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Enhancement of Source Separation Based on Efficient Stone's BSS Algorithm

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Abstract

An efficient Stone's BSS (ESBSS) algorithm is proposed based on the joint between original Stone's BSS (SBSS) and genetic algorithm (GA). Original Stone's BSS has several advantages compared with independent component analysis (ICA) techniques, where the BSS problem in Stone's BSS is simplified to generalized eigenvalue decomposition (GEVD), but it's susceptible to the local minima problem. Therefore, GA is used to overcome this problem and to enhance the separation process. Performance of the proposed algorithm is first tested through a different pdf source, followed by artifact extraction test for EEG mixtures then compared with the original Stone's BSS (SBSS) and other BSS algorithms. The results demonstrate proposed algorithm efficiency in real time blind extraction of both super-Gaussian and sub-Gaussian signals from their mixtures.

Keywords: Blind source separation, Stone's BSS, FastICA, JADE, Genetic algorithm

1. Introduction

Blind source separation (BSS) is a technique used to separate underlying sources from their mixtures blindly (i.e. without or with very little knowledge of the original sources or the mixing process). Stone's BSS is a second-order statistic algorithm was proposed by Stone [1, 2], it is a batch algorithm with low complexity and it is better than independent component analysis algorithms (ICA)[3-6]. Many researchers attempted to develop and discuss Stone's BSS [2, 7-9], Stone's BSS is used for linear mixture, convolutive mixture [2] and for nonlinear mixtures [7]. Stone's BSS and ICA are susceptible to the local minima problem [10] and based on the source distribution although the concept in BSS should be no information about sources. Therefore, GA is used to overcome these problems [10]. But unfortunately, the GA also has some shortcomings when used alone as a solution for BSS problem such as: (1) Generate random initial coefficients of separates matrix W maybe don't give the candidate solutions (2) Slow problem due to large population size to increase the candidate solutions. Due to these problems, the original Stone's BSS is used to generate the initial population to overcome the 1st problem; the 2nd problem is solved by decreasing the number of population size. Many researchers have been used BSS techniques to separate both super-Gaussian and sub-Gaussian signal [3-6, 11]. In EEG signal analysis eye blinking artifact is a super-Gaussian artifact and the power line noise is a sub-Gaussian interface [12]. Evolutionary techniques such as particle swarm optimization (PSO) and genetic algorithms have been successfully applied to solve to solve the blind source

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separation problem. PSO and GA with a new fusion of fitness function are proposed in [10] to solve BSS. GA is used to tune the half-life parameters of Stone's BSS algorithm to enhance the separation process as explained in [3] and its used successfully to recover the original sources also Stone's BSS algorithm is proved to be the best in EEG signal analysis and separation [4]. Electrooculogram (EOG) artifact and power line noise interface are extracted successfully by Stone's BSS algorithm as explained in [5]. Automatic removal approach of eye blinking and movement artifacts from EEG data based on BSS is offered by [13]. Two ICA algorithms InfoMax (IICA) and Extended-InfoMax (EIICA) were utilized to extract eye movements and power noise of 50Hz in EEG data is proposed in [12], the EIICA can isolate both super-Gaussian artifacts (Eye blinks) and sub-Gaussian interference (line noise), but IICA is only restricted to remove super-Gaussian artifacts. A comparison study between ICA algorithms was proposed in [14]. ICA algorithms have an inherent disadvantage such as: (1) Source ambiguity (2) Undetermined variances of IC. (3) The performance of ICA is decreased when the dataset is small and with large dataset the redundancy case is not sufficient to recover the independent components [15]. Stone's BSS is used instead of ICA due to these limitations [3, 4, 16]. In this paper, an efficient Stone's BSS algorithm is proposed to separate both super-Gaussian and sub-Gaussian signals from their mixtures based on the joint between BSS algorithms and genetic algorithm.

The remnant of the paper is organized as follows: Section 2 explain the Original Stone's BSS algorithm. Section 3 provides the information about the proposed algorithm. Section 4 provides the simulation results, finally the conclusions are explained in Section 5.

2. Original Stone's BSS Algorithm

Stone's BSS is based on the temporal predictability measure (TP) to separate the mixture. The conjecture of Stone is: (The TP of any signal mixture is ≤ that of any of its components) this conjecture is used to find the weight vector which gives an orthogonal projection of mixtures [1]. The BSS model is shown in Figure 1.

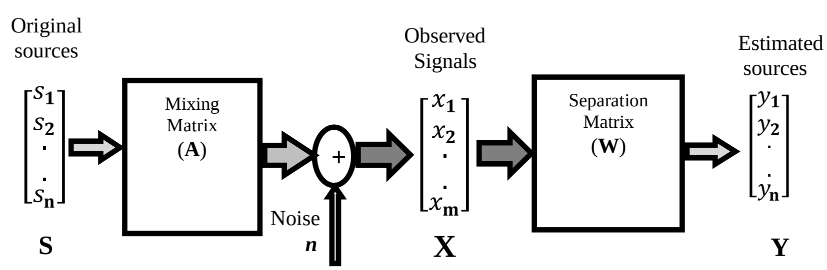


Figure 1. BSS Schematic Diagram

The mixing system without noise is:

$$\mathrm{X(k) = A\,S\,(k)} \tag{1}$$

Where $\mathrm{X(k)} = [\mathrm{x_1(k)}, \ldots \mathrm{x_n(k)}]^{\mathrm{T}}$ are the mixed signals from sensors (its known), $\mathrm{S(k)} = [\mathrm{s_1(k)}, . \mathrm{s_n(k)}]^{\mathrm{T}}$ are the sources (its unknown), superscript T refers transpose operator, $\mathrm{A} \in \mathrm{R}^{\mathrm{n \times n}}$ is a mixing matrix (unknown) and the symbol k is time or sample index. The goal is to recover S from X without knowing A, to solve this problem the separating matrix W should be founded which it is $W=A^{-1}$ in ideal case. The recovered signals are calculated by the separating model:

$$\mathrm{Y(k) = W\,X\,(k)} \tag{2}$$

Where **Y** is the permutation of **S** up to scaling factor. Stone's measure of temporal predictability of signal y(k) is defined as [1]:

$$\mathrm{F(y)} = \log\frac{V_y}{U_y} = \log\frac{\sum_{k=1}^{N}(y_{long}(k)-y(k))^2}{\sum_{k=1}^{N}(y_{short}(k)-y(k))^2} \tag{3}$$

$$y_{short}(k) = \beta_S\, y_{short}(k-1) + (1-\beta_S)y(k-1):\ \ 0 \le \beta_s \le 1, \tag{4}$$

$$y_{long}(k) = \beta_L\, y_{long}(k-1) + (1-\beta_L)y(k-1):\ \ 0 \le \beta_L \le 1, \tag{5}$$

Where N is the number of samples of y(k) , $\beta_s = 2^{-1/h_{short}}$, $\beta_L = 2^{-1/h_{Long}}$ and h_{short}, h_{Long} are half-life parameters (according to the Stone [1] the half-life h_{Long} of β_L is 100 times longer than corresponding half-life h_{Short} of β_S). Assume $y(k) = w_i^T x(k)$, $W = [w_1, w_2, \ldots w_n]$, then (3) can rewritten as:

$$F(y_i) = \log\frac{w_i C_{xx}^{long} w_i^T}{w_i C_{xx}^{short} w_i^T} \tag{6}$$

Where $\mathbf{C}_{\mathbf{xx}}^{\mathrm{long}}$ is a long-term covariance matrix ($N \times N$) between signal mixtures; $\mathbf{C}_{\mathbf{xx}}^{\mathrm{short}}$ is a short-term covariance matrix ($N \times N$) between signal mixtures; $\mathbf{C}_{x_i\mathbf{x}_j}^{\mathrm{long}}$ and $\mathbf{C}_{x_i\mathbf{x}_j}^{\mathrm{short}}$ between i_{th} and j_{th} mixtures defied as:

$$\mathbf{C}_{x_i\mathbf{x}_j}^{\mathbf{short}} = \sum_\tau \left(\mathbf{x}_{i\tau} - \mathbf{x}_{i\tau}^{short}\right)\left(\mathbf{x}_{j\tau} - \mathbf{x}_{j\tau}^{short}\right) \tag{7}$$

$$\mathbf{C}_{x_i\mathbf{x}_j}^{\mathbf{long}} = \sum_\tau (\mathbf{x}_{i\tau} - \mathbf{x}_{i\tau}^{long})(\mathbf{x}_{j\tau} - \mathbf{x}_{j\tau}^{long}) \tag{8}$$

The main aim of Stone's BSS is to maximize Rayleigh's quotient to yield un-mixing vectors; thereby generalized eigenvectors of $\mathbf{C}_{\mathbf{xx}}^{\mathrm{long}}\ [\mathbf{C}_{\mathbf{xx}}^{\mathrm{short}}]^{-1}$ are considered to solve this problem [1, 2, 17]; to find the eigenvectors ($W_1, W_2, W_3, \ldots.., W_M$) of matrix ($\mathbf{C}^{short\ -1}\mathbf{C}^{long}$) which are orthogonal in the covariance matrices :

$$\mathbf{W_i C^{short}\, W_j^t = 0} \tag{9}$$

$$\mathbf{W_i C^{long}\, W_j^t = 0} \tag{10}$$

Where

$$\mathbf{W_i C^{short}\, W_j^t} = \sum_\tau (\mathbf{y}_{i\tau} - \mathbf{y}_{i\tau}^{short})(\mathbf{y}_{j\tau} - \mathbf{y}_{j\tau}^{short}) \tag{11}$$

$$\mathbf{W_i C^{long}\, W_j^t} = \sum_\tau (\mathbf{y}_{i\tau} - \mathbf{y}_{i\tau}^{long})(\mathbf{y}_{j\tau} - \mathbf{y}_{j\tau}^{long}) \tag{12}$$

When the short-term half-life parameter h_{short} toward zero value ($h_{\mathrm{short}} \to 0$) then the short-term mean is:

$$\boldsymbol{y_\tau^{short} \approx y_{\tau-1}} \tag{13}$$

$$(\boldsymbol{y_\tau} - \boldsymbol{y_\tau^{short}}) \approx \boldsymbol{d_{y_\tau}/d\tau} = \boldsymbol{\acute{y}_\tau} \quad (14)$$

Also when the long-term half-life parameter h_{long} toward the infinity ($h_{\mathrm{long}} \to \infty$) and y has zero mean then the long-term mean is:

$$\boldsymbol{y^{long}} \approx \boldsymbol{0} \quad (15)$$

$$(\boldsymbol{y_\tau} - \boldsymbol{y_\tau^{long}}) \approx \boldsymbol{y_\tau} \quad (16)$$

Now under these conditions the expectation value for y_i and y_j are equal to zeros:

$$\mathbf{E}[\mathbf{y_i y_j}] = \mathbf{0} \quad (17)$$

Therefore; this indicate that each recovered signal y_i which can be calculated by $y_i = W_i$x is uncorrelated with every other signal y_j which also calculated by $y_j = W_j$x ; as well as if y_i and y_j are independent then the expectation value is also zero. This method is powerful for any linear mixture with statistically independent signals and it's guaranteed to separate the independent components. The temporal derivative of each recovered signal is uncorrelated with every one and the expectation value equal zero:

$$\mathbf{E}[\mathbf{\acute{y}_i \acute{y}_j}] = \mathbf{0} \quad (18)$$

Finally the separating matrix W calculated by Matlab eigenvalue function as:

$$\mathbf{W} = \mathbf{eig}(\mathbf{C^{long}C^{short}}) \quad (19)$$

This is one of the advantages of the Stone's BSS to simplify the BSS problem into generalized eigenproblem [6].

3. Proposed Algorithm: Efficient Stone's BSS (ESBSS)

Efficient Stone's BSS (ESBSS) is a joint between original Stone's BSS and a refinement process for the separating matrix W by GA. The proposed algorithm consists of two steps:

Step 1) Running the original Stone's BSS with different half-life parameters until convergence: The purpose of this step is to quickly and reliably obtain the initial separating matrix $W_{Initial}$.

Step 2) Refinement or fine-tuning of $W_{Initial}$ by genetic algorithm: GA is used as a refinement process to the coefficients of $W_{Initial}$ to obtain W_{Refine}, and then apply (2)

GA parameters:

Maximum number of Generation = 20

Population Size (Pop) = 5

Probability of Crossover = 0.95

Probability of Mutation = 0.05

Fitness function: $\mathrm{Fit(y)} = -\sum_{i=1}^{n}\left[\left|\mathrm{E}\{y_i^4\} - 3\mathrm{E}^2\{y_i^2\}\right| + \mathrm{H}(y_i) - \mathrm{H}(y)\right]$ (20)

H is the entropy of mixed signals. H is always non-negative and zero if the variables are statistically independent. The fitness function takes the same fashion in [10] based on kurtosis and mutual information for more details see [10]. One of the advantages of the proposed algorithm, all the chromosomes in the initial population are candidate solution; which generated by original Stone's BSS for several times with different half–life parameters ($h_{Long} \geq 100h_{short}$, $h_{Long} \geq 50h_{short}$, $h_{Long} \geq 25h_{short}$, $h_{Long} \geq 10h_{short}$ and $h_{Long} \geq 5\, h_{short}$).

Symmetric orthogonalization is applied before filling each population to guarantee the independence among separated sources and obtains by [10]:

$$W = W.\mathrm{Real}\ (\mathrm{inv}\big(W.W^{T}\big)^{-\frac{1}{2}}) \tag{21}$$

The proposed algorithm would be defective without orthogonalization process as mentioned in [10]. The estimated independent components are separated correctly when the fitness function is maximized, but all the estimated signals have the analogy and maximum kurtosis. Therefore, the orthogonalization process used to solve this problem. There are two methods for orthogonalization: (i) Deflationary (ii) Symmetric. The symmetric method is used in the proposed algorithm due to the higher applicability from other. For easy reference, the outline of the proposed algorithm is summarized in Figure 2.

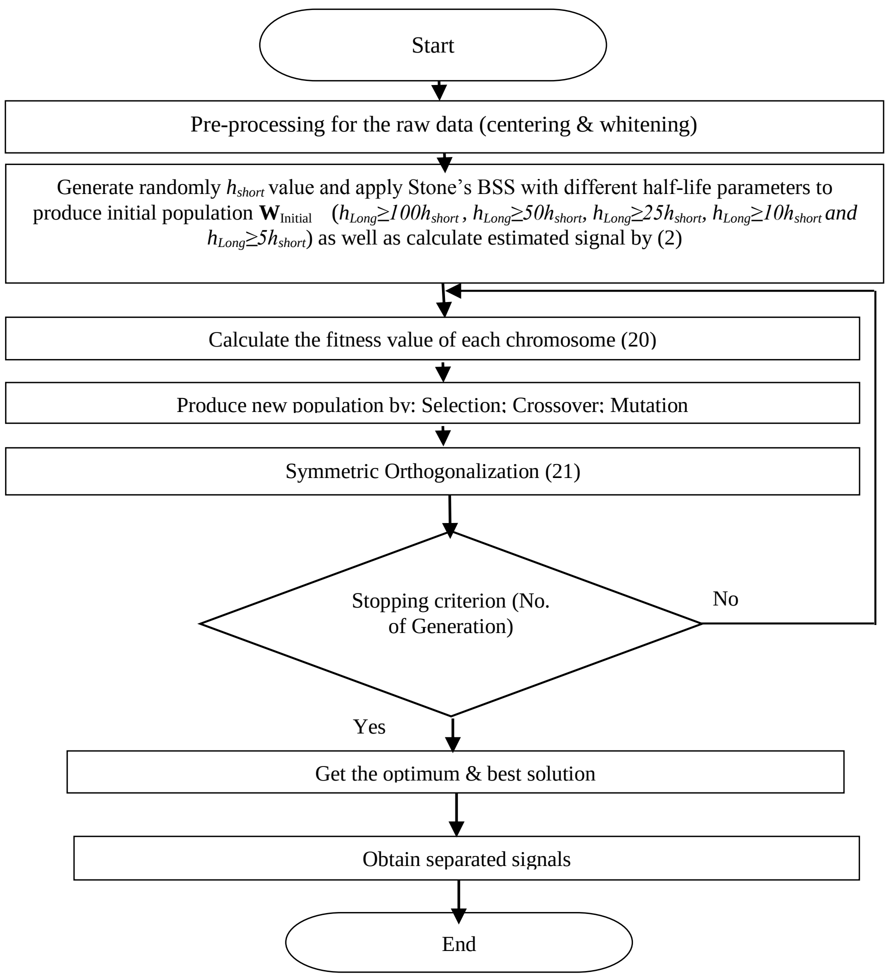


Figure 2. Flowchart of Proposed Algorithm

4. Results

The proposed algorithm is tested in two benchmarks; the first one is the simulated data for super-Gaussian, sub-Gaussian and Gaussian source; the second benchmark is to extract the EOG (super-Gaussian) and power line noise (sub-Gaussian) from real EEG data. The performance for the first benchmark is measured by the interference signal ratio ISR, but this measure is not applicable in second benchmark because there is no knowledge of the mixing process.

4.1. Benchmark One: Simulated Data

The same experiment data in [1] are tested to check the validity of the proposed algorithm with original Stone's BSS. Three sources with different pdf (super-Gaussian S1 (a music signal sp.wav), sub-Gaussian S2 (a sine wave)) and sorted Gaussian noise S3) as shown in Figure 3, mixed with random matrix A to produce Figure 4, for more details see [1]. Figure 5 shows the estimated signals (y1, y2 and y3) with corresponding sources using efficient Stone's BSS algorithm.

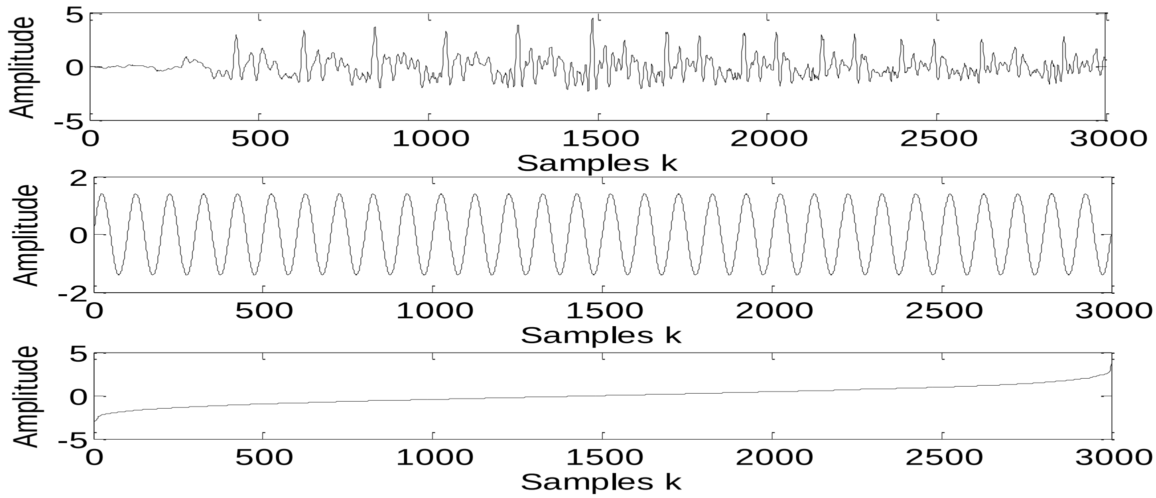


Figure 3. Original sources (S1, S2, S3) from top to bottom

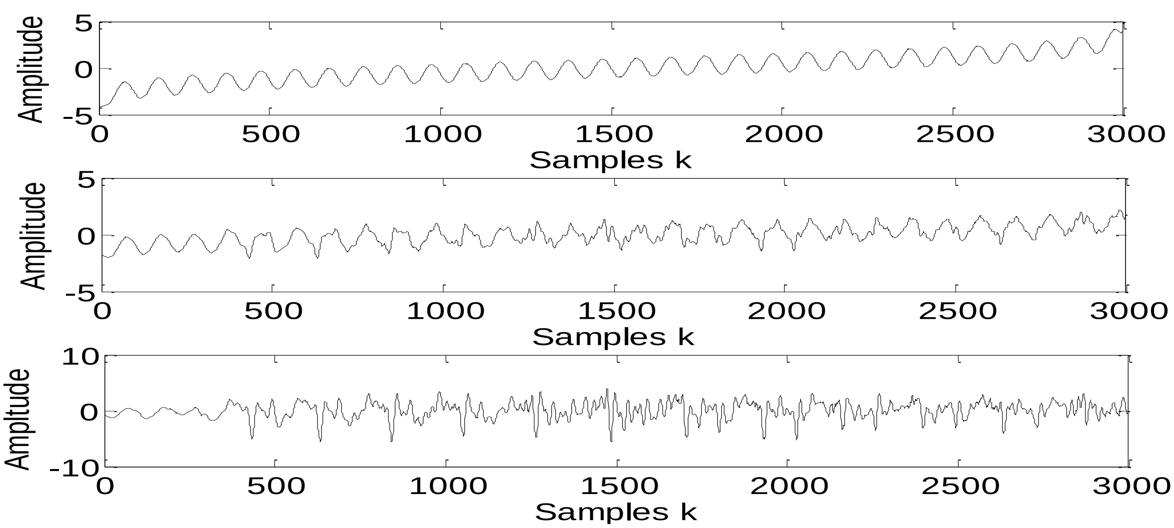


Figure 4. Mixed Signals

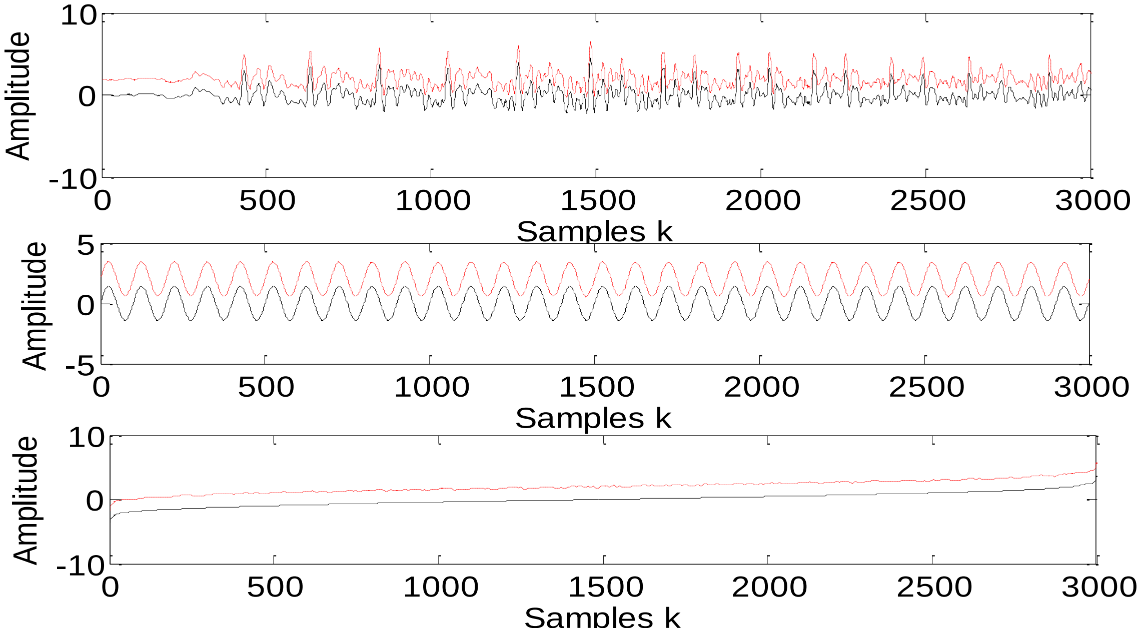


Figure 5. Three Sources (S1, S2, S3) from Top to Bottom and Corresponding Recovered Signals (y1, y2, y3) using Proposed Algorithm (ESBSS) with Shifted Vertically for Display Purposes

The performance of the proposed algorithm is evaluated by interference to signal ratio ISR measure:

$$ISR_i = 10\log\frac{E[(S_i(k)-y_i(k))^2]}{E[(S_i(k))^2]} \tag{22}$$

Where S is the original signal and y is the recovered signal. The result of the separating process is better whatever the ISR measure be less as shown in Table 1.

Table 1. Comparison of ISR Values for Different BSS Algorithms

BSS Methods	Interference signal ratio (ISR) for estimating signals (y1, y2, &y3)			ISR Mean
	y1	y2	y3	
ESBSS	-54.9703	-96.3158	-43.3786	-64.8882
EFICA	-54.8812	-75.4132	-30.9397	-53.7447
Stone's BSS	-30.394	-61.4847	-44.0291	-45.3026
FICA	-54.0022	-35.7753	-25.9105	-38.5627
JADE	-26.2113	-31.6204	-22.1245	-26.6521

4.2. Benchmark Two: Real EEG Data

Real EEG data are taken using computerized EEG device; the main goal is to separate the artifacts as independent components from EEG mixtures in the time domain without filtering process in order does not lose any useful information [18], six channels (Fp1, Fp2, C3, C4, O1,O2 and ground at Cz) are placed according to 10-20 system (Figure 6) and used to record the brain signals (Figure 7), also vEOG and hEOG channels are used to measure the eyes activates (artifacts) placed above and on the side of the left eye's socket; the sampling frequency = 256Hz for 20 second. Frontal channels (Fp1 and Fp2) are infected by eyeblink artifacts and the power line noise is present in all six channels but it's seen more strongly on the central (C3 and C4) and occipital channels (O1 and O2) as shown in the Figure 7. Figure 8 and Figure 9 shows the recovered signals by efficient fast independent component analysis (EFICA) [19] and the proposed algorithm respectively.

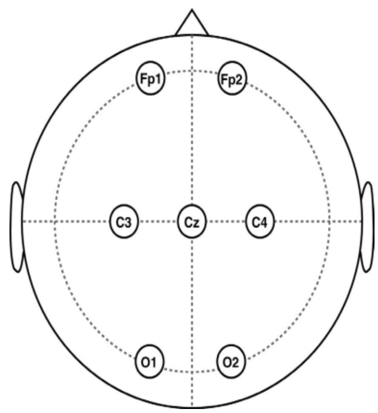


Figure 6. Placement of Electrodes (10-20) System

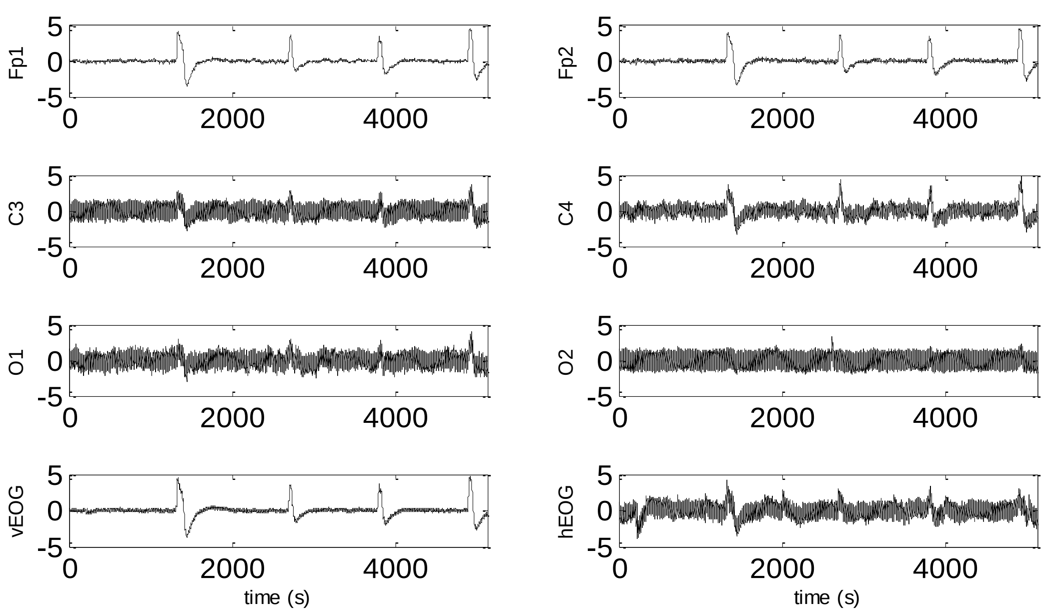


Figure 7. Recorded EEG Mixtures

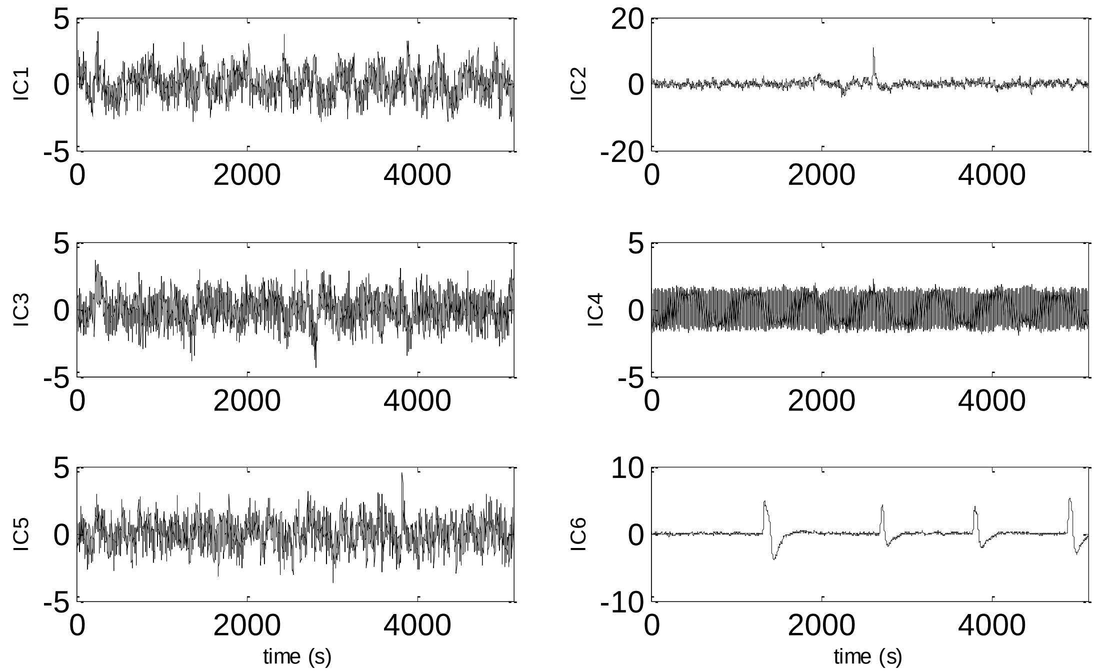


Figure 8. Extracted Independent Components by EFICA

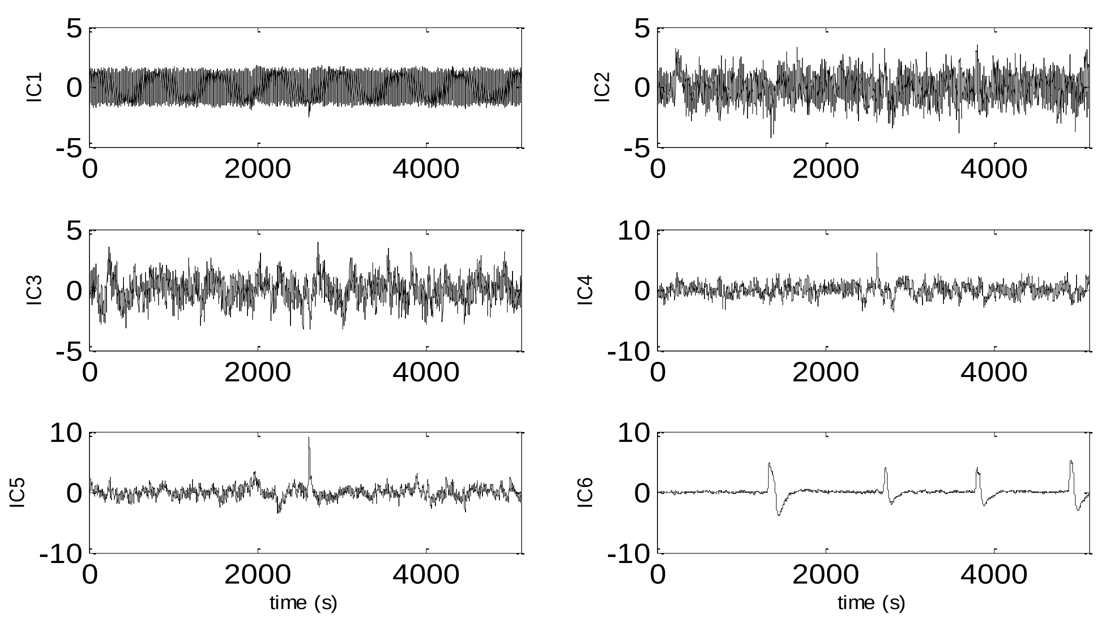


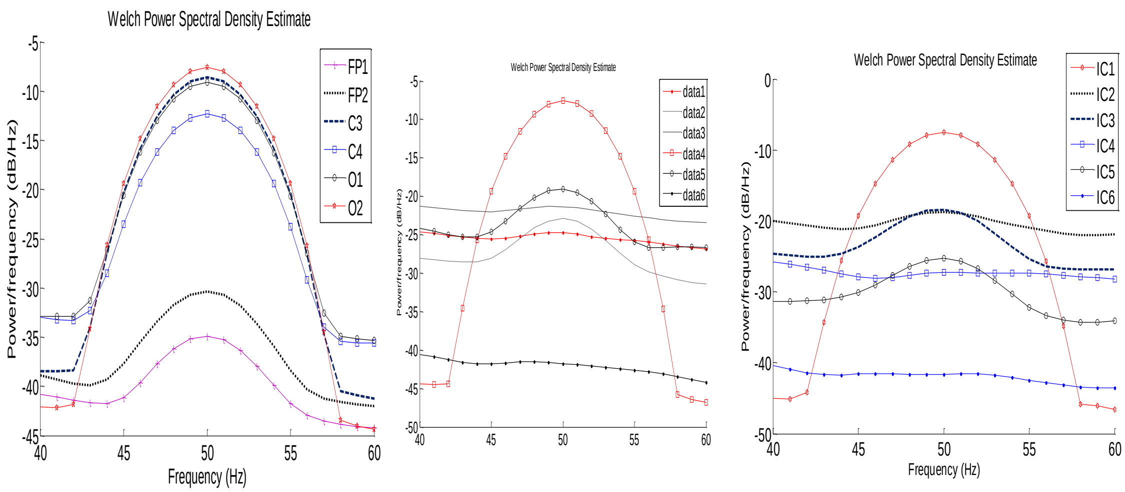
Figure 9. Extracted Independent Components by ESBSS

Visual inspection of the EEG- artifact extraction confirms that EFICA and ESBSS algorithms effectively extract eyeblink artifact and power line noise interface. However, another measure based on cross-correlation between vEOG channel and extracted eyeblink component is used to measure the best algorithm as shown in Table 2.

Table 2. Correlation Measure between vEOG with Eye Blinking Artifact for Different BSS Algorithms

BSS Algorithm	EBSS	EFICA	Stone's BSS	FICA	JADE
Correlation between vEOG & Estimated Eye blink artifact	0.9997	0.9881	0.9867	0.9554	0.9477

The frequency components of the extracted power line noise in the 50-Hz range showed that the line noise artifact was successfully decreased and removed as shown in Figure 10.



(a) (b) (c)

Figure 10. Frequency Components Around 50-Hz Frequency (a) For Recorded EEG Channels (b) For Extracted Components by EFICA (c) For the Extracted Components by ESBSS

5. Conclusion

Efficient Stone's BSS is a powerful algorithm to separate both super-Gaussian signal and sub-Gaussian signals blindly compared with original Stone's BSS and ICA algorithms as shown in the simulation and experimental results ESBSS algorithm solves many problems by connect the original Stone's BSS algorithm with genetic algorithms. But it is a little complicated in computation like EFICA. The fitness function which proposed by [10] is a very efficient choose. The Changing in the half-life parameters (h_{short}, h_{Long}) have a significant effect on the original Stone's BSS algorithms. There is no filter used to remove the power line noise from EEG mixtures, the raw data are introducing directly to the proposed algorithm in order not to lose any useful information, in particular, the gamma band (25-100Hz) lies within filter range (50-Hz).

The results obtained by the EBSS algorithm are encouraging and can use it to extract other types of artifacts such as ECG or EMG artifacts.

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