Automatic Removal of ocular Artifacts from EEG Signals

Junfeng Gao, Chongxun Zheng, Pei Wang
Key Laboratory of Biomedical Information Engineering of Education Ministry
Xi’an Jiaotong University
Biomedical Engineering Research Institute
Corresponding author:
Junfeng Gao
Email: junfengmst@163.com
Tel: +8615829382975

Abstract
Electroencephalogram (EEG) signals are often contaminated by ocular artifacts. In present study, a novel and robust technique is presented to eliminate ocular artifacts from EEG signals automatically. Independent component analysis (ICA) method is used to decompose EEG signals. In the first step, the features of topography and power spectral density of those components are extracted. In the second step, we introduce manifold learning algorithm to reduce the dimensionality of initial features. Then, a classifier is used to identify ocular artifacts components. The classifier is selected from several typical classifiers by comparing their classification performances. Classification results show that manifold learning with the nearest neighbor algorithm performs best. Finally, using an example of ocular artifacts removal, we show that the novel technique can effectively remove ocular artifacts with little distortion of underlying brain signals.

Keywords: Independent component analysis; Manifold learning; Principal component analysis

1. Introduction

Electrooculography (EOG) artifacts inevitably and frequently interfere with the electroencephalogram (EEG) signals. Eye-movement and eye-blink artifacts are the main sources of ocular artifacts. To date, many method are presented to remove EOG artifacts. Some methods based on regression in the time domain or frequency domain\(^\text{1-3}\) are proposed for removing eye blink artifacts. However, they always need a reliable reference channel. Moreover, EOG reference channel often contains brain signals which will be also removed inevitably from the EEG by the procedure of regression. Therefore, the methods based on regression may not be the best way to remove EOG artifacts.

Principal component analysis (PCA) is also used to remove EOG artifacts in recent years. The principle of this method indicates that it is not suitable for removing artifacts especially when the amplitude of artifacts is about equal to that of ictal signals\(^\text{4}\).

Blind source separation (BSS) methods have been widely used in recent years. Many studies have been proved that they are very effective in removing various artifacts from EEG signals. Independent component analysis (ICA) is a BSS method that blindly separates mixtures of independent source signals\(^\text{5-7}\). Many researchers have used ICA method to remove various artifacts from EEG effectively\(^\text{8-10}\).

Independent component (IC) is the evaluation of real signal source. The crucial step of ICA-based method removing artifacts is to identify artifact components from the ICs.

Dimensionality reduction is widely used in the field of pattern recognition. Those high-dimensional features may contain much overlapping information for classfi-cation\(^\text{11}\). Obviously, it is favorable for classification to find those low-dimensional features which practically govern the data set.

In this study, ICA was applied to decompose the EEG into the ICs. The features of topographies and power spectral densities (PSD) of the ICs were extracted, and then manifold learning algorithm, a recently popular dimensional reduction technique, was used to further process the extracted features above. Lastly, low-dimensional features were fed as input to a suitable classifier to identify ocular artifacts component (OAC). Several typical classifiers and dimensionality reduction techniques were selected to compare their respective performances. A discussion of the proposed technique was presented in the last section.

2. Methods

2.1 EEG signals
16 healthy subjects (8 males and 8 females, 8 adults with an average 31-year-old, 5 youth average 22-year-old and 3 children average 14-year-old) were selected. They were instructed to do 2-minute experiments. Electrodes were placed according to the International 10-20 System. EEG signals were recorded from the 16 channels: Fp1,
Fp2, F3, Fz, F4, T7, C3, Cz, C4, T8, P3, Pz, P4, O1, Oz, O2. The vertical EOG (VEOG) signal was recorded from the right eye (2.5 cm below and above the pupil); the horizontal EOG (HEOG) signal was recorded from the outer canthus. The amplifiers bandpass was 0.1-45 Hz and analog-to-digital conversion was done at 250 Hz. A right mastoid referred was used. During the experiment, two arrows were flashed randomly at left and right border on the computer screen at 3-s intervals. Subjects were instructed to move the eye and blink following the arrow flashing. Then, EEGLAB[^12] was used to divide the EEG data into 640 epoch datasets, and every epoch lasted for 3 seconds. Lastly ICA was applied to decompose these 3-s datasets into many ICs.

2.2 Feature extraction

Many authors have pointed that EOG artifacts have characteristic topography and PSD features. However, the PSD and topography are only used to remove artifacts by experts inspecting EEG visually[^4][^13]. To identify the OAC automatically, in the present study, these features were extracted as the recognition features. Bartlett algorithm was used to calculate initial PSD, and then the PSD of every component was sampled from 1 to 25 Hz with 0.5 Hz interval. Additionally, the topography of a component was based on the corresponding column of mixing matrix[^2], thus the 18 values of a column were used as the raw features of topography. Final feature vector was concatenation of PSD features and topography features.

At the same time, all the datasets were presented to neurophysiologist. He was instructed to select typical OACs by their time series, topographies, PSD and by the corrected effect after excluding the OAC[^2].

Lastly, the feature vectors of 1006 OACs and 1006 non-OACs were set as two initial feature vectors sets.

2.3 Dimensionality reduction

Dimensional reduction may help reveal what the underlying forces governing the feature data set are. PCA is one of the most widely used techniques. Despite its popularity PCA has several limitations. When applied in the filed of dimensional reduction, perhaps the most notable drawback is the requirement that the feature data set should lie on a linear subspace. However, for most feature data, it is unknown whether the feature data lie on a linear subspace.

In fact, PCA finds a low-dimensional embedding of the feature points, which best preserves the data variance measured in the high-dimensional input space. Multidimensional scaling (MDS)[^14], another commonly used dimensionality reduction method, can also find the true structure of data lying on or near a linear subspace of the high-dimensional input space. However, MDS preserves the interpoint Euclidean distance measured in the input space. Manifold learning[^10][^16] is a recently popular approach to nonlinear dimensionality reduction. It is viewed as non-linear analogs to PCA and an extension to MDS.

Fig.1A shows a curved surface called the “swiss roll”. From the perspective of pattern recognition, although the extrinsic dimensionality of the feature points is three, this shape can be actually parameterized by two variables. In mathematical sense, there is a two-dimensional manifold embedded in the three dimensional shape. The algorithms uncovering this manifold structure is called manifold learning. Restricted to space, only a typical manifold learning algorithm—Isometric Mapping (Isomap) was considered in present study. It constructs an embedding derived from the geodesic distance between all pairs of points[^17]. Fig.1A shows the two points are connected by a solid curve and a dashed line. The dashed line represents the Euclidean distance between two points, which can not accurately reflect their intrinsic similarity (i.e., intrinsic geometry feature), whereas the solid curve can reflect it[^14]. For the feature points as shown in Fig.1A, in order to preserve the similarity between them while reducing the dimensionality, obviously, applying MDS algorithm is not valid, whereas we can use Isomap algorithm[^11] to solve that problem effectively.

![Figure 1](image1.png)

Figure 1 Low-dimensional manifold embedded in the high-dimensional space. (A) Initial features points in three-dimensional space. (B) Two-dimensional manifold from initial structure shown in Fig.1A.

Based on the shape in Fig.1A, its embedded manifold is calculated by Isomap algorithm, which is shown in Fig.1B. In this figure, there was a curve denoted the nearest path between the two points in Fig.1A. This path was the
approximation to the geodesic distance denoted by a dashed line. Obviously, the low-dimensional feature points perfectly preserved the similarity reflected on the high-dimensional feature space.

2.4 Training and test

Two dimensional reduction techniques, PCA and manifold learning, were compared in this study. For the low-dimensional features processed by PCA, neural network (NN) was selected as the classifier. For this combined method PCA+NN, the best parameters values were chosen when the highest classification accuracy was obtained by training and test on the training samples with 5-fold cross validation (CV).

For the low-dimensional features processed by manifold learning (ML), we coupled with the $k$-nearest neighbor (KNN) algorithm as the classifier. To select the best parameter values for the method ML+KNN, during the test, suppose that parameter $d$ denotes the number of reduced dimension and was varied from 2 to 10; the nearest neighbor parameter $p$ was varied from 5 to 9; The test of the method ML+KNN was carried out by the following six steps: 1). The feature vectors of 30 OACs and 30 non-OACs were randomly selected from the two feature vectors sets (in Section 2.2), respectively. These 60 feature vectors were used as two types of feature templates. The remnant vectors in the two sets were used as a test set. This test set was then divided into many test groups. In every group there were $n$ test vectors. Then, these $n$ vectors were combined with above 60 feature templates (in the test procedure, $n \leq 6$ and was varied from 3 to 6). 2). ML was applied on those $60+n$ vectors. Thus, we could obtain the new $60+n$ low-dimensional test vectors. 3). KNN algorithm was used to classify those $n$ low-dimensional test vectors. The parameter $k$ in the KNN algorithm was set as 9. The classified results were compared with manually classified results labeled by neurophysiologist. 4). Select the next test group (i.e., another $n$ test vectors) and repeat the second and the third steps. Then, average across the classification accuracies of all test groups. Thus, the classification accuracy based on the current 60 templates was obtained. 5). Repeat the above four steps 33 times on different 60 feature templates (because there are about 1980 vectors in the two feature sets). At last, average across the accuracies of 33 times. Thus, this averaged value could basically reflect the identified capability of the method ML+KNN under the current group with the specific parameter values. 6). Select another group of parameter values and repeat the above five steps.

Finally, the highest classification accuracy with a group of parameter values was obtained, which was considered as the classification performance of the method ML+KNN.

To comparison with above two combined methods, FDA and NN were selected to train and test directly on the initial features set (i.e., not to do the preprocessing of dimensional reduction). FDA is a dimensional reduction technique in terms of maximizing the separability of different classes. It determines a projection vector that maximizes the scatter between the classes while minimizing the scatter within each class [18]. It is a typical linear classification method. At last, the performances of all above classification methods are compared in the next section.

2. Result

By the training and testing procedures above, the highest classification accuracy was obtained lastly, and the corresponding parameters values were considered as the best values suitable for the classification scheme. First, we list the best parameters values as follows: 1). For the combined method PCA+NN, the number of reduced dimension $d = 5$; the number of sigmoidal hidden nodes was equal to 5; learning rate was equal to 0.2; control precision $\epsilon = 0.01$. 2). For the combined method ML+KNN, parameter $n = 6$; the number of reduced dimension $d = 2$; the nearest neighbor parameter $p = 5$. 3). For the classifier NN, the number of sigmoidal hidden nodes was equal to 5; learning rate was equal to 0.1; control precision $\epsilon$ was equal to 0.01.

Second, the accuracies of various classification schemes with the best parameters above are listed in Table 1. It showed that FDA performed the poorest and ML+KNN the best. The classification accuracy of 81.77% indicated FDA was not suitable for identifying EOG artifacts. For the NN, classification accuracy of 92.42% was achieved. That result was notably higher than that of FDA. For the scheme of PCA+NN, the accuracy of 91.50% was even poorer than NN. This problem may arises in part from the inherent assumption in PCA that feature data lie on linear subspace. The classification accuracy of the method ML+KNN achieved the highest value of 99.79%.

### Table 1. Classification accuracies of different classification scheme (%)

<table>
<thead>
<tr>
<th>classification schemes</th>
<th>classification accuracies</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDA</td>
<td>81.77</td>
</tr>
<tr>
<td>NN</td>
<td>92.42</td>
</tr>
<tr>
<td>PCA+NN</td>
<td>91.50</td>
</tr>
<tr>
<td>ML+KNN</td>
<td>99.79</td>
</tr>
</tbody>
</table>

A dataset example of removing EOG artifacts by the presented technique is shown in Fig.2. In that figure, 18 black thin lines denote the initial EEG records. The presented technique successfully identified the IC1 and IC2 as OACs. The corrected EEG signals are shown in the same figure with gray thick lines in comparison to the initial EEG records.

For the real EEG signals, it is difficult to do an accurate evaluation of the performance of artifacts removal as we do not have a priori information available of the underlying ictal signals. Even so, by observing Fig.2, it can be found that the waveforms of some electrodes are not obviously affected by EOG artifacts. Based on the above discussion, in order to evaluate the performance of artifacts removal rationally, the measure of crosscorrelation coefficient (CC) was used in this study. The CC value of two variables $u$ and $v$ is expressed as follows:
\[ \rho(u,v) = \frac{E[uv]}{\sqrt{E[u^2]E[v^2]}} \] (1)

Figure 2. The effect of EOG artifact removal by applying presented technique. The initial EEG was represented by black thin lines, and the corrected EEG gray thick lines.

We calculated the CC value between the two waveforms on the same electrode of the initial and the corrected signals. Thus, 16 CC values (except for VEO and HEO electrodes) could be obtained, which served as a criterion for measuring the performances of artifacts removal.

Considering that initial waveforms of front 12 electrodes were drifted after blinking, we first excluded the segment of blink waveform, and then calculated CC values respectively before and after the segment of blink waveform. At last, we averaged across the two CC values at the same electrode. For the other electrodes, we calculated those by the common manner.

16 CC values between initial and corrected EEG signals are shown in Fig.3. This figure shows there are relatively low values on the front six electrodes. Observing the initial EEG shown in Fig.2, the waveforms on those electrodes, in fact, drifted seriously after blinking and moving eye. Furthermore, notice that there was another small blink waveform occurred at about 2.7s, so it was a conceivable result. The CC values on the other electrodes were significantly higher than those on front six electrodes especially on the last four electrodes. This conclusion corresponds to the actual situation that those waveforms are almost free from the influence of EOG artifacts. Above experimental results indicates that, after removing two kinds of artifacts by the proposed technique, the ictal activities were basically preserved with little distortion.

4. Discussion

The aim of this paper is to develop an online and robust EOG artifacts removal method. The significance of the proposed method lies in two aspects. First, manifold learning, a nonlinear dimensionality reduction method, is introduced to the field of EOG artifacts removal. Second, we present a simple and effective scheme of online application. For comparison, PCA, a linear dimensionality reduction method, is used in this study. In order to verify the effect of the dimensional reduction scheme, the two classified methods—FDA and NN, are selected. Classification results show that FDA is unsuitable for classifying EOG and non EOG artifacts. Furthermore, results show that PCA could not improve classification accuracy significantly. However, classification accuracies can be evidently enhanced by applying manifold learning to reduce dimensionality. Namely, it is feasible to use manifold learning to reduce the dimension of initial features.

In recent years, maybe the most successful applications of manifold learning are in the field of video and image data. However, it was worthy to mention that most previous studies about manifold learning are not used in the field of pattern recognition or online application but rather in data visualization and off-line analysis. Even though a few authors applied the method in the field of pattern recognition such as face recognition, manifold learning was applied only for the single group data set \(^{[14]}\), \(^{[15]}\) and \(^{[19]}\) instead of for the online stream data. Thus, there was no generalization power in those applications. While using manifold learning to solve the problem of online classification, unlike NN or support vector machine (SVM), there was no so-called hyperplane. All the new test samples must be constructed into a new manifold structure. That is to say, prior classification information was not available for the new classification procedure. Furthermore, too many features samples would consume much time to construct the manifold. Because of the above two characteristics, few researchers applied the manifold learning to process the classification of online stream data. However, in this study, we improved the usual way of the application of manifold learning and used the proper number of features samples to construct manifold, thus manifold learning could be introduced into the online application. In addition, the technique of using feature templates also makes
ML suitable for processing the online stream data.

In fact, the best parameter values used in the scheme have relative stability. So, if testing to select the feature templates with fixed parameter values, the time of test procedure will be very short even if there are a number of feature samples. However, SVM-based artifact removal approach \(^{15}\) requires a complex training step. Moreover, as we know, SVM cannot perform the training task for the too many training samples. So the method based on SVM seems to be not an adequate solution. The proposed method is simpler and more convenient than the SVM method for removing EOG artifacts in online application.

**Acknowledgement**

The work is supported by National Nature Science Foundation of China (#30870654).

**References**


