Improving The Accuracy Of Brain Computer Interface By Eliminating Eye Blink Arțifacts From EEG Data Using ICA

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Abstract

The accuracy of brain computer interfaces (BCI) depends upon the quality of electroencephalographic (EEG) signals from the subject. Artifacts in EEG present serious problems for EEG interpretation and analysis which also reduces the accuracy of BCI. Many methods have been proposed to remove artifacts from EEG recordings, especially those arising from eye movements and blinks. Because EEG and ocular activity mix bi-directionally, regressing out eye artifacts inevitably involves subtracting relevant EEG signals from each record as well. Regression methods become even more problematic when a good regressing channel is not available for each artifact source. Use of principal component analysis (PCA) has been proposed to remove eye artifacts from multichannel EEG. However, PCA cannot completely separate eye artifacts from brain signals, especially when they have comparable amplitudes. Here, a new and generally applicable method for removing a wide variety of artifacts from EEG records based on blind source separation by independent component analysis (ICA) is used. Our results on EEG data show that ICA can effectively detect, separate, and remove contamination from a wide variety of artifactual sources especially due to Eye Ball movement, Eye Blink and Multiple Eye Blinks in EEG records. Thus removing these artifacts resulted in improving the accuracy of BCI.

Key Words: Electroencephalography (EEG), Artifacts, Independent Component Analysis (ICA), Brain Computer Interfaces (BCI), Electro-oculography (EOG).

1. Introduction

Due to the low conductivity of the skull, EEG measurements have very low signal strengths, typically a few microvolts. Thus, noise reduction is critical in developing a successful BCI system. Of the many noise sources, the most irreducible are the ones that originate from physiological processes. These so-called artifacts are mainly due to various muscle activities whose electrical influences corrupt the EEG measurements. The artifacts due to eye movements are called ocular artifacts. This is measured in terms of Electro Oculogram (EOG). Heart activity as measured in Electro Cardiography (ECG or EKG) and other muscle activities measured in Electro Myography (EMG) around the EEG measurement sites also interfere with the measurements. In this paper we implementated ICA algorithm technique to remove the ocular artifacts and study their effects in the final performance of the BCI system. Of the different sources of artifacts mentioned above, the strongest are the artifacts due to eye blinking and movements. There is a voltage

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difference between the retina and cornea and this acts as a dipole source. Eye movements change the orientation of this dipole and induce varying artifacts. Blinking also changes the resistance of the pathway across the eye. Rejecting EEG segments with artifacts larger than an arbitrarily preset value is the most commonly used method for dealing with artifacts in research settings. However, when limited data are available, or blinks and muscle movements occur too frequently, as in some patient groups, the amount of data lost to artifact rejection may be unacceptable. Several proposed methods for removing eye movement artifacts are based on regression in the time domain or frequency domain. However, simple regression in the time domain for removing eye artifacts from EEG channels tends to overcompensate for blink artifacts and may introduce new artifacts into EEG records. The cause of this overcompensation is the difference between the electrooculographic (EOG)-to-EEG transfer functions for blinks and saccades. Saccade artifacts arise from changes in orientation of the retinocorneal dipole, whereas blink artifacts arise from alterations in ocular conductance produced by contact of the eyelid with the cornea. The pickup of blink artifacts on the recording electrodes decreases rapidly with distance from the eyes; whereas the transfer of saccade artifacts decreases more slowly, so that at the vertex the effect of saccades on the EEG is about double that of blinks.

Regression methods in either time or frequency domain depend on having a good regressing channel (e.g., EOG), and share an inherent weakness that spread of excitation from eye movements and EEG signals is bi-directional. Therefore, whenever regression based artifact removal is performed, relevant EEG signals contained in the EOG channel(s) are also cancelled out in the "corrected" EEG channels along with the eye movement artifacts. The same problem complicates removal of other types of EEG artifacts. For example, good reference channels for each of the muscles making independent contributions to EEG muscle noise are not usually available [4].

Makeig, Bell, Jung, and Sejnowski proposed an approach to the analysis of EEG data based on a new unsupervised neural network learning algorithm, independent component analysis (ICA). They showed that the ICA algorithm can be used to separate neural activity from muscle and blink artifacts in spontaneous EEG data and reported its use for finding components of EEG and event-related potentials (ERP) and tracking changes in alertness [3]. Other techniques proposed for EEG artifacts elimination are "Combined polynomial neural network and decision tree techniques"[6], "Two adaptive algorithms (*time varying* and *exponentially weighted*) based on the H" [7] and "The combination of geometric methods based on maximum SFA and short-time PCA and time-delay embedding" [8]. All these techniques are proposed for specific type of artifact, not a single method could eliminate all possible types of artifacts.

2. Brain Computer Interface

A brain–computer interface (BCI) is a system that analyzes the brain-electrical activity of a subject and tries to generate appropriate feedback actions, thus enabling the user to communicate with a computer by willfully altering his or her brainwaves [9]. Brain Computer Interface (BCI) tries to read intentions from the electrical activity of the brain. Instead of the standard communication channel between a human being and a computer involving keyboard and mouse, physically disabled individuals who are unable to reliably use their hands depend on alternative solutions. One possibility is given by systems that are based on the analysis of signals related to muscular activity. With the newest progress in modern computer technology, the attempt to devise a direct link between the human brain and a computer became more and more popular [10]. The main challenge in brain computer interfaces is to identify the particular EEG signal components that can be successfully used as control commands. Eye blinks and eye movements did not serve as a source of artifactual control, but EOG artifacts tended to reduce the accuracy of EEG recordings and inhibit EEG-based control [13].

3. Electroencephalography

EEG or electroencephalogram is a test of the brain's electrical activity. Nerve cells in the brain called neurons send off small electrical impulses toward surrounding cells. An EEG is used to detect these impulses with the help of an amplifier. The EEG traces are then used to diagnose diseases and analyze symptoms. Our brains are active 24 hours a day, so an EEG can be made whether a patient is awake or asleep. An advantage to an EEG test is the vast amount of information that can be obtained without invasive procedures. Until now, EEG has largely been used for diagnosis and treatment of epilepsy. EEG, electroencephalography, is the recording of voltages from the brain. In special circumstances, the recording can be done directly from the brain surface, but normally electrodes on the scalp are used [11].

Originally, it was thought that EEG potentials present a summation of the action potentials of the neurons in the brain. Later theories however indicate that the electrical patterns obtained from the scalp are actually the, result of the graded potentials on the dendrites of neurons in the cerebral cortex and other parts of the brain, as they are influenced by the firing of other neurons that impinge on these dendrites [3].

4. Artifacts

Movement of the eyes and eyelids can be separated into blink, lid movement and eye movement. Eye movement artifact itself result from movement of the corneo-retinal dipole (the cornea being positive with respect to the retina) as the globe moves. The lids, on the other hand, have a shunting effect on the external electric field of the corneo-retinal dipole). Although the lower lid may move entirely synchronously with eye movement, the upper lid may not reach its final position for a short time after completion of the eye movement when the eyes are open. This lag, during a change of the point of fixation vertically (e.g. during a saccade) gives rise to the 'rider' artifact in the electro-oculogram (EOG) recorded bipolarly from electrodes above and below the eye. Correspondingly, these authors suggested that it might be possible to avoid rider artifact in the vertical EOG by recording from an electrode below the eye against a remote reference.

Blinking consists primarily or exclusively of lid movement. It is therefore not surprising that the distributions over the scalp of the electric field of eye movement and of lid movement are different, that from lid movement being more limited. In addition to artifacts arising during the waking state, rapid eye movements can contaminate the EEG from anteriorly placed electrodes during REM sleep. And slow horizontal or lateral eye movements can contaminate the EEG during drowsiness and light sleep. A rhythmic eye movement artifact in preterminal and terminal patients can stimulate a rhythmic EEG and therefore result in erroneous evaluation of the latter [14, 15].

Blink artifact may be diminished in frequency of occurrence by fingers applied lightly on the lids and when the eyes are open, by steady fixation. Eye movements can be dimished, by having the individual to fixate his own pupil in a mirror, or to view a stimulus so designed as to required constant fixation [1, 2]

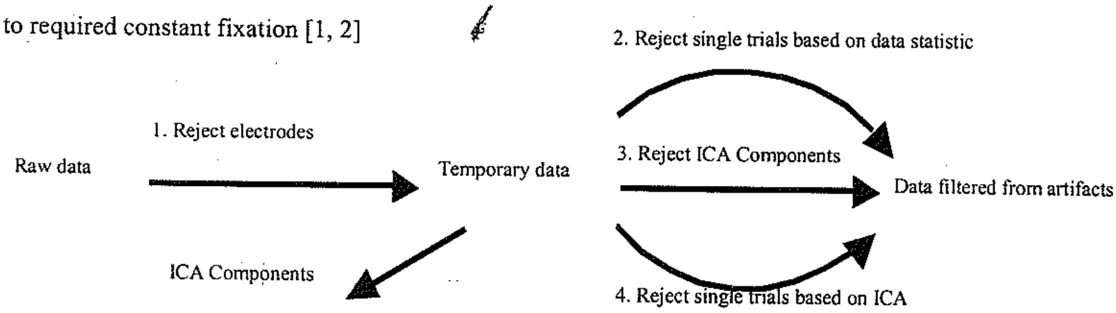

Figure 1 : Schema for combining different types of rejection. After rejecting bad electrodes (1) and computing ICA, the algorithm combines three types of rejection. Trials can be rejected depending on the data statistics or the independent component statistics (respectively 2 and 4). Subtraction of artifactual independent components n also be performed (3).

5. Independent Component Analysis

Recently, blind source separation by Independent Component Analysis (ICA) has received attention because of its potential applications in signal processing such as in speech recognition systems, telecommunications and medical signal processing. The goal of ICA is to recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. In contrast to correlation-based transformations such as Principal Component Analysis (PCA), ICA not only decorrelates the signals (2nd-order statistics) but also reduces higher-order statistical dependencies, attempting to make the signals as independent as possible.

Having estimated these higher statistical properties of the signal, one might ask, why should we go further? All the measures used so far are based on raw potential values at single electrodes. However, EEG activity at different electrodes is highly correlated and thus contains redundant information. Also, several artifacts might be represented at the same set of electrodes and it would be useful if one could isolate and measure these artifacts based on their projection to overlapping electrode subsets. This is what ICA does [3, 5]. One can imagine an n-electrode recording array as an n-dimensional space. The recorded signals can be projected into a more relevant coordinate frame than the single-electrode space: the independent component space. In this new coordinate frame, the projections of the data on each basis vector i.e. the independent components are maximally independent of each other. Assessing the statistical properties of the data reprojected onto these axes, one might be able to isolate and remove the artifacts more easily and efficiently. As shown in Fig. 1, using high-order statistics of the raw data and of the independent components, it may be able to semi automatically reject trial artifacts [12].

One may believe that artifacts might be detected more accurately using high-order statistical measures of the signals, regardless of the exact implementation of these measures. This approach allows experimenters to use information in the data that was taken into account by standard rejection methods [5].

6. Algorithm

In contrast with decorrelation techniques such as PCA, which ensure that output pairs are uncorrelated ($(u \; u_j) = 0$, *for all i, j*), ICA imposes the much stronger criterion that the multivariate probability density function (p.d.f.) of u factorizes:

$$f_u(u) = \prod_{i=1}^{N} f_{u_i}(u_i) \tag{1}$$

Statistical independence requires all higher-order correlations of the u to be zero, while decorrelation only takes account of second order statistics (covariance or correlation). Bell and Sejnowski (1995) derived a simple neural network algorithm based on information maximization ("infomax") that can blindly separate super-Gaussian sources (e.g., sources that are "on" less often than a Gaussian process with the same mean and variance). The important fact used to distinguish a source, s_i, from mixtures, x_i, is that the activity of each source is statistically independent of the other sources. That is, their joint probability density function (p.d.f.), measured across the input time ensemble, factorizes. This statement is equivalent to saying that the mutual information between any two sources, s_i and s_j is zero:

$$I(u_1 u_2, \ldots, u_N) = E\left[\ln \frac{f_u(u)}{\prod_{i=1}^{N} f_{u_i}(u_i)}\right] = 0 \tag{2}$$

where E [.] denotes expected value, ($s_i \; s_j$) are actual sources and ($u_i u_j$) are desired outputs. In equation (2) only ($u_i u_j$) are shown since properties of ($s_i \; s_j$) are being implemented on ($u_i u_j$). Unlike sources, s_i's, which are assumed to be temporally independent, the observed mixtures of sources, x_i's, are statistically dependent on each other, so the mutual information between pairs of mixtures, I (x_i, x_j) is in general positive.

The blind separation problem is to find a matrix, **W**x such that the linear transformation

$$u = Wx = Was \tag{3}$$

reestablishes the condition $I(u_i u_j) = 0$ for all $i \neq j$.

Consider the joint entropy of two nonlinearly transformed components of **y**:

$$H(y_1, y_2) = H(y_1) + H(y_2) - I(y_1, y_2) \tag{4}$$

where $y_i = g(u_i)$ and $g(\,)$ is an invertible, bounded nonlinearity. The nonlinearity function provides, through its Taylor series expansion, higher-order statistics that are necessary to establish independence. The form of the nonlinearity $g(u)$ plays an essential role in the success of the algorithm. The ideal form for $g(u)$ is the cumulative density function (c.d.f.) of the distributions of the independent sources. When $g(u)$ is a sigmoid function, the algorithm is then limited to separating sources with super-Gaussian distributions [3]. Maximizing this joint entropy involves maximizing the individual entropies, $H(y_1)$ and $H(y_2)$, while minimizing the mutual information, $I(y_1, y_2)$, shared between the two. Thus, maximizing $H(y)$, in general, minimizes $I(y)$. When this latter quantity is zero, the two variables are statistically independent.

7. Results

For illustration purpose one data set of 10-seconds with 30 channels is used. That is input matrix 'X' (original EEG) is having 30 rows and output matrix 'U' (corrected EEG) is also having 30 rows. Data was recorded on a polysomnography machine with 256 Hz sampling frequency.

Fig. 2 shows a 10-s portion of the recorded EEG time series and its ICA component activations are shown in Fig. 3. The "corrected" EEG signals obtained by removing selected EOG component from the data are shown in Fig. 4. The eye blink artifacts at 0.5 s, 4 s, 5.5 s & 9.2 s (see Fig. 2) were isolated to ICA component 1. Its scalp map indicates that it accounted for the spread of EOG activity to frontal sites. After eliminating this component and projecting the remaining components onto the scalp channels, the corrected EEG data were free of these artifacts.

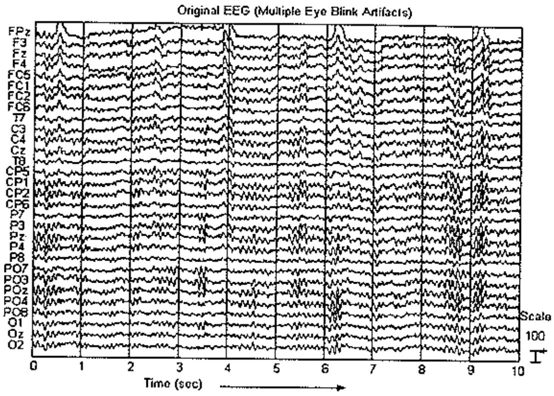

Figure 2

Table 1: The effect of removing artifacts in terms of the average classification accuracy.

Data Set	Accuracy	
	Without Artifact Removal (%)	With Artifact Removal (%)
1	39.0	42.1
2	58.2	64.5
3	59.4	66.2

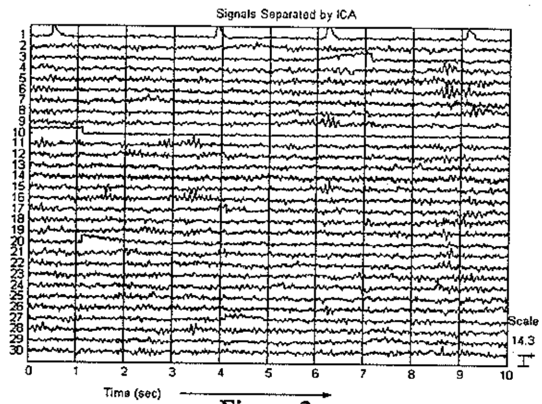

Figure 3

Removing EOG activity from frontal channels revealed alpha activity at time points like 9.2 s that occurred during the eye blink but was obscured by the eye artifact in the original EEG traces. Close inspection of the EEG records (Fig. 2) confirmed its existence in the raw data. Table 1 shows the improved accuracy of BCI for different datasets along with dataset-1shown in this paper.

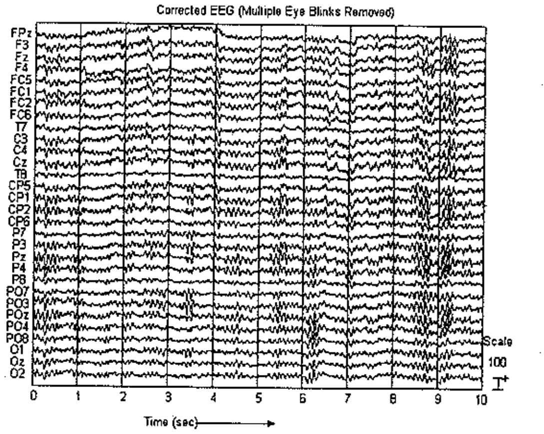

Figure 4

8. Conclusion

Ocular artifact removal is a necessary step in getting the best performance out of a BCI system. A simple model of linear propagation of the artifacts into the EEG data and a least square estimation of the propagation constants will not yield satisfactory results. A slightly more complicated model is necessary to take care of the temporal correlations present in the data.

However, a model too detailed may not be appropriate due to implementation considerations such as speed vs. marginal performance increment. The efficiency of an artifact removal algorithm can be studied in terms of the performance (classification accuracy) of the brain computer interface system that implements it. We have studied various methods of increasing complexity and found that the most complex one i.e., ICA works best. ICA opens new and useful windows into many brain and non-brain phenomena contained in multichannel EEG records by separating data recorded at multiple scalp electrodes into a sum of temporally independent components.

In many cases, the temporally independent ICA components are also functionally independent. In particular, ICA appears to be a generally applicable and effective method for removing a wide variety of artifacts from EEG records, because their time courses are generally temporally independent and spatially distinct from sources of cerebral activity. Thus, by eliminating the multiple eye blink artifacts we may accurately implement Brain Computer Interfaces.

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