American Journal of Engineering Research (AJER)
e-ISSN : 2320-0847 p-ISSN : 2320-0936
Volume-03, Issue-02, pp-240-247
www.ajer.org

Research Paper Open Access

Blind Source Separation Using Artificial immune system

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Abstract: - Independent component analysis is a computational method to solve blind source separation. Blind source separation is defined as the separation of source signals from received signals without any prior knowledge of the source signals. Independent Component Analysis looks for the component that are statistically independent and nongaussian. The most traditional algorithm used is FASTICA algorithm. It is the algorithm which uses Newtonian Iteration approximation .Independent component analysis based on FASTICA algorithm faced two main disadvantages.One is that the order of the independent components is difficult to be determined and the suitable source signals are not isolated.In order to overcome these disadvantages, an improved ICA algorithm based on Artificial Immune System is used.AIS is an attractive technique and it is advantageous over other techniques such as it can be easily implemented and has great capability of escaping local optimal solutions. It has the great capability of providing better signal separation when compared to FASTICA algorithm.The goal of the proposed AIS-ICA algorithm is to use AIS to determine the separating matrix of ICA by means of which order of independent component analysis is determined and suitable source signals are isolated. The Artificial immune system is based on natural immune system principles and it can offer strong and robust information processing capabilities for solving complex problems. Artificial immune system is based on clonal selection principle that can be used to optimise functions. The steps involved in CLONALG are initialisation, cloning, mutation and selection. In case of initialisation, initialise the population randomly and select the function to maximise. In the second step, the best antibody being cloned the most. In case of mutation, the worst antibodies are mutated higher.The final step is selection in which antibodies are selected for next iteration. It describes the basic principles of immune response to an antigenic stimulus. It is population based algorithm and its only variation operator is mutation.

Keywords: - *Independent component analysis, artificial immune system, signal separation, heuristic algorithm*

I. INTRODUCTION

Blind source separation (BSS) is to separate the source from the received signals without any prior knowledge of the source signal. Problems related to BSS have become an active research area in the fields of statistical signal processing and unsupervised neural learning. Independent component analysis (ICA) is one of the most used methods for BSS. The goal of ICA is to recover independent sources when given only sensor observations that are unknown linear mixtures of the unobserved independent source signals. It has been investigated extensively in image processing, financial time series data and statistical process control. For ICA, many effective algorithms have been proposed, the most used traditional algorithm is FastICA algorithm that uses the approximate Newtonian iteration algorithm. But in practical application, it often leads to local minimum solution and the suitable source signals are not isolated. Moreover, the order of the independent components (ICs) is difficult to be determined. These two problems are the main drawbacks of FastICA algorithm. To overcome these disadvantages, an improved ICA algorithm based on artificial immune system (AIS) (called AIS-ICA) is presented. They are one among many types of algorithm inspired by biological systems, including evolutionary algorithms, swarm intelligence, neural networks and membrane computing. AIS are bio-inspired algorithms that take their inspiration from the human immune system. Within AIS, there are many different types of algorithm, and research to date has focused primarily on the theories of immune networks, clonal selection and negative selection. It is based on natural immune system principles, and it can offer strong and robust information processing capabilities for solving complex problems. There are various applications of AIS, and they include data analysis, scheduling, classification, fault detection and security of information systems. Since AIS has many advantages over other heuristic techniques such as it can be easily implemented and has great capability of escaping local optimal solutions, it is used in this study to develop the AIS-ICA algorithm.

II. METHODOLOGY

I.ICA

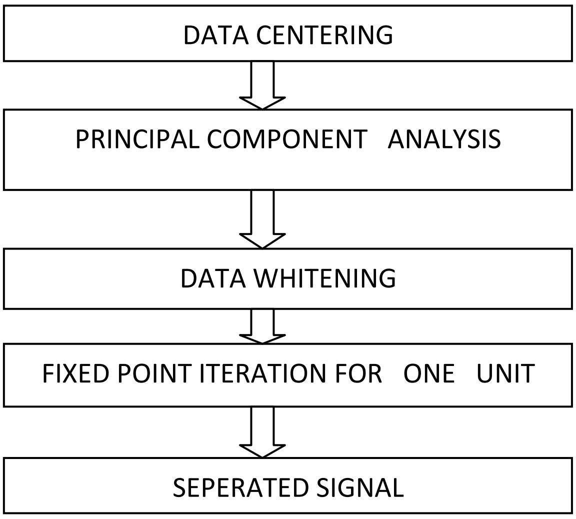

Fig 1: block diagram of existing work

DATA CENTERING

The input data X is centered by computing the mean of every component of X and subtracting that mean. The data centering can be defined as the difference between data vector(X) and mean(X) and it is given by

$$X_c=X-E\{X\} \quad (1)$$

PRINCIPAL COMPONENT ANALYSIS

It is one of the pre processing tool for ICA. It is used to find the eigen values and the eigen vectors in order to whiten the given data. The drawback is that the concept of correlation is used.

DATA WHITENING

The main goal of whitening is to transform the data vector linearly as result of which newly obtained data vector is white i.e. the components are uncorrelated and the variance equal to unity or the covariance matrix equal to identity matrix. Whitening can be done using Eigen value decomposition which can be defined as follows

$E*D*E^T$

Where E is the Eigen Vector, D is the Eigen value, E^T is the transpose matrix of Eigen vectors

Since eigen values are single component wise operation the above equation can be written as

$Z=E*D^{-1/2}*E^T$

FASTICA ALGORITHM FOR ONE UNIT

The FASTICA algorithm for one unit estimates one row of demixing matrix that is extremum of contrast functions. It is an algorithm which maximises the non gaussianity of statistical independence. Non gaussianity can be measured by two methods namely Kurtosis contrast function and negentropy. Kurtosis can be classically dehined as follows

$$\mathrm{Kurt}(b) = E(b^4) - 3(E(b^2))^2 \quad (2)$$

If variable b is assumed to be zero mean and unit variance, the right hand side simplifies to $E(b^4) - 3$. This shows that kurtosis is simply a normalised version of the fourth moment $E(b^4)$. For a Gaussian b, the fouth moment equals $3(E(b^2))^2$. Thus, kurtosis is zero for a Gaussian random variable and non zero for most non Gaussian random variables.

Unlike kurtosis,negentropy is determined according to the information quantity of differential entropy. Entropy is a measure of the average uncertainity in a random variable. The differential entropy H of random variable b with density f(b) is defined as H(b)=- $\int p(b)\log p(b)db$. According to a fundamental result of information theory, a Gaussian variable will have the highest entropy value among a set of random variables with equal variance. For obtaining a measure of non-Gaussianity, the negentropy J is defined as follows:

$J(b) = H(b_{gauss}) - H(b)$

The negentropy is always non negative and is zero if and only if b has Gaussian distribution. Since negentropy is very difficult to compute, an approximation of negentropy is proposed as follows:

$$J(b) \sim [E\{G(b)\} - E\{G(0)\}]^2 (3)$$

Where 0 is a Gaussian variable of zero mean and unit variance , and b is a random variable with zero mean and unit variance. G is a non quadratic function , and is given by $G(b) = b^4$.

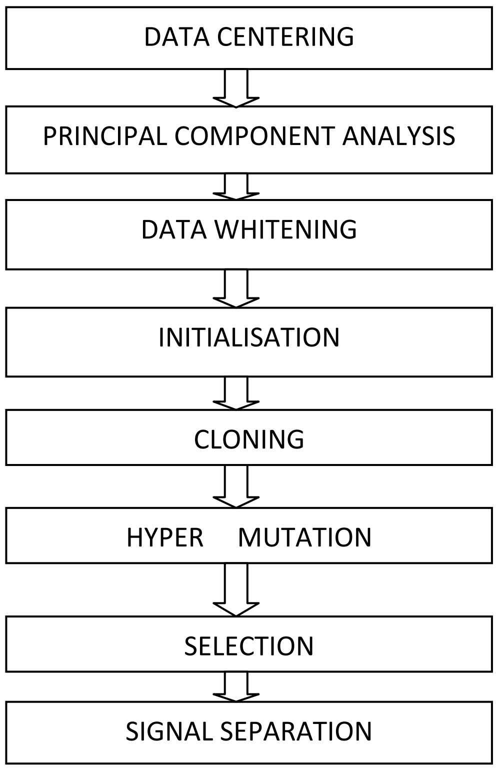

Fig 2:Block diagram of proposed work

DATA CENTERING

The input data X is centered by computing the mean of every component of X and subtracting that mean. The data centering can be defined as the difference between data vector(X) and mean(X) and it is given by

$X_c = X - E\{X\}$

PRINCIPAL COMPONENT ANALYSIS

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DATA WHITENING

The main goal of whitening is to transform the data vector linearly as result of which newly obtained data vector is white i.e. the components are uncorrelated and the variance equal to unity or the covariance matrix equal to identity matrix. Whitening can be done using Eigen value decomposition which can be defined as follows

$$E*D*E^T (4)$$

Where E is the Eigen Vector, D is the Eigen value, E^T is the transpose matrix of Eigen vectors

Since eigen values are single component wise operation the above equation can be written as

$$Z = E*D^{-1/2}*E^T (5)$$

INITIALISATION

It is the process in which variables are assigned. The function that is to be maximsed or minimized should be selected.Initialise the population randomly.

CLONING

Antibody's affinity corresponds to the evaluation of the objective function given by the antigen.The antibodies are cloned; the best antibody being cloned the most and worst being cloned the least number of times.

HYPER MUTATION

The clones are mutated in inverse proportion to their affinity. The best antibody's clones are mutated lesser and worst antibody's clones are mutated most.The mutation can be uniform, gaussian or exponential.

SELECTION

It is the final step involved in CLONALG algorithm. It is the process in which best antibodies are selected for next iteration.

III. SIMULATION RESULTS

The input signal is then passed through the mixing matrix as a result of which mixed signals will be produced. The proposed AIS ICA and FASTICA algorithm will be used to separate the original signal. The artificially generated mixtures are used to evaluate the effectiveness of the proposed AIS ICA algorithm compared with that of FASTICA algorithm. Six simulated signals are used as input source signals which are as follows:

a. Modulated sinusoid:

*P(t)= 2*sin(t/149)*cos(t/8)+0.2*rand()*

b. Square wave:

*Q(t)= sign(sin(12*t + 9*cos(2/29))) + 0.1 *rand()*

c. Sawtooth:

*R(t)= (rem(t, 79)-17)/23+0.1*rand()*

d. Impulsive curve:

*S(t)= ((rem(t,23)-11)/9)^5) + 0.1*rand()*

e. Exponential:

*U(t)= 5*exp(-t/121)*cos(37*t) + 0.1*rand()*

where the rem function returns a result that is between 0 and sign(e)*abs(z). If z is a zero,rem returns NaN(not a number). The rand function generates a set of uniformly distributed pseudo random numbers.

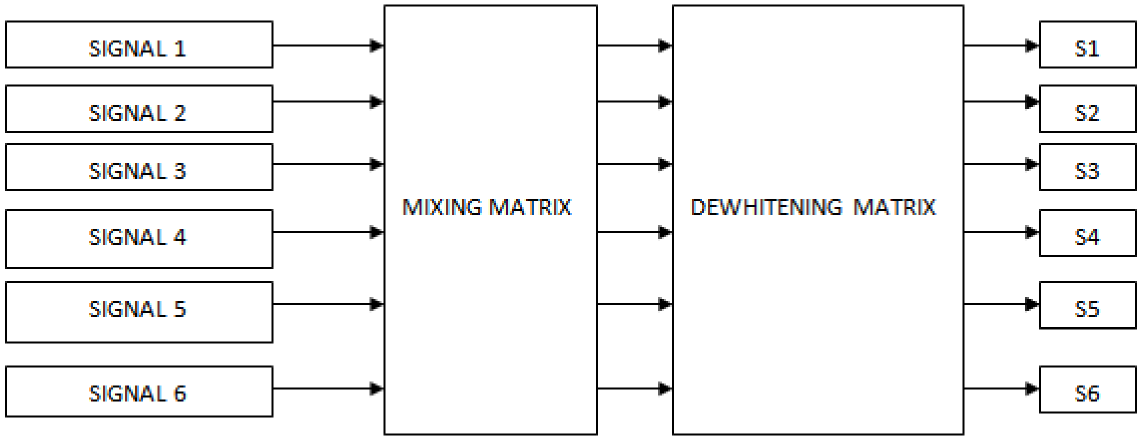

Fig 3:Block diagram of separating six signals

Where s1,s2,s3,s4,s5,s6 represents separated signals

The input signals waveforms are given below as follows

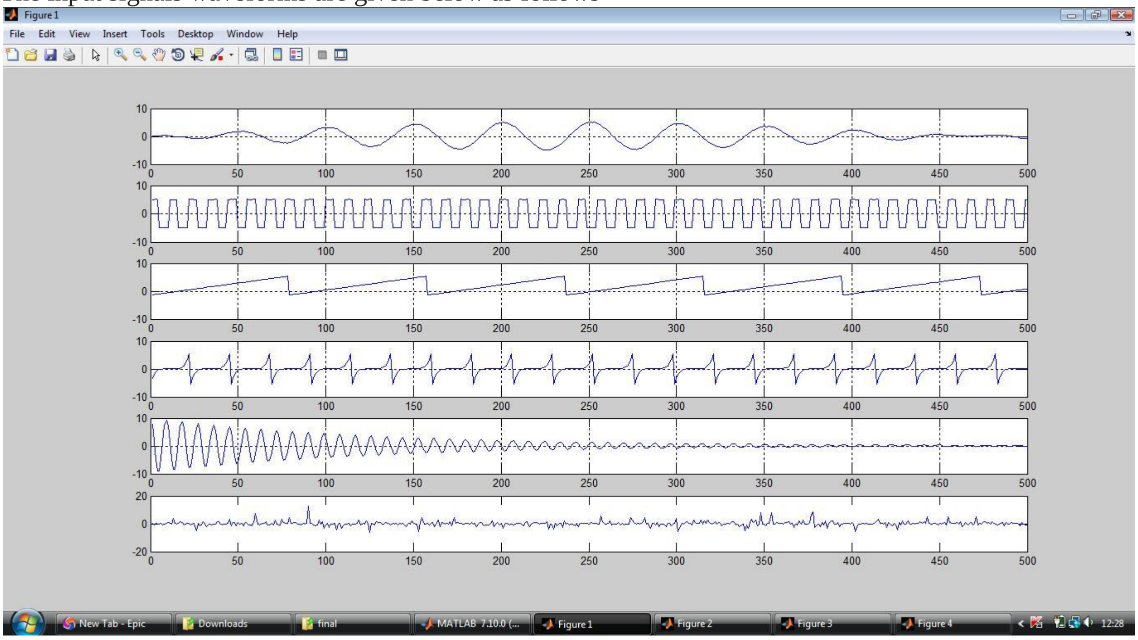

Fig 6:Input signals

The first to sixth I/p represent modulated sinusoid, square wave,sawtooth wave, impulsive wave, exponential and spiky noise respectively.The input signals are passed through the 6×6 mixing matrix as a result of which the mixed signals are generated. The mixed signals are passed through FASTICA and AIS-ICA algorithm by means of which signals will be separated. The mixed signal wave forms are as follows

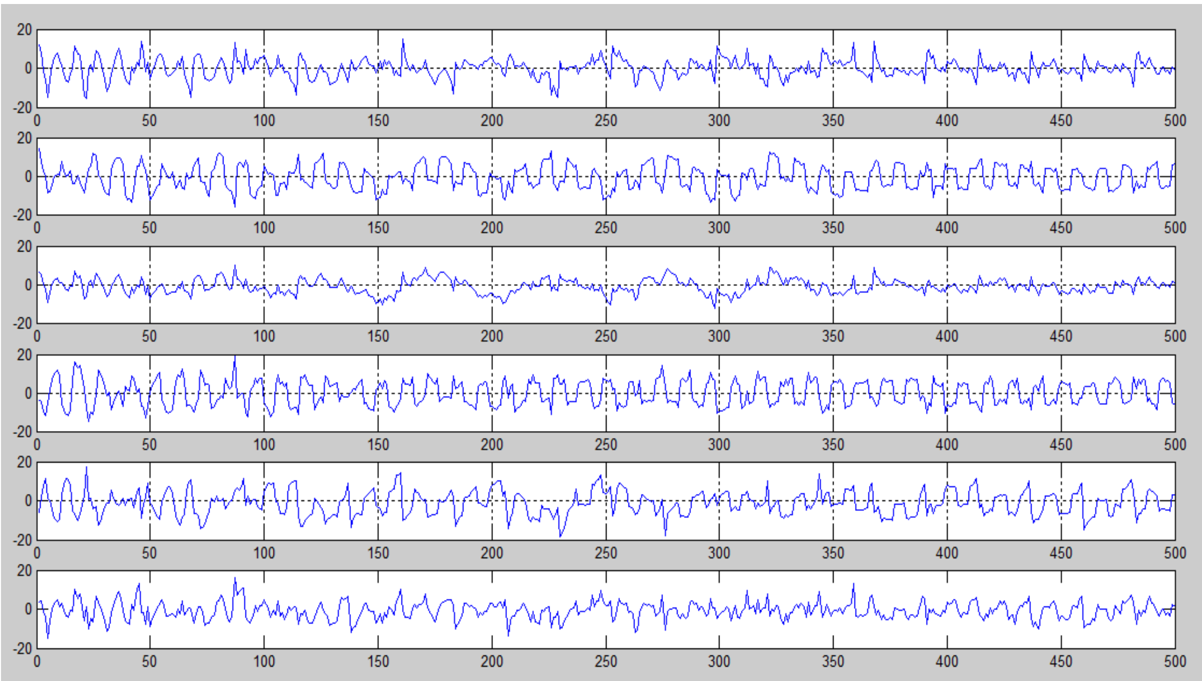

Fig 7: Mixed signals

The separated signals of FASTICA and AIS-ICA are as follows:

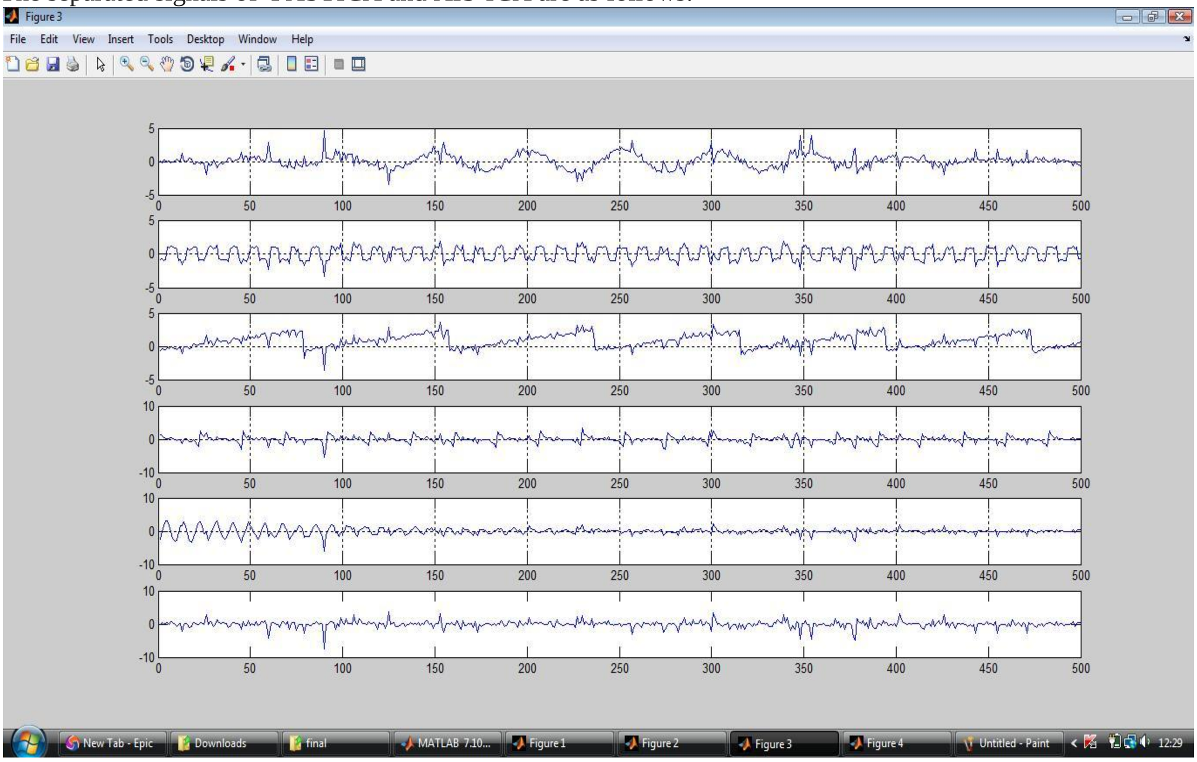

Figure 8: FASTICA

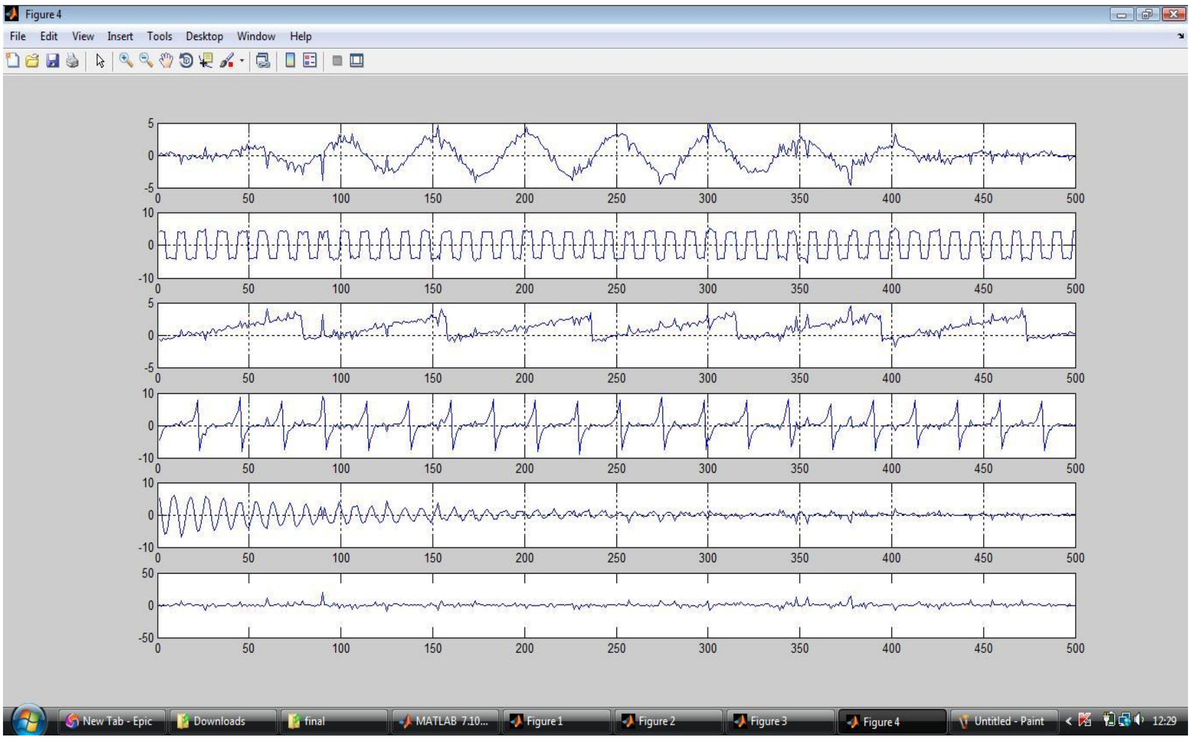

Figure 9 AIS-ICA

It can be seen that FastICA couldn't separate the independent components clearly, whereas the proposed AIS-ICA separates them clearly. That is, it can be seen that the source signals separated by the AIS-ICA algorithm are more accurate than those separated by the FastICA algorithm.

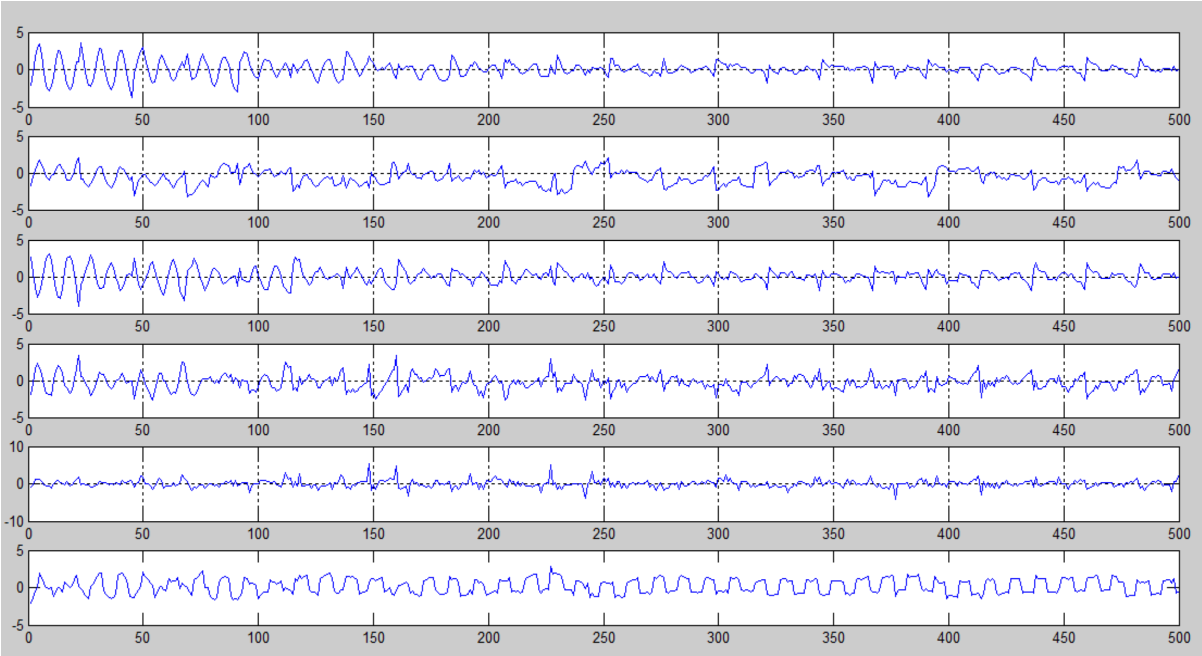

Figure11:FASTICA by 1st round

AIS-ICA

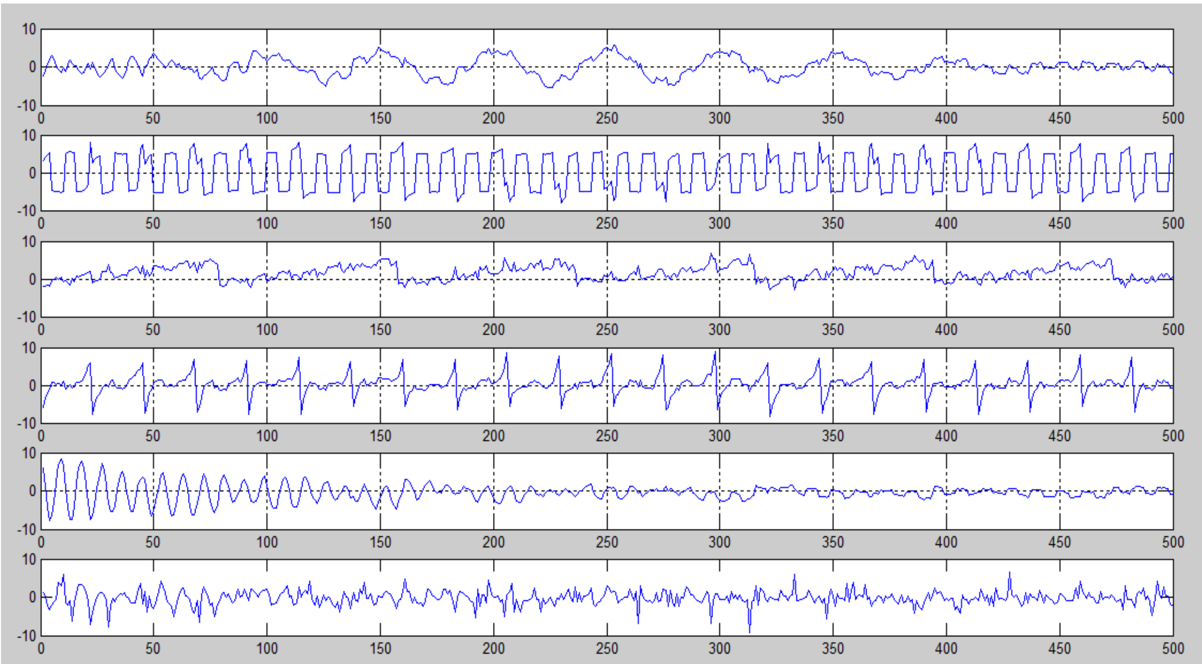

Fig 9(a): AIS-ICA by 1st round

From the above rounds of FASTICA and AIS ICA, the following information can be inferred:

- AIS-ICA provides better separating results compared to that of FAST-ICA.
- The order of IC can be easily determined by AIS-ICA

IV. CONCLUSION AND FUTURE WORKS

Independent component analysis separates mixed signals blindly without any information of the mixing system. FASTICA is the most popular gradient based ICA algorithm, but it has two disadvantages order of the ICs is difficult to be determined and easy to obtain local minimum. In order to overcome these two disadvantages, an improved ICA algorithm based on AIS is used. In the proposed AIS-ICA algorithm, it is used to determine the de mixing matrix of ICA. Simulation results from the artificial signal data showed that the AIS-ICA algorithms provides better separating results than that of FASTICA algorithm. The order of ICs can be determined by the proposed AIS-ICA algorithm. The future work indicates AIS ICA has to applications aiding problems involved in claasification,fault detection and security of informational systems.

4.1 FUTURE WORKS

The future work indicates AIS ICA has found to be in many involved in claasification,fault detection and security of informational systems. It also aids the problems involved in control of growing of memory cells and also the mutation and cloning are taken randomly. So a new classifier called as proposed particle swam optimisation is used to attain an optimal value. The future works aids to be applied in EEG signal classification by means of which normal and abnormal signals can be easily classified with high accuracy.

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