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Classification of Thoughts into Wheelchair Control Commands using Neural Network

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Abstract

This paper presents the use of neural network classification thought- based commands for wheelchair control. The advantage is to assist the locked in people who are not able to use physical interfaces like joysticks or buttons. Electroencephalogram (EEG) was used to discriminate motor imagery mental tasks, such as imagination of left hand, right hand, both hands and both feet. The four task classifications were mapped into a wheelchair movement, such as forward, left, right, and backward. The motor imagery command data were collected from seven participants. A wireless device (Enobio) with 8 dry electrode recording was used. Discrete wavelet transform and Multiyear perceptron were utilized for signal processing. The results show that the proposed system provides a good classification performance with an average classification rate of 81.046%.

Keywords: Brain computer interface; EEG; Wavelet Transform; Multilayer perceptron (MLP).

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1. Introduction

Brain computer interface (BCI) is one of neuroscience fields that connect the human brain with the outside world (computer) [1]. the control strategies of the user and determining appropriate user's mental tasks for control [2, 3]. Based on the operation mode EEG-based BCIs are divided into two classes: independent (self-paced or asynchronous) and dependent (cue-paced or synchronous) [4] BCI is divided into seven categories Based on neuro-mechanisms:, slow cortical potential (SCP), visual evoked potential (VEP), P300, sensorimotor, response to mental task and combinations. Sensorimotor rhythms (SMR) are created by the primary sensory and motor cortice**s**. However, 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 for a specific purpose [1]. BCIs have offered valuable options for highly disable patients with complete loss of their ability to move or speak, to live more independently. The recent developments of BCI-based schemes to control wheelchairs have promoted new opportunities for disabled patients. More so, thought-based wheelchair controls using EEG technology could allow patients to not only communicate with the surrounding but also navigate around them. As a result, the impact on reducing health care cost could potentially be achieved.

Most studies on brain control wheelchair used input signal as sensorimotor rhythms to modulated voluntarily by motor imagery (MI) [5,6]. Different protocols have been investigated for brain control wheelchair using asynchronous control [7-9], or using synchronous control [10].

From literature noted that the strength of any BCI application depends on the machine learning, which used to transform the EEG signal into corresponding commands. In [11], the authors recorded two classes imagination right-hand and left-hand movement from three subjects. They were able to classify these two classes, they achieved an accuracy of 80% using a neural network classifier, and concluded that the increasing number of sessions did not improve accuracy.

The reference [12] presented a three class, such as left/right hand and foot imagination movements for the BCI system for the translation commands to operate a wheelchair.

The current brain control wheelchair only allows simple movements; two or three directions by using an asynchronous control (motor imagery) [8, 9]. In this paper, we utilized asynchronous, (motor imagery) and the number of commands was increased to four, namely forward, left, right, and backward directions.

2. Materials and Methods

2.1 General structure of BCI system

The protocol of BCI system is shown in Figure 1. The procedure stared with the following step: First collected the data from the cognitive tasks (motor imagery), followed by pre-processing the signal using EEG lab. Next, signals are converted into predominant features that are associated with the related motor imagery task. The features were translated into Multilayer perceptron for classification processes. The results provide four output classifications which relate to the four wheelchair navigation commands (front, left, right, and back movements).

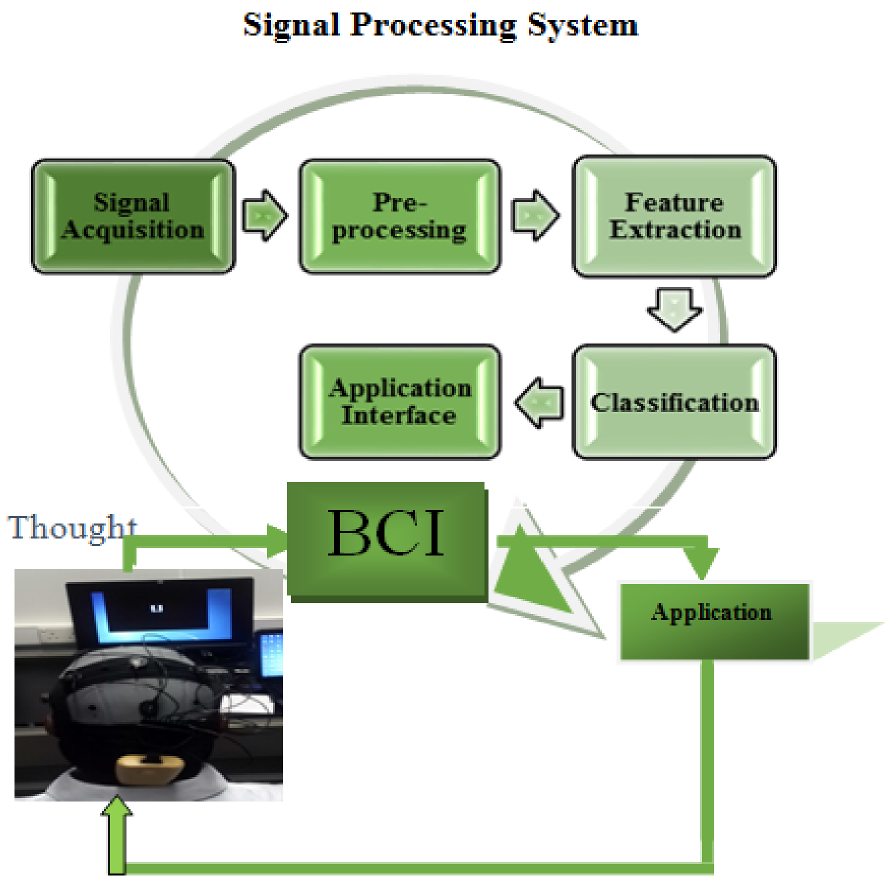


Figure 1: General structure of BCI system

2.2 EEG data acquisition and pre-processing

In the experiments, seven healthy subjects voluntarily (2 females and 5 males) participated. The age range was from 20 to 38 years. An Enobio EEG system was used to acquire the EEG signals through 8 electrodes (F3, F4, T7, C3, Cz, C4, T8 and Pz). The sampling rate was 500 Hz. The impedance of the electrodes was kept below 5 kΩ. The reference and ground electrodes were placed on the right ear lobes. The procedure of the experiment was started by each subject set in a chair and wearing the headset to detect the motor imagery task, such as left hand, right hand, both hand and both feet movements). The data collected for one session consisted of five runs. Each run has 22 trails per 2 minutes. The session starts with two screens, one for subjects and the other for experimental software. During the session, the screen display an arrow, such as up down left or right, or t either be blank as shown in Figure2. The arrow was appearing on the screen for 3 seconds; during this time, the subject should continuously imagine open and close respective hand (s) /feet. When the screen was black the subject relaxed.

2.3 Feature extraction using Discrete Wavelet Transform

In order to make the wavelet transform more practical, to reduce the redundancy. The parameters (a, b) of DWT are sampled. First, we define the sampling grid $a = a_0^m, b = nb_0a_0^m$ and the define of a DWT basis as [13].

$$\{\psi_{mn}(t)\} = a_0^{\frac{-m}{2}}\,\psi(a_0^{-m}t - nb_0)\; m, n \in Z \qquad (1)$$

If the set $\{\psi_{mn}(t)\}$ is complete for some $\psi(t)$, a and b, then they are called affine wavelets. Therefore, we can express any $f(t) \in L^2(R)$ in the superposition of

$$f(t) = \sum_m \sum_n d_{m,n}\,\psi_{mn}(t) \qquad (2)$$

Where the defined of discrete wavelet transform coefficients as eq.3.

$$d_{mn} = \left(f(t), \psi_{mn}(t)\right) =$$

$$\frac{1}{a_0^{m/2}} \int f(t)\,\psi(a_0^{-m}t - nb_0)dt \qquad (3)$$

Such complete wavelet transform sets $\{\psi_{mn}(t)\}$ are called frames.

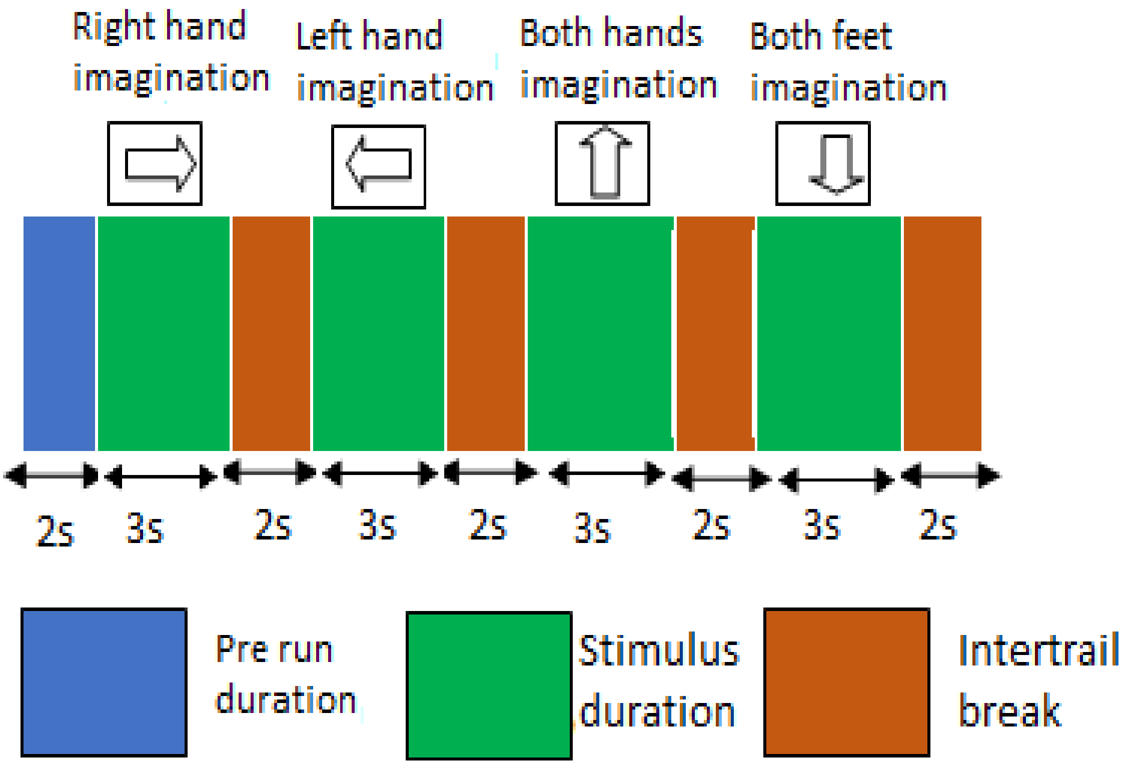


Figure 2: Timing of the imagination task. The cue stimulus in the form of an arrow indicates the side of imagination

The DWT main purpose is to decompose the EEG data into multi–resolution subsets of coefficients, namely approximation coefficient (cA) and detailed coefficient (cD). In this paper, the spectrum features for different motor imagery task from the EEG signals are used. The shape of the characteristic nature of the mother wavelet function should be similar to the original signal under the processing, as in [14]. In this work, we considered coif5, db8, db20, sym8 and sym12 wavelet functions for extracting the spectrum features from the EEG signals. The decomposition level was seven levels. The wavelet transform results in a seven details and one approximation with the frequency associated with beta (13-30 Hz) and mu (8-12 Hz) rhythms. We decided to extract the features from the details cD4 and cD5 which they provide proper representation for the mu and beta rhythms. Figures. 3 (a) and 3 (b) show the example of alpha and beta power for subject 6 using right-hand imagination with db8 wavelet, for one second time window.

2.4 Classification using Multi-layer Perceptron (MLP)

A high structure about ten billion neurons are contain of the human brain. They are intelligence level and densely interconnected resulting in a complex architecture. Artificial neural networks (ANNs) were seen as attempts to reproduce potentialities of human brain, which its learning ability. ANNs consists of a number of artificial neurons interconnected together by synaptic weights to form a network [15]. Each neuron is modeled by the following mechanical model.

$$y = f(\sum_{i=1}^{n} w_i \ x_i + \theta) \qquad (4)$$

Where y is perceptron architecture and (x_i) is set of n inputs, each related to a weight (w_i) and (f_i) which is activation function.

Multilayer perceptron (MLP) networks have an input layer, an output layer, one or more hidden layers, For each layer defined a weight matrix (w_i). The classification problems with non-linear separable patterns solve with ANNs topology and is also used as a universal function generator [15].

In this work, the ANN used has three layers, with 10 neurons in the hidden layer. It used the log sigmoid function as a transfer function. The input for the network were DWT features and the output were four classes related to motor imagery movements which are left, right, backward and forward.

Table 1: Accuracy results achieved using different wavelet families

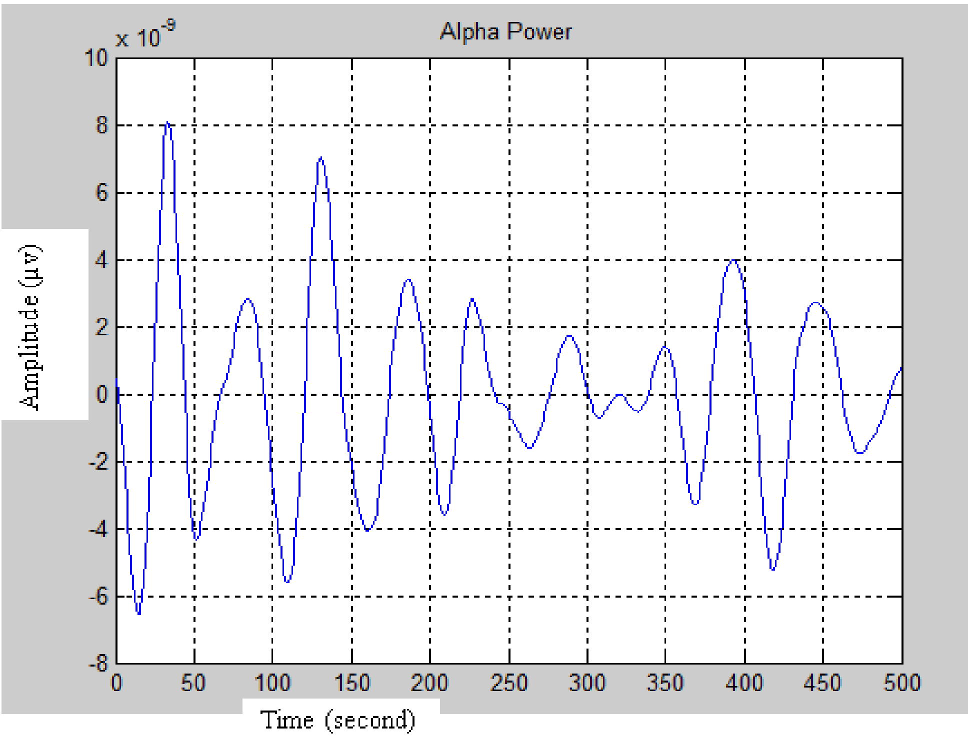
Subject	**MLP Accuracy % of Wavelet families**				
	db8	**db20**	**Sym8**	**Sym12**	**Ciof5**
S1	75.26	73.47	87.5	70.66	87.16
S2	82.43	79.39	84.12	79.34	77.24
S3	83.38	89.39	90.92	69.13	74.16
S4	80.74	79.73	90.36	87.16	84.80
S5	84.12	81.42	88.51	85.47	79.39
S6	71.43	80.08	78.27	75	81.84
S7	79.48	82.84	88.69	72.01	81.72

3. Results and Discussion

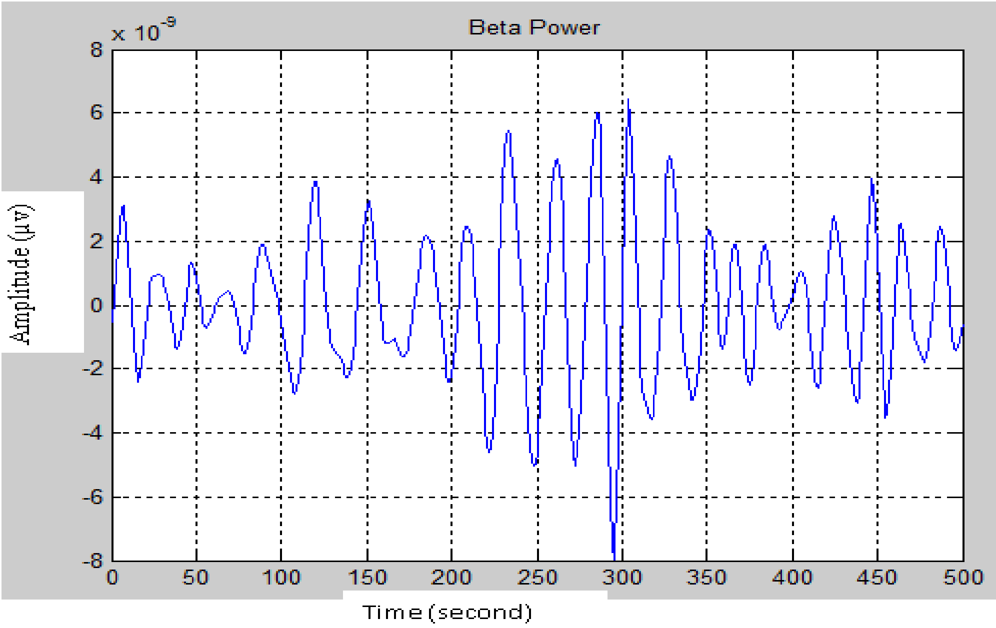
This work presents how to analyze the effect of feature extraction and determine the accuracy of the command classifications for the brain-controlled wheelchair. Experiments were conducted using ten-fold cross-validations using the MLP classifier, which was as a function of different wavelet families such as db8, db20, sym8, sym12, and coif5. The classification accuracy and results involving seven subjects are shown in Table 1 and Figure 4 below. The highest accuracy obtained is 90.92% for subject 3. The lowest performance relates to subject 1, with the corresponding accuracy of 70.66%. If we compare the highest accuracies in all subjects we can note that the sym8 wavelet outperforms the other wavelet families in most cases. In brief, the average accuracy for the seven subjects is 81.046%. Hence, the use of MLP algorithm with sym8 wavelet is a good choice due to its relatively high accuracy.

4. Conclusion

This study aimed to provide a user an appropriate motor imagery task that can be reliably implemented for total lock-in people. In this paper, the offline task classification showed that good classification performance. Our results suggest that the use of the multilayer perceptron with discrete wavelet transform represents a promising choice for future online thought controlled wheelchair BCI implementations.



(a)



(b)

Figure 3: Plots of (a) alpha and (b) beta based power, based on db8 wavelet for subject 6, using the imagination of right hand

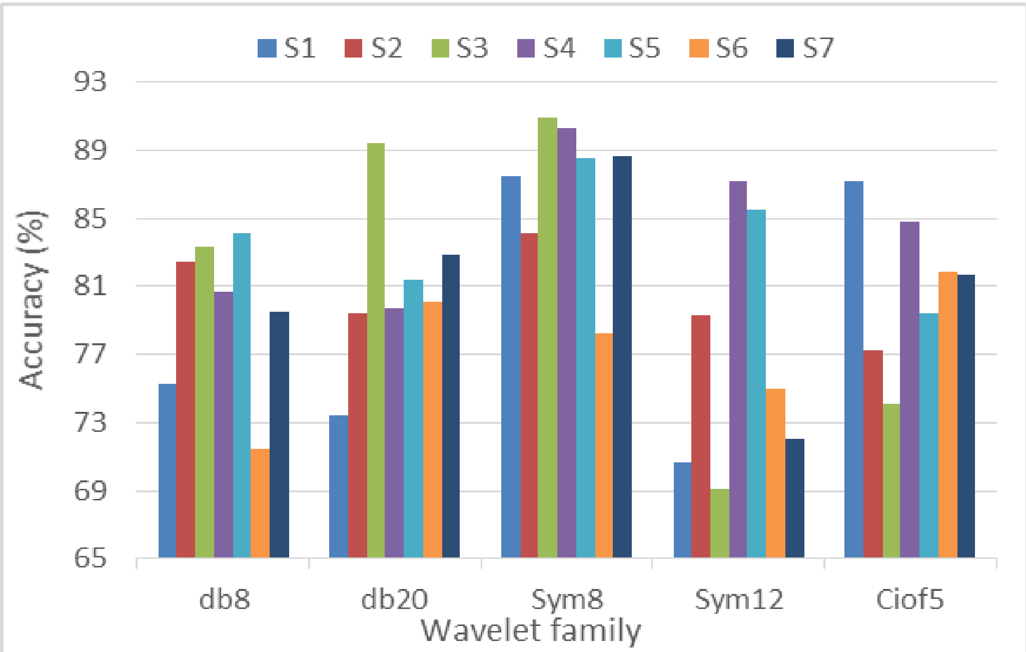


Figure 4: Comparing the accuracy of MLP classifier using different wavelet family features for all subjects

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