Mental Tasks Signal Classification

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Abstract

Electroencephalogram (EEG) signal is an important source of information for knowing brain processes. To interpret the brain activity, Matching Pursuit Based EEG signal classification is proposed. This system includes three main components which are Preprocessing, Feature extraction and Classification. In the preprocessing step, Wavelet Packet Independent Component Analysis (WPICA) method is used to remove some unwanted noise of EEG recording. Matching Pursuit (MP) with Wavelet Packet Dictionary is used to extract the features of EEG signal. The k Nearest Neighbor (kNN) classified the extracted MP features. In this work, the Keirn and Aunon EEG dataset is used in the experiments. The feature extracted from MP based wavelet packet dictionary achieved over 90% accuracy in two seconds length of brainwave signal in five mental tasks classification.

1. Introduction

Brain Computer Interface (BCI) provides a new communication mode between human's brain and computer. Mental activity leads to the changes of electrophysiological signals of brain such as the EEG signal. The BCI system detects such changes and transforms it into a control signal which can be used in various applications such as video game, motion of a wheel chair etc. There are two types of BCI, invasive and non-invasive BCI. The latter one does not need any surgical operation to record the brain wave signal and EEG is a type of non-invasive BCI. EEG signals is used in BCI to provide an effective way to help people who have severe motor disabilities. BCI let them to communicate with their outside world just using brain signals. Translating the brain's activities, it needs the pattern recognition and classification techniques.

EEG is one of the most clinically and scientifically exploited signals that are recorded from humans' brain. As the non-stationary nature of EEG signal, it is hard to extract the distinct feature for classifying EEG signal.

Mental tasks dataset used in this study has five brain activities which are baseline, multiplication, letter composing, figure rotation and counting. It was recorded by Keirn and Aunon, and the main reason of recording is to describe the alternative mode of communication between human and computer [24]. Mental tasks EEG signal are recorded from seven subjects. But some of the previous studies don't use the EEG signal records from all subjects. Some tried to classify the EEG signal of four subjects or five subjects, etc.

Most of the mental classification systems from the literatures have good accuracy the discrimination of baseline task from other four tasks such as Mental Multiplication, Figure Rotation, Counting and Letter composition Task. On the other hand, they learned pair tasks instead of five class classification. So it still needs an efficient feature extraction method to classify accurately all five classes of mental tasks. This system used Matching pursuit based time-frequency dictionary (Wavelet Packet dictionary) for extraction of features from mental tasks signal. Matching pursuit with other time frequency dictionary (Gabor dictionary) is commonly used in the analysis of epileptic EEG signal [1, 16].

2. Related Work

Keirn and Aunon analyses with three types of features from 2 seconds segments. Three types of feature extraction methods that are Wiener-Khinchine (W-K), Burg Spectrum and AR Coefficient are used. Keirn achieved the best classification results using a Fourier Transform based on AR coefficients. Classification accuracy of task pair is achieved 84.6% using a quadratic Bayes classifier over five subjects, 20 data records. 2 seconds segment and quarter second segment over 15 records got similar classification rate of tasks pairs. EEG records of the same person vary one recording to the next; it explained that the statistics of the brain waves are non-stationary over extended periods of time [24].

C. W. Anderson and Z. Sijercic made some experiments in classification of half second segment of six channel data. It got accuracy range of 71% for one subject and 38% for another subject of five tasks from four subjects. Two and three-layer feed-forward neural networks are trained using 10-fold cross-validation by Neural Network classifier. Autoregressive (AR) model is used to extract the features from the EEG signals. It uses 36 coefficients as inputs to the classifier [4]. Alternatively, C. W. Anderson et al. also test quarter second windows of six-channel data using multivariate autoregressive (AR) models to extract the features of EEG signal. The feed-forward neural network using cross-validation procedure is used to discriminate the two mental tasks, Baseline and Multiplication. Neural Network classified the mental tasks using the 36-component features vector. The result of 91.4% achieved for two tasks classification [5]. Two subjects' data from Keirn and Aunon dataset is used. Artifacts are removed by the maximum signal fraction analysis (SFA). EEG signal's features are represented from short-time PCA. Linear discriminant analysis (LDA) classified the 324 features vectors with an accuracy of about 80% for each mental task [6]. K-L transform and frequency-based representation are used in the classification of quarter second segments with Neural Network. Average accuracy reach about 90% in the 10 seconds period of time and it was concluded that it take long time and not usable in practical way [7]. Many researches related with mental tasks signal classification used the Neural Network Classifier with different function. J. Huaping classified the mental tasks using probabilistic neural network PNN network [13]. R. Palanippan also used Multi-Layer Perceptron Neural Network (MLP-BP NN) to classify the 144 features into the baseline and other mental tasks with accuracy of 97.5% over data of four subjects. It classified the mental tasks dataset spectral power and power difference in 4 bands: delta and theta, beta, alpha and gamma as feature vectors. Multiplication task got the best accuracy for some subjects. They mentioned the relationship between the number of hidden units and classification accuracy for each subject [18].

M. Tolić and F. Jović used the features of EEG signals extracted by Discrete Wavelet Transform. And Neural Network is used as classifier for discrimination of task pairs. Mean classification accuracy for the recognition of all five tasks was 90.75% and mean classification accuracy for the recognition of two tasks (baseline and any other mental task) was 99.87%. It work over half second segment and 36 features. For training and testing data are partitioned randomly. Accuracy is average of 20 repetitions of classification. The highest accuracy got from subject 1 in the classification of five EEG trials for each tasks of the first day. They mentioned that the accuracy depend on the number of input samples and number of neurons for each subjects [15]. L. Zhang et al. got classification accuracy of 2 Class is 77.3% and also it achieved 65.9% for 3 class, 58.2% for 4 class and 52.8% for five mental tasks. They used 90 features from 1 second segments of four subjects EEG mental task signal using CCA (Canonical correlation analysis) for preprocessing, Welch period gram algorithm for feature extraction and Fisher discriminant analysis (FDA) for classification. Cross-validation approach is used in classification. For each classification, one trial from each mental task is used as test cases. Training and Testing were conducted for ten or fifteen times for each classification according to the number of the corresponding trials. The sizes of the training set and the test set varied with the changes of the subject and the number of classes [14].

X. Li et al. made some experiments on EEG Signal of mental and cognitive tasks using features of wavelet packet entropy and Granger causality. These features were classified using a multiple kernel learning support vector machine (MKL-SVM) based on a gradient decent optimization algorithm. Keirn and Aunon Dataset is used in experiment on the data of 7 subjects. They classified the five mental tasks into 2 Class, 3 Class, 4 Class and 5 class classifications by comparing the tasks. They got the accuracy for each type 99.20%, 81.25%, 76.76%, and 75.25% respectively [22].

H. Liu et al. emphasis on the effect of wide subbands on the mental tasks EEG signal classification. Time-domain regression method is applied to remove the artifact from EEG signal. Totally 60 frequency domain features as the sum of weighted of power spectral values are extracted from each subband at each channel. Fisher Linear Discriminant was used to perform the task-pairs classification. Experiments on one second signal segment are tested separately according to the recording section. Average classification accuracy of 98.3% is achieved from experiments of the 130 task pairs of three sections. It was concluded that the gamma EEG signal are useful in mental task classification. Holdout cross validation method is used to separate the 80 percent training data and 20 percent testing data [12].

In this proposed system, it classifies the EEG signal of different length such as half second segment, one second segment and two seconds segments. Moreover, knowing the effects of different channels on the human's mental behavior, it used the brain wave signal from different numbers of channels. These are analysis of 7 channel data combining 6 EEG channels (C3, C4, P3, P4, O1, O2) with one Electrooculography (EOG) channel, analysis of only 6 EEG channel data and two channel data (pair channel data).

3. Mental Tasks Classification System

In this study, the Keirn and Aunon EEG dataset is used in experiment. The EEG signal recordings from that Dataset are recorded from the seven persons. Electrode cap is used to record EEG signals from positions C3, C4, P3, P4, O1, O2 and EOG channel based on 10-20 standard of electrodes placement as in Figure 1. C3 and C4 are placed from the central line of hemisphere and P3, P4 is on the parietal lobes of the brain. O1 and O2 are kept to the Occipital lobe. They recorded the brain wave signal with the sampling frequency of 250 Hz. And each trial is 10 seconds long and it has totally 2500 samples per trial.

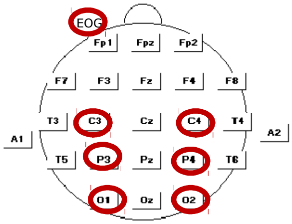

Figure 1. Electrode Placement of EEG Recording

The five mental tasks are Baseline task, Multiplication task, Figure Rotation task, Counting task and Letter Composing task.

The EEG classification system has three steps namely: Preprocessing, Feature Extraction and Classification as in Figure 2. The input to the system is the brain wave signal.

In the classification, the k nearest neighbors (k-NN) classifier is used in experiment to classify five mental tasks. The output of the system is the type of mental tasks of the given EEG signal.

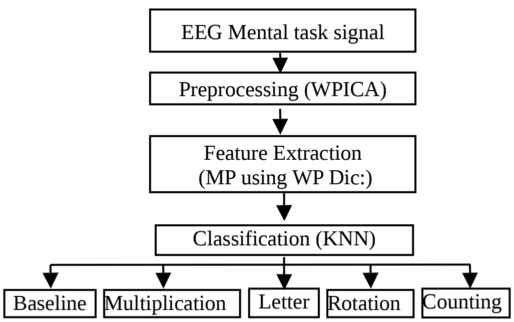

Figure 2 Architecture of Proposed System

3.1. Preprocessing

As shown in Figure 2, in the preprocessing stage, Wavelet packet Independent component analysis (WPICA) is applied for artifacts removal. Contamination of EEG activity by eye movement, eye blinks and automatic body response is a serious problem. To remove these artifacts of mental task signal, WPICA (Wavelet Packet Independent Component Analysis) is applied in this study. Wavelet packet decomposition performs before independent component analysis (ICA) [2]. The input signal is decomposed to form the wavelet packet tree with same numbers of nodes. The way of selecting the important node in this study is different from other [21]. For each node, the quality criterion is the proportion of the normalized coefficient of the node and it is computed using equation 1.

$$Quality\ Criterion = \frac{\sum_{i=0}^{c} |x_i|^2}{\sum_{i=0}^{c} |x_i|} \quad (1)$$

where c is the number of cell in each node and x_i is the coefficient at cell i. Wavelet Packet Decomposition remove the low amplitude noise. It selects the node with maximum quality criterion. The selected node is allowed to pass to the informax ICA. Noise caused by eye blinks has higher amplitude than the usable signal. So the main function of ICA is to remove the high amplitude noise. ICA learns the mental tasks signal from the unwanted artifact by using different learning rate and adjusting the weight changes at each step [3, 9].

3.2. Feature Extraction

In the feature extraction step, Matching Pursuit (MP) based time-frequency dictionary (wavelet packet dictionary) is used to extract the features of the signals. MP is a technique of time frequency signal analysis and decomposes the signal into linear expansion of waveforms. Waveforms from a very large class of functions were fitted to the local signal structures in a recursive procedure. MP uses maximum correlation value as a criterion to search and select the atoms [19].

Table 1. Feature Extraction Algorithm

Initialization: $R^0=x$; and $i=0$;
//Residual R, iteration i, input signal x
While(i ≤max_iteration)

1. Decompose the signal R^i to form Dictionary
2. Find the atom with absolute maximum coefficient over the whole dictionary;
3. Update the residual by subtracting the corresponding atom;
4. $R^{i+1}=R^i- (R^i,\psi_{\Upsilon i+1})$
5. $i=i+1$

end
$\psi_{\Upsilon i+1}$= coefficient of wavelet packet atom

MP decomposed the input signal and extracts the time and frequency features such as frequency, scale, position and amplitude. These conventional features are not used in our research. According to the nature of MP algorithm, one atom is subtracted each iteration. The selected atom must have the absolute maximum amplitude over the whole dictionary. The absolute maximum amplitude of selected atom is used as feature for classification of mental tasks in this study. The main idea of using that feature is that the maximum correlation coefficient may vary according to the type of mental tasks. For atomic decomposition, MP used the orthonormal bases Wavelet Packet Dictionary [17, 20]. As it is the orthonormal bases and it processes the input signal's samples with the power of 2. So the numbers of inputs samples of EEG mental tasks in this experiment are 128, 256 and 512 samples respectively. The feature extraction algorithm is shown in Table 1.

Wavelet Packet is the generalization of wavelet transform and it associated with both time and frequency domain. Wavelet Packet can be represented by a filter bank constructed from quadrature mirror filter. In the Wavelet Packet Decomposition, both the detail and approximation coefficients are decomposed to create the full binary tree. High and Low pass filter with down sampling is used to decomposed the signal. As wavelet packet dictionary is overcomplete dictionary, for a given N samples, it includes $NLog_2N$ waveforms. Wavelet Packet dictionary is a family of orthonormal bases and wavelet packet atoms are indexed by Scale, frequency and position. Daubechies (db10) wavelet packet function is used in this study [11, 23].

3.3. Classification

The extracted features are classified using k nearest neighbor (k-NN). The k nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions) [25]. If the training set is given as $\{x_i,y_i\}$, x_i is the 60 or 70 Matching Pursuit features, i=1,…,70 for 7 channel data and i=1,…,60 for 6 channel data, and y_i is the Mental Task i, here i=1,…,5 as this system is based on 5 mental tasks. For new data point x_i*, the distances between x_i* and x_i, are calculated based on the Euclidean distance function.

$$D\left(x_i^{¿}, x_i\right)=\sqrt{\sum_{i=1}^{n}\left(x_i^{¿}, x_i\right)^2}$$

(2)

where n is the dimension of vector.

Rank all the distance D(.,.) in increasing order. Among the k nearest neighbors, assign the new data point to class or mental task y_i according to the majority voting. The value of k keeps 1 in this study.

4. Experiment

In the mental dataset, each trial of EEG signal is 10 seconds long. The trial is segmented into about half second, one second and two seconds segments with 0.25 step times. So it got 32 segments per trial for two seconds length partition, 36 segments for one second length partition and 38 segments for half second length partition per trial. The total segments for different signal length of each subject are described in Table 2. These total segments of features data are partitioned using hold out cross validation in two third training and one third testing of each subject. The accuracy shows in the tables of this section are average of 10 times classification. In the experiment, accuracy is the overall correctness of the models and is calculated as the sum of correct test cases divided by the total number of test cases.

Table 2. Total Segments for Three Signal Length

Sub	trials	Total Segments		
		Half second	One second	Two seconds
S1	50	1900	1800	1600
S2	25	950	900	800
S3	49	1862	1764	1568
S4	49	1862	1764	1568
S5	75	2850	2700	2400
S6	50	1900	1800	1600
S7	25	950	900	800

The quality of Wavelet Packet feature is compared with the features extracted using Cosine Packet Dictionary [17, 20]. Moreover, the performance of the system is compared with the results of well-known Classifier such as Support Vector Machine (SVM) and Least Square Support Vector Machine (LSSVM) [8, 10]. Three types of experiment based on channel numbers are performed.

In the experiments, it is based on the numbers of channel. Experiment I is related with 7 channels data and Experiment II is about the results of 6 channels data. Experiment III is mentioned the results of pair channel data.

4.1. Experiment I

Five mental tasks classification results of 7 channel data (combining of six EEG channels and one EOG channel) are performed using Wavelet Packet Feature and Cosine Packet Feature on three different signal lengths are describe in Table 3, 4 and 5. MP extracts 10 atoms per each channel, so 7 channels data has totally 70 feature vectors for classification.

According to the Table 3, 4 and 5, the longer the segment is, the better the accuracy it achieved. It can be seen that the accuracy of wavelet packet features is better than those of cosine packet feature except from KNN classification of one second length of Table 4.

Table 3. Accuracy of 7 channel in half second segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	45.6%	41.4 %	43.3 %	40.9%	39.1 %	35.2 %
S2	47.2%	40.5 %	45 %	37.3%	39.4 %	33.8 %
S3	37.2%	35.8 %	36.2 %	39.%	37.3 %	36.2 %
S4	62.8%	59.1 %	54.8 %	55.9%	57.5 %	45.7 %
S5	43.6%	44 %	36.4 %	40.5%	45.5 %	33.2 %
S6	53.2%	50.8 %	46.3 %	48.5%	50.4 %	42.7 %
S7	57.9%	52%	53.1 %	49.2%	44.7 %	45.1 %
avg	54.4%	51.5 %	47.7 %	44.5%	44.8 %	38.8 %

Table 4. Accuracy of 7 channel in one second segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	65.8%	70 %	57.8 %	68.9 %	72.5 %	55.7%
S2	63 %	69.3 %	59.3 %	60.5 %	68.6 %	50.1%
S3	54.7%	62.1 %	48.3 %	52.7 %	61 %	43.2%
S4	77.4%	82.4 %	68.2 %	71.7 %	80.1 %	60.5%
S5	60.1%	68.2 %	48.9 %	59.9 %	69.5 %	43.5%
S6	68.4%	67.7 %	58.7 %	71 %	76.5 %	56.5%
S7	74.5%	76.2 %	59.6 %	66.8 %	76.3 %	56.2%
avg	66.3%	70.8 %	57.3 %	64.5 %	72.1 %	52.2%

Table 5. Accuracy of 7 channel in two seconds segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	89.7 %	94.1%	76.2%	87.6%	92.9%	75.9 %
S2	83.3 %	89.9%	73.7%	79.8%	89.1%	73.4 %
S3	80.7 %	88.4%	63.3%	76.7%	84.7%	58.8 %
S4	95.6	97.5%	86.3%	92.7%	96 %	83.3

	%					%
S5	87.1%	92.1%	69.9%	85.3%	89.5%	62.7%
S6	91.6%	93.9%	76.8%	89.5%	92.6%	77.9%
S7	91.2%	95.4%	84.5%	87.4%	93.8%	73.3%
avg	88.5%	93.1%	75.8%	85.6%	91.2%	72.2%

According to the experiments, KNN got the reasonable accuracy and got better accuracy than other classifiers except from half second segment classification.

4.2. Experiment II

Five mental tasks classification results of 6 EEG channel data are performed using Wavelet Packet Feature and Cosine Packet Feature on three different signal lengths are describe in Table 6, 7 and 8. In 6 channels data, it has totally 60 features vectors for classification.

Table 6. Accuracy of 6 channel in half second segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	42.7%	39.9%	39.2%	36.7%	36 %	33.6%
S2	40%	37.9%	38.5%	38.9%	35.7%	35.5%
S3	33.6%	32%	32.3%	31.4%	29.%	31.9%
S4	58.8%	56.8%	53.1%	53.6%	53.8%	47.9%
S5	40.5%	41.9%	37.4%	37.4%	38.3%	35.7%
S6	40%	38.2%	39.2%	42.5%	38.5%	40.7%
S7	47.2%	42.1%	48.4%	43%	42.4%	45.1%
avg	43.3%	41.3%	41.2%	40.5%	39.1%	38.6%

Table 7. Accuracy of 6 channel in one second segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	63.2%	66.4%	54.9%	54.9%	60.1%	48.2%
S2	58.9%	70%	56.4%	55.2%	59.6%	50.7%
S3	47.1%	53.9%	41.6%	41.8%	49.5%	37.8%
S4	71%	78.8%	65.5%	64 %	70.6%	56.6%
S5	61.8%	71.9%	51.8%	57.6%	64.3%	49.5%
S6	54.3%	60.4%	47.1%	51.4%	55.6%	45.7%
S7	65.8%	69.5%	62.5%	63%	65.3%	55.6%
avg	60.3%	67.3%	54.3%	55.4%	60.7%	49.2%

According to the experiment, accuracy of 6 channel data is slightly lower than 7 channel results. Moreover, the classification accuracy of 6 channel Cosine Packet features is lower than 6 channel Wavelet Packet Features classification results.

Table 8. Accuracy of 6 channel in two second segment

	Wavelet Packet Feature			Cosine Packet Feature		
Sub	LS-SVM	KNN	SVM	LS-SVM	KNN	SVM
S1	82.2%	86.8%	73.6%	76.4%	82.8%	67.1%
S2	83.1%	87.4%	75.4%	78.8%	84.5%	73.4%
S3	73.4%	84.3%	61.3%	70.9%	78.4%	58.3%
S4	88.9%	94%	81.5%	83.4%	90.8%	73.6%
S5	86.9%	91.6%	74.1%	84.8%	88.7%	71.9%
S6	81 %	85.4%	74.8%	79.2%	82 %	66.6%
S7	83 %	86%	76.2%	78.8%	84.7%	70.6%
avg	82.7%	88 %	73.8%	78.9%	84.6%	68.8%

4.3. Experiment III

This section mentions about pair channels analysis. Two channel data from the same location of electrode placement in EEG data acquisition are classified such as C3 and C4 channel data, P3 and P4 channel data, O1 and O2 channel data. Classification of Pair channel data are tested in two seconds segments of Wavelet Packet features. O1, O2 data in two channels got the better classification accuracy compared with other pair of channel data.

Although 7 channel and 6 channel data analysis can define the Figure Rotation Tasks mostly, EEG signal of C3, C4 channel is not good to define Figure Rotation Task and it is good for other tasks especially for classification of baseline tasks and letter tasks as in Figure 3.

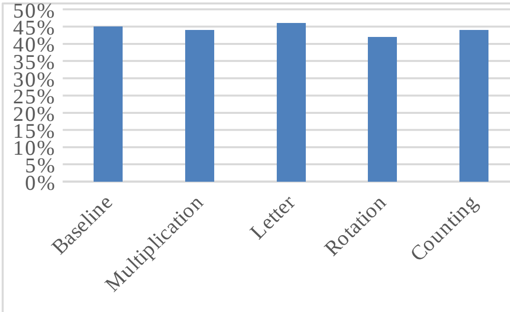

Figure 3. Classification Rate of Each Mental Task via C3, C4 Channel Data

Parietal Lobe is associated with Mathematical ability so that P3, P4 channel data achieve the best accuracy in discrimination of multiplication tasks as in Figure 4.

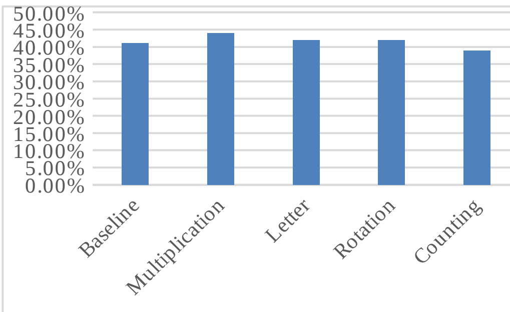

Figure 4. Classification Rate of Each Mental Task via P3, P4 Channel Data

EEG signal from Occipital Lobe can classify most of the Figure Rotation Tasks because Occipital Lobe is responsible for vision, shape and movement as in Figure 5.

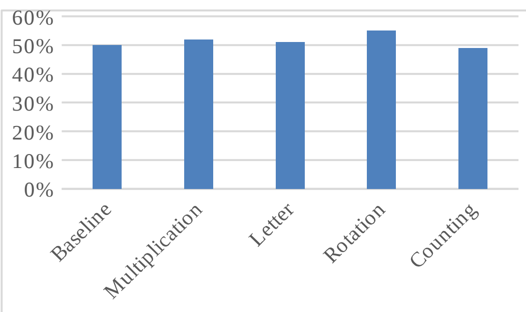

Figure 5. Classification Rate of Each Mental Task via O1, O2 Channel Data

5. Conclusion

According to the experiment, the longer the segment, the better the Classification accuracy it achieved. For two seconds segments, it can able to classify most of the tasks correctly. Wavelet Packet Features are more suitable for mental classification than Cosine Packet Feature with better accuracy. Classification accuracy of LSSVM is slightly better than KNN in half second length of EEG signal. KNN is suitable for classification of mental activities with better classification accuracy compared with other classifiers. 7 channel data including EOG signal using 70 features has better accuracy than only EEG 6 channel data classification using 60 features. According to the pair channel analysis, O1O2 influenced the mental activities with over 50% classification accuracy in five mental tasks using 20 features while 6 channel data classification get 88%.

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