Al-Furat Journal of Innovations in Electronics and Computer Engineering (FJIECE)
ISSN -2708-3985

Purification of Brain Signals Using Various Blind Source Separation Techniques

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https://doi.org/10.46649/fjiece.v3.1.6a.15.4.2024

Abstract. *There are lot of challenges when analyzing the brain signals that did not yet have a basic solution, as there are electrical activities between neurons in the brain, related to all activities in the body. This activity can be seen using a non-surgical technique that is called EEG (i.e. Electroencephalography) such as the appearance of artifacts through the registration process, which increases the difficulty of analyzing the signals of the brain, so the technique of blind source separation (BSS) has been used to overcome the problem of artifacts and to separate the main sources (Mixed) without making noise around the original sources.. Therefore, the system for rejecting all artifacts based on the algorithms for separating the blind source has been proposed, by making a comparison between four separation algorithms and choosing the best ones according to criteria. After passing a data set simulated through those criteria, the proposed system can remove the artifacts including Electrocardiogram (ECG), Electrooculogram (EOG) as well as a power line noise interference (LN)) and other EEG mixtures. The proposed method's influence is checked by two performance indexes Interference to signal ratio (ISR) and (SNR) signal to noise ratio. The results indicated that the BEFICA algorithm is the best and most efficient, as it achieved the highest ratio of VSNR among four separation algorithms due to its developmental advantages.*

Keywords: *BCI, EEG, Blind Source Separation, STONE, FICA, BEFICA, EFICA, ISR, SNR.*

1. INTRODUCTION

EEG has become an increasingly popular way to analyze brain signals. EEG contributes greatly to brain-computer communication (BCI)[1]. The EEG is a complex, unexpected signal that results from hundreds of millions of neurons in the brain EEG mixtures that contain high amounts of the data on the brain activity that reflects the brain state's electrical activity [2]. Through it, we can diagnose many diseases by tracking EEG signals. Now, the most important problem in the field of EEG signal analysis in the neuroscience researches has become especially significant for the clinical diagnosis of brain diseases [3]. An important part of BCI systems is feature extraction algorithms. A key step in pre-processing for cleaning brain signals from artifacts is the artifact removal techniques, and making the EEG signal more relevant and clearer in the case of analysis. Since the artifacts have a great influence on the diagnosis, therefore,

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these unwanted signals must be removed before the final decision [4]. a known technique for separating these signals is the Algorithms of Blind Source Separation (BSS)[5], a broad

There is range of applications covered by the BSS, the most important of which are communication, speech signal, neurophysiological signal, image processing, and medical signal processing, used to extract the primary sources from the received signals, there are several techniques that have been proposed to clean the brain signal. As each technology has its pros and cons., each according to its process, the method considers all the BSS technologies a good way to separate signals[6].

1.1 EEG ARTIFACTS

The signals of artifact produced from several sources like the AC power sources contaminates the EEG signals throughout the recording process. Line noise may interfere with the electrodes that depend on the source [7]. One of the common artifacts in EEG data is Eye Blinking artifacts in EEG data, resulting in a signal of high amplitude [8]. In addition to that, the Muscle Activity artifact MEG is the result of electrical activities that result from muscle cramps that occur when the patient chews, swallows, or speaks [9]. These artifacts, which usually involve major disturbances Electrocardiogram ECG or heartbeat artifacts, This type of artifact, which reflects the activity of the heart, gives a rhythmic signal of brain activity [10] that occurs if the electrode is placed on or near any blood vessels [11], as shown in Figure 1.

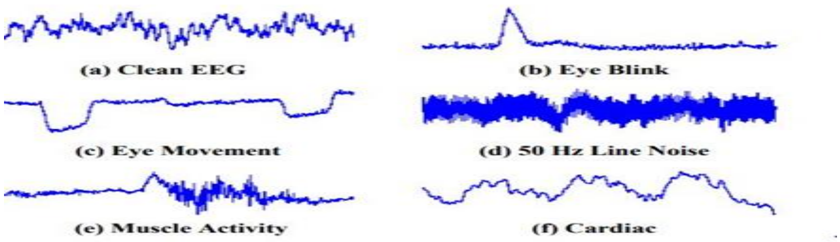

Figure 1 Artifact waveforms [11]

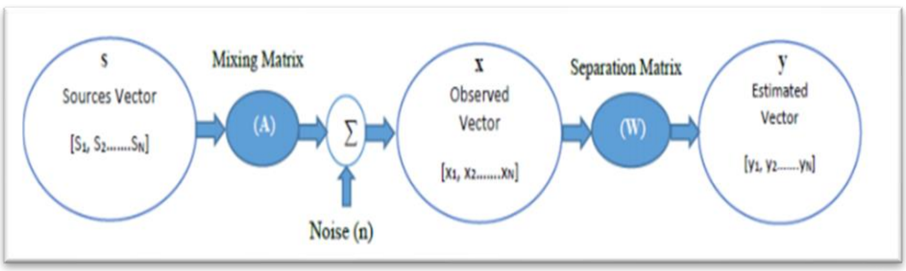

Figure (`1) diagram of the BSS technique

1.2 BLIND SOURCE SEPARATION (BSS)

BSS technologies change a set of mixed signals to another. The recovered sources are independent of each other; the approach is utilized to separate signals' sources with no prior knowledge [12]. Several algorithms were developed to solve the BSS problem, such as Independent Component Analysis (ICA) [9], which is of high importance, especially in the BSS field. The BSS diagram is shown in Figure 1.

The mixing equation is:

$$x(k) = AS(K) \quad (1)$$

Where:

$$X(K) = [x1(K), \dots\dots, xm(K)]^{t} \quad (2)$$

Where superscript t refers to the transpose operator; $A \in Rm^{*}n$ indicates the matrix of mixing. The symbol (k) represents the index of the sample or time. The model of separating considers the extracted equation as shown:

$$EY(K) = WX(K) \quad (3)$$

where E denotes a matrix of scaling and permutation, and the recovered source is:

$$Y(K) = [y1(K), yn(K)]^{t} \quad (4)$$

The issue of BSS is estimating the optimal separating matrix W, which is A^{-1}, A wide range of strategies were used for BSS[13], which is designed on the basis of the central limit theory (CLT). It seeks to identify a weight vector so that the acquired signal from the mixture that related to signal mixes is considered to be non Gaussian. The BSS approach, such as ICA, tries to maximize its quantity from statistical independence between signals. Info-max-dependent ICA increases the entropy of the signal instead of its independence and achieves the same results. Rather than using higher-order statistics (HOS), a few approaches use second-order statistics (SOS) for some sources, such as SOBI[14]. Lately, the BEFICA algorithm presented an approach of BSS with the ability to profit from various allocations that are related to original signals and from various changes, and it's an expansion of the EFICA with regard to piecewise stationary as well as non Gaussian signals, which was shown by real-world signals and simulations.[15].

1.3 BEFICA algorithm

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BEFICA has been advanced on the basis of a piecewise stationary model. It might also have optimal performance, for instance, achieving the Cramer Rao bound of the model with constant variance signals and yielding a considerable enhancement in real-world signals' separation. In addition, the concept of BEFICA includes the next 3 steps that are similar to the original EFICA, which is described previously.
The underlying equation represents the Independent Component Analysis (ICA) [16]:

$$X = AS \qquad (5)$$

In representing a vector related to independent random variables (RVs), each one of them is considered a strange original signal. In exercise, $Ni.i.d$ recognition of x is obtainable, which were mixtures of signals through unknown $\times d$ regular mixing matrix A. In addition, utilizing an assumption of independence

regarding $S1, \ldots, Sd$, the main aim is estimating the de-mixing transform A-1 up to indeterminable order, is the goal to estimate, scales, and signs of its rows. Several methods for separation to $i.i.d$ There are some signals in[17-20] then some algorithms have been changed and developed[21, 22] to reach accuracy close

to the Crramer -Rao minimum (CRLB) [23]. The bound, for an ´ unbiased estimator $\widehat{W}$ of A^{-1} is

$$\mathrm{CRLB}[\,\mathrm{G}_{K\ell}\,] = \frac{1}{N}\,\frac{K\ell}{\kappa_{\kappa}\,\kappa_{\ell} - 1} \quad , k \neq \ell \qquad (6)$$

Where $\mathbf{G} = \widehat{\mathbf{W}}\mathbf{A}$ represents a gain matrix that might be close to identity1, and $\mathcal{K}_k = \mathbf{E}[\ \psi_k^2\ (\chi)]$ which $\psi_k = -f_k'(\chi)\ /\ f_k\ (\chi)$ represents the score function related to probability knowledge of score functions or their proper estimation is vital for algorithms to achieve the bound. There are other algorithms to non stationary and non Gaussian scenario (NSGS) via Pham[24].
The Extended EFICA is called the BEFICA algorithm, which has been tailored to piecewise stationary signals obeying the equation (3.6). The conception contains the three next steps that were comparable to that of the original EFICA as follows:

Separation of EEF1 via FastICA homologous for obtaining a pre-estimation of the W-degradation matrix.
EEF2 - fine-tuning of every row of W via FastICA from one unit with the contrast function.
EEF3 - Refinement for the most definitive and accurate estimate of the entire de-blending matrix.
The second and third steps improve the accuracy, which could be performed using only the correct non-linear g (I) k functions. The first step could be done adaptively using the signals that are separated from it [15]. The symmetric FastICA is considered as one of the major ways for reliable and fast pre estimation of $\widehat{\mathbf{W}}$, maybe not theoretically enough for different non-Gaussian signals [22] enhancements, that might be reached in the case of using only non-linear functions g(I)k which were adequately selected from the first step,. This might be adaptively reached with the use of separated signals, precisely, the score functions on each block I might be assessed as [22] optimum choice of non-linearities.[15] .
The main steps of the BEFICA are shown in the algorithm(1).

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Algorithm (1) BEFICA Algorithm
Input: signals after whitening operations **Output**: Analyzed signals
Continuous of Algorithm (1) **Start** **Step1**: find the Mixture observation signals based on equation (1) **Step2**: Use a whitening process for transforming covariance matrix of zero-mean to a matrix of identity **Step3:** use rate Contrast function for the symmetric part of Block EFICA (EEF1) **Step4:** one unit FastICA complete each one of the iterations via normalizing the vector w k, symmetric FastICA estimates d iterations in parallel and achieves a symmetric orthogonal . **Step5:** predetermine all original signals via symmetric FastICA **Step6:** Separating the symmetric FastICA for getting of De-mixing matrix W. **Step7:** fine tuning (additional one-unit FastICA iterations utilizing non-linearities that have been indicated in step (2) **Step8**: refinement for getting the final and most accurate estimate of whole demixing matrix. End

2. MATERIALS AND METHODS

2.1. Proposed System

Figure (3) shows the suggested system, which is utilized for filtering the brain signals that are emitted from the brain for predicting people's actions to apply such a system in a large way, and there is a need for a number of data to test and train this system. The proposed system includes some basic stages for performing and verifying all related tasks. There are two main stages; the first stage is referred to as signal acquisition, while the other is referred to as EEG signals analysis, which is contained on multi-BSS to analyze the signals it can eliminate noise and artifact with more accuracy. The outline of the suggested system is explained in several stages.

Fig (3) Block diagram of the suggested system

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2.2. Collecting Data Set

With regard to this stage, collecting the signals of the brain by invasive or non-invasive acquisition and prepare them for processing. This step involves collecting the information that has been obtained from EEG device, which includes the simulation Data, which is a standard, a dataset consisting of 7 channels ICALAB [25] as follows: a-EEG For eyelash. b- EOG, EOG2 c- Gaussian noise d- ECG signal. e- Power line noise g- EMG signal. Each channel contains one signal with a sampling rate of 250Hz. It also contains zero mean, unit variance, and 500 samples. Figure (4) shows the bio-7 Database signal. Then mixed them as illustrated in Figure (5).

As we notice in Figure (5), the product of the mixing matrix, differences between mixing matrix output and the source is very obvious due to all signals mixed randomly. It consists of (EEG For eyelash, EOG1, EOG2, Gaussian noise, ECG signal, Power line noise, and EMG) signals.

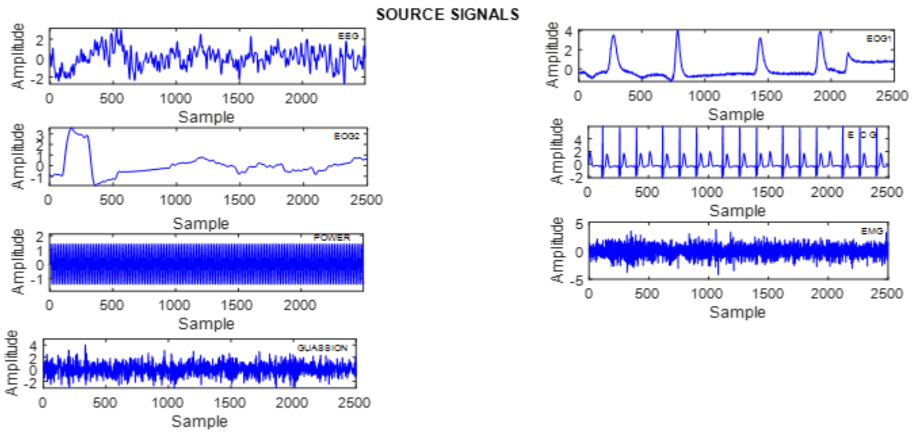

Fig (4) the Abio-7 Database signal/ input signal

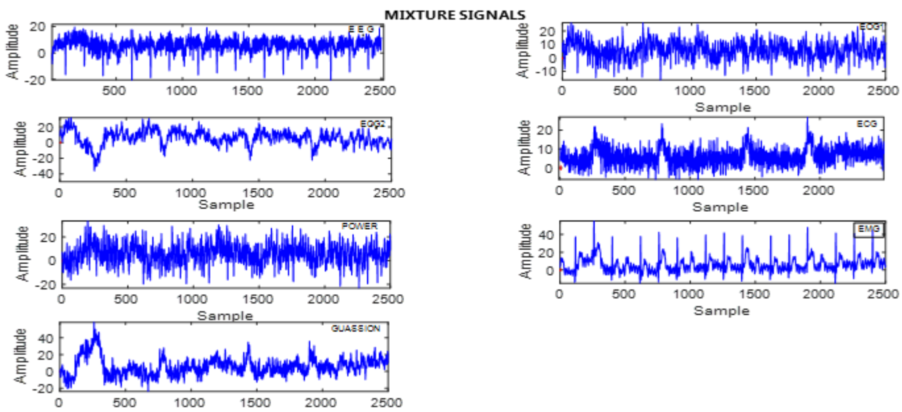

Fig (5) mixture of simulation data

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2.3 *EEG signals analysis stage*

The presented system, which is considered the processing stage, consists of two stages.

a. **Pre-processing:** where the first stage starts by the bleaching process for further processing.
b. **Analyzing data:** It is the second stage, which begins by the analysis and the process is done by using BSS separation using algorithms (STONE, FICA, BLOCK, and EFICA).

The suggested system's general algorithm steps have been shown in **algorithm (2)** to show the main step.

Algorithm (2).
Input: analyzed data/simulation **Output**: separated data
Start **Step1**: read the data set **Step2**: bleaching process **Step3** apply the blind sources separation BSS. **End.**

3. RESULTS AND DISCUSSION

3.1. RESULTS

This section presents the results that have been acquired from the suggested methodology, as can be seen in the algorithm **(2).** Data is processed via blind source separation. And The results and comparison between the four BSS algorithms have been implemented. STONE, EFICA, BEFICA & FICA algorithms have been used. Then restored successfully. The figures below are showing all sources of signals of algorithms :

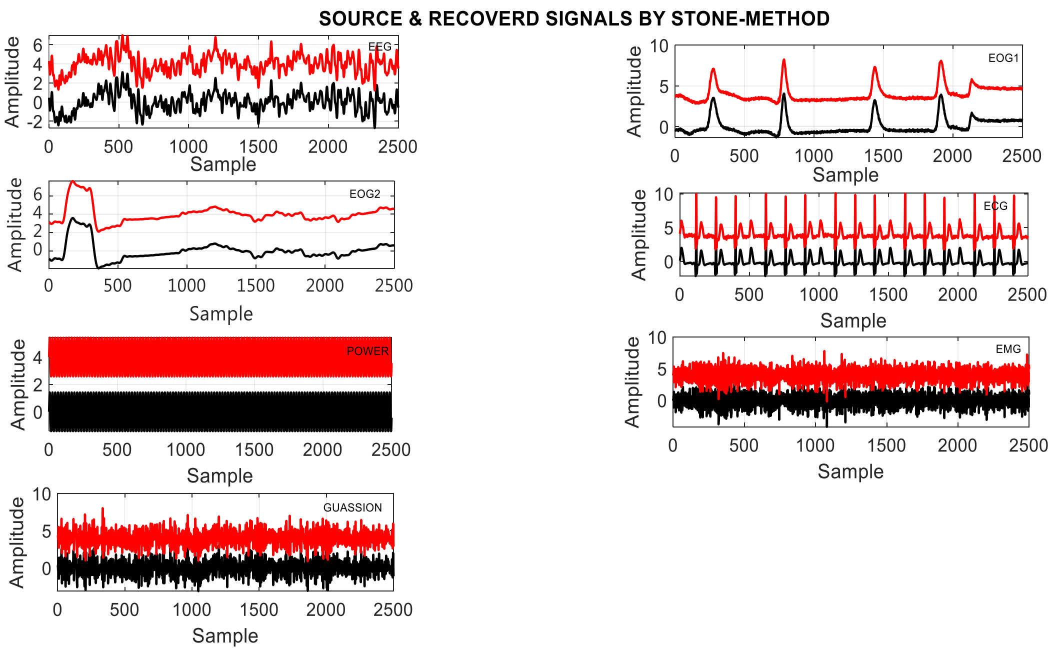

Fig 6 source and restored signals by Stone algorithm

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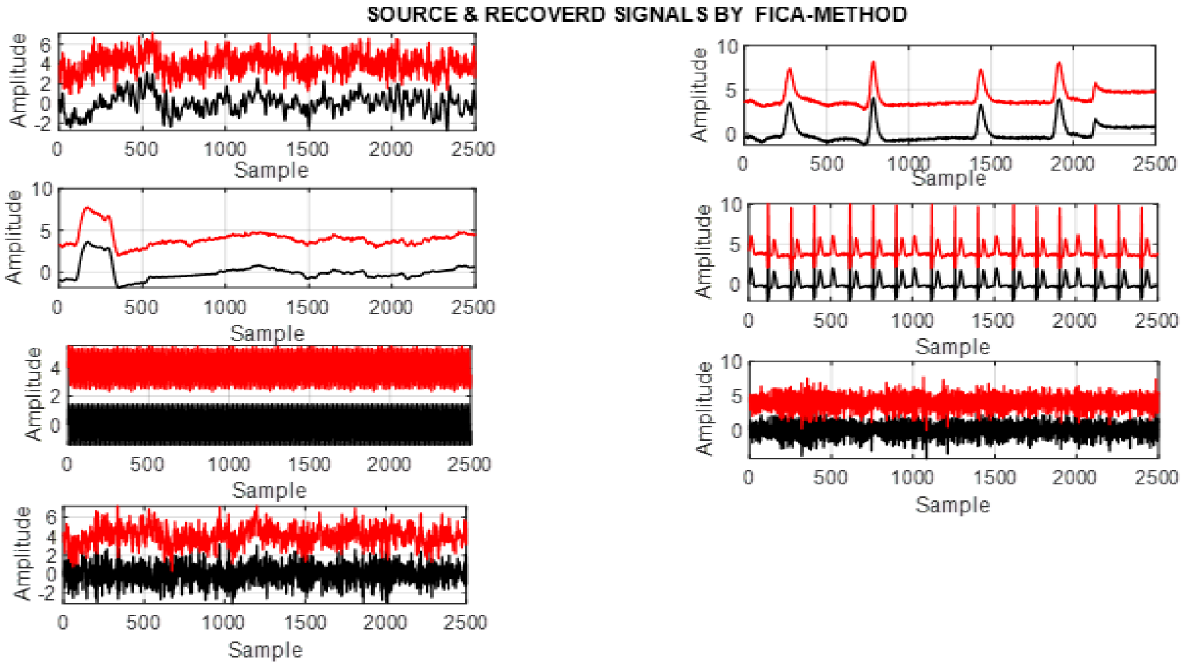

Fig 7 source and restored signals by FICA algorithm

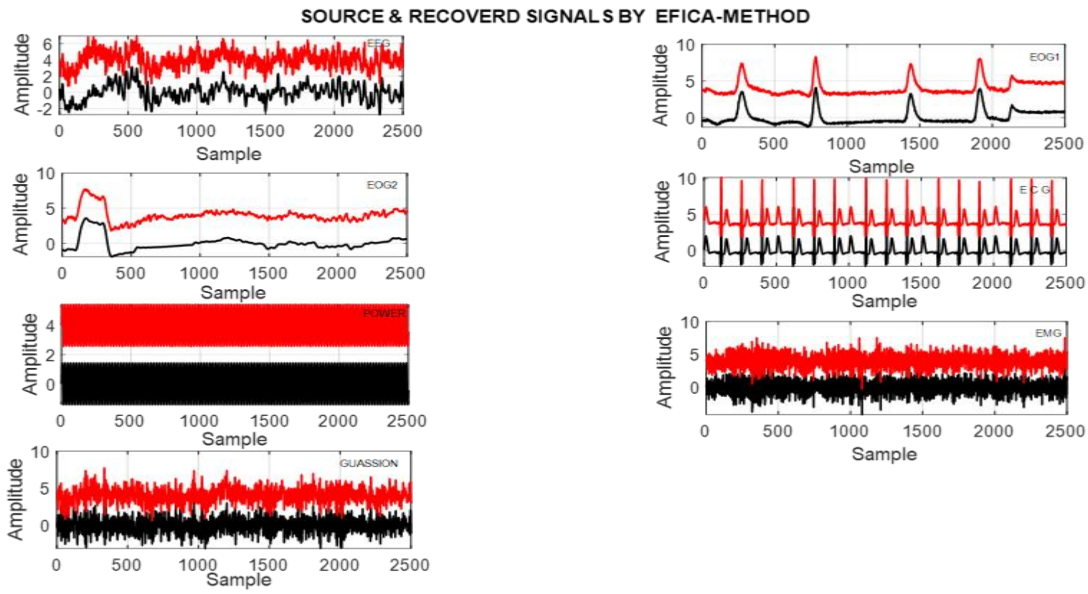

Fig 8 source and restored signals by EFICA algorithm

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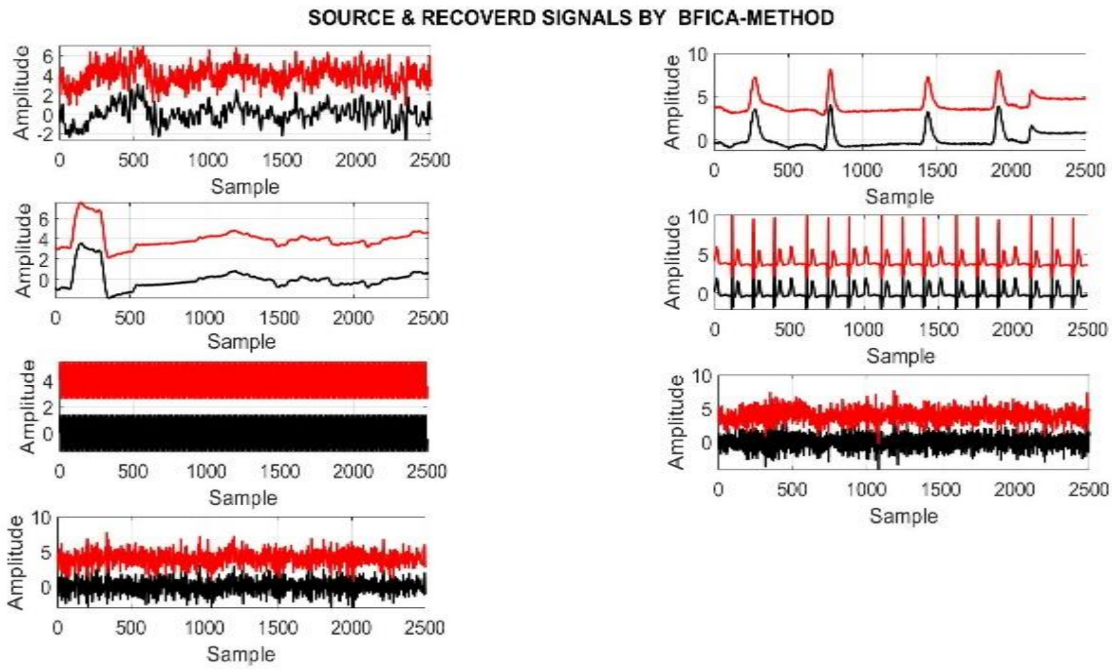

Fig 9 source and restored signals by BEFICA algorithm

The previous signals illustrate the input and output signals that have been represented in black and red color sequentially as shown in the figures (5, 6, 7, 8), but at the same time, they do not give us an idea about the ratio of separation in each algorithm, so we can confirm this through table (1) to know the difference between the algorithms by calculating (SNR) standard until reaching the choice of the best quality.

Table (1) average SNR in dB for each single algorithm

BSS ALGORITHM	STONE	FICA	EFICA	BEFICA
SIGNAL TO NOISE RATIO (SNR)	21.2800	13.7899	16.1518	22.5233

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Table (2) SNR and ISR in dB for each extracted signal

Method	Criteria	Signals						
		EEG	EOG1	EOG2	GAUSSIQN	ECG	P.LIONE	EMG
STONE	SNR	10.040	6.464	5.879	7.529	8.333	10.02	8.385
	ISR	-10.040	-6.464	-5.879	-7.529	-8.333	-10.02	-8.385
FICA	SNR	4.479	17.96	38.07	21.224	59.91	6.261	9.740
	ISR	-4.479	-17.96	-38.07	-21.224	-59.91	-6.261	-9.740
EFICA	SNR	10.82	17.22	20.13	20.414	19.43	8.005	8.1001
	ISR	-10.82	-17.22	-20.13	-20.414	-19.43	-8.005	-8.1001
BEFICA	SNR	212.6	21.16	16.25	20.044	19.33	14.860	2,747
	ISR	-212.6	-21.16	-16.25	-20.044	-19.33	-14.860	-2.747

The output signals indicated that the separation ratio is different from one algorithm to another as shown in the above table, where the BEFICA algorithm outperformed the other four algorithms, following modifying its parameters, the most important of which is Fine-tuning regarding each row of W with using one unit FastICA with contrast function and the refinement for getting the final and most accurate estimate regarding the whole de-mixing matrix as shown in the algorithm (1).

Therefore, when comparing the values of the SNR results for all BSS algorithms, found the BEFICA algorithm was (22.52) dB. STONE BSS (21.28) dB comes after the EFECA algorithm (16.15) dB, and the lowest value in terms of the SNR standard is FICA (13.78) dB, as illustrated in figure (10). It is indicated that BEFICA BSS has better performance in recovery and problem solving than other BSS algorithms.

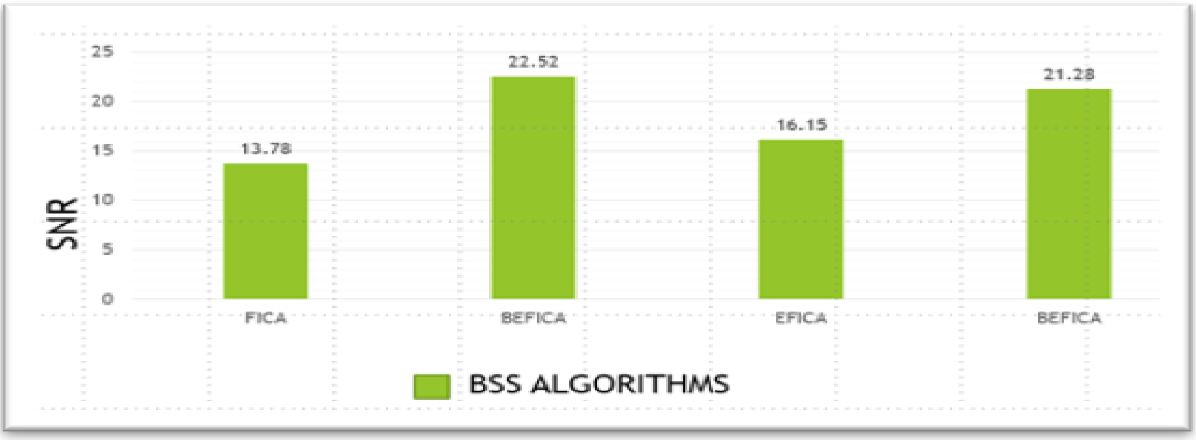

Figure (10) Results Obtained for Execute the BSS Algorithm

3.2. DISCUSSION

For more clarification, table (2) has been made to compare all restored signals (EEG, EOG, ECG, Power line, EMG, Gaussian) depending on the calculated signal to noise ratio (SNR) and the noise interference ratio (ISR) for each extracted signal. After being passed on the four separation techniques BSS. Tables (1&2) can prove that the BEFICA BSS algorithm records SNR's highest value compared to the other BSS algorithms.

4. CONCLUSIONS

In this paper, a novel and accurate approach was obtained when using algorithms like (STONE, FICA, BEFICA, an EFICA) to separate different types of noise, due to the high specifications of the BEFICA algorithm after testing it with the SNR and ISN standards.. Has proven the ability to take advantage of the variable distribution of the original signals and their differential contrast, which appears through simulations with real-world signals. This paper aims to be a resource for all BCI researchers. Where basic knowledge about brain waves is measured as EEG. Then the focus has been made on specific algorithms that can completely separate the EEG signals to isolate and eliminate side effects (noise).

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