Enhancing EEG Signals in Brain Computer Interface Using Wavelet Transform

Eltaf Abdalsalam Mohamed, Mohd Zuki B. Yusoff, Nidal Kamel Selman, and Aamir Saeed Malik

***Abstract*—Brain-computer interface (BCI) is a hardware and software communication system that enables humans to interact with their surrounding without the involvement of peripheral nerves and muscles by using control signals generated from electroencephalographic activity. In this paper, we report on results of developing motor imagery feature extraction method for BCI. The wavelet coefficients were used to extract the features from the motor imagery EEG and the Bayes Net, SVM and RBFN were utilized to classify the pattern of left, right hand movement and forward imagery. The performance was tested using dataset from BCI competition III and satisfactory results are obtained with accuracy rate as high as 99.0674%.**

***Index Terms*—Brain computer interface, EEG, wavelet transform, bayes net, SVM, and RBFN.**

I. Introduction

A brain computer interface (BCI) or a brain machine interface (BMI), refers to a technology which attempts to provide communication methods between human brain and the outside world without the involvement of peripheral nerves and muscles by using control signals generated from electroencephalographic activity. BCI creates a new non-muscular channel for relaying a person's intentions to external devices such as computers, and assistive appliances that is particularly attractive for individuals with severe motor disabilities. The interface would improve their quality of life and at the same time reduce the cost of intensive care [1]. BCI system can be divided into two categories in term of recording methods: an invasive and a non-invasive BCI [2]. The invasive approaches provide a much higher spatial resolution and signal-to-noise ratio (SNR) in comparison to the non-invasive one. However, the non-invasive BCI type is considered to be very safe and more practical; hence, it is widely used by researchers worldwide to monitor brain activities. A normal non-invasive BCI requires electrodes to be attached into the human scalp to monitor brain electrical activities, which are also known as electroencephalogram (EEG). Other non-invasive BCIs include magnetoencephalography (MEG) and positron emission tomography (PET) [3]-[8]. EEG-based BCIs are divided into two classes based on the operation mode: dependent (cue-paced or synchronous) and independent (self-paced or asynchronous) [9]. In any case, the functionalities of EEG-based BCIs can be divided into four subsystems: signal acquisition, signal processing, translation of signal features into commands, and the application of the BCI for a specific purpose [10]. The schematic diagram of BCI is described as in Fig. 1. For the EEG signals recognition method, there are many methods that have been proposed. For example, P. A. Pour *et al*. [5], and Y. Wang *et al.* [11] extracted event-related synchronization and desynchronization (ERD/ERS) from EEG during right and left hand motor imagery then used for the pattern recognition. L. Yong *et al.* [12] utilized motor imagery pattern recognition method based on wavelet transform.

In this work, we have extracted a significant component for pattern identification from motor imagery. These components appear in various frequency bands and dominant bands usually depend on a subject. Therefore, we will identify significant frequency bands by using multi-resolution analysis in order to extract these components.

II. Math Methodology

A. EEG Data Acquisition.

The data sets were obtained from BCI competition III, with the following information; 3 normal subjects, 4 non-feedback sessions. The subjects were sat in a normal chair, with relaxed arms resting on their legs. There were 3 tasks;

1) Imagination of repetitive self-paced left hand movements (left class).
2) Imagination of repetitive self-paced right hand movements (right class).
3) Generation of words beginning with the same random letter (forward class).

All four sessions of a given subject were acquired on the same day, each lasting 4 minutes with 5-10 minutes breaks in between. The subject performed a given task for about 15 seconds and then switched randomly to another task at the operator's request. EEG data are not split in trials since the subjects are continuously performing any of the mental tasks. The algorithm should provide an output every 0.5 seconds using the last second of data. Sampling rate was 512 Hz. Raw EEG signals contain the 32 EEG potentials acquired at a given time instant in the following: (Fp1, AF3, F7, F3, FC1, FC5, T7, C3, CP1, CP5, P7, P3, Pz, PO3, O1, Oz, O2, PO4, P4, P8, CP6, CP2, C4, T8, FC6, FC2, F4, F8, AF4, Fp2, Fz, and CZ.

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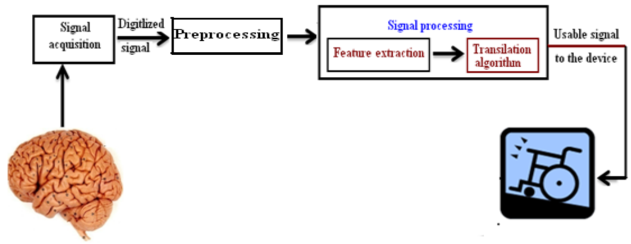


Fig. 1. Basic BCI system.

B. Procedure

The procedure step of raw EEG data is presented in Fig. 2. First, the data were filtered using low and high pass band filters (preprocessing), decomposition of EEG signals into the frequency sub-bands using The Continuous Wavelet Transform (CWT), a set of features were extracted from the sub-bands to represent the distribution of wavelet coefficients according to the characteristics of motor imagery EEG signals. The combination features of wavelet coefficients are used as an input vector. Finally different classification methods were utilized to classify the computed features.

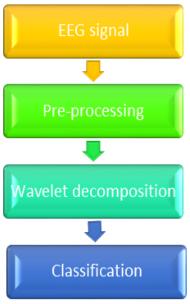


Fig. 2. Raw EEG processing.

C. Feature extraction using Continues Wavelet Transforms

Classic Fourier transform has succeeded in stationary signals processing. However, an EEG signal contains non-stationary characteristics. Thus, it is not suitable to directly apply Fourier transform to such signals. Short time Fourier Transform (STFT) was applied to analyze EEG signals which were a time-frequency analysis method. However, it has been noted that the short time Fourier transform depends critically on the choice of the window. Wavelet transform brings a solution to this problem which has advantages of a multi- resolution analysis method that could give a more accurate and signal temporal localization [13].

Continuous Wavelet Transform (CWT) is a method based on the short time Fourier transform's (STFT) window shifting process [14]. Continuous wavelet decomposition $wt(a, \tau)$ of a signal $X(t)$ via a mother wavelet $\phi\ (a, \tau)$ is given by equation (1).

$$wt(a,t) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} (x(t)\phi^{*}\ \tfrac{(t-\tau)}{a})dt \qquad (1)$$

The resulting coefficients $wt(a,t)$ represent the similarity of the original signal with each many shifted and scaled mother wavelet functions (a, τ), where (τ) and (a) represent a shift and a scale factors, respectively. The transformation product is a set of coefficients structured in a way that enables not only spectrum analyses of the signal, but also spectral behaviors of the signal in time. This is achieved by decomposing the signal, breaking it into two components, each component carrying information about the source signal. Filters from the filter bank used for decomposition come in pairs; they are low pass and high pass filters. The filtering is succeeded by down sampling (obtained filtering result is "re-sampled" so that every second coefficient is kept) [15]. The filter bank implementation of wavelet transform for three-level wavelet decomposition is shown in Fig. 3. In this work, the multi-resolution analyses of four different wavelet functions, namely Daubechies (db2 and db4), symlets (sym4 and sym5) were used to decompose the EEG signals into five different frequency bands (delta, theta, alpha, beta and gamma). These wavelet functions were chosen due to their near optimal time-frequency localization properties. Moreover, the waveforms of these wavelets were similar to the waveforms to be detected in the EEG signal. Therefore, the extraction of EEG signal features was more likely to be successful. Table I presents the bandwidth and frequencies at different levels of decomposition with sampling frequency of 512 Hz. The decomposition labels are chosen to retain those parts of the signal that correlate well with the frequencies required for the classification of the signal. Since the EEG signals do not have useful frequency components above 30 Hz, the computed wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. Therefore, the computed detail and approximation wavelet coefficients of the EEG signals were used as the feature vectors representing the signals. These features represent the frequency distribution and the amount of changes in the frequency distribution. D6 decomposition which is within the mu rhythm and D5 which is within the beta rhythm were chosen to represent the feature vectors. Statistical analyses over the set of wavelet coefficients were computed to reduce the total dimension of the feature vectors.

The seven levels decompositions are shown in Fig. 4.

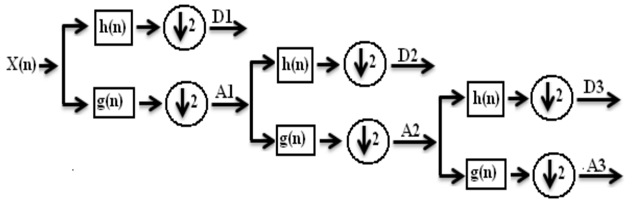
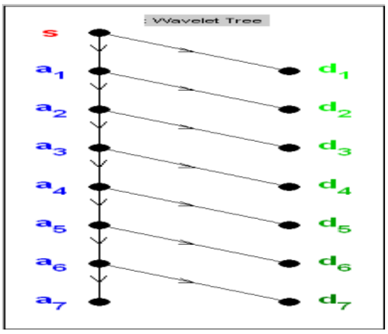


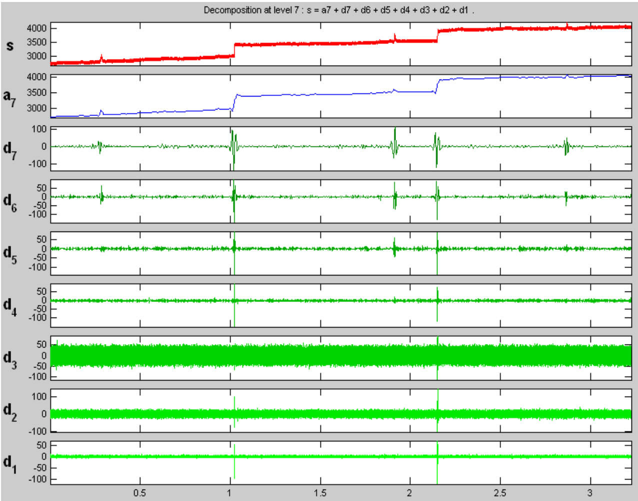
Fig. 3. Filter bank implementation of wavelet decomposition.

TABLE I: EEG SIGNAL DECOMPOSITION AT DIFFERENT FREQUENCY BANDS WITH A SAMPLING OF FREQUENCY 512 HZ

Frequency range Hz	Decomposition label	Frequency bands	Bandwidth Hz
0- 2	A7	Delta	2
2 - 4	D7	Theta	2
4 - 12	D6	Alpha	8
12 - 32	D5	Beta	20
32 - 80	D4	Gamma	48
80- 192	D3	Noises	112
192 - 448	D2	Noises	256
448 - 1024	D1	Noises	576



(a)



(b)

Fig. 4. (a) CWT decomposition tree from decomposition level 7. (b) Examples of one class (left) signal using wavelet multi-resolution with sym4 wavelet and 7 level decomposition, Wavelet coefficient subsets (D1-D7, A7) of left hand imagery from the subject 1.

D. *Classification by Conventional Methods*

In this work the different classification methods such as Support vector Machine (SVM), Bayes Net and Radial Basis Function Network (RBFN)) were applied into the different wavelet family in order to choose the best wavelet function that will give higher accuracy.

III. RESULTS

From the study we have got 2 wavelet coefficients (D5, D6) for each channel, giving a total of 14 features for a motor imagery task. These features were selected as inputs for the classification. Classification results of the system were reported by using a m-fold cross-validation method. The data from each set were randomly divided into (m) complementary subsets; one of the subsets was used as the validation set and the other nine subsets were put together to form training sets. Then in order to reduce variability, this procedure was repeated (m) times and the average classification results were computed. In this study, all obtained results were presented by using 10-, 15- and 20-fold cross-validation and four wavelet functions (represented in the MATLAB Wavelet toolbox) such as Daubechies (db2 and db4), Symlets (sym4 and sym5) with decomposition level of 7 being examined and compared. Fig. 5. Shows wrongly classified and rejection classification of sample for different wavelets by using a 20-fold cross-validation. We can see that the sym4 wavelet offers lower wrongly classified sample, and rejection rate and the db4 is marginally higher than the sym4. Hence, the sym4 wavelet was chosen for this application. Table II-IV describe the classification of test samples using 10-, 15-, and 20-fold cross-validation, respectively. The number of sample correctly classified, wrongly classified, rejected and true/false positive rate classification were tested with 2-, 5- and 10-fold cross-validation, respectively. We can see that the best result is 99.07% correctly classified with 0.8808 rejected samples.

In Table V, the average performance was achieved by using 10-, 15-, and 20-fold cross-validation. It can be seen that the 20-fold cross-validation achieves the best performance. The reason for this could be that there are more training samples in this test. However, the difference is small and the average accuracy is above 99% which demonstrates the generalization ability of our method.

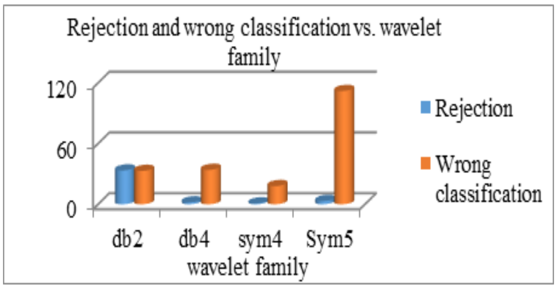


Fig. 5. The number of wrongly classified and rejected obtained for different wavelet when the motor imagery task were classified using the proposed method.

TABLE II: CLASSIFICATION OF TEST SAMPLES BY 10-FOLD CROSS-VALIDATION FOR THE DIFFERENT WAVELET FAMILY

Wavelet family	Classification methods	Total samples	Correctly classified	Wrongly classified	True positive rate (TP)	False positive rate (FP)	Rejection rate
db2	Bayes Net	962	929	33	0.966	0.018	3.43
	SVM	962	398	564	0.414	0.414	58.63
	RBFN	962	647	315	0.673	0.180	32.74
db4	Bayes Net	1930	1896	34	0.982	0.009	1.76
	SVM	193	1648	282	0.858	0.066	14.24
	RBFN	1930	1566	364	0.811	0.081	18.86
Sym4	Bayes Net	1930	1904	26	0.987	0.007	1.35
	SVM	1930	1652	278	0.856	0.067	14.40
	RBFN	1930	1552	378	0.804	0.085	19.59
Sym5	Bayes Net	3848	3732	116	0.970	0.015	3.01
	SVM	3848	2313	1535	0.601	0.254	39.89
	RBFN	3848	2317	1531	0.602	0.231	39.89

IV. Conclusion and Future Work

In this works, we implemented the wavelet transform feature extraction method to acquire fewer feature spaces of motor imagery task, and in combination with the cross-validation, with deferent classification method. The proposed method was successfully applied to EEG signals for motor imagery task. The results including classification accuracy and reject rate showed that the proposed system cans effectively possible movement. The average classification performance was generally better than or near to some literatures. The best accuracy can achieve 99.067%. Our proposed system using EEG can provide an important assistant to directly control a wheelchair so as to help the patient with severe paralysis. Future work will consider other more exotic classifiers such as fuzzy logic, neural networks or other hybrid pattern classifiers.

TABLE III: Classification of Test Samples by 15-Fold Cross-Validation for the Different Wavelet Family

Wavelet family	Classification methods	Total samples	Correctly classified	Wrongly classified	True positive rate (TP)	False positive rate (FP)	Rejection rate
db2	Bayes Net	962	933	29	0.970	0.016	3.0146
	SVM	962	398	564	0.413	0.414	58.6279
	RBFN	962	640	322	0.665	0.181	33.4719
db4	Bayes Net	1930	1897	33	0.983	0.008	1.7098
	SVM	193	1655	275	0.858	0.066	14.2487
	RBFN	1930	1566	364	0.811	0.081	18.8601
Sym4	Bayes Net	1930	1904	26	0.987	0.007	1.3472
	SVM	1930	1652	278	0.856	0.067	14.4041
	RBFN	1930	1552	378	0.804	0.085	19.5855
Sym5	Bayes Net	3848	3732	116	0.970	0.015	3.0146
	SVM	3848	2313	1535	0.601	0.254	39.8909
	RBFN	3848	2317	1531	0.602	0.231	39.8909

TABLE IV: Classification of Test Samples by 20-Fold Cross-Validation for the Different Wavelet Family

Wavelet family	Classification methods	Total samples	Correctly classified	Wrongly classified	True positive rate (TP)	False positive rate (FP)	Rejection rate
db2	Bayes Net	962	931	31	0.968	0.017	33.4719
	SVM	962	397	565	0.413	0.414	58.7318
	RBFN	962	623	339	0.648	0.190	35.239
db4	Bayes Net	1930	1894	36	0.981	0.009	1.8653
	SVM	193	1651	279	0.855	0.067	14.456
	RBFN	1930	1582	348	0.820	0.077	18.0311
Sym4	Bayes Net	1930	1913	17	0.991	0.004	0.8808
	SVM	1930	1651	279	0.855	0.068	14.456
	RBFN	1930	1591	339	0.824	0.077	17.5648
Sym5	Bayes Net	3848	3726	122	0.968	0.015	3.1705
	SVM	3848	2313	1535	0.601	0.254	39.8909
	RBFN	3848	2375	1473	0.617	0.223	38.2796

TABLE V: the Obtained Average Classification Accuracy and the Corresponding Reject Rate for Classification of Motor Imagery Task with *M*-Fold Cross-Validation

***m*- fold cross validation**				
Measures	***M* =10**	***M* =15**	***M* =20**	**Classification methods**
Accuracy (%)	99.0674	98.65	99.12	Bayes Net
	85.39	85.60	85.54	SVM
	83.52	80.41	82.43	RBFN
Rejection rate (%)	0.9326	1.35	0.8808	Bayes Net
	14.92	14.40	14.46	SVM
	16.48	19.59	17.56	RBFN

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