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Analysis of The Inter-subject and Inter-session Variability Phenomena Effect on the MI-EEG Datasets using The Brain Topographic Map

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ABSTRACT

Keywords
BCI
Spatial filter
Inter-subject variability
Inter-session variability
Topomap

The development of existing diagnostic technology has resulted in the developing the Brain Computer Interface (BCI). BCI is expected to connect the human nervous system with the outside world to provide more efficient communication and control in human body. Motor Imagery (MI) is the type of brain signal that commonly used in BCI practice. MI allows us to be able to control the movement of certain limbs only by imaginative processes. Although the MI-EEG signal has great potential, MI signal processing is still difficult to be done. MI signal has abstract pattern, making it difficult to distinguish one type of movement from another, especially if the MI signal used is not only from one subject and at the same recording time. This phenomenon is called inter-subject and inter-session variability. Based on this problem, authors conducted a study using the WPT-CSP method. This method will decompose signals into multiple frequency bands, and then filtered using spatial filter to obtain a better temporal and spatial resolution for the MI signal. The results of this method are then displayed on the Brain Topographic Map (Topomap) to show the activity level of the brain regions. The dataset used in this study is dataset 2a from Brain-Computer Interface Competition (BCIC) IV. The results of the research show that the phenomenon of inter-subject and inter-session variability can be observed more easily using the Topomap. These results also indicate that a new method is needed to overcome this phenomenon.

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]. Many algorithms have been proposed to deal with this problem. The most frequently used algorithm is spatial filtering[9] with CSP as a type of spatial filtering which has high performance and good results in the field of BCI.

Several studies have been conducted to optimize CSP, including using Feature Weighting and Regularization (FWR) on CSP to utilize all features in CSP results to avoid loss of information and

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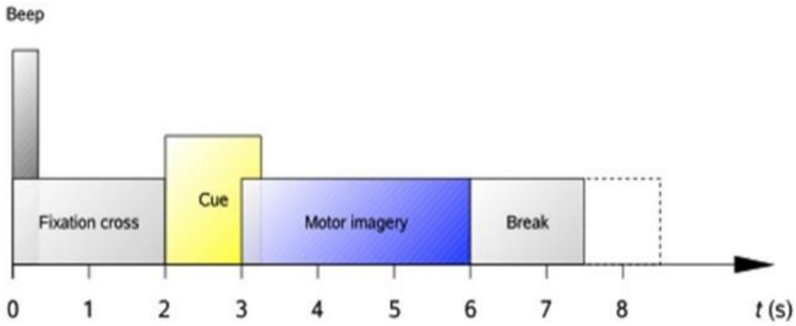
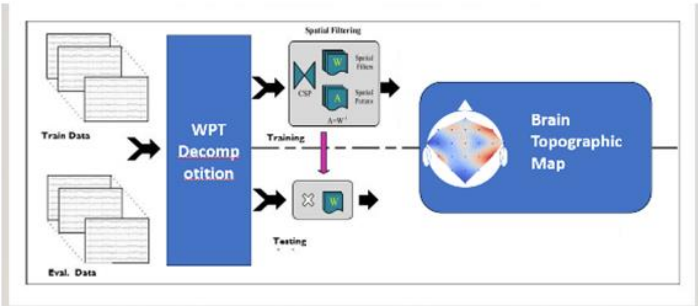
avoid overfitting[8]. Another study implemented Temporally Constrained Sparse Group Spatial Patterns to overcome problems in using multiple specific frequency bands and time windows for each subject due to differences in ability to respond to different information[10]. Another study is to utilize the 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.



(a)



(b)

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

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.

2. Method

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

2.1. Datasets Descriptions

To study the phenomenon of inter-subject and inter-session variability, the 2a Brain Computer Interface Competition IV (BCIC IV) dataset is used [12]. This dataset was taken from 9 subjects (as a form of inter-subject variability) who performed MI tasks in the form of left hand (class 1), right hand (class 2), feet (class 3), and tongue (class 4) movements. EEG recordings were made using 22 electrodes following a 10-20 system with a sampling rate of 250 Hz. Recording was done in 2 sessions, session 1 for training data and session 2 for evaluation (eval) data on different days (as a form of inter-session variability). The datasets were acquired from the GitHub website, and the data processing was carried out in the Electromedical Engineering Department laboratory at Kadiri University. The recording paradigm time is shown in Fig. 1.a.

Fig 1. (a) shows an illustration of the recording time for dataset 2a, where this process is carried out with an average of 8 seconds of data retrieval. Fig 1. (b) shows the method used in this study starting from data decomposition using the WPT then continuing with spatial filtering using the CSP, and the last process is by illustrating the WPT-CSP results data into the Brain Topographic Map.

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2.2. Experimental Methods

Suppose that the MI-EEG signal model:

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

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

1) Step 1: Decompose the signal using the WPT on the basis of wavelet rbio 2.2. This wavelet basis was chosen because it can provide the best feature extraction results for MI-EEG [13].
2) Step 2: Applying CSP to find a spatial filter that matches the data from step 1. CSP starts by looking for covariance samples on a single trial assumption, so the average covariance matrix is obtained as follows:

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

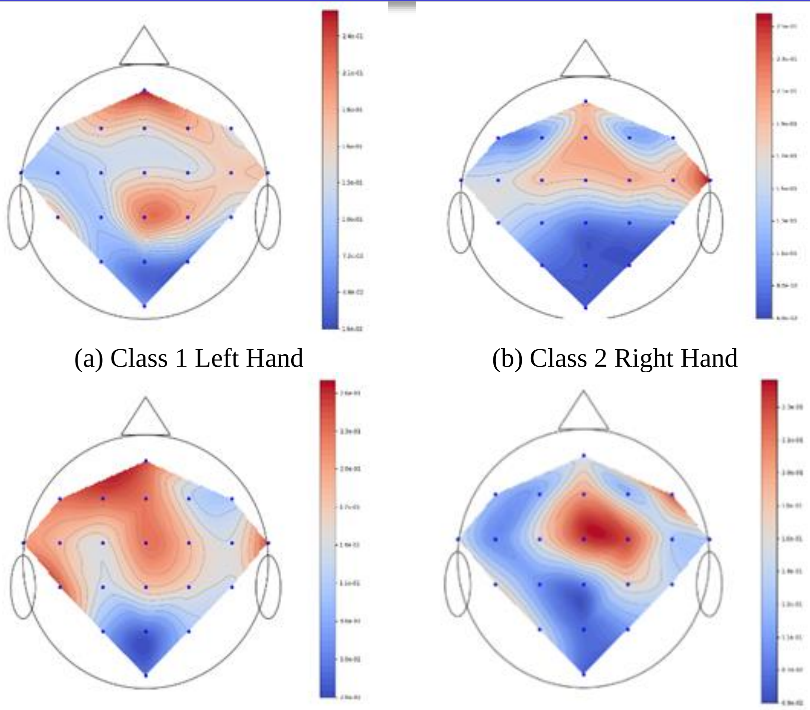
   C_y is the mean of the covariance matrix, E_j is the input data, n_y is the number of experiments for each class, and y is the number of existing classes. Next step is to look for a partial filter that will maximize class 1 variance (C1) and minimize class 2 variance (C2) as follows:

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

   The next step is to simplify the data into a single value for each channel, and project the data (X) into the following equation:

   $$A = WX \quad (4)$$

   where A is a Spatial Pattern obtained by projecting data in the form of an X matrix into the Spatial Filter W. The CSP modification is needed for multi-class cases such as in dataset 2a, so the Joint Approximate Diagonalization (JAD) strategy is used. JAD will diagonalize several covariance matrices according to the number of labels or classes given, or it can be said that this strategy has the same principles as ICA (Independent Component Analysis)[14].
3) Step 3: Illustrate the results of the WPT-CSP in the form of a Brain Topographic Map (Topomap).



(a) Class 1 Left Hand (b) Class 2 Right Hand

(c) Class 3 Feet (d) Class 4 Tongue

Fig 2. Topo Map Illustration for Class 1-4

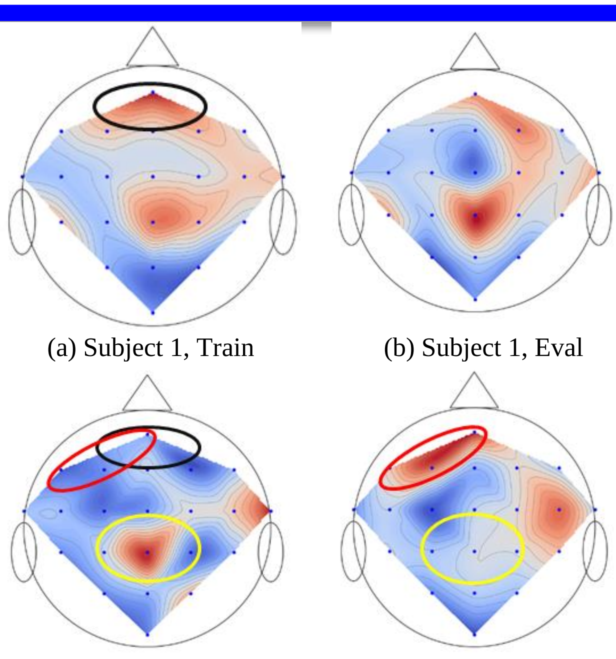
Topomaps are visual representations of activity on the surface of the brain (cortex). This representation shows the spatial distribution of neuronal activity in a given region[15]

3. Results and Discussion

Fig. 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 Fig 3.



(a) Subject 1, Train (b) Subject 1, Eval

(c) Subject 5, Train (d) Subject 5, Eval

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

Fig 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 Fig 3.a. is a Topomap for subject 1 in session 1 (train session), the Fig 3.b. is a Topomap for subject 1 in session 2 (eval session), the Fig 3.c. is a Topomap for subject 5 in session 1, and the Fig 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 (Figures 3.c. and 3.d.). These two figures show the difference in some of the cortex region that marked by red circles. In sessions 1 (Fig 3.c.) shows higher ERS activity while in session 2 (Fig 3.d.) showed higher ERD activity. The difference between the two figures 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 Fig 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 Fig 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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