Kinesthetic Motor Imagery Based Brain-Computer Interface for Power Wheelchair Manoeuvring

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***Abstract*— Patients who are suffering from diseases like motor neurone diseases (MND), or trauma such as spinal cord injury (SCI), and amputation is not able to move. This paper presents work on combining the power wheelchair designed to aid the movement of the disabled patient, and a Brain-Computer Interface can be used to replace conventional joystick so that it can be controlled without using hands. The brain signal emanated during Motor Imagery tasks can be converted into control signal for power wheelchair manoeuvring. In this research, five subjects are requested to perform six Kinesthetic Motor Imagery tasks, and Electroencephalography (EEG) signals are recorded. The elliptic filter was used to remove power line noise. Three features, namely Fractal dimension (FD), Mel-frequency Cepstral Coefficients (MFCCs) and a combined feature of FD with MFCCs were extracted and evaluated by using Multilayer Perceptron Neural Network (MLPNN). The Levenberg-Marquardt training algorithm is used to train the networks, and the classification result of the MLPNN using a combined feature of FD with MFCCs achieved an average accuracy of 91.7%. The developed model is tested and evaluated with the simulated virtual environment created by MATLAB graphical user interface (GUI). The result suggests that the combined feature of FD with MFCCs and MLPNN can be used to classify Motor Imagery signal for directional control of powered wheelchair.**

***Index Terms*—Artificial Neural Network; Brain-Computer Interface; Kinesthetic Motor Imagery; Powered Wheelchair.**

I. INTRODUCTION

Differentially enabled (DE) communities suffering from diseases like stroke, cerebral palsy, motor neurone diseases (MND) including amyotrophic lateral sclerosis (ALS), or trauma such as spinal cord injury (SCI) and amputation is facing movement impairment issues.

The wheelchair was invented to aid the movement of disabled patients and had gone through development for many centuries. A manual wheelchair consists of a seat, two footrests, two small front wheels and two large rear wheels. It can be moved by turning the rear wheels with hand rims by the occupant, or by pushing the handles by a second person. The long duration of wheel turning can be very tiring, especially places with uneven terrains or landscape.

The electric-powered wheelchair was then invented to assist injured veterans during World War II. The electric-powered wheelchair consists of essential components similar to a manual wheelchair, but with additional components like electric motor, joystick controller and battery. Electricity drives it from the battery, and the joystick can control the direction of the wheelchair. Henceforth, the DE communities can easily travel for longer distance without the need of aid from the others.

However, the severe motor disabilities of the DE communities prevent them from using conventional augmentative methods, including power wheelchair that requires voluntary muscle movement of the patients to move the joystick [1]. The clinician reported that managing of steering and manoeuvring tasks by using the existing joystick-based power wheelchair interface is extremely difficult or impossible for approximately 40 percent of patients who receive power wheelchair training [2].

To overcome this issue, a Brain-Computer Interface (BCI) can be used to replace the joystick for controlling a power wheelchair. BCI is a communication system where it connects a functional human brain and a device to be controlled [3]. It provides an alternative pathway where the brain's normal output channels of peripheral nerves and muscles are bypassed [1].

By translating the brain signal into an equivalent control signal, BCI allows its user to gain control over the connected device without performing any muscular action. Thus, it can be an anticipated solution for the DE communities to overcome their physical limitations and interact with the external environment [4].

II. METHODOLOGY

The Brain-Computer Interface (BCI) has the potential to replace or restore motor function for the Differentially Enabled (DE) communities since it does not use normal neuromuscular output pathways [1,5]. By converting Electroencephalogram (EEG) signals generated by Kinesthetic Motor Imagery tasks into appropriate command, a person's intention can be used to control the direction of a power wheelchair.

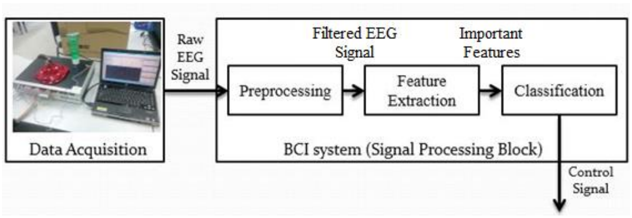

Figure 1: Block diagram of BCI system

To be able to convert the raw EEG signals into a suitable control signal for a power wheelchair, there are a few important stages that need to be performed. Figure 1 shows the four stages that involved in a general BCI system, namely data acquisition (DAQ), signal preprocessing, feature extraction and classification.

A. Data acquisition

The EEG signals were recorded at a sampling rate of 256Hz using a 19-channel EEG amplifier (Mindset-24). A unipolar 19-channel EEG cap along with electrode attachments and applied with conductive gel were placed on the subject's scalp based on International 10-20 electrode placement system [6]. Electrodes were connected only to the channel locations, C3, C4, Cz as only kinesthetic motor imagery (KMI) related tasks are considered in the experimental study [7]. The ground and reference electrode were attached to the left and right mastoids.

Five healthy volunteers (three males and two females) aged 21-30 years were involved in this research. None of them had a history of neurological or other diseases that might affect the experimental result. Before starting the experiment, the participants were briefed about the experimental procedures and requested to sign a written consent form.

As the classification of KMI tasks based on the same body movements is involved, the proposed protocol requires the imagination of moving six different body parts (left hand, right hand, left leg, right leg, left palm and right palm) [8]. This six MI tasks together with relaxing function were then associated with four different directions (forward, backwards, left and right) and three control flag for stop, on and off status.

Each task was recorded for 12 seconds, followed by relaxing period of 10 seconds. The experiment was repeated for ten such trials. The sampling frequency was 256 Hz, and therefore a total of 3072 samples was recorded for each test. The database consists of 150 set of samples (3 channels x 10 trials x 5 subjects) for each task.

B. Pre-processing

This section discussed the pre-processing stages including noise removal, segmentation and validation. Digital filters are used for the noise removal stage. By using a fifth order band-stop elliptic filter with 49-51 Hz cut-off frequency, 0.01 ripple factor and 60 dB stopband attenuation, the 50 Hz power-line noise can be eliminated from the EEG signals [9].

The signal offset that might cause by electrode artefact can be removed by using a high pass filter with near zero cut-off frequency [9]. After filtering low-frequency components of the signal, the signal will become zero-mean distribution. Thus, another fifth order high-pass elliptic digital filter with 1 Hz cut-off frequency, 0.01 ripple factor and 60 dB stopband attenuation was designed.

Figure 2 shows the frequency response of the designed filters (a,b) and the frequency spectrum for the raw and filtered signal (c). The first one second and final one second of the filtered signal were removed. The remaining ten seconds samples (2560 samples) were considered for this study.

The segmentation process takes place after filtering of raw EEG signal. The filtered EEG signal is being divided into multiple frames of the fixed-size window. The window size was experimentally selected as 640 sample. Instead of straightforward segmentation, each frame was overlapped by 50% such that each of the frames contains 50% signal from the previous frame and the next frame.

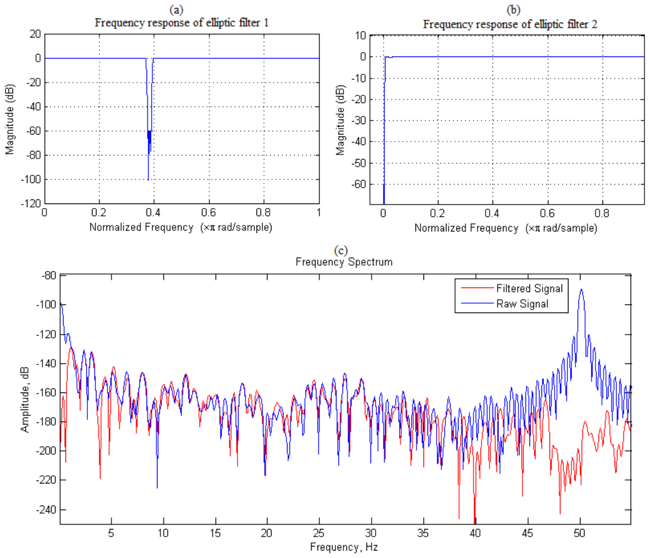

Figure 2: (a) Frequency response of Elliptic band stop filter with 50 Hz cut-off frequency; (b) Frequency response of Elliptic high pass filter with 1 Hz cut-off frequency; (c) Frequency spectrum of raw EEG signal vs filtered EEG signal

Therefore, a database of 490 frames (7 frame x 10 trials x 7 tasks) of samples is formulated for each subject. Each of the segmented frames is convoluted with Hann window function to minimise discontinuities during segmentation [10].

To validate that the signal recorded exhibits the properties of an EEG signal, Analysis of Variance (ANOVA) test is performed. For all the five subjects, seven tasks and ten trials, five segmented frames from each trial were selected randomly for ANOVA test.

The probability value that is more than 0.05 would indicate that there is 95% confidence that the segments are the same, which violated the stochastic nature of EEG signal. Such trial will be rejected, and the recording of that trial will be restarted. All the trials had passed ANOVA test, with probability value lower than 0.05.

C. Feature Extraction

This section discussed feature extraction algorithms selected to extract the prominent features of the Kinesthetic Motor Imagery (KMI) signal. In this research work, five feature extraction methods are being employed:

i. Higuchi Fractal Dimension (FD)
ii. Mel-frequency Cepstral Coefficients (MFCCs)
iii. Combined feature of FD with MFCCs (FD+MFCCs)

Fractal dimension is a non-linear time domain feature, which measures descriptive quantitative that provides a statistical ratio of complexity [11,12]. It can clearly discriminate the signal with different complexity, despite their scaling properties [13].

The index calculated is a fractional value, where a more complex signal gives higher fractal dimension value and vice versa [14]. There are several techniques to measure the fractal dimension, such as box counting, information, correlation, generalised dimension, and Higuchi method.

Recently, Kesić & Spasić [15] had reviewed the applications of Higuchi's fractal dimension (FD) in basic and clinical neurophysiology. Higuchi's method provided the most accurate estimation, although its accuracy decreases with increasing noise ratio. The advantages of speed, precision and cost-efficient of applying FD is the reason why it is widely used. Moreover, the combined application of FD with other non-linear approaches ensures reliable and accurate analysis of a wide range of neurophysiological signals.

To calculate fractal dimension, the segmented frame was first separated into k sets of time series by using Equation (1).

$$X_k^m = x_m, x_{m+k,} x_{m+2k}, \ldots, x_{m+n_f * k} \quad (1)$$

where $n_f = \left[\frac{N-m}{k} \right]$ and $m = 1, 2, 3, \ldots, k$

The length of series X_k^m is calculated as follows:

$$L_m(k) = \left(\left(\sum_{i=1}^{n_f} \left| (x_{m+i*k}) - (x_{m+(i-1)*k}) \right| \right) \frac{N-1}{n_f * k} \right) / k \quad (2)$$

Using the mean length value L_k, the fractal dimension value F_d is computed by using Equation (3).

$$F_d = -\frac{\log(L_k)}{\log(k)} \quad (3)$$

By taking k = 2, 3, 4, 5 and 6 [12], five fractal dimension values were obtained for each segmented frame. Thus, a database of FD features consisting of 490 rows (7 frames x 10 trials x 7 tasks), and 15 columns (5 features per channel x 3 channels) was formulated and associated to the respective MI task.

A Mel-frequency cepstral coefficient is a feature extraction method originally used in speech recognition system [16]. It is being applied in EEG tasks classification recent years and achieved high classification accuracy up to 90% [17,18]. MFCCs contain filter banks that model the ability of the human ear to resolve frequencies non-linearly across the audio spectrum [19]. To compute MFCCs, the segmented frame was converted into the frequency domain by using Short Time Fourier Transform (STFT). Mel-frequency cepstrum is then calculated by mapping the FFT spectrum onto a mel scale based triangular band-pass filter banks. Using Equation (4), ten triangular filter banks which equally spaced along the Mel scale that covered 0-100 Hz were designed. The frequency nodes for the created filter banks are located at [0, 8.6, 17.2, 26.0, 34.8, 43.8, 52.9, 62.1, 71.4, 80.8, 90.4, 100.0] Hz. Each triangular filterbank was formed by three continuous frequency nodes, with overlapping of 50% as shown in Figure 3.

$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700}) \quad (4)$$

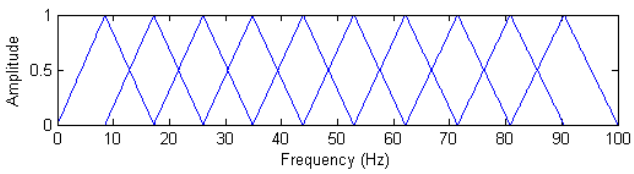

Figure 3: 10 Mel filter banks across 0-100 Hz with 50% overlapping

The Mel scaled output was then logarithmically transformed and discrete cosine transform (DCT) was applied as represented in Equation (5). Thus a database of MFCCs featured consisting of 490 rows (7 frames x 10 trials x 7 tasks) and 30 columns (10 features per channel x 3 channels) and associated to the respective MI task was formulated.

$$C_n = \sqrt{\frac{2}{k}} \sum_{k=1}^{K} (\log S_k) \cos\left[n(k-0.5)\frac{\pi}{k} \right] \quad (5)$$

where S_k is the output of the filter bank, K is the length of S_k, and C_n is the cepstral coefficients.

The third feature set was developed by combining FD features with the MFCCs features. Thus, a database consisting 490 rows (7 frames x 10 trials x 7 tasks) and 45 columns (5+10 features per channel x 3 channels) were formulated.

D. Classification

This section discussed the nonlinear classifier selected, namely Multilayered Perceptron Neural Network (MLPNN) for classifying the MI tasks. It was frequently employed by researchers in a complex application, especially in the biosignal recognition application. The three feature databases (FD, MFCCs and FD+MFCCs) were normalised and then used to develop three different network models for each subject. The performance of the different models will be tested by using wheelchair simulator developed by MATLAB Graphical User Interface (GUI).

The features extracted are used as input vector of the networks. There are totally three different features used in this research, and each feature set gives different numbers of the input vector. The details of the numbers of neurones are provided in Table 1.

Table 1
Network Parameters

	Feature Sets		
	FD	MFCCs	FD+MFCCs
Input Neurons	3 x 5 = 15	3 x 10 = 30	3 x 15 = 45
Hidden Layers		1	
Hidden Neurons		10	
Output Neurons		7	
Initial Weight Value		random	

The number of hidden neurones is experimentally selected as 10. The number of input neurones is multiplied by three as there is three channel (C3, Cz and C4) while the number of output neurone is set to 7 as there are seven tasks. The weights value is randomised initially.

To ensure the generalisation capability of the network, the database is being randomly divided into three sets. 65% of the database is used for training, while 10% for validation and remaining 25% for testing [20]. The training stops when the MSE of the validation set increases and the weights vector before increment of validation MSE will be saved. The network training will otherwise continue until it reached the following criteria:

- Maximum epoch: 1000
- Maximum training time: 100 minutes
- Minimum performance: 1e-7
- Minimum gradient: 1e-7

As these criteria were set at a minimal value, the network training considered a failure if the training parameters reach these standards. Over-fitting may happen due to overtraining of the system. The network model will lose its generalisation capability when it overfits.

The best well-performed feature extraction algorithm is compared and selected based on the classification result. The trained networks are then tested in a simulated virtual environment created using MATLAB Graphical User Interface (GUI) for visualising the accuracy of the system output.

The GUI divides routeing protocol into five by five blocks and indicating the direction of a wheelchair with a blue arrow. The pathway between each block can be redesign by selecting ‘Redraw Route’ button. The GUI will choose a frame (640 samples) at a random time from a random trial of the corresponding task, based on the required task at each step. The selected frame will be preprocessed, and its features will be fed into MLPNN. Green or red colour indicates the classification correctness at respective block or line.

The route simulation will always start with Task 6, representing ‘On’ and robot chair will start moving. At each block, the robot chair will ‘Stop’ (Task 1), ‘Turn Left’ (Task 2) or ‘Turn Right’ (Task 3) according to the route designed. The connection between each block representing ‘forward’ (Task 4) and ‘Backwards’ (Task 5) movements and the route will always end with ‘off’ (Task 7). Upon reaching the last block, the wheelchair will continue to move in a reverse direction, and start over infinitely once it reaches the first block.

III. Result and Discussion

By using MLPNN, the ability of five feature extraction methods is tested and evaluated. The combined feature of FD with MFCCs has yielded highest classification accuracy among all five feature extraction methods. It appeared that the low accuracy member in both FD based MLP and MFCCs based MLP was improved by around 15% when the two features were combined.

On top of that, the performance variance of the combined feature of FD with MFCCs was the lowest, indicating that it can provide a reliable classification output. This result suggests that the fusion of time domain and frequency domain features is very efficient for increasing classification performance and able to discriminate the KMI tasks better.

The Combined feature of FD with MFCCs and MLPNN is employed in the designed MATLAB GUI for wheelchair route simulation. Figure 5 shows the example of the simulation performed. The top right figure always display the 20 newest classification result, the red line represents network output, and the green line represents the target. The misclassification rate of a particular task can be observed quickly through the bar chart at the bottom right of the GUI.

Table 2
Classification Accuracy for FD based MLPNN

Accuracy (%)	Subject				
	1	2	3	4	5
Training (65%)	73.0	75.8	71.4	97.8	97.8
Validation (10%)	49.0	61.2	61.2	89.8	87.8
Testing (25%)	49.6	55.3	52.9	85.4	89.4
Overall (100%)	64.7	69.2	65.7	93.9	94.7

Table 3
Classification Accuracy for MFCCs based MLPNN

Accuracy (%)	Subject				
	1	2	3	4	5
Training (65%)	87.7	97.8	72.3	100.0	100.0
Validation (10%)	73.5	69.4	77.6	98.0	95.9
Testing (25%)	66.7	74.0	59.4	97.6	96.8
Overall (100%)	81.0	89.0	69.6	99.2	98.8

Table 4
Classification Accuracy for FD+MFCCs based MLPNN

Accuracy (%)	Subject				
	1	2	3	4	5
Training (65%)	90.3	96.5	83.3	100.0	100.0
Validation (10%)	71.4	69.4	73.5	91.8	98.0
Testing (25%)	66.7	78.1	71.5	100.0	97.6
Overall (100%)	82.5	89.2	79.4	99.2	99.2

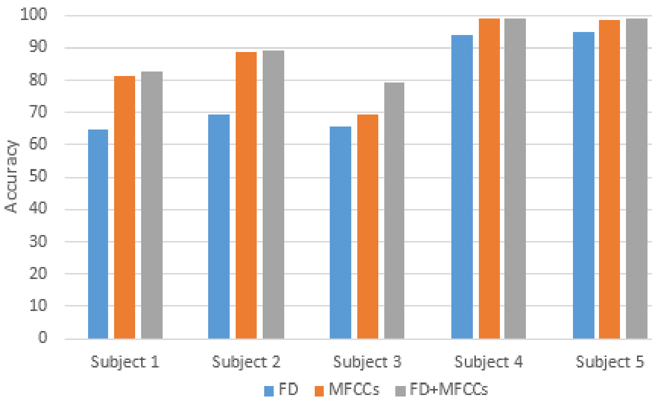

Figure 4: Overall Accuracy for FD, MFCCs and FD+MFCCs based MLP

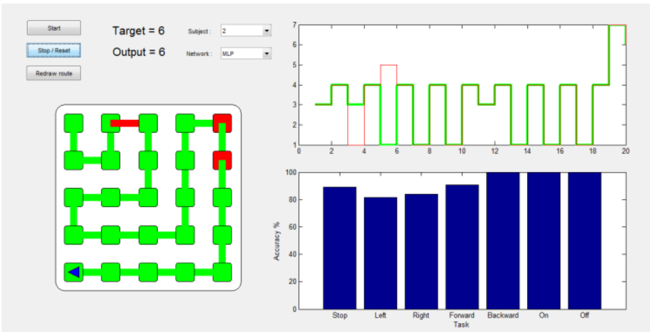

Figure 5: Wheelchair route simulator created by using MATLAB GUI

IV. Conclusion

In this research, three different feature extraction methods were applied for the classification of six different KMI tasks. The use of the combined feature of FD with MFCCs (FD+MFCCs) resulted in consistently higher classification accuracy compared to Higuchi Fractal Dimension (FD) feature and Mel-frequency Cepstral Coefficients (MFCCs) feature. This result suggests that the combined feature of FD with MFCCs can be used as a promising feature extraction method in motor imagery based BCI.

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