

Blind Source Separation with Conjugate Gradient Algorithm and Kurtosis Maximization Criterion

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Abstract : Blind source separation (BSS) is a technique for estimating individual source components from their mixtures at multiple sensors. It is called blind because any additional other information will not be used besides the mixtures. Recently, blind source separation has received attention because of its potential applications in signal processing such as in speech recognition systems, telecommunications and medical signal processing. Blind source separation of super and sub-Gaussian Signal is proposed utilizing conjugate gradient algorithm and kurtosis maximization criteria. In our previous paper, ABC algorithm was utilized to blind source separation and here, we improve the technique with changes in fitness function and scout bee phase. Fitness function is improved with the use of kurtosis maximization criterion and scout bee phase is improved with use of conjugate gradient algorithm. The evaluation metrics used for performance evaluation are fitness function values and distance values. Comparative analysis is also carried out by comparing our proposed technique to other prominent techniques. The technique achieved average distance of 38.39, average fitness value of 6.94, average Gaussian distance of 58.60 and average Gaussian fitness as 5.02. The technique attained lowest average distance value among all techniques and good values for all other evaluation metrics which shows the effectiveness of the proposed technique.

Keywords:- Kurtosis Maximization, Conjugate Gradient Method, Blind Source Separation, Ant Bee Colony, Sub-Gaussian and Super-Gaussian signal.

I. INTRODUCTION

Blind source separation has received considerable attention among researchers as it has vast application and has both theoretical significance and practical importance [9]. A number of blind separation algorithms have been proposed based on different separation models [10]. Blind source separation is to recover unobservable independent sources from multiple observed data masked by linear or nonlinear mixing. In BSS, the source signals and the parameter of mixing model are unknown. The unknown original source signals can be separated and estimated using only the observed signals which are given through unobservable mixture [5]. Its numerous promising applications are in the areas of speech signal processing [1], [2], medical signal Processing including ECG, MEG, and EEG [3], and monitoring [9,13]. The problem of source separation is to extract independent signals from their linear or nonlinear mixtures. So-called blind source separation (BSS) is to recover original source signals from their mixtures without any prior information on the sources themselves and the mixing parameters of the mixtures [11,14]. The algorithm is susceptible to the local minima problem during the learning process and is limited in many practical applications such as BSS that requires a global optimal solution [10, 12, 16].

Several techniques have been proposed in the literature for blind source separation that are mainly classified based on optimization algorithm [15, 17] and non-optimization algorithm [3-8] like genetic algorithm and particle swarm optimization for blind source separation. EM algorithm based techniques are employed. In our previous paper, ABC algorithm was utilized to blind source separation and here, we improve the technique with changes in fitness function and scout bee phase. Fitness function is improved with the use of kurtosis maximization criterion and scout bee phase is improved with use of conjugate gradient algorithm. The technique is composed of three modules, namely signal mixing module, weight matrix generation module and source separation module. The input source signals are combined and multiplied with a reference signal to have the mixed signal. From the mixed signal, we have to recover the source signals without having prior knowledge. This is accomplished by generating a weighting matrix by the use of Artificial Bee Colony with the aid of

conjugate gradient algorithm and kurtosis maximization criteria. This generated matrix is multiplied with the mixed matrix to obtain the estimated source matrix.

The rest of this paper is organized as follows. Section 2 gives a brief description of the related works and the proposed technique in detailed in section 3. The experimental analysis and discussions are presented in section 5 and section 6 gives the conclusion.

II. REVIEW OF RELATED WORKS

There has been several works in the literature associated with blind source separation. In this section, we discuss the some of those works. HamedModaghegh, SeyedAlirezaSeyedin [18] have presented an active steganalysis method in order to break the block-discrete cosine transform (DCT) coefficients steganography. Their method was based on a combination of the Blind Source Separation (BSS) technique and Maximum A posteriori (MAP) estimator. Sawada *et al.* [1] have presented a blind source separation method for convolutive mixtures of speech/audio sources. Here, frequency-domain mixture samples were clustered into each source by an expectation-maximization (EM) algorithm. Duong *et al.* [2] have investigated the blind source separation performance stemming from rank-1 and full-rank models of the source spatial covariances. For that purpose, they addressed the estimation of model parameters by maximizing the likelihood of the observed mixture data using the EM algorithm with a proper initialization scheme. Reju, V.G. SooNqeeKohet *al.* [3] have proposed two algorithms, one for the estimation of the masks which were to be applied to the mixture in the TF domain for the separation of signals in the frequency domain, and the other for solving the permutation problem. The algorithm for mask estimation was based on the concept of angles in complex vector space. Diogo *Cet al.* [5] have presented a method to perform blind extraction of chaotic deterministic sources mixed with stochastic signals. This technique employed the recurrence quantification analysis (RQA), a tool commonly used to study dynamical systems, to obtain the separating system that recovers the deterministic source.

Takahata *et al.* [6] have reviewed some key aspects of two important branches in unsupervised signal processing: blind deconvolution and blind source separation (BSS). It also gave an overview of their potential application in seismic processing, with an emphasis on seismic deconvolution. Xiao-Feng Gong and Qiu-Hua Lin [7] have considered the problem of blind separation for convolutive speech mixtures. The problem of permutation correction was solved in the method by simultaneously extracting and pairing two adjacent frequency responses, and exploiting the common factors shared by neighboring cross frequency covariance tensors. Sheng lixie *et al.* [8] have presented a time-frequency (TF) underdetermined blind source separation approach based on Wigner-Ville distribution (WVD) and Khatri-Rao product to separate N non-stationary sources from many mixtures. The improved method was proposed for estimating the mixing matrix, and after extracting all the auto-term TF points, the auto WVD value of the sources was found out.

III. PROPOSED BLIND SOURCE SEPARATION WITH CONJUGATE GRADIENT ALGORITHM AND KURTOSIS MAXIMIZATION CRITERION

Blind source separation (BSS) is a technique for estimating individual source components from their mixtures at multiple sensors without any additional other information. In this paper, blind source separation of super and sub-Gaussian Signals is proposed utilizing conjugate gradient algorithm and kurtosis maximization criteria. In our previous paper, ABC algorithm was utilized to blind source separation and here, we improve the technique with changes in fitness function and scout bee phase. Fitness function is improved with the use of kurtosis maximization criterion and scout bee phase is improved with use of conjugate gradient algorithm.

A. Signal Mixing Module

In this module, the input source signals are combined and multiplied with a reference signal to have the mixed signal. The block diagram of the module is given in figure 1.

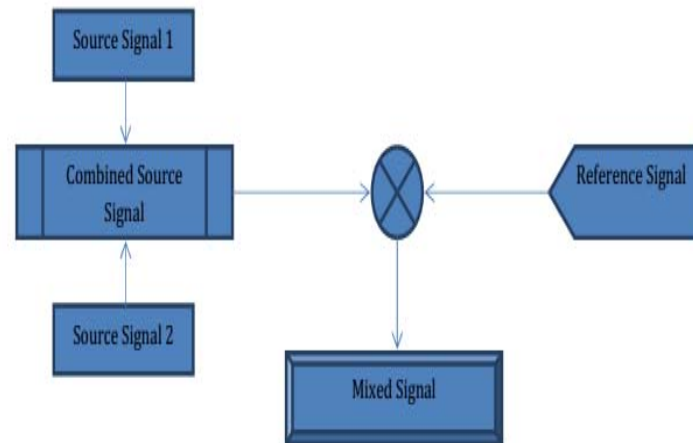


Figure 1: Block diagram of the signal mixing module

The input source δ consists of two signals which are represented by δ_i , where $0 < i \leq 2$ in our case. Let each of the signals be expanded to be represented as:

$$\delta_1 = \{\alpha_1, \alpha_2, \dots, \alpha_m\} \quad (1)$$

$$\delta_2 = \{\beta_1, \beta_2, \dots, \beta_m\} \quad (2)$$

Where α_j and β_j , for $0 < j \leq m$ are speech coefficient values and m is the length of the signal. The two source signals are combined to form the source signal. This is carried out by combining the matrices of two signals (each having dimension $1 \times m$) to form the source signal matrix (having dimension $2 \times m$) by use of linear and non-linear schemes. Mathematically, the combination process can be represented as:

$$\delta = \begin{bmatrix} \delta_1 \\ \delta_2 \end{bmatrix} = \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \\ \beta_1 & \beta_2 & \dots & \beta_m \end{bmatrix} \quad (3)$$

A reference mixing signal is required for obtaining the mixed signal. The reference signal is normally an assumed one. The reference mixing signal (having dimension 3×2) can be represented by:

$$R_M = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \end{bmatrix} \quad (4)$$

The reference mixing signal R_M (having dimension 3×2) is multiplied with the combined source signals δ (having dimension $2 \times m$) to have the mixed signal X (having dimension $3 \times m$).

$$X = R_M \times \delta = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \end{bmatrix} \times \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \\ \beta_1 & \beta_2 & \dots & \beta_m \end{bmatrix} \quad (5)$$

B. Weight Matrix Generation Module

From the mixed signal, we have to recover the source signals without having prior knowledge. This is accomplished by generating a weighting matrix by the use of Artificial Bee Colony with the aid of conjugate gradient algorithm and kurtosis maximization criteria. This generated matrix is multiplied with the mixed matrix to obtain the estimated source matrix.

The Artificial Bees Algorithm is an optimization tool, which provides a population-based search procedure. The ABC algorithm simulates the intelligent foraging behaviour of a honey bee for solving multidimensional and multimodal optimization problem. In population-based search procedure, each individual population called foods positions are modified by the artificial bees while the bee's aim is to discover the places of food sources with high nectar amount and finally the one with the highest nectar. The colony of artificial bees contains three

groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making decision to choose a food source is called an onlooker and a bee going to the food source visited by it previously, is named an employed bee. A bee carrying out random search is called a scout.

In each cycle, the search consists of three steps: sending the employed bees onto the food sources and then measuring their nectar amounts; selecting of the food sources by the onlookers after sharing the information of employed bees and determining the nectar amount of the foods; determining the scout bees and then sending them onto possible food sources. Here, the position of a food source represents a possible solution of the optimization problem and the nectar amount of a food source corresponds to the fitness of the associated solution. At the initialization stage, a set of food source positions are randomly selected by the employed bees and the population of the positions is subjected to repeated cycles of the search processes of the employed bees, the onlooker bees and scout bees. Provided that the nectar amount of the new source is higher than that of the previous one the bee memorizes the new position and forgets the old one. Otherwise she keeps the position of the previous one. Here, if a position cannot be improved further through a predetermined number of cycles called limit then that food source is assumed to be abandoned.

In our case, ABC is employed to find out the weight matrix so as to aid in the signal recovery. Initial matrix would be random which would be updated in each step with aid from the kurtosis fitness function and conjugate gradient based scout bee phase. The weighting matrix is of the size 2×3 and initially the colony is assumed to have six different matrices as the initial population. Let these initial population matrices be represented as:

$$P = [P_1 \ P_2 \ P_3 \ P_4 \ P_5 \ P_6] \quad (6)$$

Where each matrix P_i is defined as:

$$P_i = \begin{bmatrix} \rho_{11} & \rho_{12} & \rho_{13} \\ \rho_{21} & \rho_{22} & \rho_{23} \end{bmatrix}, 1 \leq i \leq 6 \quad (7)$$

Where ρ_{11} ($0 < i \leq 2, 0 < j \leq 3$) are randomly generated values. The matrices are evaluated using the kurtosis maximization criteria.

Kurtosis Maximization criteria based fitness function

Fitness functions are used to find the best matrices that would give best recovered output. In our case, we use kurtosis maximization based fitness function and entropy based fitness function. Kurtosis is any measure of the peakedness of the probability distribution of a real-valued random variable. One common measure of kurtosis is based on a scaled version of the fourth moment of the data or population. In our case, the weighting matrix is multiplied with the mixed matrix to yield recovered signal δ^* . Hence, it can be written such as:

$$\delta^* = P \times X \quad (8)$$

Let us define a matrix q which is the inverse of P matrix. The function is found out over arbitrary taken G number of points. Then, the g^{th} kurtosis value for the i^{th} iteration is given by:

$$kurt_g(i) = E\{[q^T(i)\delta^*(i)]^4\} - 3 \quad (9)$$

The g^{th} kurtosis value for the i^{th} iteration is given by:

$$kurt_g(i+1) = kurt_g(i) + \sum_{j=1}^N \sum_{k=1}^g \frac{\partial kurt_k(i)}{\partial q_j(i)} \Delta q_j(i) \quad (10)$$

Where $\Delta q_j(i) = q_j(i+1) - q_j(i)$. Equation 10 can be expanded using Taylor series to become:

$$kurt(i+1) = kurt(i) + 4[D]^3_i[\delta^*]_i + \Delta q(i) \quad (11)$$

$$\text{Where, } [D]_i = \begin{bmatrix} q^T(i)\delta_1^*(i) & \dots & 0 \\ \dots & \dots & \dots \\ 0 & \dots & q^T(i)\delta_G^*(i) \end{bmatrix}.$$

Hence, kurtosis based fitness function has been defined and can be represented as f_k . Suppose the entropy of mixed signals is represented by $\Gamma_{(i)}$, then the entropy based function (f_e) can be defined by:

$$f_e = \frac{1}{\sum_{i=1}^m \Gamma_{(i)}} \quad (12)$$

The combined fitness function is given by:

$$fitness = \alpha \cdot f_k + \beta \cdot f_e \quad (13)$$

The generated matrices are evaluated using this combined fitness function. Initially, best matrix from the initial six random generated matrices is found out and taken for further processing.

Employed bee and onlooker bee phase

In the initial phase, best matrix (represented by B) from the generated matrices was found out using the fitness functions. In employed bee phase, the values of all the six matrices are changed with respect to the best matrix found out. The updation of the matrix is carried using the formula:

$$V_i = B + \phi(B - P_i) \text{ for } 0 < i \leq 6 \quad (14)$$

Where, V_i is the updated value of initially taken P_i matrix and ϕ is randomly produced number in the range $[-1,1]$. The matrix updation is given by:

$$\begin{aligned} V_1 &= B + \phi(B - P_1) \\ V_2 &= B + \phi(B - P_2) \\ V_3 &= B + \phi(B - P_3) \\ V_4 &= B + \phi(B - P_4) \\ V_5 &= B + \phi(B - P_5) \\ V_6 &= B + \phi(B - P_6) \end{aligned} \quad (15)$$

Hence, all the matrices values are updated to obtain updated six matrices represented by $V = [V_1 V_2 V_3 V_4 V_5 V_6]$. Best matrix among the updated matrices is found out using the fitness function and is represented as C .

The best matrix obtained using the employed bee phase is again improved in the onlooker phase. Here, an element in the best matrix is replaced by an arbitrary value in the range $[1,6]$ each time so as to result in six new matrices. Suppose is C represented as:

$$C = \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \end{bmatrix}$$

Then six new matrices are given by:

$$\begin{aligned} F_1 &= \begin{bmatrix} \sigma_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \end{bmatrix}, & F_2 &= \begin{bmatrix} c_{11} & \sigma_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \end{bmatrix}, & F_3 &= \begin{bmatrix} c_{11} & c_{12} & \sigma_{13} \\ c_{21} & c_{22} & c_{23} \end{bmatrix} \\ F_4 &= \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ \sigma_{21} & c_{22} & c_{23} \end{bmatrix}, & F_5 &= \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & \sigma_{22} & c_{23} \end{bmatrix}, & F_6 &= \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & \sigma_{23} \end{bmatrix} \end{aligned} \quad (16)$$

Hence, all the matrices values are updated to obtain updated six matrices represented by $F = [F_1 F_2 F_3 F_4 F_5 F_6]$. Best matrix among the updated matrices is found out using the fitness function and is represented as L .

Scout Bee Phase

Normally, in scout bee phase random matrices are generated but in our case, we employ conjugate gradient method for having better result. The conjugate gradient method is an algorithm for the numerical solution of particular systems of linear equations, namely those whose matrix is symmetric and positive-definite.

Consider the system $\delta^* = L \times X$. Initially, residual at the k^{th} step is found using the equation:

$$R_k = \delta^* - LX_k \tag{17}$$

Then we have to find the direction P_k given by:

$$P_k = R_k + \beta_k P_{k-1}, \text{ for } i > 0; P_0 = R_0 \tag{18}$$

Where, scalar constants are given by the equations:

$$\beta_k = \frac{-R_{k+1}^T L P_k}{P_k^T L P_k} \tag{19}$$

$$\alpha_k = \frac{R_k^T R_k}{P_k^T L P_k} \tag{20}$$

New X_k is computed as:

$$X_{k+1} = X_k + \alpha_{k-1} P_{k-1} \tag{21}$$

The process is continued for certain number of iterations to yield new matrix. This entire process is carried out for all six onlooker bee phase matrix outputs to generate new six matrix represented by $U = [U_1 U_2 U_3 U_4 U_5 U_6]$.

Hence, in a single iteration we obtain 24 matrices and from these 24, the best six matrices are chosen using fitness function value and given as input to the next iteration. This six would act as the initially generated matrices in the iteration. The same process of employed bee, onlooker bee phase and scout bee phase is continued until the user required threshold is reached. The best matrices after all the iterations are taken as the final weight matrix ψ .

C. Source Separation Module

In this module, the obtained weighting matrix is multiplied with the input mixed matrix to have the recovered signal. The block diagram of the source separation module is given by figure 2.

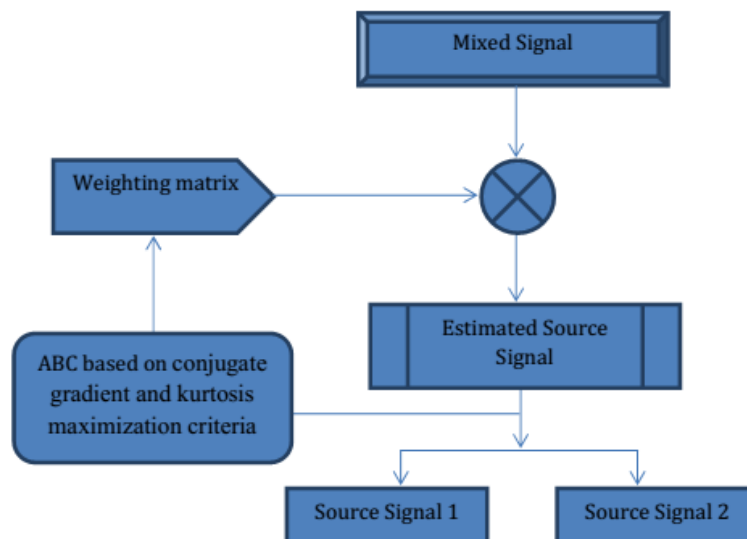


Figure 2: The block diagram of the source separation module

The estimated source matrix δ^* is obtained multiplying the mixed matrix X with a weighting matrix ψ . Here, the matrix size of ψ is 2×3 . This weighting matrix is generated with the help of ABC algorithm. Final weighting matrix obtained can be written as:

$$\psi = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} \end{bmatrix} \tag{22}$$

Recovered signal can be given by:

$$\delta^* = \psi \times X = \begin{bmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} \end{bmatrix} \times \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \\ \gamma_{31} & \gamma_{32} \end{bmatrix} \times \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \\ \beta_1 & \beta_2 & \dots & \beta_m \end{bmatrix} \tag{23}$$

Hence, signal has been recovered by the proposed technique.

IV. RESULTS AND DISCUSSIONS

In this section, results and discussions for the proposed blind source separation are given and analysed. Comparative analysis is also made by comparing to other existing techniques. In section 4.1, experimental set up and database details are given and in section 4.2 evaluation metric details are given. Simulation plots are given in section 4.3 and detailed analysis is given in section 4.4.

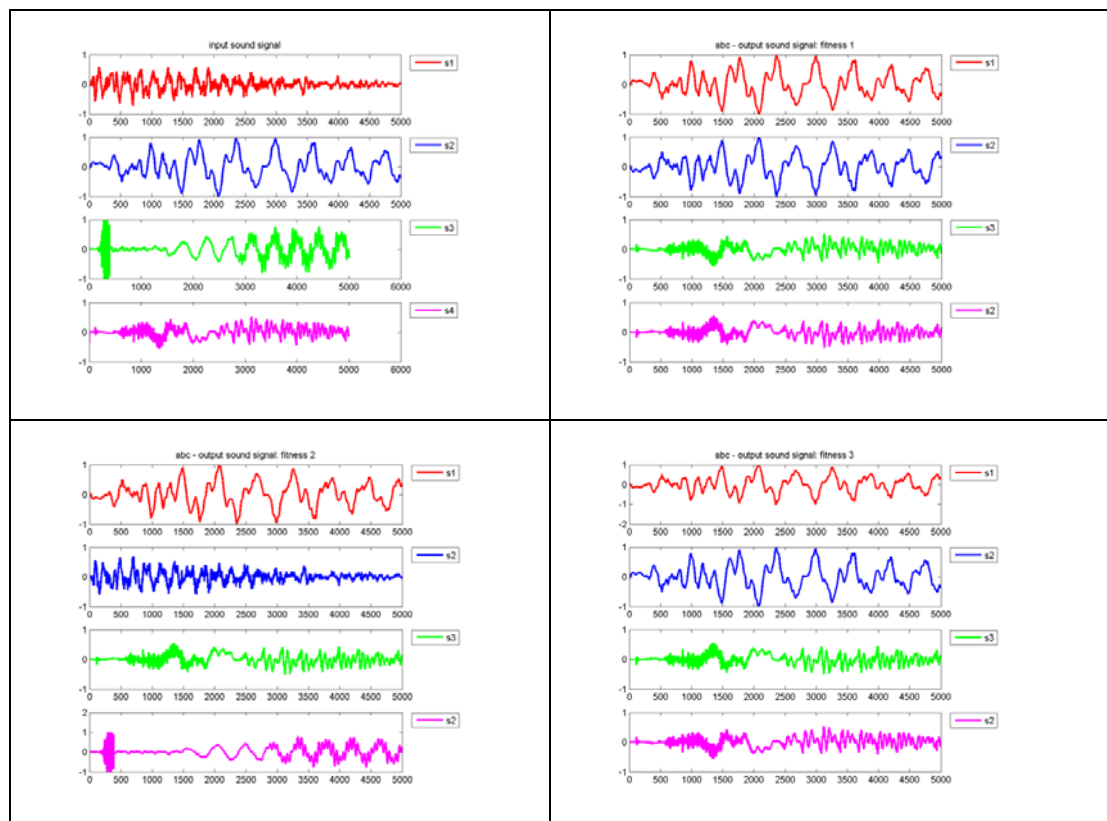
A. Experimental set up and evaluation metrics employed

The proposed technique for signal separation is implemented in MATLAB on a system having 6 GB RAM with 64 bit operating system having i7 Intel Processor. The evaluation metrics used for performance evaluation are fitness function values and distance values. Final function values contains both normal and that of Gaussian, similarly distance includes sound distance and Gaussian distance. Distance measure provides the distance between the original signal and the extracted signal through blind source separation.

B. Simulation Results

The simulation results obtained for the proposed technique and other techniques are given in this section. Table 1 shows simulations for sound signal and table 2 shows the Gaussian signal simulations. Each table shows the input sound signal, output signal using ABC having fitness 1, output signal using ABC having fitness 2, output signal using ABC having fitness 3 (proposed technique), output signal using ABC previous technique and output signal using Genetic Algorithm.

TABLE 1. Simulations for sound signal



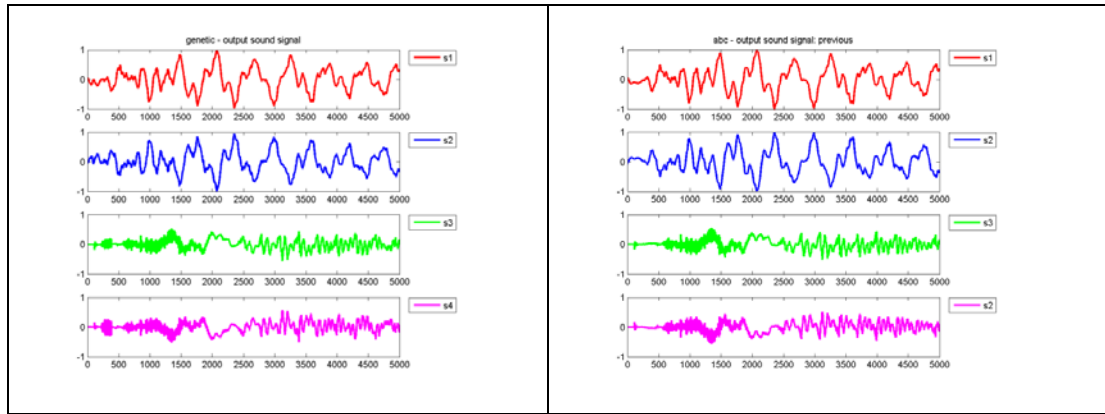
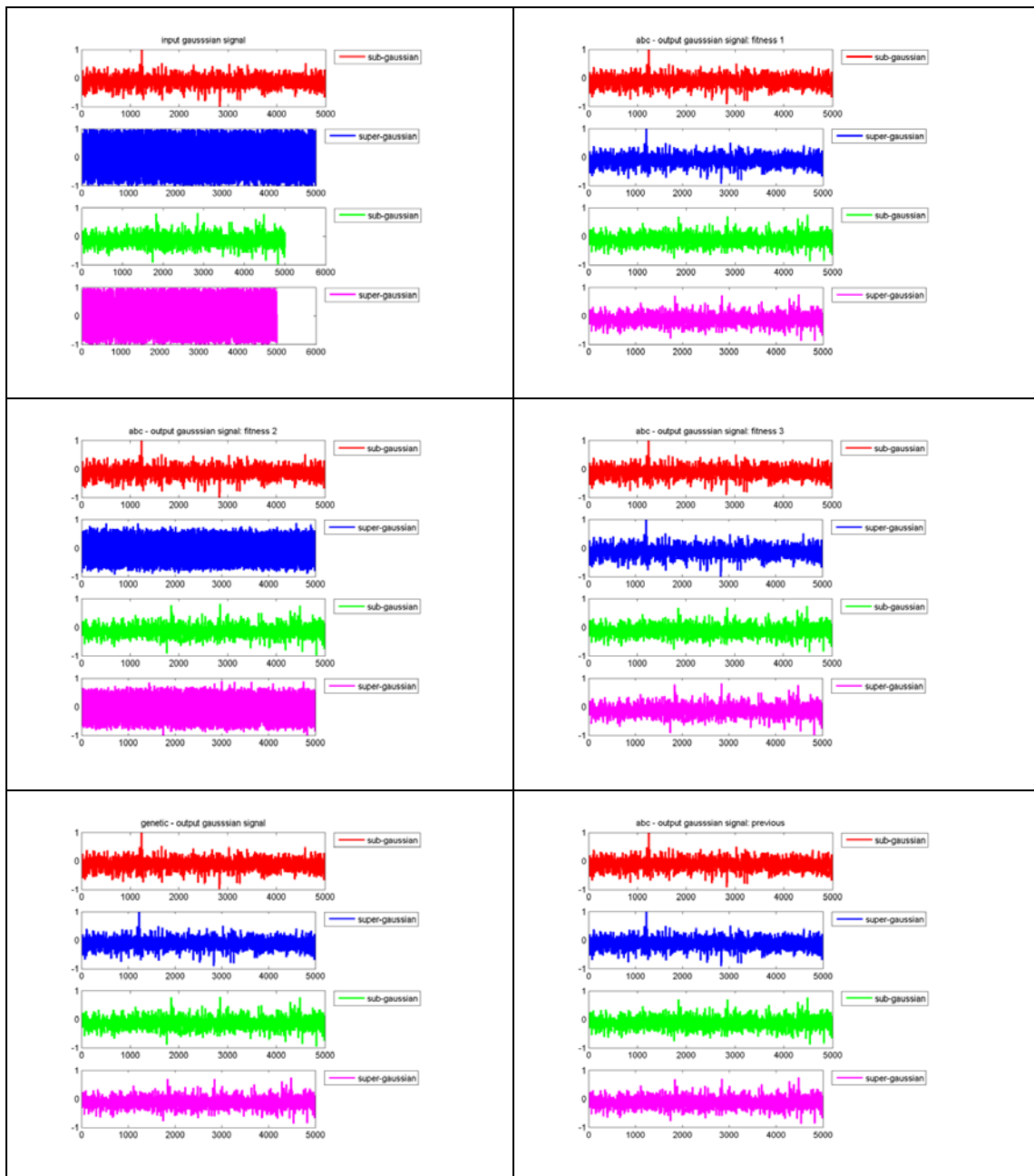


TABLE 2. Simulations for Gaussian signal



C. Comparative Analysis

In this section, comparative analysis is carried out by comparing our proposed technique (ABC with fitness 3) with ABC fitness 1, ABC fitness 2, ABC-previous method and Genetic algorithm. The comparative analysis is made with the evaluation metrics of distance and fitness functions.

TABLE 3. Evaluation metrics values

| | <i>Average Sound Distance</i> | <i>Average Fitness value</i> | <i>Average Gaussian Distance</i> | <i>Average Gaussian Fitness value</i> |
|---------------------------------|-------------------------------|------------------------------|----------------------------------|---------------------------------------|
| ABC-Fitness 1 | 38.75 | 6.97 | 63.1 | 1.88 |
| ABC-Fitness 2 | 55.46 | 4.15 | 59.48 | 5.24 |
| ABC-Fitness 3 (Proposed) | 38.39 | 6.94 | 58.60 | 5.02 |
| ABC-Previous | 38.45 | 6.97 | 60.75 | 1.87 |
| GA | 40.85 | 6.76 | 60.82 | 1.83 |

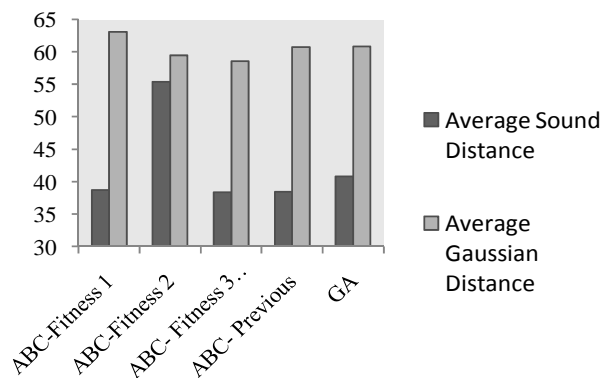


Figure 3: Comparative distance values by various techniques

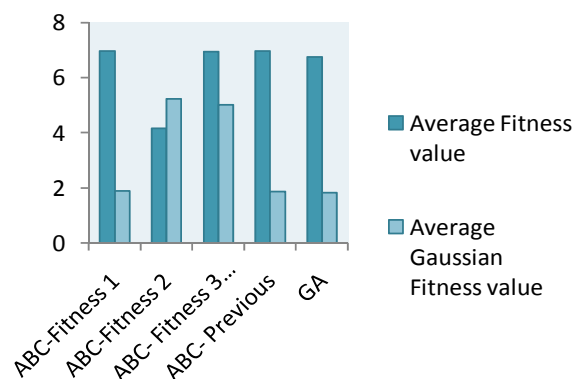


Figure 4: Comparative distance values by various techniques

Inferences from tables 3 and figures 3 and 4:The comparative analysis is made with the evaluation metrics of sound distance, Gaussian distance, fitness functions and Gaussian fitness functions.

- Comparative analysis is carried out by comparing our proposed technique (ABC with fitness 3) with ABC fitness 1, ABC fitness 2, ABC-previous method and Genetic algorithm.
- Table 3 gives the evaluation metrics values. Figure 3 gives the comparative distance values by various techniques and figure 4 gives the comparative distance values by various techniques.
- From the results, we can observe that our proposed technique has obtained good results by obtaining low distance metrics and high fitness values.
- The technique obtained average distance of 38.39, average fitness value of 6.94, average Gaussian distance of 58.60 and average Gaussian fitness as 5.02.
- The technique yielded lowest distance among all techniques and good values for all other evaluation metrics which shows the effectiveness of the proposed technique.

V. CONCLUSION

In this paper, blind source separation of super and sub-Gaussian Signal is proposed utilizing conjugate gradient algorithm and kurtosis maximization criteria. The technique is composed of three modules, namely signal mixing module, weight matrix generation module and source separation module. The evaluation metrics used for performance evaluation are fitness function values and distance values. Comparative analysis is also carried out by comparing our proposed technique to other prominent techniques. The technique achieved average distance of 38.39, average fitness value of 6.94, average Gaussian distance of 58.60 and average Gaussian fitness as 5.02. The technique attained lowest average distance value among all techniques and good values for all other evaluation metrics which shows the effectiveness of the proposed technique.

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Dr. Chandra Shekhar Rai is a Professor with the University School of Information Technology since September, 2011. He served the University as Associate Professor from 2007 to 2011 and Reader from 2004 to 2007. He was lecturer with the same School from 1999 to 2004. He obtained his M.E. degree in Computer Engineering from SGS Institute of Technology & Science, Indore in 1994 and completed Ph.D. in area of Neural Network from Guru Gobind Singh Indraprastha University in 2003. He has earlier worked as a lecturer at Guru Jambheshwar University, Hissar. He has many publications in International/national journals and conferences. He was conferred with “Best Teacher Award” of the University for the academic year 2007-2008 and second best researcher award of the University in the area of engineering and technology in 2010. He was Chairman, University Center for IT Services & Infrastructure Management (UCITIM) from 2007 to 2012. His teaching and research interests include: Artificial Neural Systems, Computer Networks and, Signal Processing.