ISSN (Print) : 0974-6846
Indian Journal of Science and Technology, Vol 8(20), DOI: 10.17485/ijst/2015/v8i20/79066, August 2015 ISSN (Online) : 0974-5645

Motor-Imagery Task Classification using Mel-Cepstral and Fractal Fusion based Features

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Abstract

A brain-actuated wheelchair can be used to aid the movement of differentially enabled communities who face much difficulties while commuting from one place to another. In this research work, the active brain signals emanated from subjects while performing four different kinesthetic motor imagery tasks are recorded using Electroencephalography (EEG). Three different feature sets, namely, Fractal Dimension (FD), Mel-Frequency Cepstral Coefficients (MFCCs) and combined features of FD with MFCCs are extracted from the recorded EEG signals. The extracted features are then associated to classify the type of motor imagery tasks and three feedforward multi-layer Perceptrons trained with Levenberg-Marquardt method are developed. The performance of the three features are evaluated in term of classification rate and compared. Simple Elman network and NARX network models are then developed using the extracted features and evaluated. From the results, it is observed that the Elman network model trained with combined features of FD with MFCCs has yielded a higher classification accuracy for all the 5 subjects in the range of 98.98-100percent. The obtained result clearly indicates that the Elman network and combined features of FD with MFCCs has potential to classify the four different motor imagery tasks.

Keywords: Brain Computer Interface, Elman Neural Network, Feedforward Multi-Layered Perceptron Neural Network, Fractal Dimension, Mel-Frequency Cepstral Coefficients, Nonlinear Autoregressive Exogenous Model, Recurrent Neural Network

1. Introduction

Patients suffering movement impairment that caused by diseases like Motor Neuron Diseases (MND) or trauma such as Spinal Cord Injury (SCI) and hand amputation are having difficulties to control power wheelchair. Power wheelchairs currently available in the market are driven by a joystick. By moving the joystick with hand, a user can control the movement of the wheelchair manually. However, it was reported that approximately 40 percent of patients who receive power wheelchair training find it extremely difficult or impossible to manage steering and manoeuvring tasks using existing power wheelchair interface[1].

Since the last few decades, researchers have been dedicated to develop a hands-free interface to adapt the usability of a power wheelchair by a broader range of differentially enabled communities. The joystick controller is being replaced by various approaches such as voice command, image processing on facial expression or eye blinking or gesture recognition, bio-signal data recorded using methods such as Electronystagmography (ENG), Electroencephalogram (EEG) and Electromyography (EMG) and many other control methods[2-5]. Among these various methods, a brain-actuated power wheelchair would be more suitable for all types of users as the control action is based on the signal generated from the brain activities.

Brain Computer Interface (BCI) is a communication system where the user's command "do not depend on the brain's normal output pathway of peripheral nerves and muscles"[6-7]. It is a new communication link between the functioning of human brain and the automation system[8]. The BCI translates the brain signal into an equivalent control signal that can be used to control devices directly[9]. Thus it can be used by patients with severe

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motor impairments to communicate with other persons and interact with the external environment[10].

2. Methodology

2.1 Data Acquisition and Preprocessing

The EEG signals were recorded using Mindset 24 Topographic Neuro Mapping Instrument at a sampling rate of 256 Hz. A unipolar 19-channel EEG electrode cap was placed on the subject's scalp based on the International 10-20 system for electrode placement[11]. The reference electrode were attached on left and right mastoids.

Five healthy subjects aged 21-25 years were employed in this research (3 males and 2 females). None of them had history of neurological or other disease that might affect the experimental result. The subjects were requested to have enough rest the day before the experiment was conducted. A written consent was obtained from all five subjects after explaining the purpose of the experiment. The proposed protocol involves the imagination of moving 4 different body parts (left hand, right hand, left leg and right leg) as the classification of motor imagery tasks based on same body parts yielded lower accuracy[12]. This 4 Motor Imagery (MI) tasks were then associated to four different directions (forward, backward, left and right) and relax task for stopping condition. Each task was recorded for 15 seconds, followed by a relaxing period of 10 seconds. The experiment was repeated for ten such trials. The recorded EEG signals were then normalized to zero mean and subsequently filtered using an elliptical band-stop filter at 50 Hz for removing the power line artifacts.

2.2 Feature Extraction

As MI tasks involves in primary motor cortex, the EEG signals acquired from C3, C4 and Cz channels were used for feature extraction[13]. In this paper, Fractal Dimension (FD) features, Mel-Frequency Cepstral Coefficients (MFCCs) features and a combination of FD with MFCCs features were used for classification and their performance were evaluated.

The fractal dimension is a descriptive quantitative measure that provide statistical index of complexity of a time domain signal[14, 15]. The index calculated is a non-integer value (fractional) and a more complex signal gives higher fractal dimension value and vice versa[16]. To calculate fractal dimension, the first and the last one second signals were removed and then the remaining 13 second samples were segmented into 10 equal frames of frame size (N = 768 samples) with a overlap of 256 samples. The segmented frame was then separated into k sets of time series X_k^m by using Equation (1).

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

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

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

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

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

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

By taking k = 2, 3, 4, 5 and 6[10], five fractal dimension values were obtained for each segmented frame. Thus a database of FD features consisting of 500 rows (10 frames x 10 trials x 5 tasks) and 15 columns (5 features per channel x 3 channels) was formulated and associated to the respective MI task.

Mel-frequency cepstral coefficients is a feature extraction method originally used in speech recognition system[17]. It is being applied in EEG tasks classification recent years and achieved high classification accuracy up to 90 percent[18, 19]. MFCCs contain filter banks that models the ability of human ear to resolve frequencies non-linearly across the audio spectrum[20]. To compute MFCCs, the first second of the clean EEG signals were removed and then the remaining samples were segmented into 10 equal frames where each frame consists of 2 seconds signal (N=512 samples) with overlaps by 256 samples. The segmented frame was converted into frequency domain by using Fast Fourier Transform (FFT). Mel-frequency cepstrum are then computed by mapping the FFT spectrum onto a mel scale based triangular band-pass filter banks. Using Equation (4), 10 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 filter bank was formed by three continuous frequency nodes, with overlapping of 50% as shown in Figure 1.

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

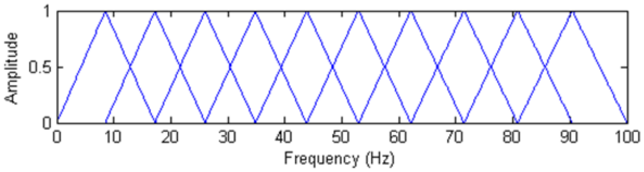

Figure 1. 10 Mel filter banks across 0-100 Hz with 50% overlapping.

The Mel scaled output were then logarithmically transformed and Discrete Cosine Transform (DCT) was applied as represented in Equation (5). Thus a database of MFCCs features consisting of 500 rows (10 frames x 10 trials x 5 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 length of S_k and C_n are the cepstral coefficients.

The third feature set was developed by combining FD features with the MFCCs features. Thus a database consisting 500 rows (10 frames x 10 trials x 5 tasks) and 45 columns (5+10 features per channel x 3 channels) was formulated.

2.1.1 Classification

A Multilayer Perceptron (MLP) consists of an input layer, one or more hidden layers and an output layer. MLP basically can be divided into Feed Forward Neural Network (FFNN) and Recurrent Neural Network (RNN). RNN is a FFNN with the addition of layer recurrent connection. Figure 2 shows the basic structure of a FFNN and Figures 3 and 4 shows the basic structure of Elman network and nonlinear autoregressive exogenous (NARX) model respectively.

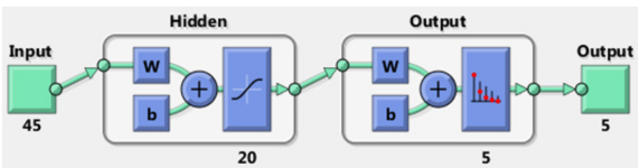

Figure 2. Basic structure of Feedforward Neural Network (FFNN).

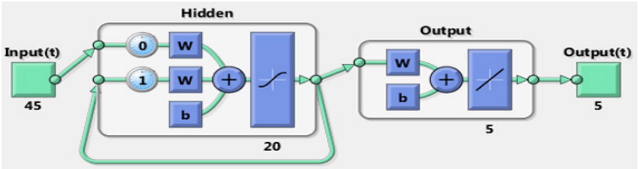

Figure 3. Basic structure of Elman network, feedback loop from hidden layer.

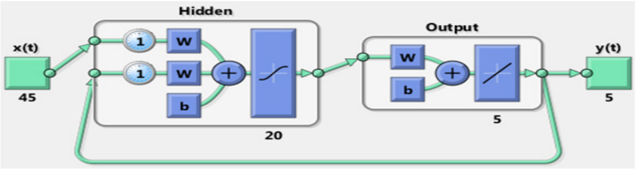

Figure 4. Basic structure of NARX network, feedback loop from output layer.

The feedback loop exhibits hysteretic behavior and therefore dynamic input-output relationship can be discovered. The main different between Elman network and NARX network is that Elman network's architecture feedbacks from hidden layer while NARX network's architecture feedbacks from output layer. The NARX network collects both delayed input-output and this enable the network to predict a time series value.

The three Feature Databases (FD, MFCCs and FD+MFCCs) developed were normalized and then used to develop three different feed forward multi-layer perceptrons for each subject. The networks were trained using Levenberg-Marquardt Algorithm (LMA). The LMA is a combination of gradient descent method and Gauss-Newton Algorithm (GNA). LMA updates network weights with gradient descent method if damping factor, λ is large and uses GNA when λ is small.

The features were evaluated in term of classification accuracy and the best performance feature was selected for further experiment. Elman network and NARX network were developed for each subject and their performance were compared with FFNN by using the selected features.

The maximum epoch was set to 1000 and the performance goal of the training was set to 1e-10. The training stops when the performance goal was met or the Mean Square Error (MSE) of the validation output continually increased for 6 time. Each model consists of 20 hidden neurons and 5 output neurons. The data samples were randomly divided and 65% of it were used for training, 10% for validating and 25% for testing the network model[21] so that it possess generalization capability. The classification was repeated by 10 times and the average classification accuracies were tabulated and shown in Table 1-5.

3. Result and Discussion

The classification accuracies of the feedforward MLPNN models for the three different features extraction methods are presented in Table 1-5. The overall classification accuracy for the three features were summarized in Figure 5. From the results, it can be observed that FD features have overall classification accuracy of 71.8-89.37% for all the 5 subjects. The classification accuracy was rather poor for subject 2, 3 and 4. The FD features have yielded a lower classification accuracy when compared to the other two features.

Further, it can be observed that the MFCCs features have higher overall classification accuracy of 87.80-97.71% which is consistently higher than that of the classification performance obtained from the FD features.

On top of that, it can be observed that the combined features of FD with MFCCs have yielded a highest classification accuracy among all the three feature sets (93.75-97.96%). Even though FD features and MFCCs features achieved lower classification accuracy for subject 2, 3 and 4, the combined features of FD with MFCCs consistently remained high at classification accuracy over 93.75%. This result shows that the combined features of FD with MFCCs is more suitable to classify the MI tasks.

The combined features of FD with MFCCs was selected as input features for comparing the performance of FFNN, Elman and NARX neural network. The classification accuracies of three different type of neural network classifiers are presented in Table 6-10 and the overall classification accuracy for the three different network classifiers were summarized in Figure 6. From the results, it can be observed that all the three classifiers have the overall classification accuracy above 90%, where FFNN achieved 93.75-97.96%, Elman network achieved 98.98-100%, and NARX network achieved 95.55-98.98%.

The FFNN has the capability of reaching 100% accuracy for training session, while it gets lower accuracy for validation and testing session. For Elman network, all three training, validation and testing session had achieved very high classification accuracy. This result suggests that the feedback of the delayed hidden neuron output greatly helped on predicting the correct MI tasks. The performance of NARX network with delayed input and output neuron was very close to Elman network. NARX network had achieved very high classification accuracy for validation and testing session, but sometimes get slightly lower accuracy for training session. It is observed that the delayed input neuron might cause more misclassification at the point where change of next task occurs. Thus, the high classification accuracy of Elman network for training, validation and testing session suggests that it has great generalization capability and is suitable for classifying motor imagery tasks.

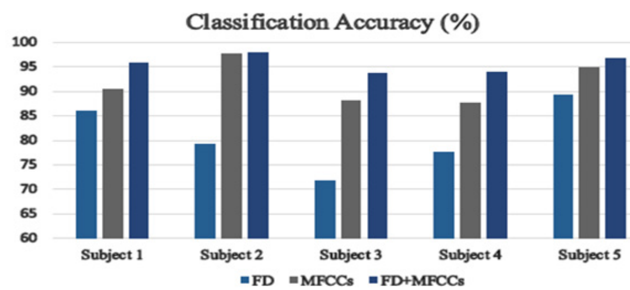

Figure 5. Overall classification accuracy of FD, MFCCs, FD+MFCCs features using FFNN for subject 1-5.

Table 1. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 1

SUBJECT 1	FD	MFCCs	FD +MFCCs
Training	89.73	93.33	100.00
Validation	83.53	80.00	91.76
Testing	78.04	87.38	86.92
Overall	86.18	90.52	95.90

Accuracy of training, validation, testing and overall results shown in percentage value *(percent)* for subject 1.

Table 2. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 2

SUBJECT 2	FD	MFCCs	FD +MFCCs
Training	82.35	100.00	100.00
Validation	72.15	92.41	97.47
Testing	74.62	93.91	92.89
Overall	79.39	97.71	97.96

Accuracy of training, validation, testing and overall results shown in percentage value *(percent)* for subject 2.

Table 3. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 3

SUBJECT 3	FD	MFCCs	FD +MFCCs
Training	73.00	93.19	100.00
Validation	71.21	77.27	86.36
Testing	68.90	79.88	80.49
Overall	71.80	88.26	93.75

Accuracy of training, validation, testing and overall results shown in percentage value *(percent)* for subject 3.

Table 4. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 4

SUBJECT 4	FD	MFCCs	FD +MFCCs
Training	80.30	92.73	99.39
Validation	76.47	78.43	84.31
Testing	70.87	78.74	84.25
Overall	77.56	87.80	94.09

Accuracy of training, validation, testing and overall results shown in percentage value *(percent)* for subject 4.

Table 5. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 5

SUBJECT 5	FD	MFCCs	FD +MFCCs
Training	96.48	100.00	100.00
Validation	75.00	87.50	100.00
Testing	76.77	84.85	86.87
Overall	89.37	94.94	96.71

Accuracy of training, validation, testing and overall results shown in percentage value *(percent)* for subject 5.

Table 6. Average classification performance of FD+MFCCs features using FFNN, ELMAN and NARX for Subject 1

SUBJECT 1	FFNN	ELMAN	NARX
Training	100.00	100.00	94.95
Validation	91.76	100.00	95.29
Testing	86.92	98.59	97.18
Overall	95.90	99.65	95.55

Accuracy of training, validation, testing and overall results shown in percentage value (percent) for subject 1.

Table 7. Average classification performance of FD, MFCCs and FD+MFCCs features using FFNN for Subject 4

SUBJECT 1	FFNN	ELMAN	NARX
Training	100.00	100.00	96.47
Validation	97.47	98.73	98.73
Testing	92.89	98.47	98.98
Overall	97.96	99.49	97.32

Accuracy of training, validation, testing and overall results shown in percentage value (percent) for subject 2.

Table 8. Average classification performance of FD+MFCCs features using FFNN, ELMAN and NARX for Subject 3

SUBJECT 1	FFNN	ELMAN	NARX
Training	100.00	100.00	98.59
Validation	86.36	96.97	95.45
Testing	80.49	98.78	97.56
Overall	93.75	99.39	98.02

Accuracy of training, validation, testing and overall results shown in percentage value (percent) for subject 3.

Table 9. Average classification performance of FD+MFCCs features using FFNN, ELMAN and NARX for Subject 4

SUBJECT 1	FFNN	ELMAN	NARX
Training	99.39	100.00	99.09
Validation	84.31	100.00	96.08
Testing	84.25	100.00	98.43
Overall	94.09	100.00	98.62

Accuracy of training, validation, testing and overall results shown in percentage value (percent) for subject 4.

Table 10. Average classification performance of FD+MFCCs features using FFNN, ELMAN and NARX for Subject 5

SUBJECT 1	FFNN	ELMAN	NARX
Training	100.00	100.00	100.00
Validation	100.00	94.87	97.44
Testing	86.87	97.98	96.97
Overall	96.71	98.98	98.98

Accuracy of training, validation, testing and overall results shown in percentage value (percent) for subject 5.

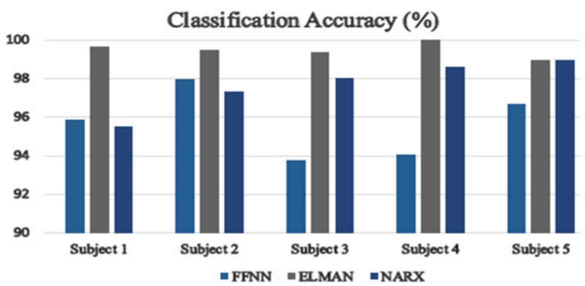

Figure 6. Overall classification accuracy of FFNN, ELMAN, NARX using FD+MFCCs features for subject 1-5.

4. Conclusion

In this research, three different feature extraction methods were applied for the classification of five different MI tasks. The use of combined features of FD with MFCCs resulted consistently higher classification accuracy compared to FD features and MFCCs features. Further, the best feature, combined FD and MFCCs was used for three different classifier. The Elman network performed better than the feedforward network and NARX network. This result suggests that Elman network and combined features of FD with MFCCs can be used as a promising pattern recognition method in motor imagery based BCI.

5. Acknowledgement

The authors would like to thank Y. Bhg. Kol. Prof. Dato' Dr. Kamarudin B. Hussin, Vice Chancellor, University Malaysia Perlis for his constant encouragement.

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