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Research Paper

Characterization of phase space trajectories for Brain-Computer Interface

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A new processing framework that allows detailed characterization of the nonlinear dynamics of EEG signals at real-time rates is proposed. In this framework, the phase space trajectory is reconstructed and the underlying dynamics of the brain at different mental states are identified by analyzing the shape of this trajectory. Two sets of features based on affine-invariant moments and distance series transform allow robust estimation of the properties of the phase space trajectory while maintaining real-time performance. We describe the methodological details and practical implementation of the new framework and perform experimental verification using datasets from BCI competitions II and IV. The results showed excellent performance for using the new features as compared to competition winners and recent research on the same datasets providing best results in Graz2003 dataset and outperforming competition winner in 6 out of 9 subject in Graz2008 dataset. Furthermore, the computation times needed with the new methods were confirmed to permit real-time processing. The combination of more detailed description of the nonlinear dynamics of EEG and meeting online processing goals by the new methods offers great potential for several time-critical BCI applications such as prosthetic arm control or mental state monitoring for safety.

1. Introduction

Brain computer interface (BCI) is an alternative communication pathway between the human brain and the external environment through a computer [1]. BCI systems are used to assist disabled people to control neuroprostheses and wheelchairs by detecting their brain electrical activity during different mental tasks [2–4]. Different techniques can be used to measure brain activity such as the electroencephalography (EEG), functional magnetic resonance imaging (fMRI), electrocorticography (ECoG), magnetoencephalography (MEG), and near infrared spectroscopy (NIRS) [5–8]. Among those techniques, the EEG-based BCI systems are the most widely used due to their relatively low cost, high temporal resolution, and convenience for users [9].

The human brain shows EEG activity over the sensorimotor cortex at mu (8–13 Hz) and beta (14–25 Hz) frequency bands when awake subject does not experience sensory or motor activities and this phenomenon is termed event-related synchronization (ERS) [10]. In contrast, the mu and beta rhythmic activities are attenuated when a subject processes motor commands or sensory stimuli and this phenomenon is termed as event-related desynchronization (ERD) [11]. Fortunately, such ERS/ERD changes can be elicited during the imagination of movements and hence can be used for EEG-based BCI systems operated by motor imagery [12,13].

Different feature extraction and classification algorithms were developed to interpret the brain electrical activity into commands for external computers or devices. Krusienski et al. studied the relative BCI performance using Phase-Locking Value (PLV) features and in combination with spectral power and coherence features [14]. Their results indicated that using spectral power features produced similar classification performance as using PLV, coherence, or any combination of these features. Brodu et al. introduced two sets of features based on multifractal cumulants and predictive complexity of the EEG signals [15]. The winner of BCI competition 2003 for dataset III extracted features using Morlet wavelets and used the Bayesian classifier to differentiate between the imagination of left and right-hand movements [16]. Xu et al. extracted statistical features over set of wavelet coefficients which were fed into a

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fuzzy support vector machine (FSVM) classifier to characterize the time-frequency distribution of the EEG signals [17]. Their results outperformed the winner of BCI competition 2003 for dataset III. Zhou et al. proposed extracting bispectrum-based features to characterize the non-Gaussian nature of EEG measurements leading to even better results for the same dataset using different classifiers [18]. On the other hand, Ang et al. proposed filter-bank common spatial pattern algorithm to optimize the subject-specific frequency band for classification of different motor imagery tasks [19]. Their technique was the winner of BCI competition 2008 for datasets 2a and 2b. Delgado et al. proposed new approach for classification of motor imagery tasks based on the hidden conditional random fields (HCRFs) [20]. The extracted features which include autoregressive (AR) modeling of the EEG signals followed by the calculation of the power spectrum were used to model the HCRFs. Their results outperformed the results obtained by the winner of BCI competition 2008 for dataset 2a [20].

Despite the relative success of the above techniques, many of the proposed feature extraction methods for EEG-based BCI systems assume linearity of the recorded EEG signals and hence ignore the well-established nonlinearity of brain electrical activity. Therefore, several methods were proposed to better model the nature of EEG signals using features derived from nonlinear dynamical modeling [21–23]. Many such features were proposed for the analysis of EEG signals at different mental states. Carlino et al. calculated the correlation dimension to differentiate between the EEG signals of healthy and schizophrenic patients [24]. Sakkalis et al. investigated three measures to detect the absence seizures; namely, a linear variance analysis approach, approximate entropy, and order index [25]. Hosseinifard et al. used four nonlinear features including correlation dimension, Lyapunov exponent, Higuchi fractal, and detrended fluctuation analysis (DFA) with KNN classifier to differentiate between normal and depression patients [26]. Banitalebi et al. calculated some chaotic indices such as mutual information, correlation dimension, Lyapunov exponent, and the minimum embedding dimension with multi-layer perceptron classifier and k-means support vector machine (KM-SVM) classifier to discriminate different motor imagery tasks [27]. Fang et al. proposed extracting features from the reconstructed phase space (RPS), which is a transformation of the EEG time series into a geometrical object embedded in a higher-dimensional space [28]. Their features included amplitude frequency analysis (AFA) and autoregressive (AR) modeling of RPS. Unfortunately, the calculation of most (if not all) of such features is notoriously time-consuming, which makes it impractical to develop online classification schemes with high information transfer rates as required for BCI. So, the development of techniques that account for nonlinear dynamical nature of EEG signals while meeting online processing goals would potentially be of significant impact on this field.

In this work, we propose a new processing framework that allows more detailed characterization of the nonlinear features of the EEG signals at real-time rates. In this technique, the phase space trajectory is reconstructed and characterized using two sets of features based on affine-invariant moments and a new distance series transform. Such features allow robust determination of the characteristics of the phase space trajectory while being rather simple to compute to meet real-time performance requirements. We describe the implementation of the new framework and perform experimental verification using data sets from BCI competitions.

2. Methodology

The phase space reconstruction method by Packard et al. [32] was proposed to reconstruct a system's attractor using one or more of its measured time series. Takens [33] showed that the reconstructed phase space (RPS) had the same dynamical properties as the true attractor of the system which produced the measured signals. Consequently, it is possible to reconstruct attractors with different topological properties using EEG measurements at different mental states assuming the human brain as a nonlinear dynamical system. Fig. 1 shows a graphical representation of the time-delay embedding procedure used to estimate RPS in this work. The embedding dimension in this figure was taken as 3 for clear illustration. For the EEG signal at the top plot, three coordinate points are required to create one point in a 3D phase space (bottom left plot). Each point in the phase space is represented by three values, which are the amplitude values of the signal at 3 consecutive time points separated by time lag τ. By repeating these steps for each time point, we can reconstruct the phase space of the underlying dynamical system and obtain an equivalent attractor as shown in the bottom right plot. The details of the time-delay embedding process used in this work are provided in Appendix A.

2.1. Preprocessing

The EEG signals were filtered using either Butterworth band-pass filter of order 3 or Chebyshev Type II band-pass filter of order 6. These filters and their parameters were utilized following the winners of competition II and IV respectively [16,19]. An additional filtering using spectral subtraction denoising method was used here for further noise rejection [36].

2.2. Feature extraction

Two sets of features are introduced in this work to represent the complexity in the phase space trajectory; namely, the moment invariant features and the distance series (DS) transform features. The moment invariant features are used to quantitatively characterize the shape of the RPS. On the other hand, DS features are computed after a transformation of the multidimensional RPS into a one-dimensional space. A set of DS-domain features are derived based on the raw values of the transformed RPS, their autoregressive model coefficients, magnitude of their discrete Fourier transform, and their wavelet decomposition coefficients.

2.2.1. Moment invariant features

Moments are quantitative measures that describe the distribution of a random variable whereby a set of moments with order ranging from zero to order infinity uniquely determine its probability density function. In this study, we consider the reconstructed attractor as m-dimensional object in the phase space and characterize its shape by moments.

Generally speaking, the moment of order p for an m-dimensional object with density function $\rho(S_1, S_2, \ldots, S_m) = \rho(S)$ where S_i is a column in the reconstructed phase space $Y_i(m)$ is given by the Riemann sum as,

$$M_{p_1 \ldots p_m} = \sum_{j=1}^{K} \ldots \sum_{j=1}^{K} S_{1j}^{p_1} \ldots S_{mj}^{p_m} \rho(S)\, dS_1 \ldots dS_m, \quad (1)$$

where $p_1 + p_2 + \ldots + p_m = p$, $0 \leq p < \infty$, and K is the length of the embedded dimensions S_i, $i = 1, 2, \ldots, m$. Similarly, the central moments are given by,

$$\mu_{p_1 \ldots p_m} = \sum_{j=0}^{K} \ldots \sum_{j=0}^{K} \left(S_{1j} - \overline{S_{1j}}\right)^{p_1} \ldots \left(S_{mj} - \overline{S_{mj}}\right)^{p_m} \rho(S)\, dS_1 \ldots dS_m\,, \quad (2)$$

where $\overline{S_1} = \frac{M_{1 \ldots 0}}{M_{0 \ldots 0}}, \ldots, \overline{S_m} = \frac{M_{0 \ldots 1}}{M_{0 \ldots 0}}$. From the above expressions, such moments will vary if an affine transformation is applied to RPS, which is a clear disadvantage when trying to characterize such