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Automated classification of non-motor mental task in electroencephalogram based brain-computer interface using multivariate autoregressive model in the intrinsic mode function domain

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ABSTRACT

Objective: In this paper, we proposed a new feature extraction approach based on the multivariate auto regressive model (MVAR) model of the sensitive intrinsic mode function (IMF) groups in the multivariate empirical mode decomposition (MEMD) domain.
Approach: We computed eigen values from the coefficient matrix of the MVAR model for classifying three different non-motor cognitive task in EEG based brain computer interface (BCI) system. In the first stage, the application of MEMD to multichannel EEG data gave rise to adaptive i.e. data driven decomposition of the multivariate time series data into a large number of IMF groups. In the second stage, the sensitive IMF groups were selected according to their task correlation factor. MVAR model of order six was developed from the five sensitive IMF groups and finally the eigen values of the correlation matrix derived from the coefficient matrix was employed for forming the feature vectors. At the last stage, the extracted feature vectors were fed to a Least Squares Support Vector Machine (LS-SVM) classifier for automatic classification of mental task EEG signals. We tested our approach on the mental task EEG data sets of three subjects.
Main result: We achieved highest value of average classification accuracy of 94.43% for binary classification of the first pair of mental task i.e baseline and mental arithmetic task using polynomial kernel and 91.65% for the second pair i.e mental arithmetic and mental letter composing task using radial basis function (RBF) with ten fold cross validation. We achieved highest value of average classification accuracy of 77.77% for three class classification employing One Vs One scheme of multiclass SVM classifier.
Significance: The performance of the binary classifier was evaluated on various parameters such as accuracy, specificity and sensitivity. The encouraging results show the potential of the proposed approach for classifying any non linear and non-stationary signals.

1. Introduction

Electroencephalogram (EEG) signal represent sneuro-electric activities of human brain under different mental states. Hence, these signals offer the possibility of classifying different cognitive task for the development brain computer interface (BCI). Keirn and Aunon [1,2] proposed that EEG signals could distinguish between various mental tasks accurately. They designed the experimental protocol and acquired EEG signals related to five non-motor imagery mental tasks which invoke hemispheric brainwave asymmetry. They used AR model coefficients and band power asymmetry ratio as features with quadratic Bayesian classifier for classifying five non-motor mental task EEG signals which was acquired by them. Later, Charles W Anderson et al. [3,4] employed MVAR model of EEG for the classification of same set of five non-motor mental task [5]. They continued the work of Keirn and Aunon [2], and derived both scalar AR model as well as multivariate AR model from the raw EEG signals without employ ingany decomposition technique. Palaniappan et al. [6,8] used spectral power differences in four bands with a NN classifier for classifying different mental tasks. Garrett et al. [7] used AR model coefficients

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as features with one linear (linear discriminant analysis, LDA) and two nonlinear classifiers (artificial neural network, ANN) and (support vector machine, SVM) for classifying spontaneous EEG during five mental tasks. Li et al. [9] studied the classification of mental task EEG signals using SVM. Gupta et al. [10] used relevant features with SVM and LDA classifiers for classifying mental task. Nan-Ying-Liang et al. [11] used AR model coefficients with extreme learning machine. Due to the assumption of linearity, these methods are not adequate in capturing the complex nonlinear dynamics contained in these signals. Extracting subtle information from these EEG signals by analyzing their extremely complex pattern is a formidable task as they are notoriously noisy, nonlinear and non-stationary. Fast, reliable and accurate classification of EEG signals related to performance of different cognitive task is the central challenge for designing real time BCI systems. Combination of best feature extraction algorithm with optimum machine learning algorithm will lead to enhanced performance of BCI system. But searching for features having more discriminatory power is yet an open research problem for improved classification of these EEG signals. Traditional FFT based non-parametric and parametric methods of EEG analysis assume linearity and stationary of the signals. All such complexities of the EEG signals call for their accurate representation in the joint time-frequency plane. But the time-frequency representation of a signal is not unique. A plethora of advanced signal processing methods such as short time Fourier transform (STFT), Wavelet transform (WT), Wavelet packet transform (WPT), S- transform etc have been employed for the time-frequency analysis of many non-stationary signals representing a wide range of natural phenomena such as seismological signals, biomedical signals etc. But the common drawback of all these techniques is that they decompose a signal based on a priori fixed bases with linearity assumption of the signal. They give sub-optimal localization in the joint time-frequency plane which makes their performance inadequate. This has given rise to the development of a new adaptive i.e. data driven method called, empirical mode decomposition (EMD) whose performance has been established to be adequate in many cases of nonlinear and non-stationary real world time series data such as earthquake data, winds, ocean acoustic signals, mechanical vibration signals, biomedical signals etc. In contrast to wavelet and other time-frequency based decomposition, EMD is a fully data driven algorithm which does not require any apriori basis function for the multi scale decomposition of the signal. EMD decomposes a signal into a set of oscillatory modes known as intrinsic mode functions (IMFs) based on local characteristic time scale of the data [12]. EMD obtains the oscillatory modes(scales) adaptively and considers the signal dynamics at the local level, making it a natural choice for generating the data scales required for multi scale analysis. Therefore, applying EMD or its multivariate extension i.e. MEMD is quite reasonable for any nonlinear and non-stationary signal like EEG. Pablo F. Diez et al. [13] employed univariate empirical mode decomposition (EMD) for classifying same set of five mental task from the mental task EEG data set [5]. They adopted univariate approach and extracted four different time domain features (RMS, Variance, Shanon Entropy, and Lempel –Ziv complexity) from the IMFs. M. Kaleem et al. [14] employed EMD and Teager Energy operator for classifying five mental task from the benchmark data set [5]. They also adopted univariate approach using one EEG channel only. For catering to the need of real world multichannel data, Rehman and Mandic [16–18] developed multivariate extension of the standard univariate EMD algorithm known as MEMD algorithm. But research work done so far employing EMD has predominantly focused on the detection of various pathological conditions. Besides, they employed one channel EEG signals with standard EMD algorithm. Standard EMD algorithm is univariate in nature. Due to this, these research works are based on the sequential decomposition of the multichannel EEG channels instead of simultaneous decomposition. But sequential analysis of multichannel EEG data using standard EMD algorithm gives rise to the twin problems of mode mixing and mode alignment. MEMD algorithm enabled us to circumvent these twin problems of its univariate counterpart by generating equal number of IMFs for all data channels.

Till date, to the best of our knowledge, published research work on EEG feature extraction methods combining EMD or MEMD with MVAR for classifying non-motor mental task in EEG based BCI system is not available. Due to this, there is ample scope for undertaking further research in this direction through deriving MVAR model based feature extraction in the MEMD domain. Therefore, the main focus of our research was to extend the work of Charles W Anderson et al. [3] through computing multivariate AR model in the MEMD domain. Our contribution in this research is twofold (a) combining MEMD algorithm with MVAR model (b) extracting the non-zero eigen values as features from the covariance matrix of the sensitive IMF groups. The novelty of our approach stems from adopting a multivariate and nonlinear approach through combining MEMD based decomposition and multivariate AR model. Though the multivariate AR model is a linear model, but it offers the advantage of modelling the inter-regional dependency within brain electrical activity.

This paper is organized as follows: After the introduction in Section 1, the EEG data set used and proposed methodology is presented in Section 2, experimental results and discussions are presented in Section 3 and Section 4 respectively, and finally conclusions are presented in Section 5.

2. Materials and methods

2.1. Non-Motor mental task EEG data sets

The benchmark EEG data sets used in this research were collected by Keirn and Aunon [1,2], from Purdue University. They performed experiments on seven subjects, 21–48 years old. The subjects were seated in a sound controlled booth with dim lighting and noiseless fans (for ventilation).

An Electro-Cap elastic electrode was used to record EEG signals from six cortical locations such as C3, C4, P3, P4, O1 and O2 based on the international 10–20 electrode placement system. The impedance of all the electrodes was kept below 5 K Ohms. These scalp electrodes were referenced to two electrically linked mastoids, A1 and A2. The signals were recorded for a duration of 10 s during each trial of a task. The sampling frequency was 250 samples per second. EEG signals were recorded on 7 subjects, who performed five different mental tasks. The tasks were

i Baseline task: In this, the cognitive activity level is zero, the subjects were asked to relax completely without thinking anything.
ii Mental arithmetic task: The subjects were given nontrivial multiplication problem in which they were asked to multiply two multi-digit numbers mentally without uttering any words or making any other physical movements.
iii Letter writing task: In this, the subjects were told to mentally compose a letter to a friend or relative without vocalizing;
iv Geometric figure rotation task: In this task, the subjects were asked to study a particular three-dimensional object for few seconds after which the object was removed and subsequently the subjects were told to visualize the object being rotated about an axis.
v Visual counting task: In this, the subjects were asked to imagine a blackboard and visualise numbers being written on it sequentially.