EEG Biofeedback and Brain Computer Interface in Games

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Abstract

This work proposes a complete structure of an EEG biofeedback platform focused on an efficient way for its users to learn how to self-regulate their cortical activity and use it as an input for Brain-Computer interfaces. This platform was tested in 20 subjects that underwent 20 short sessions of training. Although the main focus of this study was to understand the positive effect this training has in short term memory and how EEG self-regulation can be achieved, in this work we analyze the results in the perspective of a Brain-Computer interface training tool. Therefore, besides introducing our protocol, we present the mental strategies subjects used to control their EEG, their improvements along training sessions and the delays related to this kind of interface.

The positive results obtained by this training, along with the time delays necessary to voluntarily produce changes in the EEG made us consider the usefulness of this ability as input for a videogame. We briefly discuss how it is being used and why it may not be challenging or interesting for gamers and propose different uses of this additional mean of gameplay.

Author Keywords

Brain-Computer Interfaces, EEG Biofeedback, Game Interfaces

EEG Biofeedback Platform [8]

Select Channels: must be channels from locations we know that can produce voluntary EEG and exist in available portable hardware.

Select feedback feature: Power from a certain frequency band in a certain channel, some operation between bands from different/same channels.

Connectivity between brain sites.

Muscle or eye movement.

Goal 1: the feedback feature value surpasses some threshold.

Goal 2: Goal 1 is being achieved continuously for more than a certain amount of time.

What is shown?: the feedback parameter value can be shown but Goals 1 and 2 achievement must be more evident. Still they should not disturb focus.

Session structure: trials and intervals, fixed or not.

Introduction

EEG biofeedback consists in making an individual aware of his cortical activity by presenting him this measured signal. The aim is allowing its conscious control but, as the EEG is a rather complex signal, any success in voluntarily influencing it can be unperceived, making it impossible to acknowledge any change. To ease the task of understand the EEG behavior, it can be divided into several frequency bands: delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 12 Hz), the sensorimotor rhythm (SMR) (12 to 14 Hz) and beta (14 to 26 Hz). EEG biofeedback is usually focused in the amplitude of some of this frequency bands rather than the entire signal.

An EEG biofeedback system can be seen as a closed loop enclosing neuronal activity and a brain computer interface (BCI). This BCI consists in a signal acquisition device connected to a computer that processes the EEG information and translates it into stimuli to be perceived by its user. This translation can be done by calculating different characteristics of the EEG such as the EEG coherence value between different locations in the brain, the power spectrum or amplitude of a specific frequency band or electrical slow cortical potentials (SCP) [1]. The result is presented to the user through the computer screen, in the form of visual stimuli, or speakers, in the form of auditory stimuli. Ideally, after an initial learning period, the subject is able to voluntarily induce changes in his EEG that are reflected by a specific outcome in the feedback parameter. This way the subject is able to modulate any external system, using the EEG as input, alternatively or complementary to motor skills. Subjects suffering with neurological diseases that result in motor disability that lose their capabilities of communication and expressing justify these interfaces as it might be their only way of communicating [3]. These applications are limited to binary choices as they're based in high or low values of a specific frequency band or signal amplitude. SCP control has been proven to be possible by human subjects in several BCI [4] and EEG biofeedback studies [5]. A cursors vertical position can be determined by this potentials amplitude after it is calibrated to the user's amplitude range [6]. SMR rhythms are usually recorded over the sensorimotor cortex and its amplitude is related to sensory input, movement or motor imagery. Its control by human subjects is also proved to be possible and the cursors movement vertical position is also dictated by the band's amplitude. Left to right movement with a constant rate can be introduced to give access to the extra dimension [3]. The selection of a character, for example, can be done using a 6x6 matrix filled with characters. The rows and columns of this matrix flash with a certain constant rate and the user is instructed to count the number of times the flashing row and column crossing point coincides with the desired character. When this happens, because of the attentional demand similar to an oddball test, an electrical potential is evoked. At every flash, the EEG is recorded and associated with one character. After a certain amount of flashes, each EEG segment is averaged and the averaged signal with the highest amplitude is probably the one where more electric potentials were evoked leading to the conclusion that it's the option desired by the user [3]. Still, in all strategies the maximum communication bit rate is low (from 0.1 to 3.5 bits/minute [7]).

EEG Biofeedback Training

Because self-regulation of the EEG is not a usual skill, several training sessions are needed for the user to understand what cognitive strategies lead to the desired changes in the EEG. Because these sessions are based on operant conditioning, their protocol, according to M. Sterman and T. Egner, must follow certain rules in order to be effective [1]:

- Each training session should provide discrete trials separated by brief pauses.
- When the produced changes in the EEG meet the required condition (for example, increase band amplitude until a certain threshold) a reward stimulus must be presented. There must be minimum delay between the reward situation and the reward stimulus for optimal learning to occur.
- The reward stimulus must have the highest reinforcement effect.

Also, the electrode placement should be determined by the "10-20 International System of Electrode Placement" since it is based on the location of cortical regions and uses relative metric, given that head sizes vary.

Platform Features

The developed platform [8] was designed to allow different EEG biofeedback trainings and their evaluation. Besides the flexibility in defining different biofeedback protocols, it allows linear and non-linear spectral analysis, labeling the signal to check for event related potentials during different cognitive assessment tests and EEG biofeedback and tracking individual frequency bands.

Training Structure

Each training program is composed by several sessions. Based on the rules recommended by M. Sterman and T. Egner for the training effectiveness [1] each session can have several trails separated by intervals. Each trials length and number can be fixed (Figure 1) or controlled by its user (Figure 2). Letting the user decide the number of trials and how long each one lasts can be useful in the initial learning period. Here, at the end of each trial, the user can write down what cognitive strategies were used to change brain activity. This is helpful in the next sessions because the user can acknowledge what strategies produce better outcomes and use them in those sessions. After the learning period, protocol defined sessions can be used.

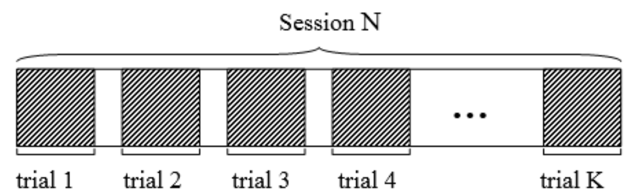

Figure 1. Number of trials is defined in the protocol as well as their duration and intervals in between.

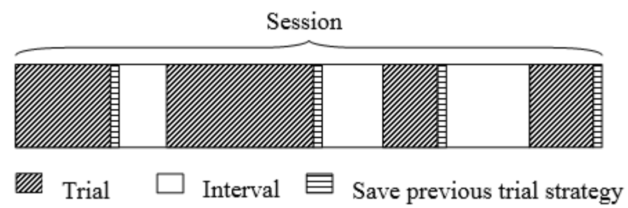

Figure 2. Adaptation session structure. User decides when to start and end trials.

TRIAL OBJECTIVES

Each trial is guided by two goals. The first, Goal 1, consists in the comparison of the value of the feedback parameter with a predefined threshold. Here, two choices can be made in the protocol: the goal is only achieved when the feedback parameter value is above a certain threshold or it is only achieved when the feedback parameter value is below a certain threshold. The second goal, Goal 2, is related to the period of time the first objective keeps being achieved continuously. If Goal 1 is being achieved continuously for more than a predefined period of time, Goal 2 is accomplished. Each trials score is based on these two goals. It is also possible to introduce trials where the user must not try to accomplish these two goals but the feedback parameter is still being fed back to him (Figure 3). By comparing the results of these trials with the results from those guided by goals it is possible to see if the user is really voluntarily changing his EEG towards the objectives.

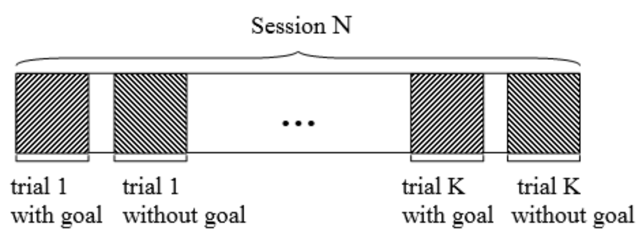

Figure. 3: Session with control trials where the subject must not try to achieve any goal.

EEG Measurement and Translation

Because each brain activity pattern has its source in different cortical locations the placing of the recording electrode in the scalp must be identifiable. It is possible to use any of the electrode placements defined in the "10-20 International System of Electrode Placement".

The training consists in the increase or decrease of the amplitude of a certain frequency band. The calculation of the feedback parameter value is done in the frequency domain by calculating the amplitude of the frequency band that is being trained relative to the whole EEG amplitude - relative amplitude (Equation 1) - or another frequency band.

$$rAmplitude = \frac{bandAmplitude}{EEGAmplitude} \qquad (1)$$

In this case, the EEG frequency of interest is considered to be between 0.5 and 30 Hz. Using the amplitude spectrum instead of the power spectrum prevents excessive skewing that results from squaring the amplitude values which increases statistical validity [1].

Individually Adjusted Frequency Bands

The boundaries of the different frequency bands referenced previously are standardized by averages of the normative population. As a consequence, each individual measure will suffer with this standardization and, more representative results would be obtained if the determination of individual frequency bands was possible. Therefore in this platform it is possible to determine the new individual boundaries for each frequency band by determining the individual alpha frequency band (IAF) and the peak alpha frequency (PAF). The PAF reflects the dominant or most frequent oscillation in the alpha band and it's a necessary value to adjust this frequency band between individuals. Activity in the alpha and theta band respond in different and opposite ways, when one synchronizes usually the other desynchronizes [2]. With increasing task demands, theta synchronizes while alpha desynchronizes the same way alpha synchronizes and theta desynchronizes when closing the eyes. This way, by plotting the EEG spectrum of a recording during a demanding task against a recording during a resting period it is possible to identify the boundaries of the individual alpha band as well as the PAF which is the frequency with the highest amplitude inside these boundaries. Another simple way to get both previous results is by plotting the spectrum of a recording where the subject has his eyes closed (alpha synchronizes and theta desynchronizes) against a recording with the subject having his eyes opened (alpha desynchronizes and theta synchronizes). See Figure 4 for an example.

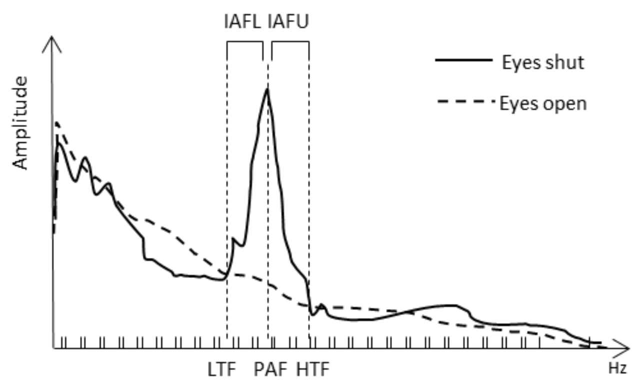

Figure 4. Individual alpha bands: IAFL – lower alpha; IAFU – upper alpha; PAF – peak alpha frequency.

The calculation of the boundaries from the other frequency bands is based on W. Klimesch method [2] where fixed length bands are applied before and after the IAF band or by the same method of labeling events that induce increases or decreases in specific frequency band amplitude. For example, the individual sensorimotor rhythm (SMR) could be calculated by plotting the EEG spectrum during an event where the subject is asked to maintain motionless (SMR increases) against the EEG spectrum during an event where the subject is allowed to move his limbs if he wishes (SMR decreases) [1].

The individualization of the frequency bands should not only be done between individuals but also between different recording sites as EEG frequencies vary between them [2].

Feedback Display

The display was created with the aim of producing a simple visual feedback but at the same time an immersive environment should be created to minimize undesired distractions. For this effect, the Microsoft DirectX™ library was used to draw tridimensional objects that would respond to the value of the calculated feedback parameter. The display contains two objects; a sphere and a cube (see Figures 5 and 6). The sphere is where the feedback parameter is reflected. Its value is directly reflected into the spheres radius and if it reaches the threshold (Goal 1) the sphere color changes. This sphere is constituted by several slices and the more slices it has, more smooth it looks. Initially, the sphere is only constituted by four slices, which is the minimum number possible, and while Goal 1 is being achieved slices are slowly added to the sphere. When Goal 1 is not achieved, the sphere loses slices slowly until it only has four of them again. The cubes height is where Goal 2 is reflected, making it rise until Goal 1 is no longer being achieved. Then the cube starts falling slowly until it reaches the bottom or Goal 2 is achieved again. So, the best outcome would be having the cube as high as possible.

Figure 5. Display when neither Goal 1 nor Goal 2 is achieved.

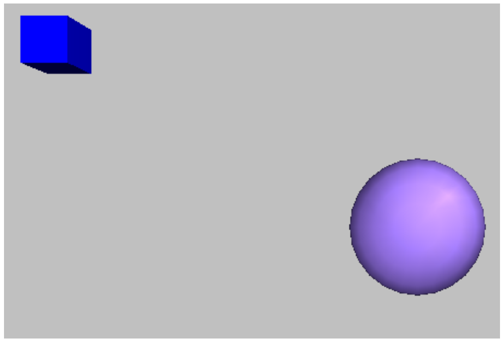

Figure. 6. Display when Goal 1 and Goal 2 are being achieved.

Materials and Methods

This study is published in [9] and focuses in memory improvement associated with this training. Here we analyze the results concerning EEG control.

Participants

A total of 32 students (22 males and 10 females, aged 20-29 years: mean=23.28, SD=3.11) took part in the experiment. Informed written consent was obtained from all participants after the experimental nature and procedure were interpreted to them. Participants were pseudo-randomly allocated to training (20 subjects) and non-neurofeedback control groups, controlling for factors such as age and gender. The protocol was approved by the Research Ethics Committee (University of Macau).

EEG recordings

During the experiment, the participants sat in a quiet room. training was done on channel Cz-M12 (M12 is the average of M1 and M2) of the "10-20 International System of Electrode Placement" with sampling frequency 256 Hz, the ground was located at forehead. The signals were amplified by a 24-channel system (Vertex 823 from Meditron Electomedicina Lda, SP, Brazil) and were recorded by Somnium software platform (Cognitron, SP, Brazil). Circuit impedance was kept below 10kΩ for all electrodes at all times.

Results

EEG Control over Training Sessions

The average relative amplitudes across all participants are shown in Figure 7. The relative amplitudes for IAF, IAFL, IAFU, IAF/theta, sigma and alpha showed an increasing trend with the training sessions while theta and delta decreased over the sessions. The increase in IAF/theta ratios resulted from an increase in IAF amplitude and simultaneous decrease in theta amplitude. Furthermore, the relative amplitudes of the different bands had linear correlation over the sessions. The R square was between 0.78 and 0.91 for the different alpha bands. This results show the increase in control over this specific frequency bands as the number of sessions advance. .

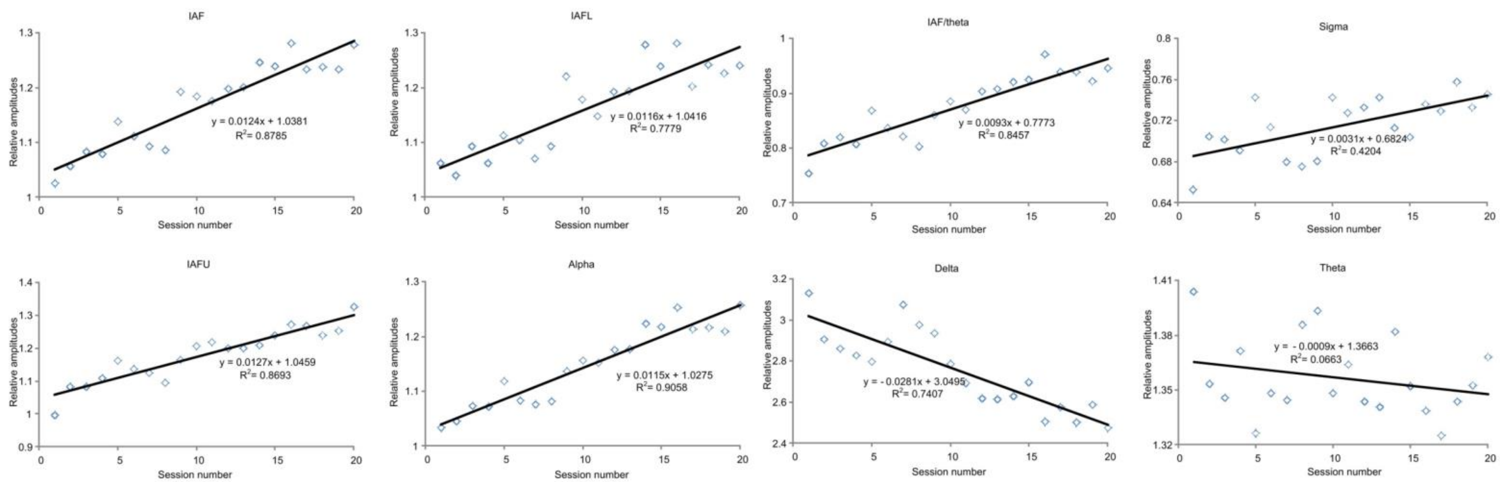

Figure 7. The average relative amplitudes across all participants over sessions, the straight line results from a linear regression and indicate a linear long-term change.

Mental strategies

In an attempt to help participants find out efficient strategies for self-regulating their EEG, after each training session, they were asked to write down which mental exercises or thoughts were used. Their effectiveness is represented in Figure 8.

Among them, the most efficient thoughts or strategies were friends (1.625), love (1.4) and family (1.1); the worst were anger (-2.0) and calculation (-0.15). The effect of some positive strategies sub types like love (lover (1.67)), nature (hometown (1.5)) and family (brothers (2.0)) stood out.

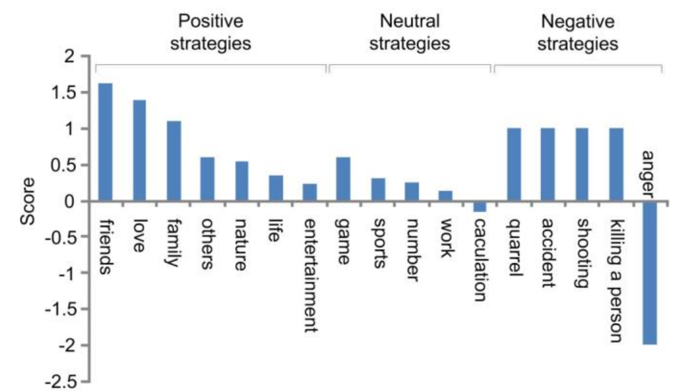

Figure 8. Strategy types scores taken from [9].

Response time.

Response time is the amount of time required to voluntarily produce a significant change in the EEG activity. We measure it as the amount of time since the beginning of the trial and the accomplishment of Goal 2. As Goal 2 is only achieved after 2 seconds of uninterrupted achievement of Goal 1, 2 seconds is the minimum possible response time. Therefore, in the following analysis we must always sum this additional 2 seconds to the results.

From the 20 subjects that participated in the training, 14 were able to decrease their average response times. Figure 9 shows the distribution of these delays for a successful subject and Figure 10 depicts the distribution of response times in all trials and all subjects in order to show the orders of magnitude we are dealing with (mean of 6 seconds).

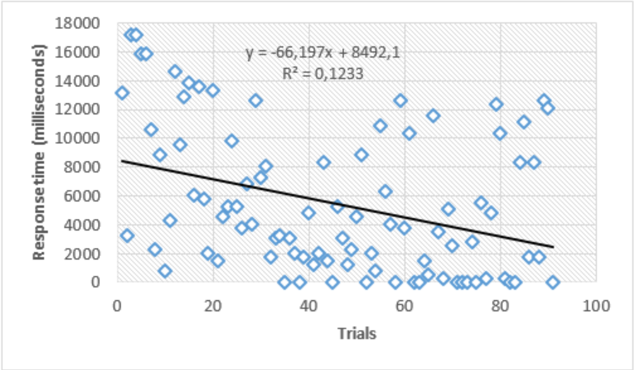

Figure 9. Distribution of response times until the achievement of Goal 2 from a successful subject.

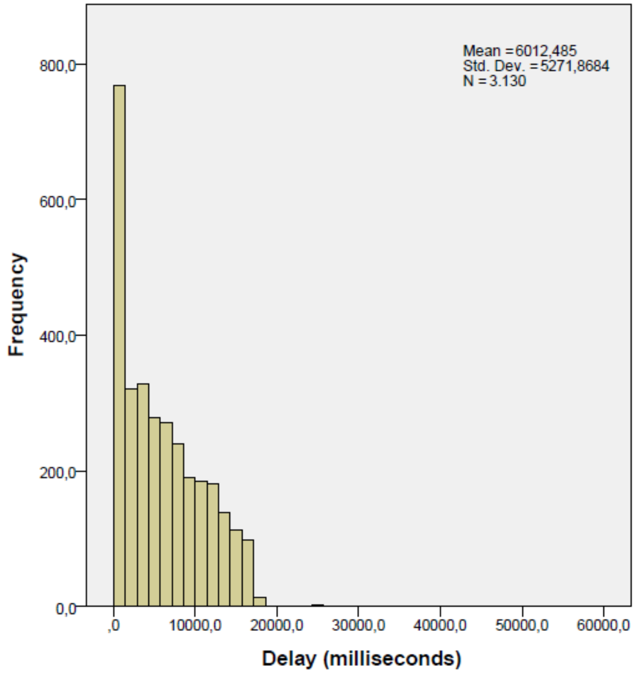

Figure 10. Distribution of response times across subjects and sessions.

We can notice that the delays of 0 milliseconds are very common and, in the subject from Figure 9, they start apearing in more advanced trials. This occurs because the subjects start changing the EEG in advance during the trial intervals and, as the trial starts, after the 2 seconds, Goal 2 is achieved.

Example of a BCI Game

Training: Before actual gameplay the gamer can train his/her EEG in the similarly to our platform. Training should be short but effective.

EEG in Gameplay: The gamer should perceive the EEG characteristic being monitored by some effect that does not affect gameplay (color or sound). Achieving Goal 1 also does not affect gameplay but must be noticed. Goal 2 (lasting achievement of Goal 1) produces a gameplay change.

Goal 2 Gameplay change: This gameplay change should affect a single player game (or multiplayer if all players have BCI) but the game must not depend on it so it is also attractive for people without BCI. It can potentiate some ability that is triggered with the conventional controllers.

Example: A spell is stronger or has an additional effect; a jump is higher; accuracy of a shot increases; running faster; slowing time

Discussion

Using this platform, it was possible to observe voluntary control over a specific EEG rhythm, the IAF band, and its increase with training. Also, in some cases, besides producing more EEG activity, the time required to produce this response also decreases although this effect is not stable and may depend on several unmeasured factors. Nevertheless, these values are centered in 6 seconds, a value that does not seem adequate for situations that require fast responses. Some projects have been using hardware like OCZ's NIA™ or Emotiv as additional remote controllers to interact with games that require precise or fast responses (for example, PONG or changing weapons with NIA™ or a recently funded Kickstarter project – "Throw Trucks With Your Mind!"). Moreover, these games tend to ignore existing controllers and leave all the effort for the BCI what can be very frustrating for someone who does not have the chance to train with proper feedback or simply, has difficulty in controlling his EEG. This, not only shortens the number of potential consumers of these interfaces but may even make them unpopular and undesired. In light of our results and our knowledge of EEG-Self regulation we can imagine BCI being used as promoted by Emotiv, to read ones emotions and translate them in the gamming environment or, to use this input as an additional experience. For example, while playing a game with a keyboard and mouse or a gamepad, the BCI (if successful) input can trigger some special effect of and ability called with the controller (ex: jump higher, stronger spell, more accuracy, etc…). This might not be so frustrating when not achieving, as the game is still playable, and can be immensely gratifying when achieved. This can be easily implemented in a game and, the game can still be enjoyable for gamers that do not possess a BCI device. As a first step for BCI in gaming, we believe this is a safe and very amusing one.

Acknowledgements

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