An Analysis of the Effect of EEG Frequency Bands on the Classification of Motor Imagery Signals

School of Mechatronic Engineering, Universiti Malaysia Perlis, Perlis, Malaysia

Abstract: The EEG frequency bands are brain rhythms that indicate the activity level of the brain. This paper investigates the effects of the sub-band frequency on the classification of motor imagery of hand movements. Ten sub-bands of 10Hz width between 0 to 100 Hz are chosen. Band power features of the sub-bands are classified using a neural classifier. Motor imagery signals recorded from the C3 and C4 channels for four tasks are used in the analysis. Classification rates of 89.23% - 94.47% were achieved for sub-band frequencies ranging from 21Hz to 40 Hz for motor imagery signals. Results show that apart from mu and beta, low gamma frequencies are also better suited for motor imagery classification.

Keywords: Elman Neural Networks, EEG, Sub-band Frequency, Motor Imagery, Band Power

1. Introduction

Motor imagery recorded at the sensory motor cortex can be used to identify the intended motor activities performed by individuals. Such thought signals can be translated to control devices; such a system is called a brain machine interface [BMI]. BMI technology provides the brain with a new communication and control channel that does not depend on the normal output pathways such as the peripheral nerves. Currently BMI systems are designed for people with motor disabilities.

Many researches around the world are devoted to the development of BMI systems [1]. EEG is the most popular modality in the design of BMI as only EEG and related methods, which have relatively short time constants, can function in most environments and they also require relatively simple and inexpensive equipment.

Through training, subjects can learn to control their brain activity in a predetermined fashion that is classified by a pattern recognition algorithm [2].

BMI systems are designed by classification or recognition of EEG patterns related to mental states. With proper training and motivation, majority of the subjects can learn to control the intensities of specific frequency bands, which can be used as a communication or control signal [3]. Features extracted from EEG signals can be obtained by frequency based and non frequency based methods. Some research groups have used non frequency methods like adaptive autoregressive model and time-space methods [4-9] to classify the EEG signals.

The EEG signal has a frequency spectrum ranging from 0.1 Hz to 100Hz which are classified into five frequency bands as delta (0.1-3 Hz), theta (4-7 Hz), alpha (8 – 13 Hz), beta (14- 30 Hz) and gamma (31-100Hz). It has been established that EEG bands are related to mental activities such as thinking and movement and are detected at different locations on the cortex. In this paper we use motor imagery signals recorded from two subjects at the c3 and c4 locations during four mental states. Our goal was to analyze each 10 Hz wide EEG sub-band’s contribution to classification of four different mental states.

Motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with real executive movements [2]. Motor imagery maybe seen as a motor act without any overt motor output. Sensory stimulation, motor behavior and mental imagery can change the functional connectivity within the cortex and results in amplitude suppression or event related desynchronization.
With proper training and motivation, majority of the subjects can learn to control the intensities of specific frequency bands, which can be used as a communication or control signal [3]. Pfurtscheller et al [4] have compared an adaptive autoregressive model (ARR) and neural network model to show an improvement in the error rate using ARR. Pfurtscheller and Neuper [2] present an ARR and Linear Discrimination approach to classify EEG signals for left and right movement from electrode positions C3, C4 and Cz, collected from a tetraplegic patient to control a hand orthosis. An accuracy of 65% was achieved after 28 training sessions. To analyze EEG signals, different methods have been proposed by various researchers: autoregressive model [5, 7], neural networks [12, 14], time-frequency analysis [6, 13, 14] and Fuzzy based classification [13].

The processing of the EEG within the motor imagery still shows open directions; most studies have relied on subjective evaluation and not objective confirmation of task performance. Motor imagery is a dynamic state in which a subject mentally simulates a given action [3]. In our earlier work [13, 14] we observed that the performance varies for different subjects for the same mental task. Hence BMI design is subject specific, our current work presents a procedure for extracting features from electroencephalogram (EEG) recorded from one subject involving motor imagery of hand movements.

2. Experiment Data

In this analysis EEG motor imagery signals collected from two healthy subjects for four mental states were used. During the recordings the subjects are instructed not to move and keep their hands relaxed. The motor imagery tasks are cued by a visual stimulus presented on a computer monitor. Each trial is 10s long, the subjects performs four tasks namely, relax, forward, left and right, for the relax task a word ‘RELAX’ appears on the monitor, for forward, left and right task an arrow pointing to upwards, left and right respectively appears on the monitor. During the relax task no mental task is performed, subjects are told to relax and try to thing of nothing in particular. This task is used as a baseline measure of the EEG and can be translated to a stop control. For the left and right task, depending on the direction of the arrow the subjects are instructed to imagine a movement of left or right arm, for the forward movement the subjects are instructed to imagine moving both their arms forward.

2.1 EEG Recording

EEG is recorded using two gold plated cup electrodes placed at the C3 and C4 locations on the motor cortex area as per the International 10 -20 Electrode Placement System [10]. The EEG signals are amplified and sampled at 200 Hz using an ADI Power lab amplifier. Each trial lasts for 10s and the signals are recorded for twenty trials per task. In this experiment the subjects are aged between 16 to 46 years. At the time of data recording the subjects are free from illness or medication.

3. Methods

3.1 Feature Extraction

The motor imagery signals are initially band pass filtered for a band pass range of 0.1 to 100Hz. Each 10s data signal is segmented into 0.5 s segments with an overlap of 0.25s. Data segments are filtered using a chebyshev band pass filter with a bandwidth of 10Hz, the sum of the power values are extracted for each segment. Finally a logarithmic transform is performed on the summed power value. 39 features are extracted for each subject per task per trial. The features are extracted for twenty such trials and are used to model a recurrent neural network. For each subject ten neural network models for each sub band of 10Hz bandwidth is developed.

3.2 Classification

The sub band frequency data are classified using an Elman recurrent neural network [ERNN]; these networks have feedback connections which add the ability to also learn the temporal characteristics of the data set. In this study ERNN architecture with three layers is used. The ERNN makes a copy of the hidden layer which is referred to as the context layer. The purpose of the context layer is to store the pervious state of the hidden layer at the previous pattern presentation [11]. This improves the classification rate and training time of the network in comparison to a feed forward neural network.

A multilayer ERNN with one single hidden layer is trained by the BP algorithm to classify the four states represented by the EEG sub band features. Each network model has 39 nodes in the input layer and 4 output nodes, the hidden layer nodes are chosen experimentally as 5. The learning rate is chosen to be 0.001 experimentally. 160 data samples are used in this experiment. The training and testing error tolerances are 0.001 and 0.05 respectively. The training and testing data are normalized using a binary normalization algorithm [12]. The ERNN is trained with 80% data set for all 10 sub band frequencies. Selections of the training data are chosen randomly. Training is conducted until the average error falls below 0.001 or reaches a maximum iteration limit of 10000.
4. Results

4.1 Significance of Different Frequency sub bands for Classification

Motor imagery task classifications are performed on each sub band frequency. From a specific sub band thirty nine features were computed and used for the four state motor imagery classifications. Figure 1 and 2 shows the average classification for the four tasks for subject1 computed on each sub band, it is seen that the sub bands 21 Hz to 30 Hz and 31 Hz to 40 Hz exhibit greater classification accuracy of 92.85% and 90.94% for subject 1 and 94.47% and 89.23% for subject 2 respectively. Classification accuracy was also seen to be significant in the sub band 11-20 Hz.

Figure 3 to 6 shows the classification accuracy versus the training rounds plot for both subjects for the ten sub band frequencies.

4.2 Classification accuracy using Mu, Beta and Gamma bands

The four task classification was also performed using mu, beta and gamma band frequencies (8 Hz to 40 Hz); thirty nine features computed from 160 signals were classified into four classes representing the four motor imagery tasks. Classification results for the two subjects are shown in Table 1. An average classification accuracy of 92% was achieved, and a maximum classification accuracy of 98.7% could be achieved using the Mu, Beta and Gamma bands.

5. Conclusion

Figure 1 and 2 shows that frequency bands 11 Hz to 40 Hz result in high classification rates for motor imagery data recorded at location c3 and c4. Most researches [3, 4, 5, and 12] on motor imagery classification have been restricted to frequency bands less than 30 Hz. Our results show that including the gamma band up to 40 Hz improves the classification rates for motor imagery. The key findings from the results presented in this paper is that Mu (8-12 Hz), Beta (13 - 30 Hz) and Gamma (31-40 Hz) band frequencies play a significant role in the recognition of motor signals recorded at the sensory motor cortex region. This work is part of study on BMI to control wheelchairs. The findings of this work will be investigated on control protocols of a BMI Wheelchair.

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7. References

Hema C.R. obtained her BE degree and MS in EEE from Madurai Kamaraj University, India and University Malaysia Sabah, Malaysia respectively and is pursuing her PhD at the University Malaysia Perlis, Malaysia. She is currently employed as lecturer at the University Malaysia Perlis. Her special fields of interest include EEG signal processing, Neural Networks and Machine Vision. She holds many research grants and has published 3 book chapters and more than 45 papers in refereed Journals and International Conferences on Signal Processing and AI. She has also received gold and bronze medals in National and International exhibitions for her research products on vision and cited as an expert in WHO IS WHO in the World. She is a member of the IEEE, IEEE EMB Society and IEEE WIE Society.

Paulraj M.P. is currently an Associate Professor at University of Malaysia Perlis in Kangar, Malaysia. His research interests are in the area of artificial intelligence, Fuzzy systems, Speech processing, acoustic engineering and biosignal processing applications. Paul grew up in India and obtained a Bachelors degree in Electrical and Electronics Engineering from Madras University, Masters Degree as well as a Doctorate in Computer science and Engineering from Bharathiyar University, India. He has published more than 100 papers in refereed journals and conferences. He has authored a book titled Introduction to Artificial Neural Networks. His field of interest is Artificial intelligence, Fuzzy systems, Speech processing and acoustic Engineering. He is a member of the Institution of Engineers, India and MISTE, India.

Sazali Yaacob received his BEng in Electrical Engineering from University Malaya and later pursued his MSc in System Engineering at University of Surrey and PhD in Control Engineering from University of Sheffield, United Kingdom. Currently, he is serving at University Malaysia Perlis as Professor in School of Mechatronic Engineering. He has published more than 150 papers in Journals and Conference Proceedings. His research interests are in Artificial Intelligence applications in the fields of acoustics, vision and robotics. In 2005, his journal paper in Intelligent Vision was awarded The Sir Thomas Ward Memorial Prize by Institution of Engineer (India). Medals in the National and International Exhibition were conferred to his work on Robotic Force sensor and Navigation Aid for Visually Impaired respectively. He received Charted Engineer status by the Engineering Council, United Kingdom in 2005 and is also a member to the IET (UK).

Abdul Hamid Adom is currently the Dean of the School of Mechatronic Engineering at University Malaysia Perlis. He received his B.E, M.Sc and PhD from LJMU, UK, his research interests include Neural Networks, System Modeling and Control, System Identification, Electronic Nose / Tongue, Mobile Robots, he holds various research grants and has published several research papers. Currently his research interests have ventured into Mobile Robot development and applications, as well as Human Mimicking Electronic Sensory Systems such as Electronic Nose and Tongue and development of Human Sensory Mimicking System for agricultural and environmental applications.

Nagarajan R. obtained his BE (Hons), M.Tech and PhD from Madras University, IIT Kanpur and Madras University respectively. He is currently with UniMAP, Malaysia, as a Professor in the School of Mechatronic Engineering. He has received awards and certificates on excellent publications, research funding, Research Fellowships for working in universities abroad and National and International Medals of Honour for his Research Products and cited as an expert in WHO IS WHO in the World. He has several contributions (more than 200) as International Journal papers, International Conference papers, Books, Book Chapters, monographs and documented research reports. His current fields of interest are in Hospital Patient Lifting Robots, Emotion Controlled Machines and Robot based SLAM. Professor Nagarajan is a Life Fellow of IE (India), a Senior Member of IEEE (USA), Member, and Association of Biomedical Soft computing (BMSA), Japan and Member, IET
TABLE I
CLASSIFICATION ACCURACY FOR MU, BETA AND GAMMA FREQUENCY BANDS

<table>
<thead>
<tr>
<th>Classification Rate</th>
<th>Subject 1</th>
<th>Subject 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>90</td>
<td>90</td>
</tr>
<tr>
<td>Mean</td>
<td>92.23</td>
<td>92.25</td>
</tr>
</tbody>
</table>

Fig. 1. Average Classification Accuracy in percentage over four tasks BMI for ten sub bands for subject 1

Fig. 2. Average Classification Accuracy in percentage over four task BMI for ten sub bands for subject 2
Fig. 3  Classification Accuracy in percentage versus training rounds for five [0.1 to 50 Hz] sub bands for subject 1

Fig. 4  Classification Accuracy in percentage versus training rounds for five [51 to 100 Hz] sub bands for subject 1

Fig. 5  Classification Accuracy in percentage versus training rounds for five [0.1 to 50 Hz] sub bands for subject 2

Fig. 6  Classification Accuracy in percentage versus training rounds for five [51 to 100 Hz] sub bands for subject 2