Blind Source Separation of Super and Sub-Gaussian Signals with ABC Algorithm

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Abstract—Recently, several techniques have been presented for blind source separation using linear or non-linear mixture models. The problem is to recover the original source signals without knowing apriori information about the mixture model. Accordingly, several statistic and information theory-based objective functions are used in literature to estimate the original signals without providing mixture model. Here, swarm intelligence played a major role to estimate the separating matrix. In our work, we have considered the recent optimization algorithm, called Artificial Bee Colony (ABC) algorithm which is used to generate the separating matrix in an optimal way. Here, Employee and onlooker bee and scout bee phases are used to generate the optimal separating matrix with lesser iterations. Here, new solutions are generated according to the three major considerations such as, 1) all elements of the separating matrix should be changed according to best solution, 2) individual element of the separating matrix should be changed to converge to the best optimal solution, 3) Random solution should be added. These three considerations are implemented in ABC algorithm to improve the performance in Blind Source Separation (BSS). The experimentation has been carried out using the speech signals and the super and sub-Gaussian signal to validate the performance. The proposed technique was compared with Genetic algorithm in signal separation. From the result, it was observed that ABC technique has outperformed existing GA technique by achieving better fitness values and lesser Euclidean distance.

Index Terms— Blind source separation, Artificial Bee Colony (ABC), Genetic Algorithm (GA), sub-Gaussian and super-Gaussian signal, fitness function, mixing.

I. INTRODUCTION

Recently, blind source separation has received considerable attention among researchers as it has vast application. The study of blind source separation in signal processing techniques is of 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 (or “signals”) from multiple observed data masked by linear or nonlinear mixing. Most of existing algorithms for linear mixing models stem from the theory of the independent component analysis (ICA). Initially, blind source separation (BSS) using ICA has received a great deal of attention for its potential in acoustics, telecommunication, image processing and radar signal communication. 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].

The problem of source separation is to extract independent signals from their linear or nonlinear mixtures. Source separation may be achieved in different ways according to the amount of available prior information. 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]. BSS techniques have received extensive attention beyond the context of signal processing due to their very weak requirement or conditions about signal sources and mixing channels [10, 14]. The separation of independent sources from mixed observed data is a fundamental and challenging signal-processing problem. This 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. Also, the neural networks have been proposed which their operation depends on an update formula and activation function that are updated for maximizing the independence between estimated signals [12]. Neural network approaches have the drawback of possibly being trapped into near-optimal solutions in situations where, the search space presents many local minima. On the other hand, Ran Chen and Wen-Pei Sung [16] have proposed a nonlinear BSS method using the radial basis function (RBF) neural network based ICA algorithm.

As an alternative, several techniques have been proposed in the literature for blind source separation that are mainly classified based on optimization algorithm [15, 16] and non-optimization algorithm [3-8]. Accordingly, genetic algorithms deal simultaneously with multiple solutions, not a single solution, and also include random elements, which help to avoid getting trapped into sub-optimal solutions [4, 13]. S Mavaddaty, A Ebrahimzadeh [15] have used two evolutionary
algorithms, namely, genetic algorithm and particle swarm optimization for blind source separation. Gonzalez, E.A et al. [13] have proposed a method for blind separation of digital signals based on elitist genetic algorithms. Also, EM algorithm to estimate the mixture model was by Sawada et al. [1] and Duong et al. [2]. Other way, Reju, V.G. Soo Nqee Koh et al. [3] have proposed an estimation algorithm based on angles in complex vector space and Diogo C et al. [5] have used convolutive-based method was given by Takahata et al. [6] and Xiao-Feng Gong and Qiu-Hua Lin [7] have taken some of those works. Sawada et al. [8] have proposed technique for blind source separation using Wigner-Ville distribution. In this paper, a method for separating the source signals using artificial bee colony (ABC) is proposed. The working procedure of the proposed algorithm principally depends on the fitness function as a main criterion in information theory and high order statistics (HOS). The first aspect is to employ a global optimization method to learn the unknown parameters of the separation system. The second aspect is to minimize a predetermined cost function that measures the independence of the outputs of the separation system. Accordingly, the ABC algorithm is used and the constraint procedure is included in employee and onlooker bee phase for the BSS. Here, the statistic-based measure is used as fitness function to separate the source signal without knowing mixture. Here, speech signals and sub and super Gaussian signals are used to perform the BSS in experimentation process. The main contribution of paper:

- Paper proposes a technique to separate super and sub Gaussian signal blindly in order to improve the signal quality.
- ABC algorithm is utilized instead of GA algorithm to blind separation problem.
- Use of evaluation metrics in order to evaluate the proposed technique.

The rest of this paper is organized as follows. Section 2 gives a brief description of the related works and the problem formulation is discussed in section 3. The proposed blind source separation technique is described in a detailed manner in section 4. The experimental analysis and discussions are presented in section 5 and section 6 gives a brief summary of our work.

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. Sawada et al. [1] have presented a blind source separation method for convolutive mixtures of speech/audio sources. In the first stage, frequency-domain mixture samples were clustered into each source by an expectation–maximization (EM) algorithm. Since the clustering was performed in a frequency bin-wise manner, the permutation ambiguities of the bin-wise clustered samples should be aligned. This two-stage structure makes it possible to attain a good separation even under reverberant conditions. Experimental results for separating four speech signals with three microphones under reverberant conditions showed the superiority of the method over existing methods. 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. They consider two covariance models and address the estimation of their parameters from the recorded mixture by a suitable initialization scheme followed by iterative expectation maximization (EM) procedure in each frequency bin. Experimental results over a stereo reverberant speech mixture showed the effectiveness of the proposed approach.

Reju, V.G. Soo Nqee Koh et 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. The algorithm for solving the permutation problem clusters the estimated masks by using k-means clustering of small groups of nearby masks with overlap. The effectiveness of the algorithm in separating the sources, including collinear sources, from their underdetermined convolutive mixtures obtained in a real room environment, was demonstrated. Diogo C et 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. The method was applied to invertible and underdetermined mixture models considering different stochastic sources and different RQA measures. A brief discussion about the influence of recurrence plot parameters on the robustness of the proposal was also provided and illustrated by a set of representative simulations.

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. Finally, they presented illustrative results of the application, on both synthetic and real data, of a method for seismic deconvolution that combined techniques of blind deconvolution and blind source separation. Their implementation of that method contains some improvements over the original method in the literature described. Xiao-Feng Gong and Qiu-Hua Lin [7] have considered the problem of blind separation for convolutive speech mixtures. The covariance tensors across frequency bins were used instead of the covariance tensors within a single frequency bin, and a tensorial scheme consisting of successive PARAFAC decompositions was developed. 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, under the assumptions that components of the same source associated with adjacent frequency bins are correlated.

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 M(M < N) mixtures. First, an improved method was proposed for estimating the mixing matrix, where the negative value of the auto WVD of the sources was fully considered. Then, after extracting all the auto-term TF points, the auto WVD value of the sources at every auto-term TF point was found out exactly with the proposed approach. Further discussion about the extraction of auto-term TF points was made and finally the numerical simulation results were presented to show the superiority of the proposed algorithm by comparing it with the existing ones. Samira Mavaddaty, Ataollah Ebrahimzadeh [15] have used two evolutionary algorithms, namely, genetic algorithm and particle swarm optimization for blind source separation. In these techniques, a fitness function that was based on the mutual information and high order statistics was proposed. In order to evaluate and compare the performance of these methods, they have focused on separation of noisy and noiseless sources. Simulations results demonstrated that proposed method for employing fitness function have rapid convergence, simplicity and a more favorable signal to noise ratio for separation tasks based on particle swarm optimization and continuous genetic algorithm than binary genetic algorithm.

Ran Chen and Wen-Pei Sung[16] have proposed a nonlinear BSS method using the radial basis function (RBF) neural network based ICA algorithm, which was built by adopted some modifications in the linear ICA model. Moreover, genetic algorithm (GA) was used to optimize the RBF neural network to obtain satisfactory nonlinear solve of the nonlinear mixing matrix. In the experiments, the GA optimized nonlinear ICA method and other ICA models were applied for image de-noising. A comparative analysis has showed satisfactory and effective image de-noising results obtained by the presented method. Gonzalez, E.A et al. [13] have proposed a method for blind separation of digital signals based on elitist genetic algorithms. Contrast function, consisting in a weighted sum of high order statistics measures (cumulants of different orders), played the role of genetic fitness function, and also guide the genetic algorithm by a Gauss-Newton adaptation applied to the genetic population, that reduces the search space and provide faster convergence rate. The use of elitism assured the convergence of the algorithm. Several experiments were conducted on digital signals and mixing models, and the high amount of simulations derived from them provided the best combination of the constant parameters in terms of separation accuracy and convergence rate.

### III. Problem Formulation

Source mixing process can be modeled with different mathematical models on the basis of its precise application and available prior information about source signals. Here, we discuss a common mixing model which can model most of genuine mixing processes with the use of mathematical models.

1. **Source Signal**: Source Signals are viewed as one of the major categories of instruments which produce reference signals for other devices. In our case, speech signals (s1 and s2) are the source signals which are represented as:

\[ s_1 = \{a_1, a_2, a_3, \ldots, a_I\} \]

\[ s_2 = \{b_1, b_2, b_3, \ldots, b_I\} \]

Where, I is the length of the signal, a and b are the signal co-efficients.

2. **Combined signal**: For combining these two signals, the two speech signals \(s_1\) and \(s_2\) are considered and these two are given in matrix by equating the sizes of \(s_1\) and \(s_2\). The possibilities for forming combinations of signals include linear and non-linear schemes, and the designation of a signal as a controller as distinct from programmer’s material. All these operations can be represented in a general way by mathematical operations (in many cases simple arithmetic operations). By combining the two signals \(S_1\) and \(S_2\), we obtain a signal \(S\). That is the source signals are combined to form the main signal and the combination is carried out with the help of matrix operations.

\[
S = \begin{bmatrix}
  s_1 \\
  s_2
\end{bmatrix} = \begin{bmatrix}
  a_1 & a_2 & \ldots & a_I \\
  b_1 & b_2 & \ldots & b_I
\end{bmatrix}
\]

3. **Reference mixing signal**: To get mixing signal, a reference signal is required which can be an assumed one. It increases the popularity of mixed signal. The assumption of mixed data makes easy the calculation of ABC algorithm. The system’s actions vary in any way necessary, so that the effects of its actions cancel, or balance with, the effects of environmental disturbances. It is a general technique where, the output of one source, or an exact reference signal from M a signal generator, is used to synchronize. So, it can be computed by simple following formula:

\[
M = \begin{bmatrix}
  r_{11} & r_{12} \\
  r_{21} & r_{22} \\
  r_{31} & r_{32}
\end{bmatrix}
\]

4. **Multiplication**: The combined signal is multiplied with reference signal to get mixed signal Y. Multiplication of the combined source signal with reference signal gives rise to having perfect signal Y. The figure 1 shows the block diagram of mixing two signals. In the block diagram we can see that the source signals (s1 and s2) are combined to form S and multiplied with reference signal M to form the signal Y represented as:
Y = M \times S

\[ Y = \begin{bmatrix} r_{11} & r_{12} \\ r_{21} & r_{22} \\ r_{31} & r_{32} \end{bmatrix} \times \begin{bmatrix} a_1 & a_2 & \ldots & a_l \\ b_1 & b_2 & \ldots & b_l \end{bmatrix} \]  \quad (3)

5) Source separation: The main purpose of proposed technique is to recover the source signal S from the received signal Y without knowing the nature of mixing matrix M. For doing this task, separating matrix W should be found and it should be multiplied with the mixed matrix, M to obtain the estimated signal \( S^* \). Figure 2 shows the mixing system where, an unknown mixing and separating system is given. Here in the diagram, we can see that S is reconstructed with the use of ABC and W matrix. Recovered signal can be represented by the formula:

![Figure 1. Block diagram of signal mixing](image1)

![Figure 2. Mixing and separating systems in blind source separation](image2)

IV. ABC Algorithm For BSS

This section presents the proposed algorithm for Blind source separation using ABC algorithm. The ABC algorithms that works based on evolutionary mechanism can be the best solution for solving BSS problem through finding optimum and accurate coefficients of separating matrix. The three phases of ABC algorithm is utilized to handle the matrix operation and the generation of new bees is used to achieve the better solution quickly. Here, the ABC algorithm is taken to solve the blind source separation problem so that the solution of our intention is 2D data. Generating the solution in 2D data is slightly difficult to from the previous best solution or global vest solution. In order to handle this situation smoothly, the matrix should be changed according to the best solution and also, the elements of the solution matrix should be changed to travel towards the even better matrix.

We have considered this as motivation and to modify the onlooker bee phase of the ABC algorithm to generate the more solution matrix by modifying the elements of the best matrix generated from the previous steps. The overall steps of the algorithm are given in figure 3. The major three phases of the ABC algorithm with the perspective of BSS is given as,

1. Employee bee phase
2. Onlooker bee phase
3. Scout bee phase

Initialization: Initialization is the primary step for finding the best separating matrix through the help of ABC algorithm. The initialization problem is very important since the new generation of solution is purely depends on the best solution (separating matrix) of initial population. In our work, the ‘N’ different separating matrices are generated to form the initial population which may contain different source signals. We consider the example where two source signals are taken. The initial colony would contain six different separating matrices each of which having the size of 2x3 since two signals are taken for mixing purpose. The signals that are considered for mixing purpose is ‘k’ length vector. So, the size of the mixing matrix considered for the proposed approach is 3x2. After mixing the signal, the size of the mixed signal is 3k so that the separating matrix of size 2x3 should be chosen to multiply it with the mixed signal of size 3xk. After the multiplication, the source signal matrix of 2xk is generated. So, finding the most suitable separating matrix of 2x3 is an ultimate task of our work. According to, the six separating matrices of size 2x3 are generated to find the most suitable one with the help of fitness function.
Figure 3. Overall steps of the ABC algorithm for BSS

1. Input signal
   - Randomly selected 6 matrixes
   - Check if \( i \leq T \)
     - If \( i \leq T \) is True, select the best matrix
     - If \( i \leq T \) is False, go to the next step
   - Find the estimated signal and fitness function
   - Select best fitness matrix
   - Change all matrix w.r.t. best selected matrix
   - Store 6 best matrices

2. Initial Population
   - Find the estimated signal and fitness function
   - Select best fitness matrix
   - Change all matrix w.r.t. best selected matrix
   - Store 6 best matrices

3. Employed Bee
   - Generate new 6 matrices from the best matrix of employee
   - Find the estimated signal and fitness function
   - Store 6 best matrices

4. Onlooker Bee
   - Generate new random 6 matrices
   - Find the estimated signal and fitness function
   - Select the best 6 matrices from the 24 matrices
   - Store 6 best matrices

5. Scout Bee
   - Find the estimated signal and fitness function
   - Store 6 best matrices

\( i \) = loop number
\( T \) = Total no. of loops
\[ R = \begin{bmatrix} R_1 & R_2 & R_3 & R_4 & R_5 & R_6 \end{bmatrix} \] (4)

Where, \[ R_i = \begin{bmatrix} w_{i1} & w_{i2} & w_{i3} \\ w_{i1} & w_{i2} & w_{i3} \end{bmatrix}, 1 \leq R_i \leq 6 \]

Here, Wij are the elements of the initial colony size generated randomly. For re-constructing the estimated signal, each of the matrix is multiplied with Y, which is given by equation 5:

\[ S_e(i) = R_i \times Y \quad 1 \leq i \leq 6 \] (5)

The above process is repeated for all the six separating matrices initialized in the first step. This task provides six estimated source signals to choose the best among them. For accomplishing this task, we make use of the fitness function which is based on the estimation of mutual information, which cancels out when the signals involved are independent.

**Fitness function:** Fitness function is a particular type of objective function that is used to summarise, as a single figure of merit, how close a given design solution is to achieving the set aims. Here, mutual information-based parameter which is dependent on the entropy of the signal is used to define the fitness function to correctly estimating the source signal from the mixed signal. The fitness function of the ABC algorithm is defined as follows:

\[ \text{Fitness} = \frac{1}{I(y)} \] (6)

\[ I(y) = \sum_{i=1}^{P} H(y_i) - H(y_1, y_2, \ldots, y_P) \] (7)

Where, H is the entropy of mixed signals.

\[ H(y) = -\sum_{i=1}^{n} p(y_i) \log_2 p(y_i) \]

\[ H(y_1, y_2, \ldots, y_P) = -\sum_{i=1}^{n} H(y_i|y_{i-1}, \ldots, y_1) \]

When fitness is maximized, the dependence among the estimated signals is minimized. So, the source signals used in the experimentation can be separated from each other successfully. Accordingly, six different matrices utilized in the initialization are evaluated with the fitness function to find out the best matrices among the colony.

**2. Employed bees:** In the initialization phase, best weighted matrixes are found out from the initial population using the fitness value. In this phase, we change all the randomly taken matrixes with respect to the best matrix found out in the initialization. Let the best random selected matrix be represented by G, where \[ G \in R_j, 1 \leq j \leq 6 \] and the selected best matrix is changed with the use of the equation:

\[ V(i) = X_{i,j} + \phi(X_{i,j} - k_{i,j}) \] (8)

Where, \[ X_{i,j} \] is the best matrix selected from initial colony and \( \phi \) is randomly produced number in the range [-1, 1]. With the help of equation given above, the six matrices from the initial population are changed to the new separating matrices with respect to the best matrix. Assume that, \[ R_3 \] is the separating matrix having the maximum fitness value in the initial population so that the generation of new separating matrices are exactly based on \[ R_3 \]. The generation of new six separating matrices is obtained as follows:

\[ G_1 = R_3 + \phi(R_3 - R_1) \] (9)
\[ G_2 = R_3 + \phi(R_3 - R_2) \] (10)
\[ G_3 = R_3 + \phi(R_3 - R_3) \] (11)
\[ G_4 = R_3 + \phi(R_3 - R_4) \] (12)
\[ G_5 = R_3 + \phi(R_3 - R_5) \] (13)
\[ G_6 = R_3 + \phi(R_3 - R_6) \] (14)

\[ G = [G_1 \ G_2 \ G_3 \ G_4 \ G_5 \ G_6] \]

For re-constructing the estimated signal, each of the matrix is multiplied with Y, which is given by equation 3:

\[ S_e(i) = G_i \times Y \] (15)

From the newly generated matrices, the signals are estimated and the best separating matrix is found out using the fitness function.

**3. Onlooker bees:** Onlooker bees phase is used to change the best solution obtained from the employee bee phase. Here, the element of the best solution is changed with the random value to obtain the better separating matrix even better with the previous one. The advantage of the onlooker bee phase is that the elements are changed instead of the matrices. This is used to fine tuning the matrices towards the best one. Assume that, \[ N_i \] is a best weighted matrix from employed bees and then, it is changed to the new six different matrices according to following equation.

\[ N_i = \begin{bmatrix} c_{i1} & c_{i2} & c_{i3} \\ c_{i1} & c_{i2} & c_{i3} \end{bmatrix} \] (16)

\[ N = r_{ij} \ll c_{ij} \]

From the above equation, we can see that, the total number of element in the best weighted matrix is six. Here, we are generating a random number in between 1 to 6 and the corresponding element is replaced with the new random number. This process generates new six matrices for finding the fitness function.

First change,

\[ N_i = \begin{bmatrix} c_{i1} & c_{i2} & c_{i3} \\ c_{i1} & c_{i2} & c_{i3} \end{bmatrix} \] (17)
Second change,
\[
N_2 = \begin{bmatrix}
c_{11} & u_{12} & c_{13} \\
c_{21} & c_{22} & c_{23}
\end{bmatrix}
\] (18)

Third change,
\[
N_3 = \begin{bmatrix}
c_{11} & c_{12} & u_{13} \\
c_{21} & c_{22} & c_{23}
\end{bmatrix}
\] (19)

Fourth change,
\[
N_4 = \begin{bmatrix}
c_{11} & c_{12} & c_{13} \\
u_{21} & u_{22} & c_{23}
\end{bmatrix}
\] (20)

Fifth change,
\[
N_5 = \begin{bmatrix}
c_{11} & c_{12} & c_{13} \\
c_{21} & u_{22} & c_{23}
\end{bmatrix}
\] (21)

Sixth change,
\[
N_6 = \begin{bmatrix}
c_{11} & c_{12} & c_{13} \\
c_{21} & c_{22} & u_{23}
\end{bmatrix}
\] (22)

Hence, the operation results in the generation of six new separating matrices represented as:
\[
N = \{N_1, N_2, N_3, N_4, N_5, N_6\}
\] (23)

After changing, the estimated signal (Se) is found out again using all the weighted matrices and the best one is selected from this signal using fitness function.

4. Scout bees: The scout bees plays a main and practical role in BSS that the algorithm would be completely defective without it. The estimate of coefficients using maximization of fitness function to retrieve independent components is not enough. In this case, some twist can happen. In order to add more new solutions so that the solution becomes more generalised and better, six random matrices are generated in the scout bee phase. Newly generated matrices are represented as:
\[
H = \begin{bmatrix}
H_1 & H_2 & H_3 & H_4 & H_5 & H_6
\end{bmatrix}
\]

\[
H_i = \begin{bmatrix}
v_{i1} & v_{i2} & v_{i3} \\
v_{i1} & v_{i2} & v_{i3}
\end{bmatrix}, 1 \leq H_i \leq 6
\] (24)

Where, 
\[
S_e(\bar{t}) = H_i \times Y
\] (25)

4) Termination: After the first cycle explained in the above section, the best six matrices are selected from the first cycle based on the fitness function and they are given to the employed bee phase to further process. The same process is continued until the user required threshold is reached. Here, the number of cycle given by the user is termination criteria used in the ABC algorithm.

V. RESULTS AND DISCUSSION

This section discusses the results obtained for our proposed blind source separation of signals using ABC algorithm. Various outputs obtained are plotted and is also compared to signal separation using genetic algorithm. The evaluation metrics is given section 5.1 and the experimental results are discussed in section 5.2. Then, the performance evaluation is given in section 5.3.

A. Evaluation metrics

Evaluation metrics used for performance evaluation is our objective function and Euclidian distance. Objective function shows the performance of the algorithm in regard to convergence of optimal solution. This measure does not need the original input signal. Euclidean distance provides the distance between the original signal and the extracted signal through blind source separation.

B. Experimental results

The proposed technique for signal separation is implemented in MATLAB on a system having 6 GB RAM with 32 bit operating system having i5 Processor. The experimental results include signal plots of input signals and the corresponding output yielded using ABC. Figure 4 gives the plot of four input signals (s1, s2, s3 and s4). Here, four input signals taken for our work is speech signal. Figure 5 gives the estimated signals using our technique. Form the figures it is clear that our technique have achieved good results. Figure 6 gives the plot of the super guassian signal (s1) and sub-guassian signal (s2) whereas figure 7 gives the estimated plot of the super guassian signal (s1) and sub-guassian signal (s2).

Figure 4. Plot of four input speech signals (s1, s2, s3 and s4)

1) Performance evaluation and comparative analysis

For evaluating the performance of the technique, we make use of parameters such as fitness, Euclidean distance and number of iterations. Fitness: In this section, we plot graphs of fitness vs. number of iterations. In the graphs, the plot of both our technique as well as technique using genetic algorithm are given for making the comparison and evaluating the tech
Figure 5. Plot of estimate of four corresponding input speech signals (s1, s2, s3 and s4) obtained by our technique.

Figure 6. Plot of the estimated super-gaussian and sub-gaussian signals.

Euclidean distance: Here, performance of the algorithm is compared with the original signal to prove the effectiveness. Figures 10 and 11 give plot of iteration vs. Euclidean distance. From both the Euclidean distance graphs, it can be observed that our technique has achieved lower Euclidean distance which shows the effectiveness of our proposed technique. In short, taking into account both fitness and Euclidean distances parameters, our proposed technique using ABC has well when compared to other technique using GA.

VI. CONCLUSION

We have presented the ABC algorithm to generate the source separating matrix in an optimal way. Here, Employee and onlooker bee phases are utilized to separate super and...
sub Gaussian signal blindly in order to improve the signal quality. The three major constraints were utilized in generating the new solutions, such as 1) considering all elements of the separating matrix, 2) taking individual element of the separating matrix, 3) randomly adding in scout bee phase. The experimentation was carried out using the super and sub-gaussian signal and speech signal to validate the performance of the ABC algorithm. Our proposed technique was also compared to other technique for signal separation which used Genetic algorithm. From the result, it was observed that our technique has outperformed other technique by achieving better fitness values and lesser Euclidean distance.

REFERENCES


