ANALYZING THE IMPACT OF MOTOR IMAGERY IN A BCI VIDEO GAME

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Abstract: This study presents the current concerns of Brain-Computer Interfaces in the context of current advances in signal preprocessing and monitoring and identification of brain activity and behavior in the context of motor imaging. It also aims to identify the possible involvement of mechanisms specific to motor execution as a form of control based on the simulation of motor function. In this paper we developed an algorithm to quantify the effects produced by the kinesthetic imagery of an upper limb as a mental training method used as input for a video game. We also propose the advanced technique used to preprocess EEG raw data recorded from three healthy subjects, followed by a power spectral density analysis to produce a graphical representation of the beta power spectrum.

Key words: BCI, EEG, PSD, motor imagery, MATLAB.

1. INTRODUCTION

EEG is an important part of BCI and serves as a basic methodology for acquiring and analyzing the activity of the brain to allow for direct interaction between the human cortex and external devices. Due to the non-invasive nature of EEG and its applications in different areas, such as cognitive enhancement, assistive technology, and rehabilitation, there has been a significant stir of interest in EEG-based BCI recently.

With uses far beyond its original medical focus, Brain-Computer Interfaces (BCIs) have actually become a fast-expanding area of study in recent years. These innovative systems are revolutionizing the way humans connect with technology and opening up new possibilities across various domains.

Brain-Computer Interfaces (BCIs) hold significant potential in the research, treatment, and forecasting of neurological disorders. They can identify distinct signal

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patterns associated with particular disorders, such as Parkinson's disease, to facilitate early identification and enhance diagnostic accuracy. In the treatment of Alzheimer's disease, BCIs have demonstrated potential in augmenting cognitive performance and enhancing memory through neural feedback mechanisms [1], [17], [21], [27]. For those who suffer from severe impairments, BCIs extend a tremendous deal of improvement in communication. These interventions are most valuable for patients suffering from diseases such cerebral stroke, amyotrophic lateral sclerosis, spinal column injury or who are totally paralyzed. For those unable to speak the goal of Brain-Computer Interface (BCI) technology is to facilitate communication by directly translating brain intent into executable commands [2], [18], [22].

BCIs have altered assistive technology, enabling inventive methods to improve accessibility for people with physical and neurological limitations. By enabling direct interaction between the human cortex and external equipment, BCIs allow users to control assistive tools through neural activity. Innovative applications encompass neural-controlled prostheses, speech-generating technological devices, and systems for smart homes adapted for accessibility [3], [19], [25].

Signal preprocessing is the major step toward improving the performance of BCI systems through the reduction of these aforementioned artifacts and enhancement of the signal quality. As research in this area keeps on expanding, BCI technology offers the potential to alter human-computer interaction and create new paths for medical applications and assistive technologies [4], [23], [26].

In the last years, Brain-Computer Interface technology, especially employing electroencephalography (EEG) signals for motor imagery (MI) activities, has been one of the important fields of investigation.

In the recent years, there has been increasing interest in BCI technology, especially in those based on motor imagery (MI) and electroencephalography (EEG). The eventual goal of this technology aims at improving direct communication between the cortex and external devices; hence it provides a wide range of applications for the assistive technologies and rehabilitation field.

Current research concentrates on the development of deeper signal processing techniques, studying innovative feature extraction methods, and applying more advanced classification algorithms in order to substantially enhance the efficiency and dependability of MI-based BCI systems [5], [20].

The electroencephalogram (EEG) is a critical tool in the monitoring of cerebral activity and behavior; however, the recorded signals usually contain artifacts that may critically affect the analytical outcome. The sources of these artifacts may be ocular movements, muscular activity, and electrical interference from external sources [6].

Electroencephalogram (EEG) plays a crucial function in recognizing brain activity and behavior. But the recording electrical activity is always affected with artifacts and then affects the analysis of EEG signals. So, it is vital to develop algorithms to properly recognize and collect the clean EEG data while encephalogram recordings. Several approaches have been presented to remove artifacts; however, the study on artifact removal seems to remain an open problem [7], [24].

Despite significant progress, there is still an open issue with the artifact elimination of the EEG signals. Researchers in that respect keep on developing new methods to improve both artifact detection and removal techniques' accuracy and effectiveness [8]. The major developments of the ongoing research in the field are creating automated, robust systems that should not only handle different artifact kinds but also preserve in essence the underlying brain-activity signals.

2. MOTOR IMAGERY AS A BCI SOLUTION

Motor-related brain activity plays a crucial role in association with motor imagery tasks as part of a significant paradigm in BCI research.

In this context, the paradigm of motor imagery is very important, considering that numerous studies have shown that both motor execution and motor imagery are closely related. A study shows that both motor imagining and the execution of walking actions engage overlapping motor-cognitive activations [9], particularly in beta and alpha strength variation patterns [9]. According to the Motor Simulation Theory, up to a certain point, the neural mechanisms behind motor imagery and motor execution are the same, at which point an inhibitory mechanism suppresses muscle activation and the resulting movement between overt action and plan encoding [10]. In theory, this presupposes that imagery practice has a form of control based on the simulation of motor function, which shows significant implications for motor learning and rehabilitation [11].

3. THE STUDY OF THE BETA WAVE

Electrical brain potentials can be captured by minimally invasive contact using headset-type EEG devices. Using this method, the waveforms and differentiated frequencies are measured while the brain activity of a region is associated with simultaneous electrical activity. Taking into account the localization of specific regions linked to motor imagery tasks, beta waves present a particular interest. Beta waves, which present oscillations in frequency between 13 - 30 Hz, are produced in the contralateral motor cortex but also in the somatosensory cortex [12], [13].

During concentration, beta wave activity is increased at the level of the frontal and occipital lobes and lower at the level of the temporal lobe [14].

The beta waves present a typical amplitude between 5 - 20 µV and a waveform as presented in Fig. 1.

Fig.1. Theta rhythm waveform [15]

4. PUSH MENTAL TASK - CASE STUDY

To implement the case study, we selected three healthy subjects who participated in a mental command training scenario used as a control input for a BCI video game developed by us previously. For the real-time measurement of brain waves, we used a neural headset equipped with 5 EEG channels with electrodes placed in the key points of the brain as shown in Fig. 2.

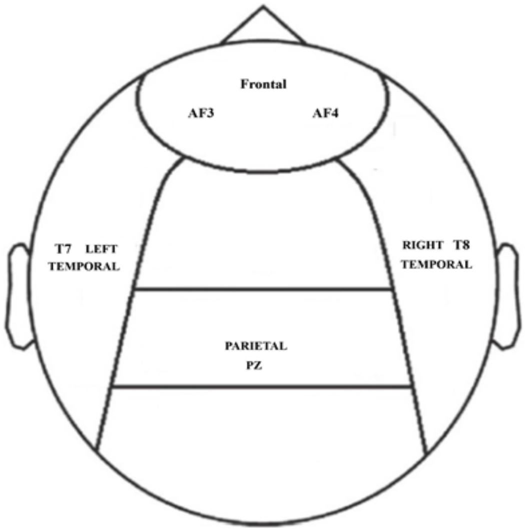

Fig. 2. Emotiv Insight headset - channel location

To train the mental task, each subject had to imagine a kinesthetic complex of arm movement that formed the push task in the time interval between the moment of pressing the training button of this command and the appearance of the pop-up window confirming the training. The mental training scenario is presented in Fig. 3.

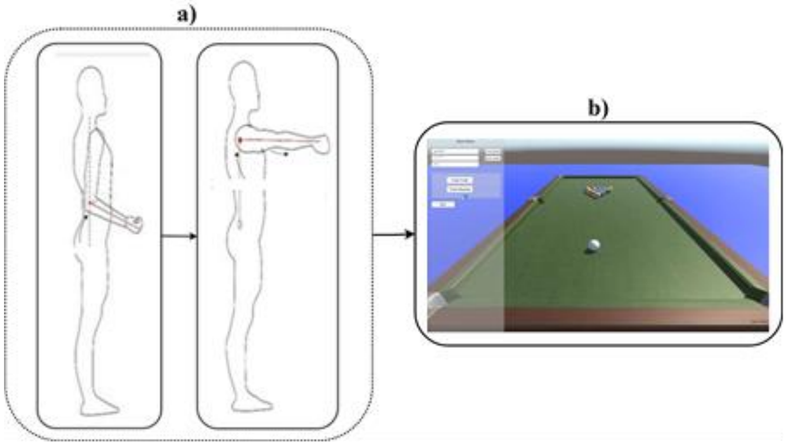

Fig.3. Train push mental task - Mental Pool Game [16]

As shown in Fig. 3. a), the kinesthetic movement complex is composed of a flexion movement of the elbow joint, followed by the same movement of the shoulder joint and an extension of the elbow joint. The interface of the chosen BCI game, made in Unity3D, on which each subject must focus for 9 seconds to memorize the trained mental command, is shown in Fig. 3 b).

5. EEG DATA ANALYSIS AND RESULTS

Each EEG dataset recorded through Emotiv Xavier TestBench software and saved in CSV format was analyzed in an algorithm developed by us, integrated in the MATLAB programming language, to determine the power spectral density distribution (PSD) of beta brainwave. The algorithm description is presented in Fig.4.

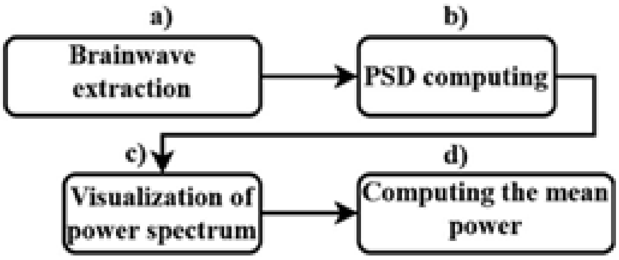

Fig.4. Determination of PSD in beta wave specter

The third step, presented in Fig. 4 c), aims to create a graphical representation of the beta power spectrum, representing the power in decibels (dB) reported to the beta rhythm frequency as a limiting point on the x-axis to the imposed frequency domain.

The fourth stage, illustrated in Fig. 4 d), calculates the average power in the beta frequency band (13 - 30 Hz) for each EEG channel by averaging the PSD values in this frequency range. The results obtained are stored in a table format included in a CSV file.

The results of beta power spectrum estimation (a) and mean power calculation (b) for subject S1 are shown in Fig. 5.

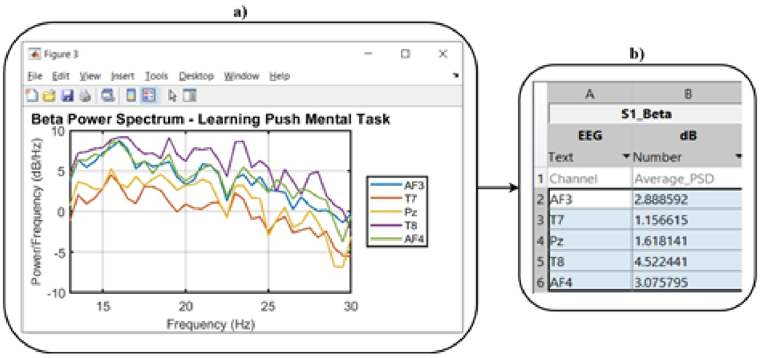

Fig.5. Result of PSD estimation for push mental task - S1 subject case

This result shows, in the case of subject S1, significant temporal asymmetry with stronger right temporal activation, while bilateral frontal activity and moderate parietal activity indicate the right-hemisphere dominance in complex upper limb movement imagery. The results obtained as a result of applying the same algorithm to the EEG dataset related to subject S2 are shown in Fig. 6.

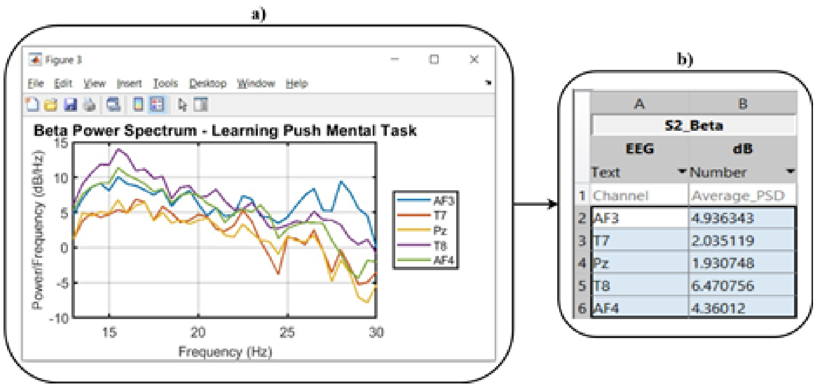

Fig.6. Result of PSD estimation for push mental task - S2 subject case

As the estimation results are presented in the case of subject S2, it can be said that this pattern shows overall higher activation levels compared to S1, particularly in the temporal and frontal regions, while maintaining a similar distribution pattern of right-hemisphere dominance.

The results of PSD estimation for the beta spectrum applied over the subject S3 dataset are presented in Fig. 7.

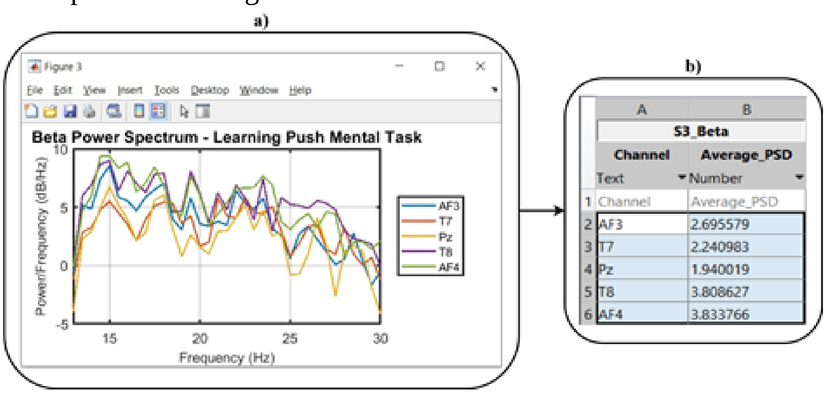

Fig.7. Result of PSD estimation for push mental task - S3 subject case

The beta power distribution during the mental push task for S3 shows moderate temporal asymmetry with slightly higher right temporal activation, while bilateral frontal activity and lower parietal activity demonstrate a more balanced activation pattern, suggesting less pronounced right-hemisphere dominance in complex upper limb movement imagery compared to S1 and S2.

6. CONCLUSIONS

The study of the activation of brain patterns on five EEG channels positioned in key regions of the brain through the prism of signal processing, filtering in the field of beta waves, power spectrum analysis, but also PSD calculation confirming the reliability of this approach in detecting the motor intention.

Also, the application of a training strategy based on kinesthetic motor imagery can prove effective, as evidenced by the consistent beta power distribution patterns across subjects. The neural mechanisms specific to complex motor planning and execution simulation were observed from the temporal asymmetry in conjunction with bilateral frontal activation and consistent parietal engagement.

Next, we propose to extend the study also to the intentional action of the learned mental command to discover if comparable mental models are involved.

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