Analysis of Matching Pursuit Features of EEG Signal for Mental Tasks Classification

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Abstract

Brain Computer Interface (BCI) Systems have developed for new way of communication between computer and human who are suffer from severe motor disabilities and difficult to communicate with their environment. BCI let them for communication by non muscular way. For communication between human and computer, BCI uses a type of signal called Electroencephalogram (EEG) signal which are recorded from the human's brain by mean of electrode. Electroencephalogram (EEG) signal is an important information source for knowing brain processes for the non-invasive BCI. In translating human's thought, it needs to classify acquired EEG signal accurately. Independent Component analysis (ICA) method via EEGLab Tools for removing artifacts which are caused by eye blinks in the recorded mental task EEG signal. For features extraction, the Time and Frequency features of non stationary EEG signals are extracted by Matching Pursuit (MP) algorithm. The classification of mental tasks is performed by Multi_Class Support Vector Machine (SVM).

Keywords: *BCI, EEG, ICA, SVM*

1. Introduction

Mental task classification by recognizing the features of Electroencephalographic (EEG) signal is an important and challenging biomedical signal analyzing problem. Such system can be utilized to enable a patient to communicate their environment without any physical movement.

The accuracy of classification has been one of the main pitfalls of the development of BCI systems which directly affect the decisions made as the BCI output. This accuracy is affected by the quality of EEG signal and the processing algorithm [13].

The processing steps of typical EEG classification system include preprocessing, feature extraction and feature classification. In the previous research the effect of feature extraction methods, how to extract the data from the channels and the type of extracted features on classification accuracy was investigated.

In the present research, the classification of mental tasks using the Purdue University EEG dataset [10]. This classification tends to discriminate the classes of five mental tasks which are baseline task, multiplication task, letter composing task, figure rotation task and visual counting task from the Dataset. These five mental tasks can be distinguished into two categories such as Mental-Relax Task and Mental-Work Tasks.

Baseline task is Mental-Relax task, while other four tasks make the mind busy. Most of the classifiers for mental tasks have good accuracy for comparing the baseline task with other four tasks. But they still get poor accuracy for classifying among other four tasks.

In this study, although the matching pursuit (MP) method extracts the time and frequency information of signal, it uses just the frequency and amplitude of the atom.

We consider that the average frequencies of one atom are not same among five tasks. Similarly, the variation of the minimum and maximum amplitude of adjacent segment is also considered to distinguish among five classes.

There are many techniques proposed in literature for EEG signal classification that includes Artificial Neural Network (ANN), extreme learning machine, Bayesian Networks and Decision Trees Classifier [2, 3, 11, 17] AdaCharles W. Anderson, Edward S. Orosz (1994) used Sutton and Matheus' algorithm for recognizing the mental task from the recorded EEG signal. They got accuracy of classification 65% [1].

CharlesW. Anderson and Zlatko (1996) also investigated in classification of mental tasks via autoregressive (AR) features by using feed forward neural networks.

The AR features are generated from the half-second segments of six-channel of five cognitive tasks performed by four subjects. The average percentage of test segments correctly classified ranged from 71% for one subject to 38% for another subject [2].

Keirn and Aunon's (1988) data consists of EEG data of five different mental tasks. The experiment tends to find suitable features for getting acceptable classification accuracy.

The spectral density was estimated using the Wiener-Khinchine (W-K) method. Bayes quadratic classifier was used for discrimination of task pairs. The accuracy of correct outputs was 90–100% for distinct cases [11].

Charles W. Anderson (1998) USE] used multivariate autoregressive (AR) models to extract features from the EEG signal of mental tasks. Neural Network Classifier is used to discriminate the mental tasks. That study got classification accuracy of 91.4% [3].

Martina Tolić and Franjo Jović (2013) extracted the features of EEG signals using Disctete 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% [17].

In Mythra, Veenaumari and Kubakaddi 2013, classified the five classes of mental tasks from Keirn and Aunon dataset. For the decomposition of EEG signals was made by discrete wavelet transform. Three classifiers namely KNN, SVM and LDA are compared. SVM classifier got the best classification results [19].

Most of the research which uses the Keirn and Aunon dataset for experiment usually uses AR features, spectral features and wavelet transform features. In this study, it tried to implement using Matching Pursuit (MP) method for feature extraction.

2. Data

The data set used in this study is Keirn and Aunon's (1988) dataset which comprises EEG signals from seven subjects performing five different mental tasks [10, 11]. EEG signal are recorded from each subject trial by trial. Each trial took 10 seconds as in Table 1. An Electro-Cap elastic electrode cap is used to record EEG signals from positions C3, C4, P3, P4, O1 and O2, based on 10-20 standard of electrodes placement.

There are totally 650 seconds for each task for experiment in that dataset. All subjects are male exact from subject five. Most are students and ages between 20 and 30. Five mental tasks namely baseline task, letter composing task, multiplication tasks, counting and figure rotation task are recorded in dataset.

Table 1. EEG Data Recording

Subject / Tasks	S1	S2	S3	S4	S5	S6	S7	Total (sec)
	trials							
baseline	10	5	10	10	15	10	5	650
Multiplication	10	5	10	10	15	10	5	650
Letter Composing	10	5	10	10	15	10	5	650
Rotation	10	5	10	10	15	10	5	650

3. Material and Methods

In this work, we have taken the mental task EEG dataset, which is publicly available in online [10]. After taking these EEG signals we designed a decision making process, which is basically based on three steps i.e. (I)To remove the noise from the EEG signal, (II)To extract Matching Pursuit based statistical features, (III)To use the multiclass LS-SVM classifier to classify the five different classes EEG signals. The flowchart of the classification system is given in Figure 4. The input to the system is one trial of Mental Task EEG signal. One trial last 10 seconds and has totally 2500 samples. In preprocessing step, the input signal are denoised the artifact. Before entering the feature extraction process, the signal must be windowing. Each window widens one second and so it has totally 10 segments. Each segment has six channels. MP decomposes from each channel and it extracts about 45 atoms. For each atom, the parameters of amplitude, scale, frequency, modulus, position and phase are measured. For each channel, 10 coefficients which are explained in section 5 are accounted.

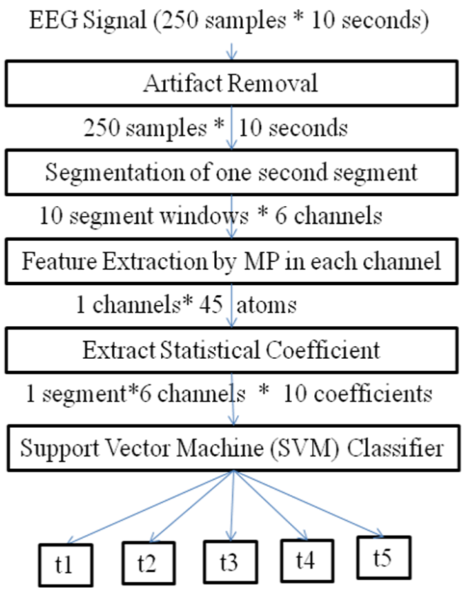

Figure 1. Architecture of Proposed System

These features are further used by LS-SVM multiclass classifier as training and testing purpose. After prediction, the performance of the classifier is determined in terms of classification Rate (CR).

4. Signal Processing

The EEG signal is susceptible to many artifacts, such as eye blinks, eye movement, muscle activity, etc. It is necessary to remove these artifacts; otherwise they will do some distortion to the analysis of the EEG signal. Additionally, it can disturb the accuracy of classification of EEG signals. Here, to eliminate the artifacts, Independent Component Analysis (ICA) is used. ICA is a method of blind source separation (BSS).

In this study we used the EEGLAB (Open Source Matlab Toolbox for Electrophysiological Research) tool for the process of ICA to remove noise from the EEG signal [6]. After importing the data to EEGLAB tool, then run the ICA, the components of multiplication task for 250 Hz are decomposed as six components according to the six electrode channels. And independent components were displayed in spatial graphs as in Figure 2. Properties that describe eye artifacts are a strong far-frontal projection in the scalp map and individual eye movements in a detailed component view. After component examination, the artificial one is removed.

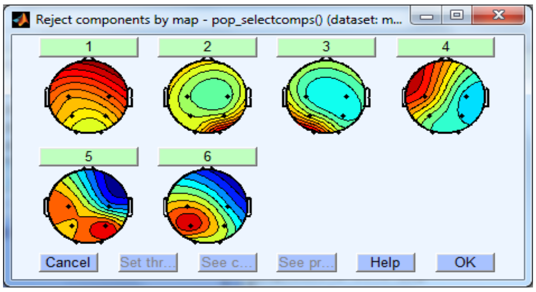

Figure 2. Components in Spatial Graph

The sample signal of trial 4, multiplication task of subject 1 is shown for 5 second in Figure 3. It has some eye blind noise in 1 second and 4 second segments.

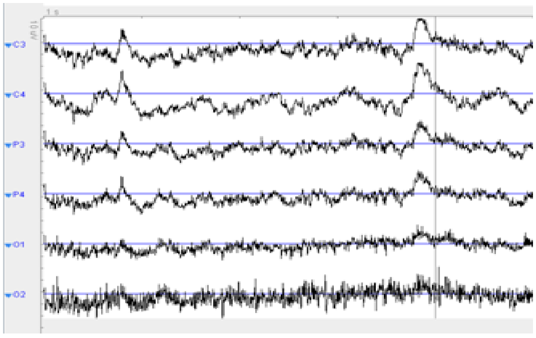

Figure 3. Eye Blind Noise

These noises can be removed by using ICA as in Figure 4.

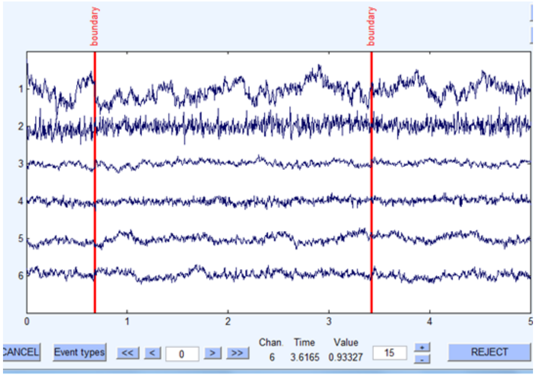

Figure 4. Removing Noise via ICA

After running the ICA, the eye blink noises are removed as in Figure 5.

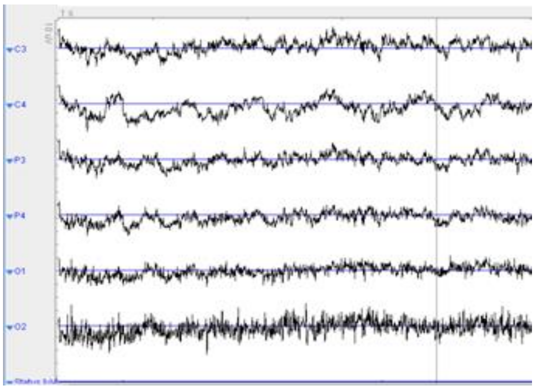

Figure 5. Signal After Removing Noise via ICA

After removing the noise via ICA, the signal data are exported to EDF file format using EEGLab to be compatible with mp5 for feature extraction.

5. Feature Extraction

Feature extraction for EEG signals includes finding signal's features that describe EEG activity with the greatest difference between the groups of EEG signals that are later classified. Feature extraction also reduces the amount of data used in classification.

Matching pursuit (MP), a technique of time frequency signal analysis, was applied to Mental Tasks classification of EEG signal as feature extraction method. MP was proposed by Mallat and Zhang (1993) [25].

5.1 Matching Pursuit Algorithm

The method relies on the approximation of the signal by functions (time-frequency atoms) chosen from a very large and redundant set. Given a set of functions (dictionary) $\{G=g_1,g_2,g_3,\ldots\ldots, g_n\}$ such that $||g_i||=1$; we can define an optimal M-approximation as an expansion minimization the error ϵ of the approximation signal F by M atoms. Such an expansion is defined by the set of indices $\{\gamma_i\}i=1\ldots M$ of chosen function $g_{\gamma i}$ and their weights W_i :

$$\mathcal{E}=||f(t) - \Sigma_{i=1 \text{ to } M} W_i \, g_{\gamma i} (t) ||= \min$$

MP (Matching Pursuit) is an iterative, non-linear procedure which decomposes a signal into a linear expansion of waveforms chosen from a redundant dictionary. In the first step, a waveform $g_{\gamma 0}$ best matching the signal f is chosen, and in each consecutive step waveform $g_{\gamma n}$ is matched to the signal's residuum $R^n f$, left after subtracting results of previous iterations:

$$R^0 f= f;$$

$$R^n f = < R^n f, g_{\gamma n} > g_{\gamma n} + R^{n+1} f \, ;$$

$$g_{\gamma n} =\arg\max g_{\gamma i} \in G \,|< R^n f, g_{\gamma i} >|$$

MP finds an atom of maximum modulus amongst all inner products in that iteration.

In this study, the implementation of MP decomposition is performed using freely available software mp5 with a user friendly interface via Svarog which is a signal analyzer tool [26].

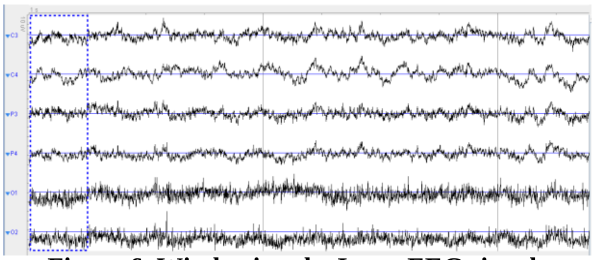

Figure 6. Windowing the Input EEG signal

The mental task EEG signals are separated as one second segment for extraction of the time frequency features for six channels as in Figure 6.

Svarog shows the time and frequency map of each extracted atoms from input signal as in Figure 7. The example of parameters of amplitude, scale, frequency and position of the extracted atoms can also see in Figure 8.

The number of atoms in one channel is totally about 45 and so for six channels, we get approximately 270 atoms in each one second window.

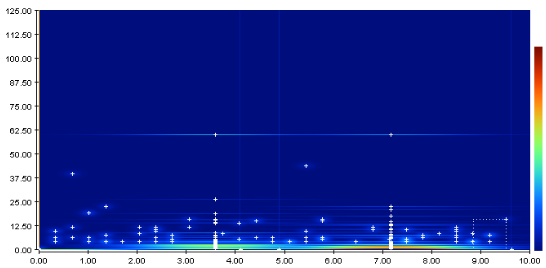

Figure 7. Time-Frequency Map of Letter Composing Task

5.1 Extraction of Statistical Coefficient

The features extracted by MP which are amplitude, position, scale and frequency are not directly feed to classifier. The statistical coefficients such as mean, variance and minimum for each channel are extracted [18, 24, and 27].

Modulus	Amplitude	Position	Scale	Frequency	Phase
18.047	0.822	0	0	1	-0.497
16.988	2.708	0.34	0.445	8	-2.654
14.827	2.363	0.34	0.445	4	0.974
11.141	1.776	0.68	0.445	19	-1.688
10.554	10.554	0.512	0	0	0
10.032	10.032	0.508	0	0	0
10.452	1.666	0.34	0.445	24	2.604
8.718	1.39	0.68	0.445	5	0.061
8.648	8.648	0.628	0	0	0
8.638	0.394	0	0	2	0.511
8.373	8.373	0.348	0	0	0
8.099	1.291	0.34	0.445	17	0.825
7.542	1.202	0.68	0.445	12	2.472
7.532	7.532	0.464	0	0	0
8.394	1.338	0.34	0.445	6	-1.613
7.609	1.213	0.34	0.445	29	-2.485

Figure 8. Parameters of each atoms of Letter Composing Task

We have 10 features for one channel as in Table 2. and so totally 60 features vector for all channels.

Table 2. Features

Mean	Mean of Modulus Values	F1
	Mean of Amplitude Values	F2
	Mean of Frequency Values	F3
	Mean of Phase Values	F4
Var	Variance of Modulus Values	F5
	Variance of Amplitude Values	F6
	Variance of Frequency Values	F7
	Variance of Scale Values	F8
Min	Minimum of Modulus Values	F9
	Minimum of Amplitude Values	F10

6. Classification of EEG Signal

According to table 2, 10 features are used to classify. So it has totally 60 features for 6 channels. It is a large numbers of parameters for running SVM classifier. We want to use combination of 4 features for each channel and totally only 24 features for all channels for classification.

After analysing, we choose the best distinct features for discriminating the mental tasks and remove some unwanted features. One-Vs-One Multi Class LSSVM based on RBF Kernal is used to classify the EEG signal.

Table 3. Results of Different No. of Features

Combination of Features	No. of Features	Accuracy
F1F2F3F4F6F7F8F9F10	54	99%
F1F2F3F4F7F8F9F10	36	99%
F1F2F3F4F8	30	98%
F1F3F4F8	**24**	**98%**

Table 3 shows the comparison of classification accuracy with different number of features. Combination of F1, F3, F4 and F8 enables less execution time and few features, which is suitable for classification.

Table 4. Comparison Results of 24 Features

Combination of Features	**No. of Features**	**Accuracy**
F1, F2, F3, F4	24	96 %
F1, F2, F3, F8	24	95 %
F1, F2, F4, F8	24	93 %
F1, F3, F4, F8	**24**	**98%**
F2, F3, F4, F8	24	83 %

The results comparison of 24 features is mentioned in Table 4. The best combination of features is F1, F3, F4 and F8 with 98% accuracy.

7. Discussion and Conclusion

It makes some experiments using the four trials of subject 1 for five mental tasks. Mean of Modulus, Frequency and Phase and variance of Scale are the best features for classification. Four Trials are used to train and two trials are used for testing. The classification accuracy is not good for untrained data.

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