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

Enhancement of Brain Computer Interface System Based on Artificial Intelligent Technique

Safaa Mahmood Hamad [1], Ali A. Al-bakri [2], Ahmed Kareem Abdullah [3]

[1] *Engineering Technical College/Najaf, Al-Furat Al-Awsat Technical University, Najaf, Iraq. sfaaldryy406 @gmail.com, aadraalia@gmail.com*

[2] *Technical College-AL Mussaib, Al-Furat Al-Awsat Technical University, Babel, Iraq. adraalia@gmail.com*

[3] *Technical College-AL Mussaib, Al-Furat Al-Awsat Technical University, Babel, Iraq. ahmed_albakri1977@yahoo.com*

https://doi.org/10.46649/fjiece.v3.1.2a.11.4.2024

Abstract. *With the rapid development of information technology, the EEG has become an increasingly popular method for analyzing brain signals. EEG signals greatly contribute to(BCI) brain-computer communication . BCI outputs are used to restore many functions in relation to individuals with a motor impairment, and these signals are complex random signals produced from hundreds of millions of neurons in EEG mixtures in the brain that contain many data about brain activity. its include artefacts which have a great influence on the diagnosis; Hence, these unwanted signals become the most important problem in EEG signal analysis. Therefore, used four blind source separation techniques (BSS), STONE, FICA, BEFICA and EFICA. The proposed system is using one of the new Antlion (ALO) optimization algorithms to improve the performance of the previous algorithms and find out which ones are the most responsive, by comparing them and choosing the best ones according to the (PSD) standard. With the use of real data, noticed through the results that the EFICA algorithm is the best response to the improvement and the most efficient, as the ratio of (PSD) was the least possible, as ALO worked to reduce the variance in the distribution of the frequency spectrum because it relied on solving constrained problems using various searches.*

Keywords: BCI, EEG, (BSS)Blind Source Separation, STONE, FICA, BEFICA, EFICA, PSD, ALO*.*

1. INTRODUCTION

BCI is an emerging rapidly growing technology as a lot of studies attempt to develop direct channels between computers and the human brain. It can be defined as a collaboration where the brain accepts and controls the mechanics of a machine as a natural part associated with the representation of the body [1]. EEG signals are captured via a brain computer interface along with individual specific activity. EEG is a marker widely used in bioinformatics due to its rich information on human activities. There is a combination of brain signals with other signals obtained from a limited set of activities related to the brain that overlap in time and space, when measuring EEG, many of the potential changes observed in EEG can come from other sources [2]. Changes are referred to artifacts and may result from sources such as subject matter or equipment. So necessary to use BSS algorithms which are an approach to primary source signals to separate from observations that are collections of the original sources, with little or no information about the source signals to deal with the confusion [3]. Therefore, the antlion ALO algorithm was used to improve the work of the separation algorithms, with its distinction of high performance, in finding the appropriate parameters to achieve the fitness equation, which in turn leads to making the algorithm more accurate in separating the effects from the original signal as will be mentioned in detail.

1.1 The Ant Lion Optimizer (ALO)

This is one of the novel algorithms inspired via nature, it is simulating the approach of hunting Ant Lion. There are 5 main prey hunting stages in this algorithm, which are, ants' random walking, building traps, trapping ants in traps, hunting prey, and rebuilding traps[4].

1.1.1 ALO Operators

Due to the fact that ants are stochastically moving in nature in the case when searching for food, a random walk was selected to model the movement of ants in the following way:

$$X(t)=[0,\mathrm{Cumsum}(2r(t_1)-1),\mathrm{Cumsum}(2r(t_2)-1)...\mathrm{Cumsum}(2r(t_n)-1 \quad \textbf{(1)}$$

In which cumsum is calculating the cumulative summation, n represents the maximal number of iterations, t represents the step of random walk (iteration), also r(t) represents the stochastic function specified in the following way:

$$r(t)=\begin{cases} 1 & \text{if rand} > 0.5 \\ 0 & \text{if rand} < 0.5 \end{cases} \quad \textbf{(2)}$$

in which t represents step of random walk , also rand represents random interval of [0,1]. For having an image of such random walk, the ants' position was saved as following:

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

$$M_{Ant} = \begin{bmatrix} A_{1,1} & A_{1,2} & . & . & A_{1,d} \\ A_{2,1} & A_{2,2} & . & . & A_{2,d} \\ . & . & & . & . \\ . & . & & . & . \\ A_{a,1} & A_{a,2} & . & . & A_{a,d} \end{bmatrix} \quad (3)$$

Figure **Error! No text of specified style in document.**(1) Cone shaped traps and hunting behavior of antlions.

In which MAnt represents the matrix to save each ant's position,Ai,j represents the value related to j-th variable (dimension) of i-th ant, n represents the number of ants, and d represents the number of variables. It must be indicated that ants were comparable to individuals in GA or particles in PSO. The ant's position indicates a specific solution's parameters. Matrix MAnt was used for saving all ants' positions (variables of all solutions) throughout optimization. To evaluate each one of the ants, fitness function was used throughout optimization and the next matrix is used for storing all ant's fitness values:

$$M_{OAL} = \begin{bmatrix} f([A_{1,1} & A_{1,2} & . & . & A_{1,d}]) \\ f([A_{2,1} & A_{2,2} & . & . & A_{2,d}]) \\ . & . & . & & . \\ . & . & . & & . \\ f([A_{a,1} & A_{a,2} & . & . & A_{a,d}]) \end{bmatrix}$$

(**Error! No text of specified style in document.**4)

In which MOA represents the matrix used to save each ant's fitness, Ai,j represents the value of j-th dimension of i-th ant, n represents the number of ants, and f represents the objective function. For the purpose of saving their fitness values and positions, the next matrices were used:

$$M_{Antlion} = \begin{bmatrix} AL_{1,1} & AL_{1,2} & . & . & AL_{1,d} \\ AL_{2,1} & AL_{2,2} & . & . & AL_{2,d} \\ . & . & . & & . \\ . & . & . & & . \\ AL_{a,1} & AL_{a,2} & . & . & AL_{a,d} \end{bmatrix} \quad (5)$$

In which $MAntlion$ represents a matrix used to save each antlion's position, ALi, j represents the $j-th$ dimension's value of $i-th$ antlion, n represents the number of antlions, and d represents the number of variables (dimension).
In which $MOAL$ represents the matrix used to save each antlion's fitness, ALi, j represents the j-th dimension's value of $i-th$ antlion, n represents the number of antlions, and f represents the objective function.

1.1.2 Random walks of ants

The random walks have all been based upon Eq. (6). The ants are updating the positions with the random walk at each one of the optimization steps.For the purpose of keeping random walks within search space, they will undergo normalization with the use of the equation below (min–max normalization)[5].

$$X_i^t = \frac{(X_i^t - a_i) \times (d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad \textbf{(7)}$$

ai represents the minimal value of the random walk of the $i-th$ variable, bi represents maximal value of random walk in $i-th$ variable, $ct\ i$ represents the minimal valu of i-th variable at the $t-th$ iteration, and $dt\ i$ represents maximal value of $i-th$ variable at $t-th$ iteration. Eq. (2.8) must be applied in every one of the iterations for guaranteeing the occurrences of the random walks within search space.

1.1.3 Trapping in the pits of the ant-lion

As it has been stated earlier, ants' random walks are influenced with the ant-lions' traps. For the purpose of mathematically modelling that assumption, the equations below have been suggested:

$$C_i^t = Antlion_i^t + C^t \quad (9)$$

$$d_i^t = Antlion_i^t + d^t \quad (10)$$

where ct is the minimal values of every variable at t-th iteration, dt represents the vector that includes maximal value of every variable at t-th iteration, ct j represents the minimal value of every variable for the i-th ant, dt j represents the maximal value of every variable for the i-th ant, and Ant-lion j indicates the location of chosen j-th ant-lion at t-th iteration. A conceptual model of such behaviour has been depicted in

1.1.4 Building trap

For the purpose of modelling antlions' hunting ability, roulette wheel is utilized. Exhibit that the ants are considered to only be trapped in one certain ant-lion. ALO must use an operator of the roulette wheel to select the ant-lions based upon their fitness throughout the optimization.

1.1.5 Sliding the ants toward the ant-lion

The ant-lions shoot sand outward the pit centre as soon as they understand that there is an ant in trap. Such behaviour slides down trapped ant which tries to escape. For the mathematical modelling of that behavior, the ants' random walk .The equations below have been suggested in that regard.

$$C^t = \frac{C^t}{I} \quad (11)$$

$$d^t = \frac{d^t}{I} \quad (12)$$

I represents a ratio, ct represents the minimal value of every variable at the t-th iteration, and dt represents the vector that includes maximal value of every variable at the t-th iteration In Equations (2.57) & (2.58), I ¼ 10w t T where t represents current iteration, T represents the maximal number of the iterations, and w represents a constant that has been defined according to current iteration (w = 2 when t > 0.1T,w = 3 when t > 0.5T,w =4 when t > 0.75T,w = 5 when t > 0.9T,and w = 6 when t > 0.95T). Fundamentally, constant w has the ability of adjusting the exploitation's level of accuracy. Those equations result in shrinking the radius of the update of the positions of the ant and imitates the sliding procedure of the ant within the pits. Which ensures the search space exploitation.

1.1.6 Catching prey and rebuilding the pit

The last hunt stage is in the case where the ant can reach the pit's bottom and is trapped in the jaw of the antlion.it has been considered that catching of the prey occurs in the case where the ant becomes more fit hich will be required then to change its location to the latest location of hunted ant for the enhancement of its chances to catch the new prey. The equation below has been suggested in that regard:

$$Antlion_i^t = Ant_i^t \ if \ f(Ant_i^t) > f(Antlion_i^t) \quad (13)$$

where Error! No text of specified style in document. $\boldsymbol{t}$ represents current iteration, Ant-lion $\boldsymbol{j}$ exhibits the location of the chosen $\boldsymbol{j-th}$ antlion at the $\boldsymbol{t-th}$ iteration, and $\boldsymbol{Antt\ i}$ represents the location of $\boldsymbol{i-th\ ant\ at\ the\ t-th}$ iteration.

1.1.7 Elitism

Elitism represents a significant property of the evolutionary approaches which allow them to be maintaining the optimal solution that have been at any optimization process stage. the optimal ant-lion that has been obtained in every one of the iterations has been saved and viewed to be an elite.It has been assumed that each one of the ants will walk randomly around a chosen antlion through roulette wheel and the elite in a simultaneous was according to the equation below:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{14}$$

$Rt\ A$ represents random walk that is around the ant-lion that has been chosen by the wheel of the roulette at the $t-th$ iteration, $Rt\ E$ represents the random walk that is around the elite $at\ the\ t-th$ iteration, and $Antt\ i$ represents the location of $i-th$ ant at the $t-th$ iteration [6].

1.2 EFICA Algorithm

EFICA is an ICA algorithm designed to separate non-Gaussian $i.i.d.$ signals. The underlying assumption is that each source signal $sk, k = 1,\dots,d$ consists of N independent realizations of a random variable ξk having [7]
a non-Gaussian distribution function $Fk(x) = P(\xi k \le x)1$The algorithm EFICA is a version of the Fast ICA [8] algorithm that features adaptive choice of the Fast ICA non-linearity. Let $gk(\cdot)$ be the nonlinear function chosen
for $k-th$ signal, $k = 1,\dots,d$ and let $g0k(\cdot)$ be its derivative. Finally, let "E" stand for the expectation operator, which can be realized by the sample mean. Then, the elements of the ISR matrix are asymptotically equal to [9].

EF $k` = 1N\ \gamma k(\gamma`\ \ \tau 2`)\tau 2`\gamma k\ \ \tau 2k(\gamma`\ \ \tau 2`)$ (15)

Where $\gamma k = \beta k - \mu 2k\tau k = |\mu k - \rho k|\mu k = E[bskgk(bsk)]\rho k$
$= E[g0k(bsk)]\beta k = E[g2k(bsk)]$
In the best possible case, i.e., when gk equals the score function ψk of the corresponding distribution.
Fk (if it exists) for all $k = 1,\dots,d$, then equation (16)is equal to the corresponding Cramer-Rao Lower Bound (CRLB) [1], which is:

$CRLBk` = 1N\kappa`\kappa k\kappa` - 1$ (17)
where $\kappa k = E[\psi 2k(sk)]$

The theoretical ISR was shown to approximate the empirical ISR very well provided that the independent components are $i.i.d.$, that means that they have no time structure. If the components are strongly autocorrelated, the theoretical ISR appears to be biased, in particular, overly optimistic.[10].

The main steps of the EFICA Algorithm shown in **algorithm (1)**

Algorithm (1) EFICA Algorithm
Input: signals after whiting operations **Output**: Analyzed signals
Start **Step 1:** construct matrix. According to Eq (2.10). **Step 2:** Use a whitening process for transforming covariance matrix of zero-mean to a matrix of identity. **Step 3**: Make The elements of the ISR matrix are asymptotically equal to [6]. **Step 4:** when gk = score function ψk of corresponding distribution Fk (if it exists) for all $k = 1,.,d,$ then equation(4) is equal to the corresponding Cramer-Rao Lower Bound (CRLB) **Step 5:** Constructed matrix which transforms whitened data to a collection of components which are maximally exclusive. **Step 6:** The theoretical ISR be biased, in case The theoretical ISR was shown to approximate the empirical ISR very well provided that the independent components. **Step 7:** The mixing matrix A can be constructed by zeroing columns will be new EEG signal that contains only task related components. **End**

2.1. Proposed System

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

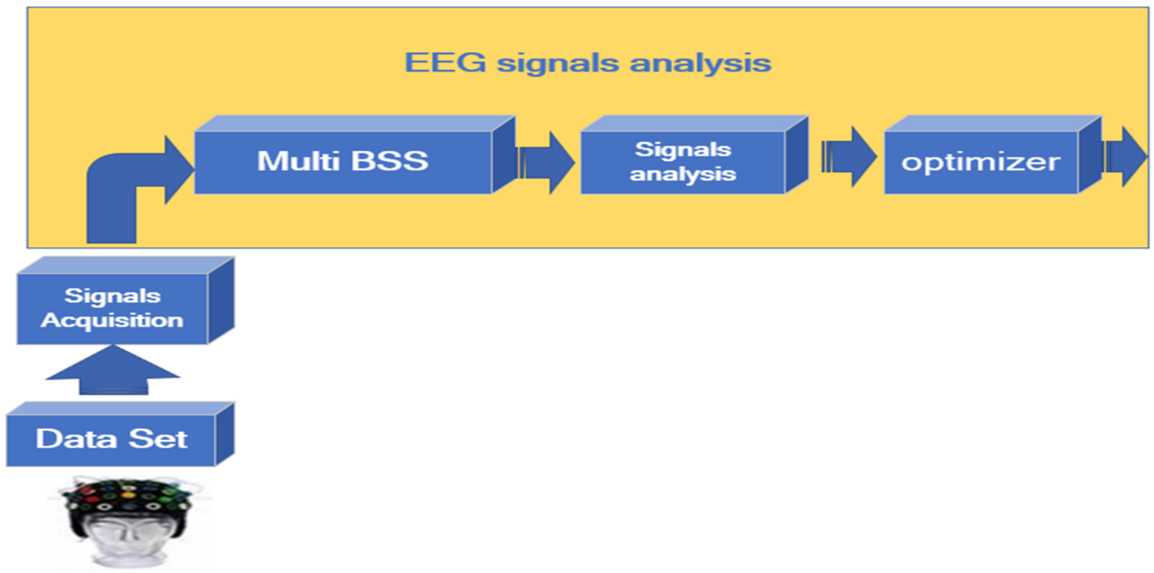


Figure (2) Block diagram of proposed system

This system has been illustrated in Figure (2) and is utilized in order to filter brain signals which are emitted from brain for the prediction of actions of people for the purpose of implementing such a system , 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 phases, the first one has been referred to as the signal acquisition stage and the second one is called EEG signals analysis stage which is contained on multi BSS to analysis the signals. And finally, the signal optimization stage with ALO (Antlion Optimizer). The proposed system's outline has been explained in several stages.

The general algorithm steps of the suggested system has been shown in the **Algorithm (2)** show the main steps.

Algorithm (2) proposed system general algorithm steps
Input: analysed data / real & simulation **Output**: optimization data
Start **Step1**: read the data set **Step2**: bleaching process **Step3** apply blind sources separation BSS **Step4**: apply optimization algorithm End

2.2. Collecting Data Set

In this stage, brain signals are collected by non- invasive acquisition after that prepared this for processing the information collected from the EEG device and filtering its , for further processing used real data,

The Real data were collected and taken from the site (Meag Mohit / EEG dataset) [11], and then the data set was imported into the proposed system for system implementation and evaluation. This dataset was generated using a computerized EEG machine, The real data were recorded using(8)electrodes for (30) seconds and sampling at(256Hz)for three movements of the eye of a (24)-year-old girl at (9:30 am) The facial activity in each recording was as follows

- Eye blinks
- Rolling the eyes
- Raising the eyebrows

In addition, a 50Hz line noise is present. The locations of the electrodes used were as follows: -
[FP1 , FP2 , C3 , C4 , O1 , O2 , VEOG , HEOG]

Table (1) shows the main specification for this data.

Table (1) Data set specification

Gender	**age**	**position**	**Kind of movements**	**Medical condition**	**situation**

Female	24	2m from computer monitor	Eye blinks Rolling the eyes Raising the eyebrows	healthy	Sit on chair

2.3 EEG signals analysis stage

The presented system which is consider processing stage consists of two stages.(a-Pre-processing)It's first stage start to bleaching process .(b- Analyzing data) The second stage is an input to the output of the first stage, and the process is linked using BSS separation algorithms[12](STONE, FICA, BLOCK, EFICA).

2.4 The optimization stage of signals

The output from the second stage will be the input to improve the EEG signals. Then the analysed data is processed using the previously mentioned optimizer (Antlion Algorithm) for all algorithms.

3. RESULTS AND DISCUSSION

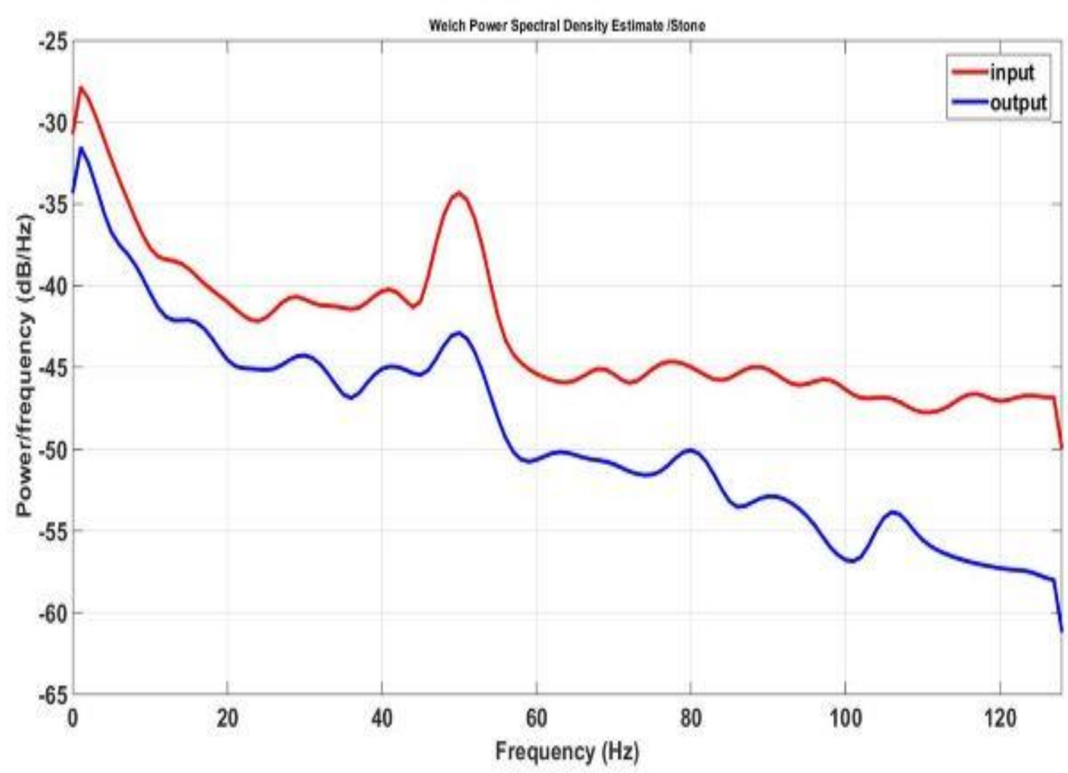
It discusses the results obtained from the proposed methodology as shown in Algorithm (2). The data is processed by separating the blind sources, improving each algorithm used from the blind separation sources by controlling the external data, then comparing it to extract the best quality from the separation process. Then the results are executed and comparison between the four BSS algorithms

3.1. RESULTS

Then restored successfully all algorithms source signals as appear in figures below:

1-Stone method with optimizer

The output signal results for 8 channels are shown after analysing the signal by separating the blind source of the BSS stone and after performing the optimization process on the algorithm for a single blinking eye movement experiment as in Figure (**Error! No text of specified style in document.**) .



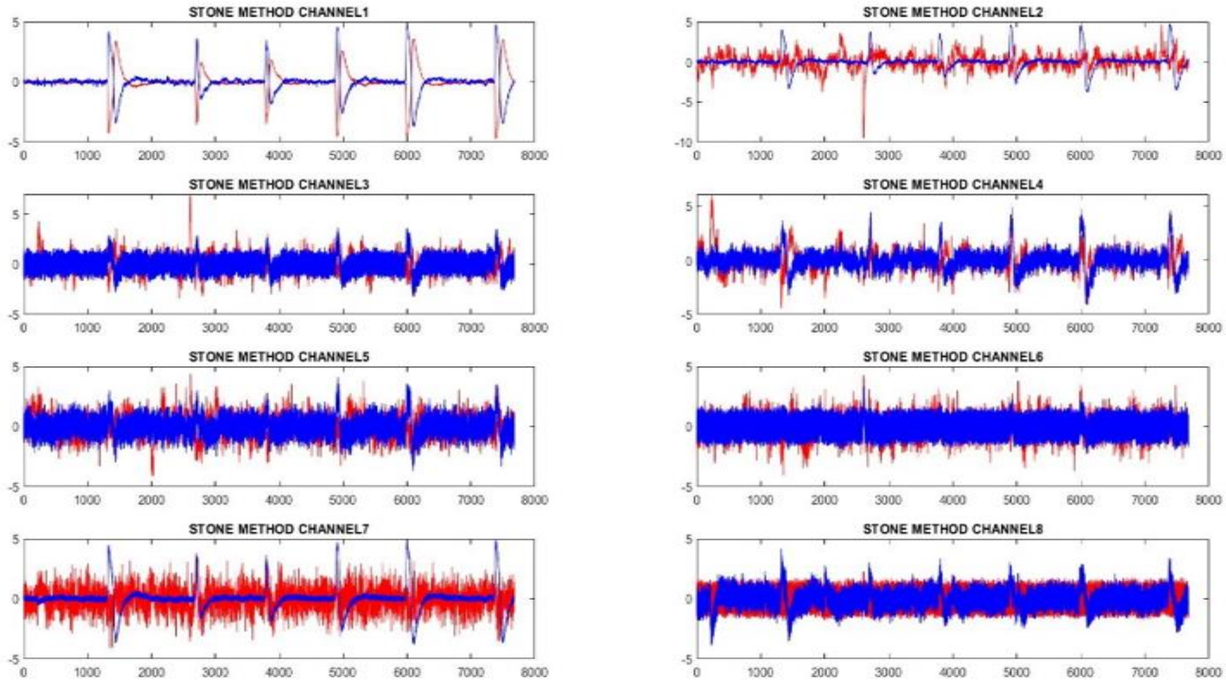


Figure (**Error! No text of specified style in document.**)Recover Sources by STONE after optimization

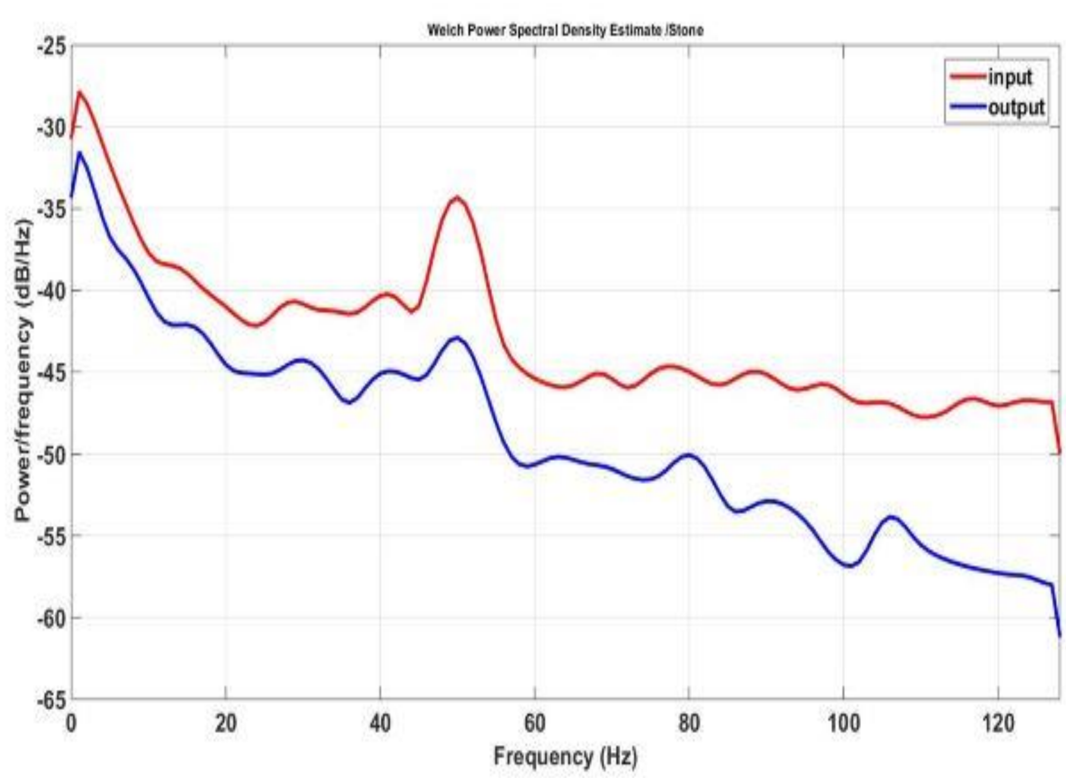
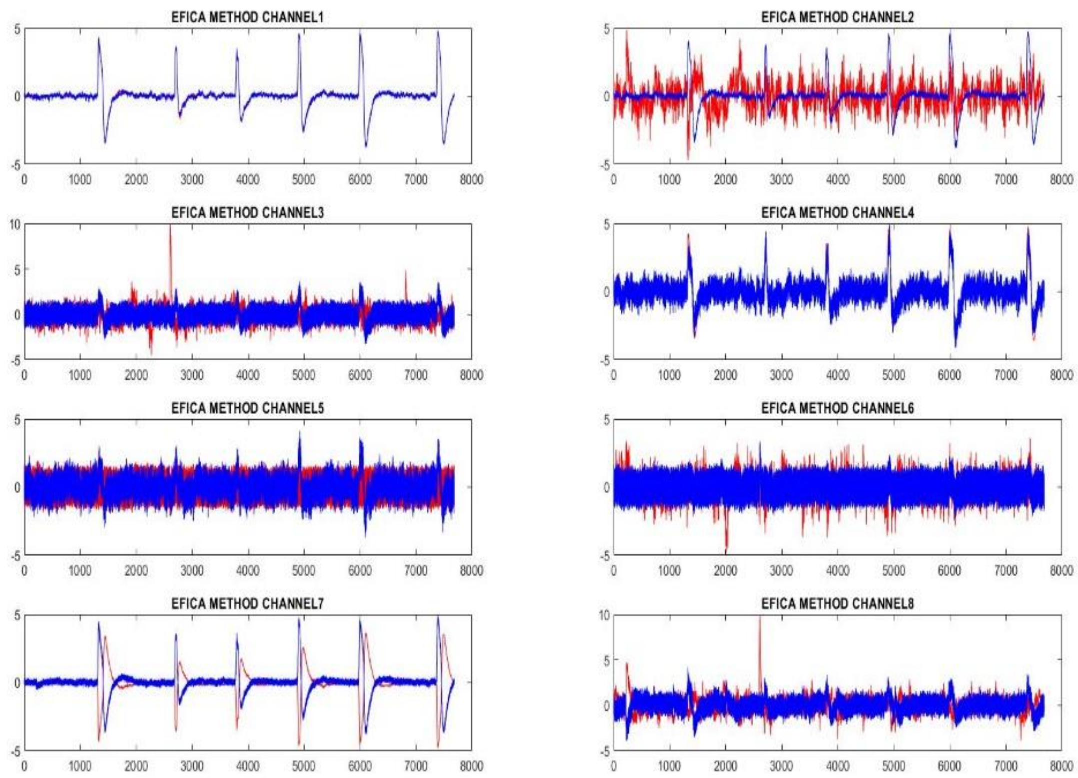


Figure (**Error! No text of specified style in document.**) PSD for signals input and output after STONE

2- EFICA method with optimizer

The results of the output signal for 8 channels are shown after analyzing the signal by separating the blind source of the BSS EFICA a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in **Error! Reference source not found.**).



Error! Reference source not found.) **Recover Sources by EFICA after optimization**

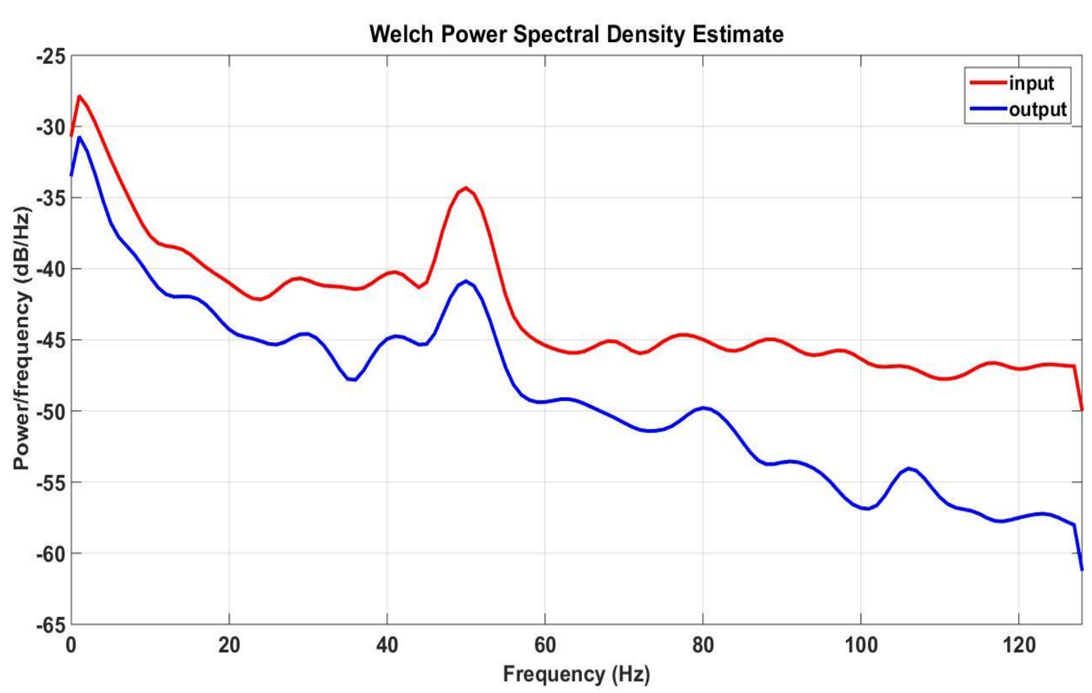


Figure 2) PSD for signals input and output after EFICA

3- **BEFICA method with optimizer**

The results of the output signal for 8 channels are shown after analyzing the signal by separating the blind source of the BEFICA BSS, a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in Figure (3).

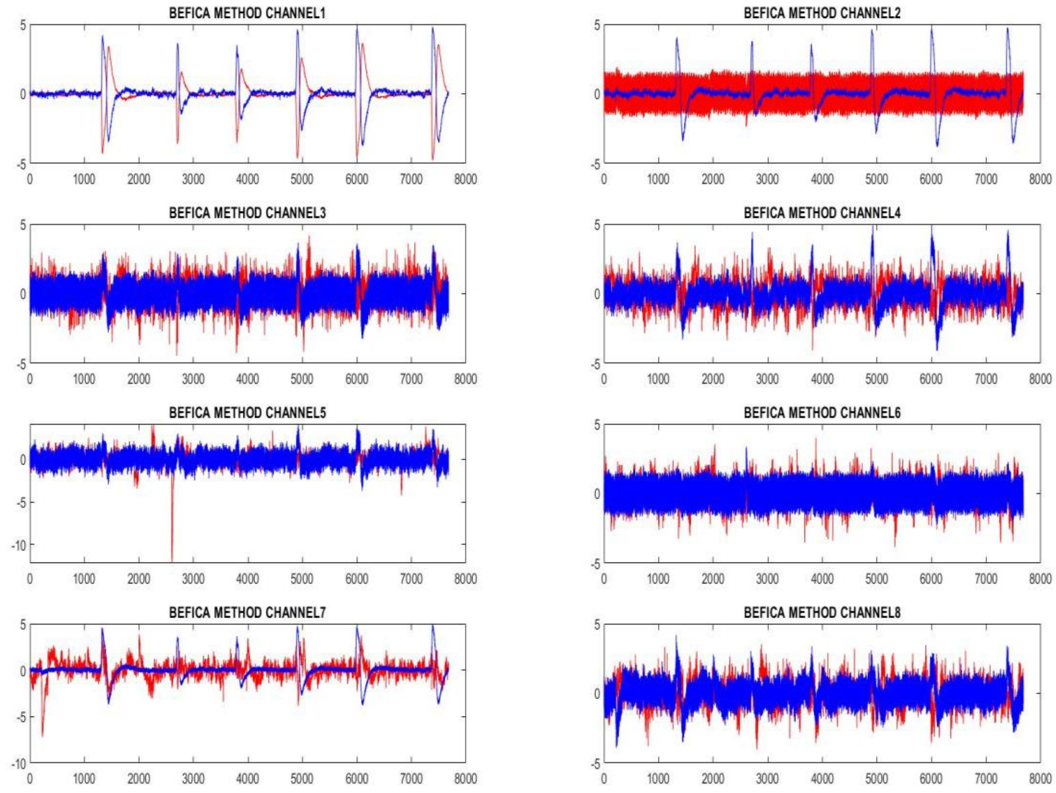


Figure (3)Recover Sources by BEFICA after Optimization

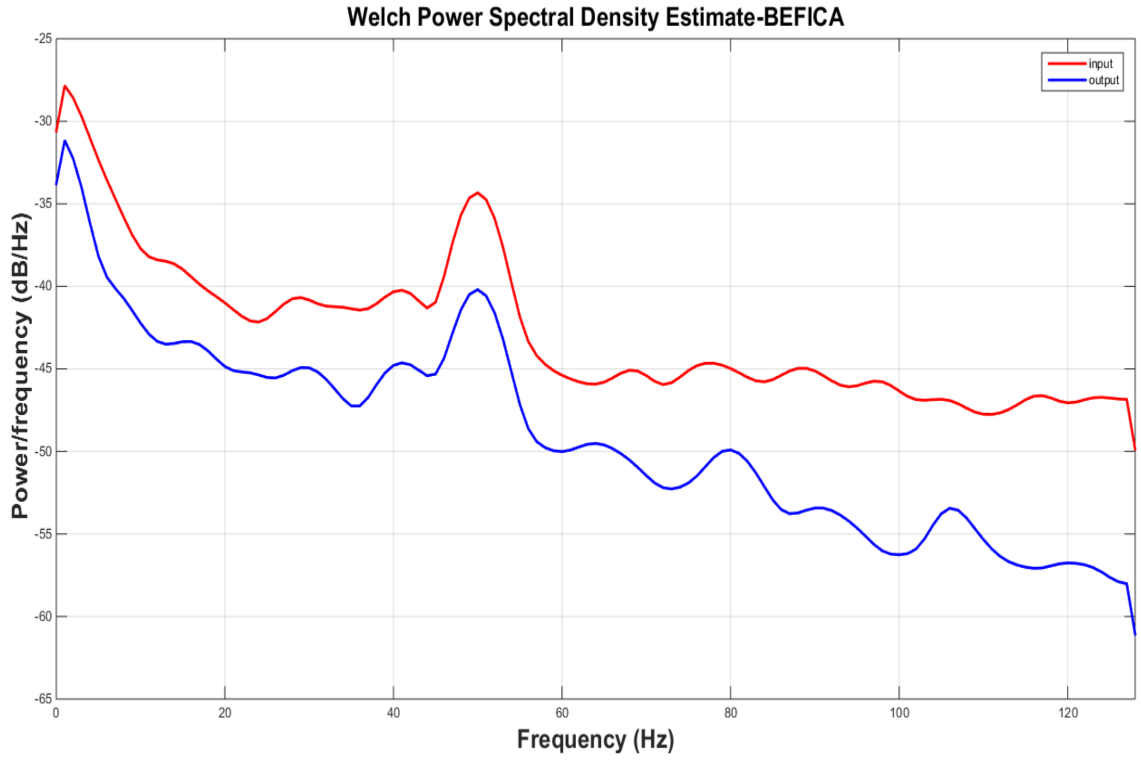


Figure (4) PSD for signals input and output after BEFICA

4-FICA method with optimizer

The results of the output signal for 8 channels are shown after analyzing the signal by separating the blind source of the BSS FICA, a single experiment of blinking eye movement and after performing the optimization process on the algorithm as in Figure (5).

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

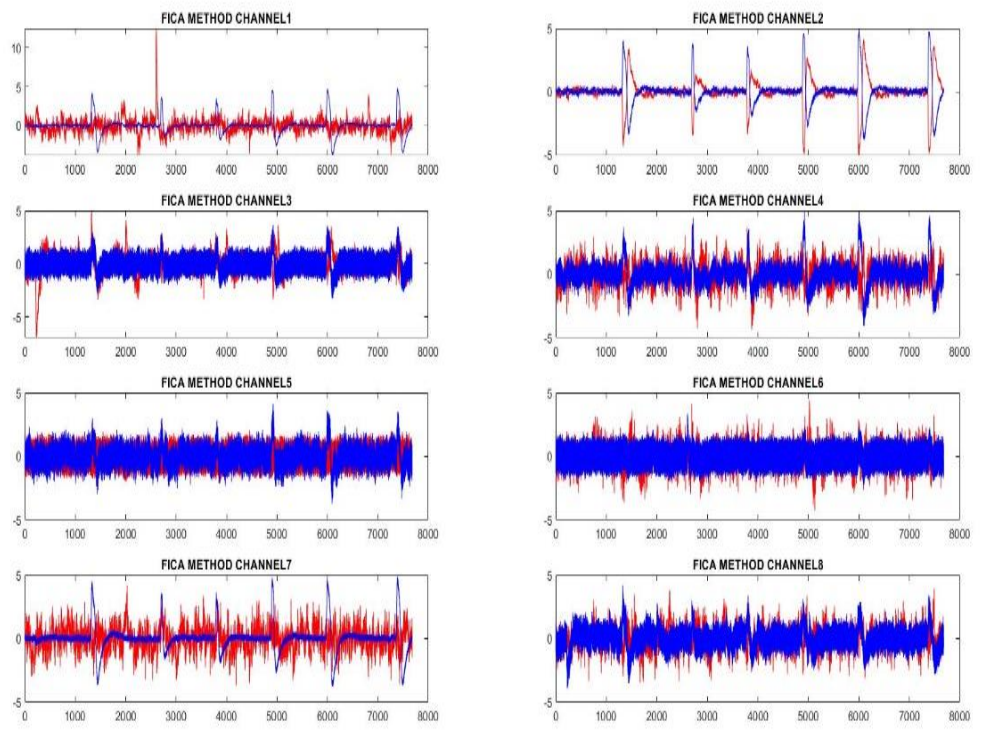


Figure (6)Recover Sources by FICA after Optimization

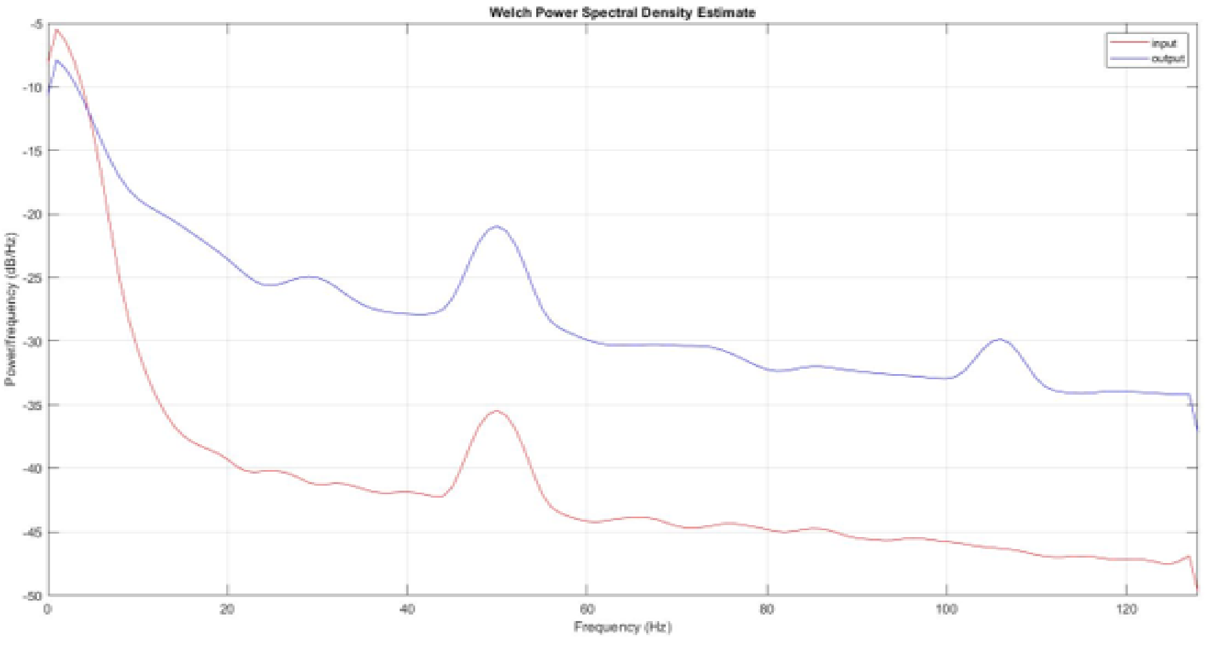


Figure (7) PSD for signals input and output after FICA

3.2. DISCUSSION

Through the drawings and results presented in the table, which we obtained after performing the optimization process using the Antlion algorithm, as its effect was clear on the EFICA algorithm, by fine-tuning its parameters, which led to a reduction in the variation in the distribution of the energy for the different frequencies, so the value of the spectral density of the energy became (0.0051) after it was high before improvement and compared to other algorithms, and the lowest quality comes after it STONE(0.0053),FICA(0.0058) , BEFICA (0.7628), as shown in **Error! Reference source not found.**) and in Figure (8,Therefore, it can be concluded that in the case of real data the EFICA algorithm was the best of them Performance after the improvement phase.

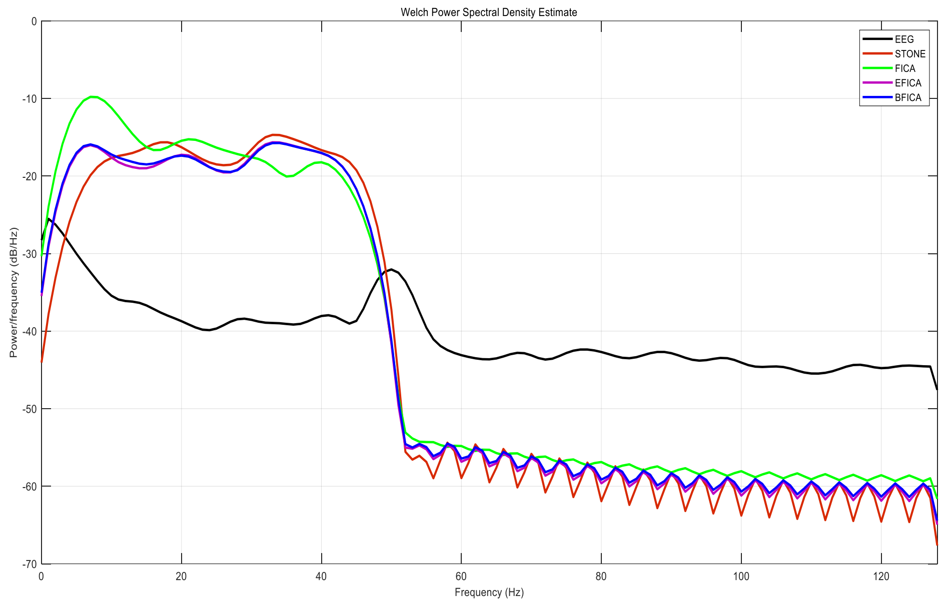


Figure (8) PSD for each algorithms after optimization

Table (Error! No text of specified style in document.**) PSD after optimization**

Data set (8) electrodes	BSS Algorithms	Optimization Algorithm	Total power
Fb1 Fb2 C3 C4 O1 O2 VEOG HEOG	STONE	Ant lion Algorithm	0.0053
	FICA		0.0058
	BEFICA		0.7628
	EFICA		0.0051

4. CONCLUSIONS

The purpose of the present paper is effectively to improve the EEG patterns. By takes the mission-related cues generated by the separation algorithms and refines them using an optimizer (the lion ant) then compares the proposed system algorithm with other systems that use other algorithms to separate the blind sources such as (STONE , EFICA ,BEFICA and FICA,). The algorithm is trained and tested with real signals (EEG obtained according to the international system measurement (10-20) using a computerized EEG system.
Since the EEG signal is a mixing of many signal sources that are generated by the brain and corrupted by different artifacts, the EFICA algorithm is a sufficient algorithm for the separation of the EEG signal into its sources (retrieved components). The function-related components are reconstructed to obtain a pure EEG signal containing no trace elements and non-task-related components.

REFERENCES

[1] Ramadan, R.A., et al., Basics of brain computer interface, in Brain-Computer Interfaces. 2015, Springer. p. 31-50.
[2] Abiyev, R.H., et al., Brain-computer interface for control of wheelchair using fuzzy neural networks. BioMed research international, 2016.
[3] Mirjalili, S., S.M. Mirjalili, and A. Hatamlou, Multi-verse optimizer: a nature-inspired algorithm for global optimization. Neural Computing and Applications, 2016. 27(2): p. 495-513.
[4] Subhodip Saha1 · V. Mukherjee1 , A novel quasi-oppositional chaotic antlion optimizer for global optimization, part of Springer Nature 2017 .
[5] Fouad, M.M., et al., Brain computer interface: A review, in Brain-Computer Interfaces. 2015, Springer. p. 3-30.
[6] Esha Gupta and Akash Saxena . 2016, Performance Evaluation of Antlion Optimizer Based Regulator in Automatic Generation Control of Interconnected Power System.
[7] Sahonero-Alvarez, G. and H. Calderón. A comparison of SOBI, FastICA, JADE and Infomax algorithms. in Proceedings of the 8th International Multi-Conference on Complexity, Informatics and Cyberneti, Orlando, FL, USA. 2017.
[8] Abdullah, A.K. and Z.C. Zhu, Enhancement of source separation based on efficient Stone'S BSS algorithm. International Journal of Signal Processing, Image Processing and Pattern Recognition, 2014. 7(2): p. 431-442.
[9] Ahmed, S.A.B., N.A. Assafi, and W.A. Elgylani, Features Extraction Techniques of EEG Signals for Brain Computer Interface Applications. 2017, Sudan University of Science and Technology.
[10] MN Hoda - 2016 - ieeexplore.ieee.org mega Scientific Calculation through Orbital Period Harsh Sharma, Naveen Rao and Mohit Sharma … A Generic Tool to Process Mongodb or Cassandra Dataset,2016.
[11] Salim, M., Design and implementation of AI controller based on brain computer interface. 2007, MS Thesis, Nahrain University.
[12] Overton, D. and C. Shagass, Distribution of eye movement and eyeblink potentials over the scalp. Electroencephalography and Clinical Neurophysiology, 1969. 27(5): p. 546.