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Defining Common Inter-Session and Inter-Subject EEG Channels using Spatial Selection Method

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ABSTRACT

Redundancy of information on brain signals can lead to reduce brain-computer interface (BCI) performance in applications. To overcome this, EEG channel selection is performed to reduce and/or eliminate a number of channels with irrelevant information. In the previous studies, there is energy calculation methods that have been proposed to perform EEG channel selection to improve BCI performance in classifying the brain command of motor imagery stimulation. In this study, channel selection scheme on motor movement signal will be experimented by using spatial selection method. This study performs the common active channel mechanism that divided into two parts: 1) common active channels between sessions, which known as common Inter-session channels and common active channels. These two techniques can be used by all subjects to interpret motor movement type known as common Inter-subject channels. In order to validate the performance of the proposed framework, CSP (common spatial pattern) is used as a feature extraction method and k-NN with k = 3 as the classification method. The obtained results shows that the proposed channel selection technique is able to choose common active channels in five combination numbers on Inter-sessions and Inter-subjects of the acquired EEG signals. Both types of common active channels are proven to improve BCI performance with an accuracy increase of up to 66%.

I. Introduction

BCI is a device or system that can be used to communicate with the brain directly. BCI allows to help the brain signal interpretation for various applications. An EEG-BCI is one of the BCI system type in acquiring the brain signal for command interpretation. EEG is categorized as inexpensive, easy, portable, and produce high temporal resolution device [1], so that EEG is widely used in for BCI applications. However, EEG has many disadvantages as the feature of the signal is commonly known to be noisy and non-stationarym [2]. Therefore, BCI systems experiencing redundancy of information which leading to poor performance in the real-engineering application. One of strategy that can be used to eliminate redundancy of brain signal information for performance improvement is by selecting EEG channels. Previously, the Channel selection has been proven to improve BCI performance by reducing or eliminating an irrelevant information in channels [3]. However, most of channel selection methods were applied in same session or specific subject even though channel selection technique across session and/or subjects is important in BCI application. In this study, channel selection technique is applied in defining channels representation across session and subjects using energy extraction method.

Energy extraction is one of channel selection method which previously known as energy calculation method [4]. Basically, energy extraction (energy calculation) method use l2-norm to empirically calculate channels energy [4]. This approach was used previously in other field to generate specific information [5]. Energy extraction method consists of two main techniques including energy calculation and energy selection. In this study, we tried to confirm two hypotheses that there is common active channels which has Inter-session robustness and that there is common active channels related with brain function which can be used for different subjects. In terms of that, we investigate the effectiveness of the channel selection using energy extraction method which was demonstrated with EEG in motor task. The feasibility of the composition of common Inter-session and Inter-subject channels will be tested for performance validation using accuracy measurement index. Overall, this common channel selection study has three purposes: (1) defining the common active channels in term of Inter-session and Inter-subject, (2) improving BCI performance using common selected active channels, and (3) defining the composition of selected channels that represent a class of motor movement brain signal.

II. Literature Review

A. Application of Channel Selection

EEG signal has many hidden information and knowledge in a channel that can be used in many BCI applications [6]. Based on the previous studies, channel selection techniques have been proved to offer improvement in BCI performance. Many applications of BCI can be optimized by using channel selection method in detecting brain-related disorder problem or medical field, such as in [7], which use channel selection to optimize BCI in epileptic detection. In another medical field, channel selection is used to reduce the calibration time for chronic stroke rehabilitation [8], [9] and to simplify the ADHD and non-ADHD discrimination with use just a few selected channels [10]. In addition, channel selection technique also can be used for other EEG related field such as in emotion detection [11], [12] and alcoholism detection.

B. Investigation of channel selection for BCI

Channels selection methods are generally divided into three types of methods: filtering, wrapping, and hybrid [13]. Filtering method is a channel selection method by using search algorithm. This method usually performs outside of the feature extraction process and optimize the BCI performance with fewer channels by removing the noisy channel [14]. Some of these filtering methods include [15] that using granger causality method. Wrapper method involves a feature extraction process for performing channel selection. Some of the wrapper methods are presented and proposed in [16],[17]. Hybrid method is a method of channel selection by combined filtering and wrapper methods where the channel selection process is done in dataset optimization and channel searching based on feature extraction. Meanwhile, several channel selection methods are configured by deep learning using CNN algorithm [18].

III. Methods

A. Channel Selection Method

This study focuses on the channel selection process as platform to incorporate common Inter-session and Inter-subject EEG channels using energy extraction method for BCI application. Prior to channels selection process, the dataset is filtered using third order Butterworth filter between 0.3 Hz and 12 Hz.

The channel selection method is divided into three main steps including (1) energy calculation for each EEG channel, (2) selection of the highest energy in channels, and (3) channels counting based on the energy level to determine excitation level in all sessions and subjects as shown in Fig. 1.

The process begins by calculating channels energy using (1) which are performed in all trials which then is averaged and represented in column vector.

$$C = c, pj \text{ , where } p_i = \frac{\sum_{j=1}^{n} A(i,j)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n} A(i,j)^2} \quad (1)$$

where C is a matrix with selected channels. c are columns then identified as channels, m and n is a number of row and column of matrix C, is average of channels energy.

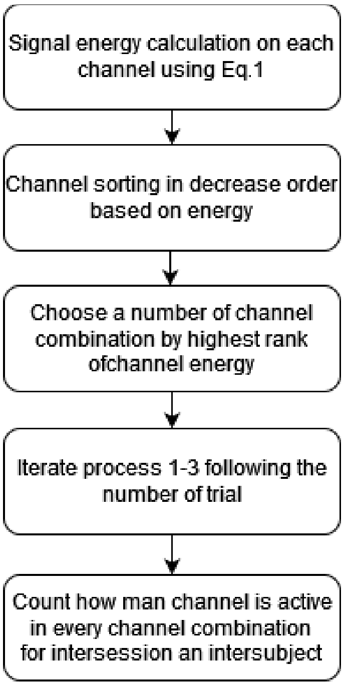


Fig. 1. Channel selection steps process

The channels with the associated energy value is then ranked in descending order. The channel with higher energy is defined as active channels and low energy channels may be considered as noise as it has no correlation with the stimulated EEG motor movement signals. The best high-energy channels are determined by the number of channels combination. The numbers of selected channels combination are 6, 5, 4, 3, and 2. In term of common Inter-session channels and common Inter-subject channels, the selected active channels are counted in all trials. The composition of common Inter-session channels is determined by active channels in between session of a subject while common Inter-subject ch annels is determined by the active channels in between subjects.

B. Experimental Setup and Protocols

In general, conventional BCI system is divided into three main processes including data pre-processing, feature extraction, and task classification. To optimize BCI system performance, the proposed BCI framework is added with channel selection process as shown in Fig. 2.

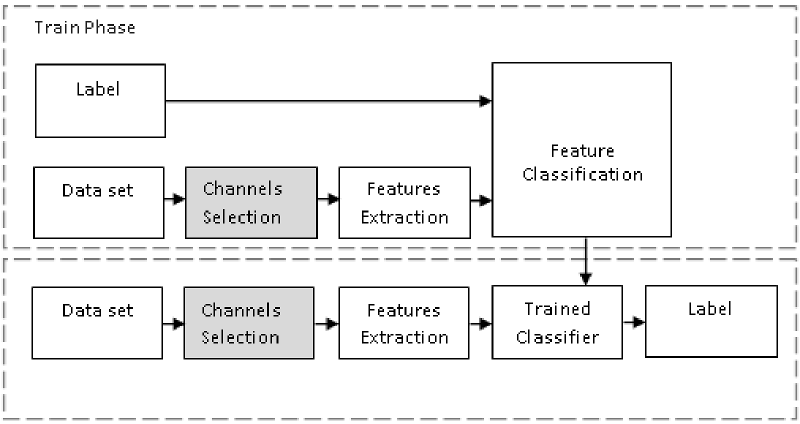


Fig. 2. Blok diagram of proposed BCI system

The proposed BCI framework consist of four processes: data pre-processing, channels selection, feature extraction, and task classification. We use two classes of motor movement dataset that collected at Biomedical Instrumentation Engineering Laboratory at Tokyo City University, Japan. The next process of proposed BCI system is channel selection. As explain in previous section, channel selection method that used in this framework is energy extraction method which has been used in several previous studies [4], [5].

As feature extraction method, CSP (common spatial pattern) is selected as the best technique which has been used in many previous studies in defining signal feature of two classes EEG signal especially for motor imagery and motor movement [19]. Because of dataset character that has small number of electrodes and the number of signal features, k-NN is used as feature classification method.

C. *EEG Analysis*

1) *Dataset Description*

The measurement procedure has been carried out in compliance with the Tokyo City University's code of ethics for medical research. The datasets are motor movement brain signal which measured using seven channels EEG (C2, Cz, C1, C3, C5, FC3, and FC5) in 200 Hz of sampling frequency from three healthy adult subjects who sitting on the chair. There are two classes of motor movement signal such as grasping right hand and raising the right leg which the instruction was instructed by slide on the screen. A black or white rectangle is placed at the corner on the instruction slides to show the starts of the movement. Output of an optical sensor placed on the monitor is recorded simultaneously. EEG signal for every subject was recorded for seven to nine seconds for hand movement and leg movement. The protocol of the EEG data collection is described in Fig. 3. In general, one subject has four sessions in different time/days of recording in which every session consisting of ten trials.

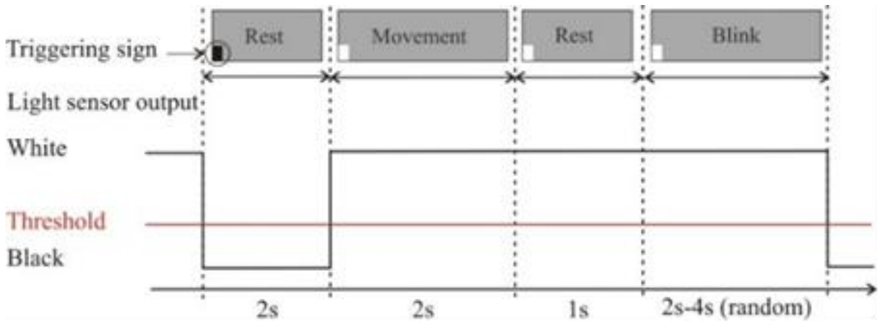


Fig. 3. Protocol setup for EEG data collection

2) *Parameter Setup*

To validate the proposed channels selection method, series of experiments have been conducted for the validation purpose. The experiment was run in full BCI process system as mentioned before. To evaluate the channels selection method, CSP is used as feature extraction method with six features of two classes motor movement EEG signal and k-NN with k = 3 is chosen as parameter. As previous studies, the data ratio between train and test trials are defined as 1:1 as shown Table 1.

Table 1. Experiment Parameter's Setup

Parameter	**Value**
Datasets Filter Mode	Third-order Butterworth
Features Extraction method	Common Spatial Pattern (CSP)
Number of features	6
Classifier method	k Nearest Neighbor (k-NN)
k	3
Ratio train and test trial	1:1

D. *Channel Optimisation and Evaluation*

The evaluation is divided into two types of testing, there are accuracy test using common channels for hand and leg movement in each subject which called as common Inter-session channels and accuracy test using common motor movement channels combination for hand and leg movement then called common Inter-subject channels. While in the second evaluation, the performance of BCI system is measured based on hand and leg movement common channels combination. In this phase, common channels combination is formed and used in all subjects. Besides presenting the result of BCI performance by accuracies, the composition in number of active channels combination will be shown for each phase of accuracies test.

The performance of the test is used to define the best composition of common channels combination for hand and leg movement. The finding will be used to prove whether selected common channels can be used for all subjects and offer better performance or not compare to the original composition of channels.

1) Inter-session Characteristics

Inter-session common channel selection is a process of defining channel selection which can be used as an optimal channel across session in different day. Inter-session selected channel is important to define the best channels active in a subject, so that various evaluation procedures in specific channels and subject to apply EEG based-BCI applications can be conducted. Although Inter-session channels process is neglected as a part of technique to improve BCI performance, it is important to solve some different EEG patterns that caused by subject preconditions such as electrode position and conductivity which will change over session or different mental condition such as attention, awareness, or task involvements which can caused a large variability of EEG pattern in between different session [20].

Inter-session is tested with aims to measure the performance of the BCI system based on the selected common channels which every subject has different common channel combination for hand and leg movement. In this phase, common channel refers to active channels which active in all sessions of a subject for hand and leg movement. The combination of common channels is applied in five numbers, there are six, five, four, three, and two active channel combinations.

2) Inter-subject Characteristics

Inter-subject channel selection is a process to generalize the selected channel across subjects or a process in addressing structural and functional information of EEG signal in appropriate channel to robust the BCI. Inter-subject selected channels represent the mental task of EEG that can be used over subjects without losing substantial of classification performance [21],[22]. EEG signal will be different over subjects because the structural and functional variability has non-stationary nature of EEG signal that of it can be caused by highly gap of emotional of subject's emotional that impossible to be uniformed and the inherent change of other environmental variables. Inter-subject common channels are selected by channels energy calculation which have high energy across subjects.

Inter-subject common channels are evaluated using accuracy parameter and channels mapping. The highest accuracy of selected channels combination will be chosen as the best inter-subject common channel's composition. Then, channels mapping will be used to define and illustrate the representative channels active for hand movement and leg movement of all subjects. The evaluation of inter-subject common channels is applied in five numbers, there are six, five, four, three, and two active channel combinations.

3) Performance Evaluation

All the evaluations were performed with accuracy. The evaluation exercise to prove the quality of proposed channels selection framework. Besides accuracy parameter, the system was evaluated using channels mapping. Channel's map is used to define the combination of active channels for hand and leg movement.

IV. Result and Discussion

A. Channel Selestion

The composition of Inter-session channels can be seen in Table 2. The mapping of channel selection test shown that all subjects have consistent channel reduction based on its energy in all combinations. Comparing to the hand movement, leg movement is more consistent as channel combination which is performed in all subjects. Especially in sbjC, the active channels composition of hand and leg movement are similar in two channels combination, such as C2 and Cz. It means hand and leg movement in sbjC cannot be differentiated and defined in all session using two combinations of channels. Based on Inter-session channel selection test, channel Cz is the most active for the leg movement over all subject in each session, while channel C2 is a dominant active channel in sbjB and sbjC for hand movement.

Table 2. Selected Common Inter-Session Channels in Numbers of Channels Combination

Subject	6		5		4		3		2	
	Hand	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***
sbjA	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C3-C5-FC5	Cz-C11-C3-C5	C3-C5-FC5	Cz-C1-C3	C3-C5	Cz-C1
sbjB	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC5	C1-C2-FC3-FC5	Cz-C1-C3-FC5	Cz-C1-FC3	Cz-C1-C3	C2-FC3	Cz-C3
sbjC	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C2-C3	Cz-C1-C3-FC5	Cz-C1-C3	Cz-C1-C3	Cz-C2	Cz-C2

Inter-subject channel selection test result is shown in channels maps on scalp that can be seen in Table 3. The composition of Inter-subject channels between hand and leg movement are similar in six and five combinations. in this channel's combination, hand and leg movement cannot be defined as a different movement. In four and three Inter-subject channel selection, hand and leg movement can be defined as a different movement. However, the best representative of Inter-subject active channel for hand and leg movement are performed in two combination of channels which are C2-FC3 channel composition for hand movement and C3-Cz channel composition for leg movement in all subjects. Even though those composition channels are not the best performance for BCI, but it offers a better performance compared to the conventional BCI.

Table 3. Selected Common Inter-Session Channels in Numbers of Channels Combination

Subject	6		5		4		3		2	
	Hand	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***
sbjA	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C3-C5-FC5	C1-C3-C5-FC5	Cz-C1-C3-C5	C3-C5-FC5	Cz-C1-C3	C3-C5	Cz-C1
sbjB	Cz-C1-C2-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C5-FC3-FC5	Cz-C1-C3-C5-FC5	C1-C2-FC3-FC5	Cz-C1-C3-FC5	Cz-C1-FC3	Cz-C1-C3	C2-FC3	Cz-C3
sbjC	Cz-C1-C2-C3-C5-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C2-C3-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C2-C3	Cz-C1-C3-FC5	Cz-C2-C3	Cz-C1-C3	Cz-C2	Cz-C2

From this result, hand and leg movement can be identified by common Inter-subject channels for all subjects which channel C2-FC3 are for hand movement and channels Cz-C3 are for leg movement. Using energy extraction method, the channel active composition of raising leg movement is shown more consistent in every channel combination numbers.

B. Test Perfomance for Inter-session common channels

The composition of common selected channels in all number of combinations are not linearly consistent in defining hand or leg movement. It because hand or leg movement active channels is intersected in all number of channel combination except in combination two active channel for sbjA and sbjB. This condition produces a lower accuracy result for sbjC in two combinations of common channel compared to the original seven channel combinations. The accuracy results can be seen in Table 4.

Table 4. Accuracies Result by Active Channels Combination in Each Subject

Subjects	**Accuracy in number of channels**					
	7	***6***	***5***	***4***	***3***	***2***
SbjA	0.55	0.75	0.80	1.00	0.93	0.85
SbjB	0.73	0.88	1.00	1.00	0.90	0.75
SbjC	0.60	1.00	0.90	0.88	0.85	0.50
Avg	0.63	0.88	0.90	0.96	0.89	0.70

Based on the averaged accuracy result, selected, and reduced channels shows better performance compared to the original. The performance accuracy of the proposed BCI framework is increased by 37.4%. The best performance is offered in four common channels combination with 52.3% performance improvement. Then for the lowest performance improvement is offered in two common channels combination with 11.1% increasing compare the original. In two common channel combinations, mostly all subjects have shown better performance except for sbjC. The deteriorated performance in sbjC for two common channel combination is found. The reason is considered that hand and leg movement cannot be defined as a different movement because both movements reflect the same active channels composition as mentioned in previous explanation.

The accuracies pattern is shown in Fig. 4. In this common channel session performance test, all subjects have shown the best accuracy at 1.00 of accuracy which are sbjA in four common channel combinations, sbjB in five and four common channels combinations, and sbjC in six common channels combination. The pattern of accuracies test result show that every subject has the best common channels composition which indicated the most active area on scalp for hand and leg movement in each subject.

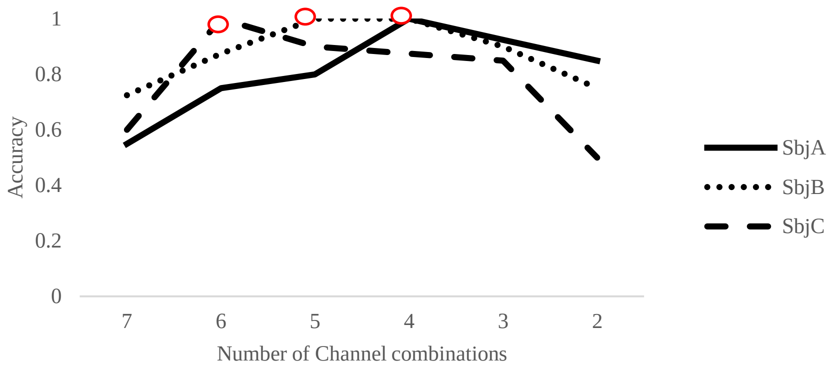


Fig. 4. Pattern graphic of accuracy test result. The red circles are the climax accuracies for all subjects.

C. *Perfomance Test for Common Inter-subject channels*

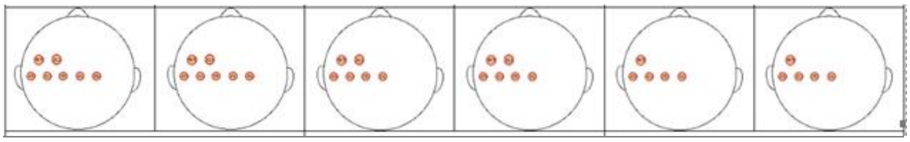
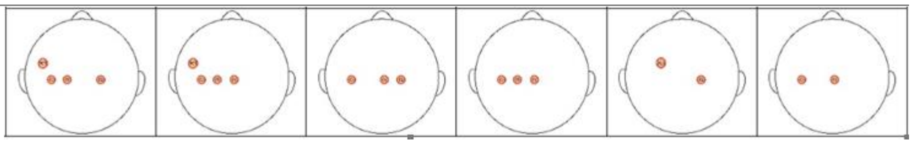
In general, the composition of common Inter-subject channel combination has an intersection channels, that is, commonly activated channels by hand and leg movement, except in two composition of common channel combination. The two combinations of common Inter-subject channels can represent signals from hand and leg motor cortex area because there is no intersection channel between hand and leg movement.

Table 5. Accuracies Test Result for Common Inter-Subject Channels

Subjects	**Accuracy in number of channels**					
	7	***6***	***5***	***4***	***3***	***2***
SbjA	0.55	0.65	0.80	0.75	0.55	0.58
SbjB	0.73	0.83	0.55	0.75	0.93	0.75
SbjC	0.60	1.00	0.55	0.80	0.85	0.63
Avg	0.63	0.83	0.63	0.77	0.78	0.65

As shown in table 5, relatively the common Inter-subject channels have produced arbitrarily same result in term of average value, all number of common active channels combination offer a better performance from 3.6% to 66.7% accuracies enhancement compared to original active channel. However, the average accuracy in five common channel combination is not better than the original. The better performance just experienced in sbjA, while in sbjB and sbjC the accuracies are lower than the original. It because the common Inter-subject channels composition in sbjA is same with common Inter-sessions channels composition for hand and foot movement. Whereas, in sbjB and sbjC common Inter-subject channels are identified as foot movement in common Inter-sessions channels composition, so that the classifier will introduce common Inter-subject channels as foot movement only and it may cause lower performance accuracies. The compositions of selected common inter-session and inter-subject are illustrated in Table 2 and Table 6.

Table 6. Selected Common Inter-Subject Channels Combination for Motor Movement EEG Signal

Common Channels	7		6		5	
	Hand	***Leg***	***Hand***	***Leg***	***Hand***	***Leg***
	Cz-C1-C2-C3-C5-FC3-FC5	Cz-C1-C2-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC3-FC5	Cz-C1-C3-C5-FC5	Cz-C1-C3-C5-FC5
						
	4		***3***		***2***	
	C1-C2-C3-FC5	Cz-C1-C3-FC5	Cz-C2-C3	Cz-C1-C3	C2-FC3	Cz-C3
						

V. Conclusion

In summary, this study presents three main objectives. The first is to find common active channels in term of Inter-session and Inter-subject. The second is to evaluate BCI performance improvement by channels selection. The third is to define two sets of common channels optimized for hand and foot movement. Energy calculation was implemented to channels selection method for motor movement EEG signals. The results show that, energy calculation method successfully provides better performance in term of classification accuracy of BCI system using common Inter-session and Inter-subject channels in all numbers of channels combinations. Besides that, hand and foot movement can be identified in different composition of two active channels. In future, the proposed common Inter-session and Inter-subject channels framework should be applied to additional motor task classes, additional subjects, and additional sessions.

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