# CLASSIFICATION OF MOTOR IMAGINARY TASKS USING ADAPTIVE RECURSIVE BANDPASS FILTER

## *Effective Classification for Motor Imaginary BCI*

Vickneswaran Jeyabalan, Andrews Samraj
*Faculty of Engineering and Technology,Faculty of Information Science and Technology, Multimedia University*
*Jalan Ayer Keroh Lama, Melaka, Malaysia*

Loo Chu Kiong
*Faculty of Engineering and Technology, Multimedia University, Jalan Ayer Keroh Lama, Melaka, Malaysia*

Keywords: Brain Computer Interface, Motor imagination, mu rhythm, adaptive filtering.

Abstract: The noteworthy point in the advancement of Brain Computer Interface (BCI) research is not only to develop a new technology but also to adopt the easiest procedures since the expected beneficiaries are of disabled. The nature of the locked-in patients is that, they possess strong mental ability in thinking and understanding but they are extremely unable to express their views. Imagination is possible for almost all of the locked-in patients; hence a BCI which does not rely on finger movements or other muscle activity is definitely an added advantage in this arena. The objective of this paper is to identify and classify motor imaginary signals extracted from the left and right cortex of the human brain. This is realised by implementing an adaptive bandpass filter with the combination of frequency shifting and segmentation techniques. The signals are captured using Electro-Encephalogram (EEG) from the C3, C4, and Cz channels of the scalp electrodes and is pre-processed to expose the motor imaginary signals. The result of classification using a simple threshold articulates the effectiveness of our proposed technique. The best results were found in the latency range of 3 to 9 seconds of the imagination and this proves the existing neuro-science knowledge.

## 1 INTRODUCTION

Brain Computer Interface (BCI) or also know, as Brain Machine Interface (BMI) is a communication interface between the brain and machine. The main purpose of a BCI is to provide a new mode of communication for people who have severe motor disabilities but being cognitively intact. (Baharan *et al*., 2005). The input, which is the brain signal, for a BCI system can be obtained invasively or non-invasively. The method of obtaining brain signals by electrode implantation is knows as an invasive approach. This method is frequently described as dangerous because it involves surgical procedures to implant the electrodes in the brain. Whereas, brain signals taken from the electrodes placed on the surface of the scalp is categorised as a non-invasive method. This method can be performed by using the Electro-Encephalogram (EEG). Various types of signals are used as an input for the EEG based BCI. For example, Visual Evoked Potential (Andrews *et al*., 2005; Andrews *et al*., 2007), Mu-rhythm (Coyle *et al*, 2005) and P300 (Donchin *et al*, 2000). In this paper we concentrate on the motor imagination signals which co-relates with the mu-rhythm.

The human brain's sensory motor cortex shows the rhythmic activities of physical motor movements. This can also be observed during motor imagination. (Pfurtscheller and Neuper, 2003). This rhythmic activity can be observed in the Alpha frequency band of an EEG signal, which is in the frequency range of 8Hz to 12Hz. Mu rhythm can be best measured from the EEG channel C3, Cz and C4.

Imagination of motor movements results in the power attenuation of the EEG signal and can be observed as features. The attenuation of the power is known as event related de-synchronisation (ERD) whereas the rebounding of the power is known as

Jeyabalan V., Samraj A. and Chu Kiong L. (2008).
CLASSIFICATION OF MOTOR IMAGINARY TASKS USING ADAPTIVE RECURSIVE BANDPASS FILTER - Effective Classification for Motor Imaginary BCI.
In *Proceedings of the International Conference on Signal Processing and Multimedia Applications*, pages 113-118
DOI: 10.5220/0001935501130118

event related synchronisation (ERS). The ERD or ERS occurs contra laterally to the intended movements. For example, for right motor movements, the ERD is observed at the left hemisphere of the brain and for the left motor movements, the ERD is found at the right hemisphere. Classifications of right or left motor movements are usually made based on the ERD of the signal.

In a normal ERD detection procedure (Kalcher and Pfurtscheller, 1995), EEG signals are usually filtered in a narrow band, squared, low pass filtered and averaged over trial. However, it is disadvantageous to use this method because useful information will be lost from the averaging over multi-trials.

In this paper we have implemented the adaptive recursive bandpass filter (Gharieb and Cichocki, 2001) to detect imaginary motor movements and to classify them according to left or right movements without observing the ERD and averaging over multi trials. Implementation of this method reduces the chances of information lost and increases the classification rate. This method has been successfully implemented on the BCI Competition 2003 dataset IIIb, which consists of 140 labelled and unlabelled trials respectively, further information of the data set, is explained in the next section.

The target signal, which contains mu rhythm, is first pre-processed by implementing a band pass filter. Then, the adaptive recursive bandpass filter is used to estimate the dominant signal, which represents the motor movements. The employed adaptive recursive filter is used to trail the centre frequency of the dominant EEG signal. The filter requires only one coefficient to be updated in order to adjust the centre frequency of the filter bandpass to be approximated with that of the input signal (Gharieb and Cichocki, 2001). The time function of the coefficient represents the distinct feature for each signal and represents either left or right imaginary motor movements.

# 2 METHODOLOGY

## 2.1 Data Set

This method was trialed on the BCI Competition 2003, dataset IIIb (BCI Competition II, 2003). The data set was provided by the Department of Medical Informatics, Institute for Biomedical Engineering, University of Graz. The signals were obtained from a 25-year-old female relaxing on a chair with armrest. The task was to control a feedback bar by means of imagining left hand of right hand movements. The data was acquired from the EEG channels C3, Cz, and C4 (figure 1), which was band pass filtered for a frequency range of 0.5 to 30Hz and sampled at 128 Hz. The experiment consists of 7 runs with 40 trials each. All runs were conducted on the same day with several minutes break in between. The data has a total of 280 trials, which consists of 140 labelled and 140 unlabeled trials with an equal number of left hand and right hand movements. Each trial consists of duration of 9 seconds. At the 3rd second a visual cue, an arrow pointing left or right is presented to indicate left or right motor movements is to be imagined.

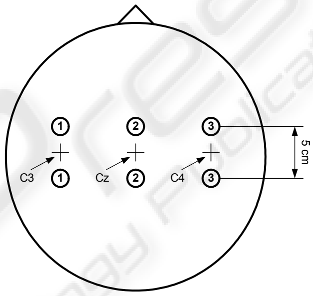


Figure 1: Electrode positions.

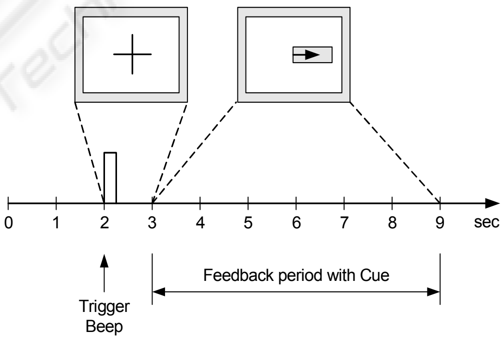


Figure 2: The timing scheme.

## 2.2 Signal Analysis

The trials were divided into two groups according to right or left motor imaginary. Signals from channel C3 and C4 of each group are first pre-processed by means of band pass filtering. A band pass filter using 7th order Butterworth filter where the pass band is 9Hz with less than 1 dB of ripple and the stop band is 11Hz with at least 6 dB of attenuation. Signals from channel Cz is ignored because it contains very little significant discriminative features (Lemm *et al.*, 2004). After band passing the signals, we could observe that the signal is densely populated by the main receptive frequencies, which are the range of 8 Hz to 10Hz at the 3rd to 9th seconds. This is because the motor imaginary task begins after the que at the 3rd second.

Then the adaptive recursive bandpass filtering (Gharieb and Cichocki, 2001) approach is applied to the signals between the ranges of 3rd to 9th seconds of each channel. This approach is employed to estimate and track the centre frequency of the dominant signal of each channel. The main advantage of this approach is that the adaptive filter updates only one coefficient (Gharieb and Cichocki, 2001). The coefficient is updated in order to adjust the centre frequency of the filter band pass to be matched with the input data (Gharieb and Cichocki, 2001). The time function of the coefficient represents the features for each signal, which is feasible to be used for classification. A fourth order Butterworth band pass filter is employed as the adaptive filter. The filter function, T (z) could be expressed as (Raja Kumar *et al.*, 1985; Raja Kumar *et al.*, 1990).

$$T(z)=\frac{D_0+D_2Z^{-2}+D_4Z^{-4}}{1+F_1C(n)Z^{-1}+(F_2C^2(n)+F'_2)Z^{-2}+F_3C(n)Z^{-3}+F_4Z^{-4}} \quad (1)$$

where

$$D_0=D_4=1/(l^2+\sqrt{2}l+1),\ D_2=-2D_0,$$
$$D_1=D_3=-4D_0,\ F_1=-2l(2l+\sqrt{2})D_0,$$
$$F_2=4l^2D_0,\ F'_2=2(l^2-1)D_0,$$
$$F_3=2l(-2l+\sqrt{2})D_0,$$
$$F_4=(l^2-\sqrt{2}l+1)D_0,$$
$$l=\cot an(\pi BP)$$

The coefficient C (n) could be expressed as

$$C(n)=\frac{\cos(\pi(H_2(n)+H_1(n))}{\cos(\pi BP)} \quad (2)$$

where

$H_1(n)$ = normalised low cut off frequency,

$H_2(n)$ = normalised high cut off frequency,

$BP$ = normalised bandwidth of the filter

$BP$ is assumed to be a constant value. Based on equation 1 and 2, it can be seen that $C(n)$ is the only coefficient that has to be updated by the adaptive filter since it is also the only coefficient which is dependant with the centre frequency, ( $H_1(n)+H_2(n)$ )/2. Hence the filter has only one centre frequency dependent, $C(n)$ to be updated. In order for the filter, *T (z)* to be self-adjusted to the centre frequency of the input signal, the output power of the filter should be maximised (Raja Kumar *et al.*, 1985; Raja Kumar *et al.*, 1990). The adaptive coefficient is updated for the maximization of the expected output power (Gharieb and Cichocki, 2001). This step can be applied by implementing a standard gradient approach (Gharieb and Cichocki, 2001). An algorithm called recursive maximum mean-squared (RMXMS) is used to update the filter coefficient (Gharieb and Cichocki, 2001). The adaptive filter further enhances the feature and provides good on-line information of the feature's distinct behaviour.

The adaptive filter becomes unstable for some low frequency waves. This is because the adaptive filter is a band pass filter and the EEG signal is a low pass signal (Gharieb and Cichocki, 2001). So, in order to solve this problem a high frequency shifting process is employed to shift the EEG frequency to the highest ones before the adaptive filtering (Gharieb and Cichocki, 2001). The updated co efficient is the used as the features that represents the signals resulting from right or left motor imaginary. Figure 3 shows the method applied graphically. Figure 4 shows the extracted features after implementing the proposed method for an average of ten trials.

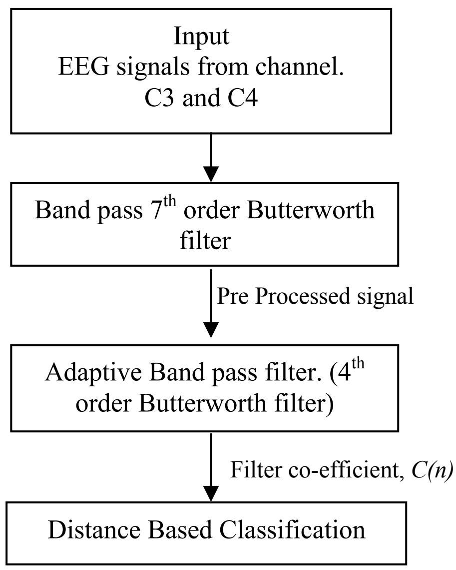


Figure 3: Signal analysis methodology.

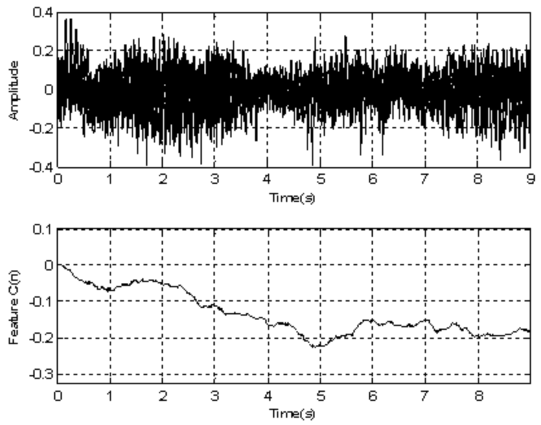


Figure 4: 10 Realisation of raw motor imaginary signals (Top). Mean values of the extracted features after performing adaptive recursive band pass filtering (bottom).

As for the classification, features from both C3 and C4 in a trial are taken. The sum values of the features during right and left imaginaries for each channel are taken respectively. The sum values represent the feature sequences. The distance of the features from C3, which is less than the features from C4, is regarded as right hand movements. Whereas, the distance of features from C3, which is more than the features from C4, is regarded as left-hand movements. Clear distinction between left and right motor imaginary could be observed in the features taken from the beginning of the imagination period.

Table 1: Classification of motor imaginary respective to the imagination period using ERD detection.

| Time | | Right hand imaginary | Left hand imaginary |
|---|---|---|---|
| **Start (s)** | **End (s)** | | |
| 3 | 9 | 73% | 71% |
| 3 | 6 | 76% | 61% |
| 3 | 5 | 63% | 51% |
| 3 | 4 | 56% | 47% |
| 1 | 3 | 44% | 53% |

Table 2: Classification of motor imaginary respective to the imagination period using adaptive recursive b/pass filter.

| Time | | Right hand imaginary | Left hand imaginary |
|---|---|---|---|
| **Start (s)** | **End(s)** | | |
| 3 | 9 | 100% | 100% |
| 3 | 6 | 100% | 98% |
| 3 | 5 | 91% | 94% |
| 3 | 4 | 61% | 90% |
| 1 | 3 | 70% | 17% |

# 3 RESULTS AND DISCUSSIONS

Experiments were conducted using the ERD detection method (Kalcher and Pfurtscheller, 1995) and also the adaptive recursive band pass filter. The classification results for both of the methods are shown in Table 1 and Table 2. It can be clearly observed that the classification results using the adaptive recursive band pass filter method outperforms the conventional ERD detection method. The classification accuracy varies according to the time of when the features are taken. Referring to Table 2, the best classification accuracy could be seen from the time range of 3$^{rd}$ to 9$^{th}$ seconds.

The results are also depicted in figures 5-10. Out of the 140 labelled trials, 70 are with right hand movement imaginaries and 70 are with left hand movement imaginaries. Four sets of figures are shown for each movement imaginaries where the features are averaged over 15, 30 and 70 trials. It can be seen that there are clear visual distinctions of the features from channels C3 and C4 resulted contra laterally from the hand movements.

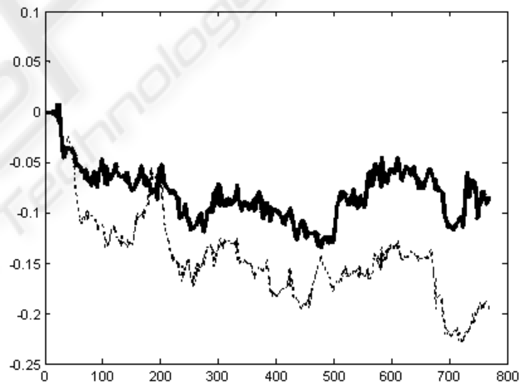

Figure 5: Average 15 right hand trials. Dark line shows C4 features. Dotted line shows C3 features.

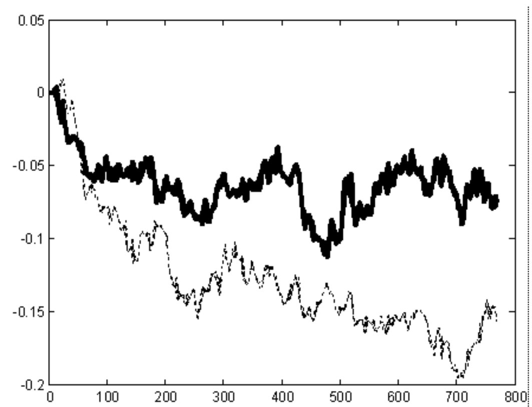

Figure 6: Average 30 right hand trials. Dark line shows C4 features. Dotted line shows C3 features.

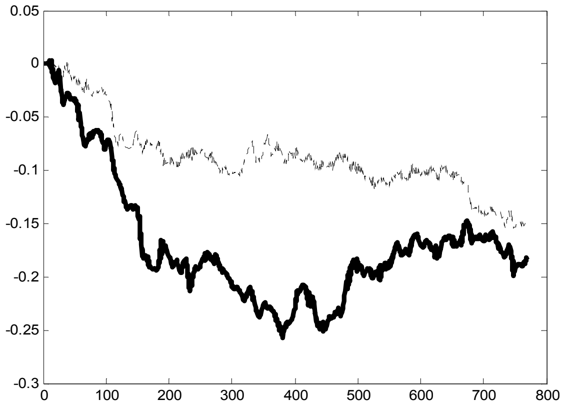


Figure 7: Average70 right hand trials. Dark line shows C4 features. Dotted line shows C3 features.

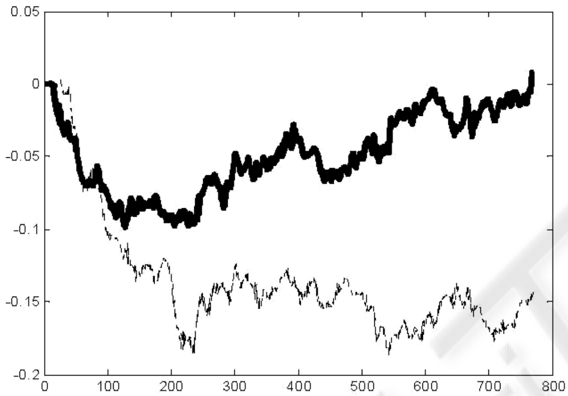


Figure 8: Average 15 left hand trials. Dark line shows C4 features. Dotted line shows C3 features.

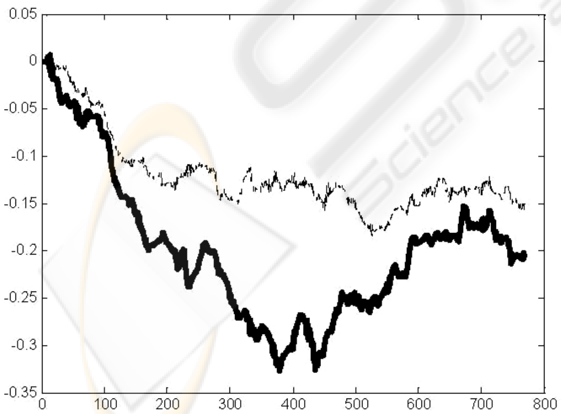


Figure 9: Average 30 left hand trials. Dark line shows C4 features. Dotted line shows C3 features.

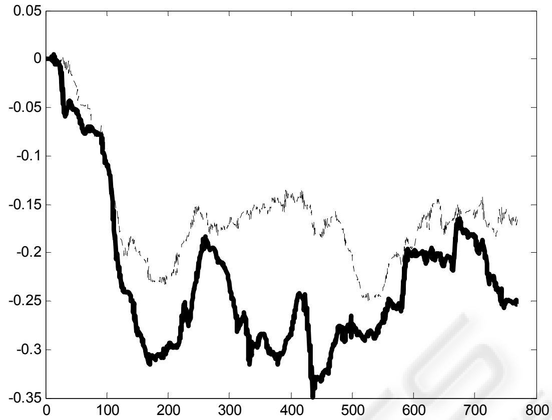


Figure 10: Average 70 left hand trials. Dark line shows C4 features. Dotted line shows C3 features.

## 4 CONCLUSIONS

From these results we could see that the features from the motor imaginary signals extracted using band pass filtering and adaptive filtering could be discriminated easily. This method enables us to obtain better classification results in comparison with the conventional ERD detection methods. Better classification results are obtained because; this method eliminates the averaging over multiple trials step, which causes useful features to be loss. This technique could be also used to isolate other rhythmic component in a signal. Although the conventional way of bandpass filtering of a signal is still feasible, this technique can be extended in identifying useful sources and components in a single trial recorded EEG signal.

## ACKNOWLEDGEMENTS

We would like to acknowledge Department of Medical Informatics, Institute for Biomedical Engineering, University of Graz for making the data available.

## REFERENCES

Baharan Kamousi, Zhongming Liu, and Bin He, 2005, Classification of Motor Imaginary Tasks for Brain-Computer Interface Applications by Means of Two Equivalent Dipoles Analysis, *IEEE Trans.Neural Sys.and Rehab. Engineering,Vol 13*.

BCI Competition II, 2003 http://ida.first.fraunhofer.de/projects/bci/competition_ii

D.Coyle, G.Prasad, and T.M.McGinnity, 2005, A Time-Frequency Approach to Feature Extraction for Brain-Computer Interface with a Comparative Analysis of Performance Measures, *EURASIP Journal on Applied Signal Processing,*Hindawi publishing corp.

E.Donchin,K.M.Spencer, and R.Wijesinghe,Themental prosthesis:Assesing the speed of a P300-based brain computer interface,IEEE Trans.Rehab.Eng.,Vol 8,pp.174-179.

G. Pfurtsheller and C. Neuper, 2003, Movement and ERD/ERS, Kluwer Academic/Plenum Publishers, Dordrecht, pp. 191-207.

J. Kalcher and G. Pfurtscheller, 1995, “Discrimination between phase-locked and nonphase-locked event-related EEG activity,” *Electroenceph. Clin. Neurophysiol*, vol. 94, pp. 381–4.

Lemm, S.; Schafer, C. and Curio, G., 2004,BCI competition 2003-data set III: probabilistic modeling of sensorimotor mu- rhythms for classification of imaginary hand movements,*Biomedical Engineering, IEEE Transactions Vol 51,* pp.1077 – 1080.

R. R. Gharieb and A. Cichocki, 2001, Segmentation and tracking of the electro-encephalogram signal using an adaptive recursive bandpass filter, *Medical & Biological Engineering & Computing 2001, Vol. 39,* pp. 237-248.

R. R. Gharieb and A. Cichocki, 2001, On-line EEG classification and sleep spindles detection using an adaptive recursive bandpass filter, *Acoustics, Speech, and Signal Processing, Proceedings. (ICASSP’01) IEEE International Conference Vol 2.*

R.V. Raja Kumar and R.N. Pal, 1985,A gradient algorithm for center-frequency adaptive recursive band pass filters, *Proc. IEEE Vol 73*,pp.371-372.

R.V. Raja Kumar and R.N. Pal, 1990, Tracking of bandpass signals using center-frequency adaptive filters, *IEEE Trans. Acoust. Speech signal processing., vol 38*, pp.1710-1721.

S.Andrews, R.Palaniappan, and N.Kamel, 2005, Extracting Single Trial Visual Evoked Potentials using Selective Eigen-Rate Principal Components, *Proceed. of World Academy of Science, Engineeering. and Tech., Vol 7.*

S.Andrews, T.Andrew and C.H.Loo, 2007, Inquisitive Impact of Different Electrode Configuration in Representing Single Trial P300 Visual Event Related Potentials*,,College Science in India.,Vol 2007.*