Analyzing and Eliminating Artifacts in EEG Signal

(using Independent Component Analysis)

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• **Abstract**— The Human Brain is the main control unit of body. It continuously monitors and controls the body activities. It receives the body related information by ionic current flowing inside the neurons of the brain. To detect any variation in the ionic current, resulting by movement of body parts is measured by Electroencephalography (EEG). These body movements tend to introduce a noise type distortion in measured EEG signal, known as artifacts. Artifacts can be introduced even due to movement or blinking of eyes. The electric dipole in human eyes is due to positive cornea and negative retina. Eye movements and blinks causes change in electric dipole. Here we are applying an adaptive method for eliminating artifacts from EEG signal, which is based on Blind Source Separation (BSS) using Independent Component Analysis (ICA). BSS using ICA can be used to effectively detect, separate and remove ocular artifacts, arising by eye movements from heavily contaminated EEG data. For performing this operation, ICA is computed with an unknown mixing vector and corresponding source signal is removed to get original EEG signal.

Index Terms— EEG, Artifacts, BSS, Blind Source Seperation, ICA , Correction of Artifact, EEGLab,

1. INTRODUCTION (EEG)

The electrical activity of brain is recorded by EEG that measures voltage fluctuations resulting from ionic current flowing within neurons of the brain. Neurons are electrically charged by membrane transport proteins that pump ions across their membranes. The recording is over a short period of time, usually 20-40 minutes. EEG activity is quite small, measured in micro-volts and frequency up to 30Hz. Low voltage, high frequency components that cannot be seen easily (or at all) in scalp during EEG, can be seen clearly in ECoG, i.e. Electrocorticography. The signal recorded from ECoG is on a different scale of activity than the brain activity recorded from scalp EEG. Further, smaller electrodes (which cover a smaller parcel of brain surface) allow even lower voltage, faster components of brain activity to be seen. The electric potentials generated by single neurons are far too small to be picked by EEG or MEG. EEG activity therefore always reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. If the cells do not have similar spatial orientation, their ions do not line up and create waves to be detected. EEG is typically recommended when there is need to distinguish epileptic seizures, psychiatric syndromes and to measure depth of anesthesia to be given to patient before operating. There are two types of EEG recording, (i) Short Term and (ii) Long Term. Short term recording is for about 20 minutes, which uses about 20 electrodes placed on scalp. Long term monitoring involves hospitalization of the patient for a period of time, typically days to weeks, during which they are continuously monitored and recorded with a video camera and an electroencephalograph. Generally, there are two types of electrodes placement for EEG recording:

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1.1 International 10-20 System

In this system, electrodes on scalp are spaced at 10% or 20% of distance of scalp by using 21 electrodes. But, in this system we can use up to 32 electrodes to get increased spatial resolution and also to record EEG from specific areas on scalp. It also monitors other activities like Cardiac action and eye movements & blinks.

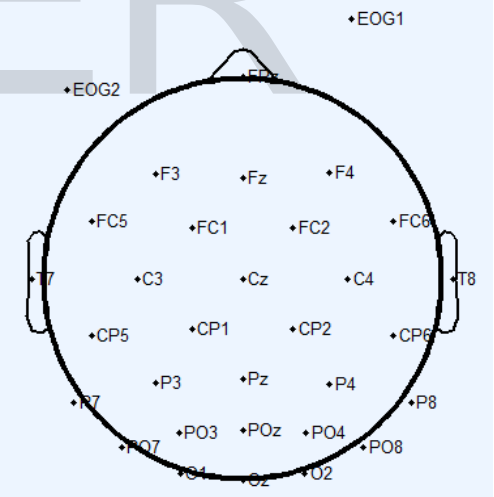

Figure 1(a) 32 Electrodes placed on scalp

The six electrodes: FPz, EOG1, F3, Fz, F4, EOG2 are placed on frontal lobe of scalp to detect artifacts arising due to eye movement and blinks, where F denotes Frontal Lobe, P for Parietal Lobe, z is for electrode placed on mid-line of scalp and EOG for Electrooculographic electrodes, i.e. to detect eye movements.

1.2 International 10-10 system

This system can contain up to 256 electrodes, more or less evenly spaced on the scalp. The Letters represents:

F: Frontal Lobe
T: Temporal Lobe
C: Central Lobe
P: Parietal Lobe
O: Occipital Lobe
Z: Electrodes placed in mid-line

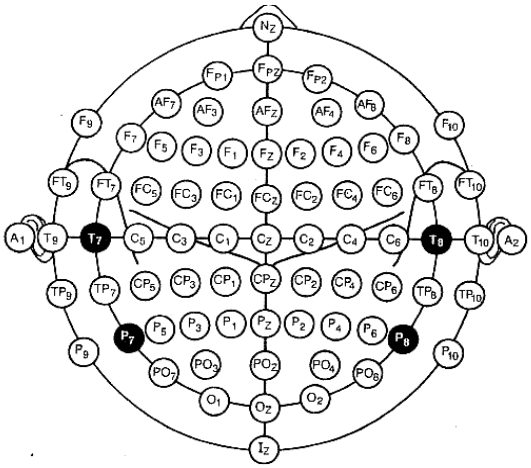

Figure 1(b) 10-10 Electrode Placement

2. ARTIFACTS

An artifact is a disturbance in a measured brain signal, not originating from brain. In other words, it is the contamination of EEG activity resulting from eye movements, blinks, muscular movements, heart and line noise that causes distortion in EEG data. These artifacts are classified in two categories: Internal and External.

External artifacts or environmental artifacts are caused by outer actions that originate from outside the human body. External artifacts results from unsatisfactory technology, present in mains A.C. frequency, battery power supply, electric field produced by external devices and cables.

Internal artifacts or biological artifacts are caused due to actions made by subject itself. Internal artifacts arise when the potential between electrodes changes as a result from eye movement or any other muscular activity. Other sources of internal artifacts include: Cardiac (heart) and glossokinetic (tongue movement)

Eye movements (blinks and saccades) are self-compiled motions of human body. Blinks artifacts arises due to alterations in ocular conductance produced by contact of the eyelid with the cornea, whereas saccades artifacts arise from changes in orientation of the retino-corneal dipole.

For eg, during an EEG session, a blink activity was reported by Channel 3 and the corresponding Event-Related Potential was also raised. Thus, this activity induced an artifact in EEG data. Now we have to eliminate this artifact from EEG signal to get the original signal.

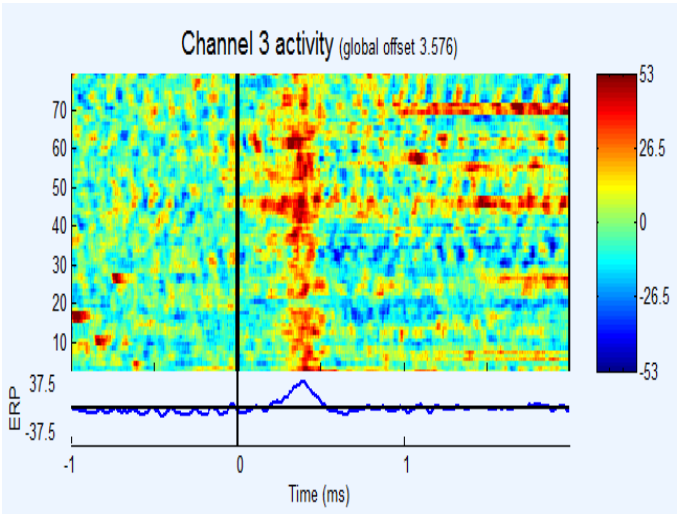

Figure 1(c) Blink activity reported by Channel 3

3. METHODS FOR CORRECTING ARTIFACTS

To eliminate such artifacts, various techniques required are,

1. Rejection,
2. Regression,
3. Blind Source Separation,
4. Independent Component Analysis.

3.1 Rejection

Rejection simply rejects heavily contaminated data, but also results in loss of important information, which is unacceptable.

3.2 Regression

The Regression method in Time or Frequency Domain is performed on parallel to EEG recording. Several proposed methods for removing eye move artifacts are based on regression in time 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 (EOG) -to- (EEG) transfer functions for Blinks and Saccades. Regression methods in either time or frequency domain depend on having a good regressing channel. As EEG and ocular activity mix bi directionally, regressing out eye artifacts 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. Regression method is acausal and thus unsuitable for real-time applications.

3.3 Blind Source Separation (BSS)

Blind Source Separation is a fundamental problem in signal processing. It is the separation of set of signal from set of mixed signals, without having information about source signals and mixing process. It relies on assumption that source signals do not correlate with each other, i.e. the signals are mutually statistically independent and un-correlated. Blind signal separation thus separates a set of

signals into a set of other signals, such that the regularity of each resulting signal is maximized, and the regularity between the signals is minimized i.e. statistical independence is maximized. The best example to understand BSS method is the case of a cocktail-party, where a number of people are talking simultaneously in a room and one is trying to follow one of the discussions. Multiple sound sources such as speakers, music or noise sources are measured by the microphones as a mixture, as shown in Fig. 3(a) and 3(b).

Imagine that in a room, two people are speaking simultaneously. There are two microphones, held at different locations. The microphones give recorded time signals, which we could denote by:
x1(t) and x2(t), with x1 and x2 the amplitudes, and t the time index.
Each of these recorded signals is a weighted sum of the speech signals emitted by the two speakers, which we denote by s1 (t) and s2 (t).
We could express this as a linear equation:

$$x_1(t) = a_{11}s_1 + a_{12}s_2 \quad (1)$$
$$x_2(t) = a_{21}s_1 + a_{22}s_2 \quad (2)$$

where a11, a12, a21 and a22 are some parameters that depend on the distances of the microphones from the speakers. It would be very useful if we could now estimate the two original speech signals s1(t) and s2(t), using only the recorded signals x1(t) and x2(t). This is called the cocktail-party problem.

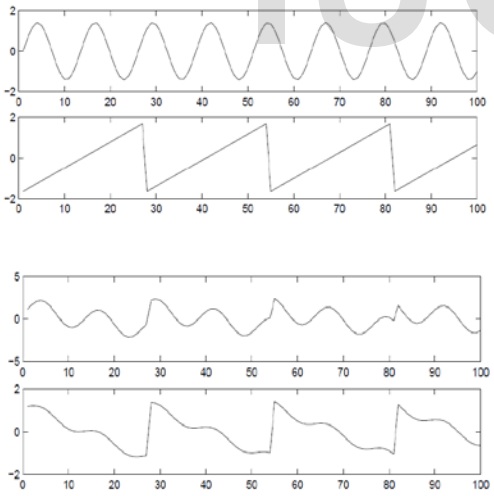

Figure 3(b) Mixture of signals

In the same way, we can co-relate this cocktail-party problem with artifacts in EEG signal. A general EEG record has large number of output signals as recorded from various channels on scalp. These signals are contaminated by artifacts, which are caused by movement of body muscles during EEG session. At that time we don't have any idea about the electric signal source, i.e. where in the brain the electrical activity is coming from, as EEG can only measure activity in general areas, not from specific neural connections. But after implementing Blind Source Separation method, we can easily detect and distinguish the original EEG signal from contaminated artifactual signal.

3.3.1 BSS Formulation:

The linear instantaneous mixing model of two source signals is,

$$X(t) = A_0 S(t) \quad (3)$$

where S(t) is the time dependent source signal vector; A0 is a 2x2 time independent unknown mixing matrix, X (t) is the known mixture signal. We wish to recover the source signal vector S, without knowing A0 (therefore blind), provided that all components of S (t) are independent random processes. In applications to sounds or images, the random processes in S(t) are non-Gaussian.

4. Independent Component Analysis (ICA)

ICA is a special case of BSS, which was originally proposed to solve Blind Source Separation problem to recover independent source signals,

$$s=s_1(t),s_2(t),\ldots s_N(t), \quad (4)$$

after they are linearly mixed by unknown matrix A, Nothing is known about the sources or the mixing process except that there are N different recorded mixtures,

$$x=x_1(t),x_2(t),\ldots,x_N(t)=As \quad (5)$$

ICA finds an unmixing Matrix 'W' that decomposes linearly unmixes the multi-channel scalp data into a sum of temporally independent and spatially fixed components. The Rows of the Input matrix 'X' are EEG signals recorded at different electrodes. The Rows of the Output data matrix are given by: U = WX. The task is to recover a version, U=Wx, of the original sources, s, by finding a square matrix, W, that inverts the mixing process linearly. ICA estimation principle is based on maximum non-gaussianity.

For EEG analysis, the rows of the input matrix x are the EEG signals recorded at different electrodes, the rows of the output data matrix U= Wx are time courses of activation of the ICA components and the columns of the inverse matrix W-1 give the projection strengths of the respective components onto the scalp sensors.

The scalp topographies of the components provide information about the location of the sources e.g., eye activity should project mainly to frontal sites, etc.. "Corrected" EEG signals can then be derived as:
x' = (W)-1u', where u' is the matrix of activation waveforms, u, with rows representing artifactual components set to zero. The rank of corrected EEG data is less than that of the original data.

The ICA algorithm can be used to separate neural activity from muscle and blink artifacts, as shown in Channel 3 of Fig. 4(a) (as composed in EEGLAB) in spontaneous EEG data and for finding components of EEG and Event-Related Potentials (ERP) and tracking changes in alertness. An Event-Related Potential (ERP) is the measured

brain response that is the direct result of a specific sensory cognitive or motor event. The study of the brain in this way provides a means of evaluating brain functioning. ERPs are measured with electroencephalography (EEG).

As the EEG data consists of recordings of electrical potentials in many different locations on the scalp. These potentials are presumably generated by mixing some underlying components of brain activity. This situation is quite similar to the cocktail-party problem, we would like to find the original components of brain activity, but we can only observe mixtures of the components.

5. RESULT

Applying ICA in EEG for eliminating Artifacts:
The data was collected from EEGLAB where in Channel 3, a blink movement was detected. Now our aim is to correct this artifact by applying ICA.

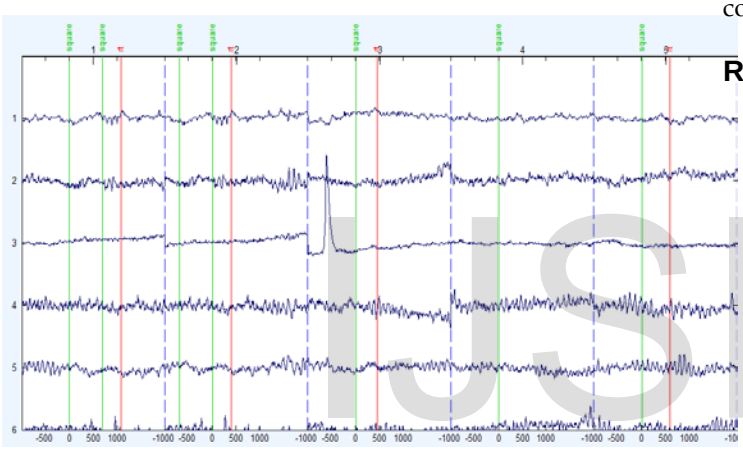

Figure 4(a) Blink activity in Channel 3

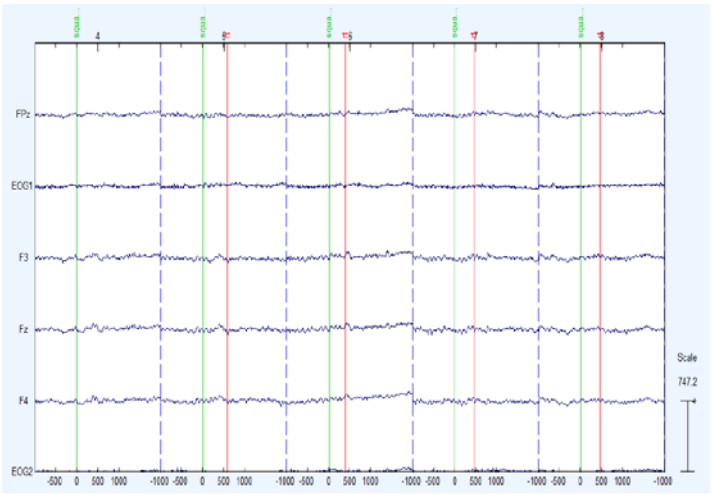

Figure 4 (b) Blink activity eliminated from Channel 3

CONCLUSION

The goal of ICA is to recover independent sources given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. ICA not only de-correlates the signals (2nd-order statistics) but also reduces higher-order statistical dependencies, attempting to make the signals as independent as possible.

Yet, ICA is limited to its approach, as we cannot determine the variances (energies) and order of the independent components.

The key finding is that although BSS using ICA is an effective and powerful tool for separating and removing contamination from EEG, the quality of the separation is highly dependent on the type of contamination, the degree of contamination, and the choice of algorithm. ICA appears to be most effective at separating muscle and blink contamination and less effective at saccadic and tracking contamination.

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