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MEL-FREQUENCY BAND STRUCTURE BASED FEATURES FOR MOTOR IMAGERY TASK CLASSIFICATION

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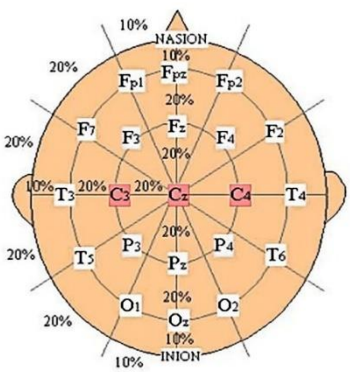
Graphical abstract



Abstract

Differentially enabled communities face much difficulties and challenges in their life time while commuting from one place to another. Power wheelchairs were designed to aid the movement of these differentially enabled subjects and a Brain Computer Interface can also be applied to replace the existing conventional joystick method of controlling the movement of a wheelchair without using hands. In this research work, a simple protocol is proposed to record the EEG signals emanated from a subject while the subject performed four different kinesthetic motor imagery tasks. The noise present in the EEG signals are removed and three different feature sets, namely, power spectral density, Mel-frequency cepstral coefficients and Mel-frequency band structure based energy features are extracted. The extracted features are then associated to the type of motor imagery tasks and three multi-layer Perceptrons trained with Levenberg-Marquardt method are developed. The performance of the three Perceptron models are evaluated in term of classification rate and compared. From the results, it is observed that the Perceptron model trained with Mel-frequency band structure based features has yielded a higher classification accuracy for all 5 subjects, which is between 92.64-97.72%. The obtained result clearly indicates that the Mel-frequency band structure based features has potential to classify the four different motor imagery tasks.

Keywords: Brain computer interface, power spectral density, mel-frequency cepstral coefficients, Multi-layered Perceptron Neural Network (MLPNN)

Abstrak

Masyarakat orang kurang upaya menghadapi banyak kesukaran dan cabaran dalam kehidupan mereka semasa perjalanan. Kerusi roda elektrik telah direkakan untuk membantu pergerakan dan Antara Muka Otak-Komputer juga boleh digunakan untuk menggantikan kaedah joystick konvensional bagi mengawal pergerakan kerusi roda tanpa menggunakan tangan. Dalam kajian ini, protokol yang ringkas telah dicadangkan untuk merakam isyarat EEG berpunca daripada empat kinestetik tugas imejan motor. Gangguan yang terhadir dalam isyarat EEG telah dihapuskan dan kuasa ketumpatan spektrum, Mel frekuensi koefisien Cepstral dan ciri-ciri berdasarkan Mel frekuensi jalur struktur telah diekstrakkan. Ciri-ciri yang diekstrak kemudiannya dikaitkan dengan jenis tugas imejan motor dan tiga Perceptron berbilang lapisan yang dilatih dengan kaedah Levenberg-Marquardt dibangunkan. Prestasi tiga model Perceptron telah dinilai dari segi kadar klasifikasi. Daripada keputusan, adalah didapati bahawa model Perceptron terlatih dengan ciri-ciri berdasarkan Mel frekuensi jalur struktur telah menghasilkan ketepatan klasifikasi yang lebih tinggi bagi semua 5 subjek, iaitu antara 92.64-97.72%. Keputusan yang diperolehi jelas menunjukkan bahawa ciri-ciri berdasarkan Mel frekuensi jalur struktur mempunyai potensi untuk mengelaskan empat tugas imejan motor yang berbeza.

Kata kunci: Antara Muka Otak-Komputer (BCI), kuasa ketumpatan spektrum (PSD), mel frekuensi koefisien Cepstral, rangkaian neural perceptron berbilang lapisan (MLPNN)

1.0 INTRODUCTION

Patients suffering from diseases like motor neuron diseases (MND) or trauma such as spinal cord injury (SCI), and amputation are not able to move. To help these movement impaired patients, special type of wheelchairs with four wheels and a seat were developed. The wheelchair users can move the wheelchair either by themselves by turning the wheel or with the aid of a second party from rear.

Power wheelchairs currently available in the market consist of an electrical motor and a joystick. By moving the joystick, a user can control the movement of the wheelchair manually. However, this is not suitable for users with amputated hands. Hence, 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 in the laboratory environment. Research and experiment with voice command, image processing on facial expression or eye blinking, bio-signal reading such as Electronystagmography (ENG), Electroencephalogram (EEG) and Electromyography (EMG) and many other control methods are being performed by the research communities since the last few decades [1-4]. Of these various methods, EEG based wheelchair control method is 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" [5-6]. It is a new communication link between functioning human brain and the automation system [7]. Thus it can be used by patients with severe motor impairments to communicate with other persons and interact with external environment [8].

2.0 METHODOLOGY

2.1 Data Acquisition and Preprocessing

A unipolar 19-channel EEG electrode cap with conductive gel applied were placed on the subject's scalp based on International 10-20 electrode placement system (Figure 1). The EEG signals were sampled at 256 Hz using Mindset-24 amplifier. Electrodes were connected to the channel locations C3, C4, Cz as only motor imagery (MI) related tasks [9] are considered in the experimental study. The ground and reference electrode were attached on left and right mastoids.

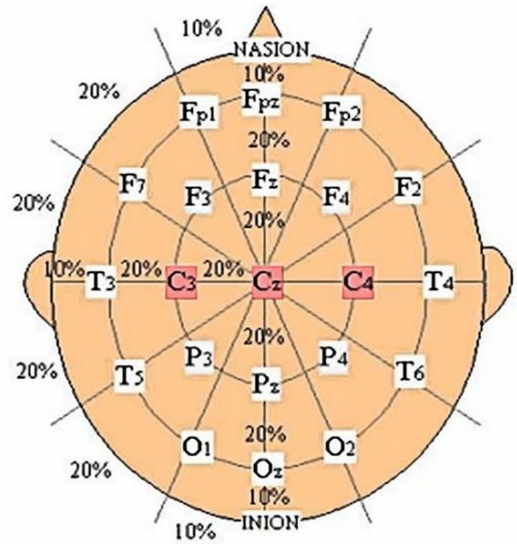


Figure 1 International 10-20 Electrode placement system. Modified from Teplan, 2002 [16]. Location C3, Cz and C4 are highlighted in red color

Five healthy volunteers (three males and two females) aged 21-25 years were involved in this research. None of them had history of neurological or other disease 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 motor imagery tasks based on the same body movements are difficult, the proposed protocol involves the imagination of moving four different body parts (left hand, right hand, left leg and right leg) [10]. This four 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 relaxation 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

The first and last two second duration of the clean EEG signals were removed and then the remaining samples were segmented into 10 frames where each frame consists of 2 seconds signal (N=512 samples) with 50% overlapping. Fast Fourier transformation was then applied to the segmented frames and converted into frequency domain using Equation (1).

$$X(k) = \sum_{j=1}^{N} x(j) e^{(-2\pi jk)/N} \quad (1)$$

Power Spectral Density (PSD) describes how the power of a signal or time series is distributed with frequency. The integral of PSD over a given frequency band computes the average power in the signal over that frequency band. PSD features were evaluated using Fast Fourier Transform (FFT) at 5 frequency bands which are Delta (0.1-3 Hz), theta (4-7 Hz), Alpha (8-13 Hz), Beta (14-30 Hz), and Gamma (31-100 Hz) [11]. Using Equation (2), the PSD features were extracted from the segmented frames of channels C3 and C4 and associated to the corresponding task. Thus for each subject, a database of PSD features consisting of 500 rows (10 frames x 10 trials x 5 tasks) and 15 columns (5 features per channel x 3 channels) and associated to the respective MI task was formulated.

$$S_{xx}(w) = \frac{1}{2\pi} \sum |X(k)|^2 \quad (2)$$

Mel-frequency cepstral coefficients (MFCCs) is a feature extraction method originally used in speech recognition system [12]. It is being applied in EEG tasks classification recent years and achieved high classification accuracy up to 90% [13-14]. MFCCs are computed by mapping the FFT spectrum onto a mel scale based triangular band-pass filter banks. Using Equation (3), 19 triangular filter banks with 50% overlapping and equally spaced along the mel scale covering a frequency range of 0-100 Hz were designed. The frequency node of the filter banks designed are located at [0.0, 4.7, 9.4, 14.2, 18.9, 23.8, 28.6, 33.5, 38.4, 43.4, 48.3, 53.3, 58.4, 63.5, 68.6, 73.7, 78.9, 84.1, 89.4, 94.7, 100.0] Hz. Each triangular filter bank was formed by 3 continuous frequency nodes, with overlapping of 2 nodes from the previous filter bank.

$$Mel(f) = 2595 \log_{10}(1 + \frac{f}{700}) \quad (3)$$

By performing convolution of FFT spectrum and using the designed 19 filter bank, for each subject, a database of Mel-frequency band structure based features (MFB) consisting of 500 rows (10 frames x 10 trials x 5 tasks) and 57 columns (19 features per channel x 3 channels) and associated to the respective MI task was formulated.

The Mel scaled signals were then logarithmically transformed and discrete cosine transform (DCT) was applied as represented in Equation (4). Thus for each subject, a database of MFCCs features consisting of 500 rows (10 frames x 10 trials x 5 tasks) and 57 columns (19 features per channel x 3 channels) and associated to the respective MI task was formulated.

$$C_n = \sqrt{\frac{2}{k}} \sum_{k=1}^{K} (\log S_k) \cos\left[n(k - 0.5) \frac{\pi}{k} \right] \quad (4)$$

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

2.3 Classification

The three feature databases (PSD, MFB and MFCC) developed were normalized and then used to develop three different feedforward multi-layer perceptrons for each subject. The networks were trained using Levenberg-Marquardt algorithm. The performance goal was set to 1e-10 and maximum epoch was set to 1000. The training stops when the performance goal was reached or the mean square error (MSE) of the validation continually rises for six epochs. Each model consists of 20 hidden neurons and 5 output neurons.

The training samples were randomly split into three different sets: 65% for training, 10% for validation and 25% for testing [15]. The classification was repeated for 10 times and the average classification accuracies for all the five subjects for the three different features were tabulated and shown in Table 1-5.

3.0 RESULTS AND DISCUSSION

The classification accuracies of MLPNN for different type of feature extraction methods are presented in Table 1-5. The lowest and highest overall accuracy for each features were highlighted in light and dark grey shades. The overall classification accuracy for the three features were summarized in Figure 2. From the results, it can be observed that the PSD feature has the lowest overall classification accuracy for all 5 subjects (overall 64.8-71.85%). Due to the limited number of frequency bands, the PSD 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 86.42-95.77% which is consistently higher than that of the classification performance obtained from the PSD features.

On top of that, it can be observed that the MFB features has the highest overall classification accuracy of 92.64-97.72% which is averagely 2.67% higher than that of the classification performance obtained from the MFCC features. This results shows that the refinement of MFCC features into MFB features is more suitable to classify the MI tasks.

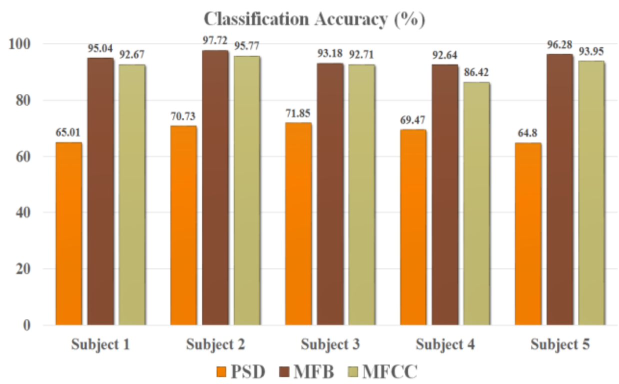


Figure 2 Overall classification accuracy of PSD, MFB, and MFCCs features for subject 1-5

Table 1 Average classification performance of PSD, MFB and MFCCs features for subject 1

Subject 1	PSD	MFB	MFCCs
Training	69.21	99.25	97.61
Validation	61.44	89.05	85.52
Testing	55.54	86.51	82.72
Overall	65.01	95.04	92.67

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

Table 2 Average classification performance of PSD, MFB and MFCCs features for subject 2

Subject 2	PSD	MFB	MFCCs
Training	76.42	99.53	98.45
Validation	65.46	95.38	90.57
Testing	58.12	93.97	90.92
Overall	70.73	97.72	95.77

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

Table 3 Average classification performance of PSD, MFB and MFCCs features for subject 3

Subject 3	PSD	MFB	MFCCs
Training	75.83	97.27	97.07
Validation	74.1	86.01	86.24
Testing	60.62	85.47	83.99
Overall	71.85	93.18	92.71

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

Table 4 Average classification performance of PSD, MFB and MFCCs features for subject 4

Subject 4	PSD	MFB	MFCCs
Training	74.55	97.61	92.65
Validation	68.44	81.25	75
Testing	56.72	84.25	74.8
Overall	69.47	92.64	86.42

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

Table 5 Average classification performance of PSD, MFB and MFCCs features for subject 5

Subject 5	PSD	MFB	MFCCs
Training	71.24	100	100
Validation	63.05	92.7	86.26
Testing	48.77	88.06	81.33
Overall	64.8	96.28	93.95

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

4.0 CONCLUSION

In this research, three different feature extraction methods were applied for the classification of five different MI tasks. The use of Mel-frequency band structure based features from MFCCs features resulted consistently higher classification accuracy compared to PSD features and MFCCs features. This result suggests that Mel-frequency band structure based features can be used as a promising feature extraction method in motor imagery based BCI.

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