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Electroencephalogram-Artifact Extraction Enhancement Based on Artificial Intelligence Technique

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Abstract Blind source separation (BSS) is an important technique used to recover isolated independent sources signals from mixtures. This paper proposes two blind artificial intelligent separation algorithms based on hybridization between artificial intelligent techniques with classical blind source separation algorithms to enhance the separation process. Speedy genetic algorithm SGA directly guesses the optimal coefficients of the separating matrix based on candidate initial from classical BSS algorithms also the separation criteria based on minimization of mutual information between the separating independent components. The proposed algorithms are tested by real Electroencephalogram (EEG) data, the experimental results indicate that the algorithms can quickly and effectively get optimum solution to linear blind source separation compared to classical BSS techniques, the proposed works are described by high accuracy and robustness.

1. Introduction

Electroencephalography (EEG) is a non-invasive medical technique used to measure the brain electrical activity, which produced from joint activity of millions of cortical neurons. These activities are measured by sensors (electrodes) placed on the human scalp [1]. The amplitude of EEG signal is in order of microvolts [2]. EEG signal was first measured in humans by Hans Berger in 1924. In 1929 he publishes the first paper to explain the technique for recording the electrical brain activity from the scalp. The main characteristics of EEG–brain signals are: easily recorded by electrodes, complex–spatiotemporal signals, very good in temporal regulation, poor in spatial resolution, and depends on the number of electrodes [3]. The rhythms of normal brain activity can be categorized into different rhythmic activity based on the level of consciousness [3] and classified according to their frequency. Each rhythm is recognized by amplitude, frequency, duration, generated brain areas, and defined according to distribution over the scalp. The frequencies of brain signal is classified into six classical brain rhythms known as delta (δ), theta (θ), alpha (α), mu (μ),beta (β), and gamma (γ). The EEG-electrodes putted on the scalp and commonly distributed based on the International 10–20 system [4]. This system is standardized in 1958 by American Electroencephalographic Society to arrange the electrodes placement on the brain scalp. The EEG device is considered to record the signal from brain but it is also collect the activities from other places in the brain [5]. In brain signal analysis; there is no one has idea about the neurons activity and the mixing process, which happen inside the brain; therefor can be modelled the human brain as a BSS problem [6]. The artifacts have high effect on the diagnosis, therefore these signals should be extracted before final decision; one of the common techniques used to separate these signals is the blind source separation algorithm (BSS).

Blind source separation (BSS) conjointly referred to as blind signal separation (BSS) is unsupervised technique in signal processing field. Wide range of applications covered by BSS such as in telecommunication, neurophysiological signal, medical signal processing, speech signal, and image processing [7, 8]. BSS used to separate or extract the underlying sources from the received signals without or with little information about the original sources [9]. The EEG signals are multichannel data, therefore the BSS techniques are perfectly convenient for their analysis [10]. There are many techniques proposed to clean the brain signal, but there is no single method is the best method, where every technique has an own pros and cons. Overall the BSS techniques are the more judicious to separate the artifact signals from EEG mixtures. A time domain regression algorithm is used to separate the EOG artifact based on the scaling factors between EOG channels and each EEG channels, which computed separately for each epoch then averaged, also the correction of vertical and horizontal artifacts by a multiple regression method is demonstrated [11]. The first application of Independent component analysis for EEG signals based on the algorithm which proposed in 1995 by Bell and Sejnowski [12, 13], and then developed was implemented by Hyvärinen and Oja to describe Fast ICA algorithm which based on the non-Gaussinity of the underling components [14]. Hybrid soft computing algorithms called Adaptive Neuro-Fuzzy Inference System (ANFIS) to extract EEG artifacts are used by [15]. ANFIS algorithm is proved by a comparison with adaptive filter and neural network using least mean square. Ref.[16] proposed Nonlinear Blind Source Separation (NBSS) Algorithm based on Particle Swarm Optimization (PSO) joint with natural gradient Algorithm. In this reference the model of NBSS is constructed which the nonlinear transfer function is simulated by the Pth order polynomial function. A novel BSS approach is presented by [17] based on a merging genetic algorithm with Stone BSS algorithm to enhance the separation process between the separated signals

The main aim of this paper is to clean the human-brain EEG signals from common artifacts based on artificial intelligent techniques. The evaluation of the proposed BSS algorithms are tested by real EEG data with nine channels.

2. EEG-Artifacts

Although EEG is designed to record the brain signals, it also records electrical activities arising from other sites in the brain. EEG signal is random weak amplitude signal with very small amplitude compared with artifact signals [5]. The recorded activity that is not of cerebral origin is termed artifact and can be classified into:

2.1 Technical Artifacts

Power line noise interference: very Strong signals produced from A/C power supplies which contaminate the EEG signal during recording process. Notch filter is used to remove this artifact which has lower frequency and harmonics, but the notch filter will also be remove the useful information (EEG data) around 50/60 Hz. Line noise can interference with some or all of the electrodes based on the source of the interference problem [18, 19]. Figure 3.1b shows the EEG signal contaminated by line noise.

Electrode artifact: this artifact is produced by varying the impedance of electrodes due to improperly attaché or poor condition

Sweating: this type of artifact is producing by sweat which effect on the impedance of electrodes

2.2 Biological Artifacts

Electrooculargram (EOG) or ocular artifacts (OA): This type of artifact is very common in EEG signal analysis, produced due to eye blinking or eye movements, eye blinking generate high amplitude signal and greater than the EEG signal by many times. It is interference with all electrodes even those at the back of the head, mostly on the FP_1, FP_2, F_7 and F_8 [5, 20]. The ocular artifacts can be measured by pairs of electrodes named EOG electrodes placed above and around the eyes. Eye movement artifact is produced by the reorientation of the retinal corneal dipole [21]. It's has a stronger effect but often occur at close interval with eye blinks. Unfortunately, EOG electrodes also interference with brain signals therefore a subtraction process form EEG signal is not a removal option [18]. Eye blinks has spikes shape (figure 3.1c), while eye movements have a square shapes as shown in figure 3.1d.

Muscle Activity artifact MEG: this type of artifact is produced due to the activity of different muscles groups and most common activity in neck and facial muscles. It's a wide frequency range and interacted with all EEG channels [22].

Electrocardiogram ECG or heartbeat artifact: this type of artifact caused when an electrode is putted on or near a blood vessel. Expansion and contraction of the vessel generate voltage changes into the recordings with a frequency around 1.2Hz [19]. It does appear like regular spikes at the same time in ECG recording process as shown in figure 3.1e.

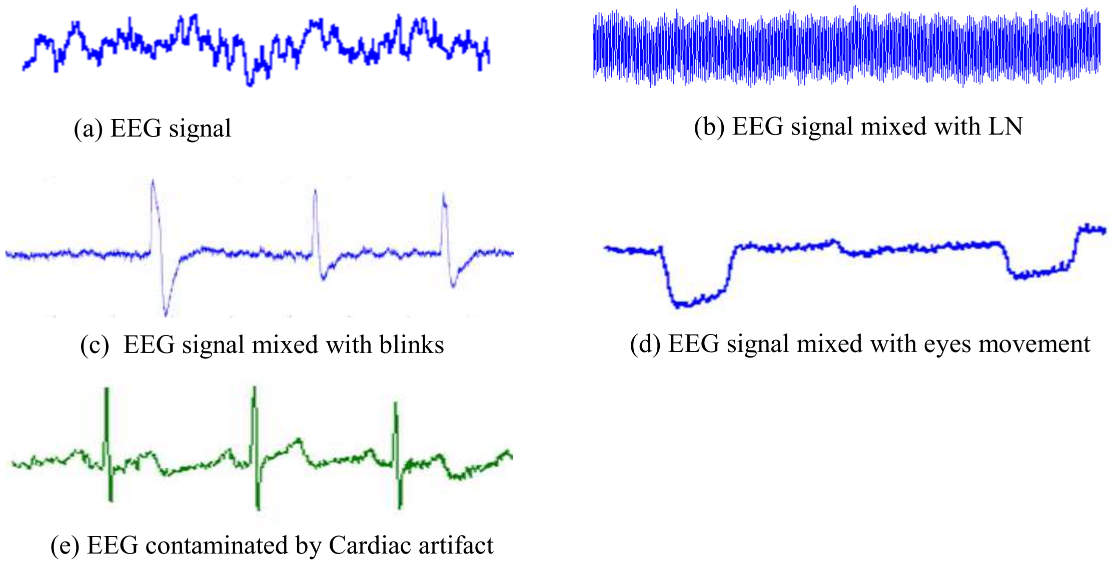

Figure 1: EEG signals contaminated by common Artifacts waveforms

3. Blind source separations

In last decades, source separation techniques have considerable attention in signal processing researchers. The source separation problem can be classified into supervised and unsupervised (blind) methods, this classification based on with/without training data. The unsupervised technique or can be named blind source separation used to recover the underline sources and can be classified into three categorize [23-25]: linear /nonlinear, instantaneous/ convolutive, and underdetermined/ over complete as shown in Figure 2

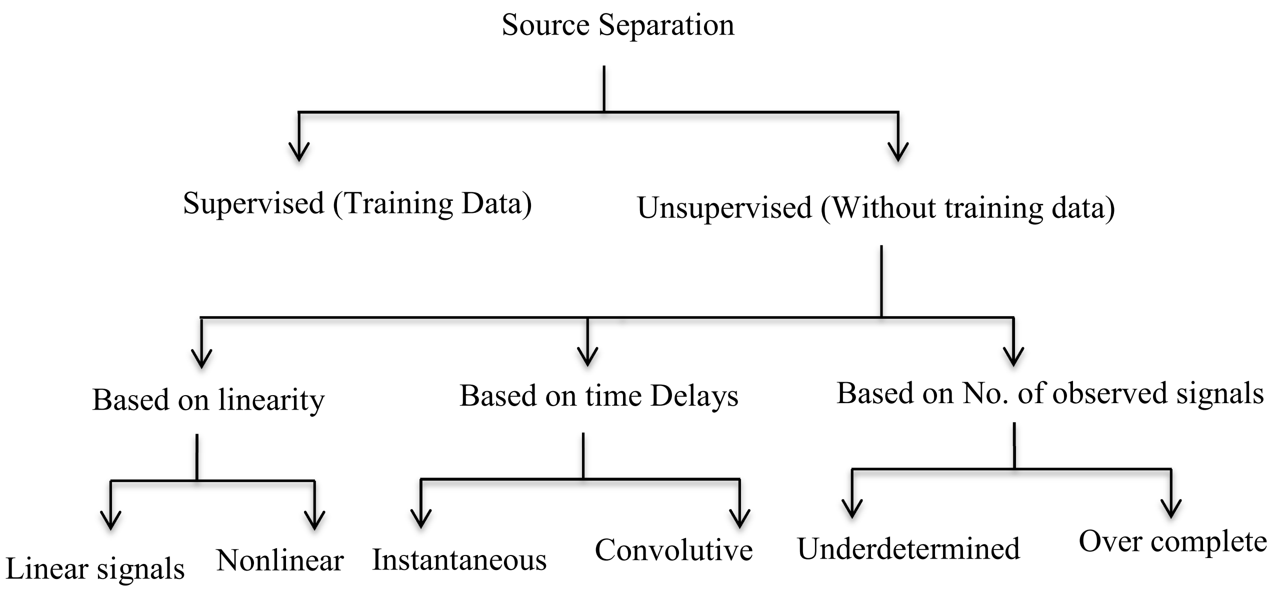

Figure 2: General classification of source separation techniques

3.1 Preprocessing

There are three pre-processing techniques applied before BSS algorithm to make the BSS problem simpler, faster, robustness, and better conditioned [26] [27] [28]:

(a) Centering process
(b) Whitening process
(c) Principle component analysis

3.2 Formulation

The BSS problem can be formulated as a mathematically by figure 3

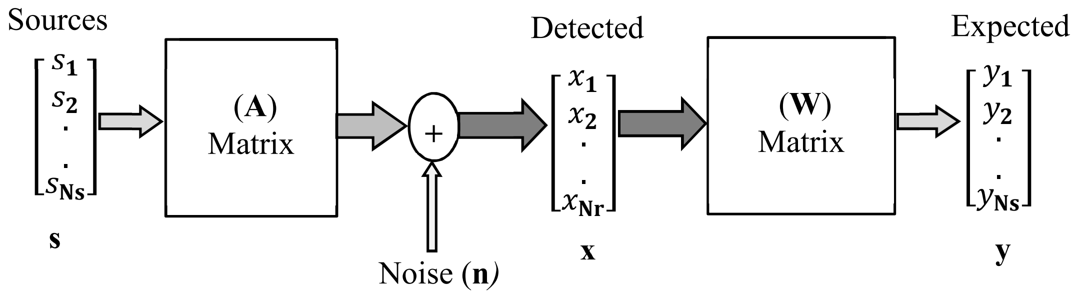

Figure 3: BSS process

A set of original sources $\mathbf{s}$ $(t) = [s_1\ (t), s_2\ (t) \ldots s_{Ns}\ (t)]^T$, mixed with $\mathbf{A}$ to produce mixtures $\mathbf{x}$ $(t) = [x_1\ (t), x_2\ (t) \ldots x_{Nr}\ (t)]^T$; the mathematical model of BSS problem without noise is:

$$\begin{bmatrix} x_1(t) \\ x_2(t) \\ \vdots \\ x_{Nr}(t) \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1Ns} \\ a_{21} & a_{22} & \cdots & a_{2Ns} \\ \vdots & \vdots & \cdots & \vdots \\ a_{No1} & a_{No2} & \ldots & a_{NrNs} \end{bmatrix} \begin{bmatrix} s_1(t) \\ s_2(t) \\ \vdots \\ s_{Ns}(t) \end{bmatrix} \leftrightarrow \mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) \qquad (1)$$

The key is to guess the sources by guess the **A** or inverse of **A**, which called **W** where:

$$\mathbf{s}(\boldsymbol{t}) = \mathbf{W}\,\mathbf{x}(\boldsymbol{t}) \tag{2}$$

System with noise is:

$$\mathbf{x}(\boldsymbol{t}) = \mathbf{A}\mathbf{s}(\boldsymbol{t}) + \mathbf{n} \tag{3}$$

Where $\mathbf{n} = [n_1(t), n_2(t) \dots n_s(t)]^T$

4. Artificial Intelligence techniques

The artificial intelligence (AI) techniques consist of Evolutionary computation (EC) and Swarm Intelligence (SI) techniques [29]. Evolutionary computation is based on the biological evolution principles while Swarm Intelligence is based on swarm behavioral patterns. The artificial intelligence used to solve many complex control problems.

4.1 Evolutionary Computation Techniques

Evolutionary computation (EC) techniques are motivated by biological ideas such as population, crossover, mutation, and survival of the fittest. They are observed a stochastic search algorithms that simulate the problem of natural selection and evolution in the biological field [30]. Generally, EC techniques classified into four main evolutionary techniques:

I. Genetic Programming (GP): GP is based on the search of the fittest program to solve a specific task. The individual is represented as tree and the focus is on genetic composition of the individual.

II. Evolutionary Programming (EP): EP is used to adjust the real valued continuous functions. EP based on selection and mutation operators without any crossover operator. The focus is on the observed characteristics of the population. The selection operator is used to determine chromosomes for reproducing and generating new chromosomes.

III. Evolutionary Strategies (ES): ES is based on the optimizing the real-valued continuous functions. ES combines selection, crossover, and mutation operators. ES adjusts the population and the optimization process by developing the strategy parameters.

IV. Genetic Algorithms (GA): GA is invented and developed by John Holland and his colleagues based on the “Evaluation Strategies” which introduced by I. Rechenberg in 1960s. GA is explained in Holland’s book “Adaption in natural and artificial system”, which published in 1975.

GA is an optimization algorithm used to establish most efficient features in a certain set of features. The GA and its variants are popular in academic and industry domain because of its intuitiveness, ease of implementation, and ability to solve highly non-linear, mixed integer optimization problems [30, 31].

The genetic algorithm consists of several sequential steps to solve the problem; at beginning; generate random initial population with limited population size from n chromosomes (initial solution); the chromosome represent one of the possible solution or contain useful information about the solution, there are many ways of chromosome encoding (Binary, Integer, Real,…). The fitness of each chromosome is evaluated according to limited fitness function, then some of important steps named GA operators (selection, crossover, and mutation) are used to modify the initial population, can be explained these operators briefly as follows:

I. Selection: The selection operator is used to increase the number of candidate solutions which have high fitness function; there are different ways to accomplish this step such as: (Roulette wheel selection, Rank selection, Poltzman selection, Steady state selection, and some others. The best chromosomes are selected to be a parent to crossover.

II. Crossover: Most important operation in GA, it is used to produce new chromosomes (offspring). Generally there are many ways to implement the crossover operator such as: (Single point crossover, multi-point crossover, Uniform crossover, Arithmetic crossover, and some others

III. Mutation: This operation is used to keep the diversity in the population; there are many ways to accomplish this such as: (Binary mutation, Uniform mutation, non-uniform mutation, and some other.

The fitness function of every new chromosome in a new population is evaluated again. Some of recommendations of the genetic algorithm parameters are explained as follow:

I. Probability of Crossover (Pc): This value should be high, about 80%-95%, to produce new chromosomes (offspring) from old chromosomes (parents).

II. Probability of Mutation (Pm): This value should be very low, about 0.5%-1%; if mutation if occurred then the part of chromosome is mutated (changed).

III. Population size (POP): The speed of obtaining the solution based on the size of population and big population doesn't improve the performance of the GA; typically suitable population size is about 50-100; furthermore, the type of software used, and the chromosome encoding are an effect on the speed to find the solution.

IV. Fitness function (Fit): The Fitness Function in biological sense could be a quality value that could be a live of the generative potency of chromosomes. In GA, the fitness function is employed to assign generative traits to the individuals within the population and so act as some live of goodness to be maximized.

4.2 Swarm Intelligence Techniques

Swarm Intelligence (SI) techniques are based on study of the behavior of a group in decentralized and self-organized system. SI system is typically prepared of a population of simple agents interacting locally with another and with their environment. The most popular of SI techniques are: Ant colony optimization (ACO) and Particle Swarm Optimization (PSO [30] .

I. Ant Colony Optimization

The Ant Colony Optimization (ACO) technique is based on the traversing problem space. ACO technique like real ants, it deposits artificial pheromone on the workspace or field in a manner that makes it possible for future ants to have better solutions or short way to access the goal . In real field the ant colonies used pheromone to find the shortest path for the food. This technique is used in a wide range of the optimization problems such as in Traveling salesman problem TS [32].

II. Particle Swarm Optimization (PSO)

The Swarm Intelligence (SI) have been utilized to solve many problems [6]. PSO is one of the evolutionary computation methods to solve optimization problems. The method can be applied to non-linear optimization problem that includes constraints without the graduate of the objective function [33]. PSO is one of the optimization techniques first proposed by Eberhart and Colleagues [12, 13]. This method is a robust in solving problems featuring non-linearity and non-differentiability, which is derived from the social psychological theory [34, 35].

5. Proposed algorithm

EEG-brain mixtures are contaminated by different artifact sources like EOG artifacts (eye movements and eye blinks), ECG artifact (heartbeat), EMG artifacts (muscle), and power line noise interference. These signals are a serious problem for EEG interpretation. Many algorithms have been presented to reject the artifact signals such as: Cutting the contaminated EEG epochs; Regression method; Filtering method; and Blind source separation as mentioned in previous section

[36]. Two artificial intelligent techniques are used to implement BSS algorithm and find the best separation matrix.

5.1 SGA based BSS (SGA-BSS)

An algorithm called Speedy Genetic algorithm (SGA-BSS) is proposed to separate different sources from their mixture. It's based on the joint between original blind source separation techniques with SGA. The proposed work contain:

Step 1: execute the BSS algorithms to obtain good initial matrix ($\mathbf{W}_{\text{Initial}}$).

Step 2: SGA is used as parameters of the separating matrix which obtained from step 1.

In step 1; the main goal of BSS techniques is to convert a multichannel signal X to separated independent components. Actually, the separated components are not fully statically independent, but they are as independent as possible. Different BSS algorithms (Stone's BSS, SOBI, FICA, EFICA, and JADE) are used to quickly and reliably obtain good initial separating matrix W_{Initial} as well as to overcome the shortcoming of GA.

In step 2; the algorithm is used to tune the W_{Initial}. The coefficient of this matrix used as an initial population and can be adapted into new population by GA operators: selection, crossover, and mutation. The independence among the components is maximized using the fitness function shown below. The main parameters of genetic algorithm:

Max. Gen.= 40

Pop. Size = 5

P_C = 0.95; PM = 0.05

Len. Of chromosome = n^2

Fitness function: $$Fit(y) = \frac{1}{I(y)+\varepsilon} = \frac{1}{\sum_{i=1}^{n} H(y_{i)} - H(y_1, y_2, \dots, y_n)} \quad (1)$$

The $(y_1, \dots, y_n)$ are separated, H entropy ; $I(y)$ mutual information; and ε equal to 0.0001. [37, 38]. For easy reference, the outline of the proposed algorithm is summarized in figure 4

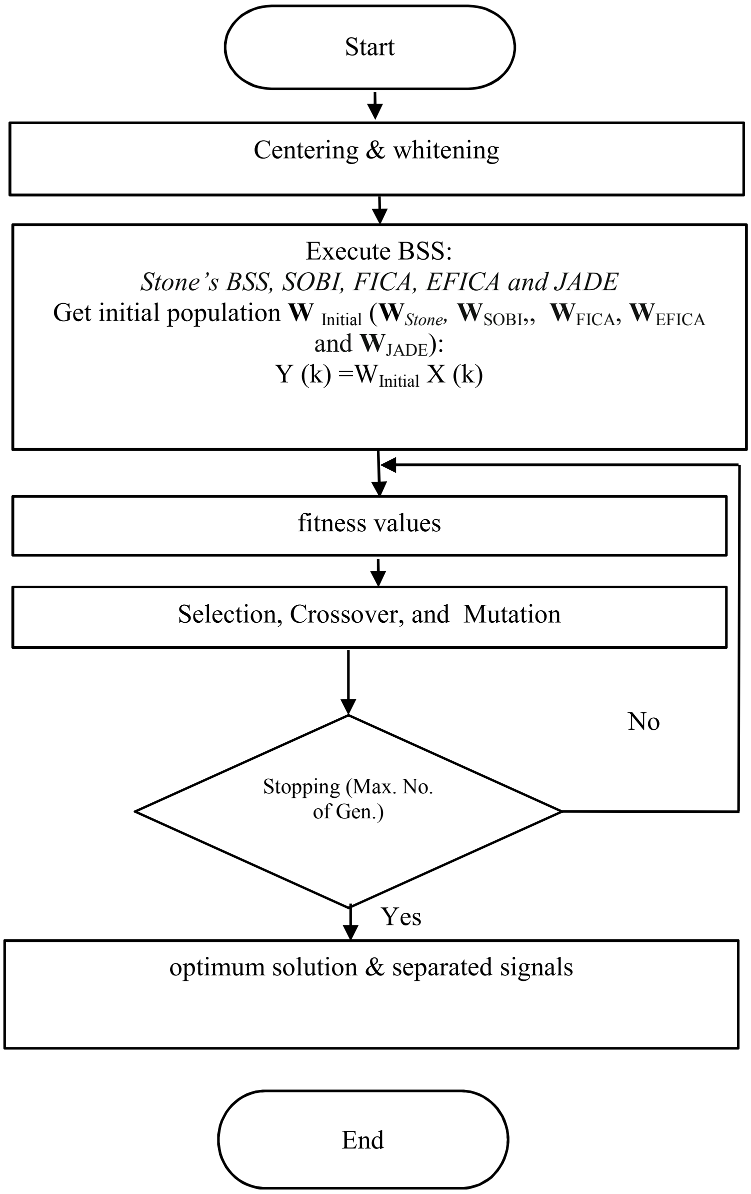

Figure 4: SGA-BSS

6. Results

Real data for EEG are taken with a sampling 256 Hz. Two studies are implemented to separate the ocular artifacts without lose any useful information from recording EEG signals. The correlation measure between EOG channels and extracted signals is used to assess the extraction process for the proposed algorithms. Nine channels are used in this study; where, six electrodes (Fp1, Fp2, C3, C4, O1, and O2) used to measure the brain signals which placed on the scalp according to 10-20 system, one electrode as a ground placed at Cz (figure 5), and two EOG electrodes (v_{EOG} & h_{EOG}) putted over the eye and on the side to measure EOG activity.

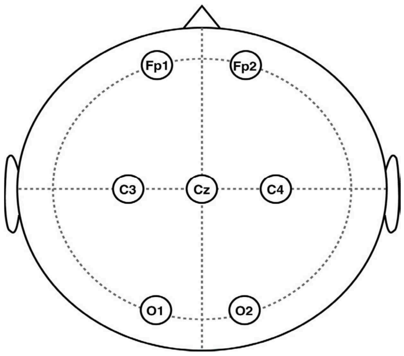

Figure 5: Electrodes positions

I. Data set I

EEG signals are mixed by eye blink and LN (50-Hz), the blinking affected on the Fp1, Fp2. All channels are mixed by LN (50-Hz) with different contamination. LN is pronounced on C3 and C4 also on O1 and O2 [22] as shown in figure 6.

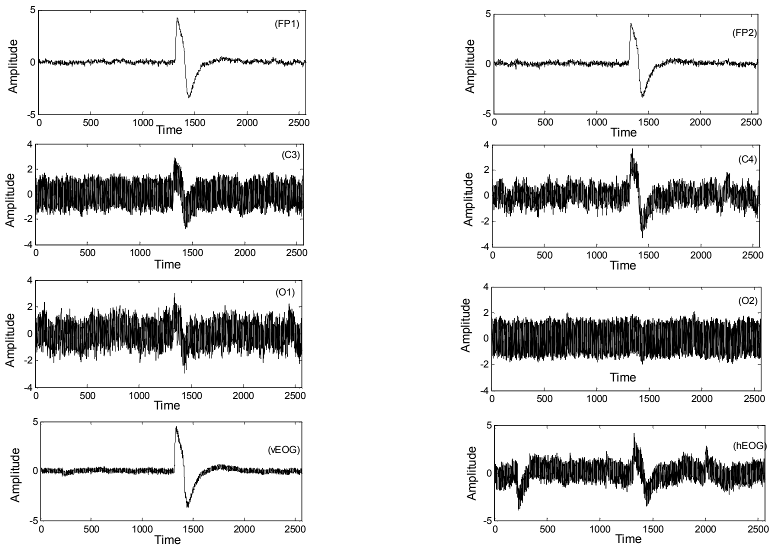

Figure 6 Data set I

Good separation of LN and eye artifact by the proposed algorithms, where the LN is separated in IC1 and the eye artifact is separated in IC6 as shown in Figure 7.

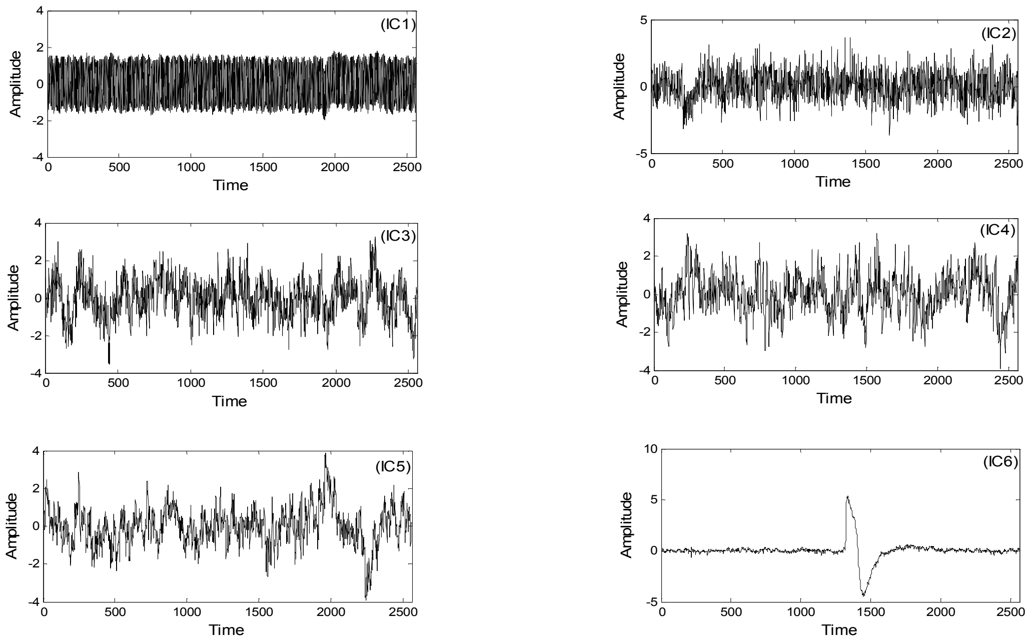

Figure 7 Separated components for Data set I by SGA-BSS

Table 1 shows the correlation between reference signal and the extracted artifact. The correlation shows that the SGA-BSS is better than BSS techniques to extract the artifact. Table 2 shows kind of separated signals according to sparsity, IC1 is LN because its value less than 1, and the IC6 is artifact due to high sparsity [39].

Table 1 Correlation measure

BSS	Correlation Artifact-reference & separated artifact
SGA-BSS	0.9439
EFICA	0.9411
Stone	0.8677
FICA	0.8594
SOBI	0.8505
JADE	0.7987

Table 2 Classify the separated signals

IC	Sparsity	type of signal
IC1	0.1641	Line noise
IC2	1.5678	brain signal
IC3	1.4921	brain signal
IC4	1.7374	brain signal
IC5	1.9785	brain signal
IC6	11.5523	Artifact

II. Data set II

EEG are mixed by eye movement and blinking also by LN. Eye artifacts existing in all channels, as shown in figure 9.

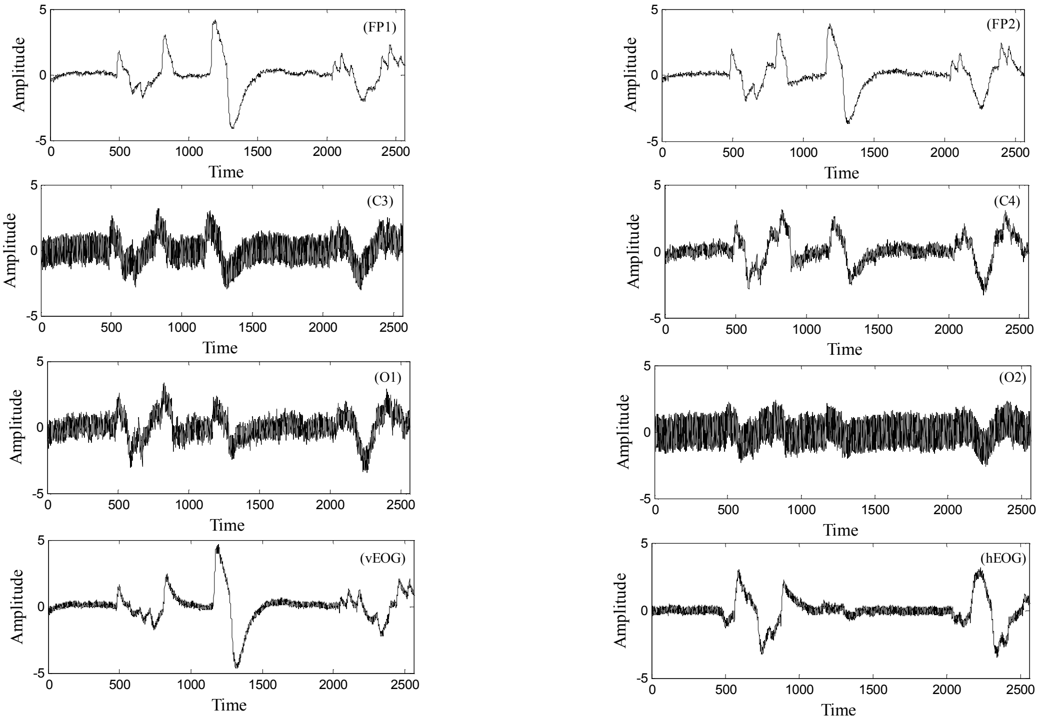

Figure 9 Data set II

Good extraction of the artifacts by SGA-BSS algorithms as shown in Figure 10. In SGA-BSS the LN is separated on IC1, and the eye artifact isolated on IC5, as well as the eye blink artifact is isolated on IC6.

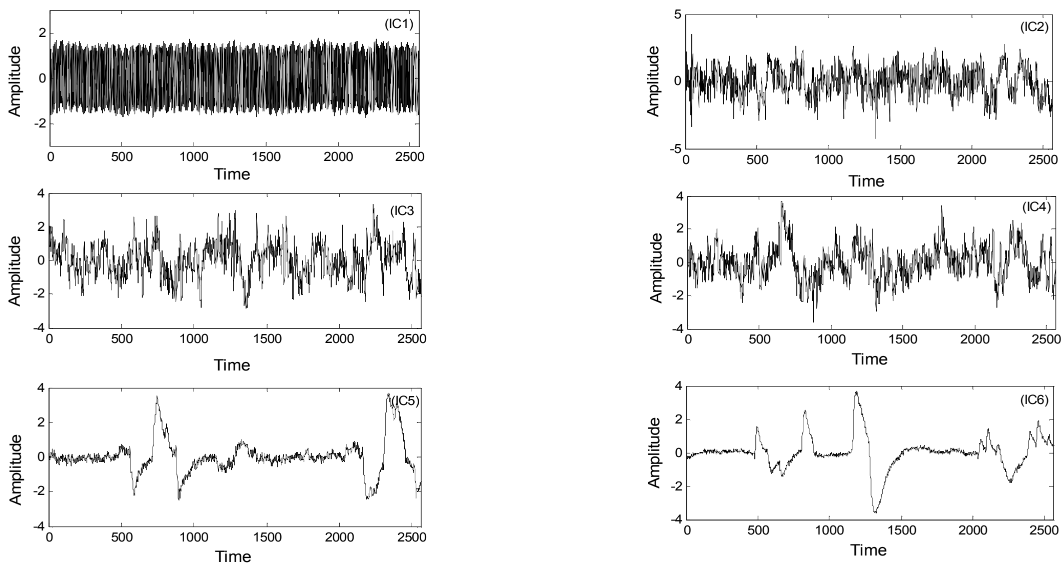

Figure 10 Separated components

The performance of the SGA-BSS is tested by the correlation measure as shown in table 3.

Table 3 Correlation measure

BSS	Correlation measure between artifact & Estimated artifact	
	(vEOG)	(hEOG)
SGA-BSS	0.9811	0.9845
EFICA	0.9801	0.9811
Stone	0.9554	0.9302
FICA	0.8753	0.7729
SOBI	0.7744	0.7689
JADE	0.7003	0.6791

Table 4 Classify the components

IC	Sparsity	type of signal
IC1	0.1521	Line noise
IC2	1.4997	brain signal
IC3	1.2434	brain signal
IC4	1.7249	brain signal
IC5	4.9024	Artifact
IC6	11.5523	Artifact

7. Conclusion

The proposed work has proven to be a useful method to extract EOG and LN from brain mixtures compared with different BSS techniques (Stone's BSS, SOBI, FICA, EFICA, and JADE). Two types of real EEG data are taken (data set-I and data set-II), in data set-I, the signals are mixed by eye blink artifact and LN 50-Hz, and in data set-II, The signals are mixed by eye muscle, eye blinking artifact and by LN.

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