A Serious Game Application using EEG-based Brain Computer Interface

Francisco José Perales and Esperança Amengual
Mathematics and Computer Science Department, University of the Balearic Islands,
Crta. Valldemossa Km 7.5, 07122, Palma de Mallorca, Spain

Keywords: Brain Computer Interface (BCI), Electroencephalography (EEG), Rehabilitation, Serious Games, Neurofeedback, Cerebral Palsy, Motor Impairment, Focus Feature, Alpha Channel.

Abstract: Serious games have demonstrated their effectiveness as a therapeutic resource to deal with motor, sensory and cognitive disabilities. In this article we consider Brain Computer Interfaces (BCI) as a new interaction mechanism that could be used in serious games to improve their rehabilitation activity thanks to the ability of neurofeedback to stimulate the cortical plasticity. We present the brief state-of-the-art of BCI serious games and the factors to be considered in order to develop this particular kind of software that could be highly complex and require experts with different knowledge and skills. We propose a new approach based on the detection of focus features in the game activity. We introduce a system able to assess the Alpha band variations in particular game tasks. Our initial target users are children with cerebral palsy and motor disabilities. The system is currently under evaluation with control users before to be operated with the target users in rehabilitation centers.

1 INTRODUCTION

Human Computer Interaction (HCI) is the discipline concerned with the study of the information exchange between humans and computer systems. Its main objective is to achieve an efficient information interchange, while minimizing the number of errors and improving user satisfaction. Ultimately, the final goal is to improve the productivity of the tasks that people carry out using computers. Usually the interaction between human and computers is performed through common peripheral devices such as the keyboard, the mouse and the display. This type of interaction unavoidably involves the operation of the neuromuscular system as intermediary. When we use the mouse or the keyboard, the brain communicates with movements which are managed through impulses that run the nervous system until they reach the appropriate muscle. But, what happens with a muscular or nervous disease? It is at this point when Brain Computer Interfaces (BCI) gains importance. This emerging technology makes direct communication interchange possible. Thanks to BCI, communication between human and computers does not inevitably imply the use of the neuromuscular system. These interfaces can be used as an additional communication band, or even as the unique possible one for people with serious diseases.

The possibility of direct communication between a computer and the user's brain, without any additional peripheral devices, opens a wide range of possibilities to develop new software applications. One of them is neuromotor rehabilitation with computer games, which in this case are named “serious games”. In general, the main goal of computer games is entertainment. Serious games are a special type of computer games which have been designed with medical or educational purposes. Like all the games, serious games have to be entertaining and fun to improve the motivation of the patient, thus improving the final results.

The use of BCI in serious games design rises to the challenge of using non-invasive brain signal acquisition devices. The choice of non-invasive techniques, such as electroencephalography (EEG), is particularly important since these techniques do not require surgery. In this way the patient will be able to use the serious game the time that will be required, whether adult or child, without added risks. Electroencephalography (EEG) is the recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current

Perales F. and Amengual E..
A Serious Game Application using EEG-based Brain Computer Interface.
DOI: 10.5220/0004678102490255
In *Proceedings of the International Congress on Neurotechnology, Electronics and Informatics* (BrainRehab-2013), pages 249-255
ISBN: 978-989-8565-80-8

flows within the neurons of the brain. In clinical contexts, EEG refers to the recording of the brain's spontaneous electrical activity over a short period of time as recorded from multiple electrodes placed on the scalp. Currently, it has been shown that there is some relation between variations in EEG signals and some processes such as perception, language, psychomotor skills, arithmetical calculus, and several emotions. Another advantage of EEG is the availability of commercial devices for electroencephalography at an affordable cost (Carrino et al., 2012). The main goal of this paper is to plot the landscape of the application of BCI to medical serious games. In section 2 we present the state-of-the-art of the use of BCI in medical serious games. In section 3 we show our proposal system designed to evaluate the user activity based in a portable and wireless EEG low cost system that measure the Alpha band amplitude variations. Finally, the conclusions and some proposals for future work are exposed in section 4.

2 BCI FOR SERIOUS GAMES

A relevant number of BCI systems have been designed to improve the quality of life of people with diseases (Kaur et al., 2012). In these cases BCI is used to perform a direct and precise control of prosthetic devices, wheelchairs (Carrino et al., 2012) and computers. However, the approach we are interested in for serious games is quite different since it focuses on the treatment or on the improvement of the disease, not in palliative care. Within this field, serious games have demonstrated their capability to boost the rehabilitation activity with regard to traditional therapy which is frequently repetitive and monotone. In contrast, serious games can include changing stimulant elements which even can not to be directly related with the therapy. In (Diaz et al., 2012) their authors describe how a simple adaptation of the game scenarios (background images) can result in positive or negative effects over the results obtained by the player, and this is a kind of stimulus that can be frequently changed with little effort in a computer program. In this sense, it is possible to find a number of serious games developed for rehabilitation purposes, but only a few of them include BCI. In (Rego et al., 2010) a taxonomy of serious games is proposed, but there is not any reference to BCI in the article. The criteria used for the classification of serious games neither consider any BCI specific aspect.

2.1 Application of BCI to Serious Games

In (Nijholt, 2009) two different approaches for the integration of BCI in games are described. The first one is aimed at controlling the game through the development of a mental gamepad. The second one is intended to get feedback, in this case named “neurofeedback”, for the improvement of the user experience by adapting the contents or the difficulty level of the game to the mental state of the player. In medical applications in particular, BCI has been integrated with the aim of neurofeedback and its effectiveness to improve cognitive skills, pain treatment, schizophrenia, depression, alcoholism, epilepsy, as well as and other psychological or neurological affections, has been demonstrated. The reason for the effectiveness of this strategy seems to be that it induces cortical plasticity, that is, the function which was performed by a part of the cerebral cortex which was damaged is now performed by other region of the cortex. A multimodal interaction strategy is also possible by combining the usual peripheral devices with BCI. In this way, it is possible to perform a cognitive training which can be improved by BCI neurofeedback (Sung et al., 2012).

2.2 Serious Games Development with BCI

In (Sung et al., 2012) the complexity of BCI serious game development is highlighted. This kind of developments involves different experts with distinct knowledge and skills: EEG and neuro rehabilitation experts, EEG signal treatment experts, and game development experts. The first group of experts has to design the rehabilitation strategy and the patterns to extract from the EEG signals. The second group has to develop the BCI component able to treat the signal. Finally, the game developers have to deal with the graphical interface, the sound and other elements of the game. Other qualities that are desirable for BCI serious games, and which still emphasize the difficulties, are the need for low-cost EEG devices and a wide range of possible users. The development of BCI serious games which satisfy the specified requirements at a reasonable cost and time is possible. A recommended strategy is the integration of a BCI framework with the drivers of the EEG device to be used and a game motor.

3 THE PROPOSED METHOD

Our objective is to assess the ability to focus on a specific mental task. We have designed a mental concentration tests based on visual and acoustic stimulus. The main idea is to evaluate if the stimulus increases or decreases the user concentration over the mental task. The user is in front of the computer screen and is required to direct his/her attention towards a specific task.

To perform this test it has been necessary to develop a system which is composed of BCI interaction and measurement physical devices, together with the software applications that support the data integration for each patient. The main limitation of this work is the inability to use standard wired EEG because of the systematic involuntary movements of the final user. Therefore, the system hardware should be the least invasive as possible. The initial constraints of our system are: wireless and a minimal set of electrodes. Several commercial systems have been evaluated and finally we have selected the NeuroBit Optima 4 and BioEraPro Software tool (BioEraPro Software, 2012) to develop the initial application.

The system architecture used in this experiment is shown in Figure 1. For the proposed study the maximum number of electrodes is limited to a maximum of 4 at frontal position. Although this constraint the analysis range, there is not currently any available version with less electrodes. Figure 2 shows a use case of the system. In any case, the initial measurements have been performed with 2 electrodes to simplify the initial configuration of the system.

More concretely, we are particularly interested on the variations of the alpha frequency components. From an initial reference we analyze the variation

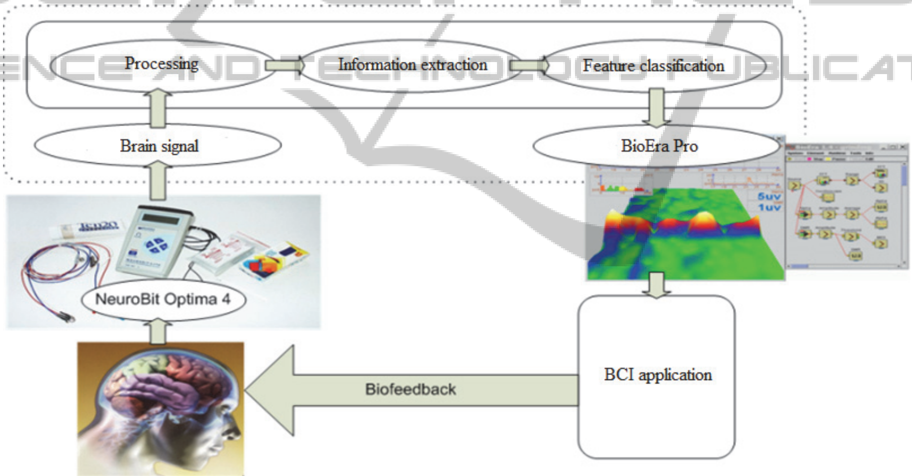

Figure 1: System architecture.

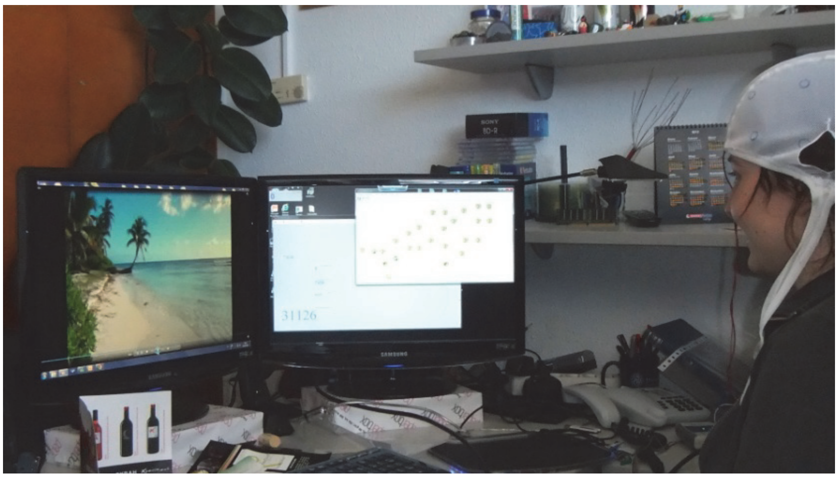

Figure 2: Control user.

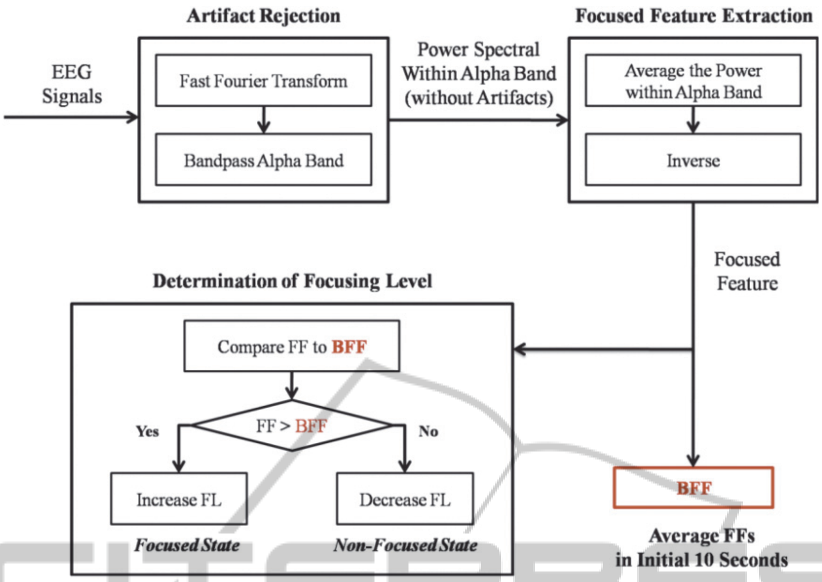

Figure 3: FF (Focus Feature) classification procedures.

through successive acoustic and visual stimuli. Our idea is based on a variant of the work developed by Lun-De Liao (Lun-De Liao et al., 2012) which focuses on the analysis of the influence of using dry or wet electrodes. We have a totally different purpose because our technique is based, not in the analysis of a particular hardware, but on the possible influence of the acoustic and visual stimuli over the concentration ability of the user. The proposed procedure follows the classical steps in a BCI system. The main objective is to capture the input signals from the electrodes and apply the Fourier transform and then apply a specific filter where we exclusively select the Alpha band whose signals describe the rhythmic activity between 8Hz and 13Hz. From these data we perform an average of the five values within the range and invert the signal. At this point we consider important to remark that ocular artifacts only affect the EEG delta and theta bands (Romero et al.,2010). Therefore it has not been necessary to use any artifact reduction method to minimize the signal interference. Formulas in (1) describe these operations. The reason of using the Alpha band is that several studies [9, 10] have demonstrated that the EEG alpha rhythm frequency decreases with changes from a relaxed state to a focused or concentrated state. Previous neurophysiologic studies (Kramer, 1991) have postulated that the mental workload could be detected in a decrease of the alpha band activity in the parietal and occipital brain areas. Moreover, as demonstrated in (Klimesh, 1999) there is a decrease of the alpha band activity when we are doing a learning task. Other recently studies (Walter et al., 2011) prove that we can classify mental states with machine learning algorithms with the analysis of the variations in time of the alpha band. These studies use sixteen electrodes placed according to the International Electrode (10-20). In the particular case of our experiment this EEG configuration is not viable due the special motor disabilities of the final users (cerebral palsy with significant spastic movements). In addition, the proposed mental task must be adapted to the cognitive level of these users. Therefore, we assume that the alpha band is the main feature used to classify the concentration state.

$$\begin{gathered} X = [X_1\, X_2\, X_3 \dots X_{511}\, X_{512}] \\ Y = [Y_1\, Y_2\, Y_3 \dots Y_{255}\, Y_{256}] \\ Y = FFT(X) \\ P_\alpha = \frac{1}{5}\sum_{n=8}^{12} Y_n \\ FF = PR_\alpha = \frac{1}{P_\alpha} \end{gathered} \tag{1}$$

Figure 3 shows the flow diagram of the software application. In this work we have adapted the flow diagram presented in (Lun-De Liao et al., 2012) to our problem with different architecture and objectives. The EEG data are captured during a period of 10 seconds and the rolling average is calculated every 10 seconds to see the tendency (Lee and Tan, 2006). This average is initially stored in a BFF (Baseline Focus Feature) which is used as a reference for the successive measurements. The average is stored in the buffer only one single time and a threshold is defined. If this threshold is exceeded, this indicates the user is moving to a concentration state. On the contrary, if activity falls below the threshold, this means the user is moving to a relaxation state. Concentration gradations are not initially considered. The performed test is composed by the following 10 second measurement steps:

1. Measurement of the initial concentration threshold
2. Measurement without any stimuli, only numerical feedback (0 = relaxation, 1 = concentration)
3. Measurement with pleasing musical sound
4. Measurement with unpleasant musical sound (>80db)
5. Measurement without sound
6. Measurement with images of a ball motion in a pathway
7. Measurement with relaxing video (smooth see waves)
8. Measurement with stressing video (city with activity)
9. Measurement without video

This procedure is repeated three times for each control user.

4 SOME INITIAL RESULTS IN TWO SET OF CONTROL USERS

As discussed in the preceding section, to obtain visual results we have established two states: concentrated and relaxed. The following table shows the values registered in 7 different control users.

From the obtained results the average of the 7 control users has been calculated. In any case, it can be observed that two of the users, user 6 and user 7 specifically, have high BFF values, as well as the rest of the values when compared with the other control users. The reason could be that they are stressed users or users with an alpha band activity which is out of the ordinary. From this sample it is difficult to infer convincing conclusions about variations in the alpha rhythms depending on the stimuli. If we construct a variations table (+ indicates an increase, - indicates a decrease), we have:

Table 1: Seven control users.

User	BFF	BFF(Without Feedback)	FF (Music)	FF (Noise)	FF(Ball Tracking)	FF(Calm Image)	FF(City Image)
User 1	18670	3500	5870	3600	8900	6000	6500
User 2	20840	4000	7200	7000	6000	3000	4300
User 3	59720	74000	34000	20700	40000	50000	35000
User 4	49970	100000	209000	70000	155000	270000	200000
User 5	22370	12000	11700	15000	30000	35000	45000
User 6	75830	137300	349000	186000	134000	180000	105000
User 7	100500	250000	450000	320000	149000	350000	200000
Mean	**49700**	**82971**	**152396**	**88900**	**74700**	**127714**	**85114**

Table 2: BFF variations seven control users.

User	BFF	BFF (Without Feedback)	FF (Music)	FF (Noise)	FF(Ball Tracking)	FF(Calm Image)	FF(City Image)
User 1	18670	-	+	-	+	-	+
User 2	20840	-	+	-	-	-	+
User 3	59720	+	-	-	+	+	-
User 4	49970	+	+	-	+	+	-
User 5	22370	-	-	+	+	+	+
User 6	75830	+	+	-	-	+	-
User 7	100500	+	+	-	-	+	-
Mean	**49700**	**82971**	**152396**	**88900**	**74700**	**127714**	**85114**

Table 3: Ten control users (new stimuli sequence).

User	BFF	BFF(Without Feed-back)	FF (Music)	FF (Noise)	FF(Calm Image)	FF(City Image)	FF(Ball Track-ing)
User 1	42004	34695	94657	48105	60421	85311	127647
User 2	33091	77423	82677	53220	102204	138000	96341
User 3	39240	57022	81677	49649	20375	95671	136361
User 4	16000	19961	78001	84430	124430	81704	143382
User 5	69271	95530	96006	314551	119806	114728	201283
User 6	15818	18000	185200	131747	101230	161300	220300
User 7	134132	227733	461333	198666	227350	217300	495285
User 8	282551	375950	560000	455500	716650	345600	391550
User 9	84901	140200	244320	374115	271111	583433	443452
User10	47154	153450	208115	145937	342769	648486	523440
Mean	76416	119996	209199	185592	208635	247153	277904
Variation	**BFF**	+	+	-	+	+	+

It is perhaps possible to deduce that music in particular enhances the capacity of concentration since in 5 users the signal increases. Something similar happens with the image of a calm beach. Furthermore, we observe that in 6 of the users the shrill noise stimulus exceeding 80 decibels results in a loss of concentration. An unexpected result is that an increment of attention appears only in 4 users. A possible reason could be that 10 seconds between stimuli are not enough to recover concentration due to the "carry over effect" (Hsieh and Lin-Chao, 2005). Based on these reflections we have considered that more experiments with control users are necessary in order to gain greater distinction among stimuli and calculate the average values of each of them at repeated intervals. A new sequence of stimuli is defined: the ball tracking stimulus is the last one, the calm and city images are interchanged. In this experiment the number of control users has been increased to 10 (7 overlapped with the ones from table 1 and table 2).

From the previous table it is possible to conclude that, although there are some divergences in the data, the average is that calm music and beach stimuli increase concentration, noise decreases concentration and the surprising finding is that the image of the city in motion also increases concentration, it does not distract. Finally the ball tracking implies concentration, which seems logical. However, it is not possible to strictly state that the acoustic or visual stimulus increase concentration for the task to perform or initially imagined because it would be possible that the increment in the attention was due to the stimulus itself. Accordingly, we would analyze more cases based on a concrete activity and combine the stimuli to see if they improve or not the goal or the performance of the main task (hybrid endogenous + exogen paradigm).

5 CONCLUSIONS AND FUTURE WORK

Serious games have demonstrated to be effective as a therapeutic resource in motor, sensory and cognitive disabilities. There is a great variety of serious games and they can be classified depending on their application area, interaction technology, monitoring capability, feedback possibilities and other properties. Advances in the treatment of EEG signals have reached the point at which there are an important number of characteristics that can be extracted and classified as the basis for BCI systems design with different objectives and forms of application. There are currently some games which integrate BCI by fundamentally following two strategies: to control some aspects of the game or to get feedback and adapt the level of difficulty of the game environment. However, in the particular case of serious games the strategy always consists in applying BCI to get neurofeedback to deal with psychopathology or neuropathology. The development of serious games is a costly and complex task which involves experts in different areas. This cost and complexity can be managed with existent frameworks which help to increase the level of abstraction of the components to be developed.

A prototype of a BCI system which assesses the concentration skills has been presented. The system is based on a classification of the Alpha band variations. The assessed users are control users who do not suffer any motor disease. The proposed system is simple, low cost, wireless, requires very little training, and has a minimum number of electrodes. Results identify certain logical trends such that relaxing music and pleasant images promote concentration, likewise a harsh noise reduces it. At all events, it is not possible to precisely infer that this is in fact what happens due to problems in video editions that do not properly separate the proposed events. This work is at a very early stage and it is still necessary to validate the results with more users, particularly with the final users which would be people who suffer from cerebral palsy. We plan to improve the defined experiments using a main task and additional visual or acoustic stimulus in order to improve the final performance of the user. The cognitive skills of each specific user will also be considered in order to adapt the game to their level of mental cognition.

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