DM

Thought-Controlled Games with Brain-Computer Interfaces

MASTER DISSERTATION

André José da Silva Ferreira

MASTER IN INFORMATICS ENGINEERING

UNIVERSIDADE da MADEIRA

A Nossa Universidade

www.uma.pt

September | 2017

Thought-Controlled Games With Brain-Computer Interfaces

MASTER DISSERTATION

André José da Silva Ferreira
MASTER IN INFORMATICS ENGINEERING

SUPERVISOR
Sergi Bermúdez i Badia

CO-SUPERVISORS
Mónica Cameirão
Athanasios Vourvopoulos

Thought-Controlled Games with Brain-Computer Interfaces

André José da Silva Ferreira

Constituição do júri de provas públicas:

Doutor Eduardo Miguel Dias Marques, (Professor Auxiliar da Universidade da Madeira), Presidente

Doutor Pedro Filipe Pereira Campos, (Professor Auxiliar da Universidade da Madeira), Vogal

Doutor Sergi Bermudez i Badia, (Professor Auxiliar da Universidade da Madeira), Vogal

Dezembro 2017

Funchal – Portugal

Thought-Controlled Games with Brain-Computer Interfaces

André José da Silva Ferreira

Master in Informatics Engineering

Supervisor:

Sergi Bermúdez i Badia (PhD)

Co-supervisors:

Mónica Cameirão (PhD)

Athanasios Vourvopoulos (MSc)

Funchal, September 2107

Abstract

Nowadays, EEG based BCI systems are starting to gain ground in games for health research. With reduced costs and promising an innovative and exciting new interaction paradigm, attracted developers and researchers to use them on video games for serious applications. However, with researchers focusing mostly on the signal processing part, the interaction aspect of the BCIs has been neglected. A gap between classification performance and online control quality for BCI based systems has been created by this research disparity, resulting in suboptimal interactions that lead to user fatigue and loss of motivation over time. Motor-Imagery (MI) based BCIs interaction paradigms can provide an alternative way to overcome motor-related disabilities, and is being deployed in the health environment to promote the functional and structural plasticity of the brain. A BCI system in a neurorehabilitation environment, should not only have a high classification performance, but should also provoke a high level of engagement and sense of control to the user, for it to be advantageous. It should also maximize the level of control on user's actions, while not requiring them to be subject to long training periods on each specific BCI system. This thesis has two main contributions, the Adaptive Performance Engine, a system we developed that can provide up to 20% improvement to user specific performance, and NeuRow, an immersive Virtual Reality environment for motor neurorehabilitation that consists of a closed neurofeedback interaction loop based on MI and multimodal feedback while using a state-of-the-art Head Mounted Display.

Keywords: Brain-Computer Interfaces, Motor Imagery, Adaptive Performance, Virtual Reality, Haptic Feedback, Serious Games.

Resumo

Hoje em dia, os sistemas BCI baseados em EEG estão a começar a ganhar terreno em jogos relacionados com a saúde. Com custos reduzidos e prometendo um novo e inovador paradigma de interação, atraiu programadores e investigadores para usá-los em vídeo jogos para aplicações sérias. No entanto, com os investigadores focados principalmente na parte do processamento de sinal, o aspeto de interação dos BCI foi negligenciado. Um fosso entre o desempenho da classificação e a qualidade do controle on-line para sistemas baseados em BCI foi criado por esta disparidade de pesquisa, resultando em interações sub-ótimas que levam à fadiga do usuário e à perda de motivação ao longo do tempo. Os paradigmas de interação BCI baseados em imagética motora (IM) podem fornecer uma maneira alternativa de superar incapacidades motoras, e estão sendo implementados no sector da saúde para promover plasticidade cerebral funcional e estrutural. Um sistema BCI usado num ambiente de neuro-reabilitação, para que seja vantajoso, não só deve ter um alto desempenho de classificação, mas também deve promover um elevado nível de envolvimento e sensação de controlo ao utilizador. Também deve maximizar o nível de controlo nas ações do utilizador, sem exigir que sejam submetidos a longos períodos de treino em cada sistema BCI específico. Esta tese tem duas contribuições principais, o *Adaptive Performance Engine*, um sistema que desenvolvemos e que pode fornecer até 20% de melhoria para o desempenho específico do usuário, e *NeuRow*, um ambiente imersivo de Realidade Virtual para neuro-reabilitação motora, que consiste num circuito fechado de interação de neuro-feedback baseado em IM e *feedback* multimodal e usando um *Head Mounted Display* de última geração.

Palavras chave: interfaces Cérebro-Máquina, Imagética Motora, Performance Adaptativa, Realidade Virtual, *Feedback* Háptico, Jogos Sérios

Table of Contents

List of Figures

List of Tables

Abbreviations

EEG – Electroencephalography

BCI – Brain Computer Interface

LDA – Linear Discriminant Analysis

MI – Motor Imagery

CSP – Common Spatial Pattern

Publications

This thesis was integrated into the RehabNet project and is realized in the context of Athanasios Vourvopoulos' PhD project at the University of Madeira, and has been presented in the following peer-reviewed publications:

A. **A. Ferreira**, A. Vourvopoulos, and S. Bermudez I Badia, "Optimizing Performance of Non-Expert Users in Brain-Computer Interaction by Means of an Adaptive Performance Engine," in Lecture Notes in Computer Science/Artificial Intelligence (LNCS/LNAI), London, UK, 2015.

B. A. Vourvopoulos, **A. Ferreira**, and S. B. i Badia, "NeuRow: An Immersive VR Environment for Motor-Imagery Training with the Use of Brain-Computer Interfaces and Vibrotactile Feedback", 2016, pp. 43–53. -Best student paper award-

C. A. Vourvopoulos, **A. Ferreira**, and S. Bermudez i Badia, "Development and Assessment of a Self-paced BCI-VR Paradigm using Multimodal Stimulation and Adaptive Performance", in Lecture Notes in Computer Science, In Press.

This work was supported by the European Commission through the RehabNet project - Neuroscience Based Interactive Systems for Motor Rehabilitation - EC (303891 RehabNet FP7-PEOPLE-2011-CIG), by the MACBIOIDI project financed by the EC through the INTERREG program (MAC/1.1.b/098), by the Fundação para a Ciência e Tecnologia (Portuguese Foundation for Science and Technology) through SFRH/BD/97117/2013, and LARSyS (Laboratório de Robótica e Sistemas em Engenharia e Ciência) through UID/EEA/50009/2013.

Software and instructions are available online in the following address: http://neurorehabilitation.m-iti.org/bci/.

1 Introduction

Stroke is a serious threat to public health, and one of the leading causes of serious, long term disability. 15 million people suffer from stroke each year, and with 50% of the survivors becoming permanently disabled. Neurorehabilitation becomes a vital support which helps in the recovery/mitigation of these injuries with therapies which can be physical, where it helps the patients regain motor functions, and cognitive, where it helps in areas such as memory, attention or executive functions.

Most motor rehabilitation therapies rely on inducing neuroplasticity by stimulating the affected limb, but recent studies have showed that movement observation also has a positive effect on the recovery process. One of the reasons for this effect, is the mirror neurons, brain areas which are activated on movement visualization and execution alike. This feature of the human brain, which is one of our basic learning instincts, makes some neuron rearrangement a possibility, which in turn plays a major part in the treatment of neurological deficits.

Researchers have used video games and virtual reality in neurorehabilitation environments. Not only it provides a safer and more controlled setting, but can also motivate the patients to perform specific tasks in ways that conventional physical therapy cannot. This can also be used to take the rehabilitation process out of the hospital and into the patient's home, making it more available and convenient.

This thesis is focused in the use of serious games applied to the health domain, and in particular to post-stroke rehabilitation of the upper limbs. This is a very exciting academic challenge with high industrial applicability and greater societal value. We believe there is much room for technology to work side by side with current physical therapy to improve and aid in the recovery process of patients suffering from disabilities related to stroke. We will be focusing specifically in BCI technology, which can provide users with motor disabilities a novel interaction paradigm, by translating brain signals (thoughts) into commands (actions).

1.1 Objectives

The main objective of this thesis is to 1) research novel methods to increase the performance of currently used BCI systems and 2) their interaction, making them easier to use by the end user while also making it more flexible and customizable for researchers and developers alike.

The final goal is to build a system which is adjustable and able to increase the sense of control specifically for the user using it, while keeping them engaged and focused on the task at hand with virtual reality, task gamification and multimodal feedback.

1.2 Document Structure

The research and development process is described within the six chapters of this thesis having the following structure: In chapter 1, we introduce the context and the objectives as well as the overall document structure. Chapter 2 comprises of literature review related to focus of this thesis. This state of the art shows us the work other researchers are performing in this area, focusing on the classification and interaction part of BCIs. In chapter 3, we present and describe the approach we took on our efforts to increase the online classification part of a BCI system. In chapter 4 we present the work done in the other part of a BCI system, the task the user is asked to perform. Chapter 5 shows the integration of the work done on the two previous chapters, including the system validation study performed with healthy users. Finally, on chapter 6 we describe the conclusions taken from the research done for this thesis.

2 State of the art

Brain-computer interfaces (BCIs) are systems that aim at providing users with alternative communication channels with a computer system. BCIs detect changes in brain signals and translate them into control commands [1]. Such systems utilize well-defined underlying relationships between users' mental state and corresponding electrophysiological signals. In non-invasive BCI's, electroencephalography (EEG) is commonly used for measuring brain activity.

EEG consists of detecting and reading the brain electrical activity. This can be done in two ways, electrodes can be inserted into the patient's scalp or they can be placed on the scalp (see Figure 1a and Figure 1b). By inserting the electrodes in the scalp, we get signals with less noise, but its more invasive, requires surgery and its more dangerous. The other way is to have the electrode placed externally on the patient's scalp. This is a faster, safer and easier way to extract EEG features, regardless of it providing noisier signals.

(a)

(b)

Figure 1 (a) Invasive EEG example with visible electrodes and wire connections on a patient's head X-Ray. Adapted from [2], (b) Non-invasive EEG headset(Enobio, Neuroelectrics, Barcelona, Spain).

Currently, the 3 main techniques for user interaction and control include: (a) Steady State Visual Evoked Potentials (SSVEP), (b) P300 BCI and (c) Motor-Imagery (MI) or Event Related Synchronization/Desynchronization BCI (see Figure 2).

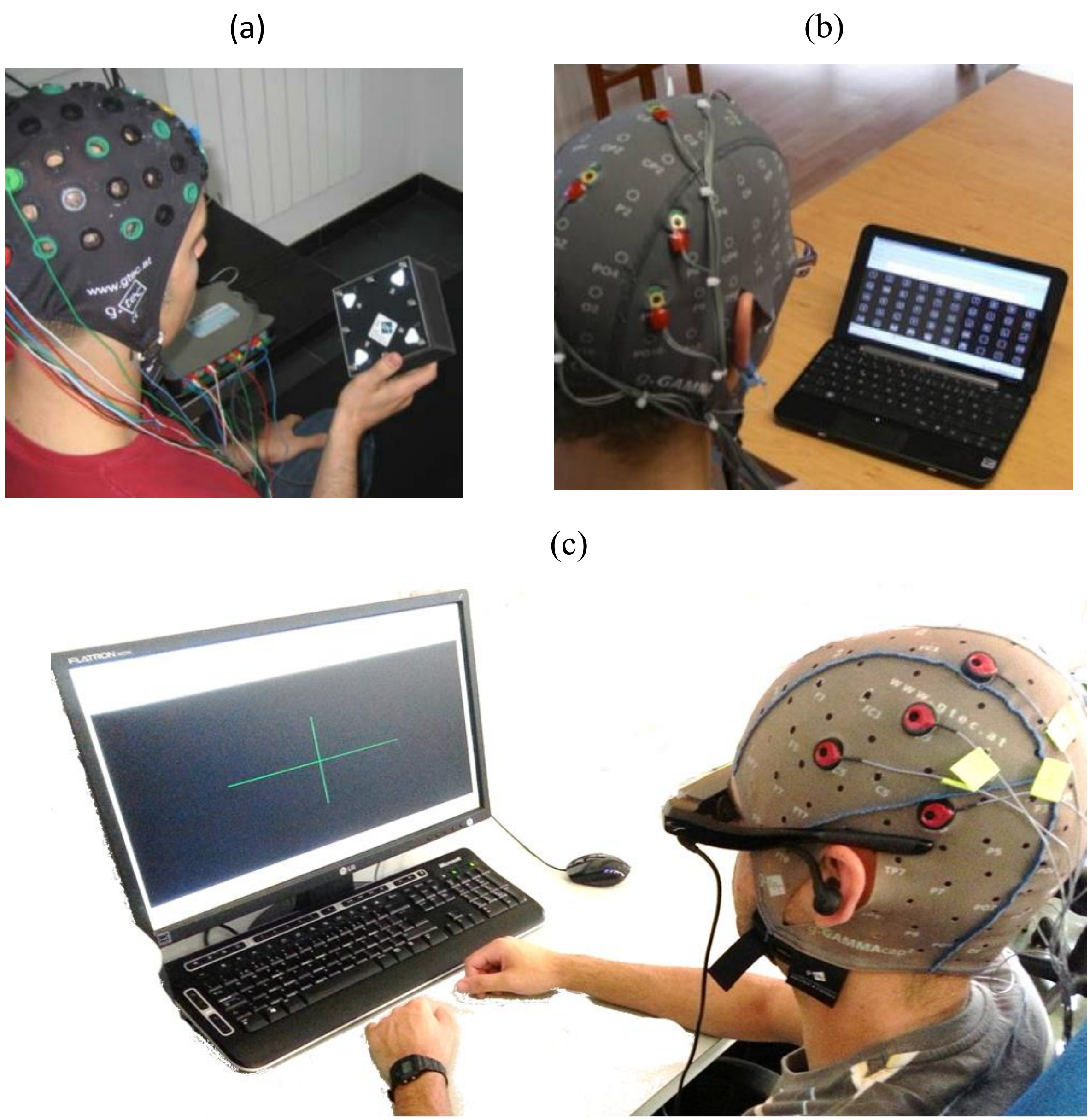

Figure 2 The three main BCI paradigms including: (a) Steady State Visual Evoked Potentials (SSVEP) [3], (b) P300 BCI [4] and (c) Motor-Imagery (MI) [5]

The electrode location over the user's head is defined by the 10-20 international system [6]. 10-20 is indicating the electrode name and position based on the hemisphere and the lobes it is located over the head (see Figure 3).

The use of these techniques in health are divided into two groups: (1) assistive and (2) restorative [7]. An important distinction between the two strategies lies into the fact that assistive BCIs are based on "replacing" the damaged motor mechanisms, and restorative on "improving" existing motor function. Assistive BCI's can provide humans with motor impairments like tetraplegia, an alternative channel for communication or control by bypassing the affected corticospinal pathways. Examples include the control of functional electrical stimulation (FES) [8], orthotic devices [9], EEG wheelchair control [10], or BCI spelling devices [11]. On the other hand, restorative BCIs, target at mobilizing plastic changes of the brain in order to achieve reorganization of motor networks and enhance motor recovery [12]. MI training based on visuo-motor imagination BCI is the most common type of BCI paradigm for motor function restoration.

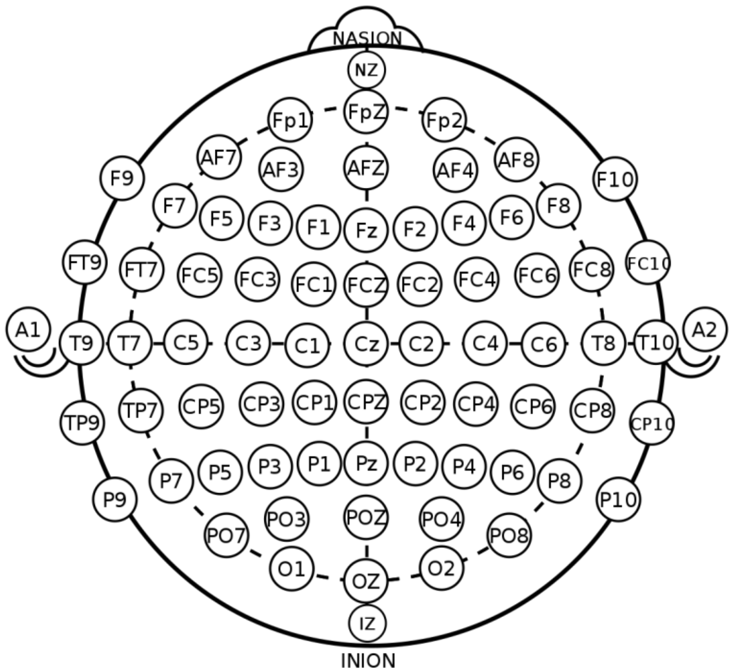

Figure 3 10-20 electrode position system for EEG studies

MI is a mental process in which the subjects imagines themselves executing a movement without carrying out the movement and without any muscle activation. It’s a state during which the representation of a specific motor action is internally activated without any motor output. In other words, motor imagery requires the conscious activation of brain regions which are also involved in movement preparation and execution, accompanied by a voluntary inhibition of the actual movement [13].

There are two types of MI strategies, Kinesthetic motor imagery and visual motor imagery. In kinesthetic motor imagery, the user feels like it’s actually performing the thought-out movement and sees it in a first-person perspective, while on visual motor imagery the user sees him/her self from a distance performing the movement, like in a third person perspective [14].

This distinction between first person and third person perspective, has also been described as a distinction between internal and external imagery. In internal imagery, the subject approximates a real-life situation in such a way that the person experiences the sensory sensations that might be expected in that situation, as opposed to external imagery, where the subject views him/her self as observing someone else performing the movement.

When performing MI, the time to complete an imagined movement is known to be similar to the time needed for actual execution of that movement. This is known as mental isochrony. This indicates that MI respects the biomechanical constraints of actual movement and that these tasks aren't merely visual imagery, and must be resolved by imagining one's own arm or hand moving [15].

These findings states that movement execution, motor imagery and action observation are all driven by the same basic mechanism and that motor imagery and action observation are considered as "offline" processes of the motor areas in the brain [16].

Within the last few years, the launch of low-cost EEG devices increased the user exposure and consequently the amount of BCI studies [17]. This rise in popularity led to the incorporation of BCIs as an alternative input to games, with early adoption by casual gamers. This has implications in terms of accessibility, level of control and BCI illiteracy [18]. Unfortunately, BCI training still requires long training periods resulting in user fatigue and low performance. This led Human-Computer Interaction researchers to work towards novel approaches to increase the communication bandwidth and quality of the BCI loop [19].

A comparative analysis on pure MI-BCI showed varying setups, algorithms and results [20] (see Table 1). Some studies report very different success rates using very similar approaches. Maximum performance scores of 89% were found on a bipolar montage (central electrodes over C3, Cz, C4) classified through a Bayes quadratic based on data from one healthy subject [21]. The lowest performance reached 61% with the same montage but using Linear Discriminant Analysis (LDA) tested with data from 2 healthy subjects [22]. Overall, all studies had very small training datasets with 2 users on average. In addition, most users had been previously trained on BCI use. Consequently, the risk of overfitting is very high, which results in poor predictive performance for the general user when it comes to actual online control. This imbalance between theoretical training performance and actual quality of the online control experienced by the general non-expert user suggests a shift in the interaction paradigm. Current MI-BCI interaction relies on time-constrained binary decisions – such as left vs. right arm motor imagery – and users undergo long, tiresome and complex periods of training so that EEG classification algorithms can reach ***acceptable*** performance rates. Here we propose to reverse the problem at hand and make MI-BCI interaction adaptive to the user, so that we can guarantee a *satisfactory* performance rates by softening decisions – making them probabilistic and non-time-constrained – depending on our confidence on the user's EEG data. That is, we argue that the primary goal should not be for users to be trained to use a BCI system but to adapt the BCI interaction to each user in order to maximize the level of control on their actions. This will allow non-expert users and low-performing users to be able to increase their control, acceptance and motivation towards MI-BCI systems.

Table 1 Classifier performance comparison [20]

Protocol	Classification	Accuracy	electrodes / channels	# of subjects, trials/subject, training set, test set
on different EEG data	Gaussian SVM	86%	2 (C3, C4) at 128Hz	2, 1000 (500/side), 400 (200 random/side, remaining 600)
	LDA	61%		
	LDA	83.6%	6 --> 3 bipolar EEG channels	5 familiar with the Graz-BCI, 360, 240, remaining without artifacts
	Boosting wth MLP's	76.4%		
	LDA	80.6%		
	Boosting wth MLP's	80.4%		
	HMM	81.4% ± 12.8%	4 --> 2 bipolar EEG channels	4 (3 familiar and 1 naive), 880, some sessions where used to train other sessions
	LDA	72.4% ± 8.6%		
	MLP	85.97%	4 --> 2 bipolar EEG channels	3, 667±107, 60%, 20%
	FIR NN	87.4%		
	HMM	75.7%	2 bipolar EEG channels (C3, C4)	-,160 (80/side), -, -
	HMM + SVM	78.15%		
on BCI competition 2003 data set III	Bayes quadratic integrated over time	89.3%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, -, -
	BGN	83.57%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, -, -
	MLP	84.29%		
	Bayes quadratic	82.86%		
	HMM	up to 77.5%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, 100, 40
	Gaussian classifier	65.4%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, 100, 40
	LDA	65.6%		
	Bayes quadratic	63.4%		
	Mahalanobis distance	63.1%		

In addition, there is an increased need for alternative motivational mechanisms and feedback approaches for BCI systems [23], [24]. Previous research in learning states that a poorly designed feedback can actually deteriorate motivation and impede successful learning [25]. On the other hand, providing extensive feedback to the user can lead to efficient and high quality learning [26]. Lotte et al. recommended a set of guidelines for a good instructional design in BCI training, in which (1) the user should only be presented with the correct classified action for enhancing the feeling of competence; (2) provide a simplified and intuitive task; (3) meaningful and self-explanatory task; (4) challenging but achievable, with feedback on progress of achievement; and finally (5) in an engaging 3D virtual environment [24].

Results from previous studies have proven mental practice of action to be useful in MI-BCI [27], and have shown beneficial effects of MI practice during stroke recovery [28]. Overall, in neurorehabilitation, there is increasing evidence that technology-mediated therapy, like robotic and virtual reality based training [29], positively affects motor outcomes compared to standard rehabilitation techniques [30], [31]. So far, the combination of BCIs and virtual environments has gained popularity, and has been proven useful to train functional upper limb pointing movements [32], [33], although the use in clinical environment is limited [34] and hardly used outside laboratory environments [35]. This is mainly due to the fact that current BCI systems lack reliability and good performance in comparison with other types of interfaces [23]. As a result, there is no solid evidence on how BCI training needs to be designed and how improvements transfer to real life [36].

Since MI leads to the activation of overlapping brain areas with actual movement, and because sensory and motor cortices can dynamically reorganize [37]–[39] (see Figure 4), MI can be an important strategy for motor learning and recovery. Hence, MI has important benefits and is currently utilized as a technique in neurorehabilitation for people with neurological impairments [40].

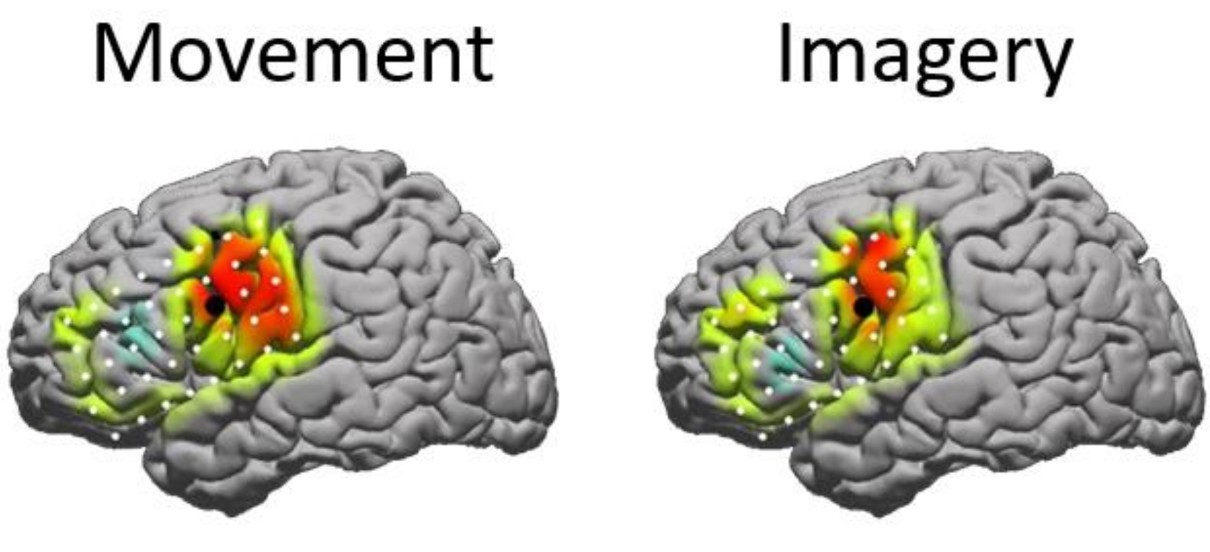

Figure 4 Overlapping cortical activity of motor movement versus movement imagery [39]

MI offers an important basis for the development of brain-to-computer communication systems called Brain–Computer Interfaces (BCIs). BCIs are capable of establishing an alternative pathway between the brain and a computer or prosthetic devices [41] that could assist (assistive BCI) or rehabilitate physically (restorative BCI) disabled people and stroke survivors [12].

More recently, Virtual Reality (VR) feedback has also been used in MI BCI training, offering a more compelling experience to the user through 3D virtual environments [42]. The fusion of BCI and VR (BCI-VR) allows a wide range of experiences where participants can control various aspects of their environment -either in an explicit or implicit manner-, by using mental imagery alone [43]. This direct brain-to-VR communication can induce illusions mostly relying on the sensorimotor contingencies between perception and action [44].

The idea of utilizing BCIs in virtual rehabilitation (virtual reality and tele-medicine for neurorehabilitation) (see Figure 5), was fostered in order to complement current VR rehabilitation strategies [45], [46] where patients with low level of motor control –such as those suffering of flaccidity or increased levels of spasticity [47]- could not benefit due to low range of motion, pain, fatigue, etc.

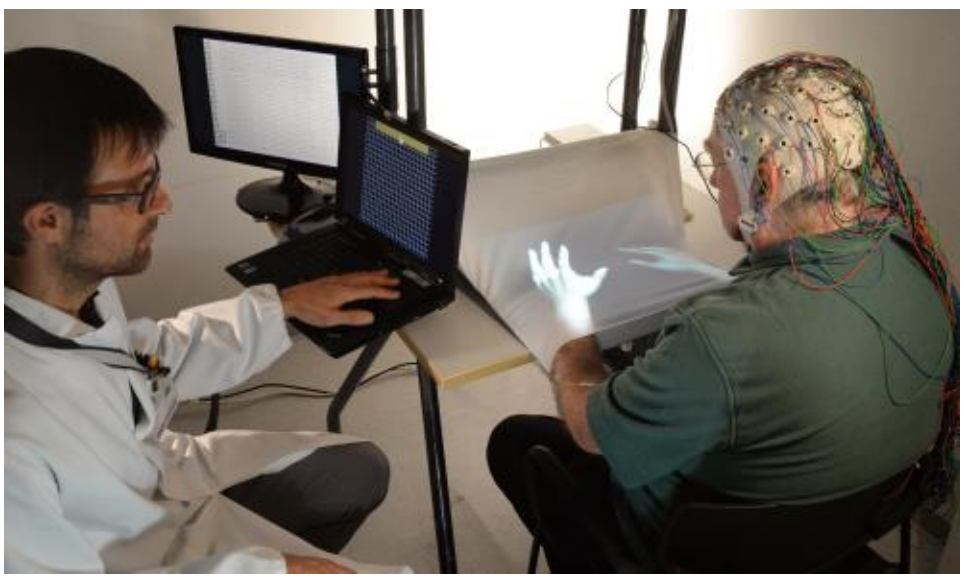

Figure 5 BCI-VR used in stroke rehabilitation [28]

The main challenge in the use of BCIs, regardless of the BCI cost, lies in the lack of reliability and good performance at the system level which inexperienced users have [5] due to BCI "illiteracy" (user's inability to produce vivid mental images of movement resulting in poor BCI performance) [18], [48]. Although previous studies have shown mixed results, the combination of haptic and visual feedback seems to increase performance [49], [50]. It has been shown that replacing the standard visual BCI feedback with vibrotactile feedback does not interfere with the EEG signal acquisition [51] and also does not impact negatively the classification performance [51], [52]. On the other hand, it has been shown to have a positive effect on visual workload measured in a multiple object tracking task (MOT) where the data revealed significant differences between visual or tactile feedback [53]. It has also been shown that with the use of haptic feedback, the user can pay more attention to the task instead of to the feedback [52], and in [54] users achieved higher scores in the vibrotactile feedback setting. Vibrotactile feedback has also been used in a hybrid BCI system [55], where MI with selective sensation (SS) were used in order to increase performance. On this system, equal vibration is applied to both wrists of the user and he/she has to imagine that the vibration to one of the sides is stronger than the other. SS combined with MI increased the overall performance of the system. In [54], it is also reported that the vibrotactile feedback applied on the user's hand significantly increases MI performance. In [56] the use of vibrotactile feedback directly applied to certain tendons is used to convey the illusion of movement to the user, and in conjunction with a virtual representation of the arm, significantly increased the accuracy of a BCI system. Further, recent findings with the use of virtual arms have shown that the combination of motor priming (physical rehearsal of a movement) preceding BCI-VR MI training can improve performance as well as the capacity to modulate and enhance sensorimotor brain activity rhythms, important in rehabilitation research [57].

Chapter 3 – Machine layer: Adaptive Performance Engine

This section was adapted from publication A: **A. Ferreira, A. Vourvopoulos, and S. Bermúdez i Badia, "Optimizing Performance of Non-Expert Users in Brain-Computer Interaction by Means of an Adaptive Performance Engine," in Lecture Notes in Computer Science/Artificial Intelligence (LNCS/LNAI), London, UK, 2015.*

3 Machine layer: Adaptive Performance Engine

In this section, we describe the various steps in the development of a MI-BCI Adaptive Performance Engine. The system focuses on increasing the sense of control on the user actions, as opposed to the EEG classifier performance. With this, we hope to better the interaction aspect of BCIs systems by decreasing both the loss of motivation and fatigue, which are factors currently associated with BCI systems.

OpenVibe was used for the acquisition of all EEG data used in this section. OpenVibe is an open source software platform for designing BCI experiments (see Figure 6).

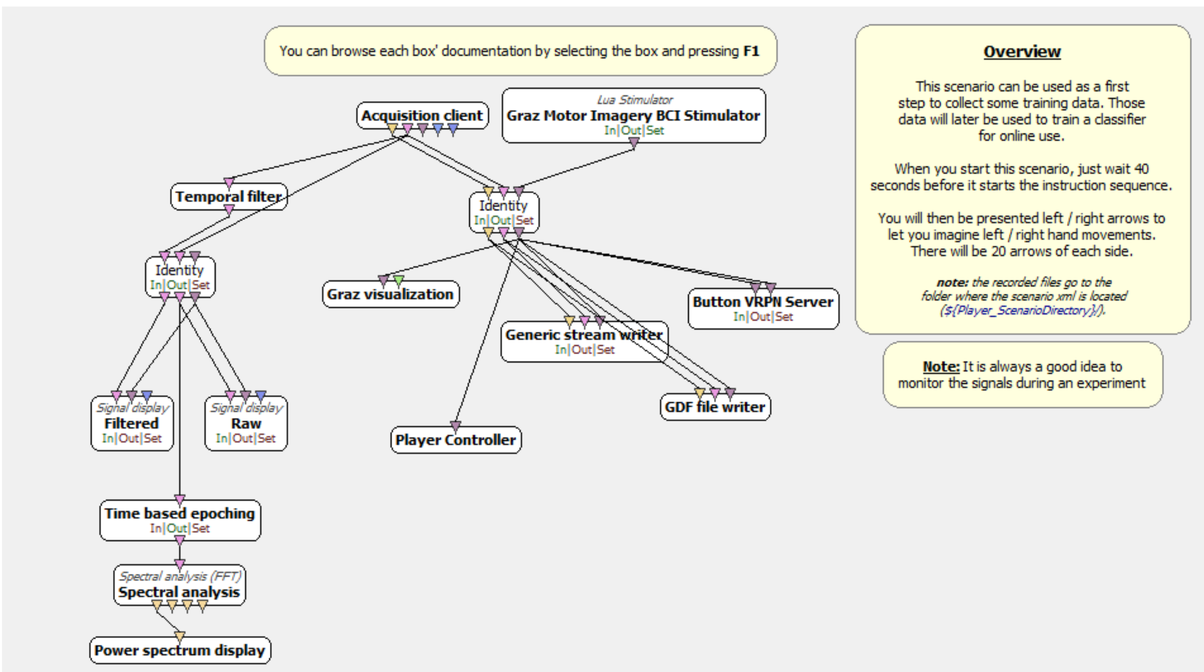

Figure 6 OpenVibe acquisition scenario used on our EEG data acquisition in a BCI MI task.

The OpenVibe acquisition server was used to connect to and get data from the EEG cap and send it to the OpenVibe designer, which is where we made the EEG signal preprocessing scenarios. The five main scenarios consisted of:

1. Signal monitoring – where we made sure we had signal consistency for all channels before starting a session.
2. Acquisition – this scenario (see Figure 6) was used as the MI training session where we presented the standard Graz visualization (see Figure 7 a) and recorded the EEG data to be used on the following scenario.

3. CSP training – here, the data gathered on the previous scenario was used to train the CSP filter which would be used on the next steps.
4. Classifier training – this step was used to train the LDA classifier which would be required to classify the EEG data and label it as being a left-hand or right-hand MI.
5. Online – in this scenario, the trained CSP filter in combination with the LDA classifier are used to classify the online EEG data and present it to the user using again the standard Graz visualization (see Figure 7 b).

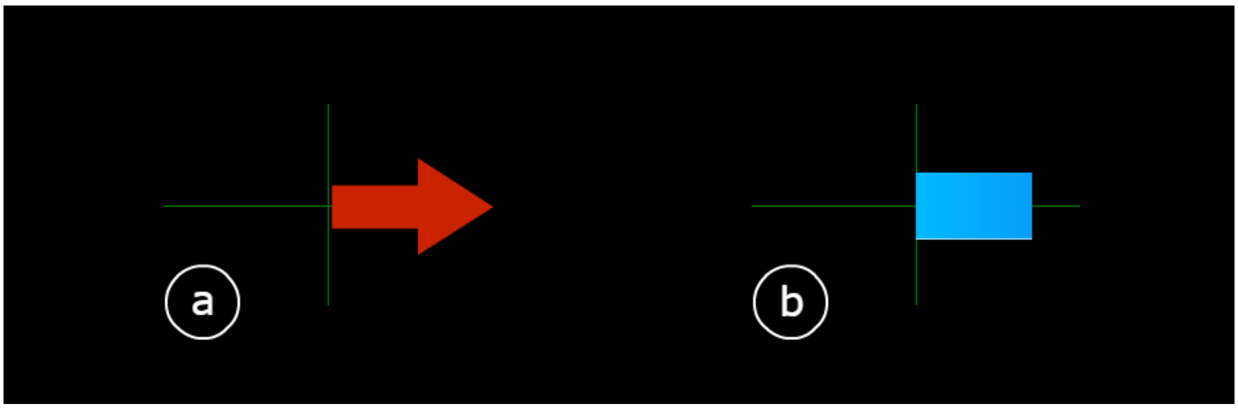

Figure 7 Graz feedback example. a) right-hand MI request; b) feedback output of a right-hand classified MI

We also had scenarios where we could replay any session and perform analysis to either the input EEG signals, LDA classifier output and Graz feedback. During these steps, all the resulting data was stored for posterior analysis.

3.1.1 Methodology

3.1.1.1 Data Acquisition and Training Datasets

The BCI set up comprised 8 active electrodes (see Figure 8) equipped with a low-noise g.MOBIlab biosignal amplifier (gtec, Graz, Austria) and a 16-bit A/D converter (256 Hz). The spatial distribution of the electrodes followed the 10-20 system configuration [58] with the following electrodes over the sensory-motor areas: FC3, FC4, C3, C4, C5, C6, CP3, CP4. For all user data, a common spatial patterns filter was used for feature extraction, and LDA for the classification of MI from EEG data. The visual stimulation was based on the Graz-BCI paradigm [59] with a standard bars-and-arrows feedback on a binary (left vs. right) MI paradigm.

Experimental data consisted of a set of 20 EEG datasets consisting of 120 trials each, acquired from 20 healthy users (28 ± 4) performing standard MI training. Participants had no previous known neurological disorder and no previous experience in BCIs. Participants gave informed consent. Data from the MI datasets was processed in Matlab (MathWorks Inc., Massachusetts, US).

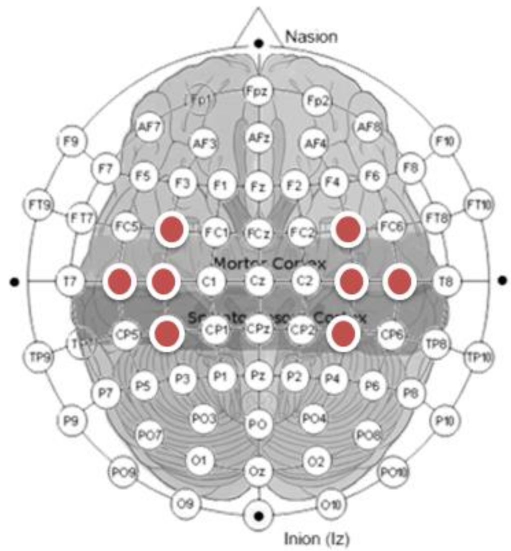

Figure 8 Electrode positioning over the sensory-motor area.

3.1.1.2 BCI - Adaptive Performance Engine

The BCI Adaptive Performance Engine (BCI-APE) is composed by 2 main components: (a) a Bayesian Inference Layer (BIL), simpler and more efficient as compared to other supervised learning techniques such as artificial neural networks, in order to formulate the input into a model, where we translate the continuous BCI classification data into probability. As for decision making, we made use of a (b) Finite State Machine (FSM) because of its efficiency and non-linear properties.

3.1.1.3 Bayesian Inference Layer

BIL works on top of the LDA EEG classifier, and is used to compute the likelihood of the classifier output for each MI class (left vs. right). This is done by modeling the data belonging to each class as a Gaussian distribution, where μ and σ indicate their mean and standard deviation values ($MI_i(\mu, \sigma), i = [left, right]$). From it, we then compute the Likelihood of a specific LDA output belonging to each MI class with:

Equation 1

$$P(i|LDA\ output) = \frac{MI_i(\ LDA\ output, \mu_i, \sigma_i)\ *\ P_i}{\sum_j MI_j(\ LDA\ output, \mu_j, \sigma_j)}$$

Where P_i indicates the prior probability of action i (0.5 for left vs. right MI). μ and σ are updated at each iteration, considering all previous history of the user for the given i MI action. $LDA\ output$ indicates the output value of the LDA classifier.

3.1.1.4 Finite State Machine

Following the BIL, the likelihood of each MI classification forwarded into a FSM. The role of the FSM is to transform binary MI classifications – such as left vs. right – into evidence-based states (S_i). Is composed of 7 states, a neutral (S_0) and three for each MI class ($S_{1/-1}$, $S_{2/-2}$, $S_{3/-3}$). Each state has a transition threshold associated with it (w_1, w_2, w_3), and can only transition to one of the nearest neighbors or stay in the same state (see Figure 9). As input, the FSM uses the difference of the posterior probabilities of left and right MI from Equation 1 and each state represents not only the class (negative and positive states represent left and right MI respectively), but also the confidence level associated to them (being $S_{3/-3}$ the most certain states).

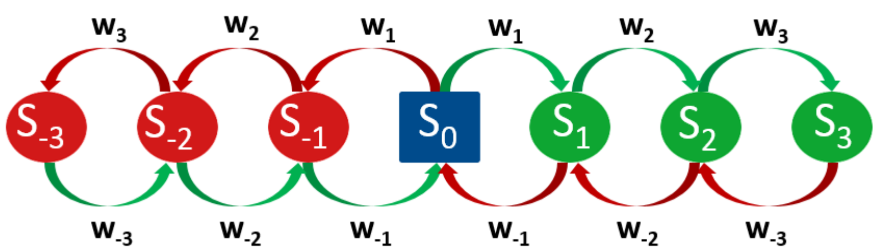

Figure 9 State machine structure. S0 represents the neutral state (indecision). The level of confidence of S-3,3>S-2,2>S-1,1, and W-3,-2,-1,1,2,3 are the state transition thresholds.

3.1.2 Results

3.1.2.1 Can performance be improved by means of the BCI-APE approach?

To answer this, we used a dataset with MI training sessions of 15 naïve users to explore the parameter space of the aforementioned state machine thresholds (w_i) from 0 up to 0.3 on a 0.05 step, which resulted in 117649 FSM parameter combinations. For each combination, we quantified the percentage of indecisions (S_0) and the correctness of decisions based on the remaining states. Results show that the FSM approach can increase performance over the original LDA classification (up to approx. 20%) at the expense of an increased amount of indecisions (Figure 10). That is, less decisions are taken but with higher confidence.

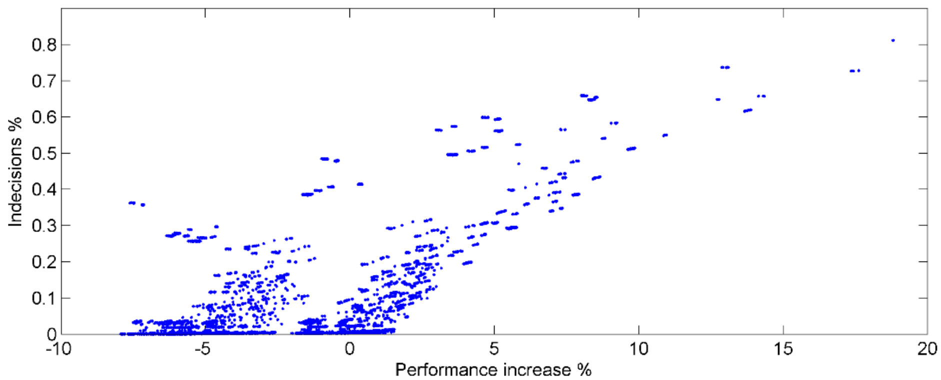

Figure 10 Performance increase vs. indecisions percentage for the 117649 FSM parameter combinations on a MI dataset of 15 naïve users.

3.1.2.2 What are the tradeoffs of an increased MI-BCI performance?

Out of the above 117649 parameter combinations, we selected those combinations that provide the greater performance improvements with the minim number of indecisions. From this data, we observe that exists a set of FSM parameters that can provide us a continuum from 0% performance increase and 0% indecisions – equivalent to standard LDA performance – to 20% performance increase and 80% indecisions (see Figure 10). As consequence, this means that we can devise an algorithm to adjust the FSM to tradeoff between decision time – or number of indecisions – and confidence on decisions.

3.1.2.3 Can APE adjust performance in real time?

Cross-referencing the best performing FSM thresholds values (W_i) with their resulting performance increase allows us to identify their relationship as illustrated in Figure 11(a). This is a crucial step, due to only a few FSM weight combinations resulting in increased performance. It was also found that $W_{-1,-2,-3}$ should be kept 0 for maximal performance. That is, thresholds should be applied to transition from indecision to any decision state, but not to transition from any state to indecision. Further, it was also found that W_3 should be kept always constant at the highest value (0.3) and that W_1 increases with the overall performance. Interestingly, the evolution of W_2 with achieved performance shows that for low W_1 values – easy to transition from indecision to the lowest confidence level of decision – W_2 should be kept high whereas for high W_1 values – difficult to transition from indecision to the lowest confidence level of decision – W_2 should be low to facilitate the transition from low to mid confidence. We used a 3[rd] degree polynomial function to model how W_1 and W_2 change depending on the achieved performance increases (x) [Figure 11(a)] (Equation 2):

Equation 2

$$W_1 = 114.42 * x^3 - 36.517 * x^2 + 4.7014 * x - 0.058208$$

$$W_2 = 87.662 * x^3 - 32.613 * x^2 + 2.4013 * x + 0.16366$$

Decisions taken at each state of the FSM have an associated performance level. That is, a MI detected based on S_3 should be more certain than in S_1. Figure 11(b) illustrates the confidence level associated with each State ($S_3 > S_2 > S_1$), and how it changes based on the FSM performance increase. In average, the confidence of S_3, S_2, and S_1 is 79.04% ± 0.25%, 68.76% ± 2.02% and 59.1% ± 5.88% respectively.

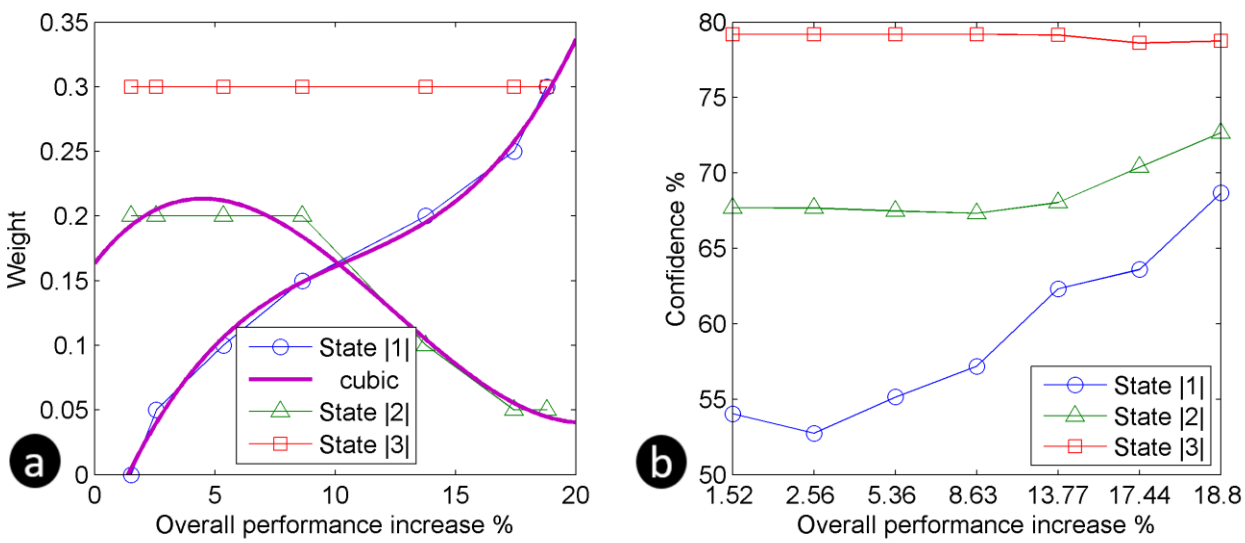

Figure 11 (a) FSM threshold weight values vs. performance increase. (b) State confidence levels vs. performance increase.

3.1.2.4 Evaluation of the complete BCI-APE system

From the training data from 15 BCI naïve users we obtained the following results: Classification performance with standard LDA 58.70% ± 7.84%; Average improved performance of BCI-APE 70.46% ± 6.90%; Average maximum performance of BCI-APE 85.37% ± 10.09%; and indecisions of BCI-APE 48.25% ± 24.62%. Further, we implemented the complete BIL + FSM based on the above models of performance increase and we tested it against a dataset from 5 different BCI naïve users containing 5x120 MI trials. The previous results are confirmed with the test data: Classification performance with standard LDA 63.93% ± 6.28%; Average improved performance of BCI-APE 71.83% ± 6.64%; Average maximum performance of

BCI-APE 88.37% ± 6.49%; and indecisions of BCI-APE 38.82% ± 19.60% (see Table 2 for a comparison with other systems).

Finally, given the lack of availability of large MI datasets containing naïve subjects, we submitted our dataset (20 users x 120 trials) on PhysioNet[1] and made available under the Public Domain for dissemination and exchange within the community.

Table 2 Classifier performance comparison, including APE. Adapted from [20]

Protocol	Classification	Accuracy	electrodes / channels	# of subjects, trials/subject, training set, test set
on different EEG data	Gaussian SVM	86%	2 (C3, C4) at 128Hz	2, 1000 (500/side), 400 (200 random/side, remaining 600)
	LDA	61%		
	LDA	83.6%	6 --> 3 bipolar EEG channels	5 familiar with the Graz-BCI, 360, 240, remaining without artifacts
	Boosting wth MLP's	76.4%		
	LDA	80.6%		
	Boosting wth MLP's	80.4%		
	HMM	81.4% ± 12.8%	4 --> 2 bipolar EEG channels	4 (3 familiar and 1 naive), 880, some sessions where used to train other sessions
	LDA	72.4% ± 8.6%		
	MLP	85.97%	4 --> 2 bipolar EEG channels	3, 667±107, 60%, 20%
	FIR NN	87.4%		
	HMM	75.7%	2 bipolar EEG channels (C3, C4)	-,160 (80/side), -, -
	HMM + SVM	78.15%		
	LDA	65% ± 3.3%	8 electrodes (FC3, FC4, C3, C4, C5, C6, CP3, CP4)	12, 120, -, -
	LDA + BCI-APE	up to 87.49 ± 7.13%	8 electrodes (FC3, FC4, C3, C4, C5, C6, CP3, CP4)	20, 120, 15 subjects, 5 subjects
on BCI competition 2003 data set III	Bayes quadratic integrated over time	89.3%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, -, -
	BGN	83.57%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, -, -
	MLP	84.29%		
	Bayes quadratic	82.86%		
	HMM	up to 77.5%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, 100, 40
	Gaussian classifier	65.4%	3 bipolar EEG channels (C3, Cz, C4)	1, 140, 100, 40
	LDA	65.6%		
	Bayes quadratic	63.4%		
	Mahalanobis distance	63.1%		

[1] http://physionet.org/

Chapter 4 – User layer: NeuRow

This section was adapted from publication B: A. Vourvopoulos, **A. Ferreira, and S. Bermúdez i Badia, "NeuRow: An Immersive VR Environment for Motor-Imagery Training with the Use of Brain-Computer Interfaces and Vibrotactile Feedback", 2016, pp. 43–53.*

4 User layer: NeuRow

In this section we describe de development and pilot assessment of NeuRow [60], a novel BCI-VR environment with multimodal feedback used for MI training. NeuRow was developed entirely in Unity, a game engine with support for 2D and 3D graphics, and the coding was done in C#. The environment was setup to be immersive, using a HMD to deliver a stereoscopic 3D view into the task scene while also providing head position tracking and point of view tracking. We also used environment synced sounds and haptic feedback delivered through vibrating motors to convey movement. The BCI MI training task was also gamified to be more pleasant to the user. Masking the task to look like a rowing game with a first-person perspective view, helped the user better visualize the arms movement. Objectives, timing and scoring usage makes the user more prone to stay interested, focused and engaged in the BCI MI task at hand. This is also helpful in keeping the user alert and awake, which can also be a problem in the standard Graz visualization BCI MI task.

4.1.1 Methodology

4.1.1.1 Experimental Setup

The experimental setup was composed by a desktop computer (OS: Windows 8.1, CPU: Intel® Core™ i5-2400 at 3.10 GHz, RAM: 4GB DDR3 1600MHz, Graphics: AMD Radeon HD 6700), running the acquisition software, the BCI-VR task, HMD, EEG system, and the vibrotactile module.

EEG Acquisition. The BCI system for the first study consisted of 8 active electrodes equipped with a low-noise biosignal amplifier and a 16-bit A/D converter at 256 Hz (g.MOBIlab+ biosignal amplifier, g.tec, Graz, Austria). The spatial distribution of the electrodes followed the 10-20 system configuration [6] with the following electrodes over the somatosensory and motor areas: Frontal-Central (FC5, FC6), Central (C1, C2, C3, C4), and Central-Parietal (CP5, CP6) (see Figure 12 a). The BCI system was connected via Bluetooth to the dedicated desktop computer for the EEG signal acquisition. EEG data acquisition and processing was performed through the OpenVibe platform [61] combined with the Reh@Panel (RehabNet Control Panel) [62] via the VRPN protocol [63] to control the virtual environment. The Reh@Panel is a free tool that acts as a middleware between multiple interfaces and virtual environments. In this case it was used to receive the raw LDA data coming from OpenVibe, parse it and encode it in the Reh@panel format and then send it to NeuRow using the UDP protocol. This encoding makes it possible to change the devices and protocols of the hardware and software behind the Reh@Panel without having to change anything on our system, as long as Reh@Panel is used as the middle layer between the physical devices and NeuRow.

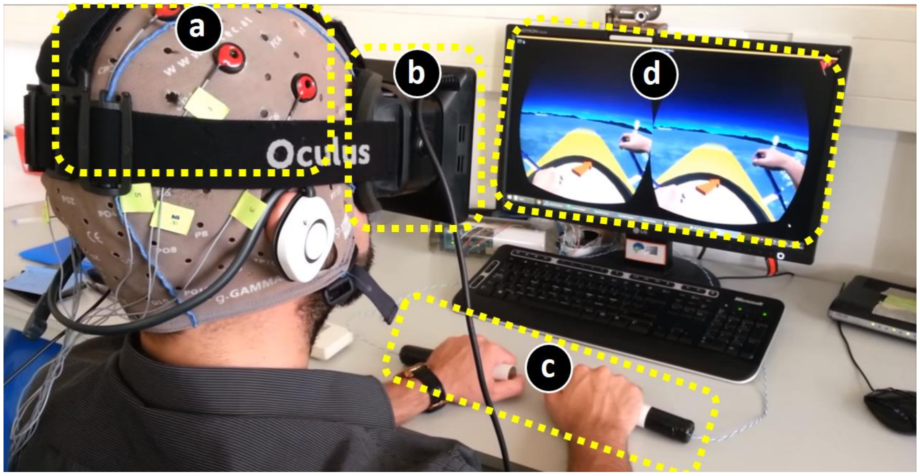

Figure 12 Experimental setup (a) EEG cap with 8 active electrodes, (b) HMD, (c) vibrotactile modules, (d) BCI feedback.

Feedback Presentation. For delivering feedback to the user, the Oculus Rift DK1 HMD was used (Oculus VR, Irvine, California, USA). The HMD is made of one 7" 1280x800 60 Hz LCD display (640x800 resolution per eye), one aspheric acrylic lens per eye, 110° Field of View (FOV), internal tracking through a gyroscope, accelerometer, and magnetometer, with a tracking frequency of 1000Hz (Figure 12 b).

Vibrotactile Feedback. A custom vibrotactile feedback module was developed with out-of-the-box components including an Arduino Mega 2560 board and vibrating motors. The vibrating motors (10mm diameter, 2.7mm thick) performed at 11000 RPM at 5V and were mounted on cylindrical tubes that acted as grasping objects for inducing the illusion of movement during the BCI task (Figure 12 c). In our setup, a pair of carton-based tubes with 12cm of length and 3cm diameter were used. Finally, 3D printed cases were produced to accommodate the vibrating motors inside the tubes (see Figure 13). All hardware and software blueprints are made available free online at http://neurorehabilitation.m-iti.org/bci/neurow/vibrotactile-module/.

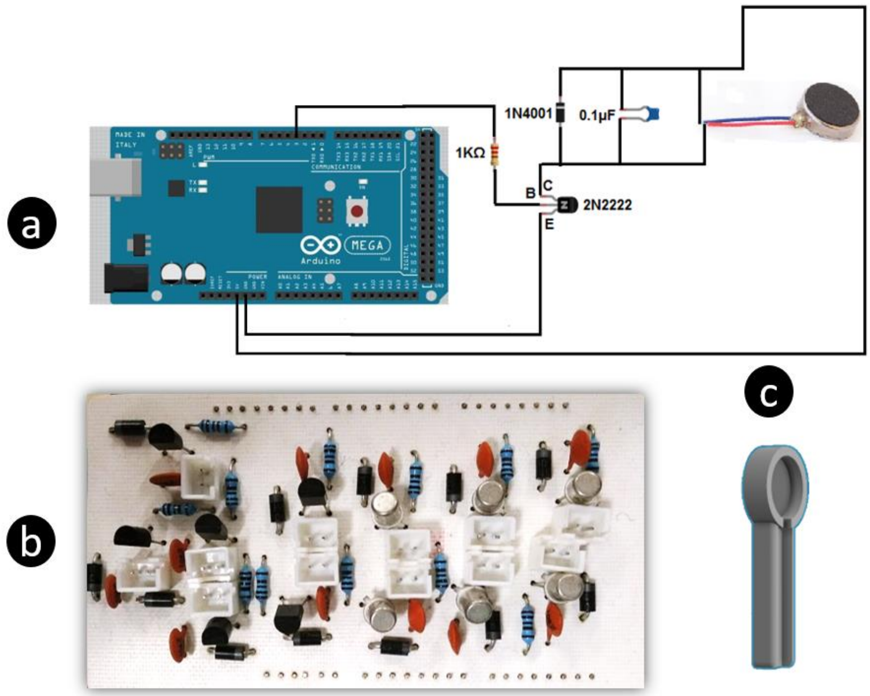

Figure 13 (a) Arduino board schematic including the necessary electronic components (for one motor), (b) custom Arduino shield, (c) 3D printed casing for motors. Code and schematics can be downloaded from: http://neurorehabilitation.m-iti.org/bci/neurow/vibrotactile-module/.

4.1.1.2 BCI Task Design

BCI-VR Training Protocol. The training protocol was designed and adapted based on the Graz-BCI paradigm [59], substituting the standard feedback presented (directional arrows) by multimodal VR feedback. The first step of the training consisted on the acquisition of the raw EEG data to train a linear discriminant classifier to distinguish Right and Left imagined hand movements. Throughout the training session, the user performs mental imagery of the corresponding hand (based on the presented stimuli). For each hand, the user is stimulated visually (VR action observation), auditorily, and haptically through the vibration on the corresponding hand (Figure 14 a). The training session was configured to acquire data in 24 blocks (epochs) per class (Right or Left-hand imagery) in a randomized order. Following the training, data are used to compute a Common Spatial Patterns (CSP) filter, a spatial filter that maximizes the difference between the signals of the two classes. Finally, the raw EEG and the spatial filter are used to train a Linear Discriminant Analysis (LDA) classifier.

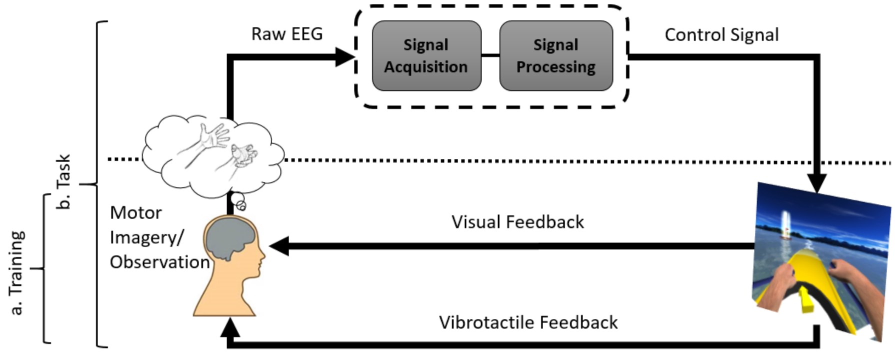

Figure 14 Neurofeedback loop. (a) During the training session, the user is performing in a randomized order MI combined with motor observation of the virtual hands rowing while vibrotactile feedback is delivered to the corresponding hand. (b) The user relies on MI combined with motor observation of the virtual hands rowing while vibrotactile feedback is delivered to the corresponding hand. (b) The user relies on MI alone to control the virtual hands in a closed-loop system after training. [60]

BCI-VR Task. The BCI-VR task was designed based on literature and previous work, incorporating important features for a successful brain-to-computer interaction in terms of feedback, protocol design, and accessibility [23]. The BCI-VR task involves boat rowing through mental imagery only with the goal of collecting as many flags as possible in a fixed amount of time. NeuRow is a self-paced BCI neurogame, meaning that is not event related, and the user controls the timing of rowing actions like he/she would do in real-life (Figure 14 b). NeuRow is a multiplatform virtual environment developed in Unity game engine (Unity Technologies, San Francisco, California, USA). Finally, NeuRow is optimized for different platforms, however with different features (Table 3). Namely:

Desktop: The standalone version for PC, supports high quality graphics for an immersive VR experience with the support of the Oculus Rift DK1 headset and the HTC Vive, the Leap Motion hand controller (Motion control, San Francisco, California, USA) available for optional motor-priming before the MI BCI session. Finally, vibrotactile feedback is supported by using custom-made hardware for controlling through USB up to 6 vibration motors (Figure 13). Data logging is supported for boat trajectory, target location, score and time.

Table 3 NeuRow features for the different supported platforms

Features/ Platform	Desktop	Android	Web
Logging	✓	X	X
VR	✓ (Oculus, HTC Vive)	✓ (Google VR)	X
Hand Tracking	✓ (Leap Motion)	X	X
Networking	✓	✓	X
Platform Independent	X	X	✓
Vibrotactile Feedback	✓ (Arduino)	X	X

Mobile: The mobile version is built for Android OS devices, receiving data via the RehabNet UDP protocol through the Reh@panel. For phones, the VR feature is utilized for VR glasses (e.g. Google VR) by applying lens correction for each eye, and using the phone gyroscope and magnetometer for head tracking, offering an immersive experience similar to the Oculus DK1 HMD.

Web browser: The web version uses the Unity web player (compatible through Internet Explorer, Firefox or Opera), does not support the networking, HMD and haptic components due to security restrictions. Instead, the web NeuRow acquires data through emulated keyboard events generated by the Reh@panel.

The in-game interface is simple, with two high fidelity virtual arms to rotate the oars, time indication, score and navigational aids (Figure 15). NeuRow can be customized with different settings, depending on the experimental setup, BCI paradigm and running platform. Through the settings, one can choose if the session is part of the MI training or self-paced online control of the boat. During training, the navigational arrow and the targets are removed to focus the user only on the multimodal MI BCI-VR task. During self-paced mode, the behavior of the boat can be changed by setting the heading speed, turn speed and cut-off angle. The cut-off angle is the allowed angle that the boat can be off-course with respect to the target flag before stopping. This serves as a protection mechanism to help the player not to deviate in excess from the target.

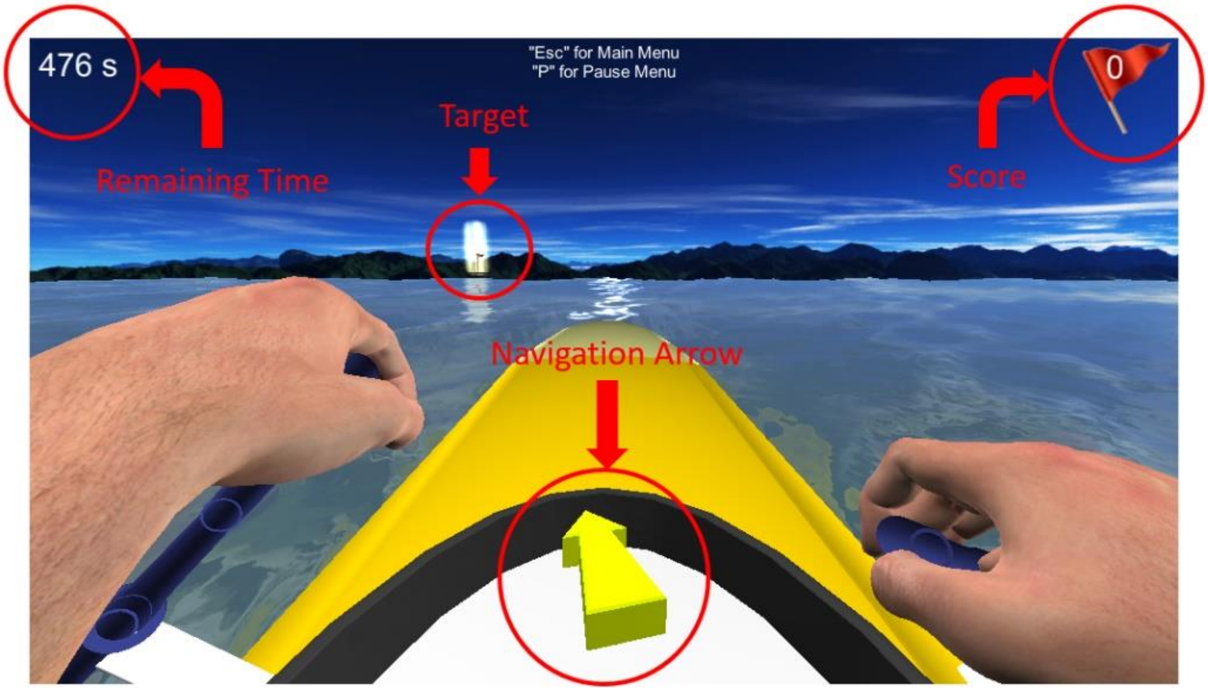

Figure 15 In-game interface. An arrow indicates the direction of the target and also the distance by changing its color (red for far blending up to green for close). Top Left: Remaining time for the end of the session. Middle: A flag with a ray acts as the game targets, Top Right: Game scoring, counting the number of targets.

4.1.1.3 Participants

A voluntary sample of 13 users (mean age of 28 ± 5 years old) was recruited for the pilot study, based on their motivation to participate in the study. All participants were male and right handed with no previous known neurological disorder, nor previous experience in BCIs. Participants were either university students or academic staff. Finally, all participants provided their written informed consent before participating in the study.

4.1.1.4 Questionnaires

Before each BCI training session, demographics and user data were gathered through the following questionnaires:

The Vividness of Movement Imagery Questionnaire-2 (VMIQ2) was used to assess the capability of the participant to perform an imagined movement (Kinesthetic Imagery) [64]. Kinesthetic Imagery (KI) questions were combined with mental chronometry by measuring the response time in perceptual-motor tasks with the help of a timer.

For assessing gaming experience we used the Gamer Dedication (GD) questionnaire, a 15 factor classification questionnaire in which participants are asked whether they "strongly disagree," or "strongly agree" with a series of statements about their gaming habits [65].

After the BCI task, the following questionnaires were administered:

- The NASA TLX questionnaire was used to measure task load considering Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration [66].
- The core modules of the Game Experience Questionnaire (GEQ) were used at the end of the BCI session. GEQ assesses game experience using Immersion, Flow, Competence, Positive and Negative Affect, Tension, and Challenge [67].
- The System Usability Scale (SUS) is a ten-item scale giving a global view of subjective assessments of usability [68].

4.1.1.5 EEG Data

Power Spectral Density (PSD). EEG signals were processed in Matlab (MathWorks Inc., Massachusetts, US) with the EEGLAB toolbox [69] for extracting the Power Spectral Density (PSD). The power spectrum was extracted for the following frequency rhythms: Alpha (8 Hz - 12 Hz), Beta (12 Hz - 30 Hz), Theta (4 Hz - 7 Hz), and Gamma (25 Hz - 90 Hz). Independent Component Analysis (ICA) was used for removing major artefacts related with power-line noise, eye blinking, ECG and EMG activity. For the current analysis, and because we were only measuring from sensory-motor areas, data were averaged for all the channels for each experimental condition.

Engagement Index. The Engagement Index (EI) is a metric proposed at NASA Langley for evaluating operator engagement in automated tasks, was validated through a bio-cybernetic system for Adaptive Automation [70], and is widely used in EEG studies for assessing engagement [71]. We therefore computed engagement index from the EEG power spectrum according to the EI formula (Equation 3), where α = Alpha band, β = Beta band and θ = Theta band.:

Equation 3

$$EI = \frac{\beta}{\alpha + \theta}$$

4.1.2 Results

In the following section, we analyzed NeuRow's BCI task performance in terms of classifier score during training, user acceptance as assessed by the SUS, GEX and TLX questionnaires, and finally the relationship between game behavior and user experience through the questionnaires and the EEG activity.

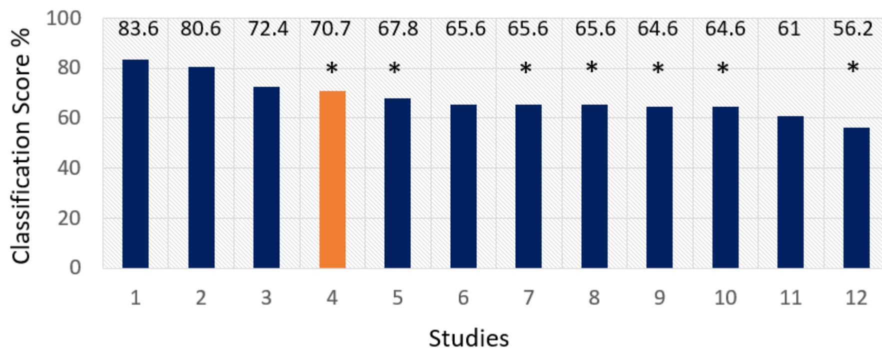

Figure 16 Ranked accuracy of performance in pure MI based BCI studies using two-classes (left and right hand imagery) with respect to LDA classification [22], [72]–[74]. The asterisk (*) over 4,5,7,8,9,10 and 12 [5], [57] indicates studies which use the same feature extraction method (BP with CSP). The data of this study corresponds to the 4th best.

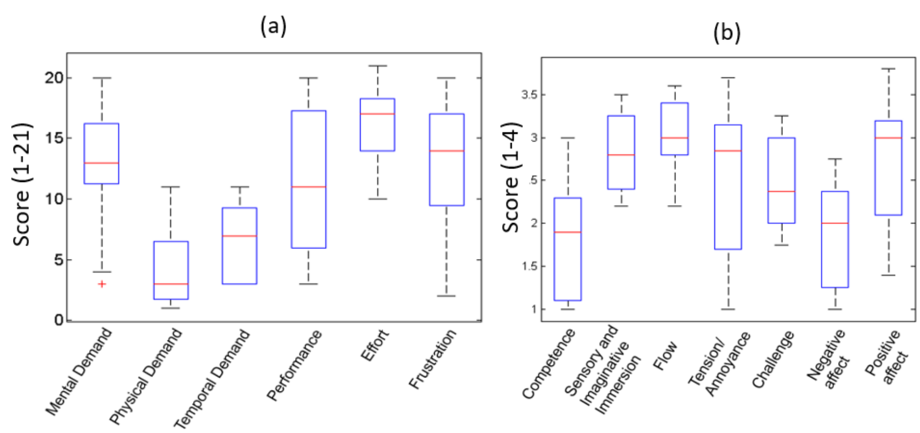

Figure 17 (a) TLX scores between 1-20 for mental demand, physical demand, temporal demand, performance, effort and frustration. (b) Scores for the GEQ core questionnaire domains.

Performance. Comparing the performance score with previous studies which used LDA classifiers in two class (left, right hand) MI, we are able to gain insights concerning the effectiveness of our BCI-VR paradigm in terms of user control [22], [72]–[74]. As illustrated in Figure 16, the comparison places NeuRow as the fourth highest with a mean performance of 70.7% out of 12 studies. Moreover, of those studies that used exactly the same feature extraction technique of band power (BP) and CSP [5], [57], NeuRow scores the highest. Finally, of those studies that used VR as a training environment [57], again NeuRow scores first.

User Acceptance. To assess different aspects of the user experience during online control of NeuRow, the mental workload, gaming experience and system usability were assessed after the task.

For workload, the NASA-TLX mean score was relatively high at 66.8/100 (*SD = 14.5*). As it is illustrated in Figure 17 a, the two lowest scores are those for physical (*M = 4.4, SD = 3.4*) and temporal (*M = 6.5, SD = 3*) demand. The highest score is on effort (*M = 16.4, SD = 5.2*) followed closely by frustration (*M = 13.3, SD = 5.2*) and mental demand (*M = 12.8, SD = 5*). Performance lies in the middle (*M = 11.4, SD = 6.2*).

From the GEQ, we extracted seven domains based on the sub-scale scoring. The highest score is in flow (*M = 3.1, SD = 0.4*) followed by immersion (*M = 2.8, SD = 0.4*) and positive affect (*M = 2.8, SD = 0.7*). A moderate score is achieved on tension/annoyance (*M = 2.5, SD = 0.9*) and challenge (*M = 2.5, SD = 0.5*). Finally, competence (*M = 1.8, SD = 0.7*) and negative affect scored the lowest (Figure 17 b).

The system usability assessed by the SUS scored a mean of 74 (*SD = 7.2*). Based on the SUS rating scale (Figure 18), our system is classified as “Good” and it is within the acceptability range [75].

User-Profile and In-Game Behavior. By assessing the relationship of the reported experience and the EEG activity with the in-game behavior (score, distance, speed, trajectory) we identified a set of correlations. As illustrated in Table 4, the total workload correlates with distance, speed and score. In addition, two TLX sub-domains have correlations. Performance is significantly correlated with distance and speed, as well as frustration is significantly correlated with distance, speed and score. Furthermore, mental chronometry (the response time in perceptual-motor tasks), significantly correlates with distance, speed and score. Finally, from the extracted EEG bands and the resulting Engagement Index, we can see that Alpha and Theta bands are reversely correlated with distance and speed. Finally, Engagement Index is interestingly correlated with all in-game metrics. In particular, distance, speed, score and trajectory smoothness.

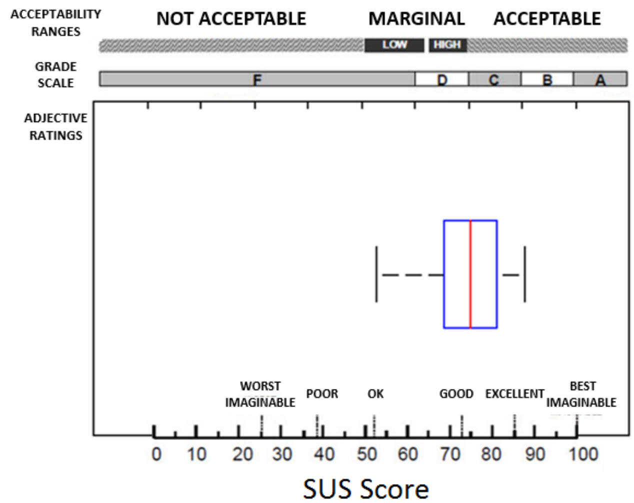

Figure 18 SUS results for all users. Acceptability scales are displayed on top (not acceptable, marginal and acceptable), followed by the grade scale (A to F) and the adjective rating (0-100).

Overall, we identified an imbalance between theoretical training performance (LDA) and actual quality of the online performance (game score and control). In current MI-BCI interaction users undergo long, tiresome and complex periods of training so that EEG classification score can reach acceptable performance rates. On the following chapter, we propose to reverse the problem and make MI-BCI interaction adaptive to the user, so that we can guarantee a satisfactory performance rates by softening decisions – making them probabilistic and non-time-constrained – depending on our confidence on the user's EEG data.

Table 4 Correlation table between reported experience, extracted EEG bands and in-game behavior. The reported values correspond to the significant correlations ($p < 0.05$).

	Distance	**Speed**	**Score**	**Smoothness**
TLX: Total	-.695	-.699	-.697	
TLX: Performance	-.595	-.599		
TLX: Frustration	-.728	-.737	-.686	
Mental Chronometry	.618	.615	.728	
Alpha band	-.611	-.607		
Theta band	-.672	-.670		
Engagement Index	-.770	-.768	-.649	-.595

Chapter 5 – Integrated System: Adaptive Performance Engine + NeuRow

This section was adapted from publication C: A. Vourvopoulos, **A. Ferreira, and S. Bermúdez i Badia, "Development and Assessment of a Self-paced BCI-VR Paradigm using Multimodal Stimulation and Adaptive Performance", in Lecture Notes in Computer Science, In Press.*

5 Integrated System: Adaptive Performance Engine + NeuRow

Following the design and development stage of NeuRow, as a next step, we conducted a complementary assessment by incorporating the APE module [76] together with the Reh@Panel. APE aims at adapting the BCI interaction to each user in order to maximize the level of control on their actions, whatever their performance level is.

The incorporation of APE with Reh@Panel was done by also implementing APE in Unity. Again, we used C# as the programing language of choice, and made APE able to work in real-time by getting the LDA data input from the UDP socket which was coming from OpenVibe while performing a BCI MI online session.

Our objective is evaluating the improvements in performance and perceived sense of control -at the user level instead of the classifier output- with the APE. For this, we integrated a state-of-the-art HMD for increased immersion and an ultraportable wireless EEG system.

5.1.1 Methodology

5.1.1.1 Experimental Setup

For this study, a dedicated desktop computer was used for delivering the multimodal feedback: the VR environment, the vibrotactile module and the HMD (OS: Windows 10 Pro, CPU: Intel® Core™ i7-6700 at 3.40GHz, RAM: 8GM DD3 1600MHz, Graphics: AMD Radeon R9 390 Series). Additionally, a second desktop (OS: Windows 10 Pro, CPU: Intel® Core™ i5-4440 at 3.10GHz, RAM: 8GM DD3 1600MHz, Graphics: AMD Radeon R7 200 Series) was utilized for the EEG data acquisition and online processing

EEG Acquisition. For EEG acquisition, the Enobio 8 (Neuroelectrics, Barcelona, Spain) system had been used. Enobio, is a wearable, wireless EEG sensor with 8 EEG channels and a triaxial accelerometer, for the recording and visualization of 24-bit EEG data at 500 Hz. The spatial distribution of the electrodes followed the same electrode placement as the first study, over the somatosensory and motor areas: Frontal-Central (FC5, FC6), Central (C1, C2, C3, C4), and Central-Parietal (CP5, CP6). The BCI system was connected via Bluetooth to the second dedicated desktop computer.

Feedback Presentation. For delivering feedback to the user, the HTC Vive HMD was used (HTC, New Taipei City, Republic of China; Valve, Kirkland, Washington, United States) (Figure 19). The Vive uses two screens, one per eye, each having a display resolution of 1080x1200 and a refresh rate of 90 Hz. Additionally, the Vive uses a gyroscope, accelerometer and laser position sensors, and operates in a 4.6 x 4.6 m (15-by-15-foot) tracking space by using two "Lighthouse" base stations that track the user's movement with submillimeter precision. The Lighthouse system uses photosensors by sweeping structured light lasers within a space.

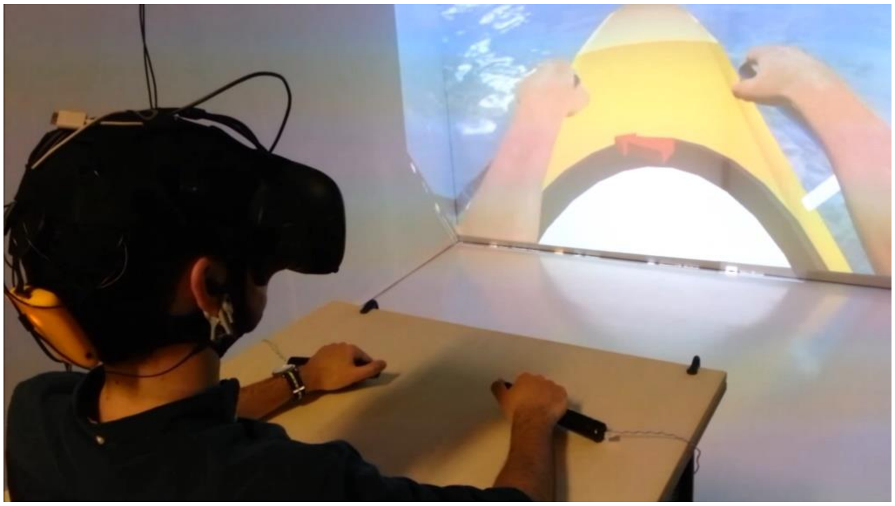

Figure 19 NeuRow setup including the HTC Vive HMD and Enobio 8 EEG headset (projected feed-back is for illustration purposes only).

5.1.1.2 BCI protocol

For both the training and the BCI task, an identical protocol and setup to the previous experiment were used. During training the NeuRow feedback had been displayed for left|right motor observation and motor imagery of the rowing task, delivering also vibrotactile feedback. Following training, two conditions were delivered in random order: (1) standard output of the LDA classifier, and (2) the APE (see Figure 21).

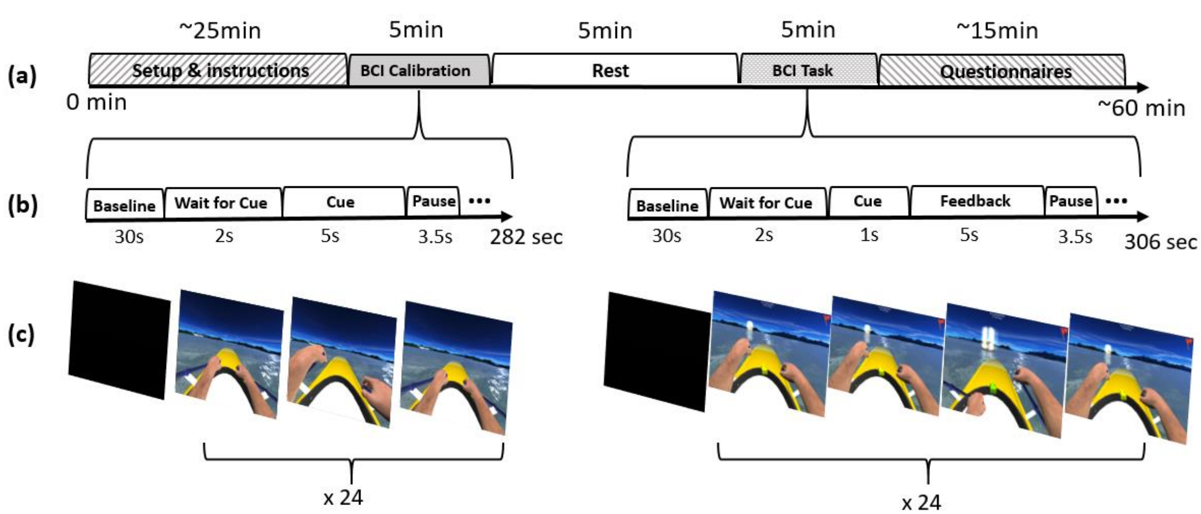

Figure 20 BCI protocol for training and online control.

5.1.1.3 Participants

For assessing the APE, a sample of 8 users (mean age of 27 ± 3.5 years old) was recruited, based on their motivation. All participants were male and right handed with no previous known neurological disorder. Four of the users had little prior experience with MI-based BCI. All participants were university students of the University of Madeira and provided their written informed consent before participating in the study.

5.1.1.4 Questionnaires and EEG data

Before each session, the Movement Imagery Questionnaire—Revised second version (MIQ-RS)) [77] was admitted to each participant. MIQ-RS is an 18-item questionnaire for mental imagery comprised of nine visual imagery and nine kinesthetic imagery items, each of which involves the movement of an arm, leg or the entire body. To complete each item, four steps are required: (1) The starting position for each movement is described, and the participant is initiating that position, (2) The movement is then described and the participant physically performs the movement, (3) The participant retakes the starting position, and images the movement without physically performing the movement, (4) Finally, the participant rates the ease or difficulty of imaging the movement on a 7-point scale anchored by 1 = very easy to picture/feel and 7 = very difficult to picture/feel. Following MIQ-RS, the Vividness of Movement Imagery Questionnaire-2 (VMIQ2) (Roberts et al., 2008) was used including the visual and kinesthetic parts of the questionnaire.

After each session, the NASA TLX questionnaire was used to measure task load considering Mental Demand, Physical Demand, Temporal Demand, Performance, Effort and Frustration [66].

Finally, on each condition, the raw EEG data were logged in order to extract the different EEG bands and the Engagement Index derived from these bands as explained in section 2.5.

5.1.2 Results

For quantifying the quality of control between the two conditions, we analyzed the in-game data (trajectory, score), perceived experience through the SOPI and TLX questionnaires, and finally, the EEG bands modulation including the Engagement Index.

Quality of Control. In terms of control, Figure 21 illustrates the in-game boat trajectories resulting from the Raw LDA control (blue) compared with the APE decision mechanism (orange) for the same task, subject, and with the in-game targets on the same positions. The trajectory with APE is steadier than the

Raw LDA control, displaying a smoother trajectory. It is also visible in the APE trial that users could perform equally both left and right turns, while the Raw LDA trajectory is generally dominated by one dominant hemisphere, resulting in frequent rotation in one direction.

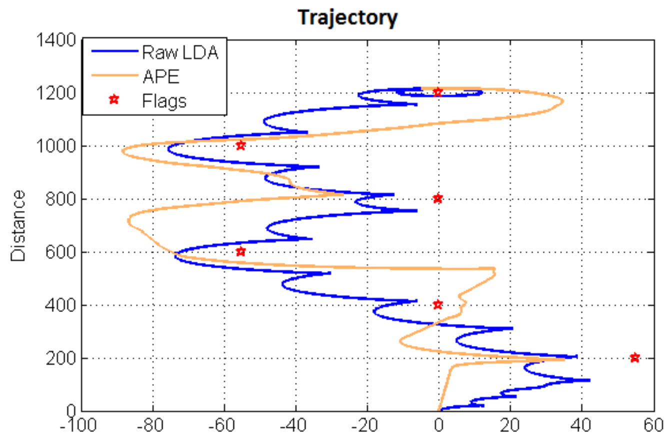

Figure 21 Example in-game boat trajectory during raw LDA classification output vs APE output for subject 1.

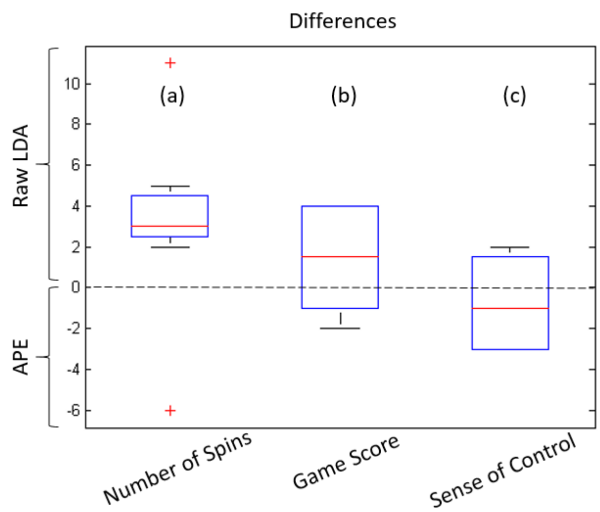

Figure 22 In-game data and self-report of control. (a) Number of boat spins (180-degree rotation), (b) game score in terms of flags captured, (c) reported sense of control.

The improvement in control is also apparent by the number of sudden trajectory changes or "spins" present during navigation, being considerably higher for Raw LDA than for APE (see Figure 22 a). When comparing the scores for both conditions, we observe that Raw LDA captures more in-game targets than APE. However, the lower performance for APE could be related to the fact that it is a statistical system that adds a third state to the LDA output, allowing for indecisions during noisy data (see Figure 22 b). Instead, the Raw LDA forces the user rowing left or right, making the boat always move towards the flags. Consequently, the added control and confidence on each decision by the APE system -which also translates to fewer decisions being made by the system- leads to more inactivity time, making the user travel less distance, therefore achieving less targets for the same time interval. Finally, the increased accuracy per decision of APE is reflected in an increased perceived sense of control during APE (see Figure 22 c). Nevertheless, neither the in-game scores nor the reported sense of control differ significantly between conditions.

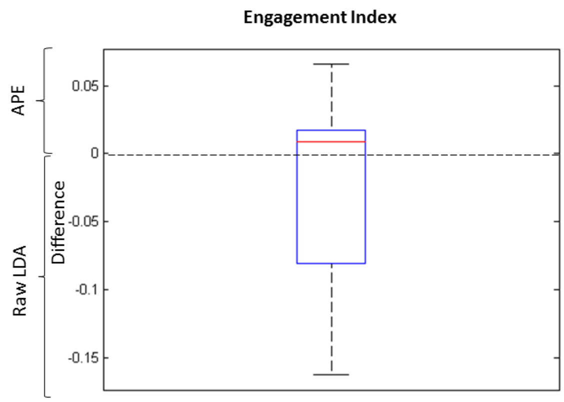

Figure 23 Difference in Engagement index as extracted by the EEG bands in Equation 3.

When designing APE, we hypothesized that an increased sense of control could provide increased engagement with the task. If a user is more engaged, he/she may try harder and for a longer period. This is important for users who require repeated MI training for rehabilitation purposes. Our assessment of engagement through the engagement index as extracted by the EEG data reveals a non-significant higher engagement during APE (see Figure 23).

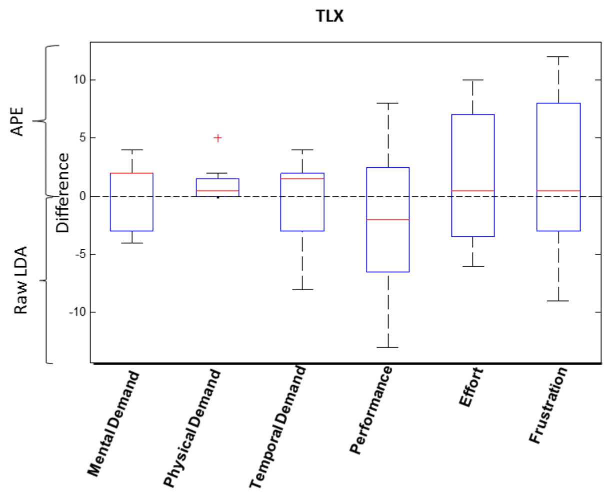

Figure 24 NASA TLX sub-domains.

Finally, based on the NASA TLX sub-domains (see Figure 24), users report increased effort and a higher workload index for the APE configuration. Additionally, the reported performance is lower and the levels of frustration are increased. This contrast with the increased sense of control and engagement during APE. This may indicate that the increased control that APE affords has as consequence higher mental, physical and temporal demands on users. Hence, making the APE setup a preferred option for users who require continuous training with a MI BCI system.

5.1.3 Discussion

Solid and systematic improvements are seen when comparing the performance achieved by APE with LDA. Existing MI-BCI classification approaches are very dissimilar in setup, algorithms, user experience, datasets, etc. This makes it very difficult to assess if differences in performance arise from training, users, algorithms or setup. Thus, it is very difficult to establish what the most appropriate MI-BCI classification approach is best. Nevertheless, when comparing BCI-APE to previous approaches – working on top of an LDA classifier and with naïve users – we observe a comparable performance with the best BCI classification algorithms (see Table 2). Further, we would expect even higher performances and lower indecisions if APE would be combined with more sophisticated and better performing classifiers than LDA.

The obtained results show interesting findings in several dimensions related with the use of adaptive performance for MI-BCI. Firstly, this system provides a real-time performance (or task difficulty) adaptation. This is important in order to balance the difficulty in terms of user control and contribute positively on the interaction level by modulating user frustration/engagement related to a certain task. If used within a game, it can provide an enjoyable experience, but when used on a rehabilitation scenario, it is of a paramount importance. Many times, in rehabilitation exercises are not performed with the correct frequency or intensity because of lack of motivation and engagement of the patient. The BCI-APE approach can be used to tackle this issue, making the patient more prone to complete the rehabilitation task at hand.

Furthermore, we identified that there is an important trade-off for this performance increase, and it comes in the form of less decisions for the same time window. Thus, depending on the response time and accuracy required, with the help of the APE model we can adjust the performance levels in real-time.

NeuRow worked well at engaging the user while preforming the MI task, however some uncertainties arose from the study. Is the used interaction paradigm the most suited for this type on users? Is the constant movement of the boat increasing the user's anxiety to perform, when trying to make the system recognize his/hers intent to go left or right? Also, is the stopping mechanism benefiting the raw sessions more that it benefits the APE session by making the boat turn around faster and continue towards the targets, and therefore, on a hemisphere biased trial, finishing the task faster? Also, should we provide pre-action feedback, making the user know his/her intentions are being detected by the system? Would this help the user perform better brain signal modulation/activation?

6 Conclusions

When we started this thesis, the goal was to go beyond the current state of the art on BCI systems, regarding performance and interaction, and at the same time making it available to everyone.

The most important aspect about availability it's price, so the system would have to be affordable. For this, we would have to use commercial, ready to use BCI systems available on the public market, and not only on the more restrictive and exclusive research market. By making this system available, would mean that more users could benefit from it. More clinics could have access to the system, and possibly, patients could have such a system at home, where it could be used daily.

As for the interaction aspect, we wanted to make it less boring and more effective, attractive and engaging, as this would make it more pleasant to the user, while at the same time endure more sessions which could also be longer. With this in mind, we gamified the MI task, making look like a rowing game. The rowing action was used to help the user have a more vivid motor imagery, and so increase the training effectiveness.

We also wanted to increase the performance of BCI systems, so the Adaptive Performance Engine (APE) was created to ensure satisfactory performances for non-expert and low-performing BCI users. BCI-APE provides a way to adapt performance accuracy on demand depending on the specific needs of users. By means of the presented model, the accuracy of standard BCI classification algorithms such as LDA can be boosted up to 20% by clustering low confidence data as an indecision state S_0 and adjusting the transition weights of a FSM on demand. Thus, for a specific BCI task a minimum acceptable performance rate can be stipulated, and by means of BCI-APE the performance rate of each user can be adjusted (0-20% performance increase) to guarantee that users can have a satisfactory experience. Thus, better performing users will have less indecisions and response times will be faster than those low-performing BCI users, which will simply need longer time to take a decision. However, their overall success rate will be comparable. Another advantage of this approach is that the confidence of a detected MI action is stratified in states ($S_3 > S_2 > S_1$) enabling designers of BCI tasks – such as neurofeedback, restorative, mental training or games – to decide what is best to do in their tasks, games or VR environment when confidence on an action is small. Thus, effectively empowering them with tools to enhance usability and improve the experience of BCI users.

We also presented the design, development and an experimental validation of NeuRow, a novel BCI-VR system for MI training, extended by a study about the perceived sense of control using APE. In terms of classification performance, the NeuRow BCI training paradigm showed higher performance, scoring the first amongst other studies with similar feature extraction and classification methodologies. This data supports a positive effect of the combination of immersive VR and vibrotactile feedback to help users to produce vivid MI (resulting in more distinct activation of sensorimotor areas of the brain), which in turn can lead to increased performance and learning. Furthermore, from the user experience point of view, we can see high mental effort as given by the TLX scales and low physical and temporal demands. Previous research in distinguishing difficulty levels with brain activity measurements indicated an average mental workload index of 26 (*SD = 12.9*) for the easy level, and 69 (*SD = 7.9*) for the hard level. The combination of low physical demand (useful in low mobility patients), increased effort (a conscious exertion of power) and good classification performance (better control that can lean in goal achievement), constitutes a very promising finding for the incorporation of this technology in stroke rehabilitation, providing new possibilities for rehabilitation programs. Moreover, increased flow and immersion to the task, in combination with increased positive affect, are good elements for enjoyment of NeuRow that can be capitalized on to further motivate and engage users in their BCI training. From the correlation analysis between user experience -subjectively measured through questionnaires but also objectively measured through EEG activity- and in-game behavior, we can see that people with increased workload will perform worse. Interestingly, we can see that users with fast response time in MI ability (as extracted from the mental chronometry assessment) performed better in the game, being it then an indicator of increased capability of MI. Further, having a fast and vivid sensation of kinesthetic imagery can be related to an increased modulation of sensorimotor rhythms, resulting in better BCI calibration and, hence, higher in-game performance. In addition, the reverse correlation of the Engagement Index with all the in-game variables shows an important connection between user engagement and in-game behavior. This relationship can help in developing a neurofeedback closed loop where the engagement of the user is used to adjust parameters of the game. This would allow a dynamic adjustment of the game based on user performance and cognitive state. Finally, we show that user control is enhanced through the APE, with a potential increased perceived sense of control and more controlled in-game trajectories. This approach could provide (1) a major assistance for new users and/or neurologically impaired people and (2) increase both perceived and actual performance.

Overall, we did manage to go beyond the current state of the art on all the proposed topics, with the goals of the thesis being achieved in a pleasing manner. We showed that APE-NeuRow, combining the use of immersive VR environment, sensory stimulation and adaptive performance, can provide a holistic approach towards MI driven BCIs. We showcased user performance, user acceptance and important features for self-paced control. Finally, NeuRow's features show promise and potential to be used for MI training in stroke motor rehabilitation.

7 Acknowledgements

I would like to express my gratitude to my supervisors Prof. Sergi Bermúdez i Badia and Mónica Cameirão for the support and guidance they provided me throughout the whole project.

I would also like to thank all members of the NeuroRehabLab team for the advices and collaboration, with a special thanks to Athanasios Vourvopoulos for his invaluable help.

Finally, I would like to thank my family and friends for their continued encouragement and support throughout this journey.

Thank you.

8 References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[2] "Invasive electroencephalography monitoring: Indications and presurgical planning," *ResearchGate*. [Online]. Available: https://www.researchgate.net/publication/262022323_Invasive_electroencephalography_monitoring_Indications_and_presurgical_planning. [Accessed: 03-Sep-2017].

[3] R. Prueckl and C. Guger, "A Brain-Computer Interface Based on Steady State Visual Evoked Potentials for Controlling a Robot," in *Bio-Inspired Systems: Computational and Ambient Intelligence*, 2009, pp. 690–697.

[4] R. Fazel-Rezai, B. Z. Allison, C. Guger, E. W. Sellers, S. C. Kleih, and A. Kübler, "P300 brain computer interface: current challenges and emerging trends," *Front. Neuroengineering*, vol. 5, Jul. 2012.

[5] A. Vourvopoulos and S. Bermúdez i Badia, "Usability and Cost-effectiveness in Brain-Computer Interaction: Is it User Throughput or Technology Related?," in *Proceedings of the 7th Augmented Human International Conference*, Geneva, Switzerland, 2016.

[6] G. H. Klem, H. O. Lüders, H. H. Jasper, and C. Elger, "The ten-twenty electrode system of the International Federation. The International Federation of Clinical Neurophysiology," *Electroencephalogr. Clin. Neurophysiol. Suppl.*, vol. 52, pp. 3–6, 1999.

[7] S. R. Soekadar, N. Birbaumer, and L. G. Cohen, "Brain–Computer Interfaces in the Rehabilitation of Stroke and Neurotrauma," in *Systems Neuroscience and Rehabilitation*, K. Kansaku and L. G. Cohen, Eds. Springer Japan, 2011, pp. 3–18.

[8] G. Pfurtscheller, G. R. Müller-Putz, J. Pfurtscheller, and R. Rupp, "EEG-Based Asynchronous BCI Controls Functional Electrical Stimulation in a Tetraplegic Patient," *EURASIP J. Adv. Signal Process.*, vol. 2005, no. 19, p. 628453, Nov. 2005.

[9] G. Pfurtscheller, C. Guger, G. Müller, G. Krausz, and C. Neuper, "Brain oscillations control hand orthosis in a tetraplegic," *Neurosci. Lett.*, vol. 292, no. 3, pp. 211–214, Oct. 2000.

[10] T. Carlson and J. del R Millan, "Brain-Controlled Wheelchairs: A Robotic Architecture," *IEEE Robot. Autom. Mag.*, vol. 20, no. 1, pp. 65–73, Mar. 2013.

[11] N. Birbaumer *et al.*, "A spelling device for the paralysed," *Nature*, vol. 398, no. 6725, pp. 297–298, Mar. 1999.

[12] B. H. Dobkin, “Brain-computer interface technology as a tool to augment plasticity and outcomes for neurological rehabilitation,” *J. Physiol.*, vol. 579, no. Pt 3, pp. 637–642, Mar. 2007.

[13] M. Lotze and L. G. Cohen, “Volition and imagery in neurorehabilitation,” *Cogn. Behav. Neurol. Off. J. Soc. Behav. Cogn. Neurol.*, vol. 19, no. 3, pp. 135–140, Sep. 2006.

[14] C. M. Stinear, W. D. Byblow, M. Steyvers, O. Levin, and S. P. Swinnen, “Kinesthetic, but not visual, motor imagery modulates corticomotor excitability,” *Exp. Brain Res.*, vol. 168, no. 1–2, pp. 157–164, Jan. 2006.

[15] L. M. Parsons, “Integrating cognitive psychology, neurology and neuroimaging,” *Acta Psychol. (Amst.)*, vol. 107, no. 1–3, pp. 155–181, Apr. 2001.

[16] M. Jeannerod, “Neural simulation of action: a unifying mechanism for motor cognition,” *NeuroImage*, vol. 14, no. 1 Pt 2, pp. S103-109, Jul. 2001.

[17] D. Marshall, D. Coyle, S. Wilson, and M. Callaghan, “Games, Gameplay, and BCI: The State of the Art,” *IEEE Trans. Comput. Intell. AI Games*, vol. 5, no. 2, pp. 82–99, Jun. 2013.

[18] B. Z. Allison and C. Neuper, “Could Anyone Use a BCI?,” in *Brain-Computer Interfaces*, D. S. Tan and A. Nijholt, Eds. Springer London, 2010, pp. 35–54.

[19] D. Tan and A. Nijholt, “Brain-Computer Interfaces and Human-Computer Interaction,” in *Brain-Computer Interfaces*, D. S. Tan and A. Nijholt, Eds. Springer London, 2010, pp. 3–19.

[20] F. Lotte, M. Congedo, A. Lécuyer, F. Lamarche, and B. Arnaldi, “A review of classification algorithms for EEG-based brain-computer interfaces,” *J. Neural Eng.*, vol. 4, no. 2, pp. R1–R13, Jun. 2007.

[21] S. Lemm, C. Schäfer, and G. Curio, “BCI Competition 2003--Data set III: probabilistic modeling of sensorimotor mu rhythms for classification of imaginary hand movements,” *IEEE Trans. Biomed. Eng.*, vol. 51, no. 6, pp. 1077–1080, Jun. 2004.

[22] G. N. Garcia, T. Ebrahimi, and J. Vesin, “Support vector EEG classification in the Fourier and time-frequency correlation domains,” in *First International IEEE EMBS Conference on Neural Engineering, 2003. Conference Proceedings*, 2003, pp. 591–594.

[23] F. Lotte, “On the need for alternative feedback training approaches for BCI,” presented at the Berlin Brain-Computer Interface Workshop, 2012.

[24] F. Lotte, F. Larrue, and C. Mühl, “Flaws in current human training protocols for spontaneous Brain-Computer Interfaces: lessons learned from instructional design,” *Front. Hum. Neurosci.*, vol. 7, p. 568, 2013.

[25] V. J. Shute, “Focus on Formative Feedback,” *Rev. Educ. Res.*, vol. 78, no. 1, pp. 153–189, Mar. 2008.

[26] J. Hattie and H. Timperley, “The Power of Feedback,” *Rev. Educ. Res.*, vol. 77, no. 1, pp. 81–112, Mar. 2007.

[27] G. Prasad, P. Herman, D. Coyle, S. McDonough, and J. Crosbie, “Applying a brain-computer interface to support motor imagery practice in people with stroke for upper limb recovery: a feasibility study,” *J. NeuroEngineering Rehabil.*, vol. 7, no. 1, p. 60, Dec. 2010.

[28] F. Pichiorri *et al.*, “Brain-computer interface boosts motor imagery practice during stroke recovery,” *Ann. Neurol.*, Feb. 2015.

[29] M. S. Cameirao, S. B. i Badia, E. D. Oller, and P. F. Verschure, “Neurorehabilitation using the virtual reality based Rehabilitation Gaming System: methodology, design, psychometrics, usability and validation,” *J. NeuroEngineering Rehabil.*, vol. 7, p. 48, Sep. 2010.

[30] K. Laver, S. George, S. Thomas, J. E. Deutsch, and M. Crotty, “Cochrane review: virtual reality for stroke rehabilitation,” *Eur. J. Phys. Rehabil. Med.*, vol. 48, no. 3, pp. 523–530, Sep. 2012.

[31] G. Saposnik, M. Levin, and Outcome Research Canada (SORCan) Working Group, “Virtual reality in stroke rehabilitation: a meta-analysis and implications for clinicians,” *Stroke J. Cereb. Circ.*, vol. 42, no. 5, pp. 1380–1386, May 2011.

[32] F. Cincotti *et al.*, “EEG-based Brain-Computer Interface to support post-stroke motor rehabilitation of the upper limb,” *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2012, pp. 4112–4115, 2012.

[33] S. W. Tung *et al.*, “Motor imagery BCI for upper limb stroke rehabilitation: An evaluation of the EEG recordings using coherence analysis,” *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2013, pp. 261–264, 2013.

[34] K. K. Ang and C. Guan, “Brain-Computer Interface in Stroke Rehabilitation,” *Journal of Computer Science and Engineering*, Jun. 2013.

[35] F. Lotte, F. Larrue, and C. Mühl, “Flaws in current human training protocols for spontaneous Brain-Computer Interfaces: lessons learned from instructional design,” *Front. Hum. Neurosci.*, vol. 7, Sep. 2013.

[36] S. Silvoni *et al.*, “Brain-Computer Interface in Stroke: A Review of Progress,” *Clin. EEG Neurosci.*, vol. 42, no. 4, pp. 245–252, Oct. 2011.

[37] P.-M. Lledo, M. Alonso, and M. S. Grubb, “Adult neurogenesis and functional plasticity in neuronal circuits,” *Nat. Rev. Neurosci.*, vol. 7, no. 3, pp. 179–193, Mar. 2006.

[38] P. M. Rossini, C. Calautti, F. Pauri, and J.-C. Baron, “Post-stroke plastic reorganisation in the adult brain,” *Lancet Neurol.*, vol. 2, no. 8, pp. 493–502, Aug. 2003.

[39] K. J. Miller, G. Schalk, E. E. Fetz, M. den Nijs, J. G. Ojemann, and R. P. N. Rao, "Cortical activity during motor execution, motor imagery, and imagery-based online feedback," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 107, no. 9, pp. 4430–4435, Mar. 2010.

[40] R. Dickstein *et al.*, "Effects of Integrated Motor Imagery Practice on Gait of Individuals With Chronic Stroke: A Half-Crossover Randomized Study," *Arch. Phys. Med. Rehabil.*, vol. 94, no. 11, pp. 2119–2125, Nov. 2013.

[41] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control," *Clin. Neurophysiol. Off. J. Int. Fed. Clin. Neurophysiol.*, vol. 113, no. 6, pp. 767–791, Jun. 2002.

[42] F. Lotte *et al.*, "Combining BCI with Virtual Reality: Towards New Applications and Improved BCI," 2013.

[43] D. Friedman, "Brain-Computer Interfacing and Virtual Reality," in *Handbook of Digital Games and Entertainment Technologies*, R. Nakatsu, M. Rauterberg, and P. Ciancarini, Eds. Springer Singapore, 2015, pp. 1–22.

[44] M. Slater, "Place illusion and plausibility can lead to realistic behaviour in immersive virtual environments," *Philos. Trans. R. Soc. Lond. B Biol. Sci.*, vol. 364, no. 1535, pp. 3549–3557, Dec. 2009.

[45] S. Bermudez i Badia and M. S. Cameirao, "The Neurorehabilitation Training Toolkit (NTT): A Novel Worldwide Accessible Motor Training Approach for At-Home Rehabilitation after Stroke," *Stroke Res. Treat.*, vol. 2012, Apr. 2012.

[46] B. Lange *et al.*, "Designing informed game-based rehabilitation tasks leveraging advances in virtual reality," *Disabil. Rehabil.*, vol. 34, no. 22, pp. 1863–1870, Apr. 2012.

[47] C. Trompetto *et al.*, "Pathophysiology of Spasticity: Implications for Neurorehabilitation," *BioMed Res. Int.*, vol. 2014, 2014.

[48] C. Vidaurre and B. Blankertz, "Towards a Cure for BCI Illiteracy," *Brain Topogr.*, vol. 23, no. 2, pp. 194–198, Nov. 2009.

[49] M. Gomez-Rodriguez, J. Peters, J. Hill, B. Schölkopf, A. Gharabaghi, and M. Grosse-Wentrup, "Closing the sensorimotor loop: haptic feedback facilitates decoding of motor imagery," *J. Neural Eng.*, vol. 8, no. 3, p. 036005, Jun. 2011.

[50] T. Hinterberger *et al.*, "A multimodal brain-based feedback and communication system," *Exp. Brain Res.*, vol. 154, no. 4, pp. 521–526, Feb. 2004.

[51] R. Leeb, K. Gwak, D.-S. Kim, and J. del R Millán, “Freeing the visual channel by exploiting vibrotactile BCI feedback,” *Conf. Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 2013, pp. 3093–3096, 2013.

[52] F. Cincotti *et al.*, “Vibrotactile Feedback for Brain-Computer Interface Operation,” *Comput. Intell. Neurosci.*, vol. 2007, p. e48937, Sep. 2007.

[53] K. Gwak, R. Leeb, J. D. R. Millan, and D.-S. Kim, “Quantification and reduction of visual load during BCI operation,” in *2014 IEEE International Conference on Systems, Man and Cybernetics (SMC)*, 2014, pp. 2795–2800.

[54] C. Jeunet, C. Vi, D. Spelmezan, B. N’Kaoua, F. Lotte, and S. Subramanian, “Continuous Tactile Feedback for Motor-Imagery Based Brain-Computer Interaction in a Multitasking Context,” in *Human-Computer Interaction – INTERACT 2015*, J. Abascal, S. Barbosa, M. Fetter, T. Gross, P. Palanque, and M. Winckler, Eds. Springer International Publishing, 2015, pp. 488–505.

[55] L. Yao, J. Meng, D. Zhang, X. Sheng, and X. Zhu, “Combining motor imagery with selective sensation toward a hybrid-modality BCI,” *IEEE Trans. Biomed. Eng.*, vol. 61, no. 8, pp. 2304–2312, Aug. 2014.

[56] D. Leonardis, A. Frisoli, M. Solazzi, and M. Bergamasco, “Illusory perception of arm movement induced by visuo-proprioceptive sensory stimulation and controlled by motor imagery,” in *2012 IEEE Haptics Symposium (HAPTICS)*, 2012, pp. 421–424.

[57] A. Vourvopoulos, J. E. M. Cardona, and S. B. i Badia, “Optimizing Motor Imagery Neurofeedback through the Use of Multimodal Immersive Virtual Reality and Motor Priming,” presented at the 2015 International Conference on Virtual Rehabilitation (ICVR), 2015.

[58] “Report of the committee on methods of clinical examination in electroencephalography: 1957,” *Electroencephalogr. Clin. Neurophysiol.*, vol. 10, no. 2, pp. 370–375, May 1958.

[59] G. Pfurtscheller *et al.*, “Graz-BCI: state of the art and clinical applications,” *IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc.*, vol. 11, no. 2, pp. 177–180, Jun. 2003.

[60] A Vourvopoulos, A Ferreira, S Bermúdez i Badia, “NeuRow: An Immersive VR Environment for Motor-Imagery Training with the Use of Brain-Computer Interfaces and Vibrotactile Feedback,” presented at the PhyCS 2016 - 3rd International Conference on Physiological Computing Syst, Lisbon, 2016.

[61] Y. Renard *et al.*, “OpenViBE: an open-source software platform to design, test, and use brain-computer interfaces in real and virtual environments,” *Presence Teleoperators Virtual Environ.*, vol. 19, no. 1, pp. 35–53, 2010.

[62] A. Vourvopoulos, A. L. Faria, M. S. Cameirao, and S. Bermudez i Badia, “RehabNet: A distributed architecture for motor and cognitive neuro-rehabilitation,” in *2013 IEEE 15th International Conference on e-Health Networking, Applications Services (Healthcom)*, 2013, pp. 454–459.

[63] R. M. Taylor II, T. C. Hudson, A. Seeger, H. Weber, J. Juliano, and A. T. Helser, “VRPN: A Device-independent, Network-transparent VR Peripheral System,” in *Proceedings of the ACM Symposium on Virtual Reality Software and Technology*, New York, NY, USA, 2001, pp. 55–61.

[64] R. Roberts, N. Callow, L. Hardy, D. Markland, and J. Bringer, “Movement imagery ability: development and assessment of a revised version of the vividness of movement imagery questionnaire,” *J. Sport Exerc. Psychol.*, vol. 30, no. 2, pp. 200–221, Apr. 2008.

[65] E. Adams and B. Ip, “From Casual to Core: A Statistical Mechanism for Studying Gamer Dedication.” [Online]. Available: http://www.gamasutra.com/view/feature/131397/from_casual_to_core_a_statistical_.php. [Accessed: 05-Jan-2015].

[66] S. G. Hart and L. E. Staveland, “Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research,” in *Advances in Psychology*, vol. 52, P. A. H. and N. Meshkati, Ed. North-Holland, 1988, pp. 139–183.

[67] W. IJsselsteijn, K. Poels, and Y. A. de Kort, “The Game Experience Questionnaire: Development of a self-report measure to assess player experiences of digital games,” *TU Eindh. Eindh. Neth.*, 2008.

[68] J. Brooke, “SUS-A quick and dirty usability scale,” *Usability Eval. Ind.*, vol. 189, p. 194, 1996.

[69] A. Delorme and S. Makeig, “EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis,” *J. Neurosci. Methods*, vol. 134, no. 1, pp. 9–21, Mar. 2004.

[70] A. T. Pope, E. H. Bogart, and D. S. Bartolome, “Biocybernetic system evaluates indices of operator engagement in automated task,” *Biol. Psychol.*, vol. 40, no. 1–2, pp. 187–195, May 1995.

[71] C. Berka *et al.*, “EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks,” *Aviat. Space Environ. Med.*, vol. 78, no. 5, pp. B231–B244, May 2007.

[72] R. Boostani and M. H. Moradi, “A new approach in the BCI research based on fractal dimension as feature and Adaboost as classifier,” *J. Neural Eng.*, vol. 1, no. 4, pp. 212–217, Dec. 2004.

[73] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller, “Hidden Markov models for online classification of single trial EEG data,” *Pattern Recognit. Lett.*, vol. 22, no. 12, pp. 1299–1309, Oct. 2001.

[74] S. Solhjoo and M. Moradi, “Mental task recognition: A comparison between some of classification methods,” in *BIOSIGNAL 2004 International EURASIP Conference*, 2004, pp. 24–26.

[75] A. Bangor, P. Kortum, and J. Miller, “Determining What Individual SUS Scores Mean: Adding an Adjective Rating Scale,” *J Usability Stud.*, vol. 4, no. 3, pp. 114–123, May 2009.

[76] A. Ferreira, A. Vourvopoulos, and S. B. i Badia, “Optimizing Performance of Non-Expert Users in Brain-Computer Interaction by Means of an Adaptive Performance Engine,” in *Brain Informatics and Health*, Y. Guo, K. Friston, F. Aldo, S. Hill, and H. Peng, Eds. Springer International Publishing, 2015, pp. 202–211.

[77] M. Gregg, C. Hall, and A. Butler, “The MIQ-RS: A Suitable Option for Examining Movement Imagery Ability,” *Evid.-Based Complement. Altern. Med. ECAM*, vol. 7, no. 2, pp. 249–257, Jun. 2010.

9 Appendix A – Consent Forms

Consent Form for Participation in Research

Study Title: Brain-Computer Interface (BCI) assessment

Investigators: Athanasios Vourvopoulos (PhD Researcher), André Ferreira (MSc Student)

Supervision: Dr. Sergi Bermudez I Badia

Purpose of this study

The purpose of this study is to evaluate user performance in a Motor Imagery Experiment using a Brain Computer Interfaces.

Procedures

You have been invited to participate in a neuroscientific experiment of the NeurorehabLab research group of Madeira Interactive Technologies Institute. The session will take place in a research laboratory on the University of Madeira. For the experiment, one session of 1 hour (including equipment setup and instructions) is required. For the procedure, first you are going to use a Brain Computer Interface (BCI), a non-invasive device to measure electric activity patterns of your brain. After verifying the connections, to be sure that the position of the electrodes of the BCI system are in the correct position, you will be given a set of instructions to carry out mental and physical. During these tasks, we will record electroencephalographic (EEG) signals. You must try to execute the tasks as well as possible in the assigned period of time. In addition, in this experiment you will need to use a Head Mounted Display. Finally, a set of questionnaires will be supplied to be fill out each session. The experimental data will be processed in such a way that your anonymity will be preserved.

Participant Requirements-

You are eligible for participation if you: are 18-65 years old, are able to read, have no past of brain injuries and no neurological disorders.

Risks

The risk associated with participation in this study are no greater than those ordinarily encountered in daily life or during the performance of standard physical activity (e.g. simple muscular stretching). The EEG electrodes are superficial and DO NOT have any risk for your health. The interaction with the tasks requires executing repetitions (physical and mental) using a BCI on your head. You may experience fatigue and/or headache in some sessions.

Benefits

The study will contribute to the development of novel rehabilitation tools that in the future will help to patients with multiple neurological and motor disabilities.

Confidentiality

By participating in the study, you understand and agree that NeurorehabLab may be required to disclose your consent form, data and other personally identifiable information as required by law, regulation, subpoena or court order. Otherwise, your confidentiality will be maintained in the following manner. Data and information gathered during this study may be used by NeurorehabLab and published and/or disclosed by NeurorehabLab to others of NeurorehabLab for research purposes. However, your personal information will never be revealed in any publication or dissemination of the research data and/or results by NeurorehabLab.

INFORMED CONSENT DOCUMENT

I understand that all information derived from the study **“Brain-Computer Interface (BCI) assessment”** is owned by the responsible research team. I give my consent for anonymous collection of data about me (results, pictures and videos), which will be stored and processed for scientific evaluation. I understand the significance of this information, and any questions I had were answered satisfactorily. I had enough time to decide on my participation in this study. I hereby consent my participation and the collection of information.

____ ____________

Signature of Participant Date

____ ____________

Signature of Investigator Date