Hand Movement Imagery Task Classification using Fractal Dimension Feature

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***Abstract*—In this paper, a nonstimulus-based Brain Machine Interface (BMI) approach is used to acquire the brain signal from ten different subjects using 19 channel EEG electrodes while performing four different hand movement imaginary tasks. Three different Fractal Dimension algorithm namely Box counting algorithm, Higuchi algorithm, and Detrended fluctuation algorithm are used to extract fractal dimension features from recorded EEG signal and associated with the respective mental tasks. Three Feed-Forward Neural Network model is developed. The performance of the three Neural Network model is evaluated in term of classification rate and compared. The performance of the developed network models are evaluated through simulation. It is observed that the neural network model trained with Higuchi algorithm has contributed high classification accuracy with the better training and testing time for all 10 subjects. The result clearly indicates that the Higuchi fractal dimension algorithm can be used as a feature to classify motor imagery task for the proposed BMI system.**

***Index Terms*—Brain Machine Interface; Feed-Forward Neural Network; Fractal Dimension; Motor Imagery.**

I. INTRODUCTION

The motor neural activity of the brain can be made to use as a control signal. The motor neural activity of the brain is translated into movement activities and can be applied to control a device such as prosthetic arm, joystick and wheelchair. The motor neural activity of the brain can be recorded from the human scalp using EEG recording equipment. The recorded motor neural activity can be then converted into its equivalent command signal. The process is going through a system which known as Brain Machine Interface (BMI). A BMI is a system that acts as link for the brain signal to communicate with computer system without going through a usual route of peripheral nerves and muscles [1]. Motor imagery is used as a predefined task in the development of BMI. Motor imagery is defined as a procedure to initiate an imagination of limb movement to produce a motor task without involving a physical motor output [2]. Decety and Grezes had defined a motor imagery as a progressive process to represent a motor act or body movement which is occurred internally within a working memory of the brain. The motor act is practice internally within a working memory without necessary translate it through anybody movement [3]. Motor imagery also can be defined as process to carry out pretended movement of arm or other parts of human body. The concept of pretended movement of arm can be defined such as preparation for movement, passive observations of action, and mental operations of sensorimotor representations [4]. Many researchers have used motor imagery as a predefined mental task along with the cue-based method [5-9].

Study on the BMI using motor imagery still showing an open discussion among the researchers. Numerous techniques of feature extraction and model classification in the development of motor imagery (MI) based BMI system also been suggested by earlier researchers. Pfurtscheller et al., recommended a spectral parameters for feature extraction technique and used Learning Vector Quantization (LVQ) neural network to classify the different mental tasks [10]. Spectral parameters as a feature extraction method also been used by many researcher [11-16]. Pfurtscheller et al., also suggest three feature extraction method namely band power feature, adaptive autoregressive (AAR) parameters and common spatial filter (CSP). They used two different classification method namely LVQ neural network and Linear Discriminant Analysis (LDA).Results showed that all the method used give a high classification accuracy between 87% to 98% after some sessions [17,18]. Siuly et al., used cross-correlation based feature extraction method. They used Logistic Regression Model as a classifier to discriminate two different limb movement motor imagery data. Accuracy rate above 85% are achieved for all five subjects [19]. In addition to the previous result, Siuly et al., proposed a hybrid classifier namely least square support vector machine to improve classification accuracy rate using the cross-correlation based feature. The result show that the accuracy rate performance is improved with a maximum improvement percentage of 7.4% [20]. Park et al. used four different feature extraction methods namely power spectral density (PSD), phase locking value (PLV), the combination of PSD with PLV and cross-correlation (CC) in their research to differentiate 2 different mental tasks acquire from eight healthy volunteers. They use LDA to classify the features. It is observed that CC feature give the best accuracy performance among the four different extraction methods [21].

In this work, we propose a simple non-stimulus-based protocol to classify different hand rotational movement using motor imagery as a predefined task. Fractal Dimension (FD) features from five different bands namely alpha 1 (8 10 Hz), alpha 2 (11-12 Hz), beta 1 (13-15 Hz), beta 2 (16-18 Hz) and beta 3 (19-25 Hz) are extracted from all the 19 channels of the EEG raw data. Finally, the extracted features are classified into four types of hand rotational movements using a Feed-Forward Neural Network model.

II. METHODOLOGY

A. Data Acquisition and Preprocessing

Mindset-24 Topographic Neuro Mapping Instrument by Nolan Computer System LLC which consists of 19 EEG bipolar channels was used to collect the brain signal. All the 19 electrodes were positioned as per the international 10- 20 method of electrode placement [22]. Figure 1 shows the position with reference to the International 10-20 standard. The EEG data are sampled with 256 Hz and of 12 bits Analog/Digital Converter (ADC) resolution.

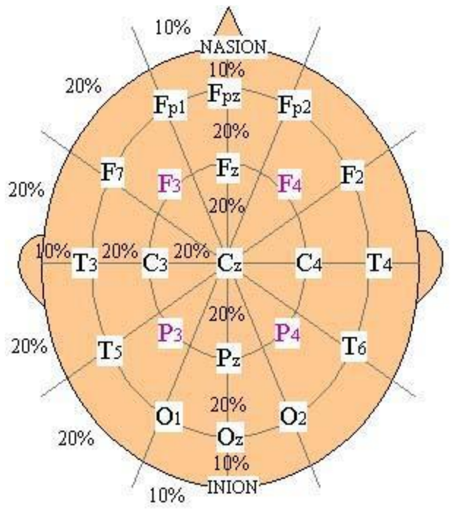

Figure 1: Electrode position from International 10-20 Standard[12]

Ten subjects with the age range of the was between 22 to 34 years old participated in this research. Subjects must be medication free and free from illness. Subjects should have enough rest, the day before the experiment was conducted. The ten subjects are right handed and have no neurological or psychiatric disorders. The proposed protocol involve four different imagery tasks. Each subject went through this four different imagery task session. Each session represents a specific hand movement task. The four different imaginary tasks employed in the experimental procedure are namely relax, right arm movement, left arm movement and both arm movement. The Subject was asked to be in state of relaxation for 2 minutes before starting the session. Before performing the imagination tasks, the subject was requested to relax and make themselves less strict and make their concentration less intense. On a single day, all the trials pertaining to the four tasks were recorded from the subject. The EEG recording process was conducted in a closed, noise free room. While a subject performs the various tasks, EEG signal emanated from the brain scalp was recorded. All the subjects were explained about the purpose of the experiment and also the experiment procedure before beginning the task. A video demonstration showing the arm movement is played for 10 seconds before starting the recording session. After the video presentation, the subjects were given a relaxation period of 60 seconds. Then the subjects were requested to imagine the specific hand movement task. Each tasks was recorded for 10 seconds. The subjects were asked to repeat the same imagination process for 10 times; simultaneously, the EEG signals corresponding to the 10 trials were recorded. Between the trails, the subjects were given a resting period of 30 seconds.

The EEG data sets recorded from the subjects must pass through the data preprocessing step before the features can be extracted. The EEG data sets recorded from the subjects exposed to noise and artifacts. That noise and artifacts will lead to inaccurate analysis. Artifacts such as eye blinks, body movements, and other sources are generated by the subjects during EEG recording process. Noise due to electrical interferences from the equipment and electrode can also impair the EEG signal. The mindset24 EEG instrument has been set to record the signal level up to a maximum level of 80µvolt (microvolt), so the eye blink artifact was considered to be removed as the signal threshold value was set to 80µvolt. It is because the signal level corresponding to eye blink artifact is 100µV. Hence, no additional step or procedure is taken in the experiment analysis to remove the eye blink artifacts (Systems, 2010; Mindset-24, 2009). A notch filter is used to remove the 50 Hz power line frequency noise from the raw EEG signal. This 50Hz power line frequency noise is due to electrical interference from the EEG recording equipment. The filtered signal was separated into frames such that each frame has 128 samples with an overlap of 64 samples (50% overlapping) between two successive signal frames. Thus the signal recorded from a channel was segmented and, 39 frames were obtained. Every signal frame was then filtered into five different sub-band frequencies using second-order Chebyshev bandpass filter. The Chebyshev filter provides a good stopband behavior and steeper roll-off which is recommended with narrow intermediate frequency ranges. The five sub-band frequencies are named as alpha 1 (8-10 Hz), alpha 2 (11-13 Hz), beta 1 (13-15 Hz), beta 2 (16-18 Hz) and beta 3 (19-25 Hz) [23][24].

B. Feature Extraction

Feature extraction is a process of transforming the raw signal data into a new form of data which can be interpreted by a classifier to obtain good classification accuracy. In this paper, Fractal Dimension (FD) features were used for classification and their performance was evaluated. FD is a measurement process to quantify the signal self-similar characteristic based on the illustrative presentation of the signal. A single non integer value (fractional) is obtained through the process. The FD feature values corresponding to the EEG signals lie between 1 and 2. Three different FD algorithm is used to computed FD feature values of the recorded EEG signal in this paper, namely Box counting algorithm, Higuchi algorithm and Detrended fluctuation algorithm (DFA). The FD feature values obtained from these algorithms are then applied to classify four types of motor imagery mental task.

C. Box Counting Algorithm

The Box-counting algorithm is one of the methods to obtain FD values from recorded EEG signal. The Box-counting algorithm is the commonly used method to figure out FD values. A self-similarity property is utilized through the box-counting algorithm in order to obtain FD values. In this method, the signal is completely covered with a collection of square boxes and the numbers of square boxes are then counted.

To calculate fractal dimension, the EEG signal was divided into 39 equal frames. Each frame of the EEG signal consists of 128 samples. To figure out FD values mathematically using box counting method, first $N(r)$ is obtained from the EEG signal frame using Equation (1).

$$N(r) = \sum_{m} \left(n_r(m)\right) \tag{1}$$

where: $N(r)$ = Total number of boxes of size r required to cover the EEG signal frame
$n_r(m)$ = Obtained from the difference between the maximum and minimum amplitude values of the data divided by the radius as shown in Equation (2).

$$n_r(m) = \left[\frac{max(x_r) - \min(x_r)}{r(m)} \right] \tag{2}$$
$$for \left\{ r \in 2^k \; k = 1,2,3,\ldots, log_2(L) - 1 \right\}$$

where: x_r = EEG signal with length L
$r(m)$ = Radius by changing a step size of k within the m-th subdivision window.

FD values can be computed mathematically using Equation (3).

$$FD = - \lim_{r \to 0} \frac{log_2 (N(r))}{log_2 \left(\frac{1}{r} \right)} \tag{3}$$

D. Higuchi Algorithm

To calculate fractal dimension, the EEG signal was divided into 39 equal frames. Each frame of the EEG signal consists of 128 samples. Let the segmented frame view as a finite set of time series with a fixed interval:

$$x(1), x(2), x(3), x(4), \ldots, x(N) \tag{4}$$

This finite set of time series was then break up into k new time series by using Equation (5) below:

$$x_m^k = x(m), x(m+k), x(m+2k), \ldots, x(m + (n_f * k) \tag{5}$$

where: $m = 1,2,3,\ldots, k$

$$n_f = \left[\frac{N-m}{k} \right]$$

The curve length of the time series x_k^m is then calculated using:

$$L_m(k) = \frac{\left\{ \left(\sum_{i=1}^{\frac{N-m}{k}} \left| x(m+ik) - x(m+(i-1)*k \right| \right) \frac{N-1}{\left(\frac{N-m}{k} \right) * k} \right\}}{k} \tag{6}$$

where: N = Number of samples in one frame

$\frac{N-1}{\left(\frac{N-m}{k} \right) * k}$ = Normalization component for the curve length of the subset time series.

The fractal dimension value F_d can be computed by using following Equation (7):

$$F_d = \frac{log(L_k)}{log(k)} \tag{7}$$

where: L_k = Mean length value for all the curve length of the subset time series.

E. Detrended Fluctuation Algorithm (DFA)

To calculate fractal dimension, the EEG signal was divided into 39 equal frames. Each frame of the EEG signal consists of 128 samples. For each frame, an integrated EEG signal is attained by employing Equation (8):

$$x(k) = \sum_{i=1}^{k} \left[x(i) - \bar{x} \right] \tag{8}$$

The amount of fluctuation for this detrended and integrated signal are then obtained using Equation (9) for a given interval length value of n and length of the signal *Nmax*.

$$F(n) = \sqrt{\frac{1}{N_{max}} \sum_{k=1}^{N_{max}} \left[x(k) - x_n(k) \right]^2} \tag{9}$$

The process for obtaining the fluctuation amount of the detrended and integrated signal is repeated for all possible value of interval length to determine the relationship between fluctuation amount $F(n)$ and the length of interval n. A relationship between $F(n)$ and the interval length n is given as $F(n) \sim n^{\alpha}$. α is represent the slope of the log2 [F(n)] versus log2(n) plot. The detrended fluctuation fractal value (FD) can be obtained by evaluating α where the detrended fluctuation fractal value (FD) is given as FD = 3-α .

F. Classification

In this paper standard Feed-forward, a neural network with one hidden layer was developed and implemented to classify the four imagery tasks of subjects. The neural network was modeled with 95 input neurons, 10 hidden neurons, and 3 output neurons. The number of hidden neurons and network learning rate were determined by trial and error method. For this case, the hidden neurons and network learning rate were chosen as 10 and 0.01 respectively. Through simulation, a number of hidden neurons and network learning rate was chosen as such that, it gives the highest classification accuracy.

Both hidden and output neurons were activated using log sigmoid activation function. Training tolerance and testing tolerance were set to 0.01 and 0.1 respectively. The network iteration process was performed until the Mean Square Error (MSE) value reached below 0.001, or maximum epoch values of 1000 has been reached. The network was trained using Levenberg-Marquardt (LM) algorithm. Binary normalization algorithm was used to normalize the training and the testing samples [25]. For each subject, the EEG data signal corresponding to the four different imagery tasks were collected, and it respective featured been extracted. Each subject has totally 1560 features samples, and we call the data set as the main dataset. Three different neural network models based on three different feature extraction algorithm were developed. Neural network model based on 70:30 training and testing data set ratios were developed. The training and testing set data were formulated by randomly selecting the data from the master data file.

III. Results and Discussion

The average classification accuracies of the Feed-Forward neural network for a different type of feature extraction methods are presented in Table 1-3. The average classification accuracy and their training and testing time for the three features was summarized in Figures 2 and 3 respectively. From the results, it can be observed that the Box-Counting feature has the lowest overall classification accuracy for all 10 subjects. Further, it can be observed that the Higuchi and Detrended fluctuation features yield a high average classification accuracy of 91%-99%, which is consistently higher than that of the classification performance obtained from the Box Counting features. This is because Higuchi and Detrended fluctuation algorithm provide a low variability comparable to Boxcounting algorithm [26]. On top of that, it can be observed that the Higuchi features show better performance than Box-counting features and DFA features in term of the training and testing time.

Table 1
Performance of Feed Forward Neural Network for Boxcounting

Subject	Average Classification Accuracy (%)	Average Training and Testing Time (second)
Subject 1	77.6	5.1
Subject 2	83.4	4.8
Subject 3	76.0	6.4
Subject 4	74.7	6.3
Subject 5	69.7	5.6
Subject 6	87.5	3.9
Subject 7	74.9	6.4
Subject 8	85.8	4.7
Subject 9	75.4	5.3
Subject 10	71.0	5.2

Table 2
Performance of Feed Forward Neural Network for Higuchi

Subject	Average Classification Accuracy (%)	Average Training and Testing Time (second)
Subject 1	96.4	3.4
Subject 2	99.1	2.7
Subject 3	96.1	2.6
Subject 4	99.8	2.1
Subject 5	91.8	3.4
Subject 6	93.2	3.1
Subject 7	99.2	2.6
Subject 8	95.0	3.3
Subject 9	93.1	3.5
Subject 10	92.5	3.1

Table 3
Performance of Feed Forward Neural Network for DFA

Subject	Average Classification Accuracy(%)	Average Training and Testing Time (second)
Subject 1	96.9	7.0
Subject 2	98.0	3.8
Subject 3	95.5	4.6
Subject 4	96.3	4.6
Subject 5	91.6	5.1
Subject 6	97.7	4.0
Subject 7	98.0	5.7
Subject 8	92.2	4.6
Subject 9	93.5	5.1
Subject 10	96.2	6.6

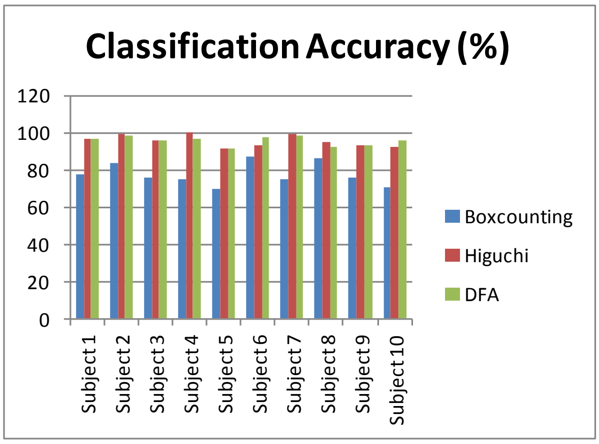

Figure 2: Average Classification Accuracy using Boxcounting, Higuchi and DFA for all 10 subjects

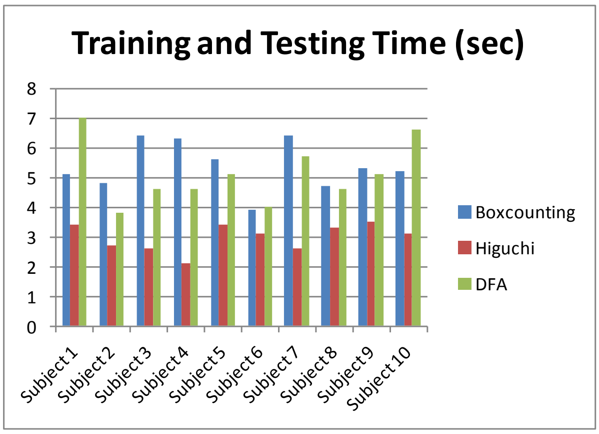

Figure 3: Training and Testing time using Boxcounting, Higuchi and DFA for all 10 subjects

IV. Conclusion

In this paper, a non-stimulus-based protocol for a BMI system to classify the different hand rotational movement using motor imagery is presented. Three different feature extraction methods were applied to the classification of four different Motor Imagery tasks.FD feature using Higuchi algorithm proposed in this paper is ideally suited to classify motor imagery as a predefined task with high classification and required less training and testing time compared to the other two FD algorithm. This result suggests that Higuchi FD based features can be used as a promising feature extraction method in motor imagery based BCI. In the future work, suitable schemes are to be developed to minimize the number of features by using statistical methods or using evaluating algorithms.

ACKNOWLEDGMENT

The authors would like to thank Dato' Professor Dr. Zul Azhar Zahid Jamal, the vice chancellor, Universiti of Malaysia Perlis for his continuous support and encouragement.

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