Classification of the Imagination of the Left and Right Hand Movements using EEG

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CLASSIFICATION OF THE IMAGINATION OF THE LEFT AND RIGHT HAND MOVEMENTS USING EEG

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Abstract-**Brain-computer interface (BCI) is a new and promising area of research which is assumed to help in solving a lot of problems especially for handicapped people. Detection of the imagination of the left and right hand movements can be used to control a wheelchair accordingly. Fortunately, modification of the brain activity caused by the imagination of the left or right hand movements is similar to the modification observed from a real left or right hand movements. The electrical activity of these modifications can be picked up from scalp electroencephalogram electrodes. In this work, we introduce a new method to detect and classify the imagination of the left and/or right hand movements. This method is based on exploring the time domain information in both alpha and beta rhythms using complex Morlet wavelet transform. Then, the fast Fourier transform is applied to explore the frequency domain information. The extracted features using both time and frequency domain information are then reduced using a feature subset selection algorithm. Then, the reduced features were fed into a multilayer backpropagation neural network to classify left from right hand movement imagination. The experimental results showed that the algorithm has reveals classification accuracy rates ranges from 97.77% to 100%, which are superior to the classification accuracy rates compared to other techniques.**

Keywords - brain **computer interface, motor imagery, feature subset selection, EEG classification**

I. INTRODUCTION

The human brain is the control unit that controls all functions the human can perform such as vision, hearing, moving…etc. However, the control commands are sent as neural signals originated from its dedicated mesial structures in its functional area, projecting into the motor cortex, located over the lateral surface of the brain [1]. From there, the neural commands are relayed through descending tracts to the spin, with most of the descending nerve fibers developing a cross over to a contralateral side. In the spin the appropriate motor groups of the destination organ are simulated, consequently the destination organ performs command action. Additionally, the neural signals of Right and left hand movements are controlled by the sensorimotor areas in the brain like all muscle movements in the human body. Fortunately, The imagination of (i.e. the concentration in) movement activates the same brain areas/functions that can be activated in programming and preparing to a real movement. Thus, neural signals of motor imagination are similar to neural signals of real movement but blocked at some corticospinal levels. Currently, a lot of techniques can monitor brain activity. These include, for example, functional Magnetic Resonance Imaging (fMRI) [2], magnetoencephalography (MEG) [3], Positron Emission Tomography (PET), Single Photon Emission Computer Tomography (SPECT) [4], single neuron recording (with microelectrodes), and electroencephalography (EEG) [5]. Although, fMRI, PET, and SPECT are more accurate, and have more spatial resolution they are not candidate for BCI applications due to its main characteristics as large device that are heavy weight and can not act as a portable device. Furthermore, single neuron recording requires that the electrodes are inserted inside the skull. Therefore, only Electroencephalogram (EEG) is candidate to monitor the electrical brain activity due to it has the following characteristics:

- Better temporal resolution.
- Portable.
- Cost effective comparable with other brain imaging techniques.

EEG picks up electrical brain activity from different brain areas using a set of electrodes attached to the skull and distributed according to certain configuration. However, this activity is oscillatory in nature due to the high population of neurons which form a highly complex network with feedback loops [6]. Furthermore, different six oscillations [7] are known to appear in the electrical brain signals, their types, frequencies and associated actions are listed in table I. When EEG signal is recorded from sensorimotor area; the alpha rhythm is called mu rhythm. From table I, one can notice that the oscillations in both alpha (mu) and beta rhythms are the most obvious indicators of movement. Moreover, Motor imagination of either right or left hand movement causes an event related to desynchronization at contra-lateral hemisphere sensorimotor representation area (i.e. attenuation of the amplitude of the beta and mu rhythms), and causes an event related synchronization at ipsi-lateral hemisphere sensorimotor representation area (i.e. amplification of the amplitude of beta and mu rhythms) [8,9]. In this research, EEG signals recorded from C3 & C4 electrode positions using the 10-20 international electrode configuration system [10] are analyzed to monitor the electrical activity of sensorimotor areas of left and right brain hemispheres through extracting a set of discriminative features that enable us to differentiate between left and right hand movement imagination. Then, the extracted features were fed into an appropriate classifier to differentiate between left hand movement imagination and right hand movement imagination.

TABLE I
ELECTRICAL BRAIN WAVES

rhythms / band	Frequency Range [Hz]	Happened during
Delta	0.5 – 3	Deep dreamless sleep
Theta	4 – 7	Drowsiness, mental imagery
Alpha (mu)	8 – 12	Relaxation, and Sensory, and Motor activity
Beta	12 – 30	Active concentration, and Motor idling
Gamma	26–100	certain cognitive or motor functions

This paper is organized as follows: section I is the introduction, section II discusses data collection, section III reviews the previous work, section IV discusses the proposed algorithm, section V shows and discusses the Results, and section VI is the conclusion

II. DATA COLLECTION

The data used in this paper consists of three data sets, first dataset is dataset III published in the 2003 international data analysis competition on BCI tasks [11], second dataset is dataset IIIb published in the BCI Competition 2005 [12], and third dataset is dataset bci7 published in [13]. All these datasets are obtained from normal persons and recorded from C3, C4, and Cz electrode positions, and have a bandwidth ranged from 0.5 to 30 Hz. The trial duration of the first dataset is 9 seconds. However, the other datasets didn't have fixed trial duration. In all Datasets the first 3 seconds is the preparation period in which no event happened, then a visual cue (arrow) is presented pointing either to the left or the right, instruct the subject to perform the imagination task till the end of trial as shown in Fig. 1. Additionally, a biofeedback signal is presented on the monitor to assist the subject to perform imagination task. Table II shows a detailed description of the three datasets. Table III shows the number of trials in each tainting set and testing set for each dataset used.

III. REVIEW ON PREVIOUS WORK

In the last decade a lot of techniques set out to perform this type of classification. Moreover, most of these techniques exhibit a successful classification rate. However, M. Zhong et al applied their methods on the three subjects of dataset IIIb, for all the subjects they used Band Power in both alpha and beta rhythms as discriminating features, these features were fed into each of the expectation propagation classifier, variational Bayes classifier, Gibbs sampling classifier, and the Laplace approximation classifier. All these classifiers reveal maximum classification accuracy rate of 89.3% with the first subject, the probabilistic SVM classifier reveals classification accuracy rate of 74.44% with the second subject, and k-nearest neighbor classifier reveals classification accuracy rate of 75.4% with the third subject [14]. Nicolas Brodu applied his methods on the three subjects of dataset IIIb, for all the subjects he used multi-fractal feature vectors as discriminating features, these features were fed into squared Euclidian distance as a classifier this method reveals maximum classification accuracy rate of 81.4% with a first subject, Linear minimum summation of squared error classifier reveals maximum classification accuracy rate of 74.1% with the second subject, and linear discriminant analysis classifier reveals maximum classification accuracy rate of 73.9% with the third subject [15]. The first winner of dataset IIIb of BCI Competition 2005 is O. Burmeister, et al. they used bandbower (BP) ratios, its differences, and MANOVA algorithm for feature selection and support vector machines (SVM), and linear combiner for classification, this method reveals classification accuracy rate of 85.3% for the first subject, 77.04% for the second subject, and 77.78% for the third subject [16]. However, The second winner methodology of dataset IIIb of BCI Competition is D. Coyle, et al algorithm which preprocess the data with prediction neural networks (PNN), then applies short time Fourier transform (STFT) followed by linear discriminant analysis as a classifier, this method reveals classification accuracy rate of 88.05% for the first subject, 78.52% for the second subject, and 81.3% for the third subject [17]. G. Pfurtscheller et al. used band power estimates as a discriminative feature in conjunction with a nonlinear neural network classifier as a classifier, this method reveals classification accuracy rate of 78%, and also used autoregressive models as a discriminative feature in conjunction with a linear discriminant analysis as a classifier, this method reveals classification accuracy rate ranged from 67.2 to 94.2%

TABLE II
DETAILED DESCRIPTION OF THE USED DATASETS

Dataset	Sampling rate (Hz)	Duration (sec)	Subjects	Number of trials		feedback (sec)
				Left	Right	
III	128	9	1st	140	140	3-9
IIIb	125	Unfixed	1st	214	217	4-8
			2nd	485	501	4-7
			3rd	592	592	4-7
bci7	128	Unfixed	1st	179	179	3-9
			2nd	180	180	3-9
			3rd	179	180	3-9

TABLE III
THE NUMBER OF TRIALS IN EACH TAINTING SET AND TESTING SET OF THE USED DATASETS

Dataset	Subjects	Train		Test	
		Left	right	Left	Right
III	1	70	70	70	70
IIIb	1	139	136	75	81
	2	242	252	243	249
	3	269	268	269	270
bci7	1	89	89	90	90
	2	90	90	90	90
	3	89	90	90	90

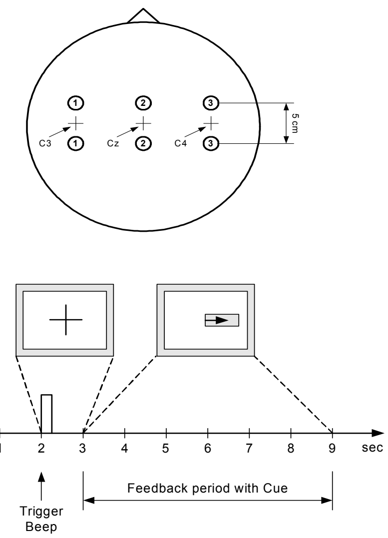

Fig. 1.Electrode positions (up) and timing scheme (down)

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[9]. C. Guger et al used common spatial patterns (CSP) algorithm applied to signals recorded from twenty seven electrodes placed over sensorimotor cortex, and well distributed around C3 and C4 electrode positions to construct the optimal spatial filters which were fed into a linear discriminant analysis, this method reveals classification accuracy rates ranged from 87% to 97% [17]. B. Obermaier et al used Hjorth parameters as discriminating features in conjunction with two hidden markov models (one to model left trials, and the other to model right trials), this method reveals classification accuracy rate ranged from 75% to 95% [18]. S. Lemm et al used causal Morlet wavelets adapted for amplitude modulations in lower and upper frequency bands (10 and 22 Hz respectively), then the transformed signals were fed into Bayes classifier, while combining information across time. Furthermore, they won in the 2003 international data analysis competition on BCI tasks for Dataset III using this method and reveals classification accuracy rate of 89.3% [19]. C. Guger, et al used adaptive auto regressive (AAR) parameters combined with linear discriminant analysis; this method reveals classification accuracy rate of 95% [20]. H. liu et al used common spatial subspace decomposition (CSSD) algorithm combined with RETA-FOCUS, 3D micro state analysis and hidden Markov model and this method reveals classification accuracy rate of 83.33%, 81.48%, and 88.89% in three subjects [21]. Siamak Rezaei1, et al applied their method on dataset III. They used autoregressive model, and adaptive autoregressive model as features extraction techniques and Bayesian network, neural network, and Bayesian classifier as classifiers and these methods reveals classification accuracy rate of 83.57%, 84.29%, and 82.86% respectively [22].

IV. Proposed Algorithm

The proposed algorithm is based on exploring time and spectral domain information of the alpha and beta rhythms, time domain information exploration is done by convolving each EEG signal recorded from C3 and C4 electrode positions with two Morlet Wavelet windows, [19] the first window is centered at frequency 10 Hz represents alpha rhythm and the second window is centered at frequency 22 Hz represents beta rhythm. In the next step, transforming the convolved signals using FFT algorithm into frequency domain to explore their spectral information, the process of exploration is followed by a feature subset selection process which aims to select the most effective frequency components to be used as discriminative features. These discriminative features were fed into a feed forward multilayer perceptron backpropagation neural network to decide the corresponding imagined hand movement; this technique is summarized in Fig. 2, and will be described briefly in the following sections.

A. Complex Morlet Transform

Wavelet transformation is applied to EEG signals recorded from C3 and C4 electrode positions in both alpha and beta rhythms which centered at the frequencies 10 Hz and 22 Hz respectively This process of transformation will start from the beginning of the forth second for all trials because at the first

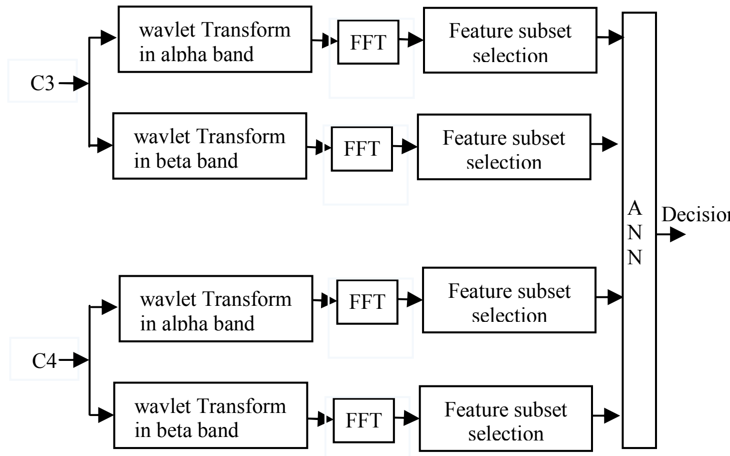

Fig. 2. The Block Diagram of proposed algorithm.

three seconds there are no motor imagination. The result of continuous wavelet transform at any time *T* and frequency *f* is the instantaneous magnitude of the convolution of a real signal *C(t)* with a wavelet Ψ which are a scaled and shifted version of the mother wavelet see (1), The mother wavelet in this method takes the form of a modulated Gauss impulse with an characteristic eigenfrequency w_0 as seen in Fig. 3. , see (2) [19].

$$a(T, f) = \frac{1}{\sqrt{S}} \left\| C(t) * \psi_{T,S}(t) \right\| \tag{1}$$

Where *a(T, f)* is the result of transformation, *S* is the scaling factor, and *T* is the temporally Shift.

$$\psi_{T,S}(t) = \frac{1}{\sqrt{S}} \pi^{-1/4} e^{(iw_0 \frac{t-T}{S})} e^{-\frac{1}{2}(\frac{t-T}{S})^2} \tag{2}$$

The scaling factor *S* depends on the main receptive frequency *f* of the wavelet and calculated using (3):

$$S(f) = \frac{w_0 + \sqrt{2 + w_0^2}}{4\pi f} \tag{3}$$

The Eigenfrequency w_0 is estimated as 10 Hz for alpha rhythm, and estimated as 6 Hz for beta rhythm [19]. This complex wavelet transform is applied to each trial resulting different four signals (i.e. the wavelet transform of signal recorded from C3 in alpha rhythm, the wavelet transform of signal recorded from C4 in alpha rhythm, the wavelet transform of signal recorded from C3 in Beta rhythm, and the wavelet transform of signal recorded from C4 in Beta rhythm).

B. Fast Fourier Transform

After transforming the signals of each trial using Morlet wavelet transform resulting four different signals, each one of these four signals are then transformed into the frequency domain representation using fast Fourier transform (FFT) [22] see (5) resulting four frequency domain signals corresponding to each one:

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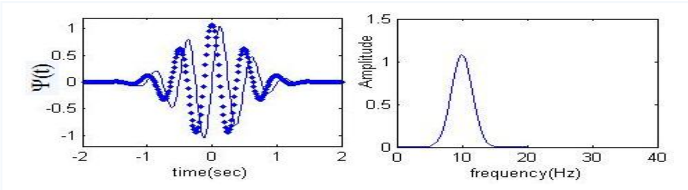

Fig. 3. Left is the shape of the real part (continuous line signal), and the Imaginary part (doted line signal) of complex Morlet wavelet both signals take the form of a modulated Gauss impulse with an characteristic eigenfrequency. Right is the shape of the spectral domain representation of this complex Morlet wavelet signal.

$$A(w) = \sum_{n=0}^{N} a(n) \quad e^{-jwn} \tag{5}$$

Where *a(n)* is time domain representation of any recorded EEG signal from C3 or C4 electrode positions at time index (*n*) which ranges from 0 to the length of that signal (*N*), and *A(w)* is the corresponding frequency domain representation having the same length of *a(n)*.

C. Feature Subset Selection

Feature Subset Selection (FSS) is one of preprocessing techniques can be used before performing any data mining task e.g., classification and clustering tasks. FSS removes irrelevant and redundant features while keeping most of discrimination information of the original features [24]. In this research Fisher Criterion see (6) (one of traditional FSS techniques) is used to choose the best features by measuring the discrimination efficiency of each feature using the following relation and then labeling and selecting features which gain the highest scores [24].

$$k(j) = \frac{|\mu_I(j) - \mu_{II}(j)|}{\sqrt{(\sigma_I^2(j) + \sigma_{II}^2(j))/2}} \tag{6}$$

Where *k(j)* is the measure of feature *(j)* effectiveness, $\mu_I(j)$: is the mean value of the feature *(j)* for class *I*, σ_I is the standard deviation value of the feature *(j)* for class I, $\mu_{II}(j)$: is the mean value of the feature *(j)* for class I*I*, and σ_{II} is the standard deviation value of the feature *(j)* for class II. However, the number of best features used is determined as five features, which is the minimum number of features per EEG signal gives the maximum classification accuracy rate for all the subjects in all datasets, which calculated using trial and error principle see Fig. 4.

D. Classifier

The output of FSS was then fed into feed forward Multilayer perceptron backpropagation neural network which used for classification [23], this feed forward Multilayer perceptron backpropagation neural network composed of twenty neurons in input layer, fifteen neurons in hidden layer, and only one neuron in output layer. However, any classification process consists of two phases (Testing Phase and Training Phase). In Training phase, it fed with features of training set in its input layer and then the network is trained to classify training set features resulting an output of 1 for every right trial and -1 for every left trial in training set. In testing phase given the testing set, the network decides left trial or right trial for every test pattern and the classification accuracy rate then calculated as a percentage of proper classified tested patterns to all testing set.

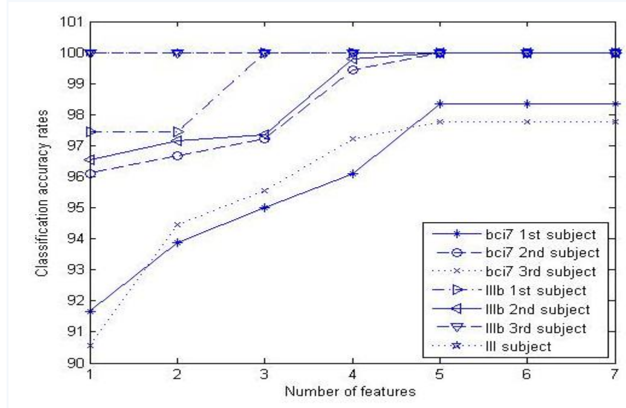

Fig 4. the change of classification accuracy rate versus the number of subset selected feature. Five, six, and seven gave the maximum classification accuracy rates.

V. RESULTS AND DISCUSSION

The Proposed algorithm reveals classification accuracy rate of 100% on the Data set III which published in competition 2003, classification accuracy rate of 100% for all subjects on the Data set IIIb which published in BCI Competition 2005, and classification accuracy rate ranged from 97.77 - 99.44% on bci7 Dataset as shown in table IV. The results show that our proposed technique is more accurate technique till now as shown in table IV. Complex continues Morlet wavelet transform was successfully applied to differentiate between the left hand movement imagination and right hand movement imagination presented in the EEG signals recorded from C3 and C4 electrode positions, authors used this method won the 2003 international data analysis competition on BCI tasks using Data set III and reveals only a classification accuracy rate of 89.3%[19].In this method wavelet features representing time domain information in both alpha, and beta bands were fed directly into a statistical classifier (i.e. naive bayes classifier). In our research we did not study time domain information in both alpha, and beta bands, but we made our study in frequency domain representation that uncovers complementary information intriguing in our discrimination power. Accordingly, this is done through transforming time domain information into its corresponding frequency domain representation using FFT algorithm. Thus, we are ready to extract the most discriminated frequencies using a feature subset selection algorithm. The most discriminate frequencies were then fed into a Multilayer backpropagation neural network revealing classification accuracy rate ranged from 97.7% to 100%.

VI. CONCLUSION

Finally, we come to the conclusion that using time domain analysis in certain frequency bands only as in [9, 14, and 19], it will give a reliable classification accuracy rate, ignoring how

TABLE IV
MAXIMUM REVEALED CLASSIFICATION ACCURACY RATE REPORTED IN THE PREVIOUS WORK AND THE PROPOSED TECHNIQUE

Dataset	Subject	Technique	Maximum revealed classification accuracy rate%
III	1st	Proposed technique	100
		In [19]	89.3
		In [22]	84.29
IIIb	1st	Proposed technique	100
		In [14]	89.3
		In [16]	88.05
		In [15]	81.4
	2nd	Proposed technique	100
		In [16]	78.52
		In [14]	74.44
		In [15]	74.1
	3rd	Proposed technique	100
		In [16]	81.3
		In [14]	75.4
		In [15]	73.9
bci7	1st	Proposed technique	99.44
	2nd	Proposed technique	97.77
	3rd	Proposed technique	98.33
Other datasets	N/A	In [17]	97
		In [18]	95
		In [20]	95
		In [9]	94.2
		In [17]	88.05
		In [21]	88.89

did the information of these two bands change with time. Fortunately, FFT algorithm is sensitive to the information change with time. Consequently, this sensitivity generates much enthusiasm and large impact on our results and also explains the improvement in the classification accuracy rate when applying FFT algorithm to the changes in alpha and beta bands, especially when reducing the complexity through reducing the number of used features using a feature subset selection algorithm, while keeping the most relevant and discriminative features [24].

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