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A New Blind Source Separation Method to Remove Artifact in EEG Signals

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Abstract—**EEG (Electroencephalogram) signals recording the brain activities which carry abundant physiological and pathological information, have great significance in the research. However, it mixed with a variety of artifacts，special the EOG (Electrooculogram), that affect the judgment, removing the artifact is of great meaning. Blind Source Separation (BSS) is popular in signal processing recently, many methods are applied to remove artifacts from EEG signals, such as Second Order Blind Identification (SOBI), Wavelet Transform (WT) and Independent Component Analysis (ICA). Stone's method is to use two different linear filters which process the same set sources, here first use to remove the EOG artifact in EEG signals, it is also a new field for the stone algorithm application. Then compared with two classical algorithms, determine the superiority of the proposed algorithm, finally give the conclusion.**

Keywords- EEG; EOG; BSS; Stone; Artifact

I. INTRODUCTION

EEG signals measure the brain activities by placing electrodes on scalp [1], which is important to detect cerebral pathologies or analysis human intention to operate the Brain Computer Interface (BCI) system. Recorded EEG signals are often contaminated by the disturbance that not produced from brain, called artifact. Artifact contains EOG, Electrocardiogram (ECG), Electromyogram (EMG), and the power line interference. Artifact is with a significantly higher amplitude and similar frequency to the EEG. Rejecting artifacts is also critical when data are used in further processing to interpret brain area activity.

BSS technique achieves significant gain in biomedical signal processing recently. The most classical algorithm is ICA which is a statistical method based on random and natural gradient [2]. Famous methods to estimate the ICA are as follows: maximize the Non-Gaussianity [3], minimize of mutual information [4], maximize Likelihood Estimation [5], and JADE algorithms [6].

A lot automatic methods removing EOG from EEG data based on BSS [7]. Two ICA algorithms InfoMax and Extended-InfoMax were used to extract EOG and power noise of 50Hz have been proposed [8]. The Extended-InfoMax ICA method can isolate both superguassian artifacts EOG and subguassian interference the line noise, while InfoMax ICA method can only remove EOG artifact. Other intelligent techniques are studied to remove EOG and extract useful EEG data, based on WT, Genetic Algorithm (GA) and so on are also be used.

Stone proposes Stone's temporal predictability method [9] with an opinion to minimize the probability density functions of source signals. He also predicts "The Stones method may be used in the analysis of medical image and EEG data". Here try to solve the EEG artifact rejection problem by stone method.

This paper is arranged as follow: BSS techniques specially focused on Stone's are presented in the next section; section three is simulation and results; the conclusions in the last part.

II. BLIND SOURCE SEPARATION

BSS is to separate the source signals from the mixed signals, without or with very little information about the original sources and the mixing process [10]. In EEG techniques, sensors are placed at the head surface, large number sources are active during each human action. There have no idea about the sources or the mixing process inside the head. Therefore, brain signal analysis can be treated as a BSS problem.

A. BSS Model

The BSS mixing and separation process schematic diagram is drawn in Figure 1, or as in [11].

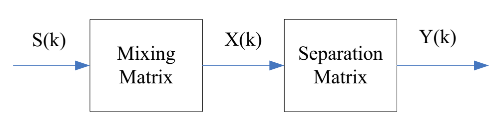

Figure 1. BSS Mixing and separation scheme.

BSS linear mixing model is with m sensors, observed mixtures, $x_1(k), x_1(k), \ldots x_m(k)$. An independent component, source signals, $s_1(k), s_1(k), \ldots s_n(k)$. Express as follows.

$$x_j(k) = a_{j1}s_1(k) + a_{j2}s_2(k) + a_{jn}s_n(k), j = 1,2,.m \tag{1}$$

$$X(k) = AS(k) \tag{2}$$

$$X(k) = [x_1(k)..x_m(k)]^T, S(k) = [s_1(k)..s_n(k)]^T \tag{3}$$

$$Y(k) = WX(k) \tag{4}$$

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$$Y(k) = [y_1(k), \dots y_n(k)]^T \tag{5}$$

Where $A \in R^{m \times n}$, symbol (k) is sample index. Separating model can be wtitten as equation (4). The recovered sources as equation (5). The BSS problem is to estimate the separating matrix W, equals to $W = A^{-1}$.

B. *Stone Alogrithm*

Stone Blind Source Separation (Stone's BSS) is second-order statistic method, based on the signal property and "the temporal predictability (TP) of any mixtures less than (or equal to) that of any of its components" [7].

Signals generally have three properties, first, gaussian probability density function based on the central limit theorem. Second, degree of statistical is independence. Third, signals are temporal predictability. First two properties are widely as a base, while in stone only the 3rd is used for the separation.

Stone predicts stone method useful in medical applications [9] and [11]. The suspect according to Xie [12] is incorrect, then modified. Mao [9] and [13] tries to measure TP which depends on the foundation that the TP of signals is predominantly different. With the difference measures, BSS is changed into a standard symmetric Eigen problem, the separation matrix is the eigenvector matrix [12] and [13]

Stone's measure TP for N-sampled by follows.

$$F(y) = \log \frac{V_y}{U_y} = \log \frac{\sum_{t=1}^{N} (y_l(k) - y(k))^2}{\sum_{t=1}^{N} (y_s(k) - y(k))^2} \tag{6}$$

The value at time k is $y(k)$, U_y contemplates the extent to which $y(k)$ is predicted by short-termmoving average (y_s), V_y for the long-termmoving, $y_s(k)$, $y_l(k)$ are as follows.

$$y_s(k) = \beta_S y_s(k-1) + (1-\beta_S) y(k-1) \tag{7}$$
$$y_l(k) = \beta_L y_l(k-1) + (1-\beta_L) y(k-1) \tag{8}$$

The $\beta_s, \beta_L \in [0,1]$ are two different parameters, and $y_l(1) = y_s(1) = y(1)$. Half-life h_L of β_L is longer than half-life h_S of β_S (here 100 times longer), the relation is equation (9). Stone proved TP of y_i for ith extracted signal with separating vector w_i as Rayleigh's entropy $F(y_i)$.

$$\beta = 2^{-1/h} \tag{9}$$

$$F(y_i) = \log \frac{\mathbf{w_i} \mathbf{C_{xx}^{long}} \mathbf{w_i^T}}{\mathbf{w_i} \mathbf{C_{xx}^{short}} \mathbf{w_i^T}} \tag{10}$$

$\mathbf{C_{xx}^{long}}$ and $\mathbf{C_{xx}^{short}}$ are signal error covariance matrices of mixed predictions by long-term and short-term predictors. Stone's BSS aims to maximize Rayleigh's entropy to get un-mixing vectors considered the generalized eigenvectors of $\mathbf{C_{xx}^{long}} [\mathbf{C_{xx}^{short}}]^{-1}$ in Stone's BSS [9]. Another TP measure [13]is

$$F(y) = \frac{1}{N} \sum_{k=1}^{N} (y_l(k) - y(k))^2 - \frac{1}{N} \sum_{k=1}^{N} (y_s(k) - y(k))^2 \tag{11}$$

The $y(k)$ is zero-mean, the covariance C difference defined as follows.

$$R_y = C(f_y(k), f_y(k)) - C(g_y(k), g_y(k)) \tag{12}$$
$$f_y(k) = y(k) - y_l(k) g_y(k) = y(k) - y_s(k) \tag{13}$$

Now the BSS is changed into the standard symmetric Eigen problem and the separation matrix is orthogonal [13].

C. *Stone's BSS*

The Stone's BSS schematic diagram is Figure 2 which is based on the responses of two different linear scalar filters to the same set of signals [11]. Fast Genetic Algorithm (FGA) is to tune Half-life (h_L , h_S) parameters.

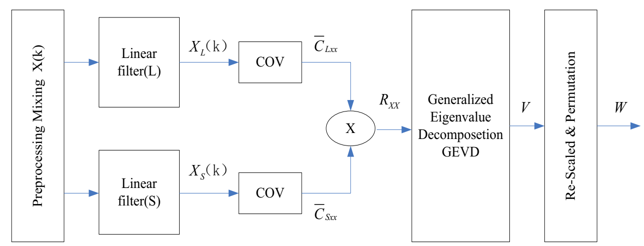

Figure 2. The modified Stone's BSS method Schematic diagram.

Where $X(k)$ are mixture observation signals after centering and whitening. $X_L(k)$ $X_S(k)$ are respectively responses of two different linear filters L and S to estimated the signals by the un-mixing matrix *W*. $\bar{C}_{L\,XX}$ and $\tilde{C}_{S\,XX}$ mean long-term and short-term covariance matrix. *V* is the eigenvector matrix.

$$R_{XX} = \bar{C}_{S\,XX} \tilde{C}_{S\,XX} \tag{14}$$
$$R_{XX} V = VD \tag{15}$$

From some research [8] and [13] some plausible assumptions and properties refer to estimate *W*.

- Assumption 1: Mixing matrix is full column rank.
- Assumption 2: Sources are mutually uncorrelated and their autocorrelation functions are not equal.
- Assumption 3: Impulse response to the first filter L are not the same from that of the second one S.
- Assumption 4: The Unmixing matrix is orthogonal separating.

If $\bar{y}(k)$ and $\bar{x}(k)$ are respectively responses of a linear filter to $y(k)$ and $x(k)$.

$$\bar{y}(k) = \mathbf{W} \bar{x} \tag{16}$$
$$C_{\bar{Y}\bar{Y}} = \mathbf{W} C_{\bar{X}\bar{X}} \mathbf{W}^T \tag{17}$$

If sources are mutually uncorrelated and their autocorrelation functions are not equal, the $X_L(k)$, $X_S(k)$ are diagonal matrices. $\bar{C}_{L\,XX}$, $\bar{C}_{S\,XX}$ and their multiplication R_{XX} are distinct diagonal matrices.

$$\bar{C}_{L\,XX} = E[\bar{X}\,\bar{X}^T] = diag(\mathrm{E}[\bar{X}_1\bar{X}_1], \mathrm{E}[\bar{X}_2\bar{X}_2]..\mathrm{E}[\bar{X}_n\bar{X}_n] \quad (18)$$

$$\tilde{C}_{S\,XX} = E[\tilde{X}\,\tilde{X}^T] = diag(\mathrm{E}[\tilde{X}_1\tilde{X}_1], \mathrm{E}[\tilde{X}_2\tilde{X}_2]..\mathrm{E}[\tilde{X}_n\tilde{X}_n] \quad (19)$$

$$R_{XX} = \bar{C}_{L\,XX}\tilde{C}_{S\,XX} = \quad (20)$$
$$diag(\mathrm{E}[\bar{X}_1\bar{X}_1]\mathrm{E}[\tilde{X}_1\tilde{X}_1], \mathrm{E}[\bar{X}_2\bar{X}_2]\mathrm{E}[\tilde{X}_2\tilde{X}_2]..\mathrm{E}[\bar{X}_n\bar{X}_n]\mathrm{E}[\tilde{X}_n\tilde{X}_n])$$

Or consider as Equation (21). From the Equations (16) and (17) can obtain the following Equation (22).

$$R_{YY} = \bar{C}_{L\,YY}\tilde{C}_{S\,YY} \quad (21)$$
$$diag(\mathrm{E}[\bar{Y}_1\bar{Y}_1]\mathrm{E}[\tilde{Y}_1\tilde{Y}_1], \mathrm{E}[\bar{Y}_2\bar{Y}_2]\mathrm{E}[\tilde{Y}_2\tilde{Y}_2]..\mathrm{E}[\bar{Y}_n\bar{Y}_n]\mathrm{E}[\tilde{Y}_n\tilde{Y}_n])$$

$$R_{YY} = [W\bar{C}_{L\,XX}W^T][W\tilde{C}_{S\,XX}W^T] = W\bar{C}_{L\,XX}[W^TW]\tilde{C}_{S\,XX}W^T \quad (22)$$

Now the problem is generalized eigenvalue decomposition, from the Assumption 4.

$$W^{\mathbf{T}}W = I \quad (23)$$

$$\bar{C}_{L\,XX}\tilde{C}_{S\,XX} = W^{-1}R_{YY}W \quad (24)$$

III. SIMULATION AND RESULT

A. Data Acquisition

EEG signals were measured by a computerized device [14], from a 24 years old healthy male, with 19 electrodes, by 10-20 international system, as Figure 3.

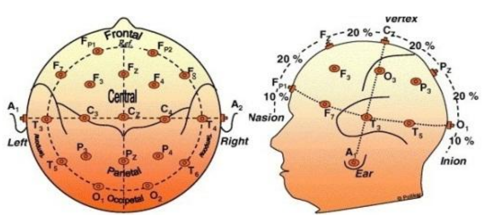

Figure 3. The 10–20 International EEG electrode placement system.

Signals are digitized at 256 Hz, trail is 10 Sec. Subject acts eyes blink before 3rd Sec, stays quiet at 3rd Sec, completes hand index movement in 5th to 6th Sec [14]. Eyes actions produce EOG. Eyes-open lead a downward peak at negative peak, eyes-close reverses. EOG amplitude peak is much higher than the EEG, Figure 4. EOG artifact is dominant in Frontal and Frontopolar channels like FP1, FP2, F7, and F8, as Figure 5.

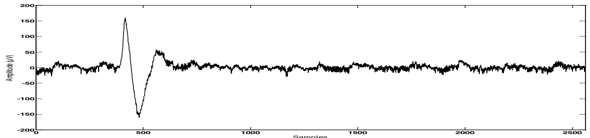

Figure 4. EEG Signal contain eye blinks.

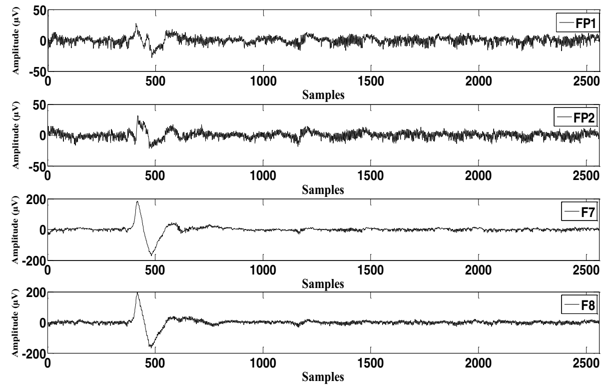

Figure 5. EEG signals with artifact for FP1, FP2, F7 and F8 channels

B. Filter processing

Filter removes subguassian interference line noise and reduces superguassian EOG artifact [8] and [14]. Here is 5-45Hz band-pass by a Windowed-Sinc FIR filter with the sampling rate 256 sample/sec, use a Blackman window. Filter kernel length M, low-pass filter kernel $h[i]$ can be calculation. Where k is filter gain, f_c is cut-off frequency, i is the index.

$$M \approx \frac{4}{BW} \quad (25)$$

$$h[i] = K\frac{\sin(2\pi f_c(i - M/2))}{i - M/2}[0.42 - 0.5\cos\cos(\frac{2\pi i}{M}) + 0.08\cos\cos(\frac{4\pi i}{M})] \quad (26)$$

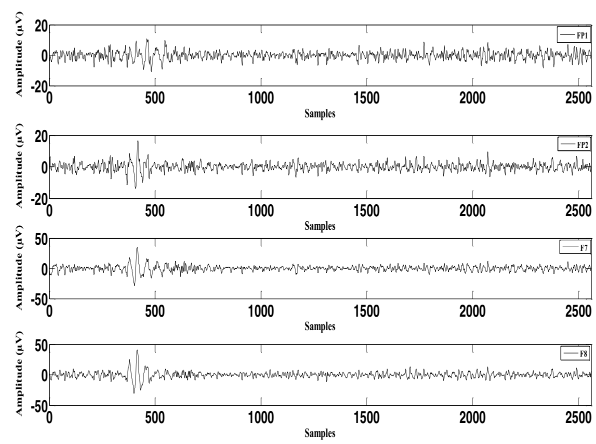

Figure 6. The 4 channels signals after Windowed-Sinc FIR filter.

As above, Figure 6 shows reduce the amplitude of the EOG by above filter.

C. Useing the BSS to Remove the Artifact

This step uses the proposed method to separate the EOG from filtered EEG signals. It can be clearly found the pure EOG artifact been isolated in IC10 and IC18 among the recovered 19 ICs as Figure 7 shows.

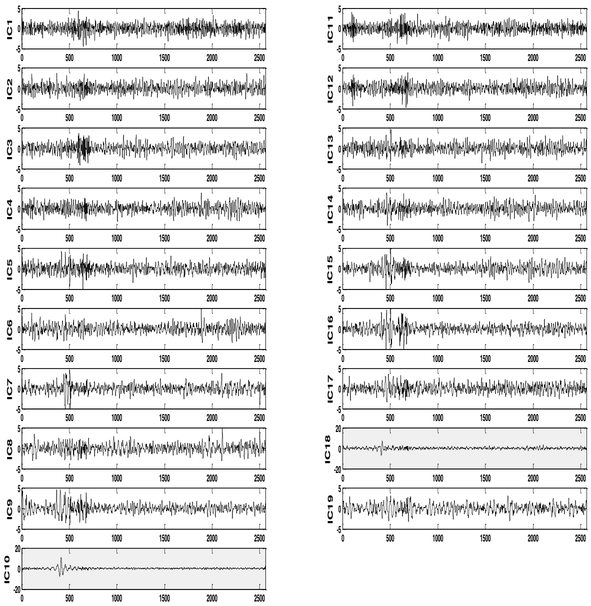

Figure 7. 19 ICs of EEG signals by using Stone's BSS , X-axis is signal Amplitude in microvolt, Y-axis is the No. of Samples.

D. *Different Methods Comparision*

Here Figure 8 compares Stone's BSS with well-known BSS methods FICA and JADE. The signal has been taken from 1.5 second ($256\times1.5=384 samples$) until the third second ($256\times3=768 samples$) which is set by the presence of EOG, to compare the resulting curves produced by different methods for FP1 channel. Clearly found that the stone's method is the best in extracting the brain signals and isolate the EOG artifacts.

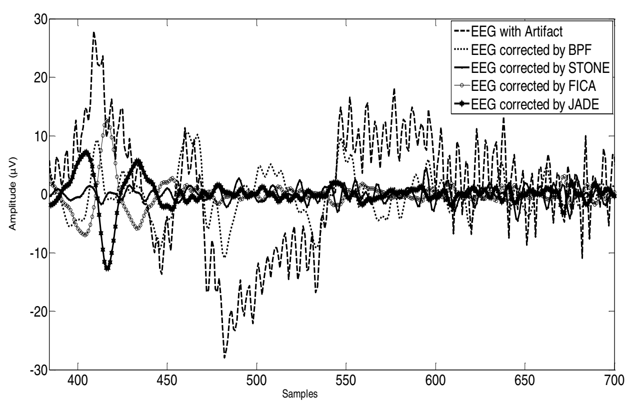

Figure 8. EEG with artifact and Corrected EEG by BPF, JADE, FICA and Stone's BSS for FP1 channel.

IV. CONCLUSION

This study brings the stone method to solve the artifact rejection in EEG signals and certifies the proposed algorithm is an efficient way to separate completely the EOG artifact from EEG. BSS based on ICA has gained a great deal of popularity, but it has some limitations, the developed method Stone's BSS to decrease the limitation and brings less complexity batch approach, separate the artifacts easily It is an efficient technology for ensuring the pure EEG signals in biomedical applications like the BCI systems.

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