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Comparison of signal decomposition methods in classification of EEG signals for motor-imagery BCI system

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ABSTRACT

In this study, three popular signal processing techniques (Empirical Mode Decomposition, Discrete Wavelet Transform, and Wavelet Packet Decomposition) were investigated for the decomposition of Electroencephalography (EEG) Signals in Brain Computer Interface (BCI) system for a classification task. Publicly available BCI competition III dataset IVa, a multichannel 2-class motor-imagery dataset, was used for this purpose. Multiscale Principal Component Analysis method was applied for the purpose of noise removal. In addition, different sets of features were formed to examine the effect of a particular group of features. The parameter selection process for signal decomposition methods was thoroughly explained as well. Our results show that the combination of Multiscale Principal Component Analysis de-noising and higher order statistics features extracted from wavelet packet decomposition sub-bands resulted in highest average classification accuracy of 92.8%. Our study is one among very few that provides a comprehensive comparison between signal decomposition methods in combination with higher order statistics in classification of BCI signals. In addition, we stressed the importance of higher frequency ranges in improving the classification task for EEG signals in Brain Computer Interface Systems. Obtained results indicate that the proposed model has the potential to obtain a reliable classification of motor imagery EEG signals, and can thus be used as a practical system for controlling a wheelchair. It can also further enhance the current rehabilitation therapies where appropriate feedback is delivered once the individual executes the correct movement. In that way, motor rehabilitation outcomes may improve over time.

1. Introduction

Brain-Computer Interface (BCI) represents a communication and control mechanism between the human brain and computers envisioned to support disabled people using their electrical activity of the brain, which is usually recorded using electroencephalogram (EEG). There are two types of BCI: spontaneous EEG, and evoked EEG based BCI systems. The former is generated as a result of specific mental activity, whereas the latter is a result of some kind of neural stimulation. A number of paradigms have recently been assessed to test the possibility of detecting few mental tasks from the EEG signals [1]. The aim is to generate distinct EEG signals by imaging certain motor activities, which are then translated into external actions [2].

In addition to having non-stationary nature, EEG signals are also susceptible to various other factors such as physical state, mood, posture, external noise, etc. Processing of EEG signals, which directly affects the classification accuracy, still represents a crucial challenge. Signal processing techniques for the motor imagery EEG mainly belong to some of the following:

- Fourier transform (FT), which can be used to calculate power spectrum (or power spectral density), whose main disadvantage is the lack of time domain information [3].
- Autoregressive (AR) model, which can be used to calculate the AR spectrum or the AR model coefficients [3]. This method is computationally efficient (being appropriate for online systems), but is also sensitive to the artifact [4].
- Common spatial patterns (CSP), a suitable spatial filtering technique for oscillatory EEG components during motor imagery aiming at multi-channel EEG data [5], and its many variations.

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- Coefficients of discrete wavelet transform (DWT) at useful frequency bands. In addition, wavelet packet decomposition (WPD) algorithm decomposes the signal into the low-frequency and high-frequency components and then the coefficients at a certain band can be extracted [6].

Gajic et al. [7] described an automated classification of EEG signals for the detection of epileptic seizures by quadratic classifiers designed in the reduced two-dimensional feature space. The original feature set consisted of statistical features in time, frequency, time-frequency domain non-linear features extracted from a few frequency sub-bands of clinical interest. The overall classification accuracy was around 99% [8].

Considering noisy signals like EEG, linear de-noising methods considerably smooth out the rapid jumps in the signal. On the other hand, the nonlinear filtering techniques like Multiscale Principal Component Analysis (MSPCA) may eliminate the noise without sacrificing substantial amount of fast changes in the signal [9]. MSPCA de-noising has been successfully applied in classifying EEG signals for epileptic seizure detection in [10]. Apart from EEG, MSPCA has been exploited for diagnosis of neuromuscular disorders using Electromyography (EMG) signals [11]. In addition, MSPCA showed its strength for diagnosis of cardiovascular diseases by classifying ECG beats [12]. The effect of MSPCA in real-time wireless BCI system was also investigated in [13]. The study involved practical motor imagery BCI system based on Mindwave Mobile Headset from one subject including two motor imagery tasks: right hand and left hand. The model combining MSPCA de-noising and statistical wavelet features showed promising results [13].

One important part of signal processing is the extraction of distinguishable features from available EEG signals, because these techniques need to adjust to dynamic characteristics of EEG signals. In essence, EEG signals are non-stationary, non-linear, and non-Gaussian. The first and second order statistics (mean and the standard deviation), despite being very limiting in analysis of signal non-linearity, have attracted large attention in biomedical signal processing [14]. Moreover, different variations of wavelet transforms and decompositions proved to be suitable because of their ability to derive dynamical features from the signals and enhanced resolution. However, even the wavelets suffer from deriving nonlinear relationships within the signal 15]. On the other hand, higher order statistics (HOS) can discover irregularities from stationarity, linearity, or Gaussianity in the signal which is a clear advantage over traditional time and/or frequency domain methods in biomedical signals analysis. In addition, HOS features can be made insensitive to shift or amplification [14]. Therefore, HOS can be used as an effective technique for the analysis of non-linear nature of weak and noisy biomedical signals like EEG.

The review of signal processing and classification methods is not very appropriate unless they are applied on the same open database. Therefore, we provide a short review of the most notable recent studies done on Dataset IVa from BCI Competition III. In [16], a novel algorithm called iterative spatio-spectral patterns learning (ISSPL) is presented. It accomplishes automatic learning of spatio-spectral filters using statistical learning theory to accomplish good generalization performance. The authors claim that the suggested method accurately determines the significant frequency bands, making it superior to other classification paradigms [16]. Modified cross-correlation based logistic regression (CC-LR) approach tries to discover a feature set to appropriately describe the distribution of MI tasks from EEG data. The study shows that the proposed method has potential to enhance the classification performance of MI tasks in BCI systems [17]. In [18], a new heuristic method for the optimal channels selection for CSP is presented. The CSP is executed to training set prior to assigning a channel score to each channel based on l_1 norm. At the end, channels having higher scores are reserved for further CSP processing to extract features. The study indicates that this technique can successfully execute the job of selecting the optimal channels [18]. Lu et al. [19] suggested a regularization and aggregation method for CSP in a small sample setting. Since Conventional CSP performance in EEG classification worsens for small number of samples, authors suggested a regularized CSP (R-CSP) technique in which they regularize the covariance-matrix to lower the estimation bias and variance. In addition, the study suggests R-CSP with aggregation (R-CSP-A), in which a few R-CSPs are aggregated providing ensemble-based solution. The results indicate that R-CSP-A considerably beats the other methods regarding overall classification accuracy [19]. Li and Lu [20] enhanced the Common Spatial Subspace Decomposition (CSSD) method, a way of an adaptive feature extraction method. EEG signals have been classified by Improved-CSSD and SVM. Improved-CSSD improved the classification accuracy for about 8.26% over the traditional CSSD. The experiments indicate that the method has a low time loss and a decent adaptability [20]. As it can be seen, no signal decomposition techniques combined with HOS features have been studied before on Dataset IVa from BCI competition III, which is an important contribution of our study.

In this paper, we compare three different signal decomposition methods for MI BCI systems. Empirical Mode Decomposition (EMD), discrete wavelet transform (DWT), and wavelet packet decomposition (WPD) are used to generate several sub-band signals from which six different statistical features (including higher order statistics) are extracted. Finally, k nearest neighbor (k-NN) algorithm was responsible for the classification task. Our approach is partly motivated by the fact that EEG frequency bands hold different energies during different imaging tasks [1,2]. In addition, statistical features calculated from these sub-band signals (coefficients) will express additional evidence for discrimination between various imaging tasks. The performance of the proposed paradigm has been evaluated on the dataset IVa of BCI competition III. Our paper represents one out of a very few studies providing a thorough comparison of signal decomposition methods together with higher order statistics in BCI signal analysis [15,21].

The rest of this paper is organized as follows: Section 2 provides more information about the dataset being used. Section 3 explains the methods: a brief description of MSPCA-based denoising method and the descriptions of signal decomposition methods. The experimental results and analysis are presented in Section 4, whereas the Section 5 provides the throughout discussion, whereas the last sections concludes the paper.

2. Dataset

Dataset IVa from BCI competition III [22] was recorded from five healthy subjects sitting in a comfy chair with arms resting on armrests. Signals from 118 EEG channels of the extended international 10/20-system were captured and then band-pass filtered between 0.05 and 200 Hz. Although the sampling frequency used was 1000 Hz, EEG signals that are down-sampled at 100 Hz were also provided and used in this paper.

Visual cues showed the type of motor imagery the subject is to execute for 3.5 s: (R) right hand, or (F) foot. Periods of length around 2 s were introduced so that the subjects could take a short break. For each of five subjects, continuous signals having 118 EEG channels and markers showing the time points of 280 cues are available. Some markers contain NaN values as target class representing the instance belonging to evaluation/test data. Table 1 shows the number of training (labelled) trials and test (unlabelled) trials for all subjects.