


Figure 3.11: Mesh renderer on Unity 3D

3D Robot: The LEGO NXT Mindstorms Robot 3D model has been used with a simple wheel animation, interacting with basic physics. A physics component includes Rigidbody as it is illustrated in Figure 3.12. Rigidbodies enable the GameObjects to act under the control of physics. The Rigidbody can receive forces and torque to make your objects move in a realistic way. Any GameObject must contain a Rigidbody to be influenced by gravity, act under added forces via scripting, or interact with other objects through the NVIDIA PhysX physics engine. A custom game controller has been designed in order to control the basic maneuvering of the robot.

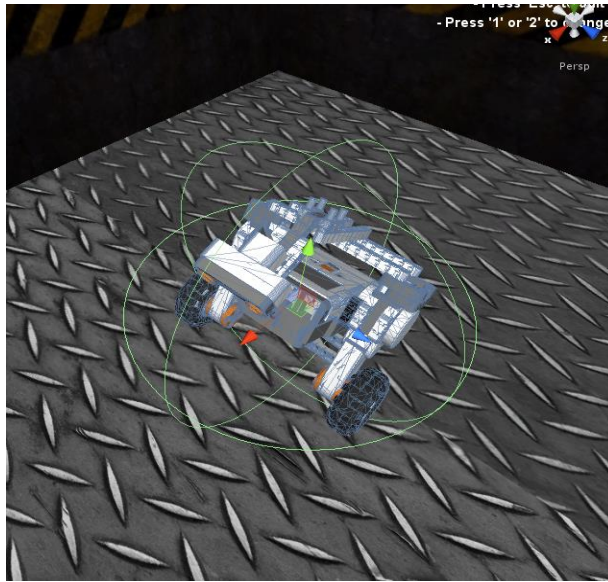


Figure 3.12: Robot model with the Rigidbody component

Camera Control: There're two camera components in the game with a follow view on top of the robot and a map view on top of the level (see Figure 3.13). Cameras are the components that capture and display the 3D world to the player. By customizing and manipulating cameras, we make the presentation of the game more realistic. Cameras can be set to render in any order, at any place on the screen, or only certain parts of the screen. The user can switch camera views by pressing 1 or 2 on the keyboard. Different views can assist the user to navigate more effectively in more complex maze design.



Figure 3.13: Left: Top map view – Right: Robot view

Both cameras are following the robot with the use of the SmoothFollow component (see Figure 3.14). The camera smooth's out the rotation around the y-axis and height. The Horizontal Distance to the robot is always fixed, and then the smoothed values to the transform's position are applied.

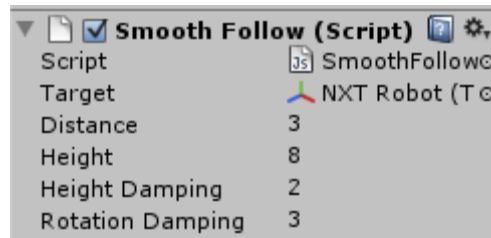


Figure 3.14: Smooth Follow Component

Lighting: Point light types have been used to illuminate the scenes and objects. Point lights shine out from a point in all directions (see Figure 3.15). They are the most common lights in computer games - typically used for explosions, light bulbs, etc. They have an average cost on the graphics processor with the point light shadows to be the most expensive.

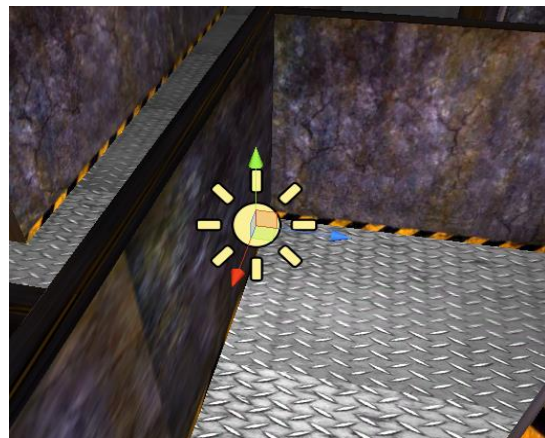
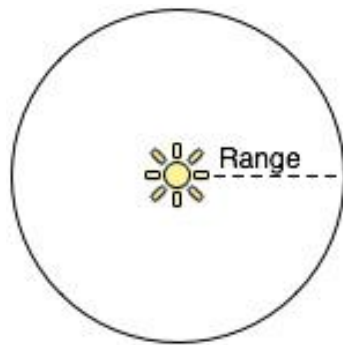


Figure 3.15: Left: Point light range – Right: Point Light Game Example

Main Menu: The “Main Menu” scene was designed by using similar components of the main game. It includes 3D objects with texture, a basic terrain, point light, a main

camera and a text mesh generating 3D geometry that displays the text strings using a mesh renderer. An additional component is only the “Skybox” used for the sky dome effect. Skyboxes are a texture wrapper around the entire scene displaying the vast beyond the 3D world. Skyboxes are rendered before anything else in the scene in order to give the impression of complex scenery at the horizon. They are a box of 6 textures, one for each primary direction (+/-X, +/-Y, +/-Z). The same components have been applied for the “Gave Over” scene (see Figure 3.16).

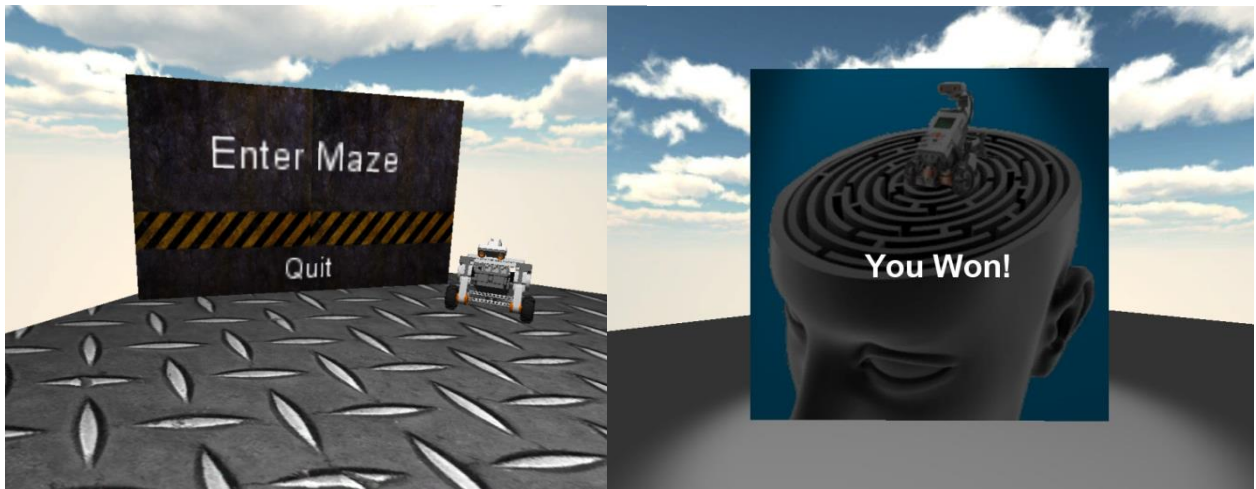


Figure 3.16: Left: Main Menu scene – Right: Game Over scene

Game Control: Each trained thought from the BCI headset is treated as a keystroke with the help of EmoKey[®]. EmoKey[®] emulates a Windows-compatible keyboard and sends keyboard input to the Windows operating system’s input queue. The application with the input focus will receive the emulated keystrokes. EmoKey[®] communicates with Emotiv EmoEngine[®] in the same manner as would a third-party application by using the Emotiv API. The Emotiv EmoEngine[®] refers to the logical abstraction of the functionality that Emotiv provides in edk.dll. The EmoEngine[®] communicates with the Emotiv headset, receives pre-processed EEG and gyroscope data, manages user-specific or application-specific settings, performs post-processing, and translates the Emotiv detection results into an easy-to-use structure called an EmoState[®]. An EmoState[®] is an opaque data structure that contains the current state of the Emotiv detections, which, in turn, reflect the user’s

facial, emotional and cognitive state. EmoState[®] data is retrieved by Emotiv API functions as illustrated in Figure 3.17.

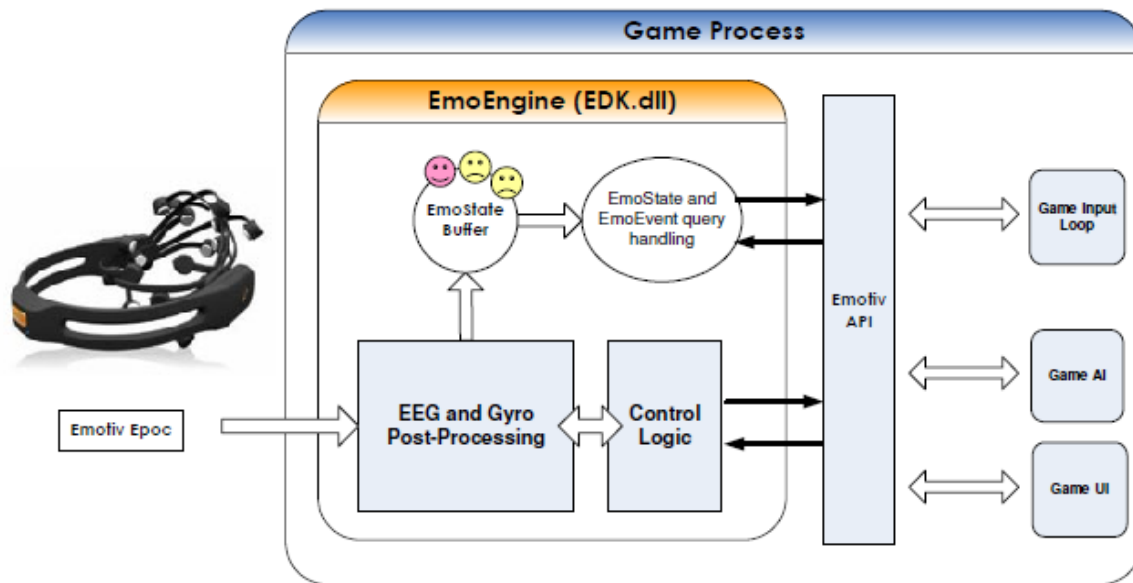


Figure 3.17: BCI headset integration with the game using Emotiv API

3.5 “Roma Nova”

The interactive game is built upon Rome Reborn⁴, (Guidi et al. 2005) one of the most realistic 3D representations of Ancient Rome currently in existence. This 3D representation provides a high fidelity 3D digital model which can be explored in real-time. Rome Reborn includes hundreds of buildings, thirty two of which are highly detailed monuments reconstructed on the basis of reliable archaeological evidence. The rest of the 25 to 30 square kilometres model is filled with procedurally-generated buildings based on accurate historical knowledge. As a result, an obvious advantage of Rome Reborn is its accurate recreation of the ancient city of Rome c.340 A.D, and is therefore readily adaptable to a serious game teaching history (see Figure 3.18).

⁴ <http://www.romereborn.virginia.edu/>



Figure 3.18 RomaNova game play

The BCI version of the game makes use of the trained profile of the user for moving the virtual avatar in four directions, assisted by expressive data. All the cognitive and expressive activity from the Emotiv SDK is treated as a keystroke, moving the virtual character around the city. A main task included the navigation in the forum and as a precision task the users had to access certain buildings. Figure 3.19 illustrates a user interacting with the game by using the neuro-headset.



Figure 3.19: Brain-Controlled RomaNova during user test

The Roma Nova project builds on previous work at Coventry University (Panzoli et al. 2010) and aims at teaching history to young children (11 to 14 years old). It allows for exploratory learning by immersing the learner/player inside a virtual heritage environment where they learn different aspects of history through their interactions with a crowd of virtual authentic Roman avatars.

The Roma Nova game has been designed using the Unity3D game engine with a 3D reconstruction of ancient Rome. The aim of the game is to navigate an avatar inside virtual Rome and interact with intelligent agents while learning at the same time. Both navigation and interaction is performed using brain-wave technology from the Emotiv headset. Figure 3.19 illustrates the brain-controlled version of RomaNova during the user testing.

Intelligent interactions are based on the three Level of Interaction Framework (LoI) which was developed in collaboration between the Serious Games Institute (SGI) and Toulouse University (Panzoli et al. 2010, Panzoli et al. 2010).

LoI is based on a simple social space metric (Panzoli et al. 2010, Panzoli et al. 2010) and it consists of three components. The first level aims to populate the characters with

authentic crowd in order to increase the immersion of the player. Characters located in closer surrounding of the player belong to the interaction level. Finally, a character inside the dialogue level interacts with the player in a natural way, ultimately using speech recognition and synthesis. All the NPCs by default belong to the background level, but as the player moves on the environment and they happen to get closer or away from the player and thus enter or exit the interaction or dialogue levels (Doulamis et al. 2012). Characters are not assigned a specific level of interaction a priori. By default, they all belong to the background. But as the player moves and/or they move freely in the environment going about their business, they happen to get closer or away from the player and thus enter or exit the interaction or dialogue levels (Panzoli et al. 2010).

4 Data Analysis Tools

In this chapter are presented the main tools for the data analysis that have been used for the raw EEG data.

4.1 EEGLab

On each training trial and game interaction, EEG data from the user scalp had been captured and stored for further analysis using EEGLAB, a Matlab toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data. Through this analysis is attempted to correlate the participants answers of the questionnaire based on their attention and engagement and with the extracted physiological data given by the Emotiv output and the raw EEG signals.

Why EEGLAB:

EEGLAB⁵ is an open-source platform which provides an interactive graphic user interface (GUI) allowing to flexibly and interactively processing EEG data and/or time/frequency analysis (TFA), as well as standard averaging methods (see Figure 4.1). In addition, EEGLAB offers a structured programming environment for storing, accessing, measuring, manipulating and visualizing event-related EEG data.

⁵ <http://sccn.ucsd.edu/eeglab/>

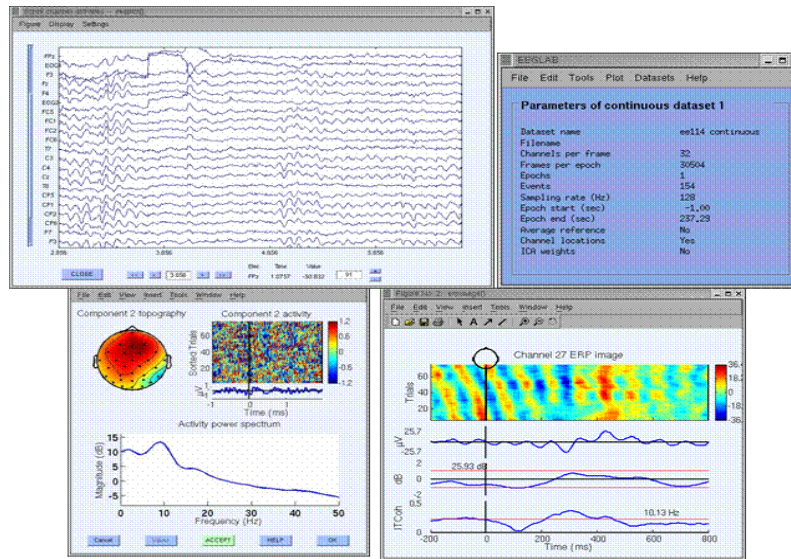


Figure 4.1: EEGLAB main Interface

4.1.1 Importing data to EEGLAB

All EEG data from the headset are extracted on a European Data Format⁶ (EDF) which is a standard format of acquisition systems for medical time series. The EDF file is then imported to EEGLAB to be analysed and remove all possible artefacts. As it was explained before, an EEG signal is a mixture of signals from many sources including eye-blinks, breathing, heartbeat, or 50 Hz line noise called artefacts. The effect of artefacts on the signal was introduced on Chapter 2.2. As it is illustrated on Figure 4.2 the blink artefacts are manually marked in order to be removed and separated from the rest of the EEG data. After the rejection process a new dataset for each user is created with “clean” data for further analysis.

⁶ <http://www.edfplus.info/>

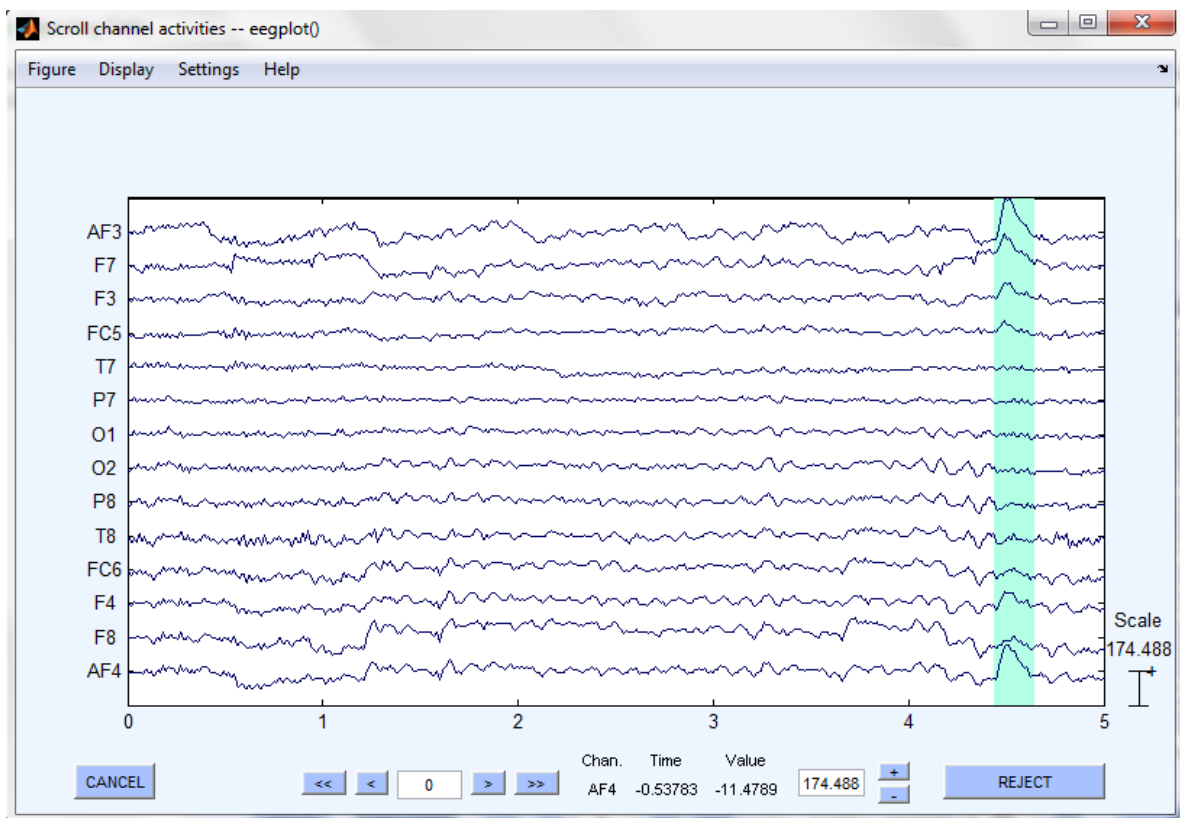


Figure 4.2: EEG manual Artefact Rejection

4.1.2 Baseline removal and preparing data for ICA

After the manual rejection of blink artefacts and other facial muscular movement components, a baseline (or "background") removal is performed. This function is mainly used for electrical artefacts removal from the EEG signal by actually subtracting a baseline estimate from the data. By rejecting the blink artefacts the data is ready to go through a standard filtering method called Independent component analysis (ICA) to extract the remaining artefacts caused by breathing, heartbeat, or 50 Hz line noise. The ICA components are signals combined from different EEG channels acting as spatial filters on the data.

4.1.3 Filtering the Data

To remove the unwanted frequencies it is common to use bandpass filtering (see Figure 4.3). The filtering option in EEGLAB, uses linear finite impulse response (FIR) and infinite impulse response (IIR) filtering. EEGLAB makes use of the `filtfilt()` routine from the Signal Processing Toolbox. If the Matlab Signal Processing toolbox is not present, EEGLAB uses a simple filtering method involving the inverse Fourier transform.

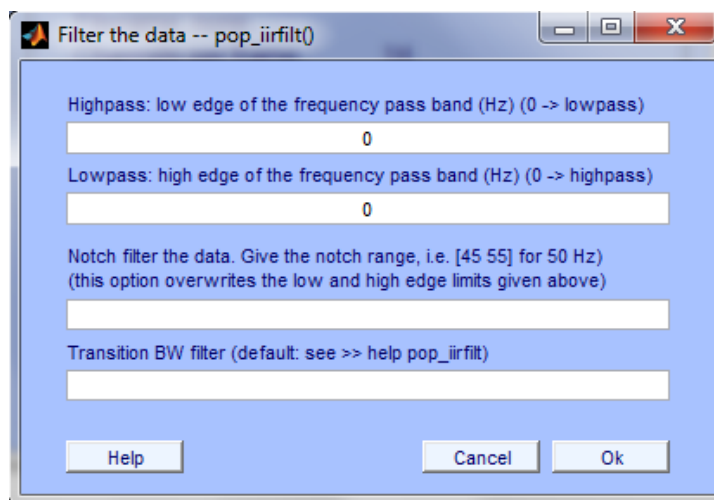


Figure 4.3 Applying the IIR filter

In practice, EEGLAB suggests the use of the IIR filter, as it is stronger (and shorter) than FIR filters.

4.1.4 Importing Channel Locations and Plotting Data

To plot EEG scalp maps and additionally to estimate source locations for data components, a map containing the Emotiv EPOC electrode locations must be loaded to EEGLAB in order to be imported to each dataset.

On Figure 4.4 the position information for electrode AF3 in Polar and Cartesian coordinates is illustrated.

Edit channel info -- pop_chanedit()

Channel information ("field_name"):

Channel label ("label")	AF3	Opt. head center
Polar angle ("theta")	-22.461	Rotate axis
Polar radius ("radius")	0.42113	Transform axes
Cartesian X ("X")	76.1528	
Cartesian Y ("Y")	31.4828	XYZ -> polar & sph.
Cartesian Z ("Z")	20.8468	Sph. -> polar & xyz
Spherical horiz. angle ("sph_theta")	22.461	Polar -> sph. & xyz
Spherical azimuth angle ("sph_phi")	14.197	
Spherical radius ("sph_radius")	85	Set head radius
Channel type		Set channel types
Reference		Set reference
Index in backup 'urchanlocs' structure	1	
Channel in data array (set=yes)	<input checked="" type="checkbox"/>	

Buttons: Delete chan, Insert chan, Append chan

Channel number (of 14): 1

Plot 2-D: Plot radius (0.2-1, []=auto) Nose along +X Plot 3-D (xyz)

Buttons: Read locations, Read locs help, Look up locs, Save (as .ced), Save (other types), Help, Cancel, Ok

Figure 4.4 Electrode position information

A 2-D visualisation of the channel location and label for the Emotiv Epoc headset is illustrated on Figure 4.5.

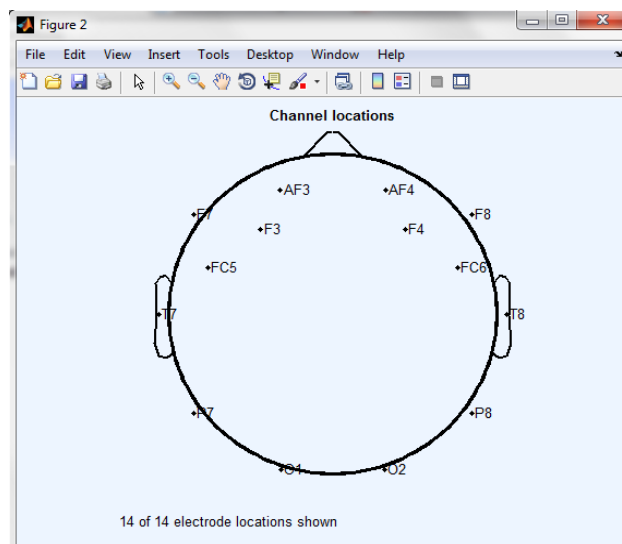


Figure 4.5 EEGLAB Channel Locations

4.1.5 Plotting Channel Spectra and Maps

To begin processing the data, the channel spectra and associated topographical maps are plotted using the 100% of the recorded data of each user. As it is illustrated on Figure 4.6 each colored trace represents the spectrum of the activity of one data channel. The leftmost scalp map shows the scalp distribution of power at 6 Hz, which in these data is concentrated on the frontal lobe and is more luckily to be generated from eye movement. The other scalp maps indicate the distribution of power at 10 Hz and 22 Hz.

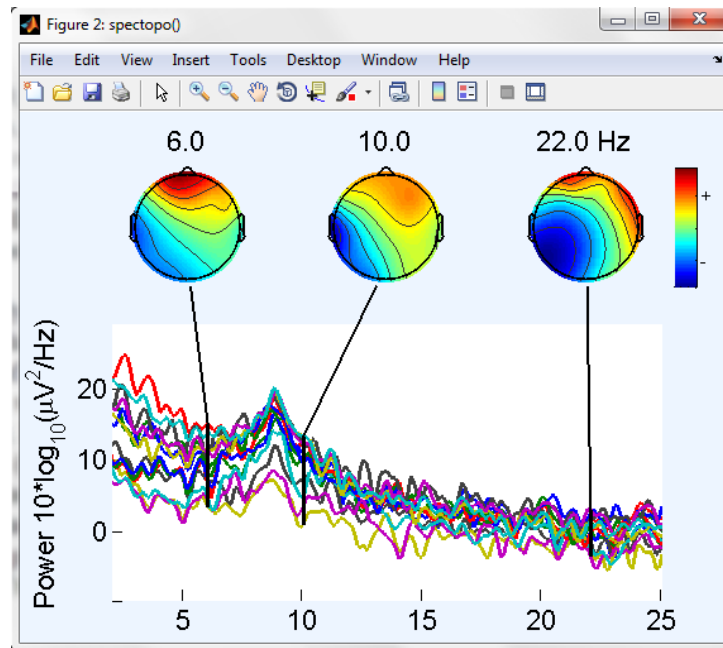


Figure 4.6 Spectra and Maps

5 User Testing and Evaluation

An overall of 31 users have been evaluated the system providing feedback for both games described in the System Architecture chapter through a questionnaire and an unstructured interview. In particular, it was tested at Coventry University – Faculty of Engineering and Computing and the Serious Games Institute (SGI) in a lab environment. Each participant had to complete a set of tasks in order to evaluate efficiently the system and the overall interaction through robot and avatar navigation. Participants in all conditions were naïve as to the purpose of the experiment and followed strictly the same procedure including: training, interaction and feedback. All participants had normal or corrected to normal vision and no reported neuromotor impairment. To avoid the differences in confounding variables, i.e. differences between conditions other than the independent variable that could cause differences in the dependent variable participants in each group were nearly balanced according to their age; their gender and their background. In Figure 5.1 the evaluation process in a lab environment is illustrated. The evaluation was conducted until the threshold of 30 users is reached/passed for statistical significance and effect reasons. Based on statistical theory, if the sample is large ($n \geq 30$) then the sample mean is normally distributed and can be used for statistical hypothesis tests (Rice 2007).

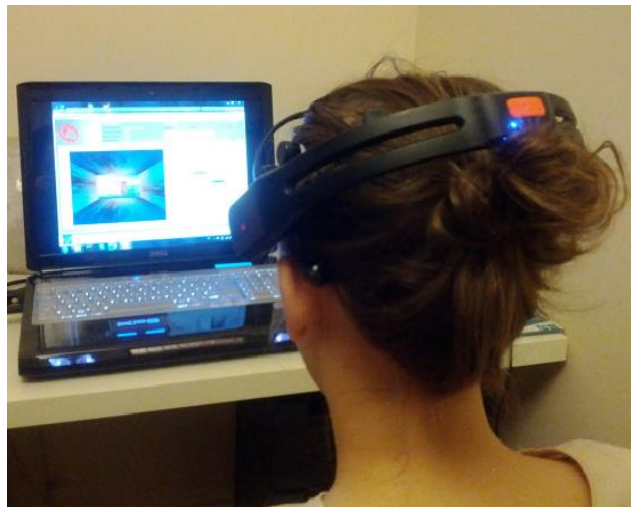


Figure 5.1 User during the training process

5.1 Apparatus and Visual Content

For this project off-the-shelf hardware components were used with the main component being the Emotiv Epoc neuro-headset (i.e. 14 electrodes and a gyroscope) described in Chapter 3. A laptop with a 64bit Intel(R) Core(TM) 2 Duo processor T7700 at 2.4GHz and 4 GB of memory was used for the experiments. The laptop is equipped with an NVIDIA GeForce 8700M GT graphics card. Standard laptop display technology, such as a 17' inch wide LCD has been used in order to display the 3D content of the application.

5.2 Procedure

It was ensured that each participant was comfortable and at ease prior to the start of the experiment. The participants were told that their data would be used anonymously; along with the data of several others and that the experiment is divided into two main stages. During the first stage of the experiment the participants' had to create and train a profile using the Control panel, calibrating at the same time the system by training the classifier with the generated EEG data. Both classifier training and calibration (EEG data classification through machine learning) and user training (familiarisation with the interface and the neuro-feedback loop) are important before interacting with the game for the first time. Then the users' had to navigate the NXT robot inside a statically designed maze and find their way to the various waypoints of the level only by using the classified actions from their trained profile.

During the second stage the participants' had to train again the classifier with new data. Following the seconds training, the interaction with the second game (RovaNova) was taking place, navigating the avatar based on the experimenter instructions. The instructions and the statements that were used during the preliminary briefing were standardized for all the participants. Initially, the participant's personal information was recorded. During all the stages of the experiment, participants were instructed to interact with the 3D objects by staying focused on the computer monitor using only their brain activity as inputs and not to physically move their limbs but to imagine the movement (in order to activate the motor area of the brain). In addition, the participants were instructed not to move the headset or talk to avoid noise and artefacts on the signal deriving from facial movement.

At the beginning of the experiment a popup window was generated in order to acquire the participant's ID and verify the connection of the headset. Once the ID had been entered the window was removed and the calibration panel was appearing with a timer measuring the initiated training session. When the timer indicated that 60 seconds of exposure time had expired, the training was stopped, ensuring that each participant was restricted to exactly 60 seconds of exposure time to the training of each action each time. When the classification percentage was in an adequate level, (above 65%), the training session was considered complete. Following the training session, participants were asked then to relax and enter the first game (Brainmaze) when they were feeling ready. After the completion of the BrainMaze game the participant had to go through the same training process. After the same exposure on the training interface and the collection of the EEG data the user had to interact with the RomaNova game and complete simple character navigation tasks based on their motor training.

User Testing Protocol:

- Each participant had to create and train a unique profile using the control panel within a time limit. The participant had to move a cube in a 3D space with brain power only in order to train the classifier above 65%.
- After the initial training each participant had to interact with the Brainmaze game. As a specific task the user had to find his/her way into the various waypoints of the level and finish.
- Following the Brainmaze game, a second training trial with the control panel was performed, re-training the classifier with new inputs.
- The best training scores (classification percentage) of the user was used in order to navigate a virtual character at the RomaNova game, following some tasks completions for a short period of time in order to capture the Affectiv[®] engagement levels and the raw EEG data.

- Finally, an online user evaluation form had to be completed by the user followed by an unstructured short interview with overall testing time around 40-50 minutes per user.

The questionnaire is a modified version of Witmer and Singer Presence Questionnaire (Witmer and Singer 1998) and QUIS User Satisfaction Questionnaire based on seven-point and nine-point Likert scale respectively (see Appendix B) and focus of the Presence Questionnaire is to measure presence in virtual environments and games (Witmer and Singer 1998). The questionnaire was composed by a total of 26 questions with a minor modification for the interface related questions for example a question of the original form: “Can you please rate the features of the interface?” transformed into: “Can you please rate the features of the Brain-Computer interface?” without changing the format of the questionnaire for validity purposes the questionnaire was presented on an online form and then transcribed into SPSS v20.0 for analysis.

6 Results

The following sections include the questionnaire analysis from the reported answers of the participants divided in three clusters of questions: i) General questions concerning the BCI experience, ii) the Interaction with the virtual Robot and iii) the interaction with the Serious Game. Finally, the raw EEG data analysis is performed with data from the training trials and the game interaction during task performance.

6.1 Demographics and General Statistics

The age of the participants can be clustered into two groups. The first includes the range of 18-25 years, with 45% and the second with range of 26-33 with 42% of the sample. The remaining 13% is between 34 to 41 years. The sample is considered to be composed with young participants. The gender distribution is 68% male and 32% female, roughly 2 out of 3 participants to be male. 77% are students with 46% to be undergraduates with the majority of the participants (93%) to use a computer in their daily activity very much (4-5 in likert scale).

Despite the daily usage only 10% is often playing games with the majority (35%) to score 2 in the likert scale. 58% had previous experience with other Natural User Interfaces (NUIs) like Microsoft Kinect or Nintendo Wii but none of the participants had any previous experience with BCI's.

6.2 Experience with the BCI

Summarising the data samples from the users, descriptive statistics have been generated in order to quantify the overall experience with the BCI. The questionnaire used the likert scale from 1-5 and in some cases from 1-9. Hence, the results are considered as ordinal measurements. The first thing that was noticed about a distribution is the shape and whether it's symmetric or skewed to one side. If the bulk of the data is at the left and the right tail is longer, we say that the distribution is skewed right or positively skewed; if the peak is toward the right and the left tail is longer, we say that the distribution is skewed left or negatively skewed.

		Can you please rate the features of the Brain- Computer interface?	Ease of Use	Ease of Learning	Usability	Satisfaction	Are you satisfied with overall performance of the BCI system?
N	Valid	31	31	31	31	31	31
	Missing	0	0	0	0	0	0
Mean		3.77	3.13	3.68	3.42	3.45	3.58
Std. Deviation		.884	.763	.979	.886	1.028	.923
Skewness		-1.073	-.708	-.194	-.354	-.058	-.661
Std. Error of Skewness		.421	.421	.421	.421	.421	.421
Kurtosis		2.220	.608	-.886	.825	-.215	.866
Std. Error of Kurtosis		.821	.821	.821	.821	.821	.821

How quickly did you adjust to the brain-control experience?	When you use brain-control how would you rate the interaction?	Did the virtual environment look realistic?	How intuitive was the BCI system to use?	Do you find useful having more than one interface in the same application assisting the BCI system?
31	31	31	31	31
0	0	0	0	0
3.03	3.32	1.26	3.29	3.68
.795	.909	.445	.783	.871
.366	.427	1.163	.314	.058
.421	.421	.421	.421	.421
-.247	-.423	-.697	-.011	-.722
.821	.821	.821	.821	.821

Table 6.1 Descriptive statistics for the BCI experience

From the reported answers on the general experience of the BCI, moderately skewed on the left are the answers concerning the rating of the BCI features, ease of use, learning, usability satisfaction and the overall performance of the BCI system (see Table 6.1). On the other hand, a small skewness on the right can be identified for the reported answers on the adjustment on the brain-control experience, the interaction rating, the realism of the virtual environment, the intuitiveness of the BCI and finally if additional interfaces can assist the BCI system. At this stage it is important to assess the skewness of the distribution to define the user preference and how he/she perceived the interaction. There are cases where answers have the same mean like the ease of learning (skewed left) with the answer on if additional interfaces could assist the BCI (skewed right) have $\mu=3.68$ but different skewness. This way it can be observed from the distribution that ease of learning has a tendency on moving towards the positive values.

Finally, from the current distribution we can have an indication that the participants had no problem on using or learning the BCI and their overall satisfaction is above average with a mean of 3.5.

6.3 Robot navigation within a VE

Based on a previous evaluation of a Brain-controlled physical robot (Vourvopoulos and Liarokapis 2011) using the Neurosky Headset that it was conducted at “The Gadget Show Live 2011” expedition at the NEC, Birmingham with 54 users, a following assessment took place to evaluate Emotiv headset with the same robot in a Virtual-Environment (VE). The experimental design was formed based on the interface complexity and the set-up time cost that it’s required by the system. Since the Emotiv software needs to be trained (unlike Neurosky) to classify the correct intended movements by the user, the experiment took place in a lab environment under controlled conditions.

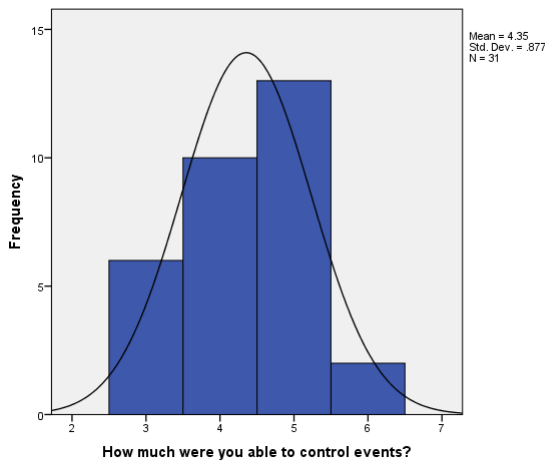


Figure 6.1: Able to control events

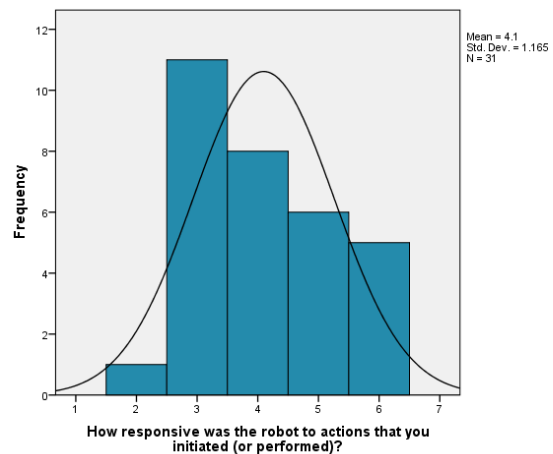


Figure 6.2: Responsiveness of the robot

Figure 6.1 indicates the ability of the users to control events. Negative skewness of -0.157 indicates a small pilling of the values at the right side of the distribution. Additionally, negative kurtosis (-0.764) is indicating a more pointy distribution (leptokurtic). Generally, as a rule of thumb, if the skewness or kurtosis is twice its standard error the data is hardly normal. On the other hand, Figure 6.2 illustrates the responsiveness of the robot’s actions. Positive skewness of 0.342 indicates the pilling up of the values at the left side, giving an indication of low values in the distribution. That can be a result of low responsiveness from the robot while the user was controlling with the BCI.

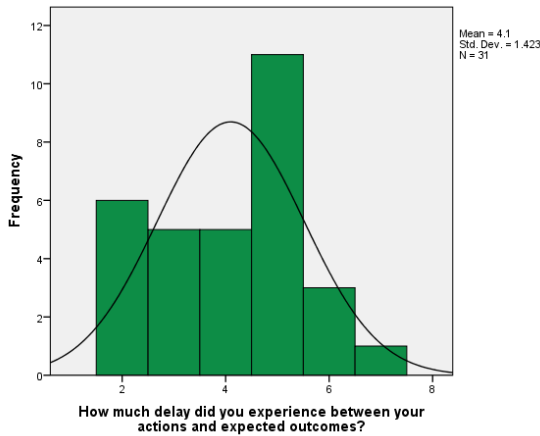


Figure 6.3: Latency between actions & outcome

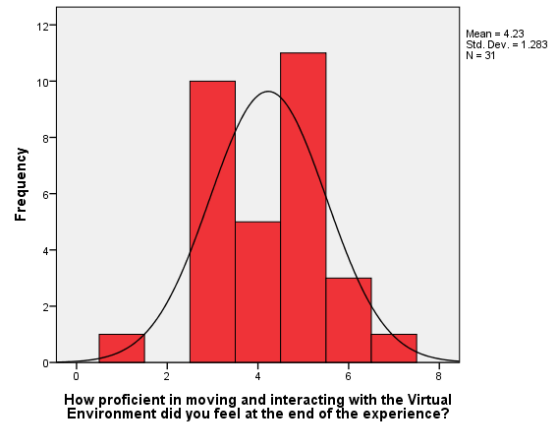


Figure 6.4: Proficiency in navigation

Figure 6.3 illustrates the latency between actions and expected outcomes. The reported answers concerning the delay of the initiated actions are distributed across all the range (with kurtosis at -0.929) with no clear indication of positive experience although the skewness is at -0.107 indicating a pilling up on the right side. Figure 6.4 measures the proficiency in moving and interacting with the virtual environment (Brainmaze). The vast majority of the answers are battling between the middle parts of the distribution, although the skew is negative with the right side to occupy the biggest part of the distribution.

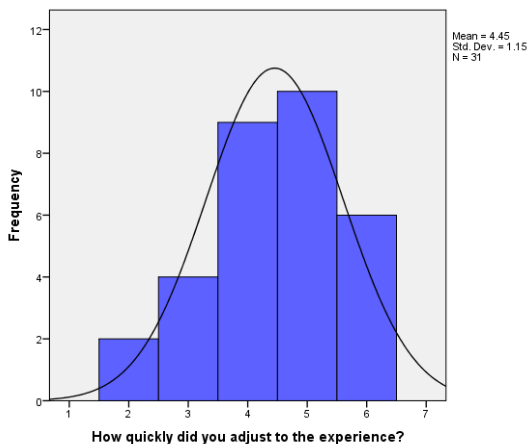


Figure 6.5: Ease of adjusting

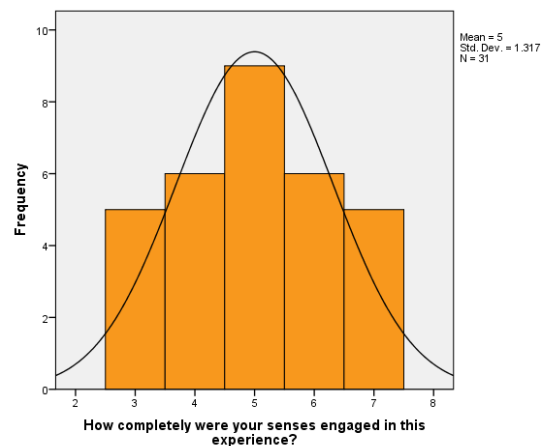


Figure 6.6: Engagement

6.3.1 User Feedback

All users had been asked to provide comments on the questionnaire anonymously but also an unstructured short interview was taking place in a light mood after the trial. These comments/suggestions are a very helpful contribution towards the improvement of the system, giving feedback that an ordinary questionnaire cannot capture. A very useful suggestion was about the Graphical User Interface (GUI) of the Game. User's found easier to focus on GUI components instead of the virtual object (robot) in order to perform the required movement. This might be a result of the training trial, in which the users had to push/pull a virtual cube and when entering the virtual environment they had to re-adapt to the new elements. It can be confirmed by reports that it was easier to move the robot by thinking the cube from the training trial, that actually pushing the robot itself. This is really interesting as they were not getting direct feedback from the robot on the screen in order to complete the moves. It is a clear indication that it would be better the training trial to include the components from the game in order for the user to get familiarised. Alternatively, assistive GUI components might be a useful addition. It was also reported that participants with more experience in computer games will have an easier time learning to use the interface due to the simulation and interaction required for a computer game. That experience makes it much easier to learn how to operate the interface. The only negative reporting's had to do with the tiredness that the system was triggering after a few minutes of interaction.

6.4 Serious Game Interaction

In the following sub-sections the methodology and the results of a formal usability evaluation study are presented, which evaluates BCI control with the use of the Emotiv Epoc headset as a potential alternative gaming controller as well as with preliminary analysis of the extracted EEG data. Furthermore, in this section the statistical validity of the Presence Questionnaire answers will be assessed, including the quantification of users' interaction with the game by using the BCI and also the sense of engagement. Finally, a correlation between the reported answers and the extracted engagement from the Emotiv Affectiv data is investigated.

6.4.1 Data Normality

Many of the statistical procedures are parametric tests based on the normal distribution. By using parametric tests for non-parametric data then the results are likely to be inaccurate. Therefore, it is important to check this assumption before deciding which statistical test is appropriate since different tests for different distributions can lead to false results (Motulsky 2010). To check for normality, we can look for normality visually, look at values that quantify aspects of a distribution (i.e. skew and kurtosis) and compare the distribution we have to a normal distribution to see if it is different.

6.4.1.1 Checking normality visually

A useful way to assess normality is to look at the shape of the frequency distributions. As it is illustrated on the histograms below (Figure 6.7, Figure 6.8, Figure 6.9), the distribution of the data look normal, especially comparing with the normal curve line that includes the majority of the data inside.

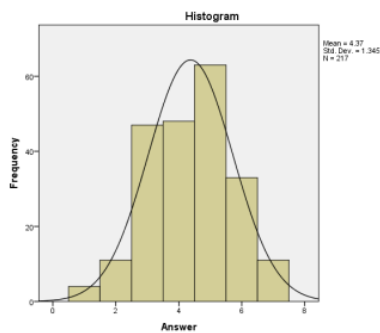


Figure 6.7: Adaption-Immersion Histogram

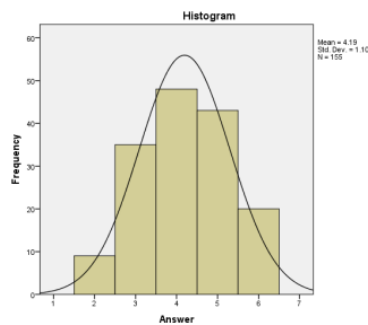


Figure 6.8: Involvement Histogram

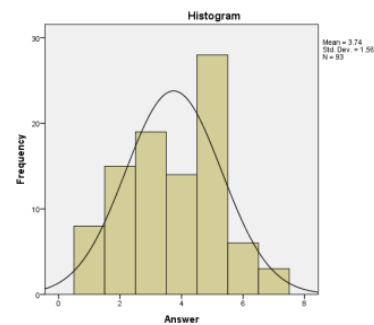


Figure 6.9: Interface Quality Histogram

Another qualitative way to inspect distribution normality is through a P-P plot (probability-probability plot). This graph plots the cumulative probability of a variable against the cumulative probability of a particular distribution (in this case we would specify a normal distribution).

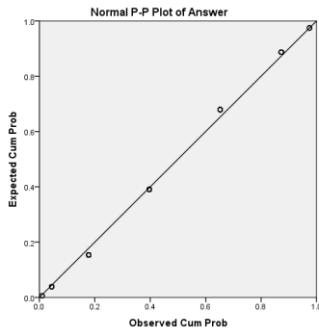


Figure 6.10: Adaption-Immersion P-P Plot

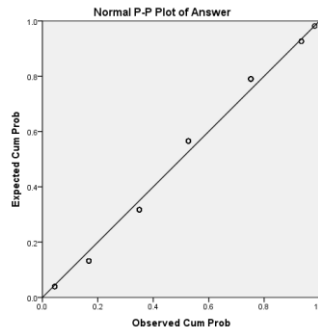


Figure 6.11: Interface Quality P-P Plot

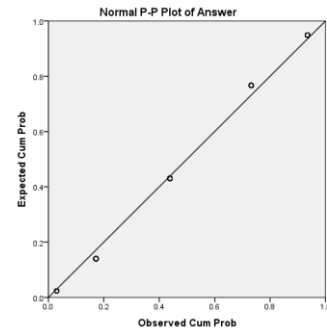


Figure 6.12: Involvement P-P Plot

As it is illustrated from Figure 6.10, Figure 6.11 and Figure 6.12 the data points fall very close to the ‘ideal’ diagonal line with very few deviating from away from the line.

Overall it can be observed from both plots that the data distribution is normal but to avoid any skewed distributions that could cause a problem in parametric tests we have to quantify the skewness and kurtosis of these distributions.

6.4.1.2 Quantifying normality

To avoid any subjective conclusions that can be derived from the visual inspection of data normality the skewness and kurtosis values have been calculated for quantifying the shape of the distribution. In addition, the **Kolmogorov–Smirnov test** and **Shapiro–Wilk test** have been used to compare the scores in the sample to a normally distributed set of scores with the same mean and standard deviation.

As illustrated in the descriptive statistics in Table 6.2 on average we can see that the reported answers are around 4 (out of 6). The other important measures for our purposes are the skewness and the kurtosis, both of which have an associated standard error. The values of skewness and kurtosis should be zero in a normal distribution. Positive values of skewness indicate a pile-up of scores on the left of the distribution, whereas negative values indicate a pile-up on the right. Positive values of kurtosis indicate a pointy and heavy-tailed distribution, whereas negative values indicate a flat and light-tailed distribution. The further the value is from zero, the more likely it is that the data are not normally distributed. For all groups the skew value is negative indicating that there’s a small piling up of values in the

left side of the distribution. For **Involvement** and **Interface Quality** the skew value is very close to zero (which is good) and kurtosis is negative. Finally, for **Adaption-Immersion group**, skewness is bigger. Additionally, there's negative kurtosis to all the groups besides Engagement indicating a more pointy distribution. As a rule of thumb, if the skewness or kurtosis is twice its standard error the data is hardly normal. In all cases the skewness and kurtosis values are smaller their standard error hence we can conclude that the data can be considered normal.

Table 6.2: Descriptive Statistics

		Involvement	Interface Quality	Adaption-Immersion
N	Valid	155	217	217
	Missing	1	0	0
Mean		4.19	3.74	4.37
Median		4	4	4.00
Mode		4	5	5
Std. Deviation		1.105	1.56	1.345
Variance		1.222	2.433	1.809
Skewness		-0.07	-0.068	-0.130
Std. Error of Skewness		0.195	0.25	.165
Kurtosis		-0.751	-0.826	-0.425
Std. Error of Kurtosis		0.387	0.495	.329
Range		4	6	6

As a final step to assess normality is the Kolmogorov– Smirnov test and Shapiro–Wilk test. These statistical tests compare the scores in the sample to a normally distributed set of scores with the same mean and standard deviation. If the test is non-significant ($p > .05$) it

tells us that the distribution of the sample is not significantly different from a normal distribution. If, however, the test is significant ($p < .05$) then the distribution in question is significantly different from a normal distribution.

Table 6.3: Tests of Normality

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Involvement	.174	155	.000	.914	155	.000
Adaption-Immersion	.172	217	.000	.944	217	.000
Interface Quality	.188	93	.000	.933	93	.000

a. Lilliefors Significance Correction

As illustrated in Table 6.3 for all groups, the K–S test is highly significant, indicating that both distributions are not normal. This result is likely to reflect the negatively skewed distribution observed for those data. The Shapiro–Wilk test does much the same thing, but it has more power to detect differences from normality. In small samples these tests can be significant even when the scores are only slightly different from a normal distribution. Therefore, they should always be interpreted in conjunction with histograms, P–P plots and the values of skew and kurtosis. For this reason based on the previously discussed frequency and probability plots the data can be considered close to a normal distribution and the parametric assumption not violated.

6.4.2 Measuring the Effect Size

In the current experimental design in order to assess the effect that **Involvement**, **Adaption-Immersion** and **Interface Quality** have to the reported sense of engagement, we perform an ANOVA (Analysis Of Variance) statistical test since the data are distributed normally.

According to Cohen's (Cohen 1988) guidelines for η^2 (Eta squared):

- Small Effect: 0.01
- Medium Effect: 0.059
- Large Effect: 0.138

Eta squared is calculated based on this formula:

$$\eta^2 = \text{Treatment Sum of Squares} / \text{Total Sum of Squares}.$$

Table 6.4: ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Involvement	Between Groups	2.041	4	.510	.630	.645
	Within Groups	21.056	26	.810		
	Total	23.097	30			
Adaption-Immersion	Between Groups	6.208	4	1.552	1.306	.294
	Within Groups	30.889	26	1.188		
	Total	37.097	30			
Interface Quality	Between Groups	2.454	4	.614	.274	.892
	Within Groups	58.256	26	2.241		
	Total	60.710	30			

As illustrated on Table 6.4, Eta squared for Involvement = **0.088**, for Adaption-Immersion = **0.16** and Interface Quality = **0.04**.

Thus, it was discovered that Adaption-Immersion had the largest effect in the perceived engagement that the user had during the interaction than the Interface Quality or the level of involvement. This can be an indication that Adaption and Immersion with the sense of Engagement can be related with the type of the interface like the Brain-Computer Interface and not so much with the quality of the game interface, game design and mechanics.

6.4.3 Correlation

This test is for quantifying the relation between the reported sense of engagement from the presence questionnaire and the Emotiv Affectiv[®] readings of engagement that are provided by the Emotiv Research SDK.

A correlation coefficient of +1 indicates that the two variables are perfectly positively correlated, so as one variable increases, the other increases by a proportionate amount. Conversely, a coefficient of -1 indicates a perfect negative relationship: if one variable increases, the other decreases by a proportionate amount.

A coefficient of zero indicates no linear relationship at all and so if one variable changes, the other stays the same. Because the correlation coefficient is a standardized measure of an observed effect, it is a commonly used measure of the size of an effect where values of ± 0.1 represent a small effect, ± 0.3 a medium effect and ± 0.5 a large effect.

Here, we will focus on bivariate correlations. A bivariate correlation is a correlation between two variables; this is the case of Pearson's product-moment correlation coefficient for parametric data.

As it is illustrated on Table 6.5, the output provides a matrix of the correlation coefficients for the two variables (reported engagement and EEG engagement). Underneath each correlation coefficient both the significance value of the correlation and the sample size (N) on which it is based are displayed. Each variable is perfectly correlated with itself (obviously) and so $r = 1$ along the diagonal of the table.

Table 6.5: Engagement Correlation

		Affectiv [®] Engagement	Engaged Senses
Emotiv's Affectiv [®] Engagement	Pearson Correlation	1	-.259
	Sig. (2-tailed)		.159
	N	31	31
Sense of Engagement	Pearson Correlation	-.259	1
	Sig. (2-tailed)	.159	
	N	31	31

Affectiv[®] Engagement (from EEG) is negatively related to the reported sense of Engagement with a Pearson correlation coefficient of $r = -.259$ and the significance value is bigger than .001. This significance value tells us that the probability of getting a correlation coefficient in a sample of 31 people if the null hypothesis were true (there was no relationship between these variables) is big. Hence, we can gain confidence that there is no relationship between the sense of engagement as it is reported though the user in the questionnaire and the extracted (averaged) engagement from the EEG headset (Emotiv Affectiv[®] suite).

6.4.4 Regression

In the previous section, the relationships between the reported sense of engagement and the extracted engagement levels from the EEG headset were examined. Taking this process a step further in this section the level of engagement from the amount of the Adaption and Immersion levels will be attempted to be predicted.

This is the essence of regression analysis: we fit a model to our data and use it to predict values of the dependent variable (Engagement) from one or more independent variables (Involvement, Adaption/Immersion and Interface Quality).

Although there are multiple independent variables, for this test a simple regression will be used with Adaption/Immersion as it is the category with the largest effect size over engagement at it is showed in the previous section.

The first table of interest is a summary of the model on Table 6.6. This summary table provides the value of R and R² for the model that has been derived. For these data, R has a value of .319 and because there is only one predictor, this value represents the simple correlation between Adaption/Immersion and Sense of Engagement.

Table 6.6: Model Summary^b

Model	R	R Square	Adjusted Square	R Std. Error of the Estimate
1	.319 ^a	.102	.071	1.269

a. Predictors: (Constant), Adaption-Immersion

b. Dependent Variable: Sense of Engagement

The value of R² is .102, which tells us that Adaption and Immersion levels can account for 10.2% of the variation in engagement. In other words, if I want to explain why engagement levels vary more than others, I can look at the variation in engagement of different Adaptability and Immersiveness levels. There might be many factors that can explain this variation, but our model, which includes only Adaption/Immersion (due to large effect), can explain approximately 10% of it. This means that 90% of the variation in engagement

levels cannot be explained by Adaption and Immersion levels alone. Therefore, there must be other variables that have an influence also.

The next part of the output reports an analysis of variance (ANOVA). As it is illustrated in Table 6.7 the relevant statistics is the F-ratio which has an associated significance value. For these data, F is 3.280, which is significant at $p > .001$. This result indicates that there is more than a 0.1% chance that an F-ratio of this magnitude would happen if the null hypothesis were true. Therefore, it is possible to conclude that our regression model is not predicting engagement significantly well.

Table 6.7: ANOVA^a on Regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	5.283	1	5.283	3.280	.081 ^b
	Residual	46.717	29	1.611		
	Total	52.000	30			

a. Dependent Variable: Sense of Engagement

b. Predictors: (Constant), Adaption-Immersion

6.4.5 Self-evaluation Interface Reports

In this section, the reported answers of the users are illustrated in the descriptive statistics tables (see Table 6.8) have been generated to quantify the overall interaction on the brain-controlled version of the Roma-Nova game. This is achieved through the analysis of the statistical data deriving from the reported answers. The questionnaire used the likert scale from 1-5 and in some cases from 1-9. The results are considered as ordinal measurements.

Table 6.8 Descriptive Statistics for Roma-Nova interaction

		Ease of Use	Ease of Learning	Usability	Satisfaction	Learning to operate the Interface	Time to learn to use the Interface	Tasks can be performed in a straight forward manner	The Interface is reliable	Correcting your mistakes
3N	Valid	31	31	31	31	31	31	31	31	31
	Missing	0	0	0	0	0	0	0	0	0
Mean		3.13	3.68	3.42	3.45	5.81	6.03	5.84	5.94	5.16
Median		3.00	4.00	3.00	3.00	6.00	6.00	6.00	6.00	5.00
Std. Deviation		.763	.979	.886	1.028	2.040	1.871	2.099	1.632	1.791
Variance		.583	.959	.785	1.056	4.161	3.499	4.406	2.662	3.206
Skewness		-.708	-.194	-.354	-.058	-.047	-.050	.020	.012	.002
Std. Error of Skewness		.421	.421	.421	.421	.421	.421	.421	.421	.421
Kurtosis		.608	-.886	.825	-.215	-1.112	-1.138	-1.346	-.393	-.102
Std. Error of Kurtosis		.821	.821	.821	.821	.821	.821	.821	.821	.821
Minimum		1	2	1	1	2	3	3	3	1
Maximum		5	5	5	5	9	9	9	9	9

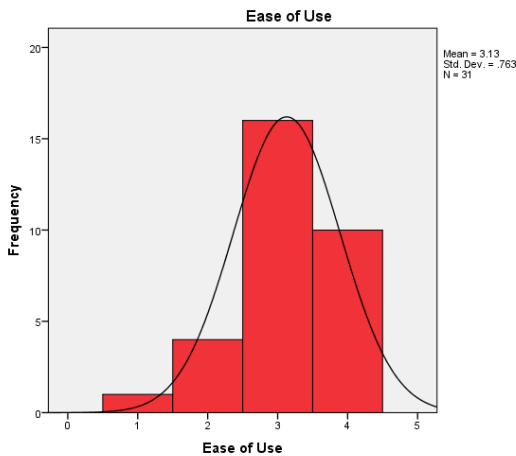


Figure 6.13 Ease of Use

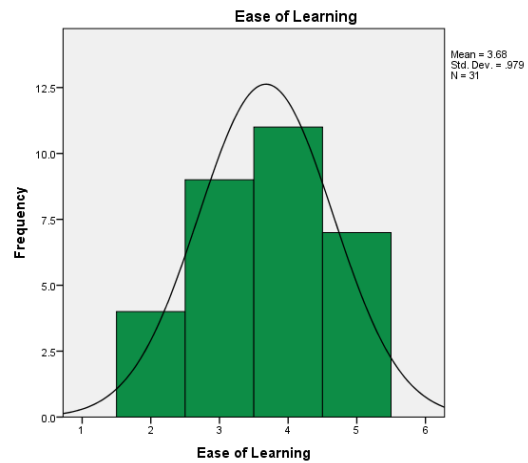


Figure 6.14 Ease of Learning

Figure 6.13 and Figure 6.14 indicate the easiness in which the users learned to operate and use the BCI within the game environment. The negative skewness of -0.708 for ease of use and -0.194 for ease of learning indicates a small piling of the values at the right side of the distribution with few low values, with the mass of the concentration to be on the higher values. On average, participants didn't find it hard to use the interface ($M=3.13$, $SD=0.763$) neither to learn to operate within the virtual environment ($M=3.68$, $SD=0.979$). Additionally, positive kurtosis of the Ease of Use with 0.608 against the negative kurtosis -0.886 of Ease of Learning is indicating a more pointy distribution (leptokurtic).

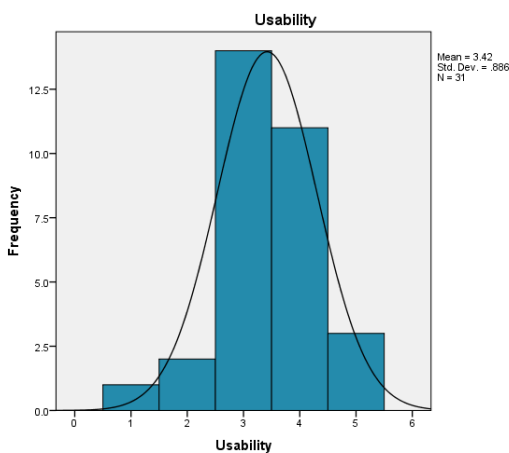


Figure 6.15 Usability

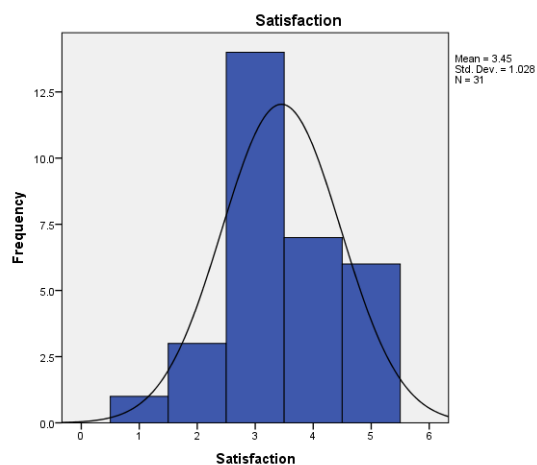


Figure 6.16 Satisfaction

The Usability (Figure 6.15) can be considered quite good on average with the piling of the values on the right side (skewness of -0.354), a mean $M=3.42$ and a positive kurtosis of 0.825. This can be considered as a very good score for Usability in a scale from 1-5. The same applies for the user satisfaction (Figure 6.16) with a negative skewness of -0.058, very close to the normal distribution with the majority of the users answering 3 and a mean of 3.45 and std. deviation of 1.028 with the majority of the answers to indicate overall good satisfaction levels.

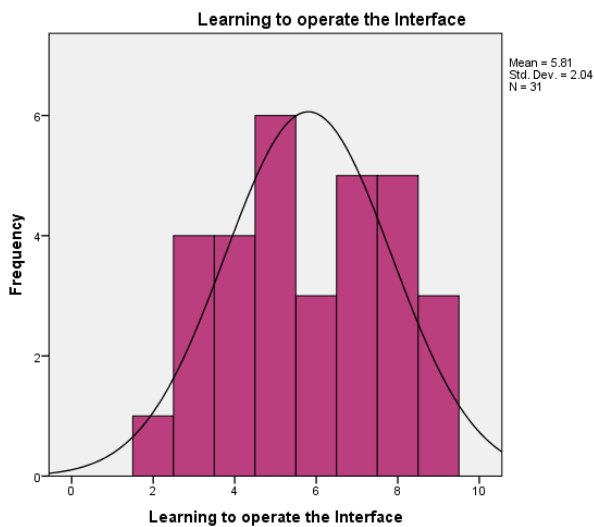


Figure 6.17 Learning to Operate the Interface

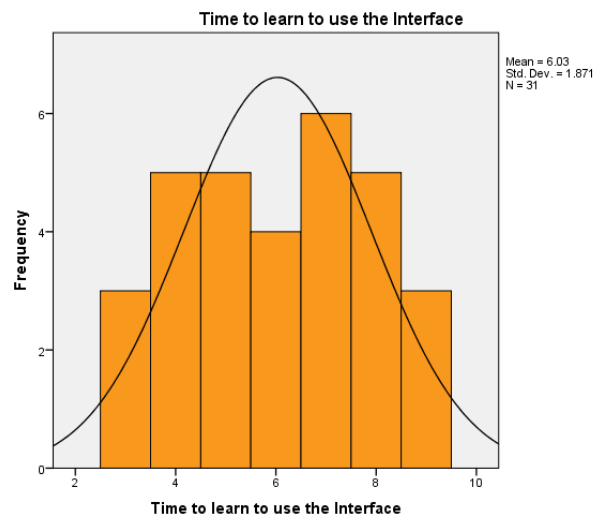


Figure 6.18 Time to learn to use the interface

The reported answers concerning the time and the learning of the user to operate the interface (Figure 6.17, Figure 6.18) are almost identical. This can be derived by the shape of the distribution with a skewness of -0.047 for learning and -0.050 for the time, kurtosis of -1.112, -1.138 respectively and finally the mean of 5.81 and 6.03 in a 1-9 scale. To quantify this relationship better, Pearson's correlation coefficient (ρ) has been calculated resulting to a positive correlation of $\rho=0.875$. The value of 0.875 (really close to 1) implies a linear relationship of the data points. Overall, the small skewness indicates a mesokurtic shape very close to a normal distribution but with a tendency to the right side. This can be confirmed by the mean values of 5.81 and 6.03 respectively. Although both distributions don't give a clear winner, with the aforementioned values we can see a positive tendency of

the users towards the learning and the time to operate the interface. Finally, the positive correlation can give us a valid relationship between the two values.

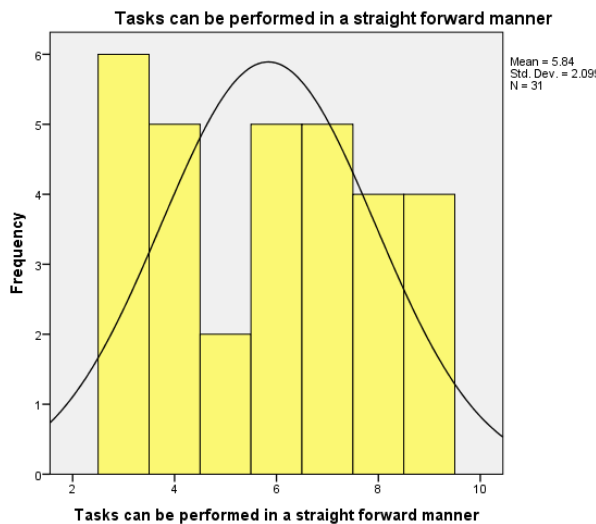


Figure 6.19 Tasks can be performed in a straight forward manner

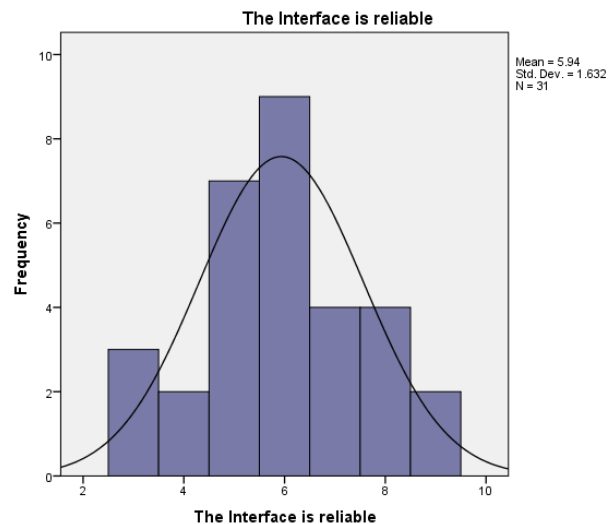


Figure 6.20 The interface is reliable

In Figure 6.19 the sense of the user on the task performance by using the BCI to control the avatar and if the control was straight forward is illustrated. The small skewness (0.020) and the platykurtic shape (-1.346) indicate a wide spread distribution of the values with no clear tendency but only the mean of 5.84 (in a 1-9 scale). For this we can assume that the manner was straight forwards but without a big confidence based on the current sample size. In Figure 6.20 a very important question is answered concerning the reliability of the BCI. The skewness is close to zero with a value of 0.012 and a negative kurtosis of -0.393. Again, the average is high with mean of 5.94 with the majority of the values in the right side of the distribution. Thus, we can conclude with confidence that the users experienced average reliability from the interface with a small positive tendency. Since this kind of report can be subjective based on the user experience and not on data from the device, it is possible that with a bigger sample the distribution will converge to a normal mesokurtic distribution.

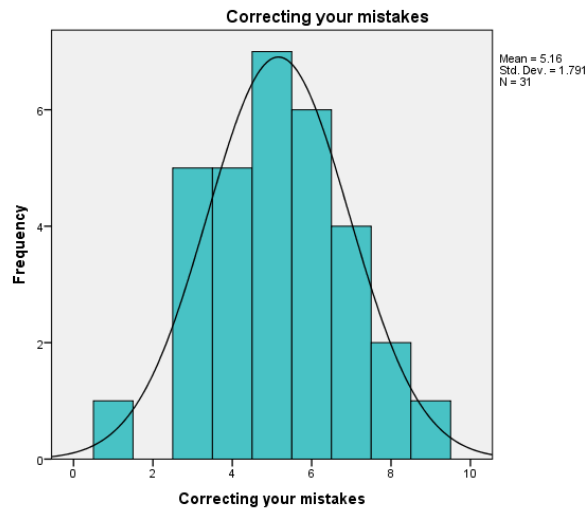


Figure 6.21 Correcting your mistakes

In Figure 6.21 the ability of the user to correct his/her mistakes is illustrated with an almost normal distribution of the values. This is confirmed by an almost zero skewness of 0.002 and the smallest kurtosis from all the previous histograms of -0.102. The mean is 5.16 but with almost zero skewness it is not possible to clearly identify a positive tendency. The ability of correcting the mistakes can possibly have a relationship between the interface reliability as it was reported in Figure 6.20. Users that had trouble in correcting their mistakes might also report a low reliability of the interface and vice-versa.

6.4.6 Word Cloud

From users comments and improvement suggestions, a word cloud have been generated (see in Appendix) in order to identify the most common words based on frequency from the text. This can give an intuition on what is the most common reported suggestion or comment for further improvement of the system but also the overall feedback of the experience. The most frequent word in the comment section is “*easier*” and “*experience*” followed by “*control*” and “*game*”. On the suggestions field the most common words are “*improve*”, “*system*”, “*turn*”, “*eye*” followed by “*better*” and “*brain*”. Extracting word frequencies from large text reports can help to quantify better the experience and help to identify and extract valuable information within the words. From the current word-cloud in relation with the unstructured interview we can see an acceptance of the system, being a unique and enjoyable experience with vast possibilities for improvements.

6.4.7 Summary of Statistics

The statistical analysis of the user data has given several results. To summarise, in Figure 6.22 and Figure 6.23 the mean value for each of the self-evaluation questions is illustrated.

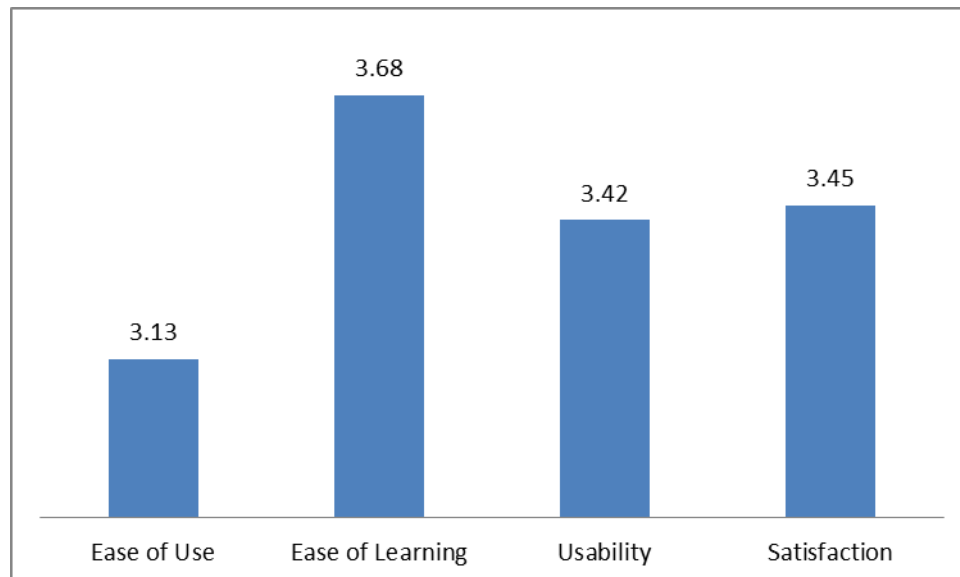


Figure 6.22 Summary of statistics in 1-5 likert scale

Overall, Figure 6.22 presents that learning the interface has the bigger score with $M=3.68$, followed by satisfaction and usability were they having almost the same mean (0.03 difference). In contrast, ease of use has the lowest mean compared with the rest. This shows that despite the learning procedure which is reported as positive (increasing over time) towards the interface, the use still remains a problem. This can be a result of the game environment or the controlling mechanisms within the game. Based on the user reports concerning the GUI (see 6.3.1 User Feedback), more assistive graphical elements on screen could significantly help the interaction and enhance learning through this loop. Summarising, ease of learning is higher by using the BCI to interact with the VE (through neurofeedback) than ease of using resulting to poor interaction within the VE that could be a product of the absence of assistive GUI elements.

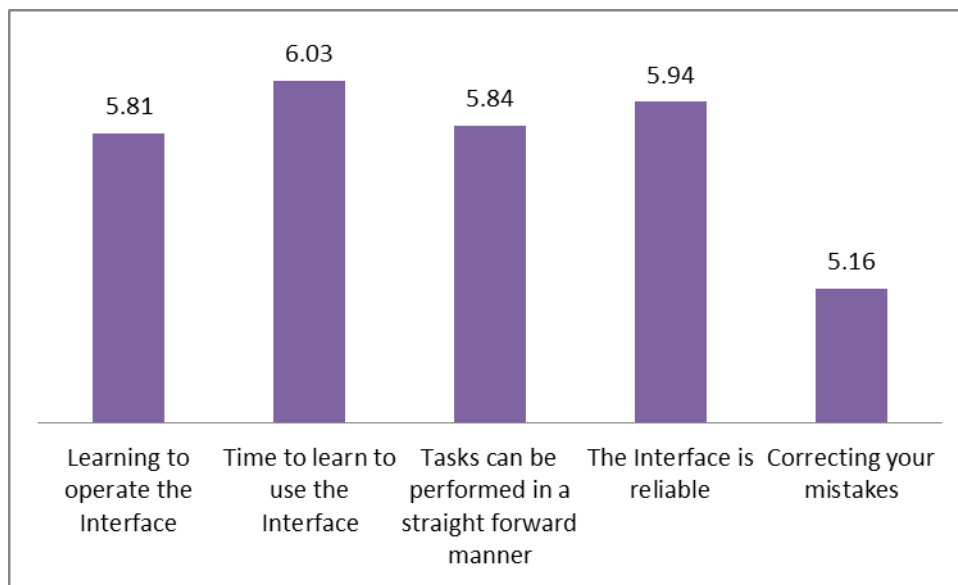


Figure 6.23 Summary of statistics in 1-9 scale

In Figure 6.23 it is possible to identify that the time to learn to use the interface has the higher mean ($M=6.03$) followed really close by the interface reliability ($M=5.94$). The required time to learn the interface can be correlated with the easiness of learning in Figure 6.22. It is obvious that all questions related with the interface are relatively high, besides the question concerning the ability of the user to correct his/her mistakes with $M=5.16$. This can be relative to the easiness of use in Figure 6.22, making obvious that by reducing

the ability of the user to correct the mistakes, the use is getting harder. This can be solved again with an assistive interface and adaptive mechanics within the game environment in order to filter out all the false-positive reactions of the user.

As a final step into assessing the brain interaction within a virtual environment is to analyse the extracted raw EEG data during task performance and the training trials before the interaction with the games.

6.5 Preliminary EEG Analysis

A preliminary analysis of the extracted EEG data during task performance (in the Roma-Nova game) and the training trials classification results are presented in the following section. This chapter constitutes a first step towards the future work of this project.

6.5.1 Cognitive workload during task performance

As it was mentioned on chapter 2, on different periodic waveforms of the EEG or rhythms there is an association with various states and in different areas of the brain. According to the U.S. ARMY Developmental Test Command (Anon.2011), Cognitive engagement is the amount of attention a person exerts during a specific task. Previous EEG results imply that performance of tasks that require mental efforts for the user to be engaged places high demands on the frontal area of the brain involved with attention (Doppelmayr et al. May). This task correlation with the Alpha rhythm was recognised for over 80 years (Berger 1933) in addition with signals from the Theta rhythms. Experiments demonstrated that augmentation of theta activity (4-7Hz) from the central frontal area and suppression of alpha activity from occipital areas were both associated with increased mental effort in response to working memory load (Gevins and Smith 2003). NASA also focused on the measurement of electroencealographic (EEG) activity in order to capture task engagement reflecting the task engagement the best (Pope, Bogart and Bartolome 1995). According to Emotiv manual, engagement is characterized by increased physiological arousal and Beta waves (12–30 Hz) along with attenuated Alpha waves. The opposite pole of this detection is referred to as “Boredom” in Emotiv Control Panel and the Emotiv API (Emotiv 2011). The company notes that this does not always correspond to a subjective emotional experience that all users describe as boredom or engagement.

6.5.2 Extracted EEG Frequency analysis

During the Serious Game interaction, users asked to perform certain tasks by controlling the avatar only with the neuro-headset. These tasks vary for low to high precision, same tasks for all participants in order to avoid high bias, guided by the experimenter. At the same time synchronised EEG activity was recorded. As it was

described in chapter 4, the data from each user was ‘cleaned’ by removing the artefacts originating mainly from blinking and facial movement. Afterwards, the data had been transformed to the frequency domain and filtered (bandpass filter) by removing the unwanted frequencies. Following the clean-up of the raw signals, datasets had been created for each user individually for identifying the most active frequencies and components/electrodes, also by visualising the data including the spectral maps (see Figure 6.24) and then the averaging of all signals. Initially from all the 14 channels we can identify which frequencies are more active and in which part of the skull are originating. In Figure 6.24 is a sample of a spectral map plot for one user. From this spectral map we can see a rise in the power between 8-10Hz. Relatively to the rest of the spectrum a high pick at 9Hz occurs for all users’ as it was discovered from the transformation in the frequency domain for all participants. This frequency is within the Alpha rhythm range (8–12 Hz) and it can be an indication of increased engagement during task performance.

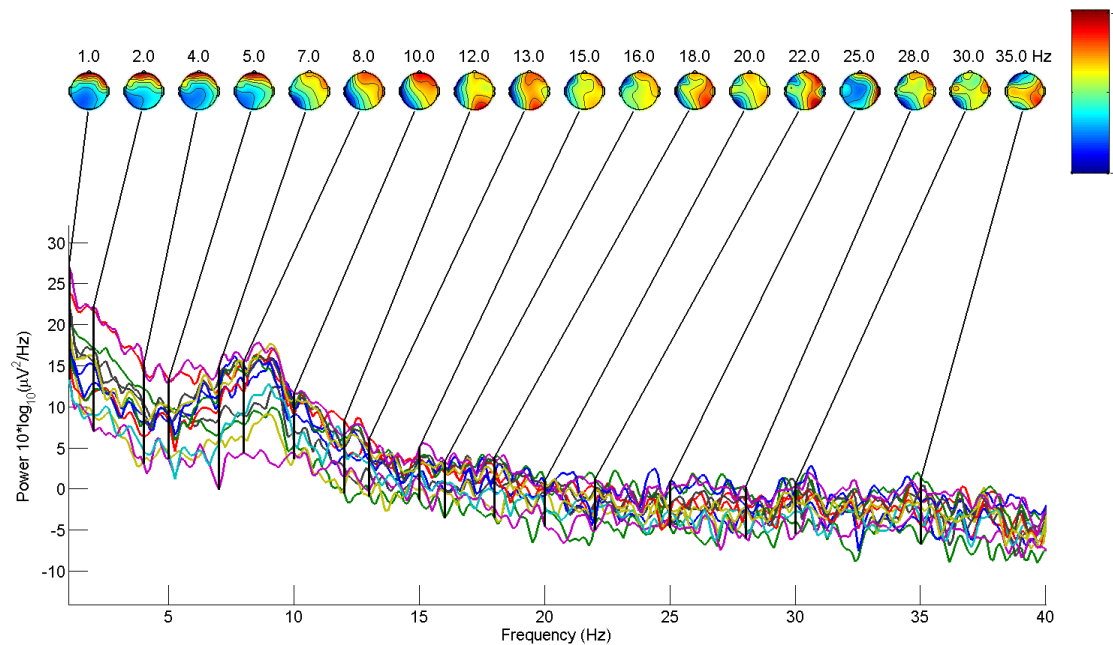


Figure 6.24: Channel spectra and maps from a single user

Clustering all the EEG data from all the participants that performed the tasks (N=31) and averaging the signal, we can identify the same peak at 9Hz as it is illustrated in Figure 6.25 and Figure 6.26.

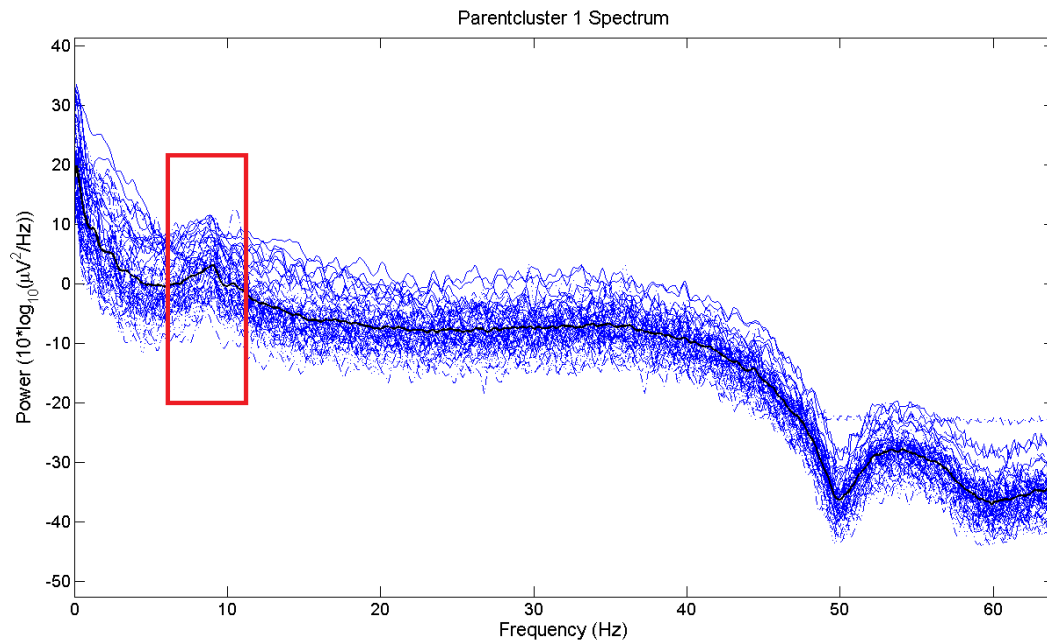


Figure 6.25 EEG signals cluster

In Figure 6.26 is illustrated a close-up of the 9Hz pick from the average of all 14 channels from all participants raw EEG data.

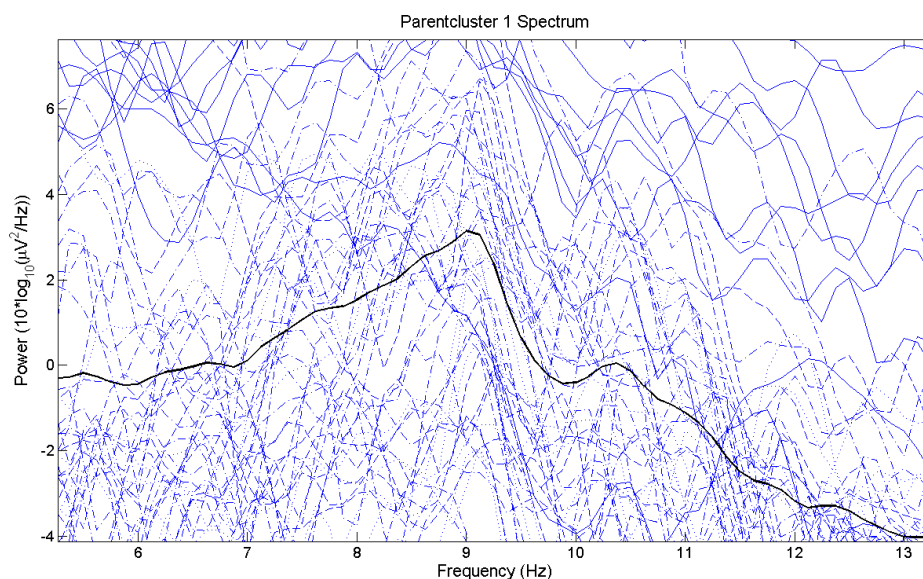


Figure 6.26 9Hz Peak on Signal Clustering

Going a step further, to identify the origin of this frequency a test from EEGLAB is performed (*spectopo*) to see which components contribute most strongly to which frequencies in the data.

Figure 6.27 illustrates the specified frequency (9Hz) and the plot of the relative topographic distribution of power. The mean spectrum for all of the supplied data is plotted and not just the pre-stimulus baseline. Finally, EEGLAB uses the *pwelch* function from the Matlab signal processing toolbox to generate the results. *pwelch* calculates the power spectral density using Welch's method (Welch 1967).

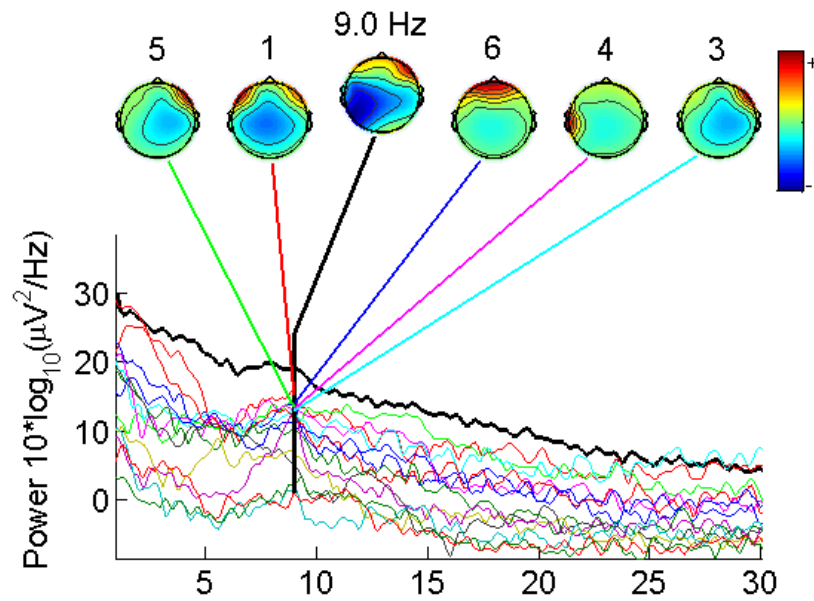


Figure 6.27 Component Activity at 9Hz of a single user

Example Output for user in Figure 6.27:

Component 1 percent variance accounted for: **41.08**
 Component 2 percent variance accounted for: **17.73**
 Component 3 percent variance accounted for: **23.92**
 Component 4 percent variance accounted for: **25.54**
 Component 5 percent variance accounted for: **27.18**
 Component 6 percent variance accounted for: **29.65**
 Component 7 percent variance accounted for: **12.25**
 Component 8 percent variance accounted for: **14.32**
 Component 9 percent variance accounted for: **4.07**
 Component 10 percent variance accounted for: **5.77**
 Component 11 percent variance accounted for: **23.82**
 Component 12 percent variance accounted for: **1.77**
 Component 13 percent variance accounted for: **1.57**
 Component 14 percent variance accounted for: **1.99**

"Percent variance accounted for" (pvaf) compares the variance of the data MINUS the (back-projected) component to the variance of the whole data. Thus, if one component accounts for all the data, the data minus the component back-projection will be 0, and pvaf will be 100%; If the component has zero variance, it accounts for none of the data and pvaf = 0%. If a component somehow accounts for the NEGATIVE of the data, however, pvaf will be larger than 100% (Delorme and Makeig 2004). According to the variance accounted for output above, component 1 accounts for more than 40% of power at 9 Hz for channel AF3 in the frontal area.

In the following Figure 6.28 is summarised the component contribution for all the participants. Marked with green are the electrodes in the left side of the scalp and with orange the right side. In Figure 6.29 is the electrode numbering as it was extracted by EEGLab based on Emotiv's head maps.

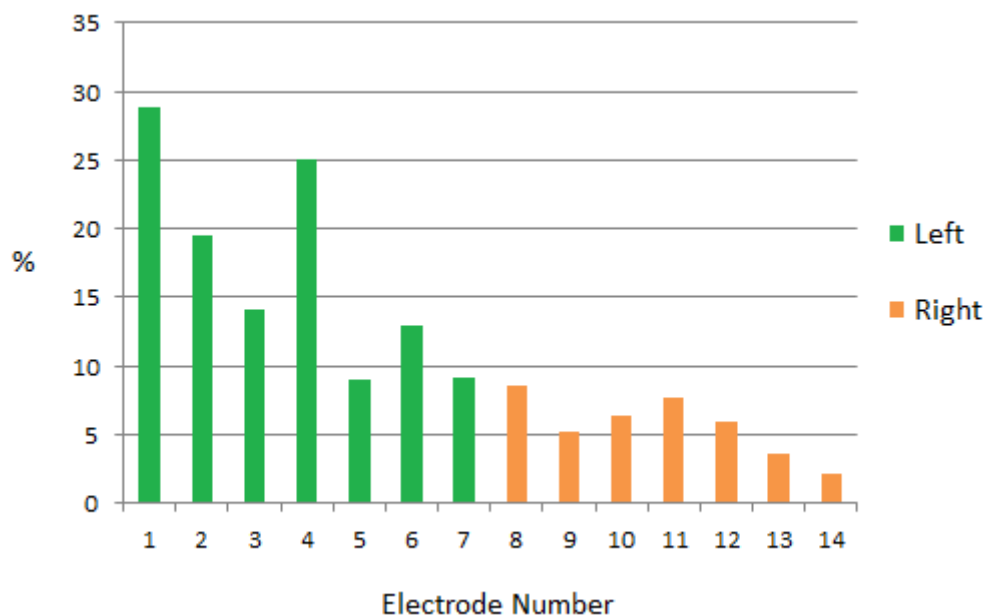


Figure 6.28 Summarised component variance with scalp side.

From the abovementioned results we can see that there's a pattern followed for each user of an increased Alpha wave at 9hz originating mainly from the left side of the scalp,

from AF3(component number 2) and FC5(component number 4) channels with the biggest contribution.

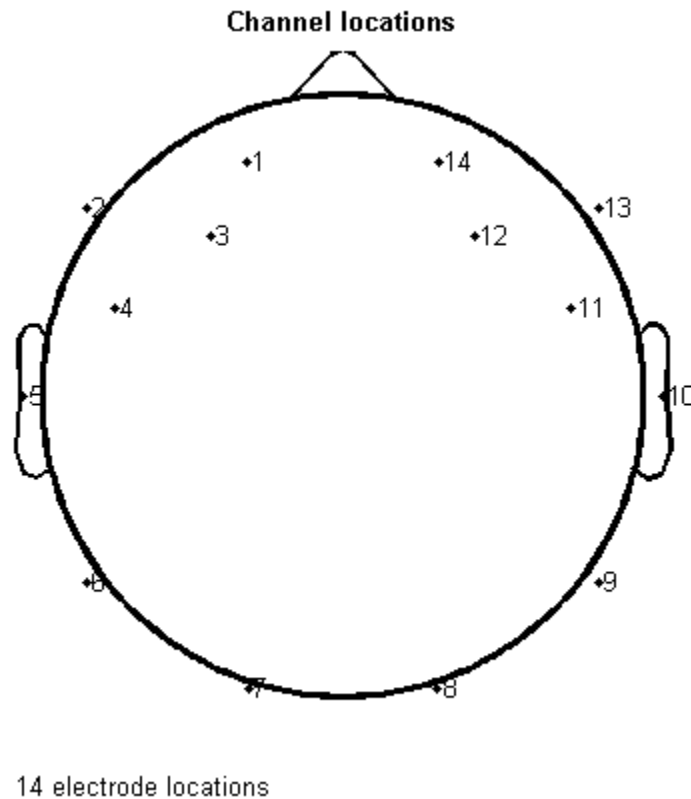


Figure 6.29 Channel Location with Component Number

The increased power on the left side of the scalp might have to do with the participant's dominant hand (handedness) or hand preference. Since the majority were right handed, the left side of the brain could provide more power at these channels. This is only a speculation and cannot be proved by current data. In addition the increased power in the frontal area within the range of the Alpha rhythm can be an indication of increased attention as it was mentioned with previous literature. The only problem in assessing the motor imagery is the electrode position as it will be described in subsection 6.5.4.

6.5.3 Training trial performance

Overall, two training sessions took place in order to train the EEG classifier through the control panel. This is a training targeted for both the classifier and also the user. On the user side it is really important to get feedback based on the brain generated events that trigger the movement of a 3D cube in space and learn how to manipulate that power. For each trial a percentage was calculated from the Emotiv panel based on the correct classification of the users' imaginary movement for left/right. Between the two trials the BrainMaze game was used in order to increase the users' cognitive workload by navigating in a medium sized maze as it is described on chapter 3 and get familiar with the interface in a task oriented virtual environment.

Figure 6.30 illustrates the correct classification (%) for both training trials as have been achieved from all users.

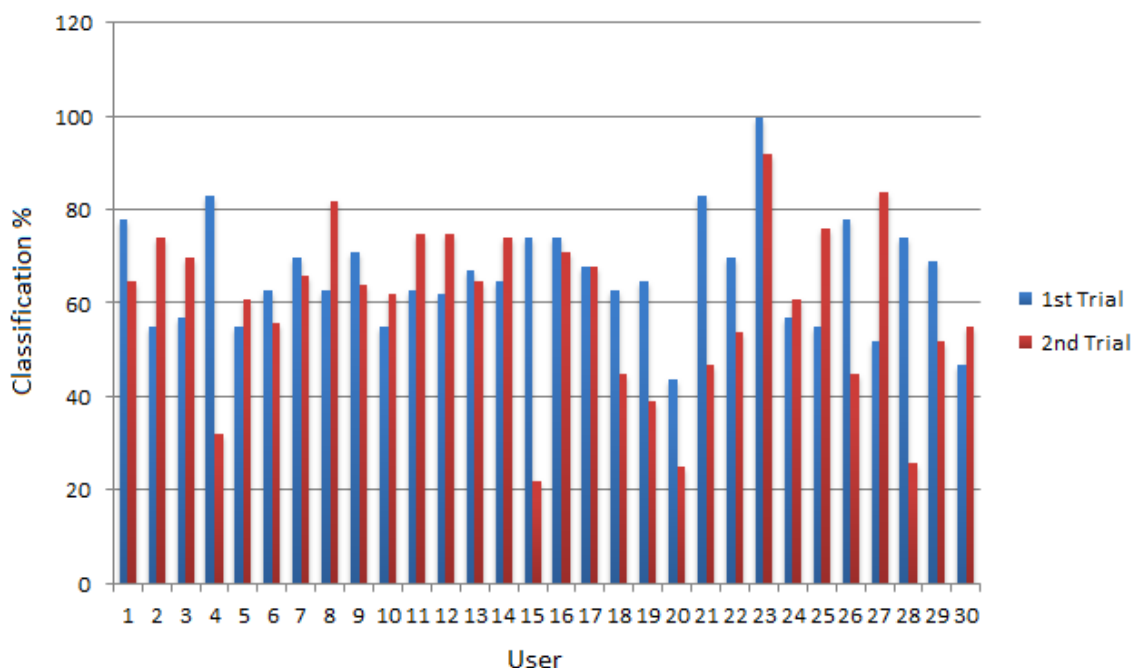


Figure 6.30 Training trials results

Figure 6.31 illustrate the difference of both trial and if this led to increased performance after the initial interaction with the game or the opposite.

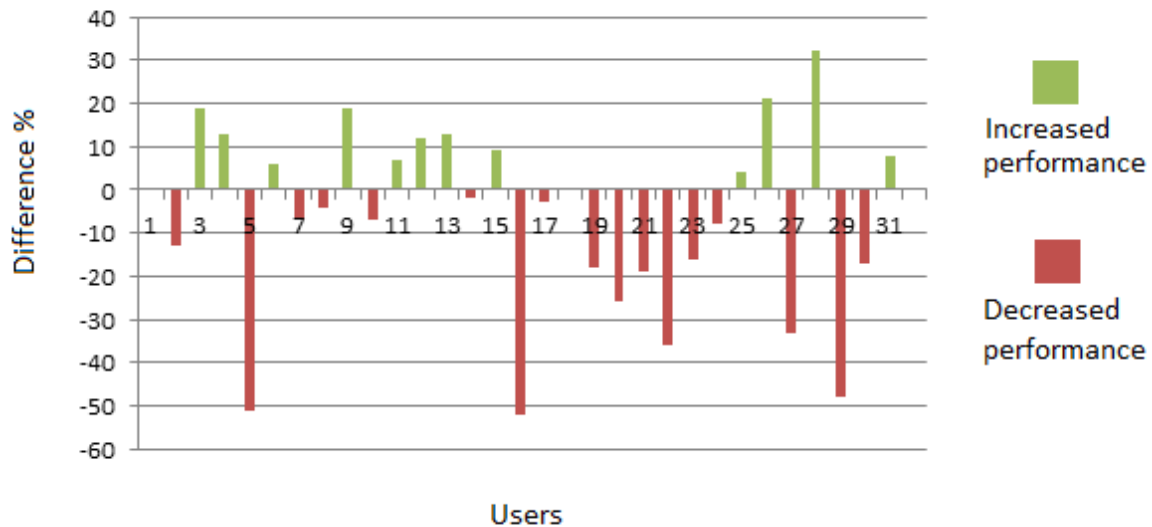


Figure 6.31 Performance Difference

From the training comparison results illustrated on Figure 6.30 and Figure 6.31, only 40% of the users increased their score and their ability to move the 3D cube by brain power alone. Based on this observation it was also reported by the participants that it was harder for them to control the virtual character over time decreasing their performance, being unable to control the same type of events.

From these results we can identify a clear decrement of overall performance of the user during a session, with the misclassified data to exceed the correct. Although the participants were getting familiarised with the interface, the increased workload prevent them to also increase performance. This was also reported by the participants after the end of the session.

6.5.4 Emotiv Headset and Motor Imaginary

As it was mentioned in Chapter 4, each participant had to move a virtual 3D cube by using 'brain' power alone through the Emotiv (training) Control Panel by creating a unique profile and train the classifier. This had to be achieved by using motor imagery, meaning that the participant had to imagine limbic movement and that actually pushes the cube. This is achieved by triggering neurons that generate almost the same electrical activity as if the limb was actually moving. In Chapter 2 it was mentioned that different areas of the brain are responsible for different functions. Hence, the area responsible for the upper limb movement would activate during the imaginary movement of the limb (Georgopoulos, Kettner and Schwartz 1988).

A first step is to locate the mu-rhythm frequencies located in the somatosensory cortex (Salmelin and Hari 1994), and those electrodes that are located over the sensorimotor cortex. Within the 10-20 system, electrodes C3, C4, P3 and P4 (Anderson, Devulapalli and Stolz 1995) or FC3, FC4, CP3 and CP4 (Wolpaw et al. 1991) are mostly used. As it is illustrated in Figure 6.32, there are no electrodes (marked blue) used by Emotiv Epoc headset (AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2) that can be used for a typical Sensory-Motor Rhythm (SMR) analysis as there's no intersection between these sets. In general, for motor imaginary channels C3 and C4 are necessary for motor classification or the adjacent electrodes (with Laplacian filtering), i.e., FC3, CP3, C5, C1 for C3 ; FCz C1, C2, CPz for Cz and FC4, CP4, C6, C2 for C4. Since the electrode position of the headset didn't provide accurate positioning over the somatosensory cortex of the brain, it cannot be assessed for SMR generation during the task performance. In addition, we can speculate that Emotiv algorithm is not using SMR activity for the classification during the training trials. Using adjacent electrodes can be very noisy and unreliable way of movement classification. Finally, is very probable that non-EEG data are used for training the classifier, like facial movement or head position.

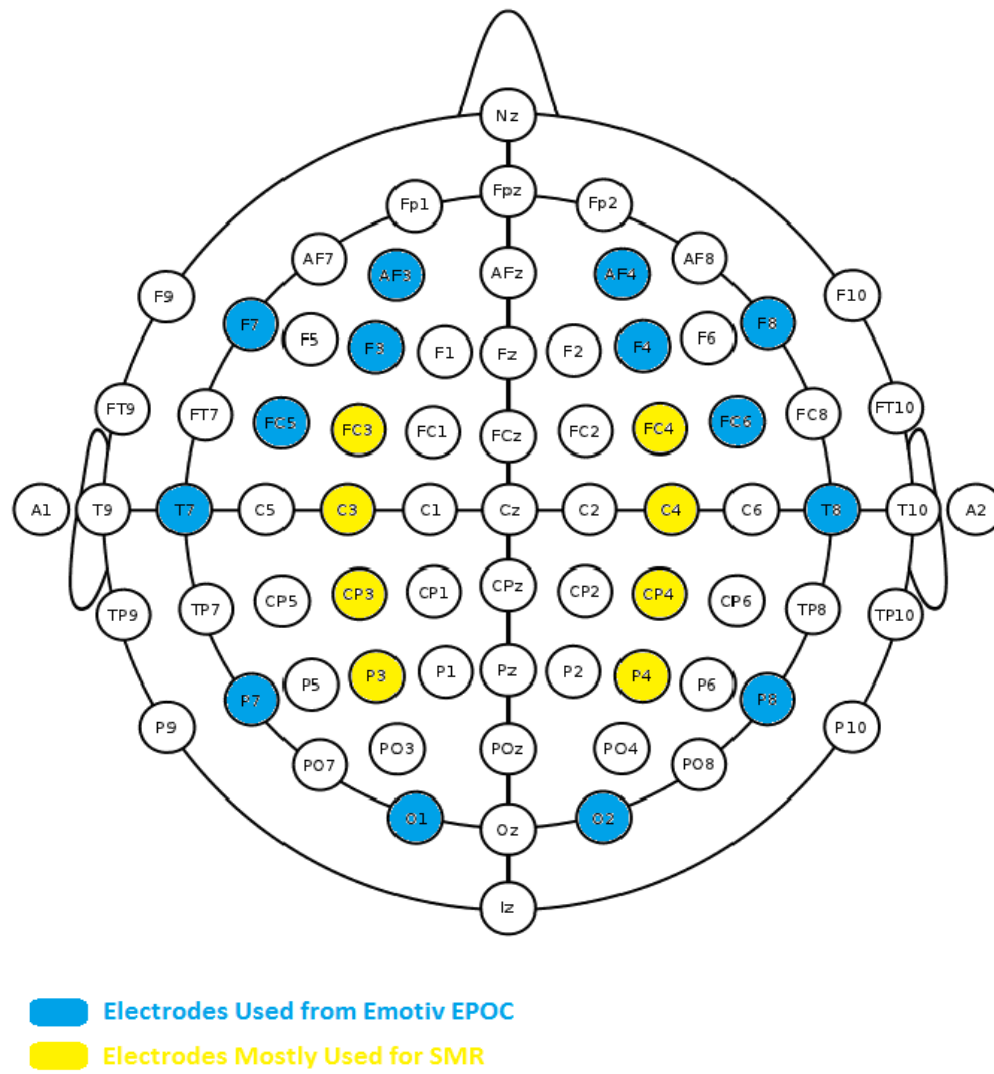


Figure 6.32: Emotiv headset electrode position with commonly used for SMR

Part III - Conclusions

7 Conclusions and Future Work

In this chapter the conclusions from the results are presented, followed by a proposed framework for designing future brain-controlled games for serious application and finally the discussion and the future work of this project based on the current findings.

7.1 Conclusions

From the interaction with the virtual robot it was found that it was easier for users to navigate by focusing on GUI elements overlaying the virtual environment rather the robot itself. For initiating an action it was found that a mental visualisation of the 3D cube (from the training trials) helped the users to concentrate better in order to move the robot which acts as the end effector. Recalling the memory of the training process seemed to activate the same mechanisms that trigger the movement of the virtual object (and match the profile on the trained classifier) rather than closing the feedback by concentrating to the robot. Overall the experience was reported as quite engaging and interesting regardless certain issues of response time and accuracy that other Natural User Interfaces (NUI's) might have.

From the Serious Game interaction, there is a strong indication that the reported answers between the Presence Questionnaire groups are coherent and not random with the assumption of homogeneity being met. It has also been discovered that Adaption/Immersion levels have the largest effect in the users' perceived engagement during the interaction rather the Interface Quality of the Virtual Environment or the level of users Involvement. The immersiveness within the game was enhanced by the unique experience such an interface can offer, with the game design and mechanics of the environment to be less important for the user in terms of engagement. On the other hand the reported engagement and the extracted from the electrophysiological data are not correlated. With the presented tables we can gain confidence that there is no relationship between the two (on this experimental setup). Finally, we can conclude that our regression model with Adaption/Immersion as the independent variable is not predicting engagement significantly well.

Furthermore, regardless the reported reliability of the interface, users were able to operate the interface successfully and relatively fast. In addition, from the self-reported answers we can identify a difference between the ease of use (low) and ease of learning (high). This can be a result of the game environment or the controlling mechanisms within the game but it gives a positive possibility since the learning procedure and the familiarization with the interface evolves over time in favour of the user. In addition, this is reflected on a low ability to correct mistakes relating with the ease of use and the small time that the user requires to learn the interface related to learning. Overall, from the user reports and comments we can conclude that poor usability triggers mistakes as a result mainly of the interface elements and the game mechanics. On the other hand, the ability of the user to adapt on this experience and learn to use the interface is considered satisfactory setting that way a base for future brain-controlled virtual environments in which the aforementioned limitations are absent.

On the preliminary EEG analysis we can see an increased Alpha wave rise in power between 8-10Hz and on average we can identify a peak at 9Hz from all users. Forty per cent (40%) of power at 9 Hz is originating from channel AF3 in the frontal area and the left side of the scalp. Increased power in the frontal area within the range of the Alpha rhythm can be an indication of increased attention but since it still remains a subjective emotional experience.

During the training trials, only 40% of the users increased their score and their ability to move the 3D cube by brain power alone. Based on this observation it was also reported by the participants that it was harder for them to move the cube over time decreasing their performance, unable to control the same type of events. This can be correlated also with the low score in ease of use reported answers.

Since the electrode position of the headset didn't provide accurate positioning over the somatosensory cortex of the brain, it cannot be assessed for SMR generation during the task performance. In addition, we can speculate that Emotiv algorithm is not using SMR activity for the classification during the training trials. Using adjustment electrodes can be

very noisy and unreliable way of movement classification. Finally, it is very probably that non-EEG data are used for training the classifier, like facial movement or head position since the activity was recorded on the frontal area and not from the motor cortex

7.2 Towards Brain-Controlled Serious Games

Moving towards to out-of-the-box BCI Games, training and adaptation is required for both the user and the machine for a successful interaction. It is a learning process in which two entities are iterating and adapting in a closed loop with the Serious Game for optimisation. We can visualise this as three different parts (see Figure 7.1), the user, the machine where the data acquisition and translation is taking place, and finally the Game or the Virtual environment where the actions are visualised and adapted to the internal elements of the game based on the inputs, closing the loop. In Figure 7.1 are illustrated two loops, the user adaptation loop and the machine learning loop both contributing to the game mechanics. From one side, while the user learns to operate the interface the game is adapted based on user performance and proficiency, on the other hand the translated electrophysiological data must be used in a meaningful way, minimising random actions that could trigger false feedback back to the user.

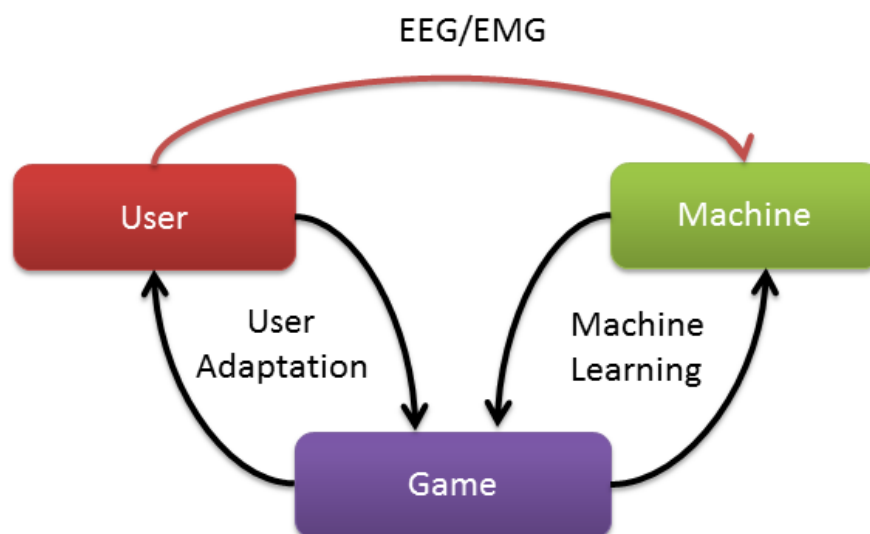


Figure 7.1 User-Machine learning procedure

Over time, the skill becomes more and more automatic. “The learning mechanism in this case is similar to learning to ride a bicycle” (Neuper and Pfurtscheller 2010). Hence, the feedback must reflect the user’s task in an appropriate way.

This can be generalised in a framework (see Figure 7.2) that describes the requirements hierarchies and level of abstraction, proposing a generalisation that can be applied for future brain controlled (BCI or Hybrid-BCI) Games. This framework relies in three pillars of requirements: Approach, Technology and Implementation.

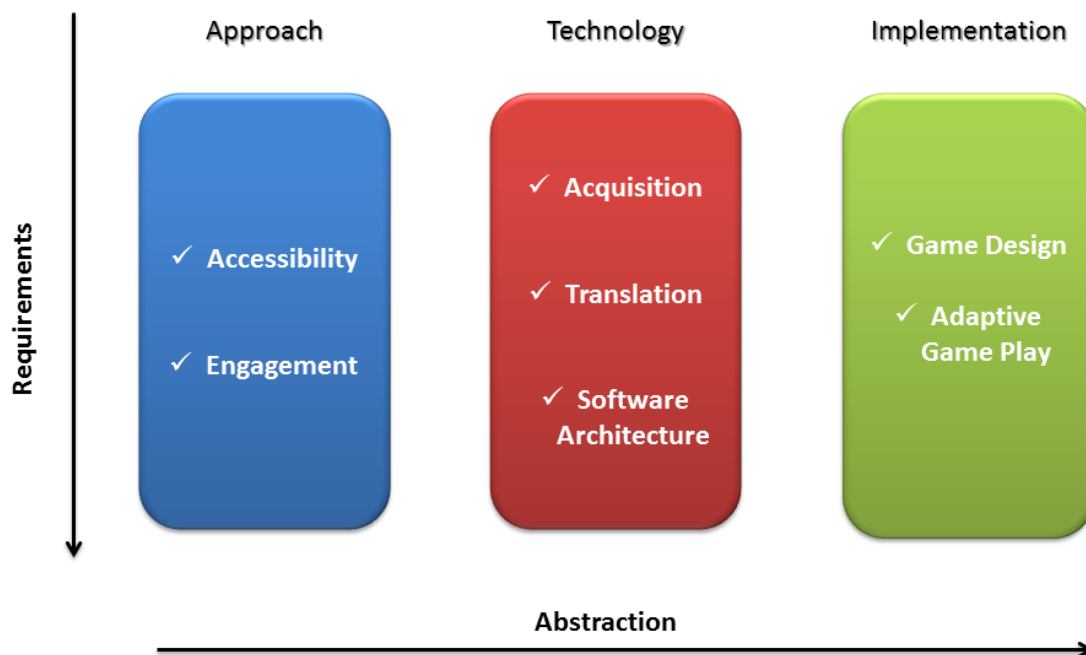


Figure 7.2 Requirements Hierarchy for BCI Games

The approach layer is based on two elements: first is the accessibility, where the user must have access to low cost equipment (no more than the average cost of other NUI’s in the market) with electrode position that covers the appropriate motor areas. Secondly, the set-up time must be kept into a minimum so it would be easy to maintain a high usage frequency and time to familiarise with the interface.

For a meaningful interaction between the user and the brain-controlled Serious Game, the acquired data must be filtered, cleaned from noise, translated and classified based on pre-defined rules. This can be achieved in the technology layer where machine learning algorithms will handle the electrophysiological data and the game events. For maximum flexibility, upgradability, and a big user base, a common development platform (open-source) must be used for future serious games that use electrophysiological data from the users. Finally, the last layer is where all data are visualised and the loop is closed, is the Implementation layer. As it was mentioned before, all current brain controlled games are proof of concepts and they do not satisfy the requirements to be categorised as games. In order to be able to create a Serious Game controlled with such a unique interface, we have to create mechanisms that will ensure a successful interaction. This can be achieved through game design principles modified for brain-control, adaptive gameplay based on user performance and in the case of medical use (e.g. neurofeedback for ADHD), gamifying the process for engaging the patients could be extremely useful.

In conclusion, this study is set out to answer the question whether BCI control can be used as an input mechanism to modern games and virtual environments, and whether the game design of current games is capable to incorporate technology which uses electrophysiological data as an input. The results from the evaluation of two brain-controlled games, including the analysis of quantified, qualified and EEG data contribute towards the main body of knowledge in game interaction through the proposed framework in system design for the new emerging field of “BCI game design” and ”neuro-gaming”. Finally, this study has reviewed the state-of-the-art of BCI systems, methodologies and games, including the most significant goals that have driven BCI research over the last 30 years.

7.3 Discussion

So far, neuroscientists know so very little on how the brain works and how certain events are correlated with certain thoughts or actions. Many scientists compare the EEG readings like a mechanic who tries to find how an engine works just by listen to it from a different room. That's how EEG recordings work from outside the scalp. Noisy , low resolution and artefact-rich signals which make the classification of simple brain activity a real challenge.

This project has presented the rational and development of a BCI controlled Serous Game that can be used by a wide range of users, from low to those with a high degree of motor control. Furthermore, the quantification of the overall BCI driven Serious Games have been performed including feedback from naïve subjects, comparison between reported answers and extracted cognitive data, offline EEG analysis during task performance, user performance during brain-control and signal classification, and finally the evaluation of a commercial BCI headset for gaming and virtual world interaction.

These results are promising and important for the development of future neuro-feedback based Serious Games ranging from entertainment, education to rehabilitation and clinical research. It has been investigated through the user testing the impact that this kind of technology has to healthy users with no previous experience on BCIs and BCI controlled games. Further results from the EEG analysis indicate that the correlation between the user replies and the physiological data is very little. Users that scored high on questions based on overall engagement didn't have the analogous extracted electro-physiological data to indicate a close connection. In addition, the performance and agility of the user was reduced over time, scoring low both on the training process and the game interaction.

Addressing these issues, the results of this research project can be used as a base forming future BCI controlled Serious Games with the use of non-invasive, non-medical EEG and EMG systems for various applications.

Hardware specification, the consent form and the generated word cloud can be found on the APPENDIX.

7.4 Future Work

The framework introduced in this thesis provides a natural guide to future research in brain-controlled games for serious application and also entertainment. Besides the feasibility of the BCI control in modern games we have to move towards specific game design principles where this kind of interfaces can be incorporated and used in their full potential without creating the sense of fatigue to the user. Future work will include the development of an adaptive gaming environment based on user performance with existing BCI technology in order to assist and enhance Serious Game and Virtual World interaction. Furthermore, findings from healthy users will be used and expanded to the medical domain in rehabilitation tools for patients with motor and cognitive deficits in serious games using neuro-feedback. For example, so far there is not available detailed information on what brain activation patterns lead to successful functional recovery in stroke patients and very little is known about how to optimally use a neuro-feedback paradigm through virtual environments or games. Based on the current limitations and the findings of this research, the target of the future work is to develop a novel neuro-feedback system with the use of low cost BCI's, and Serious Games interaction. This will allow us not only to effectively train motor function, but to monitor and to collect extensive synchronized brain activity and behavioural data on patient performance during the recovery process. Final goal is to generalize the findings of the research into a neuro-feedback paradigm for future applications either at home or in a clinical environment. Finally, since Emotiv algorithms are closed source and they can only be examined through the outputted result, custom classification techniques must be applied, simplifying the overall process.

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Appendices

APPENDIX A

A.1 Serious Games Taxonomy by Ben Sawyer, President, Digital Mill

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APPENDIX B

B.1

Consent Form

Project Title: *Brain-Computer Interfaces (BCIs) in Virtual World interaction*

Project Approval Reference:

Please read completely

Research in the current conduct study is considered of “minimal risk”. You will be asked to interact with a virtual object in a virtual environment using a physical interface. During this experiment you will be asked to examine the virtual object by manipulating the physical interface.

The monitor names for this study will be **Mr Athanasios Vourvopoulos** ([yourvopa@coventry.ac.uk](mailto:vourvopa@coventry.ac.uk)) and **Dr Fotis Liarokapis** (f.liarokapis@coventry.ac.uk). Mr Athanasios Vourvopoulos and Dr Fotis Liarokapis have also been the designers of this experiment. You are expected to participate **for approximately 30 minutes**. During the experiment you will be asked to train a user profile, interact with the game using a commercial BCI headset and on the completion of this task you will be asked to fill in a questionnaire. We will use your data anonymously, along with the data of several other participants.

Remember that your participation is entirely **voluntarily**. You can choose not to participate in part or all of the project and you can withdraw at any stage of the project without being penalized or disadvantaged in any way. Finally, we deserve the right to stop using you as a subject for any reason.

Please circle your answer to the following issues and sign below:

Do you understand this consent form?	YES	NO
Do you give your consent to be a subject in this study?	YES	NO
Do you certify that you are at least 18 years of Age?	YES	NO
Can we use your photograph in a publication?	YES	NO

Have you ever suffered from severe vertigo or epilepsy?	YES	NO
Do you give your consent for your data to be used in further research projects which have research governance approval as long as your name and contact information is removed before it is passed on?	YES	NO
<p>Signature_____ Date_____</p> <p>Name (printed) _____</p> <p>E-mail _____</p>		

B.2. Emotiv EPOC Specifications

Number of channels	14 (plus CMS/DRL references)
Channel names (Int. 10-20 locations)	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3, P4, P7, P8, T7, T8, O1, O2
Sampling method	Sequential sampling, Single ADC
Sampling rate	~128Hz (2048Hz internal)
Resolution	16 bits (14 bits effective) 1 LSB = 0.51 μ V
Bandwidth	0.2 - 45Hz, digital notch filters at 50Hz and 60Hz
Dynamic range (input referred)	256mVpp
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Battery type	Li-poly
Battery life (typical)	12 hrs
Impedence measurement	Contact quality using patented system

APPENDIX C

C.1 – Comments word-cloud

action (2) available (1) avatar (3) bc (1) best (1)
blinking (3) certainty (2)
components (3) computer (2)
control (5) difficult (4) due (2)
easier (7) experience (7)
experienced (1) eye (4) finally (1) focus (2) focusing (1)
game (5) gets (3) gui (3) interacting (2)
interesting (4) interface (3) learn (2)
mouse (1) movements (3) moving (2) neutral (1)
nice (2) offer (1) perform (2) please (1) problem (2)
pulling (4) push (4) quite (1) required (2)
respond (2) robot (3) screen (2) sensors (1) think (2)
tired (2) tricks (1) used (1) video (2) wanted (1) watching (1)

C.1 – Improvements word-cloud

actual (1) add-on (1) additional (1) algorithms (1) approx (1) backwards (1) basis (1)
believe (1) **better** (3) **brain** (3) calibration (1) continues (1)
control (2) days (1) difficult (1) easy (1) electronic (1)
expected (2) experience (1) **eye** (4) facial (1) general (1) head (1)
idea (1) **improve** (5) learning (2)
movements (3) moving (1) operating (2)
order (2) perform (2) proper (1) **pull** (2) push (1)
quite (3) removed (1) responsive (1) seemed (1) sensitive (1) sensors (1)
specific (1) sure (1) **system** (4) took (1) training (1) **turn** (4)
unresponsive (1) upgrade (1) used (1) user (1)