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Analysis of Inter-Subject and Session Variability using Brain Topographic Map

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Abstract - The study described investigates the application of Brain-Computer Interface (BCI) technology, focusing on Motor Imagery (MI) signals which enable individuals to control movements through mental visualization. A major challenge in this field is accurately distinguishing between different movements, particularly when dealing with data from multiple subjects and recording sessions, known as inter-subject and inter-session variability. To address this, the authors employ the Wavelet Packet Transform-Common Spatial Patterns (WPT-CSP) method to enhance the resolution of MI signals. They visualize the results using Brain Topographic Maps (Topomaps) to depict brain activity during MI tasks, facilitating the analysis of variability across subjects and sessions. Utilizing dataset 2a from the Brain-Computer Interface Competition (BCIC) IV, the study demonstrates the efficacy of this approach in identifying variability patterns. This research holds promise for improving BCI technology applications in various domains, and future work could explore refining signal processing techniques and validation on larger datasets. Topomap.

Keywords – BCI, Inter-subject variability, Inter-session variability, Topomap

1. INTRODUCTION

The brain is one of the most important organs in the human body. This organ has the main purpose to control the body to maintaining its survival ability, regulating body functions, and enabling humans to interact with the environment and carry out various activities. One type of technological development utilizing the brain is in the form of a Brain Computer Interface (BCI). BCI can be applied in various fields such as control of bionic arms [1], development of electrical stimulation therapy and medical rehabilitation processes [2], wheelchair control system[3], cursor control and PC applications control [4], means of communication for people with disabilities [5], as well as cognitive augmentation to improve human performance [6].

Besides all of benefits and possibility that it offered, there are also obstacles that need to be overcome in the development of BCI. These obstacles especially in the form of the low accuracy result of brain signals classification. This result could be due to the low signal-to-noise ratio (SNR) value of the EEG signal [7] and low spatial resolution [8]. Numerous algorithms have been suggested to tackle this issue, with spatial filtering being the most commonly used [9]. Among these, Common Spatial Patterns (CSP) is notable for its strong performance and effectiveness in the BCI realm. Various studies have endeavored to enhance CSP, such as employing Feature Weighting and Regularization (FWR) techniques. This approach aims to utilize all CSP features to prevent data loss and avoid overfitting, thus improving its efficacy [8]. Furthermore, another study introduced Temporally Constrained Sparse Group Spatial Patterns to address challenges associated with using multiple frequency bands and time windows for different subjects. This method aims to overcome individual variability in responsiveness to information stimuli, thereby enhancing CSP's adaptability and robustness across subjects [10].

Another study is to utilize the Wavelet Packet Transform (WPT) to decompose signals into more detailed frequency bands, so that the information used remains intact [11]. But the results from all thus studies still have relatively low accuracy and uneven between all of the subjects. These results are possible due to the phenomena of inter-subject and inter-session variability when the MI signal datasets that have been used originating from many subjects and at different recording times.

Based on this phenomenon, the authors conducted a study to investigate and analyze the results of the WPT-CSP method which were illustrated in the form of Brain Topographic Map (Topomap). The resulting Topomap will be compared between different subjects, and on the same subject but at different recording times.

(a)

(b)

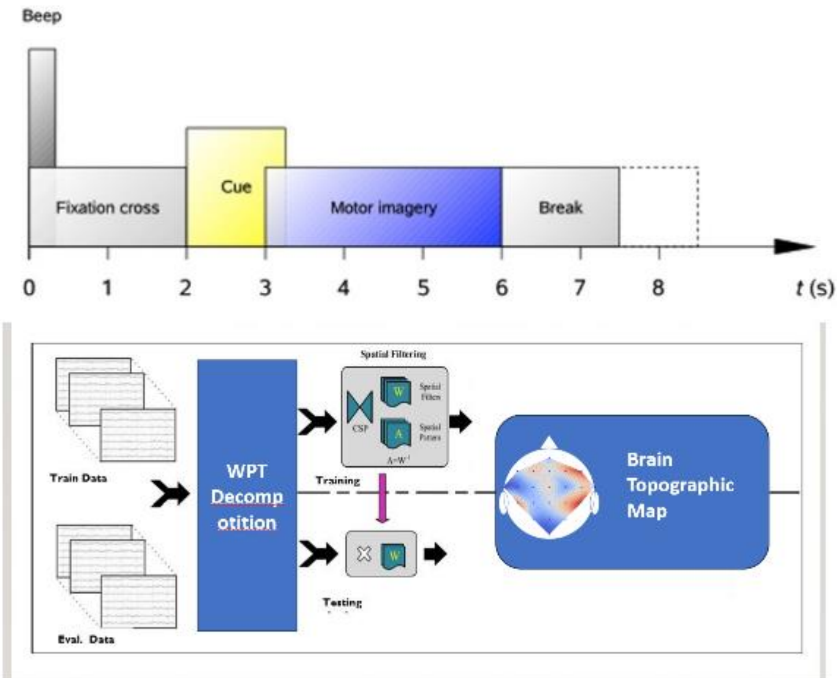


Figure 1. (a) Illustration of recording time for the BCI IV Competition dataset 2a, (b) Diagram of the research algorithm conducted.

2. RESEARCH METHOD

The research conducted was experimental research and was analyzed using qualitative methods.

2.1. Datasets Descriptions

To explore the variability among subjects and sessions, researchers employed dataset 2a from the Brain Computer Interface Competition IV (BCIC IV) [12]. This dataset consisted of EEG recordings from 9 individuals, representing inter-subject variability, as they engaged in Motor Imagery (MI) tasks involving movements of the left hand (class 1), right hand (class 2), feet (class 3), and tongue (class 4). EEG recordings were conducted using 22 electrodes following the 10-20 system, with a sampling rate of 250 Hz. The recordings were separated into two sessions:

session 1 for training data and session 2 for evaluation data, carried out on different days to introduce inter-session variability. The datasets were sourced from GitHub and processed at Kadiri University's Electromedical Engineering Department laboratory. Figure. 1(a) illustrates the timeline of the recording paradigm, with an average data retrieval duration of 8 seconds. Figure. 1(b) outlines the study's methodology, which entails data decomposition via Wavelet Packet Transform (WPT), followed by spatial filtering using Common Spatial Patterns (CSP), and concluding with the visualization of WPT-CSP results on Brain Topographic Maps.

2.2. Brain Topographic Map

A Brain Topographic Map is a visual depiction that showcases the spatial arrangement of brain activity, indicating the relative intensities of neural activity across distinct regions of the brain's surface. Generated from data sourced through methodologies like EEG (Electroencephalography) or MEG (Magnetoencephalography), these maps serve diverse purposes in neuroimaging research, clinical assessments, and applications in Brain-Computer Interface (BCI) technology [12]. By portraying patterns of brain activity linked to cognitive functions, sensory inputs, or motor activities, Brain Topographic Maps offer significant insights into the functional organization and connectivity of the brain.

Brain Topographic Maps offer a means to explore Inter-Subject and Session Variability. These maps visually depict the distribution of brain activity across space, enabling researchers to compare activity patterns among subjects and recording sessions. By analyzing these maps generated from EEG or MEG data, researchers can observe and study variations in brain activity across individuals and different sessions. This facilitates the investigation of how factors such as individual differences and session conditions impact neural activity patterns, thereby enhancing our understanding of brain function and variability.

Advantages of Brain Topographic Maps include:

- Visual Representation: They offer a clear and intuitive visualization of brain activity, making complex neural data easier to understand and interpret.
- Spatial Information: Brain Topographic Maps provide spatial information about where brain activity is occurring, allowing researchers to identify specific regions involved in various cognitive processes or responses to stimuli.
- Comparative Analysis: They enable researchers to compare brain activity across different experimental conditions, subjects, or time points, facilitating the identification of patterns and differences.
- Diagnostic Aid: In clinical settings, Brain Topographic Maps can aid in the diagnosis and monitoring of neurological conditions by revealing abnormal activity patterns or identifying areas of dysfunction.
- Research Tool: They serve as a valuable tool for studying brain function and connectivity in both healthy and diseased states, contributing to advancements in neuroscience research.
- Integration with BCI: Brain Topographic Maps are utilized in Brain-Computer Interface (BCI) applications to decode neural signals and facilitate communication or control of external devices.

Overall, Brain Topographic Maps provide a versatile and informative means of exploring brain activity and function, with applications spanning research, clinical diagnostics, and neurotechnology.

2.3. Research Procedure

Suppose that the MI-EEG signal model:

$$x_i^j(t) = [x_1^1(t), x_2^2(t), \dots, x_n^m(t)] \in R^{N\times n\times m} \tag{1}$$

Where N represents the total number of sample points, n denotes the number of EEG leads, m is the number of sampling points, and $x_i^j(t)$ (j sampling point of lead i) represents the MI-EEG signal. The MI-EEG signal undergoes further processing using the following algorithm:

- Step 1: The signal is decomposed using the Wavelet Packet Transform (WPT) based on the rbio 2.2 wavelet basis. This choice of wavelet basis was made because it yields optimal feature extraction results for MI-EEG [13].
- Step 2: Common Spatial Patterns (CSP) are applied to identify a spatial filter that corresponds to the data obtained in step 1. CSP begins by seeking covariance samples under the assumption of a single trial, resulting in the derivation of the average covariance matrix as follows:

$$C_y = \frac{1}{n_y}\sum\frac{E_j(y)E_j^T(y)}{trace\left(E_j(y)E_j^T(y)\right)} \tag{2}$$

C_y denotes the average of the covariance matrix, E_j represents the input data, ny indicates the number of experiments for each class, and y signifies the total number of classes. The next step involves seeking a partial filter with the goal of maximizing the variance of class 1 (C1) while minimizing the variance of class 2 (C2), as described below:

$$\max J(w) = \frac{w^T C_1 w}{w^T(C_1+C_2)w} \tag{3}$$

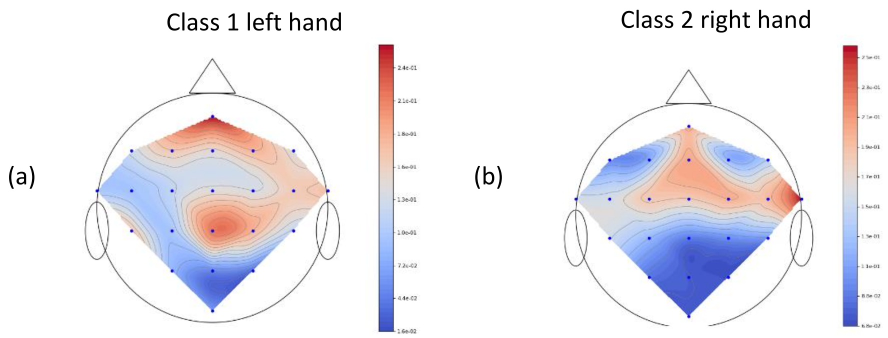
Following that, the data is condensed into a single value for each channel and projected onto the following equation:

$$A = WX \tag{4}$$

In this context, A represents a Spatial Pattern derived by projecting data, represented as an X matrix, onto the Spatial Filter W. Given the multi-class nature of cases like dataset 2a, a modification of CSP is necessary. Thus, the Joint Approximate Diagonalization (JAD) strategy is employed. JAD diagonalizes multiple covariance matrices based on the number of labels or classes provided, akin to the principles underlying Independent Component Analysis (ICA) [14].

- Step 3 involves visualizing the outcomes of the WPT-CSP process through a Brain Topographic Map (Topomap).

Topomaps are visual representations of activity on the surface of the brain (cortex). This representation shows the spatial distribution of neuronal activity in a given region [15].



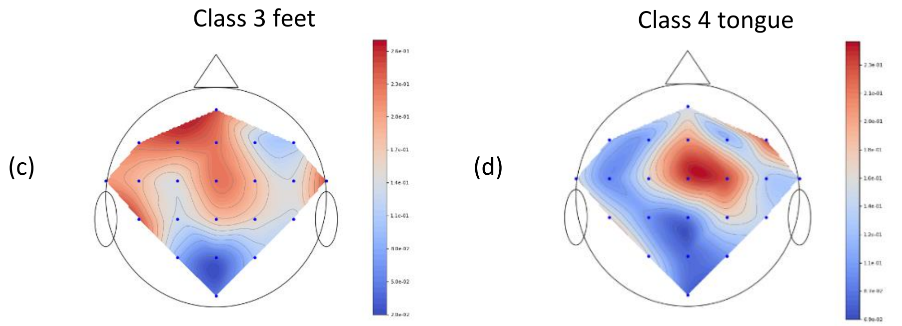


Figure 2. Topo Map illustration for: (a) class 1, (b) class 2, (c) class 3, and (d) class 4

3. RESULTS AND DISCUSSION

Figure 2 shows the results of the topographic map from the MI-EEG signal feature extraction using the WPT-CSP method. This method begins with the signal decomposition process using the Wavelet Packet Transform (WPT) method which is used to obtain all the information contained in the decomposed frequency bands. WPT will decompose data on each EEG channel into the 4 levels stages. This process was executed to produce feature information that covering all high and low frequency bands. This makes the WPT able to provide more information compared to the Discrete Wavelet Transform (DWT) [16]. The next step is to find a spatial filter using CSP for the decomposed data as its input. The spatial filter obtained in this process then used to project the MI EEG dataset into Spatial Pattern data. The Spatial Pattern data has dimensions (x,y), where x is the number of the CSP projection, and y is the sample length of the projected data.

The projected data can then be illustrated in the form of a Brain Topographic Map (Topomap) to show brain activity in certain parts of the brain. The more contrast the color differences, the better and easier to recognize the CSP pattern produced [17]. Figure 2 also shows the differences in brain activity during different MI-tasks. The dots on the Topomap represent the placement of the electrodes (channels) from the EEG. If the color value around that point is getting higher (dark red in color) then the area shows high Event Related Synchronization (ERS) activity whereas if the color value is lower (dark blue in color) then it shows high Event Related Desynchronization (ERD) activity [18].

The results of the study using the WPT-CSP CNN method [11] show less optimal classification results which may be due to the inter-subject variability and inter-session variability phenomena [19]. These phenomena caused the emergence of more complicated parameters that have to be trained using CNN. This results in very low kappa values for some subjects. The inter-session variability phenomenon can be caused by the large burden on the brain. This burden is due to the long MI-EEG recording process which results in changes of the subject's mental state over time [20]. Meanwhile, the inter-subject variability phenomenon can be caused by differences in neural connectivity between subjects (morphology and physiology aspects), or special conditions that cause difficulties for some subjects to perform BCI effectively [19]. These two phenomena can be observed more easily by observing the results of the Brain Topographic Map (Topomap) in Figure 3.

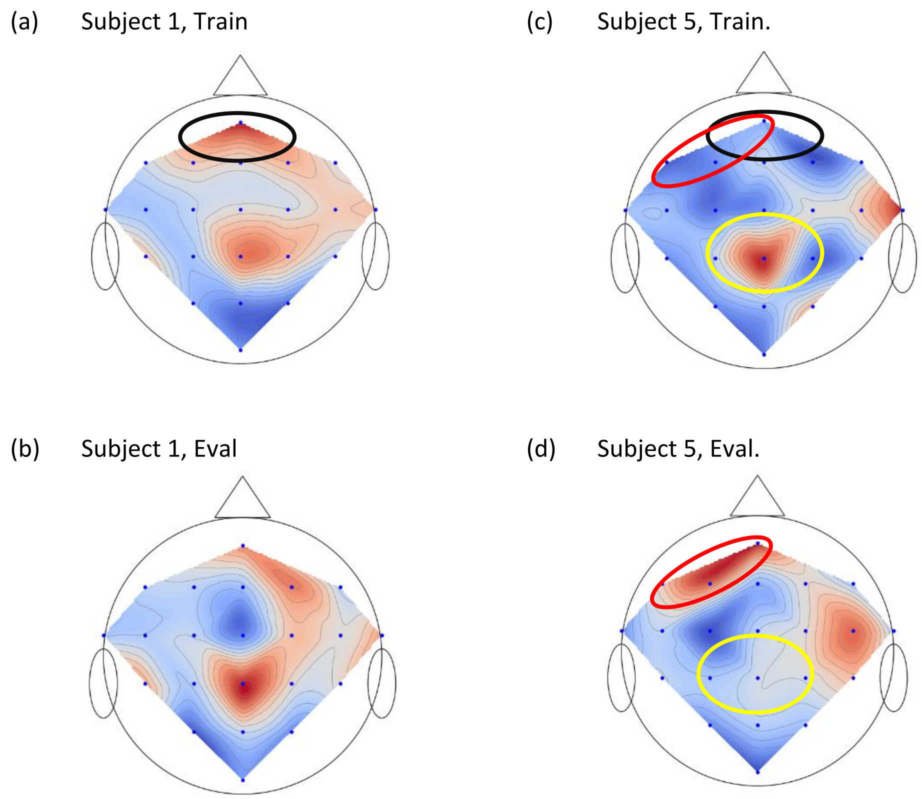


Figure 3. Brain Topographic Map for all subjects in: (a, c) train session and (b, d) eval session

Figure 3. is an illustration of the CSP projection in the form of a Brain Topographic Map (Topomap) with the MI-EEG task type for class 1 (left hand). Where the Figure 3.a. is a Topomap for subject 1 in session 1 (train session), the Figure 3.b. is a Topomap for subject 1 in session 2 (eval session), the Figure 3.c. is a Topomap for subject 5 in session 1, and the Figure 3.d. is a Topomap for subject 5 in session 2. An example of the inter-session variability phenomenon can be observed in the Topomap results from subject 5 (Figure 3.c. and 3.d.). These two Figure show the difference in some of the cortex region that marked by red circles. In sessions 1 (Figure 3.c.) shows higher ERS activity while in session 2 (Figure 3.d.) showed higher ERD activity. The difference between the two Figure can also be seen in the section marked with a yellow circle, where session 1 shows high ERD activity while session 2 shows high ERS activity, even though the type of task performed is the same and on the same subject.

Topomap results in Figure 3. section (a, c) showed the Topomap of Subject 1, meanwhile section (b, d) showed the Topomap of Subject 2. In these two sections, one can see the differences in the CSP patterns produced between subjects. These differences are due to the influence of the inter-subject variability phenomenon. The differences can be observed in the Figure 3.a. and 3.c. that was marked with a black circle, where high ERS activity occurs in the frontal part of subject 1, whereas subject 5 actually showed high ERD activity on the frontal side even though the recording was done in the same session and with the same type of class. These inter-subject and inter-session variability phenomena are most likely influence the classification results on several subjects. Based on these results, it is necessary to develop further methods to be able to overcome these obstacles in the future.

4. CONCLUSION

This study resulted in the following conclusions:

1. The inter-subject and inter-session variability phenomena can be observed in the 2a BCIC IV dataset using the WPT-CSP feature extraction method and illustrated using the Brain Topographic Map (Topomap).
2. The inter-subject variability phenomenon is shown by Topomap of subject 1 and subject 5 marked with black circles, where different event related activities occur on the frontal region of brain even though the recording was carried out in the same session and with the same type of class.
3. The inter-session variability phenomenon is shown by Topomap of subject 5 in two different sessions marked with red and yellow circles, where different event related activities occur even though the recording was carried out on the same subject and with the same type of class.

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