Rejection of Electro-oculograpic Artifacts from EEG Data Using ICA Algorithm

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Abstract- Many methods have been proposed to remove artifacts from EEG recordings, especially those arising from eye movements and blinks. Often regression in the time or frequency domain is performed on parallel EEG and electro-oculographic (EOG) recordings to derive parameters characterizing the appearance and spread of EOG artifacts in the EEG channels. 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, as in the case of muscle artifacts. 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, we used 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). Our results on EEG data of normal and autistic subjects show that ICA can effectively detect, separate, and remove contamination from a wide variety of artifactual sources especially due to EOG in EEG records. Various tests have been made on electroencephalogram (EEG) signals in order to remove ocular while conserving pathological activity. The results are compared with other methods and medical inspection has been carried out to prove that this approach yields very good performance.

Keywords – Electroencephalography (EEG), Artifacts, Independent Component Analysis (ICA), Electro-oculography (EOG)

I. INTRODUCTION

Eye movements, eye blinks, muscle noise, heart signals, and line noise often produce large and distracting artifacts in electroencephalographic (EEG) recordings. Asking subjects to fixate a visual target may reduce voluntary eye movements (blinks and saccades) in cooperative subjects during brief EEG sessions, but fixation does not eliminate involuntary eye movements and cannot be used when the subject is performing a task requiring eye movements. 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], [5].

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) of Bell and Sejnowski. 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" [8], "Two adaptive algorithms (*time varying* and *exponentially weighted*) based on the $H\infty$" [9] and "The combination of geometric methods based on maximum SFA and short-time PCA and time-delay embedding" [10]. All these techniques are proposed for specific type of artifact, not a single method could eliminate all possible types of artifacts.
In this work to illustrate the artifact rejection we used only some data sets and that too their small parts, like 2-s, 3-s, 5-s or 10-s portions with only 10 or 16 or 30 channels in different examples. The ICA algorithm is implemented in MATLAB 6.5v and also some toolbox functions are used for convenience in drawing maps and graphs.

II. 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.

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.

III. Artifacts

The traditional way of handling artifact in EEG data processing has been to exclude from the analysis those portions of the recording that to the eye are contaminated by artifact, i.e., to select 'artifact-free' portions of the record for analysis. This method is, however not reliable especially for artifacts of small amplitudes. For example, the amounts of artifactual slow activity in the delta frequency range can be underestimated. Increasingly, therefore such a manual technique has come to be supplemented and even replaced by automatic methods.

A. Artifacts due to Eye and Eyelids –

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. (The familiar upward rolling of the eyes that occurs upon attempted closure of the eyes when the lids are held open by the fingers, Bell's phenomenon, thus may only be minimally present during a normal blink).
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.
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 diminished, 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].

B. Methods of Processing of EOG Artifacts –

Of all the types of artifact, that from eye and lid movement has received perhaps the largest attention. Methods for processing of this artifact have ranged from the relatively simple to the relatively complex. It will be useful to subdivide the methods into the following types:

1) Artifact rejection, i.e., deletion of contaminated portions or epochs of the EEG, or of trials, in event-related potential studies;
2) Simple subtraction techniques, in which an empirically determined (i.e., by manually adjusting a potentiometer) percentage of the elctro-oculogram (EOG) is subtracted from the EEG;
3) Automatic subtraction techniques, in which the preceding procedure is carried out automatically by analog circuits or by a computer;
4) Frequency domain or spectral techniques, in which the EEG spectrum is either weighted if eye movement is present, or, is corrected for the EOG contamination;
5) Combined time and frequency domain techniques.

IV. Indipendent 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.

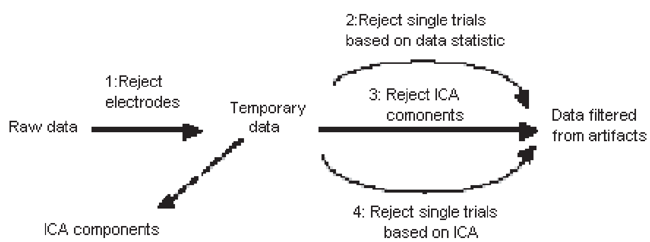

Figure 1. Schema for combining different types of rejection. After rejecting bad electrodes (1) and computing ICA, the algorithm combines three types of rejection. Trials can be rejected depending on the data statistics or the independent component statistics (respectively 2 and 4). Subtraction of artifactual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

A. ICA for EEG Artifacts Elimination –

Having estimated these higher statistical properties of the signal, one might ask, why should we go further? All the measures we have 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 we could isolate and measure these artifacts based on their projection to overlapping electrode subsets. This is what ICA does [3], [6]. 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, we 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, we may be able to semi automatically reject trial artifacts.

We believe that one may detect artifacts 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 [6], [4].

V. METHODOLOGY

A. ICA Algorithm –

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

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

Statistical independence requires all higher-order correlations of the u_i 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:

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

where E [.] denotes expected value. 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**, such that the linear transformation

$$\mathbf{u} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{a}\mathbf{s} \qquad (3)$$

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**:

$$H(y_1, y_2) = H(y_1) + H(y_2) - I(y_1, y_2) \qquad (4)$$

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.

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VI. RESULTS AND FINDINGS

For illustration purpose we used two data sets of 3-seconds each with 30 channels. That is input matrix 'X' (original EEG) is having 30 rows and output matrix 'U' (corrected EEG) is also having 30 rows.

Example 1: Removing Eye Blink Artifact –

Fig. 2 shows a 3-s portion of the recorded EEG time series. 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 artifact at 0.8 s (left side of Fig. 2) was isolated to ICA component 1. After eliminating this component and projecting the remaining components onto the scalp channels, the corrected EEG data (Fig. 4) were free of this artifact.

Removing EOG activity from frontal channels revealed alpha activity near 10 Hz 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.

Example 2: Removing Eye Movement Artifact–

Fig. 5 shows a 3-s portion of the recorded EEG time series collected from 30 EEG channels. Fig. 6 shows the derived ICA component activations. The eye movement artifact between 1 and 2 s was isolated to ICA component 5.

The “corrected” EEG signals obtained by removing the selected (EOG) component from the data are shown in Fig. 7. After eliminating this artifactual component, by zeroing out the corresponding row of the activation matrix **u** and projecting the remaining components onto the scalp electrodes, the “corrected” EEG data were free of EOG artifact.

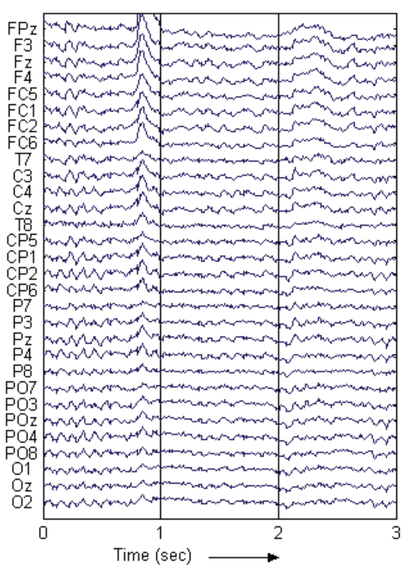

Figure 2 : Original EEG contaminated with EOG (Example 1)

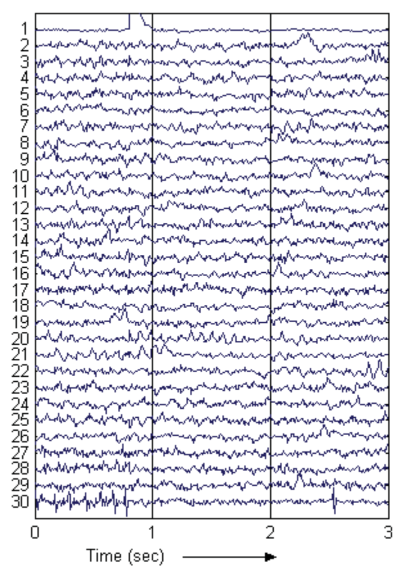

Figure 3 : Signals Separated by ICA (Example 1)

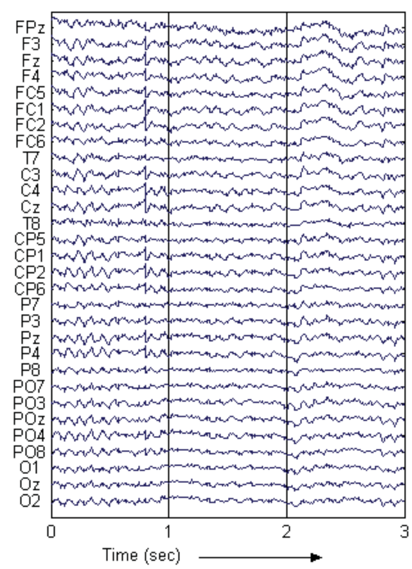

Figure 4 : Corrected EEG i.e., EOG artifact removed (Example 1)

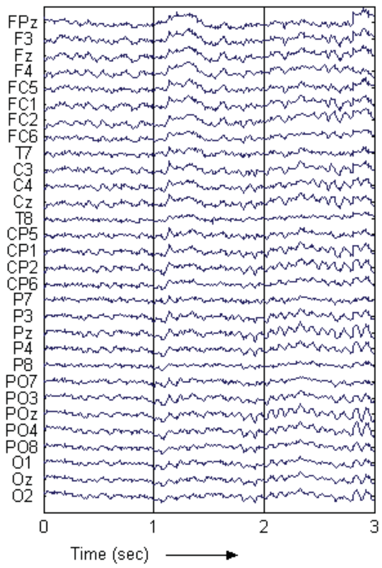

Figure 5 : Original EEG contaminated with Eye Movement Artifact (Example 2)

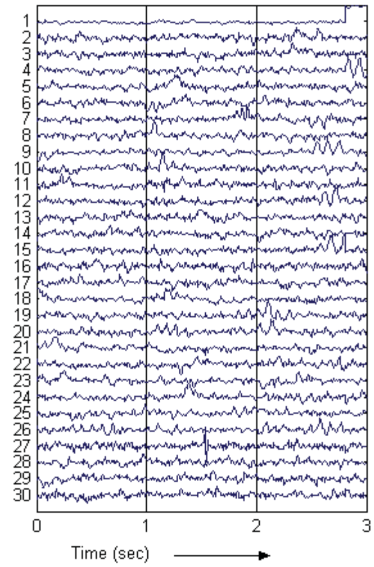

Figure 6 : Signals Separated by ICA (Example 2)

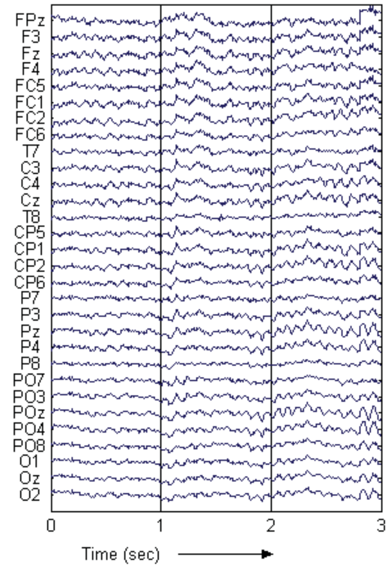

Figure 7 : Corrected EEG i.e., Eye Movement Artifact Removed (Example 2)

IV.CONCLUSION

ICA has opened new and useful window 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. However, because ICA decomposition is based on the assumption that EEG data are derived from spatially stationary brain or extra-brain generators, further research will be required to fully assess the value and limitations of this analytic method.

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