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The Impact of Mspca Signal De-Noising In Real-Time Wireless Brain Computer Interface System

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Abstract

This paper presents the practical implementation of the motor imagery BCI system using MATLAB GUI. EEG signals were recorded using Mindwave Mobile Headset from one subject for two motor imagery tasks: right hand and left hand. The offline analysis showed decent performance of the combination between MSPCA de-noising of EEG signals and statistical features extracted from WPD sub-bands. The best classifier from the offline analysis was used in the online assessment to classify new motor imagery EEG signals. The overall results show that the desirable de-noising results are obtained if MSPCA is applied on a data matrix containing signals that belong to one particular class.

1. INTRODUCTION

The idea of BCI was first introduced by Vidal back in 1973 (Vidal, 1973). Briefly, a brain-computer interface (BCI) is a system that makes the communication without any movement possible (Wolpaw, Birbaumer, McFarland, Pfurtscheller, & Vaughan, 2002). Hence, severely disabled individuals may find a BCI very promising communication system. Generally, BCI must satisfy the following four conditions (Pfurtscheller, Allison, Brunner, & Bauernfeind, 2010):

- depend on direct measures of central nervous system (CNS) activity,
- deliver user feedback,
- function in real-time, and
- depend on intended control.

In (Wolpaw & Wolpaw, 2012), a BCI was defined as a device that translates the measured CNS activity into an output that can:

- replace,
- restore,
- enhance,
- supplement, or
- improve natural CNS output.

2. LITERATURE OVERVIEW

Different approaches have been used to develop EEG based BCI systems: motor imagery, visual P300, steady-state visual evoked potential (SSVEP), nonmotor mental imagery, auditory, hybrid, and other paradigms. Although its usage has progressively decreased recently (due to visual P300 and SSVEP paradigms), the most frequently used paradigm is still the motor imagery approach. The aim is to generate distinct EEG signals by imagining certain motor activities, which are then translated into external actions (Rak, Kołodziej, & Majkowski, 2012). In this paper, the user was supposed to imagine two movements: right hand and left hand, and the BCI system tries to recognize the movements based on the generated EEG signals.

EEG-based BCI research paradigms have different goals and objectives, such as (Hwang, Kim, Choi, & Im, 2013):

- development or enhancement of techniques for signal processing, feature extraction, and classification
- development of novel BCI approaches or enhancement of existing ones
- everyday applications of BCI systems
- studies about factors affecting the performance of BCI systems

More than 50% of BCI papers based on EEG have aimed at developing or enhancing techniques for denoising, feature extraction, feature selection, and classification algorithms to improve the performance of BCI systems (Hwang, Kim, Choi, & Im, 2013). A number of methods have been proposed for elimination of different types of noise from biomedical signals. MSPCA de-noising has been effectively applied in biomedical signal processing in (Alickovic & Subasi, 2015; Gokgoz & Subasi, 2014). The positive effects of noise removal provided by MSPCA for EEG signals are thoroughly explained in our previous study as well (Kevric & Subasi, 2014). This is the first paper that demonstrates the impact of MSPCA de-noising for EEG based BCI signals.

The number of published BCI research papers has been constantly increasing in recent years, and motor-imagery-based BCI approaches are still being most extensively studied. However, the most important tendency in the recent EEG-based BCI research was the increasing effort in the development of practical BCI systems that can actually be used daily by disabled subjects to control external devices. For this purpose, we designed a Matlab GUI as a platform for real-time BCI system that will satisfy the four criteria explained in (Pfurtscheller, Allison, Brunner, & Bauernfeind, 2010). GUIs are handy since the feedback must be delivered to the user. In addition, the connection between the GUI and the EEG capturing devices is wireless, so the user does not have to manage cables and wiring. The possible application scenarios (Wolpaw & Wolpaw, 2012) of this approach will be explained and justified.

3. METHODOLOGY

3.1 Mindwave Mobile Headset

This headset contains only one channel placed on the forehead taking EEG signals with sampling frequency of 512 Hz (Figure 1). The headset can be connected to a computer or Android/iOS device via Bluetooth. Thinkgear API was used to enable Matlab connect to Neurosky headset, read and store raw EEG signals. Thinkgear API provides an option to read "Attention" levels in the range 0 – 100 for each second of recording. Totally, 140 trials for each movement had been stored as training signals. After that, signal processing and feature extraction techniques developed in this study can easily be performed on these signals.

3.2 MSPCA de-noising

Let us assume that we have the input signal matrix I_{nxm}, where n is the number of measurements (samples) and m is the number of signals. The procedure for MSPCA, as explained in (Bakshi, 1998), can be summarized in three steps. The wavelet decomposition of all signals from I_{nxm} is executed in the initial step. Then, PCA de-noising algorithm is performed for each wavelet decomposition level separately (for all signals belonging to a certain sub-band). If stated, wavelet coefficients which are greater than certain a priori threshold value can be preserved as well. The third step considers the application of PCA for all levels combined, resulting in the de-noised input signal matrix I_{nxm} (Bakshi, Multiscale PCA with Application to Multivariate Statistical Process Monitoring, 1998).

Figure 1. Mindwave Mobile Headset

3.3 Wavelet Packet Transform

The wavelet packet decomposition (WPD) extends the capabilities of the Discrete Wavelet Transform (DWT) which has been successfully applied in various EEG signal processing scenarios (Subasi & Gürsoy, 2010). Whereas DWT decomposes the approximations records only, WPD does the decomposition of both approximation and detail records into sublevels (Unser & Aldroubi, 1996; Daubechies, 1990; Learned & Willsky, 1995). Alternatively, WPD can be thought of as a continuous-time wavelet decomposition sampled at various frequencies at each scale level. Hence, WPD delivers better frequency resolution for the signal being decomposed. Another benefit of the WPD represents the reconstruction of the original signal by combining various decomposition levels (Kutlu & Kuntalp, 2012). For k levels, size of different set of wavelet coefficient (or sub-bands) in WPD will be 2^k, while in DWT it will be $k + 1$. More sub-bands in WPD means more features are extracted which can improve the classification accuracy. In this study, Daubechies4 (db4) mother wavelet function is used for WPD as it showed slightly better performance than other functions. The number of decomposition levels is chosen to be 4, which will result in 16 sub-bands. Since 6 features (Section 3.4) are extracted from these 16 sub-bands, there are totally 96 features for classification. Selection of 5 levels would double the number of features which would slow down the classification process. In addition, no increase in detection was observed once more than 4 levels were selected.

3.4 Feature Extraction

If $Y\{y_1, y_2, ..., y_M\}$ and $Z\{z_1, z_2, ..., z_M\}$ are two adjacent sub-bands, where M represents the length of a sub-band, the following six statistical features are chosen for EEG classification and expressed as:

1. Mean of coefficients' absolute values in every sub-band, μ;

$$\mu = \frac{1}{M} \sum_{j=1}^{M} \left| y_j \right| \tag{1}$$

2. Average power of the coefficients in every sub-band, λ;

$$\lambda = \sqrt{\frac{1}{M} \sum_{j=1}^{M} y_j^2} \tag{2}$$

3. Standard deviation of the coefficients in every sub-band, σ;

$$\sigma = \sqrt{\frac{1}{M} \sum_{j=1}^{M} (y_j - \mu)^2} \tag{3}$$

4. Ratio of the absolute mean values of coefficients (signal values) of adjacent sub-bands, χ;

$$\chi = \frac{\sum_{j=1}^{M} \left| y_j \right|}{\sum_{j=1}^{M} \left| z_j \right|} \tag{4}$$

5. Skewness of the coefficients (signal) in every sub-band, ϕ;

$$\phi = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \frac{(y_j - \mu)^3}{\sigma^3}} \tag{5}$$

6. Kurtosis of the coefficients (signal) in every sub-band, φ.

$$\varphi = \sqrt{\frac{1}{M} \sum_{j=1}^{M} \frac{(y_j - \mu)^4}{\sigma^4}} \tag{6}$$

Features 1 – 4 have been successfully applied in (Subasi & Gürsoy, 2010), while features 5-6 may help in extracting non-linear behavior from EEG signal (Kutlu & Kuntalp, 2012).

3.5 Machine Learning

In the offline analysis, the classifiers tested include: Support Vector Machines (SVMs), Multilayer Perceptron (MLP), Decision Tree (C4.5), Random Forest (RaF), *k*-Nearest Neighbour (kNN), and Rotation Forest (RoF). The Matlab GUI allows a user to test the performance with and without MSPCA de-noising. Motor imagery EEG signals are classified using the best classifier obtained from the offline analysis.

4. RESULTS

4.1 Offline Analysis

The analysis with and without MSPCA de-noising has been carried out. Prior to process of feature extraction from 280 EEG signals, EEG signals are decomposed into sub-band signals using 4-level WPD techniques. Six statistical features were extracted from the resulting sub-bands. This set of feature vectors is fed as input to different data mining tools which will try to classify EEG signals into two groups: right hand or left hand using 10-fold cross-validation. Classification accuracy for right hand, left hand and overall accuracy using 10 fold cross-validation are given in Table 1.

Table 1. Classification Accuracy (right hand, left hand, and overall) with and without MSPCA de-noising.

Classifier	**Accuracy without MSPCA**			**Accuracy with MSPCA**		
MLP	72.1	69.3	70.7	85.7	86.4	86.1
C4.5	73.6	75.0	74.3	83.6	84.3	83.9
k-NN	70.0	77.9	73.9	82.9	92.9	87.9
SVM	74.3	72.9	73.6	87.9	84.3	86.1
Ran.Forest	80.7	68.6	74.6	85.7	92.9	89.3
Rot.Forest	77.9	80.0	78.9	87.9	91.4	89.6

4.2 Real-time BCI system

The real-time BCI system implemented as Matlab GUI for online analysis is showed in Figure 2.

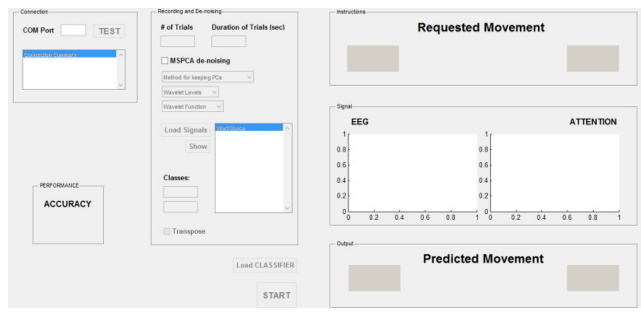

Figure 2. Matlab GUI for online analysis.

The GUI contains several sections:

- Connection
- Recording and De-noising
- Instructions
- Signal
- Output
- Performance

The "Connection" section handles the connection of Mindwave Mobile Headset to a computer over Bluetooth through a COM port. Once the connection was established, a user may proceed with the next step (Recording and De-noising) which requires the following information:

- The number of trials
- The duration of trials in seconds
- The activation of MSPCA de-noising
- Importing the trained classifier

The number of trials indicates how many motor imagery movements will be conducted in the online testing. The duration of trials should be the same as the duration of EEG signals in the training dataset. The best trained classifier from the offline analysis (Rotation Forest in this research) can be imported using the "Load CLASSIFIER" button.

The "Instructions" section shows the type of motor imagery task the user will be asked to perform (either right or left). After the trial (recording) is finished, motor imagery EEG signal and "Attention" levels during the recording period are presented to the user in the "Signal" section. The EEG signal is then decomposed into 16 sub-band signals using 4-level WPD and six statistical features were extracted from each sub-band, generating 96 features in total. The loaded Rotation Forest Classifier will use these 96 features to classify the trial and the result will be shown in the "Output" Section (Figure 3). When the user executes the inserted number of trials, the classification accuracy in online testing is presented to the user in the "Performance" section.

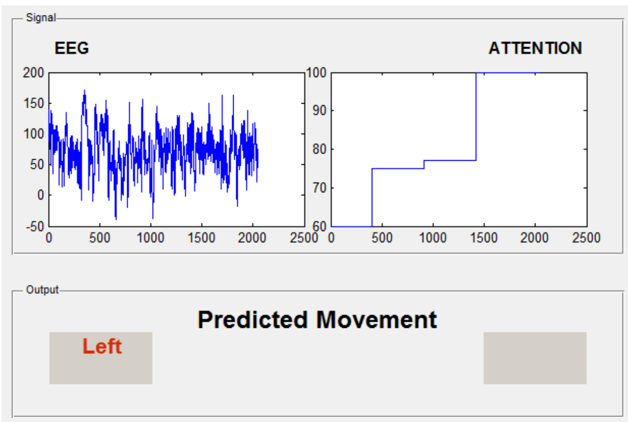

Figure 3. The EEG signal and the predicted output.

The activation of MSPCA de-noising within the "Connection" section of the GUI did improve the classification accuracy as demonstrated in offline analysis (Table 1). MSPCA is a multivariate technique being applied on a signal matrix (or a set of signals from different channels). However, Mindwave Mobile headset provides only one channel for recording. In addition, MSPCA gives the best de-noising effect when it is applied on a signal matrix that belongs to one class. Therefore, the button "Load Signals" within "Recording and De-noising" section allows the user to import data matrix of EEG signals that belong to either right hand or left hand imagery. For proper de-noising results, the imported matrices should contain the training EEG signals used in the offline analysis. This GUI is not to be compared to any other existing GUI application because it is still in its early stages. Once more wired and wireless devices are connected and more signal processing and feature extraction methods are added, the proper comparison can be made.

5. CONCLUSIONS

The practical implementation of the real-time BCI system for motor imagery task confirmed the effectiveness of MSPCA de-noising of EEG signals. In fact, the overall results show that desirable de-noising results are obtained if MSPCA is applied on a data matrix containing signals that belong to one particular class. There are number of BCI applications where the user is requested to perform a certain trial at the moment like in stroke rehabilitation. MSPCA may even increase the responsiveness in certain games where only one movement is possible or very logical to be performed at the moment. In addition, this paradigm does not exclude the usage of more than two motor imagery movements.

The GUI may be improved to produce a powerful educational instrument. Topics related to "Digital Signal Processing" and "Machine Learning" can be taught and presented in fun an interactive way using the GUI. The programming skills of students can be improved as they try to add compatibility with more devices or integrate other signal processing and feature extraction methods into the GUI. In addition, the paradigm presented in this paper will be implemented for the purpose of controlling a wheelchair or tricycle in the future.

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