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Blind Source Separation Techniques Based Eye Blinks Rejection in EEG Signals

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Abstract: In neurophysiological signal analysis, Ocular Artifacts (OA) are raised differently in Electroencephalographic (EEG). Rejection process of these artifacts is an important research area and finding a method for successful removal of OA incompletely is still a challenge. In this study, Stone blind source separation method (Stone's BSS) is used to correct the EEG signal by separating OA signals completely, this is a new application for Stone's BSS in brain signal analysis and there is no one use this method in this field, such that almost previous works based on Independent Component Analysis (ICA), which has some inherent disadvantages. In addition, the modified Stone's BSS is presented here to interpret how Stone's BSS deploys generalized Eigenvalue decomposition to obtain the un-mixing matrix based on the responses of two different linear scalar filters to the same set of signals. Therefore, this study opened a new direction field for Stone's BSS applications. Stone's BSS method depends on signal temporal predictability measurement for separation processes. A comparison with two well-known BSS algorithms (JADE, FICA) in order to check the Stone's BSS effectiveness. It is an efficient method to correct the EEG data and can apply it in medical applications as expected. The main purpose of this study is to ascertain the effect of using Stone's BSS as compared to an Independent Component Analysis (ICA) in isolating the ocular artifacts and correct the EEG data. This method is identified as being of importance in this application and it's a new direction in the brain signal analysis.

Key words: Blind source separation, stone's BSS, EEG analysis, ocular artifact, BCI, EOG

INTRODUCTION

The Electroencephalography (EEG) is a medical instrument that measures the electrical activity of the brain which are mixed complex spatiotemporal signals and have several sources that lead to the complexity in the identification process. EEG data contaminated by different types of artifacts during the recording process. Almost the biologically artifacts are more worried than external artifacts, Improving and developing technology can decrease the external artifacts, like line noise artifact, but biological artifact signals must be extracted and removed after the recording process (Knight, 2003).

Artifact removal is very necessary to make easier EEG data for representation and interpretation of the brain signal perfectly to perform a suitable function in brain computer interface system (Kumar *et al*., 2008). Ocular Artifact (OA) is the electrical signals produced by Eye-blinks or movement of eyeballs. These artifacts in millivolts and they contaminate the EEG signals which are in micro-volts, also the frequency range of EEG signal is 0 to 64 Hz and the OA occur within the range of 0 to 16 Hz (Krishnaveni *et al*., 2006a). The removing process of OA from EEG signals is very important for automated and visual analysis of implied brain wave activity. These artifact sources increase the difficulty in analyzing and interpreting of the recorded EEG data, therefore it is very important to design a procedure to decrease or eliminate these artifacts from brain signals (Kumar *et al*., 2008).

Most individuals seen in recent years, the blind source separation BSS techniques have a significant and formal area attentions in biomedical signal analysis (Xue *et al*., 2006). The most considerable method is Independent Component Analysis (ICA) as a statistical method to extract and separates the independent components ICs of the signal. ICA is based on random and natural gradient (Sun *et al*., 2003; Mavaddaty and Ebrahimzadeh, 2011). The famous methods estimate the ICA model by maximizing the Non-Gaussianity (Hyvarinen, 1999a), minimizing mutual information (Comon, 1994), maximizing Likelihood Estimation (Hyvarinen, 1999b) and JADE algorithms (Cardoso and Souloumiac, 1993).

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A class of second-order statistic method called Stone's temporal predictability method is proposed by Stone (Stone, 2001) with a view to minimize the probability density functions of the source signals. Automatic removal of electro-ocular artifacts from EEG data procedure based on Blind Source Separation (BSS) is presented in Joyce *et al.* (2004). Two ICA algorithms InfoMax (I-ICA) and Extended-InfoMax (EI-ICA) were utilized to extract eye movements and power noise of 50 Hz in EEG data is proposed by Xue *et al.* (2006), it is proven that (EI-ICA) method can isolate both superguassian artifacts (Eye blinks) and subguassian interference (line noise), but (I-ICA) method is only restricted to remove superguassian artifacts (eye blinks).

Given the importance of this aspect, the soft computing and intelligent techniques are studied to remove Electro Oculo Gram (EOG) artifacts and extract useful EEG data, such as in Kumar *et al.* (2008). Since an Ocular Artifact in the EEG data is removed based on Wavelet Transform (WT), also in Chambayil *et al.* (2010) Artificial Neural Network (ANN) is trained to detect EOG artifact and focused on eye blink detection using kurtosis.

The main purpose of this study, using Stone's BSS method as compared to an ICA in isolating the ocular artifacts and correct the EEG data.

OCULAR ARTIFACTS IN EEG

Electroencephalogram (EEG) is a biological signal that demonstrates the electrical activity of the brain measured by placing electrodes on the scalp (Jain *et al.*, 2012). An artifact is considered as a disturbance in a measured brain signal not produced from the brains. Generally can be classified the artifacts into external and internal categories.

EEG signals often contaminated by strong Ocular Artifacts (OA) produced from eye movements and eye blinks especially in the EEG recorded from frontal and frontpolar channels (FP1, FP2, F7 and F8) (Krishnaveni *et al.*, 2006b). The eye and brain activities have physiologically separate sources, so the recorded EEG is a superposition of the true EEG and some portion of the EOG signal (Krishnaveni *et al.*, 2006a). The interpretation of eye related signals, a downward peak at the negative peak shows an event of eyes-open and a positive peak show an event of eyes-close. Also the amplitude of these peaks will be significantly higher compared to the brain signal as shown in Fig. 1 (Chambayil *et al.*, 2010).

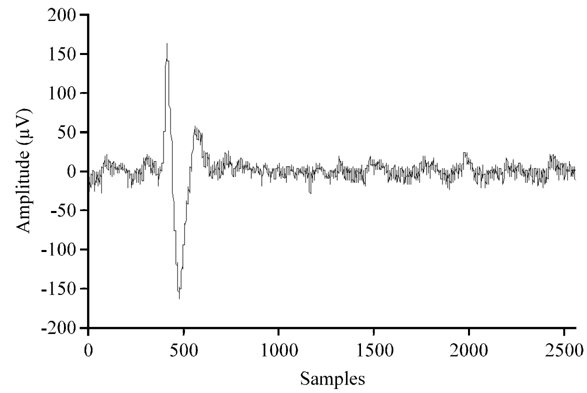

Fig. 1: Contaminated EEG signal by eye blinks

BLIND SOURCE SEPARATION

Blind Source Separation (BSS), also known as blind signal separation, is a method of separating the underlying source signals from the observations (mixed signals), which are the mixtures of the original sources, without the aid of information (or with very little information) about the original sources or the mixing process (Tahir, 2010). In a non-invasive technique (EEG), the sensors (electrodes) are sited at the surface or around the head (scalp) at very close distance. For each action of the human, a lot of numbers of sources (neurons) are active (stimulus). Each sensor (electrode) is measuring a mixture of these stimuli from sources and each sensor measures a different mixture depending upon its distance from the sources as shown in Fig. 2.

As these are non-invasive techniques, no idea about the sources and the mixing process that has occurred inside the head. Therefore, cerebral signal analysis can be considered as a blind source separation BSS problem. EEG data represent a projection of a set of signals, which are a mixing of cerebral and artifact signals, onto the sensor (electrode) sites. BSS reduces mixtures of neural and non-neural variables to independent components of each other. Different methods of measuring independence provide different BSS algorithms (Joyce *et al.*, 2004).

ICA is a linear transform of multidimensional data designed to make the output vectors as statistically independent as possible. ICA is used to separate unknown source signals from their linear mixture and extract the features (Lisha *et al.*, 2005).

The schematic diagram for mixing and separation process in BSS is drawn in Fig. 3 (Abdullah *et al.*, 2012).

Typical linear mixing model of BSS with m observed mixtures ($x_1(k)$, $x_1(k)$, ..., $x_m(k)$) of an independent component ($s_1(k)$, $s_1(k)$, ..., $s_n(k)$):

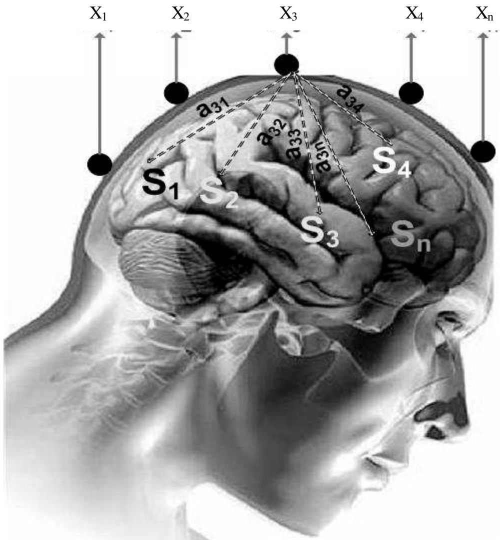

Fig. 2: Brain signal analysis: Blind source separation problem (Tahir, 2010)

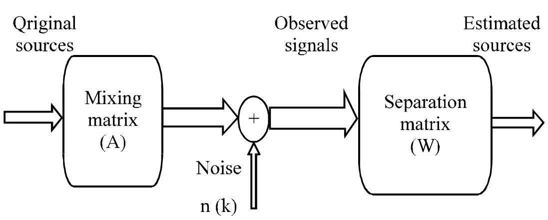

Fig. 3: Mixing and separation scheme in BSS

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

They can be written as follows:

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

Where:

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

$$S(k) = [s_1(k), s_n(k)]^T \tag{4}$$

where, Superscript T refers transpose operator; $A \in R^{m \times n}$ refers mixing matrix. Symbol (k) is time or sample index.

And finally the separating model is:

$$EY(k) = WX(k) \tag{5}$$

where, E is a permutation and scaling matrix and the recovered sources is:

$$Y(k) = [y_1(k),...,y_n(k)]^T \tag{6}$$

BSS problem is to estimate the best separating matrix W, that ideally equal to A^{-1}.

A new method was proposed by Stone (2001), for source separation belong to a kind of second-order statistic method, called by Stone's BSS, based on the property for the signal and established on the conjecture that: "the Temporal Predictability (TP) of any mixture is less than (or equal to) that of any of its components" (Stone, 2001).

Generally there are three useful properties of the signals:

- A Gaussian probability density function based on the central limit theorem
- Degree of statistical independence
- Temporal predictability

The first two properties (1 and 2) have previously been used as a base for the separation but in stone's BSS only the 3rd property has been used for the separation. Stone expects this method may be useful in the analysis of medical applications (Stone, 2001; Abdullah *et al*., 2012).

However, Stone's conjecture according to Xie *et al*. (2005) is incorrect and modified, then can be considered the modified conjecture as a theoretical basis for BSS problem. Another view by Ye and Li (2007) has introduced a temporal predictability measure based on difference and on the fact that temporal predictability of the signals is predominantly different. By using the difference measure, the BSS problem is simplified to a standard symmetric Eigen problem and the separation matrix is the eigenvector matrix.

Fast Genetic Algorithm (FGA) is used with the modified stone's BSS method to generate and tune Half-life (h_L, h_S) parameters, which used by Stone's method, to enhance the separation process and this algorithm is based on the responses of two different linear scalar filters to the same set of signals (Abdullah *et al*., 2012).

Recently, significant research developed to modify Stone's BSS method to solve BSS problem; Stone's BSS method based on short-term and long-term predictors. Trials for a weight vector which backup orthogonal projection of signals such that each extracted signal is maximally predictable. It's a batch method with low complexity. Stone's measure of Temporal Predictability (TP) for N-sampled signal (Stone, 2001) is:

$$F(y) = \frac{\log V_y}{U_y} = \log \frac{\sum_{t=1}^{N} (y_l(k) - y(k))^2}{\sum_{t=1}^{N} (y_s(k) - y(k))^2} \quad (7)$$

where, y(k) is the signal value at time k. U_y contemplates the extent to which y(k) is predicted by short-term moving average (y_s). In contrast, the term V_y is a measure of the overall variability in y that is measured by the extent to which y(k) is predicted by long-term moving average (y_s). Predicted values y(k), $y_s(k)$ of y(k) are both exponentially weighted sums of signal values measured up to time (k-1), such that recent values have a larger weighting than that indistinct past:

$$y_s(k) = \beta_s y_s(k-1) + (1-\beta_s) y(k-1) \quad (8)$$

$$y_l(k) = \beta_L y_l(k-1) + (1-\beta_L) y(k-1) \quad (9)$$

According to Stone's method, βs.βL ϵ[0,1] are two different parameters and $y_l(1) = y_s(1) = y(1)$. Half-life h_L of β_L is much longer (typically 100 times longer) than corresponding half-life h_S of β_s and the relation is:

$$\beta = 2^{\frac{-1}{h}} \quad (10)$$

Stone has presented TP of y_i for ith extracted signal with separator vector w_i as Rayleigh's entropy as follows:

$$F(y_i) = \log \frac{\left(w_i C_{xx}^{long} \; w_i^T\right)}{w_i C_{xx}^{short} \; w_i^T} \quad (11)$$

where, C_{xx}^{long} and C_{xx}^{short} are signal error covariance matrices of mixed predictions by long-term and short-term predictors, respectively. Stone's BSS aims to maximize Rayleigh's entropy to yield un-mixing vectors. Later, generalized eigenvectors of $C_{xx}^{long} \; [\, C_{xx}^{short} \,]^{-1}$ are considered as un-mixing vectors in Stone's BSS (Stone, 2001). Another TP measure is presented by Ye and Li (2007) in the same strategy of Stone's measure as mentioned above:

$$F(y) = \sum_{k=1}^{N} (y_l(k) - y(k))^2 - \frac{1}{N} \sum_{k=1}^{N} (y_s(k) - y(k))^2 \quad (12)$$

For signal series y(k) with zero-mean, the covariance C difference is defined as:

$$R_y = C(f_y(k), f_y(k)) - C(g_y(k), g_y(k)) \quad (13)$$

Where:

$$f_y(k) = y(k) - y_l(k) g_y(k) = y(k) - y_s(k)$$

R_y implies the difference measure in the mean value sense. In this measure, the blind source separation problem is changed to the standard symmetric Eigen problem and separation matrix is orthogonal (Abdullah *et al*., 2012).

MODIFIED STONE'S BSS ALGORITHM

The modified Stone's BSS method based on Ye and Li (2007) interpretation is presented in this section and explanation, how Stone's BSS deploys generalized Eigenvalue decomposition to obtain the un-mixing matrix; proposed theory is based on the responses of two different linear scalar filters to the same set of signals. Indeed, the response of linear filter to signals is a comprehensive case which includes short-term and long-term linear predictors used by Stone's BSS too. Linear filters are assumed as scalar filters rather than matrix filters unless stated otherwise (Abdullah *et al*., 2012). Figure 4 shows the schematic diagram for the theoretical foundation of the modified Stone's BSS method.

Where that:

- X (k) = Mixture observation signals
- X_L (k) = Filter Response (L)
- X_S (k) = Filter Response (S)
- $\bar{C}_{L\,xx}$ = Long-term covariance matrix
- $\tilde{C}_{S\,xx}$ = Short-term covariance matrix
- $R_{XX} = \bar{C}_{L\,xx} \; \tilde{C}_{S\,xx}$
- V = Eigenvector matrix $R_{XX}V = VD$
- W = Un-mixing matrix

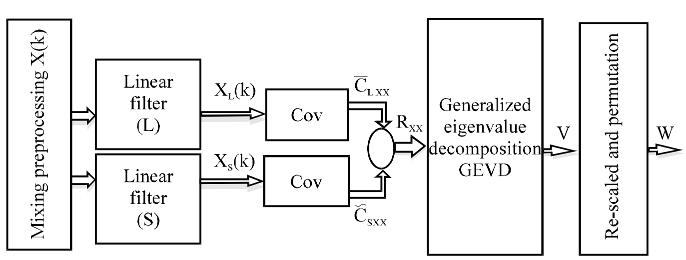

Fig. 4: Schematic diagram of modified Stone's BSS method

The preprocessing of BSS consists of (Centering and Whitening), from the most basic and necessary preprocessing is to center the received observation mixture of signals x, i.e., subtracts its mean vector m = E [x] so as to make x zero-mean. Another useful preprocessing strategy called whitening; the observed vector x linearly transforms to obtain a new vector $\tilde{x}$ which is white, i.e., its components are uncorrelated with unity variances or covariance matrix of $\tilde{x}$ equals the identity matrix (Hyvarinen, 1999a):

$$E[\tilde{x}\tilde{x}^T] = I \tag{14}$$

Eigenvalue decomposition (EVD) of the covariance matrix is a popular method for whitening. From Cichocki and Amari (2005), vector of m mixture $X(k) = [x_1(k),..., x_m(k)]^T$ has been received by m sensors. BSS considers the best estimate of un-mixing matrix $W_{m\times n}$ in order to estimate n unknown sources as mentioned by Hyvarinen (1999b):

$$Y(k) = [y_1(k), y_2(k), ..., y_n(k)]^T$$

$X_L(k)$ and $X_S(k)$ are, respectively responses of two different linear filters L and S to estimated (recovered) the signals by W. From Ye and Li (2007) some plausible assumptions and properties refer to estimate W such as:

- **Assumption 1:** Mixing matrix is full column rank
- **Assumption 2:** Sources are mutually uncorrelated and autocorrelation functions are not equals
- **Assumption 3:** Responses of sources to first filter (L) are not the same from their responses to the second filter (S)
- **Assumption 4:** Unmixing matrix is orthogonal separating
- **Property 1:** If sources signals are mutually uncorrelated then response of linear filter are also mutually uncorrelated and covariance matrix of the response signals is a diagonal matrix
- **Property 2:** If $\bar{y}(k)$ and $\bar{x}(k)$ are, respectively responses of a linear filter to y(k) and x(k):

$$\bar{y}(k) = W\bar{x} \tag{15}$$

$$C_{\bar{y}\bar{y}} = WC_{\bar{x}\bar{x}}W^T \tag{16}$$

The covariance matrices of $X_L(k)$ and $X_S(k)$ are diagonal matrices because the source signals S(k) are mutually uncorrelated (Assumption 2):

$$\bar{C}_{LXX} = E[\bar{X}\bar{X}^T] = \mathrm{diag}(E[\bar{X}_1\bar{X}_1], E[\bar{X}_2\bar{X}_2], ..., E[\bar{X}_n\bar{X}_n]) \tag{17}$$

$$\tilde{C}_{SXX} = E[\tilde{X}\tilde{X}^T] = \mathrm{diag}(E[\tilde{X}_1\tilde{X}_1], E[\tilde{X}_2\tilde{X}_2], ..., E[\tilde{X}_n\tilde{X}_n]) \tag{18}$$

As shown $\bar{c}_{LSS}$ and $\tilde{c}_{SXX}$ are distinct diagonal matrices their multiplication R_{XX} is a diagonal matrix:

$$R_{XX} = \bar{C}_{LXX}\tilde{C}_{SXX} = \mathrm{diag}(E[\bar{X}_1\bar{X}_1]\,E[\tilde{X}_1\tilde{X}_1], E[\bar{X}_2\bar{X}_2]\,E[\tilde{X}_2\tilde{X}_2], ..., E[\bar{X}_n\bar{X}_n]\,E[\tilde{X}_n\tilde{X}_n]) \tag{19}$$

Or can be said:

$$R_{yy} = \bar{C}_{Lyy}\tilde{C}_{Syy} = \mathrm{diag}(E[\bar{y}_1\bar{y}_1]\,E[\tilde{y}_1\tilde{y}_1], E[\bar{y}_2\bar{y}_2]\,E[\tilde{y}_2\tilde{y}_2], ..., E[\bar{y}_n\bar{y}_n]\,E[\tilde{y}_n\tilde{y}_n]) \tag{20}$$

From Eq. 15 and 16:

$$R_{yy} = [W\bar{C}_{LXX}W^T][W\tilde{C}_{SXX}W^T] = W\bar{C}_{LXX}[W^TW]\tilde{C}_{SXX}W^T \tag{21}$$

Now, can be representing the problem as generalized eigenvalue decomposition (Stone, 2001) and from the Assumption 4:

$$W^TW = I \tag{22}$$

$$\bar{C}_{LXX}\tilde{C}_{SXX} = W^{-1}R_{yy}W \tag{23}$$

Then, the un-mixing matrix W is organized of the eigenvector matrix of Eq. 23, also they are orthogonal. Half-life h_L of β_L is much longer (typically 100 times longer), subsequently these values are being affected on the responses of two linear filters . Since two employed linear filters are error terms of short-length and long-length prediction.

SIMULATION RESULTS

The EEG signals are recorded and processed firstly by temporal filter (FIR filter) and then by spatial filter (Blind source separation) techniques: FICA, JADE, EI-ICA and Stone's BSS. In order to compare the results with previous studies, as in Salim (2007), the same procedure is taken but with different blind source separation technique, also the simulation result compared with Extended-Infomax (EI-ICA) as demonstrated by Xue *et al.* (2006). In this study a modified Stone's BSS method is used instead of Independent Component Analysis (ICA) algorithms. To illustrate experimental demonstration of validity of the BSS method in details, the procedure is divided into three steps:

Step 1: EEG signal acquisition: One healthy subject, male, 24 years old was participated in the work. EEG signals were measured using a computerized EEG device (Fig. 5), 19 electrodes, 10-20 international system and referenced against forehead (Fig. 6) in Ibn-Rushd Hospital-Baghdad-Iraq for more details see Salim (2007).

According to the specification of the computerized EEG device the recorded signals were digitized at 256 Hz. The trail length is 10 sec (10 sec×256 Hz = 2560 samples), during which the subject was allowed to perform random artifacts (eyes blinking) before 3rd sec. At 3rd sec the subject stays quiet and stays without any action. From 5th to 6th sec, the subject performs the left or right hand index movement depending on the part of the session Salim (2007).

The effect of ocular artifacts will be dominant in the Frontal and Frontopolar channels like FP1, FP2, F7 and F8 (Krishnaveni *et al*., 2006b). Figure 7, show the contaminated EEG signals by eye blinks for frontal and frontpolar channels FP1, FP2, F7 and F8.

Step 2: Filtering process using temporal filter: Generally the first step for EEG signal processing is a filtering process to remove subguassian interference (line noise), DC. Drift and reduce superguassian artifacts (eye blinks) (Xue *et al*., 2006; Salim, 2007). Here, a temporal filter is used with 5-45 Hz band-pass filter and implemented by a Windowed-Sinc FIR filter with a sampling rate of 256 sample sec^{-1} and filter kernel length M of 1024 calculated according to:

Fig. 5: Computerized EEG system (Ibn-Rushd Hospital-Baghdad-Iraq)

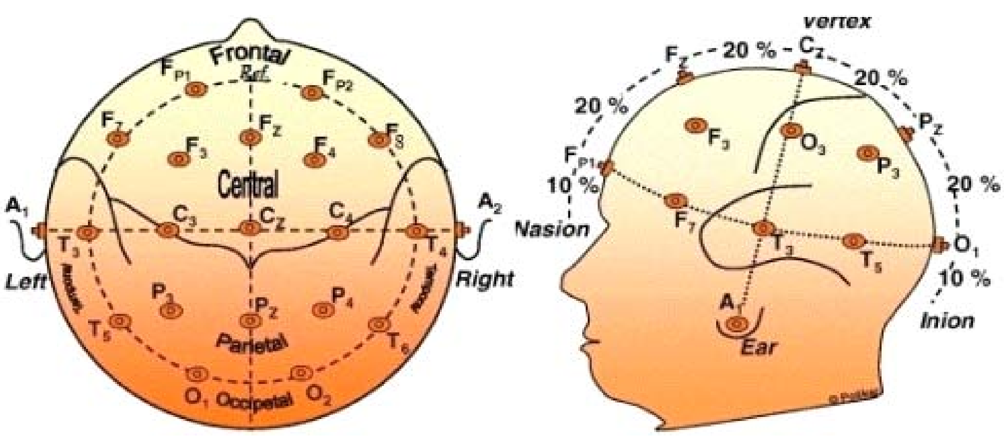

Fig. 6: The 10-20 International EEG electrode configuration system

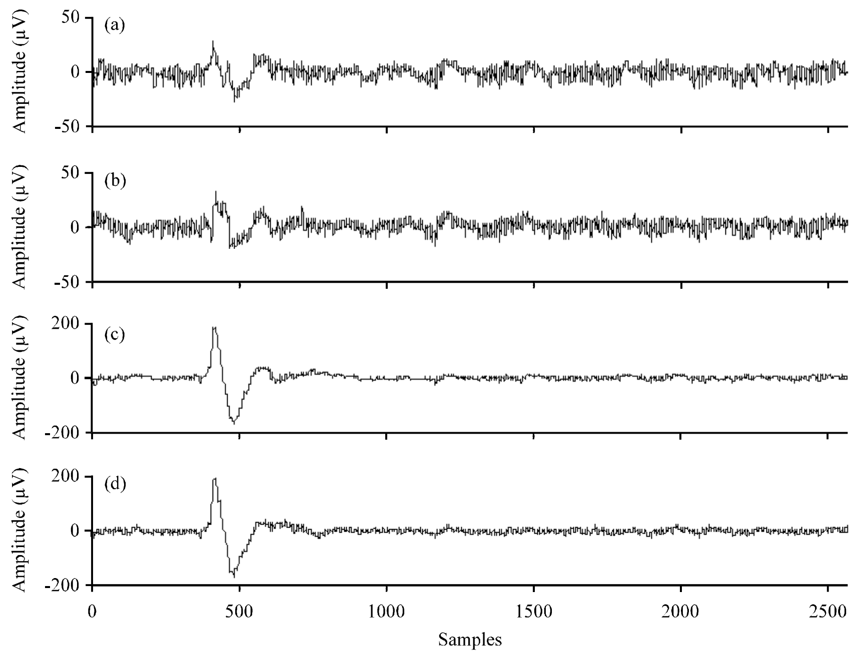

Fig. 7: Contaminated EEG signal for (a) FP1, (b) FP2, (c) F7 and (d) F8, channels

$$M \approx \frac{4}{BW} \tag{24}$$

where, BW is a width of transition band.

A Blackman window has been used in this implementation. The filter kernel of the low-pass filter is calculated according to:

$$h[i]=K\frac{\sin(2\pi f_c(i-M/2))}{i-M/2}\left[0.42-0.5\cos\left(\frac{2\pi i}{M}\right)+0.08\cos\left(\frac{4\pi i}{M}\right)\right] \tag{25}$$

where, h[i] is a filter kernel, k is a filter gain, M is the kernel length filter, f_c is a cut-off frequency and i is the index. The algorithm of calculating the filter kernel of the band-pass filter with cut-off frequencies of f_{c1} = 5 Hz and f_{c2} = 45 Hz is shown below (Salim, 2007):

- Values confirmation: let M = 1025, S_{rate} = 256, $f_1 = f_{c1}/S_{rate}$, $f_2 = f_{c2}/S_{rate}$
- Calculate low-pass filter kernel at f_1
- Calculate low-pass filter kernel at f_2
- Normalize both filter kernels
- Change the low-pass filter kernel of hh to high-pass filter using spectral inversion
- Add the low-pass filter kernel hl to the high filter kernel hh to obtain a band-reject filter kernel
- Change the band-reject filter kernel to a band-pass filter using spectral inversion

The filtered signal is obtained by convolve the input signal with the filter kernel. Figure 8 shows the effect of temporal filters (Windowed-Sinc FIR filter) to reduce the amplitude of the ocular artifact.

Step 3: Processing the EEG data by BSS: Rejecting contaminated trials causes substantial data loss and restricting eye blinks limits the experimental designs possible and may impact the cognitive processes under investigation (Kumar *et al*., 2008). In this step, use Stone's BSS to separate the ocular artifacts from filtered EEG signals.

Figure 9 shows the Independent Components (ICs) found by Stone's BSS method and it can be clearly found from this figure that the pure eye blink artifacts were isolated in IC10 and IC18 successfully, as indicated by potential contour maps in Fig. 10. The EEG signals are cleaned from an artifact and then can be use this data for classification and extract the main features as a next step in Brain Computer Interface (BCI).

Stone's BSS method has been compared with well-known BSS algorithms as shown in Fig. 11. The signal has been taken until the 3rd sec (256×3 = 768 samples) which is set by the presence of Eye artifact to compare the resulting curves produced by different methods for FP1 channel. Clearly stone's method is the best from other by extracting the brain signals and isolate the eye blink artifacts.

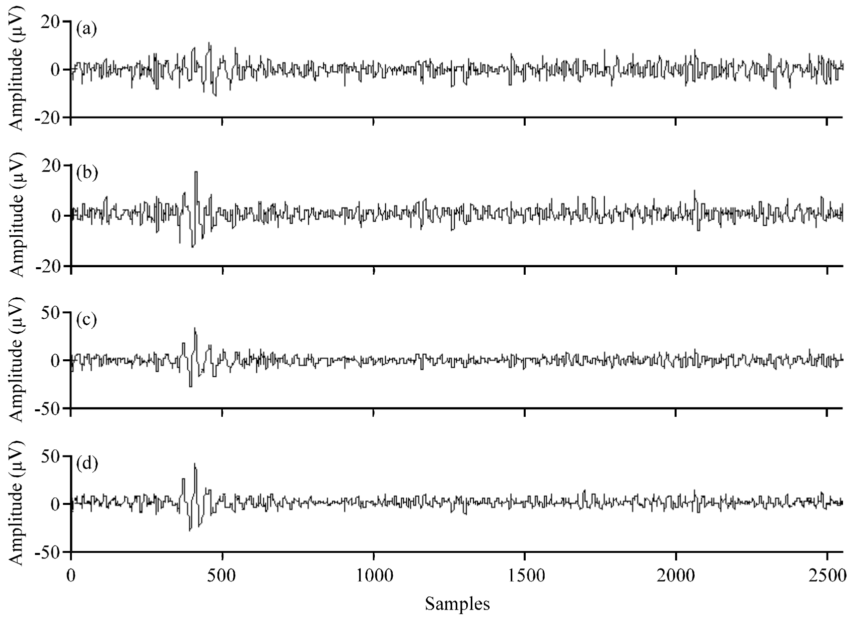

Fig. 8: Reduced contaminated EEG signals using Windowed-Sinc FIR filter for (a) FP1, (b) FP2, (c) F7 and (d) F8, channels

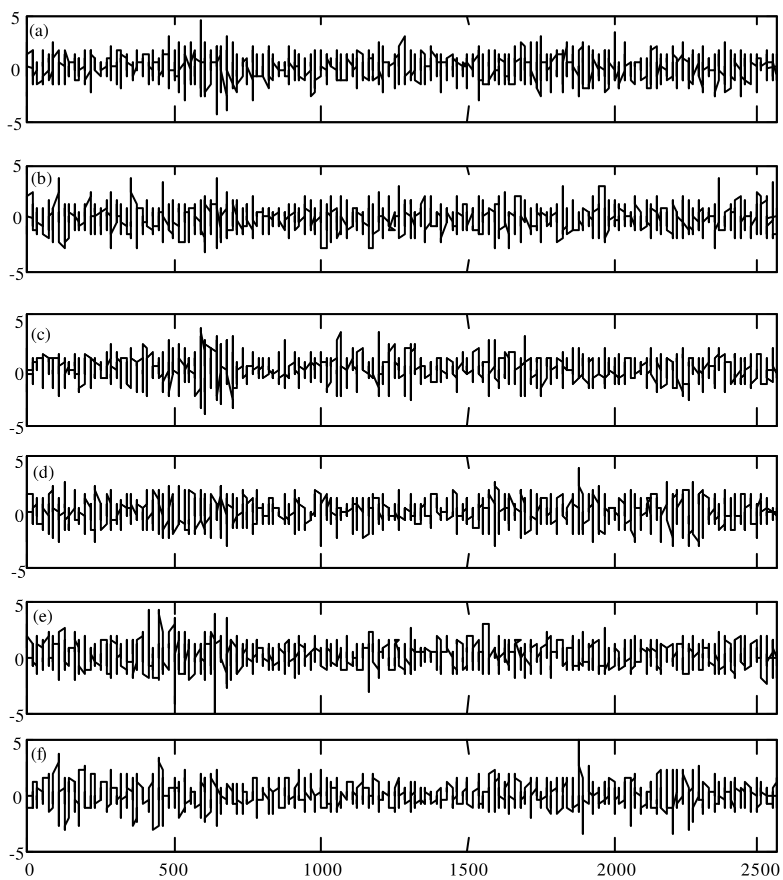

Fig. 9(a-s): Continue

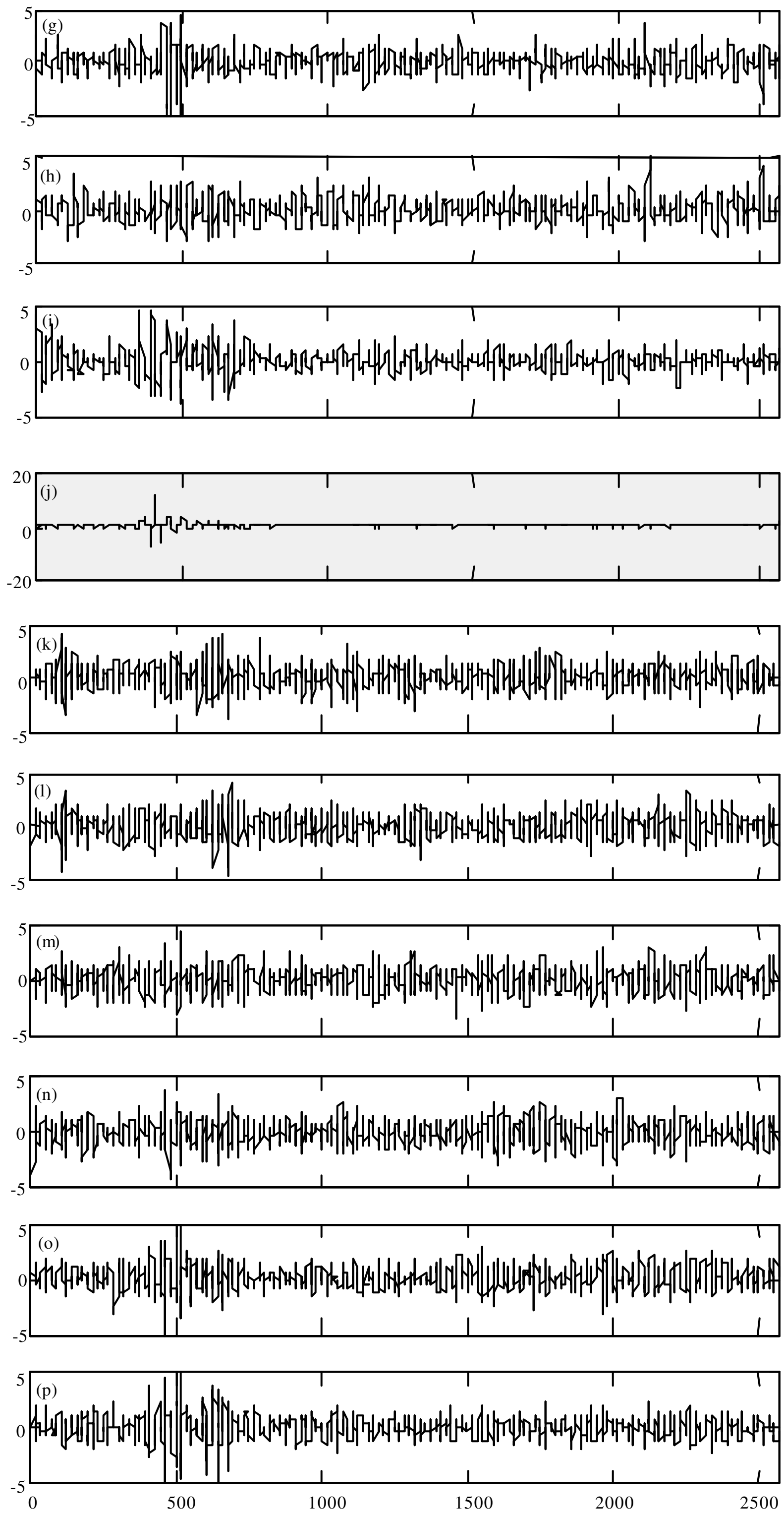

Fig. 9(a-s): Continue

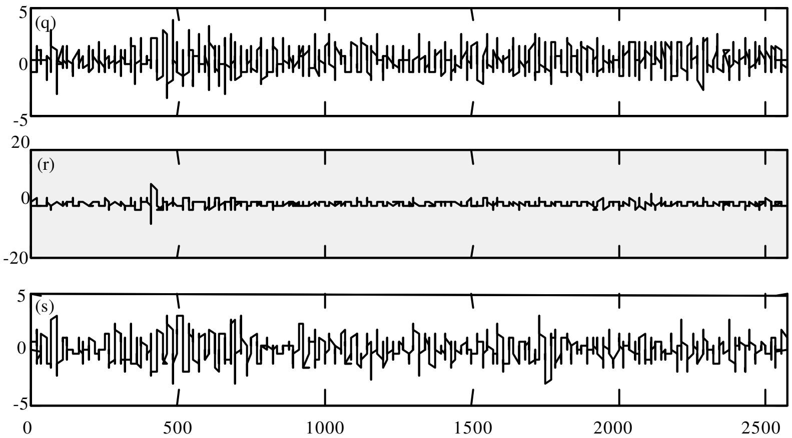

Fig. 9(a-s): 19 independent component of EEG signals using Stone's BSS, X-axis represent signal Amplitude in microvolt and Y-axis represent No. of samples (a) IC 1, (b) IC 2, (c) IC 3, (d) IC 4, (e) IC 5, (f) IC 6, (g) IC 7, (h) IC 8, (i) IC 9, (j) IC 10, (k) IC 11, (l) IC 12, (m) IC 13, (n) IC 14, (o) IC 15, (p) IC 16, (q) IC 17, (r) IC 18 and (s) IC 19

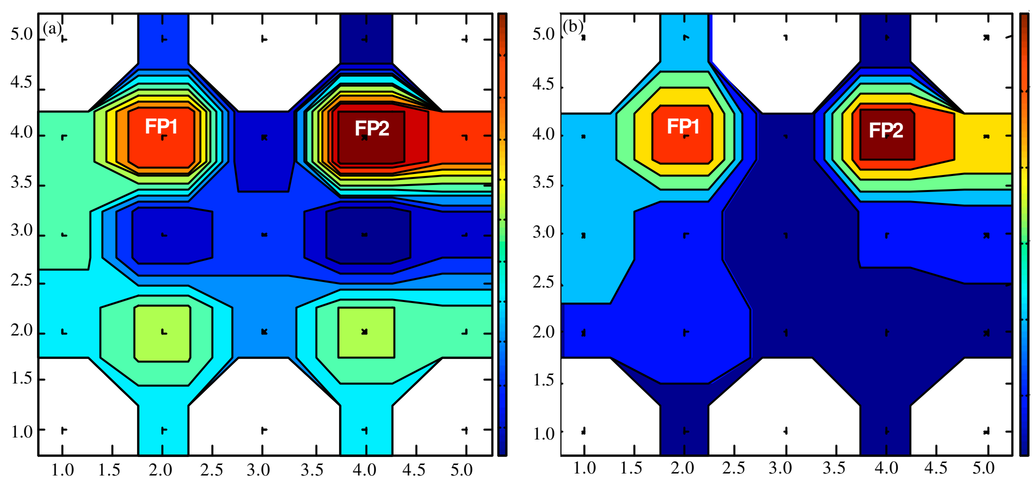

Fig. 10(a-b): (a) Potential contour map IC10 (b) Potential contour map IC18

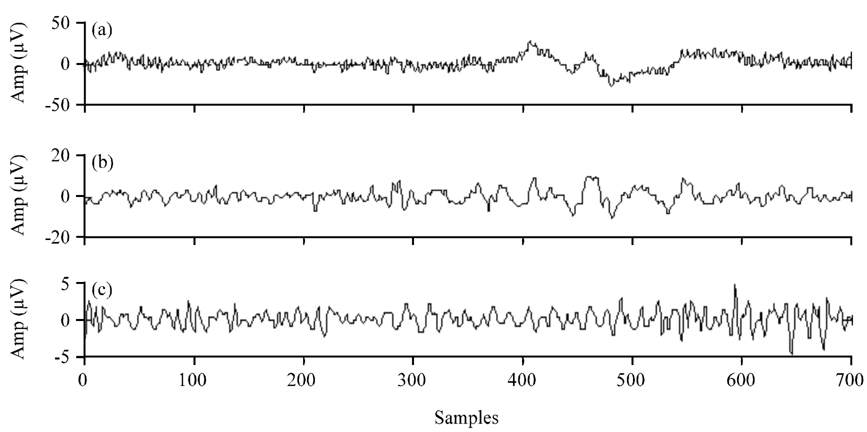

Fig. 11(a-f): Continue

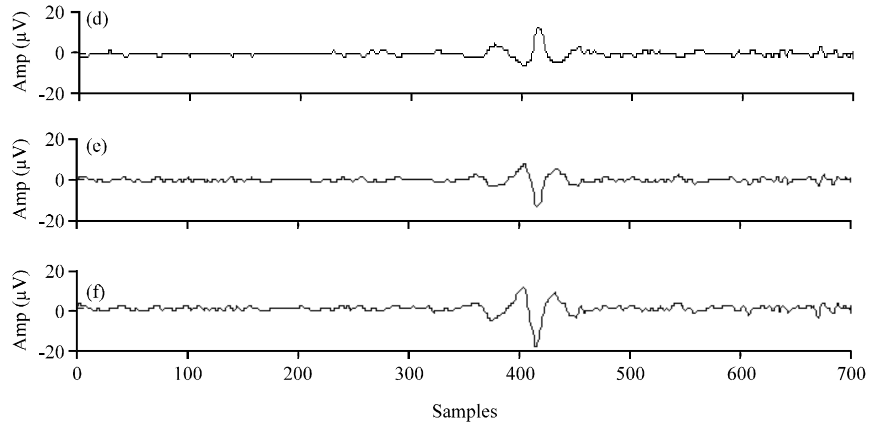

Fig. 11(a-f): EEG signals for frontal channel (FP1) (a) Raw EEG signal, (b) After Band pass filter, (c) After Stone's BSS, (d) After FICA, (e) After JADE and (f) After EI-ICA

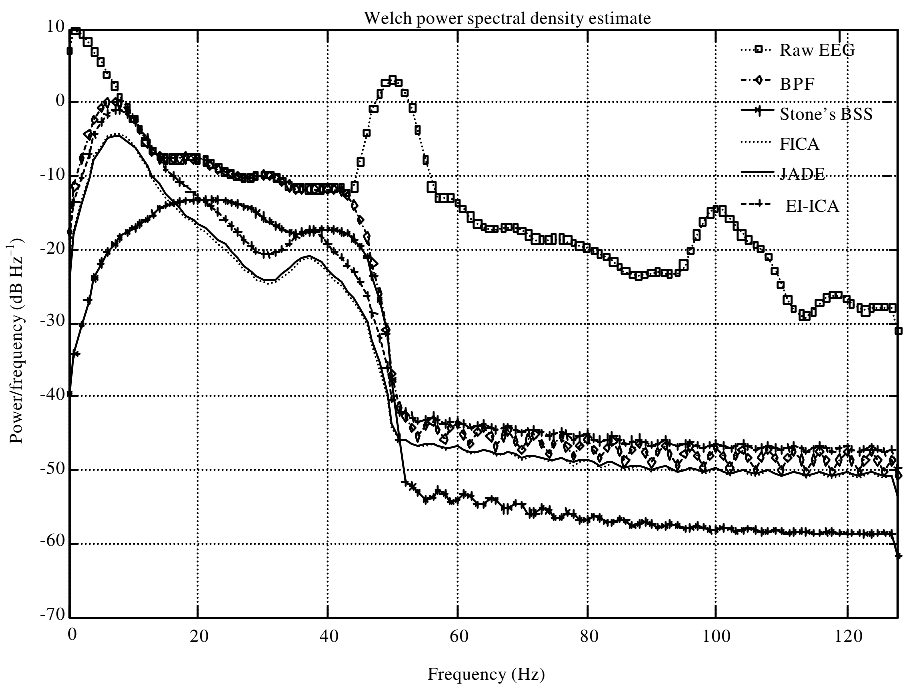

Fig. 12: Spectra of frontal channel (FP1) computed using power spectrum from Raw EEG signal and different types of BSS techniques

One of the most important properties of eye blink artifact, it has lower frequency components compared with the EEG data (Hellyar *et al*., 1995). Therefore, can be exploited this feature to identify the eye blink artifacts also the time domain features are more suitable for this type of artifact (Yoo *et al*., 2007).

Figure 12 shows spectra of Frontal channel (FP1) computed using power spectrum from Raw EEG signal and different types of BSS techniques (Stone's, FICA, JADE, EI-ICA). As shown in Table 1 the values of total power spectrum for eye blink artifact without BSS methods are absolutely high but its very low when Stone's BSS approach is used.

Table 1: Total power value of frontal channel (FP1) with and without BSS techniques

Method	Total power
Without BSS	
Raw EEG	61.8373
BPF	10.7556
With BSS	
Stone's BSS	1.1563
FICA	3.0860
JADE	3.0419
EI-ICA	6.8397

CONCLUSION

This study introduces, a method to separate the eye blinks artifacts based on Stone blind source separation method, hence it's proved that, the Stone's BSS method is an efficient method to separate completely these artifacts from EEG signal without removing significant and useful information (data). However, BSS based on independent component analysis has gained a great deal of popularity in the bio signal analysis, but it has some limitations, therefore must be developed another method like the Stone's BSS method to decrease the limitation and minimize the complexity of the work . In all cases, artifacts were adequately attenuated. It is concluded that the Stone's BSS method gives less complexity, easy to separate the artifacts and is an efficient technique for improving the quality of EEG signals in biomedical analysis.

The contribution presented here, use a Stone's method to separate an ocular artifact in EEG signal, i.e., a new application for this method in brain signal analysis, as expected in Stone's study. In the proposed method, a temporal filter (Windowed-Sinc FIR filter) is used to remove subguassian interference (line noise), DC. Drift. It can be seen that, this type of filter is very good for this purpose but can't remove a superguassian artifact (eye blinks) only reduce it, and then the spatial filter is used to separate completely these artifacts. Finally the Stone's BSS method holds promise toward brain signal analysis and a quite powerful technique and suitable for EEG signal processing in clinical engineering.

Open problem and suggestions: A great challenge in the brain signal analysis is for non-invasively assess the physiological changes take place in various parts of the brain. To extract the pertinent information (data) for diagnosis, expert knowledge not only in medicine but also in statistical signal processing analysis is required. In brain signal processing, one important task is how to automatically detect, extract and eliminate noise and artifacts, then how to enhance the extracted signals and classify the brain sources.

Numerous artifacts may appear in EEG signals such as potentials related to cardiac activity Ballisto Cardio Gram (BCG), Myogenic potentials Electro Gyo Gram (EMG) artifacts. It can be expected, the Stone's BSS is a useful method for these artifacts. Also can be extended this study by using various soft computing techniques with a Stone's BSS method to produce a modified method.

The next step is a classification process to extract main features of cleaned EEG signals and to determine the mental task which used in Brain Computer Interface system (BCI).

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