35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

A Self Produced Mother Wavelet Feature Extraction Method for Motor Imagery Brain-Computer Interface

W.-L. Yeh, Y.-C. Huang, J.-H. Chiou, J.-R. Duann and J.-C. Chiou

Abstract—**Motor imagery base brain-computer interface (BCI) is an appropriate solution for stroke patient to rehabilitate and communicate with external world. For such applications speculating whether the subjects are doing motor imagery is our primary mission. So the problem turns into how to precisely classify the two tasks, motor imagery and idle state, by using the subjects' electroencephalographic (EEG) signals. Feature extraction is a factor that significantly affects the classification result. Based on the concept of Continuous Wavelet Transform, we proposed a wavelet-liked feature extraction method for motor imagery discrimination. And to compensate the problem that the feature varies between subjects, we use the subjects' own EEG signals as the mother wavelet. After determining the feature vector, we choose Bayes linear discriminant analysis (LDA) as our classifier. The BCI competition III dataset IVa is used to evaluate the classification performance. Comparing with variance and fast Fourier transform (FFT) methods in feature extraction, 2.02% and 16.96% improvement in classification accuracy are obtained in this work respectively.**

I. Introduction

Stroke is now one of the leading causes of death in the world, and the stroke survivors may suffer from permanent upper limb paralysis, which may significantly impact their employability. People who suffered from slight motor disabilities need more effective therapies to rehabilitate, and others who suffered from severe motor disabilities but are still cognitively intact need an alternative method to interact with the environment. Brain-computer interface (BCI) provides not only an alternative communication channel which messages convey to the external world do not pass through the brain's normal motor output pathways but also a new motor therapies that reorganize the neural networks and improve motor control.

Based on the different electroencephalographic (EEG) signals features, there are many various BCI systems. One of the practical BCI systems is based on motor imagery (MI). Unlike the steady state visually evoked potential (SSVEP) BCI system [1][2], whose operating task is an unnatural behavior, the event-related desynchronization (ERD) and event-related synchronization (ERS) phenomena which are natural behaviors of human [3][4] occur when subjects execute or think of moving their limbs. There are sufficient evidences that using a rehabilitation protocol involving motor imagery practice in conjunction with physical practice leads to enhance functional recovery for paralyzed limbs [5][6][7].

For performance and reliability of such BCI applications, classifying the motor imagery accurately becomes a key point to concern. However, the uncertainty of idle states, and the variation among subjects of the precise timing and frequency bins when ERD/ERS occur make classification more complicated. To compensate the various situations to each subject, the machine learning approach is utilized. Feature extraction is one of the significant factors that affect the success of classification. For a preferable classification result, an efficient feature extraction technique is needed. In this paper we propose a feature extraction technique and use a publicly available dataset from BCI competition III to verify the performance.

This paper is organized as follow: In Section II, the signal processing flow and the feature extraction technique is described in detail. Then a publicly available dataset is used to evaluate the performance of our signal processing technique. And the result is compared with two commonly used feature extraction methods in Section III. Finally we give a conclusion in the last section.

II. Methodology

A. Data Description

BCI competition III Dataset IVa is used for test in our study. This publicly available dataset is provided by Fraunhofer FIRST, Intelligent Data Analysis Group (Klaus-Robert Müller, Benjamin Blankertz), and Campus Benjamin Franklin of the Charité-University Medicine Berlin, Department of Neurology, Neurophysics Group [8][9]. This dataset contains EEG data of five healthy subjects recorded with 118 channels BrainAmp system. 118 channels EEG were measured at positions of the extended international 10/20-system. The signals were digitized at 1000 Hz sample rate and 16 bit (0.1 uV) accuracy. To reduce the computational loading, we down sampled the EEG data to 500 Hz.

During the recording session, the subjects sat in a comfortable armchair with arms resting on armrests and were instructed to perform three motor imagery tasks, left hand,

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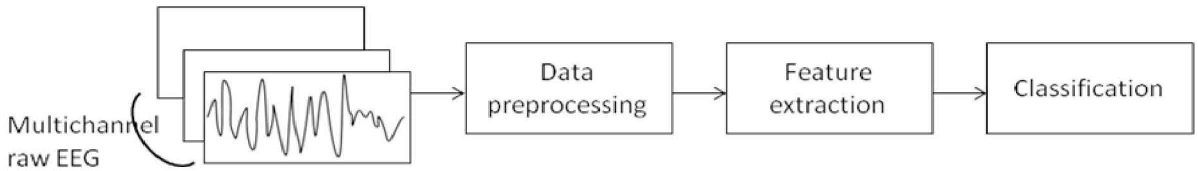

Figure.1 The conventional signal processing architecture

right hand or right foot, for 3.5 s after the visual cue. The motor imagery tasks were intermitted by periods of random length, 1.75 to 2.25 s, in which the subject should relax.

For manipulation of upper limbs paralyzed subjects, the two tasks we want to discriminate are hand movement imagery and relax. So we divide the data into relax periods and right hand motor imagery periods, and then use these two tasks of data for classification.

B. Signal Processing Architecture

The conventional signal processing architecture [10] for motor imagery based BCI is illustrated in Fig.1. The multichannel raw EEG data will be preprocessed first. Then the features are extracted from the preprocessed EEG data. After the feature extraction stage, we can use these features to train our classifier to classify which task the subjects are executing. In the following sections, we will discuss each stage of the architecture in detail.

C. Data Preprocessing

The recorded brain waveforms are associated with some artifacts which are from eye blinking and the electrical noise from the recording systems. Considering the α wave (8~13 Hz) ERD and β wave (14~30 Hz) ERS phenomena, EEG recordings were band-pass filtered from 5 Hz to 40 Hz using a 8 order zero-phase IIR Butterworth filter.

To reduce the computational complexity and avoid the interference from irrelevant channels, 16 electrodes in the area of motor cortex are chosen as shown in Fig. 2.

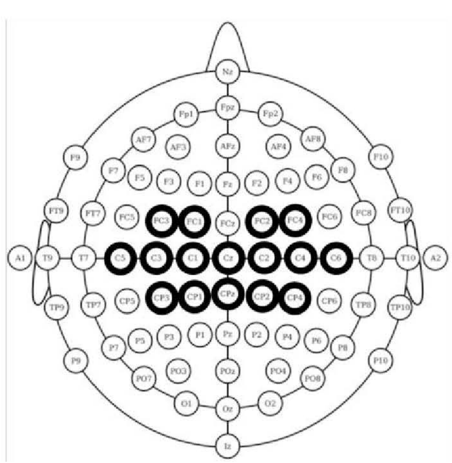

Figure.2 16 chosen electrodes

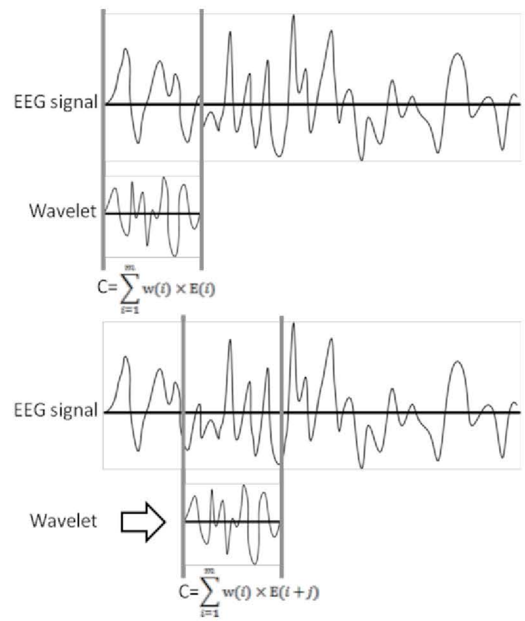

Figure.3 Computational synoptic diagram

D. Feature Extraction

In order to obtain excellent classification results, an effective feature extraction method is very important. There are quite a number studies proposed different feature extraction methods like autoregressive (AR) models, FFT and other time-frequency analysis [11][12][13] for motor imagery applications BCI systems.

Based on the concept of Continuous Wavelet Transform, we propose a wavelet-liked feature extraction method. We compute the correlation coefficients between the wavelet and the EEG signal, and the correlation coefficients are employed as our features. Otherwise, to overcome the problem that the feature variation among subjects, we segment the subjects' own EEG signals from relax period as our mother wavelet. Because the subjects' own EEG signals contain the right frequency band that the ERD/ERS phenomena occur, the scale factor is omitted the scale factor when performing Continuous Wavelet Transform. The mother wavelet is derived by performing cross validation. Fig. 3 shows the computational schematic.

We move the window and calculate the correlation coefficient in each window. Then we set a threshold to abandon the correlation coefficient which is lower than the threshold. This means that we only select the correlation coefficient that is related enough as our feature. Next we sum up the correlation coefficients which are greater than the threshold in each window. The Equation of correlation coefficient processing is shown in (1) and (2). Where c is the correlation coefficient, c_{th} is the threshold we set, w is the wavelet; E is the EEG signal segment we want to classify. Moreover, n and m are the number of samples of EEG segment and the wavelet respectively. According to above parameters, we can get a feature vector $C = [c_1, c_2, \ldots c_{16}]$ from 16-channel EEG data.

$$c = \sum_{j=1}^{n-m} a(j) \times \frac{\sum_{i=1}^{m} w(i) \times E(i+j)}{\sum_{i=1}^{m} E(i+j)^2} \quad (1)$$

$$a(j) = \begin{cases} 1 \ , \sum_{i=1}^{m} w(i) \times E(i+j) > c_{th} \\ 0 \ , \sum_{i=1}^{m} w(i) \times E(i+j) < c_{th} \end{cases} \quad (2)$$

E. Classification

Linear discriminant analysis (LDA) is chosen as our classifier. The linear discriminant analysis is one kind of Bayes classifiers which are based on computing the likelihood of each class. Under the assumption that the class distributions obey known Gaussian distributions with equal covariance, the linear discriminant analysis is low complexity and is not being affected by small variation.

III. Experiment & Result

In this paper, we compare the performance of our feature extraction algorithm with two commonly used features, time domain signal variance and FFT feature. And the performance measure is the overall classification accuracy. To evaluate the performance of the three different kinds of feature extraction methods at the same baseline, the same signal processing flow as shown in section II except for the feature extraction method is performed.

The variance of a time domain signal segment represents the power of this signal. There are many studies focus on how to perform coordinate transformation on signal variance, like Common Spatial Pattern (CSP) algorithm [14][15], to enhance the classification accuracy. For comparison we directly use the signal variance without performing coordinate transformation to train our classifier.

Because the ERD/ERS phenomena which the power is suppressed and enhance in α (8~13 Hz) and β (14~30 Hz) band respectively occurs during subjects doing motor imagery, time-frequency analysis is an important method to extract the feature. FFT is an effective way to extract the frequency feature [16][17]. We use 256-point FFT and select the 8~30 Hz components to classify.

Classification result of the five subjects in BCI competition III Dataset IVa and the average accuracy of them are shown in Fig. 4. Most of the classification accuracy by using the proposed feature extraction method is superior to the other two methods. Due to the insufficient 28 trials in subject ay, the result of this subject is inconsiderable. Fig. 4 indicates that the average accuracy that utilizes the wavelet-liked feature extraction method surpasses 2.02% and 16.96% of the other two methods respectively.

Another interesting result is that the classification accuracy variance among subjects is the most unobvious. It is because that the mother wavelet is chosen by the subjects' own EEG signals.

IV. Conclusion

In this study, we have proposed a new technique to extract the effective feature for two classes of motor imagery BCI. The performance of this work has been verified by a publicly available dataset and derived more accurate results than variance and FFT methods.

The characteristic of our work is that we produce the mother wavelet by the subjects' own EEG. So the features vary among subjects can be compensated adaptively. For this reason, choosing the EEG segment as mother wavelet is important.

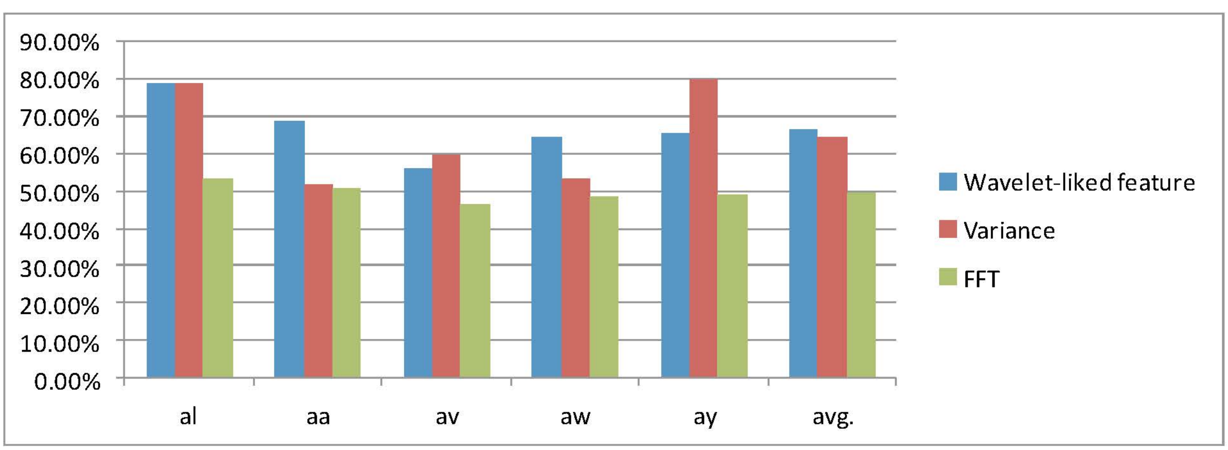

Figure.4 Classification result for five subjects

ACKNOWLEDGMENT

This work was supported in part by the National Science Council, Taiwan, R.O.C. and "Aim for the Top University Plan" of the National Chiao Tung University and Ministry of Education, Taiwan, R.O.C.. This work was also particularly supported by R&D Piloting Cooperation Projects between Industries and Academia at Science Parks under Contract Number: 100A20 and the UST-UCSD International Center of Excellence in Advanced Bioengineering sponsored by the Taiwan National Science Council I-RiCE Program under Grant Number: NSC-101-2911-I-009-101. The authors would like to thank National Chip Implementation Center (CIC) for chip fabrication.

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