ORIGINAL ARTICLE

Investigating the Effect of Stimulus Type on Electroencephalogram Signal in a Brain-Computer Interface System with Interaction Error

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Abstract

Purpose: Brain-Computer Interface (BCI) systems are a new channel of communication between human thoughts and machines without the aid of neuromuscular systems. Although BCI systems exhibit several advantages, they yet have a long road ahead to reach a flawless state. For example, error occurrence is one of the problems in these systems, leading to Error-Related Potentials (ErRP) in the brain signal. In this study, Electroencephalogram (EEG) signals in the condition of system error occurrence are investigated. Since local information on the EEG signal channels alone cannot reveal the secrets of the brain, functional connectivity was used as a feature in this research.

Materials and Methods: In this research, 32 channel EEG signals with a sampling frequency of 256 Hz were recorded from 18 participants while interacting with a BCI system which has an interaction error. Two types of stimulus were used, including visual and tactile ones. Moreover, the Inter-Stimulus-Interval (ISI) was changed during the task. After pre-processing, brain functional connectivity was calculated between all channel pairs in four groups (visual, tactile, combined visual-tactile (ISI=3.5), and combined visual-tactile (ISI=2)) using Magnitude-Squared Coherence (MSC) measure.

Results: The results showed a significant difference in frontal-right temporal connectivity between correct and error classes in tactile stimulation, in visual stimulation significant differences in frontal-occipital connectivity, in visual-tactile (ISI=3.5) stimulation significant differences in left temporal-occipital connectivity (P-value< 0.001), and in visual-tactile (ISI=2) stimulation significant differences in central-occipital connectivity were seen (P-value< 0.01).

Conclusion: This study shows that using brain functional connectivity features along with local features can improve the performance of BCI systems.

Keywords: Electroencephalogram; Brain-Computer Interface; Error-Related Potentials; Brain Functional Connectivity; Statistical Analysis.

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1. Introduction

The Brain-computer Interface (BCI) system is regarded as a connective bridge between human thoughts and computers [1, 2]. Electroencephalogram (EEG) signals are commonly used in BCI systems, due to their high temporal resolution, simple accessibility and low cost [3]. EEG electrodes are mounted on the surface of the participant's head and the electrical activity of the neurons is recorded. Subsequently, the signal processing is carried out to identify the participant's command. Today, EEG-based BCI systems can be categorized in three main paradigms, including Event-Related Potentials (ERPs)-based BCI, Steady-State Visually Evoked Potential (SSVEP)-based BCI, and Motor Imagery (MI)-based BCI systems [4]. In Motor Imagery-based BCI Systems (MI-BCI), the participant has to imagine a movement of his\her body limb in a specific direction and then in the BCI system, depending on the type of motor imagery, a specific command will be executed. This command can cover a wide range of tasks such as moving a robotic arm, controlling a wheelchair, moving a computer mouse pointer, and moving a prosthetic limb attached to a disabled person [5, 6].

Although a lot of brain information can be obtained via local brain analysis, this information alone cannot reveal all the secrets of the brain. Thus, in addition to exploring functional segregation (activation of specific brain areas or local brain regions), functional integration (Coordinated activation of a large number of neural assemblies in various regions of the cerebral cortex on a large scale) must also be considered [7].

In 2009, Grosse-Wentrup used brain connectivity to investigate signal transmission across the skull during the left-hand and right-hand motor imagery. Observed connectivity patterns show that functional connectivity during MI in the gamma band (above 35 Hz) is the strongest brain connectivity in all frequency bands. In addition, there was a significant difference in brain connectivity between MI and rest (p-value <0.01). However, there was no significant statistical difference between functional connectivity during MI in the right-hand and left-hand groups [8]. In [9], it was found that functional connectivity correlates with MI-based BCI learning. According to their findings, there was a significant and positive relationship between regional connectivity and learning rate (p-value <0.035).

In many BCI systems, EEG signal power changes in different frequency bands (Band-Power) are used to detect differences between various motor imagery patterns. Martin Blinger *et al*. proposed a method to derive single-trial connectivity from Vector Autoregressive (VAR) models of EEG independent components in a BCI system. Based on their findings, it has been shown that full-frequency normalized Directed Transfer Function (DTF) and direct DTF give classification results comparable to Band-Power, whereas other methods, such as partial directed coherence, work significantly weaker [10].

One major problem in BCI systems is the erroneous functionality of the system, user, or operator, which can cause the whole system to malfunction. If the user is concentrated on the outcome of an action and the outcome is contradictory to one's expectations, a cognitive state of error occurs in the brain that produces an error-related potential. In general, the error potentials are divided into four groups according to their cause, including response error-related potential, feedback error-related potential, observation error-related potential, and interaction error-related potential [3]; the latter is the main focus of this research. If an error occurs in the system function in an interactive task, the resulting error is called an interactive error.

Ahkami *et al.* [11,12] investigated the effect of variation in the intervals of the stimulation presentation on error-related potentials (ErRPs). To demonstrate the error potential, a BCI-based protocol was used to get the right and left commands and act in the opposite direction 30% of the time to show the error potential. To this end, the participant was asked to move the red rectangle to the green one by imagining the left-hand movement, or right-foot movement, which triggered the move toward the left and right directions, respectively. Considering that the user always imagines the movement correctly, 30% of the commands were executed with errors. In this study, two types of stimuli, such as visual and tactile, were used in the BCI system. Then, the effect of change in the intervals between stimuli presentation was investigated. According the results of to this study, the components related to tactile stimulation occurred significantly (p-value <0.05) later than the components related to visual stimulation. Moreover, by increasing the distance between stimulus presentations, the individual's response to error was somewhat faster. Furthermore, by performing independent component analysis and source localization, activity in the Anterior Cingulate Cortex

(ACC) region was detected in the brain of individuals when observing an error [13]. This region had been previously founded as an error processing center in other studies [14, 15], although there is still controversy about the exact role of the ACC.

Zhang *et al.* first introduced brain connectivity features to detect error-related signals in a BCI system. 16 subjects participated in this study to record the signal while observing the moving stimulus in both directions for correct or error. Then, the combination of waveform features and brain connectivity features was extracted from FCz, Cz, Cpz, Fz channel signals. Moreover, the brain connectivity and waveform features have been extracted. Linear Discriminant Analysis (LDA) classification was then used to identify the correct experiments and the error ones. Based on their results, the combined features lead to the highest classification accuracy (85%). The results also showed that brain connectivity within the theta band (7-9 Hz) contains more information for distinguishing error than other frequency bands. Zhang *et al.* provided evidence that using brain connectivity features detection improves BCI systems' performance [16]. The relationships between dorsal Anterior Cingulate Cortex (dACC) functional connectivity and Error-Related Negativity (ERN) amplitude were investigated in [17]. Their findings imply that the level of dACC seeded functional connectivity with the supplementary motor region is associated with the ΔERN (incorrect – correct responses) amplitude, with higher ΔERN amplitude characterized by more functional connectivity between these regions. In addition to the dACC, additional analysis revealed that functional connectivity in the caudate, cerebellum, and a variety of areas in the error-monitoring network was associated with variation in ΔERN amplitude. In this research brain functional connectivity during a BCI task with 30% of interaction error is investigated. In order to study the effects of stimulus type and Inter-Stimulus-Interval (ISI), the stimuli are presented to the participants in four groups of visual, tactile, visual-tactile with ISI=3.5, and visual-tactile with ISI=2.

2. Materials and Methods

The block diagram of this research approach is presented schematically in Figure 1. The methodology followed in this work can be generally divided into three main steps of preprocessing, brain functional connectivity calculation by Magnitude-Squared Coherence (MSC) measure, and the statistical analysis. The details of these steps are studied in this section.

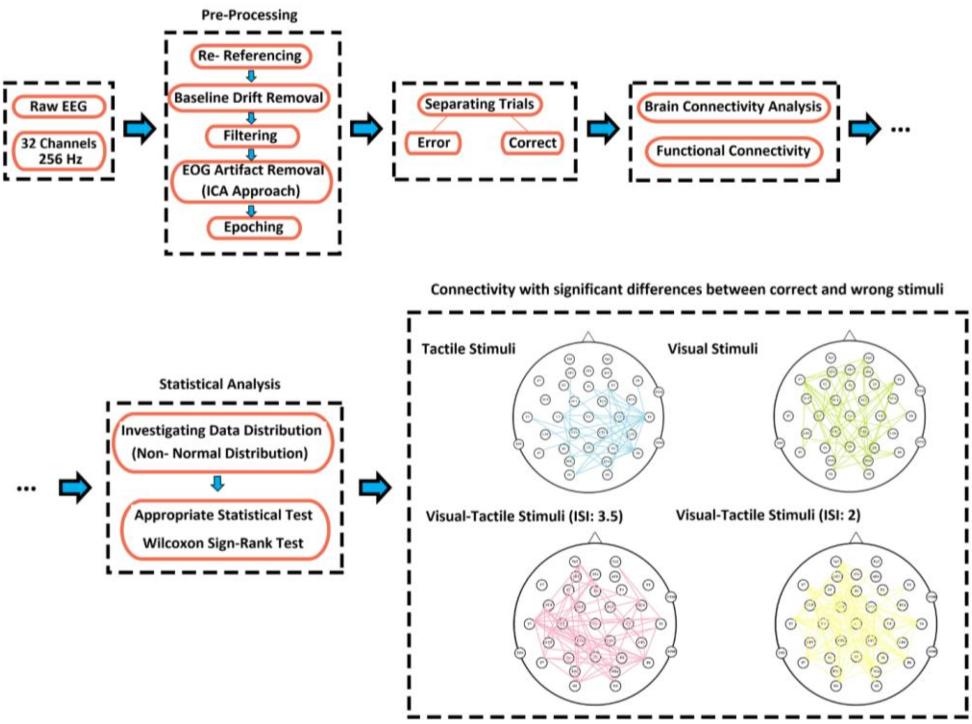


Figure 1. The block diagram of this research's methodology

2.1. Dataset

The dataset used in this research is supplied from [11, 12]. 32-Channel EEG signals with a sampling frequency of 256 Hz were recorded from 18 healthy participants. The participants were in the age range of 24 to 25 years old. The BCI task was with an interaction error (System does not respond as expected) 30% of the time. During the task, there were two rectangles (red and green) on the screen with one step distance and the participants were asked to move the red rectangle toward the green one by imagining a movement in the intended direction (whether right-leg motor imagery if the green rectangle is on the right side of the red one or left-hand motor imagery for the counter wise condition). Assuming that the user does his/her work without any error, the system moves the red rectangle in the opposite direction from the green one 30% of the time, leading to the system's interaction error. In this study, the participants are informed of the final direction of the red rectangle via three types of stimulation: 1) visual: rectangle motion on the screen; 2) tactile: vibration on his/her wrists via vibrators affixed on them; and 3) dual stimulation mixed with these two stimuli.

In some researches, the effect of attention on EEG signals has been studied especially in Attention Deficit Hyperactivity Disorder (ADHD) individuals [18, 19]. It has been shown that one of the issues that must be taken into account during data recording is the participants' "attention" during the experiment. In 10 experimental recordings, all participants reported that more than 5 seconds were too much for motor imagery, causing fatigue and inattention. People also reported that they could work with the system for about 45 minutes, after which it would cause fatigue and inattention. According to these results, two values of ISI (tISI1) and (tISI2) were selected for this study. The details of the stimuli are provided in the following:

Visual stimulation: In each test with this kind of stimulation, after presenting the rectangles on the screen, the individual is given time, tISI1, for his/her motor imagery. Afterward, the red rectangle moves along the target direction. No vibration is applied to the vibrators in this stimulation. The trial is completed in 1.2 seconds.

Tactile stimulation: In each test with this kind of stimulation, after presenting the rectangles on the screen, the individual is given time, tISI1, for his/her motor imagery. The direction, which the rectangle is supposed to move to, will be conveyed to the participant via a vibration feedback system, although no movement will be seen on the screen. After 1.2 seconds, a message which indicates whether the movement was correct or incorrect is shown to the user.

Dual stimulation: In each test with this kind of stimulation, after the displaying of the rectangles on the screen, the individual is given time, tISI1or tISI2 for his/her motor imagery. The direction, which the rectangle is supposed to move to, will be conveyed to the participant via a vibration feedback system, although no movement will be seen on the screen. After 1.2 seconds, the red rectangle moves toward the desired direction (to apply the visual stimulus as well as tactile one).

2.2. Magnitude Squared Coherence

In this research, MSC was used as a criterion of brain functional connectivity. MSC is a type of criterion that uses a linear model to estimate a signal with a real or complex value from another signal that has a real or complex value. The MSC is defined between the two signals x(t) and y(t), which is shown in Equation 1.

$$C_{xy}(f) = \frac{|G_{xy}(f)|^2}{G_{xx}(f)G_{yy}(f)} \tag{1}$$

Where $G_{xy}(f)$ is the cross-spectral density and $G_{xx}(f)$ and $G_{yy}(f)$ are the auto spectral density. The values measured using MSC are the real numbers ranging from 0 to 1 at each frequency. If the MSC for all frequencies is 0, the two signals are not linearly dependent. If MSC is 1 for all frequencies, it means that these two signals are linearly dependent [20].

2.3. Statistical Analysis

Statistical analysis is used to interpret and analyze the findings of this study.

2.3.1. Normality of Data Distribution

The data distribution was first evaluated using the Kolmogorov-Smirnov test to select the appropriate statistical test. Due to the non-normal distribution of data in any group, a non-parametric Wilcoxon test was considered for further analysis.

2.3.2. The Wilcoxon Signed-Rank Test

The Wilcoxon signed-rank test is a non-parametric statistical test. The Wilcoxon Signed-Rank Test is used to examine two dependent samples or to match two samples. In this study, comparisons of brain connectivity were conducted in four groups as follows.

1. Tactile stimulation (when the direction of the movement was correct) with tactile stimulation (when the direction of the movement was wrong).

2. Visual stimulation (when the direction of the movement was correct) with visual stimulation (when the direction of the movement was wrong).

3. Visual-tactile stimulation (when the direction of the movement was correct) with visual-tactile stimulation (when the direction of the movement was wrong) when ISI is 3.5.

4. Visual-tactile stimulation (when the direction of the movement was correct) with visual-tactile stimulation (when the direction of the movement was wrong) when ISI is 2.

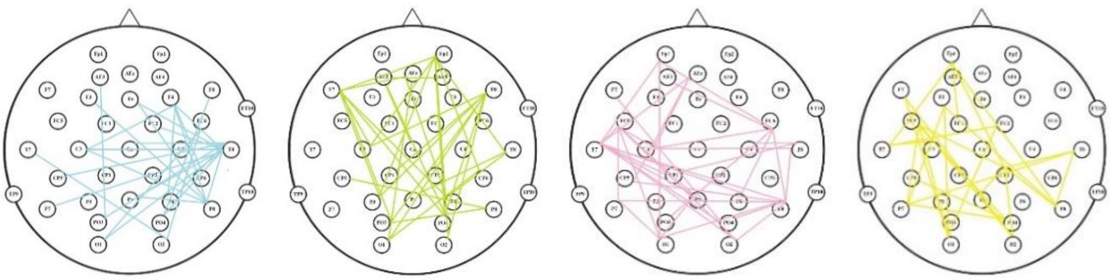
3. Results

EEG signals were segmented according to correct and error cases in all four stimulus conditions (visual, tactile, and visual-tactile (ISI=3.5), and visual-tactile (ISI=2). Then the brain connectivity for visual, tactile, visual-tactile (ISI=3.5), and visual-tactile (ISI=2) conditions was calculated for all possible channel pairs of 18 participants, and compared in both correct and error cases. Since a large number of brain connectivity between channel pairs was significantly different in the statistical analysis, its representation on the head may lead to a fully connected graph without much useful information. So just the strongest (top ten percent) connectivity was considered in this research. Some considerable results are as follows:

In tactile stimulation, the brain connectivity of 26 pairs of electrodes between correct and error cases is significantly different (p-value < 0.001). As shown in Figure 2 part A, the frontal-right temporal brain connectivity showed the most significant differences (accounting for 23.07% of all brain connectivity). Moreover, a bar graph of error and correct groups connectivity median in the condition of tactile stimulation is shown in Figure 3 part A.

In visual stimulation, the brain connectivity of 30 pairs of electrodes between correct and error cases is significantly different (P-Value< 0.001). As shown in Figure 2 part B, the frontal-occipital brain connectivity showed the most significant differences (accounting for 33.33% of all brain connectivity). Moreover, a bar graph of error and correct groups connectivity median in the condition of tactile stimulation is shown in Figure 3 part B.

In visual-tactile (ISI= 3.5) stimulation, the brain connectivity of 35 pairs of electrodes between correct and error cases is significantly different (P-Value< 0.001). As shown in Figure 2 part C, the brain connectivity of an occipital-left temporal showed the most significant differences (accounting for 11.42% of all brain connectivity). Moreover, a bar graph of error and correct groups connectivity median in the condition of tactile stimulation is shown in Figure 3 part C. In visual-tactile (ISI=2) stimulation, the brain connectivity of 25 pairs of electrodes between correct and error cases is significantly different (P-Value< 0.01). As shown in Figure 2 part D, the central-occipital the brain connectivity showed the most significant differences (accounting for 16% of all brain connectivity). Moreover, a bar graph of error and correct groups connectivity median in the condition of tactile stimulation is shown in Figure 3 part D.



A B C D

Figure 2. The significantly different brain connectivity between two groups of (A) tactile stimulation- correct case and tactile stimulation- error case; (B) visual stimulation- correct case and visual stimulation- error case; (C) visual-tactile (ISI=3.5) stimulation- correct case and visual-tactile (ISI=3.5) stimulation- error case; and (D) visual-tactile (ISI=2) stimulation-correct case and visual-tactile (ISI=2) stimulation- error case

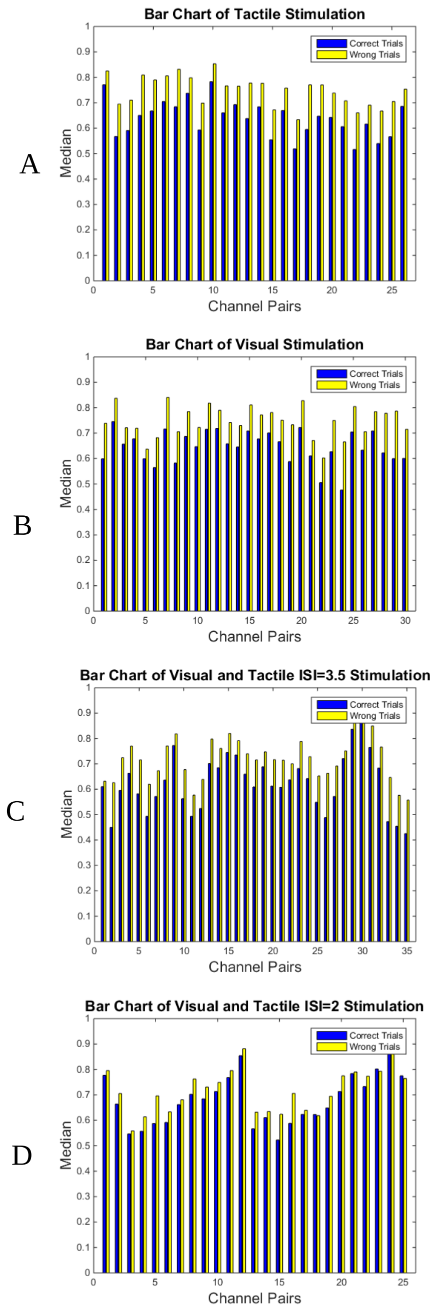


Figure 3. The median comparison between two groups of error and correct trials in (A) tactile stimulation, (B) visual stimulation, (C) visual-tactile (ISI=3.5 stimulation, and (D) visual-tactile (ISI=2) stimulation)

4. Conclusion

In this research, during a BCI task with interaction error, the brain functional connectivity was studied. To this end, the dataset related to a motor MI-BCI was used [11, 12]. Brain connectivity based on MS-Coherence in two conditions was investigated; the first was when there was an error in the system (error case) and the second was when there was no error in the system (correct case). Subsequently, the existence of significant differences in these two cases was investigated using appropriate statistical tests. After detecting the non-normal distribution of the data, the Wilcoxon signed-rank test was used for statistical analysis of MS-Coherence between error and correct classes in the four groups (visual, tactile, tactile-visual (ISI= 3.5), and tactile-visual (ISI = 2).

Based on the results of this research, in tactile stimulation, there is a significant difference between correct and error classes in frontal-right-temporal connectivity, and also in visual-tactile (ISI= 3.5) stimulation, there is a significant difference between left-temporal with occipital regions and it is in line with the previous study because of involving the temporal lobe [13, 17, 20-23]. Previous studies have shown that the visual cortex is located in occipital regions and this part of the brain is mostly activated in response to a visual stimulus [24]. In the visual stimulation of the current research, the most significant differences were seen in frontal-occipital connectivity. Also in visual-tactile (ISI=2) stimulation, there is a significant difference between central with occipital regions, which is in line with the effect of visual stimulation [23 -25]. In visual, tactile and visual-tactile (ISI=2) activated frontal and central regions of the brain and this was in line with the previous study because of error-related potentials, [13, 23, 25]. This study showed that examining functional integration, in addition to examining functional segregation, could help improve brain-computer interface systems.

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