Reducing Dataset Size in Frequency Domain for Brain Computer Interface Motor Imagery Classification

[1]Ch.Aparna
Assoc.Professor,
Dept of CSE,
RVR&JC College of Engineering,
Chowdavaram – 522019

[2]Dr J.V.R.Murthy
Professor,
Dept of CSE,
JNTU,
Kakinada – 533004

[3]Dr.B.Raveendra Babu
Director – Operations,
DELTA Technology & Management Services Pvt Ltd,
Hyderabad – 500081

[4]Sri M.V.P.Chandra Sekhara Rao
Assoc.Professor,
Dept of CSE,
RVR&JC College of Engineering,
Chowdavaram – 522019

***Abstract*—Brain computer interface is an emerging area of research where the BCI system is able to detect and interpret the mental activity into computer interpretable signals opening a wide area of applications where activities can be completed without using muscular movement. In Brain Computer Interface research, for classification of EEG signals the raw signals captured has to undergo some preprocessing, to obtain the right attributes for classification. In this paper, we present a system which allows for classification of mental tasks based on a statistical data obtained in frequency domain using Discrete cosine transform and extracting useful frequencies from the same with application of decision tree algorithms for classification.**

Keywords;BCI, Discrete cosine transform(DCT), Butterworth filter, EEG, Decision tree.

I. INTRODUCTION

Brain Computer Interface system looks a promising communication solution for physically impaired people and the future as how we interact with computers [1, 2]. Peripheral muscular activity is not required for a Brain Computer Interface communication system as it enables a subject to send commands to electronic devices by the brain thought process [3, 4].

By producing different brain activity patterns that are identified by the system and translated into commands, the user can control a BCI. This identification depends on a classification algorithm in most existing BCI i.e., a feature vector representing an algorithm that aims at automatically estimating the class of data. Due to the rapidly growing interest for EEG-based BCI, a considerable number of published results are related to the investigation and evaluation of classification algorithms. [5,6]

Translating brain activity into a computer command is the main aim of BCI. Regression [7] or classification [8] algorithms can be used to achieve this motive. Classification algorithms are most popularly used to identify brain activity patterns.

In this paper, we consider a BCI system as a pattern recognition system and focus on the classification after due preprocessing.

For accurate classification of a given BCI system, it is essential to what features need to be used, what their properties are and how they are used. Feature extraction has been attempted using amplitude values of EEG signals [9], Band Powers (BP) [10], Power Spectral Density (PSD) values [11] [12]. In this paper we investigate the BCI data in the frequency domain using Discrete Cosine Transform and remove unwanted frequencies and noise using Butterworth filter.

This paper is organized as follows: Section II deals with discrete cosine transform and Butterworth filter, Section III deals with the dataset, section IV discusses the decision tree algorithms, section V deals with the experimental setup and result analysis and section VI includes conclusion.

II. TRANSFORMATION AND FILTERING

The discrete cosine transform (DCT) is a transform method for converting a time series signal into elementary frequency components and is very popularly used in image compression. In this paper we develop some simple functions to compute the DCT and to preprocess the provided BCI system EEG data.

The discrete cosine transform[13] of a list of n real numbers $s(x)$, $x = 0, ..., n-1$, is the list of length n given by:

$$S(u) = \sqrt{2/n}\; C(u) \sum_{x=0}^{n-1} s(x) \cos\frac{(2x+1)u\pi}{2n} \qquad u = 0,\ldots,n$$

$$\text{where} \quad C(u) = 2^{-1/2} \quad \text{for } u = 0$$
$$= 1 \quad \text{otherwise}$$

Where each element of the transformed list *S(u)* is the inner product of the input list *s(x)* and a *basis vector*. The constant factors are chosen so that the basis vectors are orthogonal and normalized.

The list $s(x)$ can be recovered from its transform $S(u)$ by applying the inverse cosine transform (IDCT):

$$s(x) = \sqrt{2/n} \sum_{u=0}^{n-1} C(u)\, S(u) \cos\frac{(2x+1)u\pi}{2n} \qquad x = 0,\ldots,n$$

$$\text{where} \quad C(u) = 2^{-1/2} \quad \text{for } u = 0$$
$$= 1 \quad \text{otherwise}$$

This equation expresses *s* as a linear combination of the basis vectors. The coefficients are the elements of the transform *S*, which may be regarded as reflecting the amount of each frequency present in the input *s*.

Ideal filters allow a specified frequency range of interest to pass through while attenuating a specified unwanted frequency range. Band pass filters pass a certain band of frequencies. The Butterworth filter is a filter that can be constructed out of passive R, L, C circuits. The magnitude of the transfer function for this filter is Magnitude of Butterworth Filter Transfer Function given by

$$|H(\bar{\imath}\omega)| = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2n}}}$$

where n is the order of the filter and w_c is the cutoff frequency.

III. DATASET USED IN OUR WORK

Data set provided by University of Tübingen, Germany, Dept. of Computer Engineering and Institute of Medical Psychology and Behavioral Neurobiology, and Max-Planck-Institute for Biological Cybernetics, Tübingen, Germany, and Universität Bonn, Germany, Dept. of Epileptology[14] is used for this work. In the experiment a subject has to imagine movements of either the left small finger or the tongue. Signals were recorded using 8x8 electrodes placed on the contralateral motor cortex. All recordings were performed with a sampling rate of 1000Hz and after amplification were stored as microvolt values. Each trail was recorded for 3 second duration. 278 such trials are used for analysis. The recordings were started only after 0.5 seconds after the visual cue ended to avoid visually evoked potentials.

IV. DECISION TREE ALGORITHM

Classification and regression trees (CART) produces output that is either classification or regression based on the dependent variable which can either be categorical or numeric respectively. CART is a non-parametric Decision tree learning method.

Decision trees algorithms work on the principle of rules formed by values of certain variables in the provided data set

- Rules are selected based on how values can differentiate observations based on the dependent variable
- Once a rule is selected, the same logic is applied to each recursive node.
- Child node creation stops when CART detects no further gain can be made.

Each branch of the tree ends with a terminal node

- Each observation should always fall in one terminal node
- Each terminal node should be unique by a set of rules.

QUEST is a binary-split decision tree algorithm for classification .

- QUEST uses an unbiased variable selection technique by default
- QUEST uses imputation instead of surrogate splits to deal with missing values
- QUEST can easily handle categorical predictor variables with many categories .

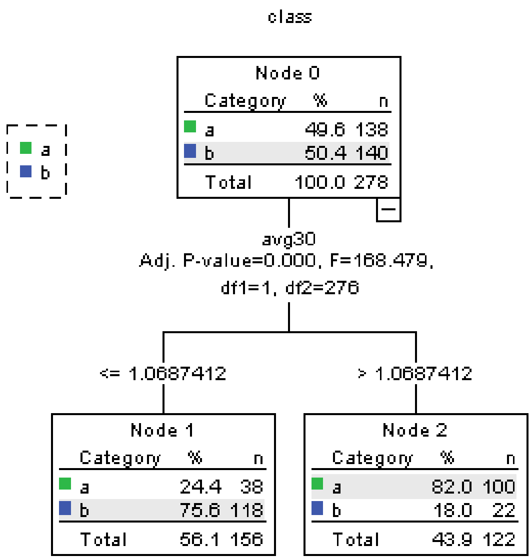
V. EXPERIMENTAL SETUP AND RESULTS

A program was developed to handle the time series epoch and the time series graph plotted. Discrete cosine transform was applied to convert the time series data to frequency domain. Butterworth filter was used as a band pass filter to eliminate frequencies outside the desired range of 5Hz to 30 Hz. The maximum value, the minimum value and the mean was computed for each channel for all the epochs and recorded. The data so created was used as the input to the decision tree classifier.

The classifier accuracy of QUEST is shown along with the tree in table 1 and figure 1.

Table 1 : Individual classification accuracy and overall accuracy using QUEST.

Observed	Predicted		
	a	b	Percent Correct
a	100	38	72.5%
b	22	118	84.3%
Overall Percentage	43.9%	56.1%	78.4%



. Figure 1.The QUEST Decision tree

We also used the classical CART technique and the results obtained are shown in table 2 and figure 2.

Table 2: Individual classification accuracy and overall accuracy using CART

Observed	Predicted		
	a	b	Percent Correct
a	118	20	85.5%
b	32	108	77.1%
Overall Percentage	54.0%	46.0%	81.3%

From the above analysis it is observed that decision trees are able to classify fairly well in the proposed method and CART has been found to classify better than QUEST in the proposed preprocessing method.

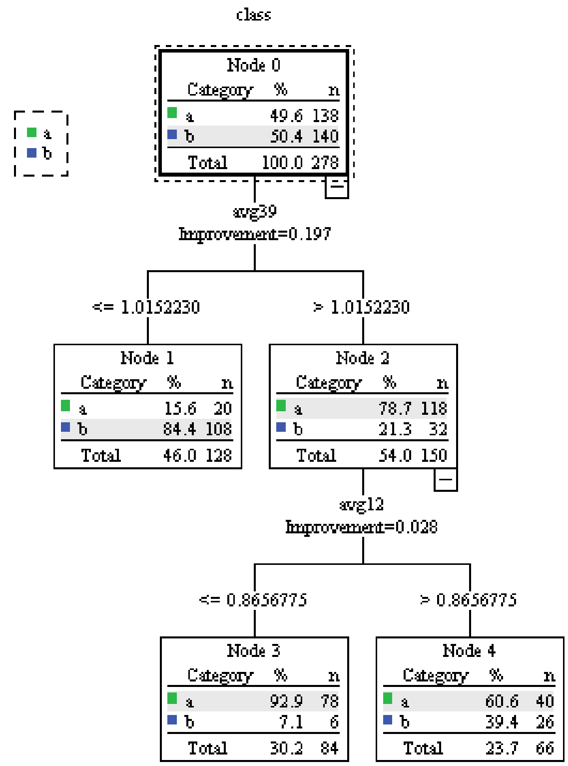


Figure 2. The CART decision tree

VI. CONCLUSION

In this paper a frequency domain method is proposed for preprocessing the EEG data using Discrete cosine transform and eliminated unwanted frequencies to remove noise and other brain related neural activity using Butterworth filter. The proposed method in preprocessing the data could be used successfully for classification. Further work needs to be done in the area of electrode selection using clustering techniques which will further speed up the process of classification which is crucial for any BCI system

REFERENCES

[1] Jonathan R. Wolpaw, Nils Birbaumer, Dennis J. McFarland, Gert Pfurtscheller, and Theresa M. Vaughan. Brain-computer interfaces for communication and control. *Clinical Neurophysiology*, pages 767–791, MAR 2002.

[2] T.M. Vaughan et al., "Brain-computer interface technonolgy: a review of the second international meeting," IEEE Trans. Rehab. Eng., vol. 11, pp. 94-109, 2003.

[3] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan. Braincomputer interfaces for communication and control. Clinical Neurophysiology, 113(6):767-791,2002.

[4] T. M. Vaughan, W. J. Heetderks, L. J. Trejo, W. Z. Rymer, M. Weinrich, M. M. Moore, A. K ubler, B. H. Dobkin, N. Birbaumer, E. Donchin, E. W. Wolpaw, and J. R. Wolpaw. Brain-computer interface technology: a review of the second international meeting. IEEE Transactions on Neural Systems and Rehabilitation Engeneering, 11(2):94{109, 2003.

[5] D. J. McFarland, C. W. Anderson, K.-R. Muller, A. Schlogl, and D. J. Krusienski. Bci meeting 2005-workshop on bci signal processing:

feature extraction and translation. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 14(2):135 { 138, 2006.

[6] R. O. Duda, P. E. Hart, and D. G. Stork. Pattern Recognition, second edition. WILEYINTERSCIENCE,2001.

[7] D. J. McFarland and J. R. Wolpaw. Sensorimotor rhythm-based brain-computer interface (bci): feature selection by regression improves performance. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 13(3):372{379, 2005.

[8] W. D. Penny, S. J. Roberts, E. A. Curran, and M. J. Stokes. Eeg-based communication: a pattern recognition approach. IEEE Transactions on Rehabilitation Engeneering, 8(2):214-215, 2000.

[9] M. Kaper, P. Meinicke, U. Grossekathoefer, T. Lingner, and H. Ritter. Bci competition 2003- data set iib: support vector machines for the p300 speller paradigm. IEEE Transactions on Biomedical Engeneering, 51(6):1073{1076, 2004.

[10] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer. Eeg-based discrimination between imagination of right and left hand movement. Electroencephalography and Clinical Neurophysiology, 103:642{651, 1997.

[11] S. Chiappa and S. Bengio. Hmm and iohmm modeling of eeg rhythms for asynchronous bci systems. In European Symposium on Artificial Neural Networks ESANN, 2004.

[12] J. R. Mill_an and J. Mouri~no. Asynchronous BCI and local neural classi_ers: An overview of the Adaptive Brain Interface project. IEEE Transactions on Neural Systems and Rehabilitation Engineering, Special Issue on Brain-Computer Interface Technology, 2003.

[13] *Andrew B. Watson,* Image Compression Using the Discrete Cosine Transform, *NASA Ames Research Center, Mathematica Journal, 4(1), 1994, p. 81-88.*

[14] Thomas Lal, Thilo Hinterberger, Guido Widman, Michael Schröder, Jeremy Hill, Wolfgang Rosenstiel, Christian Elger, Bernhard Schölkopf, Niels Birbaumer. Methods Towards Invasive Human Brain Computer Interfaces. Advances in Neural Information Processing Systems (NIPS), 2004