Biomedical Signal Processing and Control 39 (2018) 378–389

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Classification of non-motor cognitive task in EEG based brain-computer interface using phase space features in multivariate empirical mode decomposition domain

Suman Dutta [a,*], Mandeep Singh [a], Amod Kumar [b]

[a] Department of Electrical and Instrumentation Engineering, Thapar University, Punjab, India
[b] Central Scientific Instruments Organization, Chandigarh, India

ARTICLE INFO

Article history:
Received 15 February 2017
Received in revised form 29 June 2017
Accepted 1 August 2017
Available online 30 August 2017

Keywords:
Electroencephalogram
Multivariate empirical mode decomposition
Intrinsic mode function
Phase space reconstruction
Singular value decomposition
Least square support vector machine

ABSTRACT

The purpose of this research paper is to present a new framework for EEG feature extraction based on the combination of multivariate empirical mode decomposition (MEMD) and phase space reconstruction (PSR) for classifying a small set of non-motor cognitive task EEG signals in mental task based multi-task brain computer interface(BCI) system. Our proposed approach employed phase space analysis of the intrinsic mode functions (IMFs) generated by MEMD based decomposition of the six channels EEG signals. The combination of two powerful signal processing techniques i.e. MEMD with phase space reconstruction (PSR) enabled us to characterize the nonlinear and non-stationary nature of the dynamics underlying a particular cognitive task more accurately. Our proposed approach consists of three stages, 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 set of IMF groups. All the member IMFs within a group have common oscillatory frequency but different amplitude and cortical origin. In the second stage, a small subset of IMF groups was selected according to their task correlation factor and subsequently represented in the two dimensional phase space through their trajectory matrices. In the third stage, largest singular values of the trajectory matrices corresponding to a subset of sensitive IMFs were employed for forming the feature vectors. Finally, the extracted feature vectors were fed to a least square support vector machine (LS-SVM) classifier for binary i.e. pair wise classification of these mental task EEG signals. With the new feature vectors, it is shown that LS-SVM with RBF kernel provides accuracy of 83.33% in classifying between mental arithmetic and mental letter composing. The performance of this classifier was evaluated on various parameters such as accuracy, specificity and sensitivity. The classification results show the potential of the proposed approach for classifying any non-linear a non- stationary signal.

1. Introduction

Electroencephalogram (EEG) signal represents neuro-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). 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. 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 a small set of five non-motor imagery mental tasks [3]. They considered these tasks as these could invoke hemispheric brainwave asymmetry. They used AR model coefficients and band power asymmetry ratio as features with quadratic Bayesian classifier for classifying these five non-motor mental task. Later, Charles W Anderson et al. [4,5] employed multivariate AR (MVAR) model of EEG for the classification of same EEG data set related to five non-motor mental task [3]. 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 employing any decomposition technique. Palaniappan et al. [6,8,9] used spectral power differences in four frequency

* Corresponding author.
E-mail addresses: dsuman1970@gmail.com (S. Dutta), mandy_tiet@yahoo.com (M. Singh), csioamod@yahoo.com (A. Kumar).

http://dx.doi.org/10.1016/j.bspc.2017.08.004
1746-8094/

bands with a NN classifier for classifying different mental tasks. Garrett et al. [7]. used AR model coefficients 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. Nan-Ying-Liang et al. [10] used AR model coefficients with extreme learning machine for the classification of same set non-motor mental task EEG signals. Li et al. [11] studied the classification of mental task EEG signals using SVM. Gupta et al. [12] used relevant features with SVM and LDA classifiers for classifying mental task. Tolic, M & Jovic, Franjo [13] used discrete wavelet transformed (DWT) based features with back propagation neural network (BPNN) for classifying same EEG data set [3] .They achieved average classification accuracy of 90.75%.

Xiaoou Li et al. [14] classified same set of mental task EEG signals using multiple kernel learning support vector machine (MKL-SVM). Agarwal et al. [15] used power spectral density (PSD) with back tracking search optimization based neural classifier (BSANN) for classifying same EEG data set. Zin Mar Lwin & Mie Mie Thaw [16] employed Gabor based Matching Pursuit (MP) based feature extraction with SVM classifier for classification of non-motor mental task. Hendel Mounia et al. [17] employed hybrid self organizing map probabilistic quadratic loss multi-class SVM. Hariharan, M., et al. [18] classified mental tasks using Stockwell transform. All these approaches have the limitation that they assumed the underlying signal generating mechanism to be linear and stationary. Due to this assumption of linearity and stationarity, 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. 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 [19]. 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. [20] employed univariate empirical mode decomposition (EMD) for classifying same set of five mental task from the mental task EEG data set [3]. 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. [21] employed EMD and Teager Energy operator for classifying five mental task from the benchmark data set [3]. They also adopted univariate approach using one EEG channel only. For catering to the need of real world multichannel data, Rehman and Mandic [22] developed multivariate extension of the standard univariate EMD algorithm known as MEMD algorithm. But most of this research work had focussed on one channel EEG signal 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.

The review of literature has confirmed that brain activity exhibits some kind of chaotic type deterministic nonlinear behaviour. Therefore, applying nonlinear methods such as EMD or its multivariate extension i.e. MEMD coupled with phase space reconstruction is quite reasonable for EEG time series analysis. Nonlinear measures hold the capacity to capture subtle changes occurring in any non-stationary signal since the system dynamics become prominently visible in their reconstructed phase space. So, nonlinear dynamical methods using phase space reconstruction provide the ability to go deeply into the subtle dynamics shown by the signal more accurately. This has motivated the researchers across different domains to employ phase space analysis as a promising tool for modelling any nonlinear phenomenon. It has been shown that the PSR of IMFs are like fertile ground for investigating new features for classifying EEGs. Lee, Lim, Kim et al. [23] used Euclidian distance based features computed from phase space representation (PSR) of wavelet coefficients for classification of normal and epileptic seizure EEG signals. Very recently, Pachori, R.B. & Patidar, S [24] applied univariate EMD on EEG signals to obtain IMFs and employed 95% ellipse area of SODP of IMFs as new features for classification of epileptic seizure and seizure free EEG signals. They obtained 97.75% classification accuracy with this method. Sharma, R & Pachori, R.B. [25] applied EMD on EEG signals and extracted 95% area parameter from the 2D PSRs of IMFs and IQR of Euclidian distances computed from 3D PSRs. But these research work done using phase space reconstruction so far had focussed on the detection of various pathological conditions. Besides, they employed one channel EEG signals with standard EMD algorithm. To the best of our knowledge, no research report is available in the literature presenting combined application of MEMD on multichannel EEG signals related to non-motor mental task for BCI applications.

The main focus of our research was to illustrate the substantial advantages of employing combination of MEMD based decomposition and phase space reconstruction as a framework for extracting nonlinear features from a subset of sensitive IMFs. In this work, our main contribution lies in the extraction of SVD based novel features from the two dimensional phase space representation(2D PSR) of sensitive IMFs of EEG signals instead of original EEG signals or their IMFs directly. We have constructed the PSR of the selected IMFs of EEG signals by taking fixed values of time lag and embedding dimension. Reconstructed phase space (RPS) is a promising tool for investigating the nonlinear dynamics of a signal. The nonlinear dynamical behaviour of a single channel EEG signal can be visualized using PSR(for $d = 2$ or 3). In this work, we have confined our discussion to the value of embedding dimension(' d ') 2 because of their simplicity in visualization. Phase space of the sensitive IMFs were reconstructed considering the value of time lag (τ) 1 as considered by Takens. Due to the amplitude and phase modulated (AM-FM) characteristics of the IMFs, their phase space trajectory matrices follow special geometry. In view of this,we have been motivated to use singular value decomposition (SVD) of these trajectory matrices since the singular values can unravel the special geometrical structure of the IMFs. The novelty of our approach lies in the combination of multivariate extension of standard EMD (MEMD) based decomposition of the EEG signals into IMFs and their