Research of Blind Signals Separation with Genetic Algorithm and Particle Swarm Optimization Based on Mutual Information

Samira Mavaddaty
Department of Electrical and Computer Engineering
Babol Noshirvani University of Technology,
Babol, Iran
Email: s.mavaddaty@stu.nit.ac.ir

Ataollah Ebrahimzadeh
Department of Electrical and Computer Engineering
Babol Noshirvani University of Technology,
Babol, Iran
Email: e_zadeh@nit.ac.ir

Abstract

Blind source separation technique separates mixed signals blindly without any information on the mixing system. In this paper, we have used two evolutionary algorithms, namely, genetic algorithm and particle swarm optimization for blind source separation. In these techniques a novel fitness function that is based on the mutual information and high order statistics is proposed. In order to evaluate and compare the performance of these methods, we have focused on separation of noisy and noiseless sources. Simulations results demonstrate 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. Also, particle swarm optimization enjoys shorter computation time than the other two algorithms for solving these optimization problems for multiple sources.

Keywords: *Blind source separation, mutual information, high order statistics, Continuous and Binary genetic algorithm, Particle swarm optimization.*

1. Introduction

Blind source separation (BSS) has important applications in many area of signal processing such as medical data processing, speech recognition and radar signal communication [1-4]. 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]. In the literature, the theory of BSS has been approached in several ways and as a result, various algorithms have been proposed. For example independent component analysis (ICA), principle component analysis (PCA), high order statistical cumulants and others [6-8]. The most important and simplest of them is ICA as a statistical method that its purpose is to find components of signal which have the most statistical independence. ICA is based on random and natural gradient [9]. 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 [10]. These algorithms depend on the distribution of source signals. Since this separation is executed blindly and there is no information about source signals, the distribution function of source signals should be estimated early. Consequently, it leads to reduce the accuracy of problem solving. Thus, developing new BSS algorithms on the basis of global optimization independent of gradient techniques is an important issue [11-15]. The BSS problem is identified as a popular search among researchers because it can work based on evolutionary algorithms such as continuous genetic algorithm (CGA) and binary genetic algorithm (BGA), PSO and so on [16, 17]. It is obvious that GA and PSO are successful evolutionary algorithms that provide heuristic solutions for combinatorial optimization problems.

In this paper, the BSS approach for linear mixed signals is studied to get the coefficients of separating matrix by using PSO and both forms of GA. The operation of these algorithms principally depends on the fitness function which in this paper uses mutual information (MI) as a main criterion in information theory and high order statistics (HOS) of kurtosis [18, 19, 20]. MI is a main quantity that measures the mutual dependence of the two variables. Also the kurtosis is a simple and necessary criterion for estimating dependency among signals [21]. This paper proposes the fusion of these important criteria as a suitable fitness function for separation of different sources in linear BSS model. Using this fitness function in evolutionary algorithms, it does not need to have activation functions like what is required in neural network [22]. The simulation results demonstrate the BSS scheme based on PSO and CGA is robust to achieve global optimal solutions from any initial values of the separation system. These results show high accuracy, suitable SNR and fast convergence of these evolutionary algorithms than BGA. The BGA has bad convergence and lower values of accuracy and SNR in source separation for more than three sources. The analyses show the convergence of BSS using PSO is essentially faster than CGA and BGA for any number of original signals. Thus, PSO is totally effective for this kind of optimization problems especially in applications that needs high speed or low cost for time computations.

2. Linear Mixing Model and Separating Process

Assume that there exist n unknown signal $s_i, i = 1,\ldots,n$ which are as mutually independent as possible. It is supposed that the source signals in linear model of BSS are linearly mixed together With a matrix $A_{n\times n}$ that is unknown:

$$x = As \qquad (1)$$

Where $s = [s_1,\ldots,s_n]$ and $x = [x_1,\ldots,x_n]$ are $n-$dimensional source and mixed signals and n is the number of sources. The goal in solve of BSS problem is to discover the source signals from x without knowing the nature of mixing matrix A. For doing this task, separating matrix W should be found that it is $W = A^{-1}$ in ideal situation:

$$y = Wx \qquad (2)$$

So that $y = [y_1,\ldots,y_n]$ includes $n-$dimensional estimation of source signals. A general model of BSS problem with sparse representation, which illustrated as Figure 1 includes three procedures: an unknown mixing model, a recognition of mixing matrix and a source signal retrieval process.

3. Preprocessing of BSS

A. Centering

One of the most basic and necessary part of preprocessing is to center mixing signals x so as to subtract its mean vector $m = E\{x\}$ that means convert x to a zero-mean signal $\tilde{x}$ [8]. This step should be executed because kurtosis basically obtains as follows:

$$\mathrm{Kurt}(x) = \frac{E\{x^4\} - 3\left(E\{x^2\}\right)^2}{3\left(E\{x^2\}\right)^2} + \frac{12\left(E\{x\}\right)^2 E\{x^2\}}{\left(E\{x^2\}\right)^2} - \frac{4E\{x\}E\{x3\} + 6\left(E\{x\}\right)^4}{\left(E\{x^2\}\right)^2}$$

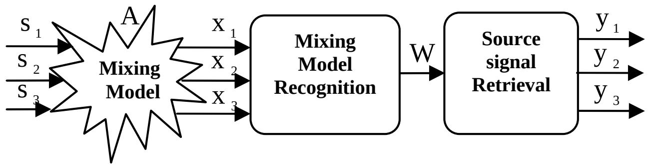

Figure 1. *The general BSS flowchart consisting of unknown mixing model, recognition of mixing model and source retrieval operation*

The assumption of mixed data centering, makes easy the calculation of kurtosis. So, the kurtosis can be computed by simple following formula:

$$\mathrm{Kurt}(x) = \frac{E\{x^4\}}{\left(E\{x^2\}\right)^2} - 3 \tag{4}$$

After estimating the mixing matrix W with centered data, the estimation by adding the mean vector of x back to the centered estimates of s is completed. The mean vector of s is given by $W^{-1}m$, where m is the mean that was subtracted in the preprocessing.

B. Whitening

Another useful preprocessing is to whiten the observed signals [23]. This means that before considering the application of the ICA algorithm (and after centering), the observed signal x is linearly transformed so that a new signal $\tilde{x}$ obtains which is white, i.e. its components are uncorrelated and their variances are equaled in unity. In other words, the covariance matrix of $\tilde{x}$ equals the identity matrix:

$$E\{\tilde{x}.\tilde{x}^T\} = I \tag{5}$$

The whitening transformation is always feasible. One popular method for whitening is to use the eigenvalue decomposition (EVD) of the covariance matrix $E\{\tilde{x}.\tilde{x}^T\} = EDE^T$ where E is the orthogonal matrix of eigenvectors of $E\{\tilde{x}.\tilde{x}^T\}$ and D is the diagonal matrix of its eigenvalues, $D = \mathrm{diag}(d_1, ..., d_n)$. Whitening can now be calculated by:

$$\tilde{x}=ED^{-1/2}E^{T}x=\underbrace{ED^{-1/2}E^{T}A}_{\tilde{A}}s=\tilde{A}s \qquad (6)$$

The benefit of whitening is that it works based on the fact that the new mixing matrix $\tilde{A}$ is orthogonal. This characteristic of separating matrix reduces the number of parameters needs to be estimated. Instead of estimating the n^2 parameters which are the elements of the separating matrix, the new orthogonal separating matrix is estimated that $n(n-1)/2$ contains degrees of freedom.

4. GA and PSO Algorithms for BSS

The algorithms that work based on evolutionary mechanism can be the best solution for solving BSS problem through finding optimum and accurate coefficients of separating matrix. According to these algorithms, Primary population can be converted into a new population that independence among its components is maximized using a suitable fitness function. Since GA and PSO intrinsically use evolutionary technique, we take advantages of us as a successful and fast algorithm to jump out of the potential local minimum.

A. Fitness function

There are two types of contrast function of BSS which are based on information theory and high order statistics. The former methods include one of the mentioned types. The fitness function proposed in this paper takes the fusion of two criteria, kurtosis and mutual information. The kurtosis is a very simple and essential measure that can be defined as:

- Kurtosis < 3 for sub Gaussian signal
- Kurtosis = 3 for Gaussian signal
- Kurtosis > 3 for super Gaussian signal

According to central limit theorem that is totally practical in ICA, the distribution of a sum of independent random variables tends toward a Gaussian distribution. Thus, a sum of two independent random variables usually has a distribution that is closer to Gaussian than any of the two original random variables. In BSS, if the kurtosis of estimated signals is maximized and distanced from the kurtosis of Gaussian signal then the reverse of the theorem is confirmed and independence among estimated signals is guaranteed. So the fitness function can be defined based on the sum of the absolute values of kurtosis in estimated signals. Another natural measure of dependence between signals is inspired by information theory that is minimization of mutual information. The mutual information I between n random variables $y_i, i=1,...,n$ using the concept of differential entropy is defined as follows:

$$I(y_1, y_2,..., y_n)=\sum_{i=1}^{n}H(y_i)-H(y) \qquad (7)$$

That H is the entropy of mixed signals and $Y=[y_1, y_2,..., y_n]$. The entropy is always non-negative, and zero if and only if the variables are statistically independent that it takes the form:

$$H(Y)=-\sum_{i=1}^{n}P(y_i)-\log P(y_i) \qquad (8)$$

Thus, mutual information takes into account the whole dependence structure of the variables, and not only the covariance, like PCA and related methods. So, the fitness function can be defined as:

$$J(y) = -\sum_{i=1}^{n}[\left|E\{y_i^4\} - 3E^2\{y_i^2\}\right| + H(y_i) - H(y)] \quad (9)$$

Where $y_1,...,y_n$ are estimate of source speech signals. The dependence among the estimated signals is minimized when Fitness is maximized. In this method, it is not necessary to assume that the sources have the same sign of kurtosis, because the absolute of fitness function is directly maximized. So the super Gaussian signals and sub Gaussian signals can be separated from each other successfully.

B. Orthogonalization

The Orthogonalization plays a main and practical rule 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. Doing these steps until now, outputs of BSS algorithm are n similar speech signals that are the estimate of source signal that its kurtosis is maximum. It should be mentioned that algorithm does its task correctly because only when fitness function is maximized that all n estimated signals have the analogy and maximum kurtosis. So the orthogonalization is applied in order to avoid this problem. The orthogonal separating matrix can be obtained by orthogonalization and satisfies (5). The orthogonalization is applied to GA and PSO before fitting each population. When fitness function is maximized, estimated signal is mutually independent as possible. Two main methods for orthogonallization exist: Deflationary and Symmetric orthogonalization. Usually Symmetric orthogonalization is used in ICA because of higher applicability and obtains through the following formula:

$$W = W.\mathrm{Real}(\mathrm{inv}(W.W^T)^{-1/2}) \quad (10)$$

Doing Symmetric orthogonalization as the last necessary step for BSS, independence among separated signals is guaranteed. The structure of the BSS based evolutionary algorithm is shown in Figure 2.

5. Evaluating Criteria

In order to check the effectiveness of the proposed algorithm, the Euclidean distance of the two vectors: the kurtosis of the estimated and source signals as error of proposed method is investigated. The results of the separating process are better whatever this criterion be less. Also, we utilize the SNR (signal-to-noise ratio) to confirm the accuracy of Euclidean distance as evaluating criteria. We define SNR as:

$$SNR_i = 10\log\frac{E\left[(s_i(t))^2\right]}{E\left[\left(y_i(t) - s_i(t)\right)^2\right]} \quad (11)$$

6. Simulation

In this experiment, n speech signals are selected from TIMIT database and are combined by an unknown mixing matrix with n^2 random values in uniform.

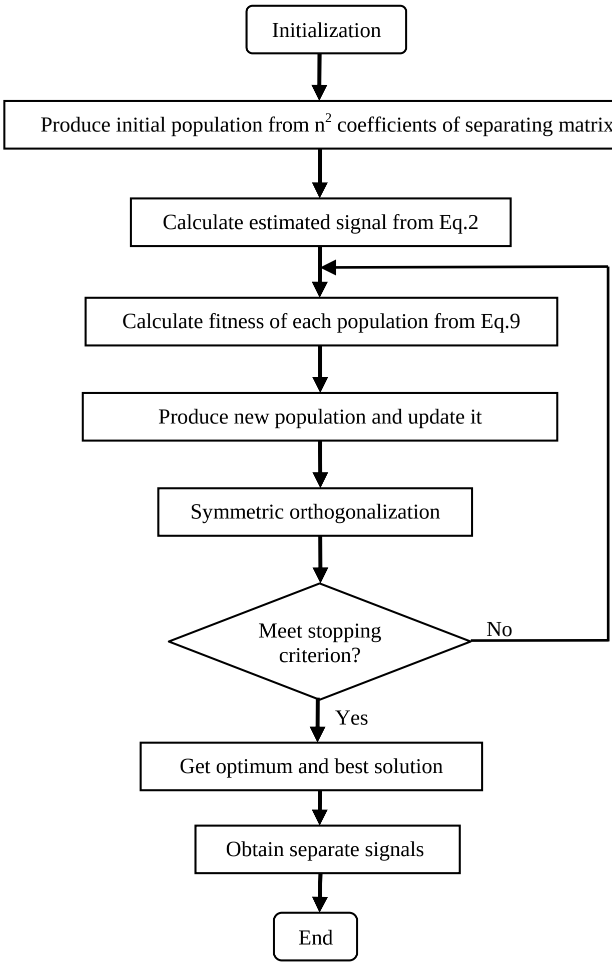

Figure 2. *Structure of BSS based evolutionary algorithms*

distribution in the range $[-1,1]$. The population size is $N = 80$. Regarding genetic operator parameters, crossover and mutation probability per chromosome are $p_c = 0.5$ and $P_m = 0.0025$, respectively. Learning factors in PSO are $C_1 = C_2 = 2$. Also, in the simulation with binary genetic algorithm, each chromosome is encoded with eight bit strings.

A. Separation of source signals

In this experiment, all of the three source signals are the speech signals that are super Gaussian. The sample length is selected 14000. The mixing matrix A is randomly chosen as:

$$A = \begin{bmatrix} -0.0864 & -0.0524 & 0.0773 \\ 0.1585 & 0.9921 & -0.4158 \\ -0.6555 & -0.8930 & 0.3430 \end{bmatrix}$$

Figure 3 represents 14000 samples from the source signals s_1, s_2, s_3 that their kurtosises are 8.585, 4.7775, and 17.447, respectively. The mixed signals x_1, x_2, x_3 are shows in Figure 4. The separate signals y_1, y_2, y_3 using CGA, BGA and PSO algorithms are shown in Figure 5-7.

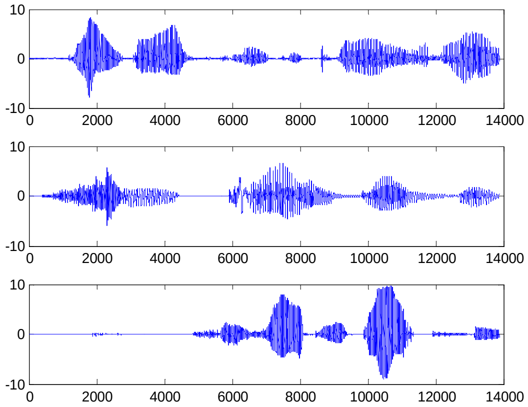

Figure 3. *Original source signals* s

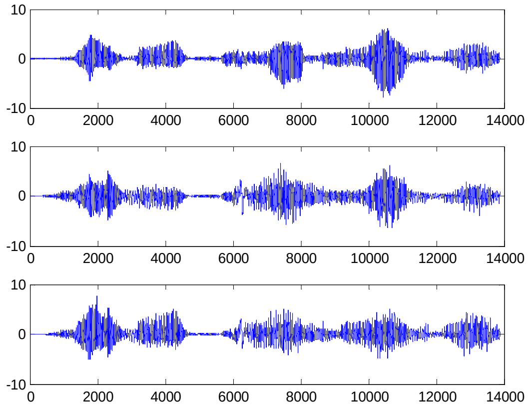

Figure 4. *Signals* x *mixed with unknown matrix* A

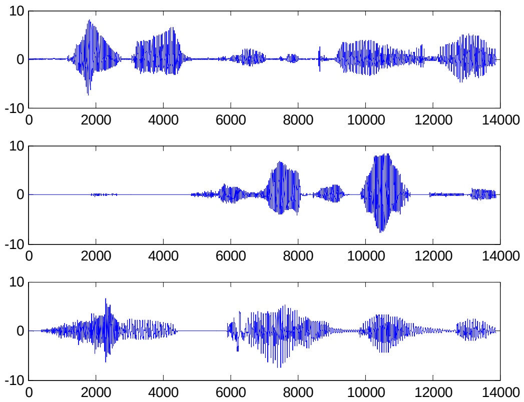

Figure 5. *Separate signals* y *obtain based on CGA*

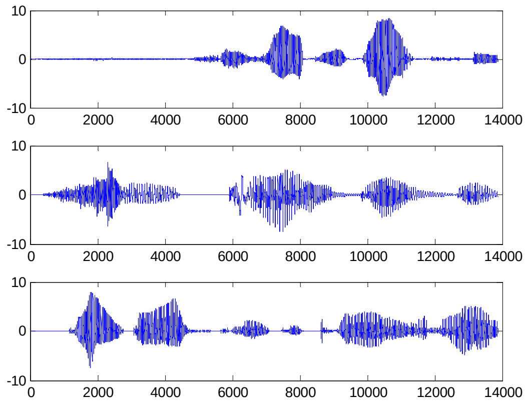

Figure 6. *Separate signals* y *obtain based on BGA*

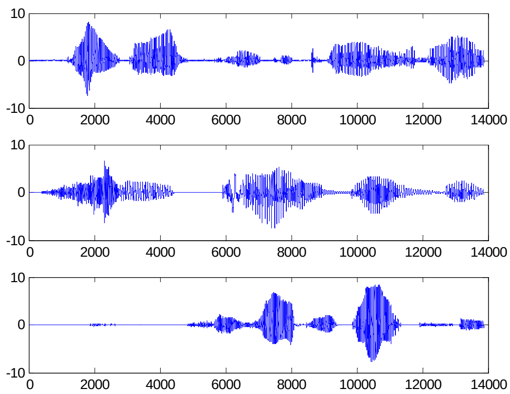

Figure 7. *Separate signals* y *obtain based on PSO algorithm*

The separated signals based on these three methods apparently are not different and maybe seem that the solving the BSS problem based on these methods result in the same accuracy. But, In addition to objective criterion, subjective criterion should be concerned. Some parameters obtained by using these algorithms are shown in Table I. According to these results it is obvious that CGA and PSO work better than that of BGA with higher accuracy. Also, Table II gives the Euclidean distance criterion or error in this paper and SNR of estimated signals. SNR values show that sources and obtained signals have the greatest relationship and dependency. The results of other comparison are shown in Table III that demonstrates the Correlation matrixes of separated signals based these three algorithms. Also, this experiment redone on several speech signals and mechanism of these algorithms are considered. According to this experiment, it is clear that BSS based on CGA and PSO can separate up to three speech signals successfully. Also, the applicability and efficiency of PSO for separating signals for more than ten source signals considerably is better than CGA. Indeed PSO works better than CGA in this condition with high speed and accuracy and fast convergence. These characteristics are notable because many original sources usually exist in transfer channel for data transmission that separation of them without losing data is main and necessary. Figure 8 shows the error of applying CGA, BGA and PSO to speech signals for different number of sources.

For more studies on the effectiveness of these algorithms in estimation of signals, the speed of each algorithm with increasing of the number of original signals is considered. The diagram of time computation versus the number of sources is shown in Figure 9. According to this experiment, the speed of BSS using PSO noticeably is faster than CGA and BGA for any number of original signals because PSO has no genetic operators. It should be mention that time for converging of fitness function in BGA is a few more than CGA because BGA has an addition step in its procedure. BGA firstly converts each chromosome to an encoded binary string and works with the binary strings to minimize the cost function and then decodes them to evaluate the fitness. But CGA directly deals with chromosomes.

Figure 10 compares the best values of fitness function of the purposed algorithms for blind source separation problem based on CGA, BGA and PSO. The abscissa

Table 1. *Comparison among three algorithms*

Parameter	PSO	BGA	CGA
Population	20	50	50
Optimum Fitness	39.774	39.288	39.398
Average Fitness	39.773	39.169	39.397
Worse Fitness	39.771	39.093	39.396
Iterative Time(sec)	27	90	73
Kurtosis(y_1)	17.448	17.443	17.445
Kurtosis(y_2)	8.5853	8.584	8.584
Kurtosis(y_3)	4.7774	4.7830	4.7763

Table 2. *Comparison of Euclidean Distance criterion and SNR for three algorithms*

	PSO	BGA	CGA
SNR of (y_1)	10.367	18.456	14.688
SNR of (y_2)	28.657	14.345	10.847
SNR of (y_3)	11.321	13.985	12.467
Euclidean Distance	0.0019265	0.002661	0.0019951

Table 3. *Correlation matrixes of separated signals for three algorithms*

PSO	BGA	CGA
$\begin{bmatrix} 1 & 0.00040 & 0.00004 \\ 0.00348 & 0.99999 & 0.00119 \\ 0.01270 & 0.00069 & 0.99992 \end{bmatrix}$	$\begin{bmatrix} 0.99997 & 0.00286 & 0.00438 \\ 0.01255 & 0.99868 & 0.00202 \\ 0.00360 & 0.012029 & 0.99992 \end{bmatrix}$	$\begin{bmatrix} 1 & 0.00117 & 0.00059 \\ 0.00218 & 0.99999 & 0.00357 \\ 0.00136 & 0.00176 & 0.99984 \end{bmatrix}$

represents 200 iterations and y-axis represents the best cost of fitness function in each generation. The turbulence of BSS based on BGA causes that this algorithm converges with distortion. The BSS based on BGA in separation of multi source fails to find the optimum with a population size of 80 in 200 generations. The BSS based on CGA and PSO on the other hand finds the optimum without a doubt and usually finds the optimum within less than hundred generations. As a result, CGA and PSO transform each population to the better population using suitable operators based on proposed fitness function correctly. It is definite the success of

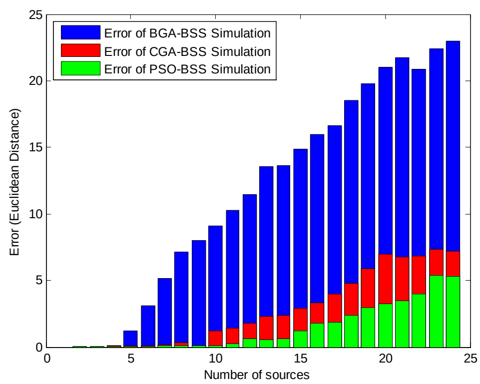

Figure 8. *The error diagram with increasing the number of speech sources in simulation of CGA, BGA and PSO*

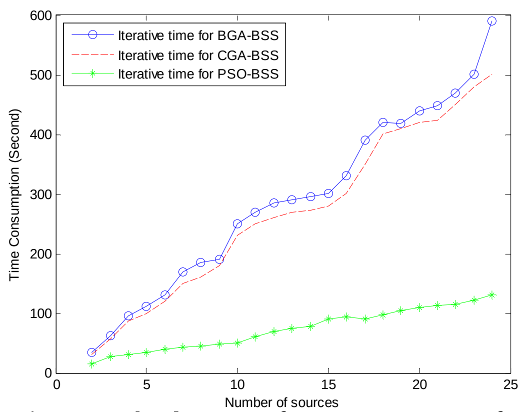

Figure 9. *The diagram of time computations for different number of source signals using CGA,BGA and PSO in BSS problem*

these algorithms depends on the definition of fitness function using kurtosis.

B. Separation of signals in the presence of noise

Industrial research is developing blind source separation algorithms to provide enhanced separation of mixed signals or mixtures of signal plus noise or interference. So, in this experiment an experimental demonstration by mixing signals with random noise signal in interval $[-1,1]$ is provided.

Figure 11-15 show the source signals that are two speech signals and a random noise signal, mixed signals and the estimated signals based on CGA, BGA and PSO. The kurtosises of sources are 8.585, 4.7775, and -1.1946 respectively. Table IV gives the Euclidean distance and SNR values of estimated signals. The SNR values show that sources and obtained signals for BSS problem based on CGA and PSO have the most similarity. The effectiveness of these algorithms in reduction some of noises from speech signals such as white noise, factory noise and babble noise is indicated in experimental results. The error diagram of applying these evolutionary algorithms to speech signals in the presence of noise is shown in Figure 16. It is deduced from the results of separating based on PSO that estimated signals are separated with fast convergence and high accuracy in less time than other algorithms.

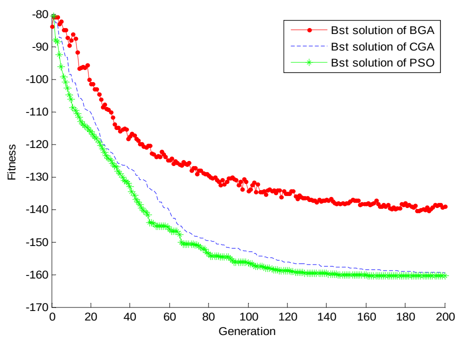

Figure 10. *The best fitness for BSS based on BGA, CGA and PSO forsolving BSS problem*

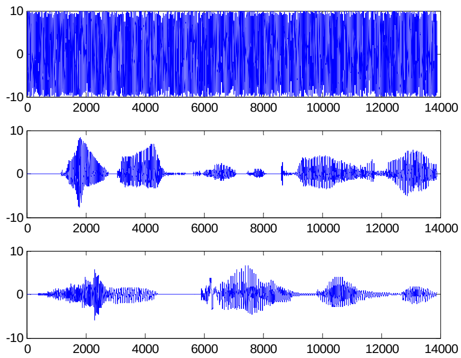

Figure 11. *Two speech signals and noise signals as input sources*

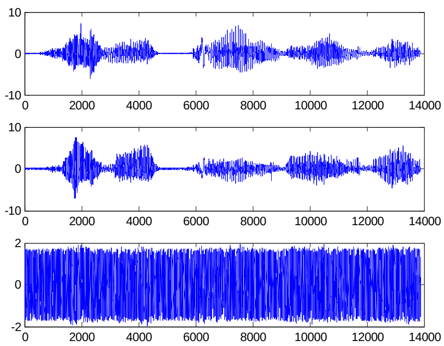

Figure 12. *Mixed speech signals with random noise*

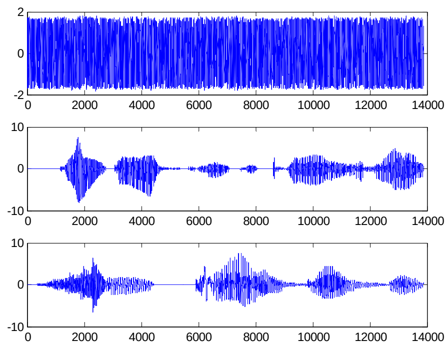

Figure 13. *Separate signals y obtain from CGA algorithm*

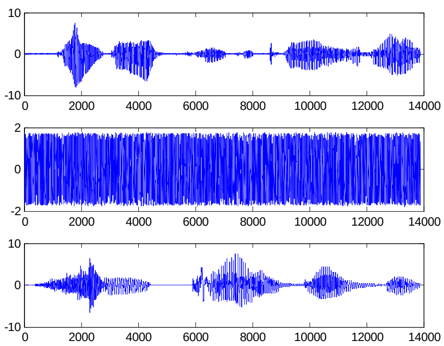

Figure 14. *Separate signals y obtain from BGA algorithm*

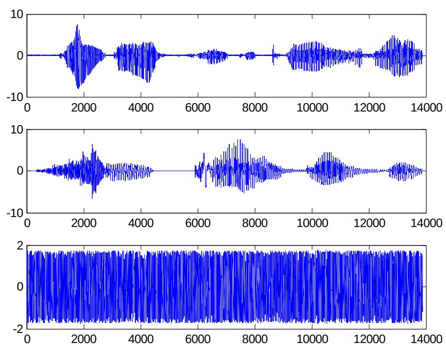

Figure 15. *Separate signals y obtain from PSO algorithm*

C. Separation of signals mixed with sub Gaussian signals

In this simulation, the proposed algorithm is applied to signals with sub Gaussian signals such as cosine wave that is probably mixed with original signals in undesirable environmental conditions. The result is shown in Table V. Once again, it is concluded that the proposed method based on CGA and PSO achieve the successful separations of signals from their linear mixtures.

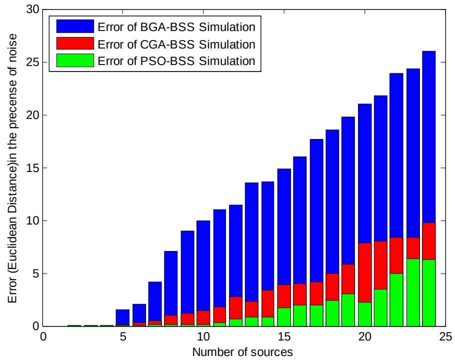

Figure 16. *The error diagram with increasing the number of speech sources in simulation of CGA, BGA and PSO for solving BSS problem in the presence of random noise*

Table 4. *Comparison of Euclidean Distance criterion and SNR for three algorithms in the presence of white noise*

Parameter	PSO	BGA	CGA
SNR of (y_1)	19.943	13.423	19.424
SNR of (y_2)	10.935	18.072	11.497
SNR of (y_3)	8.932	7.345	8.877
Euclidean Distance	0.0046896	0.0089968	0.0012222

Table 5. *Comparison of Euclidean Distance criterion and SNR for three algorithms for original signals mixed with cosine wave*

Parameter	PSO	BGA	CGA
SNR of (y_1)	20.636	13.914	23.416
SNR of (y_2)	13.192	19.446	13.21
SNR of (y_3)	9.532	7.987	8.732
Euclidean Distance	0.0012731	0.011623	0.0027212

Conclusion

In this paper, the estimation of sources signals was executed using the evolutionary mechanism of continuous and binary genetic algorithm and particle swarm optimization. The proposed algorithm is based on mutual information and high order statistics of kurtosis. We concluded that continuous genetic algorithm and particle swarm optimization are practically effective without turbulence in converging to separate different number of source signals. But binary genetic algorithm has divergence and low accuracy. According to the proposed simulations, in applications that need high speed and minimum cost of time computations, PSO obtains better results than CGA and BGA for solving separation problems in multiple sources signals. The experimental results indicated the effectiveness of this method in reducing some noises such as random noise, white noise and babble noise from speech signals. Also, it showed that there is no limitation on distribution of the original signals to enable the system to extract up to three sources from the observed signals. The proposed methods overcome the local minima problem occurred in the conventional gradient-based and neural network methods, and yields global optimal solutions to linear blind source separation problems.

References

[1] M. Kadou, K. Arakawa, ***"A Method of Blind Source Separation for Mixed Voice Separation in Noisy and Reverberating Environment"***, IEICE Tech. Rep., vol. 108, no. 461, SIS2008-81, pp. 55-59, March 2009.
[2] Z. Ding, Y. Li, ***"Blind Equalization and Identification"***, Marcel Dekker, 2001.
[3] A. Hyvarinen, et al., ***"Independent Component Analysis"***,John Wiley & Sons Co, 2001.
[4] H. Yin and I. Hussain, ***"Blind Source Separation and Genetic Algorithm for Image Restoration"***, Advances in Space Technologies, 2006 International Conference, Issue, Page(s):167 – 172, Sept 2006.
[5] J.F. Cardoso, C.N.R.S, and E.N.S.T., ***"Blind signal separation: statistical principles"***, Proceedings of the IEEE, vol.86, NO 10, pp.2009-2025, OCT. 1998.
[6] M. Kuraya, U. Atsushi, Y Shigeru and K. Umeno ***"Blind source separation of chaotic laser signals by independent component analysis"***, Optics Express, Vol. 16, Issue 2, pp. 725-730, Jan 2008.
[7] Z. Shi, Z. Jiang and F. Zhou, ***"A fixed-point algorithm for blind source separation with nonlinear autocorrelation,"*** Journal of Computational and Applied Mathematics, 223 908–915, 2009.
[8] J. LeBlanc and P. Leon, ***"speech separation by kurtosis maximization"***, proc. ICASSP.vol.2, pp 1029-1032, 1998.
[9] S. Sun, J. Zheng and D. Wu, ***"Research on blind source separation based on natural gradient algorithm"***, journal of airforceering university (natural science edition), vol. 4, pp. 50-54, Jun 2003.
[10] S. Sun and J. Zheng, ***"Blind source separation of communication signals of different magnitudes"***, Journal of china institute of communications, vol 25, pp. 132-138, June 2004.
[11] Y. Tan, J. Wang, ***"Nonlinear blind source separation using higher order statistics and a genetic algorithm,"*** IEEE Transactions on evolutionary computation, vol. 5, no. 6, Dec 2001.
[12] S. Kai, W. Qi and D. Mingli, ***"Approach to Nonlinear Blind Source Separation Based on Niche Genetic Algorithm"***, Proceedings of the Sixth Interrnational Conference on Intelligent Systems Design and Applications, 2006.
[13] P. Zheng, Y. Liu, L. Tian, Y. Cao, ***"A Blind Source Separation Method Based on Diagonalization of Correlation Matrices and Genetic Algorithm "*** Fifth World Congress, Vol. 3, Issue, pp. 2127 – 2131, vol.3, June 2004.
[14] X. Y. Zeng, Y. W. Chen, Z. Nakao and G. Yamashita, ***"Signal separation by independent component analy-sis based on a genetic algorithm"***, 5th International Conference, Vol. 3, Issue, vol.3, pp. 1688-1694, 2000.
[15] K. Wang, W. Zhang, ***"Blind Source Separation Based on Chaotic Immune Genetic Algorithm with High order Cumulate"***, IEEE International Conference, Volume, Issu, pp. 139 – 143, Dec. 2006.
[16] W. Yu, L. Zhenxing and L. Chinghai, ***"Improved Particle Swarm to Nonlinear Blind Source Separation"***, International Symposium on Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications, Aug 2007.
[17] Y. Gao, S. Xie, ***"A blind source separation algorithm using particle swarm optimization"***, Proceedings of the IEEE 6th Circuits and Systems Symposium, Vol. 1, Issue , pp. 297 - 300 Vol.1, 31 May-2 June 2004.
[18] F. Abrard, Y. Deville and J. Thomas, ***"Blind partial separation of underdetermineed convolutive mixtures of complex sources based on differential normalized kurtosis"***, Neurocomputing, pp .2071–2086, 2008.
[19] M. Taoufikib, A. Adiba snd D. Aboutajdine, ***"Blind separation of any source distributions via high-order statistics"***, Signal Processing, pp. 1882–1889, 2007.
[20] A. K. Nandl, ***"Blind Estimation Using Higher Order Statistics,"*** Kluwer Academic Pub, 1999.
[21] S. sun, J. Zheng. ***"Blind source separation of communication signals of different magnitudes"*** Journal of china institute of communications, vol 25, pp. 132-138B, June 2004.
[22] A. Hyvärinen and E. Oja, ***"Independent Component Analysis:Algorithms and Applications"***, Neural Networks, vol 13, pp. 411-430, 2000.