Mental Task Motor Imagery Classifications for Noninvasive Brain Computer Interface

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Abstract - **A Brain computer interface (BCI) has introduced new scope and created a new period for developers and researchers giving alternative communication channels for paralysed peoples. Motor imagery refers to where EEG signals that being obtained while the subject is imagining or performing a motor response. This work is to examine this area from Machine Learning and exploit the Emotiv System as a cost-effective, noninvasive and also a portable EEG measurement device. The experiment was carried out based on Emotiv control panel focusing on cognitive commands such as (forward, backward, left and right). The data were preprocessed to remove the artifact as well as the noise by using EEGlab toolbox. Wavelet transforms namely Daubechies and symlets were used for feature extraction. The Multilayer perception (MLP), Simple logistic and Bagging were utilized to classify the mental tasks motor imagery. The performance of classifications was tested and satisfactory results were obtained with the accuracy rate 80.4% using the Simple logistic classifier.**

***Keywords* — Brain computer interface; EEG; Wavelet transform, MLP; simple logistic; Bagging.**

I. INTRODUCTION

BCI is an artificial system that connects brain activity to the outside world by using electroencephalography as the signal extractor. This interface creates a new communication which could help the motor disabled people to obtain individual activities using a device such as a wheelchair. Furthermore, intensive care cost could be reduces [1]. A 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 is considered to be more safe and more practical; hence, it is widely used by researchers worldwide to monitor brain activities. A normal non-invasive BCI requires electrodes/ electroencephalogram (EEG) to be attached into the human scalp to monitor brain electrical activities. Other non-invasive BCIs include magnetoencephalography (MEG) and positron emission tomography (PET) [3]. EEG based BCIs -are divided into two classes based on the operation mode: dependent (cue-paced or synchronous) and independent (self-paced or asynchronous) [4]. 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 ease of use in a specific purpose as shown in Fig.1[5]. Based on neuro mechanisms BCI is divided to seven categories: visual evoket potential (VEP), sensorimotor, slow cortical potential (SCP), P300, response to mental task and combinations. Sensorimotor rhythms (SMR) are created by the primary sensory and motor cortices. SMR based BCI's divided into two: event related synchronization (ERS) and event related desynchronization (ERD), which detected as mu rhythm and beta, the mu rhythm from 8 to 12Hz and the beta rhythm from 13Hz to 26Hz have been particularly useful as BCI control signals. [6]. as shown in table. 2.

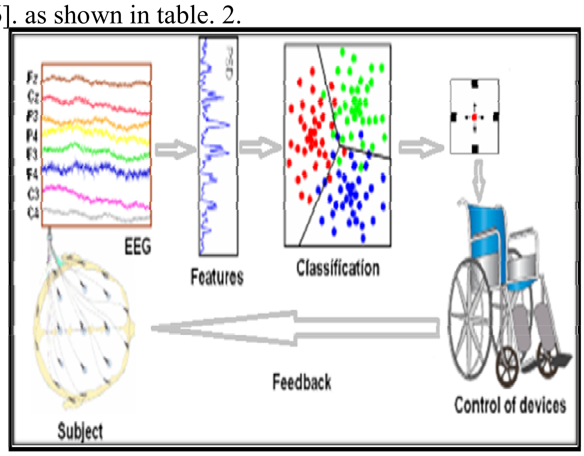

Fig. 1: Basic BCI system.

In recent years BCI researchers were attempted different computational techniques to detect and classify Mental Tasks Motor Imagery. Power Spectral Density (PSD) as a detector and Linear Discriminate

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Analysis (LDA) as classifier were used by [7 - 11]; Band Power (BP), LDA,[12]; Wavelet packet transform (WPT), Neural Network,[13 and 14]; Wavelet transform, Neural Network, [15 and 16]; Band Power, fuzzy inference systems, [17]; Wavelet transform, (LDA and SVM), [6]; Base on the literature view point, the use of wavelet transform method to detect the EEG signal is efficient. The present study explains how significant components were extracted from the motor imagery base on frequency and domain bands difference by using multi-resolution analysis method.

II. METHODOLOGY

A. EEG Data Acquisition

The EEG neuroheadset (Emotiv EPOC) providing access to raw EEG data is presented in Fig. 2 There are 14 channels which are attached bases on the 10- 20 standard system, as shown by Fig. 3 the primary reference point sensors are located above and behind the ears. The secondary reference point sensors are located below and behind the ears. The sampling rate is 128 Hz. The signals from the brain are sent through the wireless device (dongle) attached to a personal computer that is used to perform the analysis [18]. The EPOC headset specification is shown in Table. 1.

The experiments took place in Universiti Teknologi PETRONAS (CISIR Lab 14) for five healthy male subjects, age (26-35) using Emotiv EPOC and Emotiv control panel (cognitive suite) as shown in fig. 4 and Emotiv Tech Bench which using to record data as shown in fig 5. The experiments procedure was started by wearing the headset while relaxing on the chair to detect mental task command (forward, backward, right and left). The datasets for each command was created. The preparation time was 2 minutes, the session starts with training the neutral brain data (during which the subject was relaxed and not focusing on anything in particular) for 8 seconds. Then the subject was trained by saying which direction he/she wanted to train. The concentration on each movement was recorded through a 40 second. The times required for each subject to perform period the experiment was 10 minutes.

Fig. 2. Signal acquisition device.

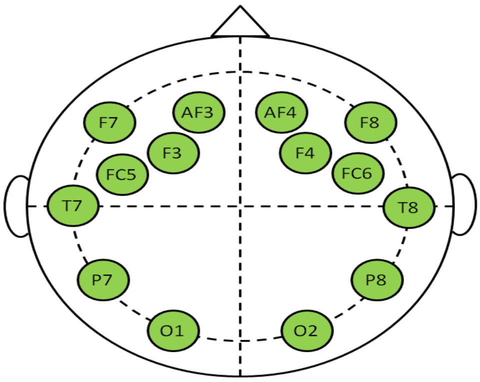

Fig. 3 Emotiv EPOC Neuroheadset sensor placement [14]

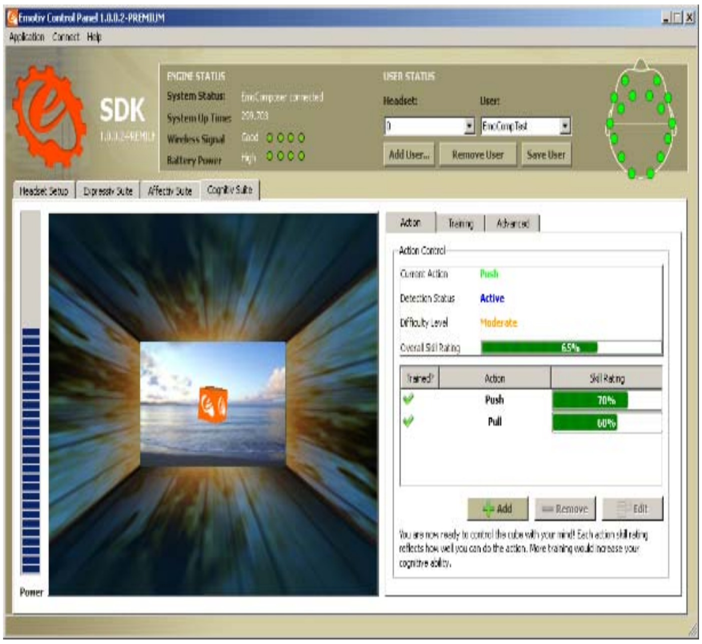

Fig. 4 Virtual cube used for training to control actions in the Emotive Cognitive suite.

TABLE. 1 EMOTIV EPOC NEUROHEADSET SPECIFICATIONS [14].

Parameter	Value
Number of channels	14 Channels
Sampling Rate	128 Hz
Sampling Resolution	14 bits
Sampling Method	Sequential. Single ADC
Bandwidth	0.2 – 45 Hz
Dynamic Range	8400 µV (pp)
Connectivity	2.4 GHz wireless band

B. Procedure

The procedure mainly started with preprocessing the EEG data using EEGlab (pass band filter 1 - 20 Hz) while the artifacts removal method contained Independent Component Analysis (ICA) and liner filter.

Feature extraction stage has been performed using Continuous Wavelet Transform methods. As a results a sets of features was obtained from the wavelet coefficient distribution based on mental task motor imagery. The combined wavelet coefficients were arranged in a matrix as features. Finally different classification methods were utilized to classify the features.

a. Feature extraction using Continuous Wavelet Transforms

From a literature view the use of the Fourier transform method to extract feature from stationary signal was found to be effective. Consequently, EEG signal contains non-stationery character and it is not suitable to use Fourier transform or short time Fourier Transform (STFT) because they depends on windows choice. The use of Wavelet transform has advantages of a multi-resolution analysis which could give more accuracy and signal temporal localization as well as overcome the problem of non-stationarity [19]. The decomposition procedure was performed using continuous wavelet equation (1).

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

The coefficients $wt(a,\tau)$ denote the original signal similarity through shifting and scaling mother wavelet functions (a,τ), whereas $x(t)$ is original signal, $\phi^{*}(a,\tau)$ is mother wavelet, (a) and (τ) are scale and shift factors. The results were sets of coefficients achieved by decomposing the signal into two components (detailed and approximate coefficients). The filtrations were performed using low and high pass filters by signal down sampling. The results were re-sampled to keep the second coefficients (detail coefficients) [20]. Fig. 6 shows the three level filtrations procedure.

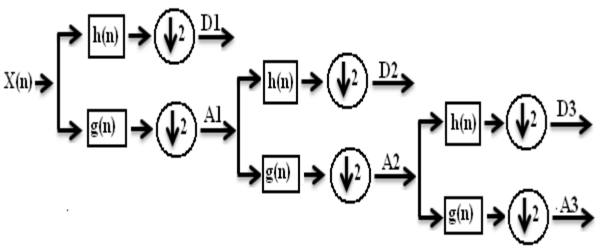

Fig. 6. Wavelet decomposition filter bank

In this paper the multi resolution of two wavelet families, Daubechies (db4) and symlets (sym4) were used due to near optimal time frequency and the waveform similarity. The signals were decomposed to five frequencies namely Delta, Theta, Alpha, Beta and Gamma with 128 Hz sampling frequency as presented in Table. 2.

TABLE. 2. DECOMPOSED EEG SIGNAL AS FUNCTION OF FREQUENCY 128HZ.

Frequency range (Hz)	Decomposition label	Frequency band	Bandwidth (Hz)
0- 2	A5	Delta	2
2 - 4	D5	Theta	2
4 - 12	D4	Alpha (mu)	8
12 - 32	D3	Beta	20
32 - 80	D2	Gamma	48
80- 192	D1	Noises	112

The decomposition labels were chosen to retain the signal part that correlated with the classification frequency. The computed coefficients had shown the signal energy distribution in frequency and time. These computed detail coefficients (D3and D4) were interred as features that present frequency distribution change, as shown in Fig. 7 the wavelet decomposition is shown in Fig. 8.

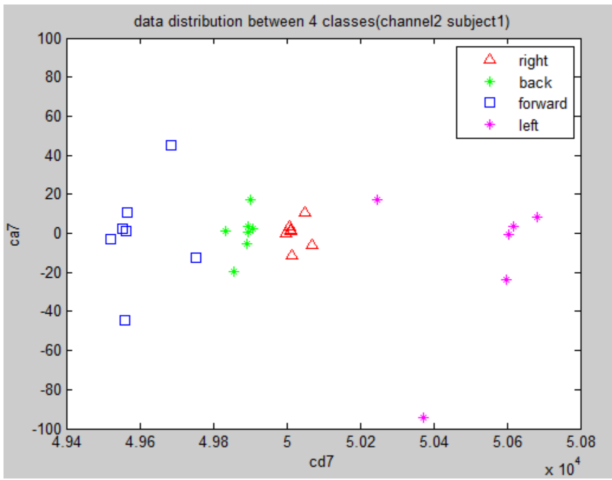

Fig.7. Examples of data distribution between four classes (right, left, forward and backward) from subject1 using wavelet multi-resolution with db4 wavelet, 7 level decomposition.

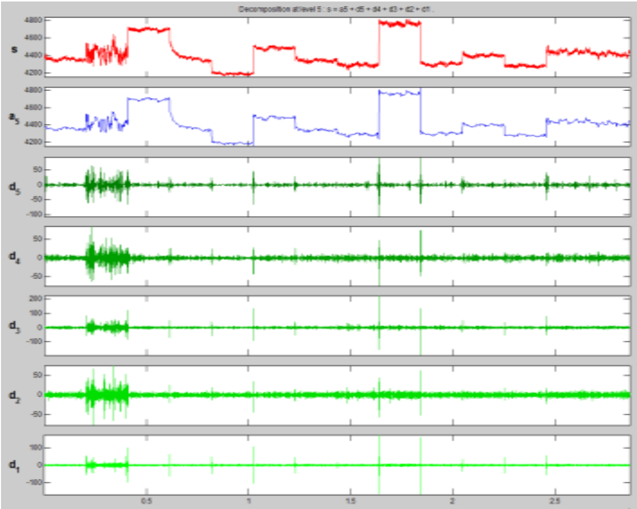

Fig. 8. Example of one command (right) signal using wavelet multi-resolution with db4 wavelet, 5 level decomposition, Wavelet coefficient subsets (D1-D5, A5) of right hand imagery from the subject 1

b. Classification by conventional methods

In this work different classification methods such as Simple logistic, Meta (Bagging) and Multilayer perception (MLP) were applied into the different wavelet families in order to choose the best wavelet function that could give higher accuracy.

III. RESULTS

Accordingly to the frequency range of Beta and Alpha D3 and D4 were selected as classification input. A total of 28 features per channel were obtained. The classification results were presented using 10 fold cross validations. The data for each set was divided into ten sets, nine sets for training and one set for validation. Table. 3 shows a classification result in term of, a sample number, correct and wrong classification, and rejection rate. It is observed that the simple logistics method with db4 wavelet family gives best accuracy of 80.4% and 19.5 reject samples.

TABLE. 3. CLASSIFICATIONS AS FUNCTION OF WAVELET FAMILY AT 10 FOLD CROSS VALIDATION.

Wavelet family	Classification methods	Total samples	Correctly classified	Wrongly classified	Rejection rate%	Accuracy rate%
db4	**Simple logistic**	97	78	19	19.6	80.4
	MLP	97	70	27	27.8	72.2
	Bagging	97	74	23	23.7	76.3
Sym4	**Simple logistic**	97	74	23	23.7	76.3
	MLP	97	68	29	29.9	70.1
	Bagging	97	72	25	25.8	74.2

VI. CONCLUSION AND FUTURE WORK

In this work the wavelet transform method was implemented as the mental task motor imagery features extractor. Thus, several classification methods were applied. The results indicated that the proposed methods are feasible and the accuracy of classification in rate is better. In the future, more exotic classification techniques could be applied for instance, fuzzy logic.

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