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Classifying Single Trail Electroencephalogram Using Gaussian Smoothened Fast Hartley Transform for Brain Computer Interface during Motor Imagery

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Abstract: Problem statement: Brain-Computer Interface (BCI) is a emerging research area which translates the brain signals for any motor related actions into computer understandable signals by capturing the signal, processing the signal and classifying the motor imagery. This area of work finds various applications in neuroprosthetics. Mental activity leads to changes of electrophysiological signals like the Electroencephalogram (EEG) or Electrocorticogram (ECoG). **Approach:** The BCI system detects such changes and transforms it into a control signal which can, for example, be used as to control a electric wheel. In this study the BCI paradigm is tested by our proposed Gaussian smoothened Fast Hartley Transform (GS-FHT) which is used to compute the energies of different motor imageries the subject thinks after selecting the required frequencies using band pass filter. **Results:** We apply this procedure to BCI Competition dataset IVA, a publicly available EEG repository. **Conclusion:** The evaluations of preprocessed signals showed that the extracted features were interpretable and can lead to high classification accuracy by various mining algorithms.

Key words: Data mining, Brain-Computer Interface (BCI), Fast Hartley transform (FHT), Electroencephalogram (EEG), Motor Imagery (MI), Common Spatial Pattern (CSP), Event-Related Desynchronization/Synchronization (ERD/ERS), Discrete Wavelet Transform (DWT), Fourier Transform (FT)

INTRODUCTION

An emerging technology is Brain-Computer Interface (BCI) which enables paralyzed people to communicate with the external world. The changes in the brain signals are translated into operative control signals using Electroencephalogram (EEG)-based BCI. In analyzing the brain signals Motor Imagery (MI) is the state during which the depiction of a particular motor action is internally reactivated within the working memory without any overt motor output. This is governed by the principles of motor control (Sharma *et al*., 2006). Motor Imagery (MI) produces measurable potential changes in the EEG signals termed as Event-Related Desynchronization/Synchronization (ERD/ERS) patterns.

The time, frequency and spatial non-stationarity of these patterns result in high inter subject and intra subject variability in MI-based BCIs (MI-BCIs). One of the most effective algorithms for MI-BCI is based on Common Spatial Pattern (CSP) technique (Ramoser *et al*., 2000; Guger *et al*., 2000). The success of CSP in BCI application greatly depended on the proper selection of subject specific frequency bands. In the literature, common sparse spectral spatial pattern (CSSSP) (Dornhege *et al*., 2006) sub band CSP (SBCSP) (Novi *et al*., 2007); Filter bank CSP (FBCSP) (Ang *et al*., 2008) and adaptive FBCSP (Thomas *et al*., 2008) have been proposed for choosing the optimal frequency band automatically.

The FBCSP (Ang *et al*., 2008) uses CSP features from a set of fixed band pass filters and feature selection algorithm based on mutual information to effectively choose the subject-specific features. This selection process selects features from the relevant frequency components. As the subject-specific frequency components carry distinct features, the proposed method uses a subject-specific FB selection before feature extraction to enhance the accuracy of the FBCSP framework. Classification algorithm is the core

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of a BCI in which the EEG signals are mapped into the space of epochs. They are then classified using decision functions learned on the training set composed of labeled signals. The classification performance depends on the choice of the pre processing techniques (Vautrin *et al*., 2009). A large training session becomes beneficial to lay down the decision rules that allow the classification of the user's intention (Birbaumer *et al*., 2008).

The energy distribution over uniform frequency sub bands given by the Fourier transform is an example of apriori choice of signal features. In previous studies (Do Nascimento and Farina, 2008; Farina *et al*., 2007), it has been proposed the marginal of the Discrete Wavelet Transform (DWT) for feature extraction and the feature space was selected by optimizing the mother wavelet of the decomposition. The DWT (Birgale and Kokare, 2010) marginal reflects the average signal intensity over dyadic sub bands. The dyadic decomposition is well suited to describe and discriminate signals whose discriminative information is mainly at low frequencies since the frequency resolution is higher for low frequencies than for high frequencies.

In this study we propose to measure energy of specific motor imageries in the brain signal using our proposed Gaussian Smoothened Fast Hartley Transform (GS-FHT) along with the Chebyshev filter and data resembling. The resultant data obtained was classified using IB1 and Alternating Decision tree. This study is organized as follows. Section 2 describes the features of the data set used in this study. Sections 3 and 4 describe the preprocessing techniques and the classification algorithms analyzed in this study respectively. Section 5 analyzes our results.

MATERIALS AND METHODS

Data set: We used the IV A dataset used in the brain computer interface competition provided by Intelligent Data Analysis Group. This data set consists of recordings from five healthy subjects who sat in a chair with arms resting on armrests. Visual cues indicated for 3.5 s which of the following 3 motor imageries the subject should perform: (L) left hand, (R) right hand, (F) right foot. The presentation of target cues was intermitted by periods of random length, 1.75-2.25 s, in which the subject could relax. Given are continuous signals of 118 EEG channels and markers that indicate the time points of 280 cues for each of the 5 subjects (aa, al, av, aw, ay). Subject aa was used in our study.

Preprocessing of EEG signals: The regular Hartley transform's kernel is based on the cosine-and-sine function, defined as:

$$\text{cas}\,(\nu t) = \cos(\nu t) + \sin(\nu t)$$

Hartley transform compared to Fourier transforms is a real function. The Hartley transform pair can be defined as follows Eqn. 1 and 2:

$$H(\nu) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} f(t)\,\text{cas}(\nu t)\,dt \qquad (1)$$

$$f(t) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} H(\nu)\,\text{cas}(\nu t)\,d\nu \qquad (2)$$

A very important property of Hartley Transform is its symmetry Eqn. 3:

$$H\{f(t)\} = H(\nu),\ H\{H(t)\} = f(\nu) \qquad (3)$$

This has the advantage of using the same operation for computing the transform and its inverse. Another important feature is that the transform pairs are both real which provides good computational advantages for Hartley Transform (HT) over the Fourier Transform (FT).

Many of the familiar complex relations in the Fourier domain have very similar counter parts in the Hartley domain. Let F (ω) and H(ν) be the FT and HT of a function f(t) the n it is to verify the following Eqn. 4 and 5:

$$\begin{aligned} &af(t) + bg(t) \Leftrightarrow aF(\nu) + bG(\nu), f(t/a) \\ &H(\nu) = \left[\Re\big(F(\omega)\big) - \Im\big(F(\omega)\big)\right]_{\omega=\nu,} \end{aligned} \qquad (4)$$

$$\begin{aligned} &X(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n)\,\text{cas}\left(\frac{2\pi nk}{N}\right), k = 0,1,2,....N-1, \\ &F(\omega) = \left[\varepsilon\big(H(\nu)\big) - o\big(H(\nu)\big)\right]_{\nu=\omega,} \end{aligned} \qquad (5)$$

where, $\Re$, $\Im$, ε, O denote real, imaginary, even and odd parts. Other properties in the Hartley domain are Eqn. 6:

$$\begin{aligned} &af(t) + bg(t) \Leftrightarrow aF(\nu) + bG(\nu), \\ &f(t/a) \Leftrightarrow |a|F(\nu), f(-n) \Leftrightarrow F(-k), \\ &f * g(t) \Leftrightarrow \frac{1}{2}\begin{bmatrix} F(\nu)G(\nu) + F(-\nu)G(\nu) + \\ F(\nu)G(-\nu) + F(-\nu)G(-\nu) \end{bmatrix}, \\ &\frac{d}{dt} f(t) \Leftrightarrow -\nu F(-\nu), \int f(t)\,dt \Leftrightarrow -\frac{1}{\nu}F(-\nu), \\ &\text{cas}(at) \Leftrightarrow \sqrt{2\pi}\,\delta(\nu - a), \\ &f(t)\cos(\nu_0 t) \Leftrightarrow \frac{1}{2}\left[F(\nu - \nu_0) + F(\nu + \nu_0)\right] \end{aligned} \qquad (6)$$

HT's discrete formulation DHT is given by:

$$X(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x(n) cas\left(\frac{2\pi nk}{N}\right), k = 0,1,..N-1$$

Which is applied to the discrete-time function x(n) with period N. The properties of the DHT are similar to those of the Discrete Fourier Transform (DFT) and Fast Hartley Transform (FHT) (Bracewell, 1984) which is similar to the familiar Fast Fourier Transform (FFT). Some of the properties of DHT are listed:

$$af(n) + bg(n) \Leftrightarrow aF(k) + bG(k)$$
$$f(-n) \Leftrightarrow F(-k)$$

Obtaining energy values using regular Fast Hartley Transform introduces artifacts associated with EEG signal measurement. To reduce the artifacts we propose a normalization of the obtained energy using Gaussian methods on the Fast Hartley Transform. The normalization provides the benefit to the system performance by desensitizing the system to the signal amplitude variability.

The proposed model is defined as Eqn. 7:

$$f(x,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} * X(k) = \frac{1}{\sqrt{n}} \sum_{x=0}^{N-1} x(n) cas\left(\frac{2\pi nk}{N}\right), k = 0,1,..N-1 \quad (7)$$

Chebyshev filters are used to separate one band of frequencies from another. The EEG energy was computed in the 5-15 Hz region to primarily capture the Beta waves in the EEG signal which is closely linked to motor behavior and is generally attenuated during active movements. Chebyshev filter was primarily used for its speed. Chebyshev filters are fast because they are carried out by recursion rather than convolution. The design of these filters is based on the z-transform.

Classification algorithms: Data mining (Poovammal and Ponnavaikko, 2009) involves the extraction of non trivial information from potentially large database. A primary function of data mining is classification with popular classification algorithms based on decision tree (Syurahbil *et al.,* 2009), Neural network and support vector machine. Clustering can also be effectively used for unsupervised learning problems (Alfred *et al*., 2010). An Alternating Decision Tree (AD Tree) (Pfahringer *et al*., 2001) is a machine learning rule for classification and is a generalization of decision tree that have connections to boosting. It consists of decision nodes and prediction nodes. Decision nodes specify a predicate condition and Prediction nodes contain a single number. AD trees always have prediction nodes as both root and leaves. An epoch is classified through AD Tree by following all paths for which all decision nodes are true and summing any prediction nodes that are traversed. This is different from binary classification trees such as Classification and Regression Tree (CART) or C4.5 in which an instance follows only one path through the tree.

The AD Tree algorithm's fundamental element is the rule which consists of a precondition, condition and two scores. A condition is a predicate which is in the form of attribute comparison value. The tree structure can be derived from a set of rules by making note of the precondition that is used in each successive rule.

IB1 classifier is a simple instance-based learner that uses the class of the nearest k training instances for the class of the test instances. IB1 uses a weighted overlap of the feature values of test instance and a memorized example. The metric combines a per-feature value distance metric with global feature weights that account for relative differences in discriminative power of the features.

RESULTS

The results obtained are tabulated in Table 1 and Fig. 1.

Table 1: Comparison of classification accuracy using FHT with Chebyshev filter and proposed G-FHT for energy computation

Classifiers	G-FHT	FHT
AD Tree	79.5952	75.000
IB1	83.9826	80.3571

Percentage of correctly classified instances

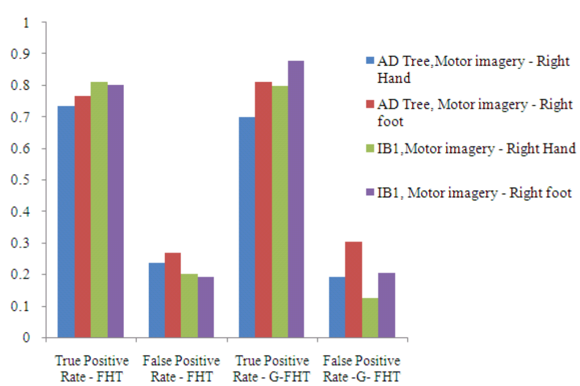

Fig. 1: True positive and false positive rates for FHT and G- FHT under different classification schemes

DISCUSSION

An application was built using labview and GS-FHT with Chebyshev filter was implemented. The epoch occurring for a time period of 3.5 at a sampling rate of 100Hz was input to the application. The maximum and average energy was computed. Screen shots of output are shown in Fig. 2 and 3.

The energies were computed for 59 EEG electrodes for 280 instances of motor imagery cues of right hand and right foot. The energy values from each electrode were used as attributes for predicting the class label. A tenfold cross validation was used to train the algorithms.

CONCLUSION

The energy from the preprocessed EEG epoch was extracted using a combination of Fast Hartley transform and Chebyshev filter. The data was resembled and classified using AD tree and IB1. The classification result so obtained was tabled in the previous section.

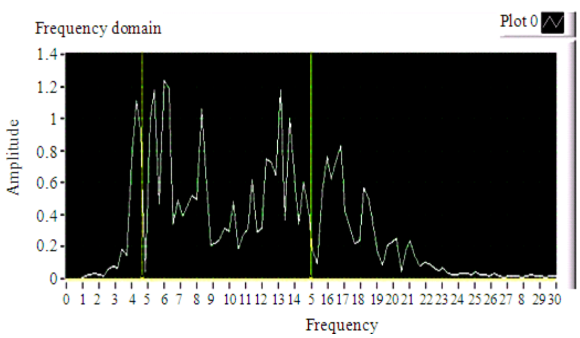

Fig. 2: A three second epoch

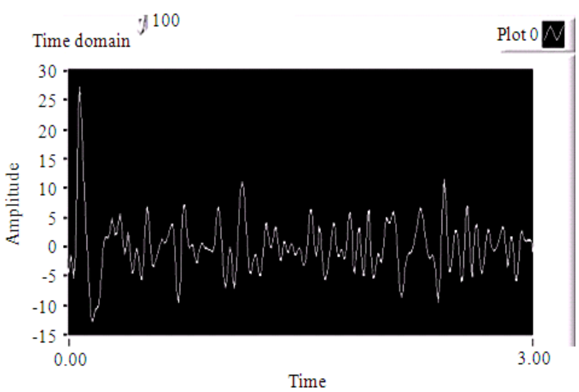

Fig. 3: Signal in frequency domain with the yellow vertical lines indicating area of interest

The proposed GS-FHT algorithm was implemented under the same setup and the result obtained is promising keeping in mind the goal of reducing the preprocessing time. Further work need to be done to improve the classification accuracy to bridge the man - machine gap by understanding the human semantic factor. Fuzzy logic could be an area of work to identify relevant feedback automatically and provide the necessary feed back to the classifier to improve classification.

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