Comparative Study of QPSO and other methods in Blind Source Separation

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Abstract. Many techniques are introduced as solutions of the Blind Source Separation mechanisms, as an Independent Component Analysis (ICA), which became most commonly used in this field. ICA methods exploit one of two properties: sample independency and/or non-Gaussianity. In our study, cocktail-party problem processed using ICA method. In this paper, we studied the performance of three technics with independent component analysis are standard FastICA, PSO, and QPSO; and compare the results of each algorithm with others according to the number of metrics (objective as SNR and SDR and subjective as signals plotting and playing). The implement of these algorithms were be made with two source signals and three source signals. As in evaluation process, the QPSO gives more accuracy results than other technics in the signals separation process. Many input speech signals of sampling frequency 8KHz, that achieve IID. also well condition, were tested for different speeches for men and/or women, also music.

Keywords. Blind Source Separation, Independent Component Analysis, Quantum Particle Swarm Optimization, Particle Swarm Optimization, FastICA, Unsupervised Machine Learning.

1. Introduction
One of the Digital Signal Processing problem is the Blind Signal (Source) Separation; it aims to estimate the hidden signals using a number of statistically features about these sources. The BSS emerged during the late 1980s and extended in all many signal-processing fields. Many references talk about the BSS [1,2,3].

In the BSS, number of signals received via number of sensors, and manipulated to restore the source signals. It assumed that received data are produced by interactions among hidden sources.

Most common mechanisms for processing the hidden data is an Independent Component Analysis (ICA) method. It is a statistically mechanism for separating a mixture signals into sub-components supposing; the mutual statistically independence among the observation signals exploited to recover the source signals. ICA techniques employ one of two features: sample independency and/or non-Gaussianity. [1, 2]
The independently supposition is valid in many cases, also the blind separation of the mixture (observation) sources give extremely outputs. The mechanisms, which use the statistically features of the observation signals, separate the components via maximizing the statistically independence of the separated (recovered) signals. The feature Non-Gaussianity is exploited to gauge the independency for the observation signals, by the Kurtosis or the Negentropy measurements [4].

The ICA techniques include two directions; linear ICA and non-linear ICA based on the mixture method. Linear ICA comprise many manners as: Non-linear PCA [2], SOBI [2,16], JADE [6], EASI [7,8], INFOMAX (as so-called Bell-Sejnoski) [8], FastICA [8], RADICAL [9]; and other methods. All the ICA techniques suppose that the recovered sources (observations) are generated by invertible filter driven via the Independent Identical Distribution (IID.) random operation [2]. Furthermore, all ICA techniques use same operations as pre-processes such as centering and sphering (whitening).

This paper studied the performance of two evolutionary optimization algorithms as Particle Swarm Optimization (PSO), and Quantum Particle Swarm Optimization (QPSO). Moreover, compare them with the standard FastICA depending on some objective evaluation metrics (as SNR (signal to noise ratio) and SDR (signal distortion ratio)). In addition, subjective gauges (as play the signals and plot the signals). The implement of these algorithms were be made with two source signals and three source signals.

One of the probabilistic techniques is the QPSO mechanism. It not needs velocity of particles, implementation easy, and require low parameters. In addition, it represent as a optimizing solution for large number of the statistical and engineering problems [10,11].

We implement cocktail-party issue solved by the ICA method with Kurtosis function and Negentropy function as an objective function, with above-mentioned algorithms. Also the study appear that the QPSO gives more accuracy than other algorithms in signal separation. The speeches signals that tested were 8KHz sample frequency for different speakers men and/or women and/or music.

The other parts of this work ordered as following: section two review the surrounding theory, which include the principles of ICA, FastICA, PSO, QPSO, and evaluation criteria (SNR, SDR). In section three, we present the comparative study. Section four state the results and evaluate it by number evaluation gauges. The section five contain the conclusion. Lastly, section six show the references of the paper.

2. Surrounding Theory

2.1. Independent Component Analysis (ICA)

It is one of the statistically mechanisms that based on the statistical properties of the observation signals to recover the original source signals. It is assuming that mixed original signals are statistically independent in the absence of any pre-knowledge about the received (mixed) signals. The mathematically model of the source signal and the received signal:

\[ x(t) = As(t) \]  

Where \( s(t) \) denote original signals, \( x(t) \) represent mixed signals, \( A \) is the mixture matrix used as mixing parameters, so \( t \), automatically time parameter. The main function of the ICA is to find the inverse of the \( A \), (represented as \( W \)) to produce \( y \), as in the following linear formula:

\[ y(t) = Wx(t) \]  

Where \( y(t) \) represent a recovered signals of \( s(t) \), whereas \( W \) represent an evaluated matrix of an inverse of the mixed matrix that used in the separation process. More ICA methods consist of two main operations; first: whitening operation, in this operation running some of the statistical decorrelation operations as second-order statistical operations. The goal of this operation is estimating the orthogonal matrix that used to achieve the independently in the next step [1,2].

The results of the independence assumption is the estimated original signals then mapped into the contrast function (optimization step) which used to maximize the independence among the estimated signals.
2.1.1. Pre-processes of ICA

• **Centering**: include find the average (mean) of the mixed signals, then subtraction of the mean from the mixed signals itself:

\[ x' = x - E[x] \]  
(3)

After that, summing the average (mean) vector to the vector of the recovered signal vector:

\[ s = s'+A^{-1}E[x] \]  
(4)

• **Sphering (Whitening)**: whiten the observation signals \( x \). To achieve the decorrelation of the mixed signals and get the unit variance, performing the linear formula, as in equation (5):

\[ x^* = ADA^{1/2}x^T \]  
(5)

Where \( A \) represent eigenvector of \( E[xx^T] \), and \( D \) denote the eigenvalues of \( E[xx^T] \). The goal of sphering (whitening) operation is to orthogonal the matrix \( A \). There are number of the estimated parameters in the orthogonal mixing matrix, also, it has \( n(n-1)/2 \) free coefficients. [2]

2.1.2. Contrast (Objective) Functions in ICA

• **Negentropy (Negative Entropy)**: The deferential entropy used to measure the random variables. The entropy function of the discrete variables is:

\[ H(X) = -\sum P(X=a_i) \log P(X=a_i) \]  
(6)

Here, the \( H \) is the entropy function of the observation signals. The entropy of variables that in the Gaussian state is larger than other variables. The negative-entropy (Negentropy) measurement used to determine non-Gaussian variables, as the following model:

\[ J(y) = H(y_g) - H(y) \]  
(7)

where \( y_g \) represent the Gaussianity variables. The \( J(y) \) is non-negative, also for the Gaussianity variables equal to zero. Also, Negentropy measurement is statistically robust, but expensive in the computation operations. Therefore, in the most applications, used the approximations of the negentropy based on kurtosis, as in the function(8). [2,16]

\[ J(x) \approx \frac{1}{12} k_3(x)^2 + \frac{1}{48} k_4(x)^2 \]  
(8)

Where \( y \) and \( v \) denote to zero mean Gaussian vectors, and \( G \) is no quadratic function.

• **Kurtosis**: is fourth order cummulant, used as a non-Gaussianity measurement,

\[ \text{kurt}(y) = E[y^4] - 3(E[y^2])^2 \]  
(9)

Kurtosis could have three signs: + superGaussian, - subGaussian, and 0 Gaussian. This metric used because it cheaper computationally than other metrics.

2.2. Standard FastICA Method

It learning rule determines the direction of the unit vector “\( w \)”; also find the transformation \( w^Tx \) to maximize the non-Gaussianity of the observed signals. Non-Gaussianity is gauged by the Negentropy measurement. [1,16]

This method is depend on a fixed-point iteration manner to find a maximum of the non-Gaussianity of \( w^Tx \). It could be formulated as the iteration of the Newton approximation method. The basic form of this method can be summarized as:

Randomly set the initial weight vector \( W \).

Repeat until convergence:

1. Suppose \( w' = E[xg(w^Tx)] - E[g'(w^Tx)]w \)
2. Suppose \( w = w'/||w'|| \)

Properties of the FastICA Algorithm

There are number of desirable features founds in this algorithm compared with other linear existing methods for ICA:

The result of its convergence is cubic according to its assumptions model.

It easily to use in some linear mixing problems.

It separates the components of non-Gaussian distributions, directly.
Could choose any nonlinear optimization suitable function to optimize the performance of this method.
It can estimate the components one-by-one.
The FastICA can be improved by using neural algorithms.

2.3. Particle Swarm Optimization (PSO)
One of the new optimization methods, which derived from the birds flocking environment, is so-called Particle Swarm Optimization (PSO), devised by Kennedy and Eberhart [12].
The PSO method begins randomly with some particles, then search about best state than the initial state of current particles then change the particle state for the optimum state depends on its experiences. This method modified its factors based on two variables: position and velocity of the current particle in number of dimensions, then update these variables for all particles. The searching step and the modification steps repeated n times until achieve the optimality or up to pre-defined of iterations. The mathematical model for this method can illustrated as in equation (10) and equation (11).

\[ v_i(t+1) = wv_i(t) + c_1 r_1(t)(pbest_i(t) - x_i(t)) + c_2 r_2(t)(gbest(t) - x_i(t)) \]  \hspace{1cm} (10)

\[ x_i(t+1) = x_i(t) + v_i(t+1) \] \hspace{1cm} (11)

The \( v \) is the velocity of a particle, \( x \) represent the position, \( pbest \) is a best personal position of \( P \). Also, the \( gbest \) is best global position of all \( P \)’s in the work space in the specified dimensions, \( w \) denote to the convergence speed parameter called an “inertia weight”, \( r_1, r_2 \) random parameters valued in the range [0 to 1], and \( c_1, c_2 \) are so-called the acceleration constants [10,12].

2.4. Quantum Particle Swarm Optimization (QPSO)
As a new version of the PSO method devised by Jun Sun and others is so-called Quantum Particle Swarm Optimization (QPSO) in 2004 [10,11,13]. This method summarizes the PSO parameters into fewer parameters (ignore the velocity parameter) and easier in implementation than PSO. It used as a solution for a lot of number of optimization problems. The conceptuality of the QPSO can illustrated as:

Suppose that each single particle search in the workspace with a \( \delta \) chance with a particular direction, surrounding the point \( p_{ij} \). Simplicity, by regarding the particle in a particular dimension, with a center of the chance. By solve Schrödinger relation of a particular dimensional \( \delta \) potential, it gave probability equation \( Q \) and distribution transform \( F \) as in the following equations (12) and (13) respectively.

\[ Q(X_{i,j}(t+1)) = \frac{1}{\Delta t_{ij}(t)} e^{-2P_{ij}(t)X_{i,j}(t+1)/L_{ij}(t)} \] \hspace{1cm} (12)

\[ F(X_{i,j}(t+1)) = e^{-2P_{ij}(t)X_{i,j}(t+1)/L_{ij}(t)} \] \hspace{1cm} (13)

Here, the \( L_{ij}(t) \) is the standard deviation of distribution. In this algorithm, the position of the particle could be calculated by the Monte-Carlo estimated scheme as in equation (14).

\[ X_{i,j}(t+1) = P_{ij}(t) \pm \frac{L_{ij}(t)}{2} \ln(1/u), \quad u = \text{random}(0,1) \] \hspace{1cm} (14)

To measuring \( L_{ij}(t) \), by using the mean of the local best position for all particles \( pbest \), so-called mean best position \( m(t) \), considered as a global point, as in equation (15).

\[ m(t) = (m_1(t),...,m_n(t)) = \left( \frac{1}{M} \sum_{i=1}^{M} P_{i,1}(t), \frac{1}{M} \sum_{i=1}^{M} P_{i,2}(t), ..., \frac{1}{M} \sum_{i=1}^{M} P_{i,n}(t) \right) \] \hspace{1cm} (15)

Here, \( P \) is \( pbest \) position of particle \( i \) and \( M \) is population size. The \( L_{ij}(t) \) is:

\[ L_{ij}(t) = 2\beta |m_i(t) - X_{i,j}(t)| \] \hspace{1cm} (16)

and thus the position is:

\[ X_{i,j}(t+1) = P_{ij}(t) \pm \beta |m_i(t) - X_{i,j}(t)| \ln(1/u) \] \hspace{1cm} (17)

The \( \beta \) is contraction expansion parameter, is dominance of the convergence of the method. The equation (17) and the PSO algorithm represent the QPSO algorithm.

2.5. Performance Measurements
To calculate the performance of the system, some objective measurements (SNR and SDR) [3,14,15], and some subjective measurements (plotting and playing the speech signals) are used as an evaluation gauge.
**Signal-to-Noise Ratio (SNR):** Best range of SNR is 0 to 1, but the best results closest to 0. It is calculated as:

$$\text{SNR} = 10 \log_{10} \left( \frac{\sum_{i=n}^{\infty} s^2(n)}{\sum_{i=-\infty}^{\infty} (s(i) - \hat{s}(i))^2} \right) \text{ (dB)}$$  \hspace{1cm} (18)

The parameter $s$ represent the source signals, and $\hat{s}$ denote the recovered signals.

**Signal to distortion ratio (SDR):** the SDR is one of the SNR measurements family used to gauge the ratio between the original signals and the distortion signals. In the BSS, the studies represent one of the observed signals as a distortion signal. The SDR suppose that a higher value is good and desired. The SDR formula is:

$$\text{SDR} = 10 \log_{10} \left( \frac{\sum_t s(t)^2}{\sum_t (s(t) - \hat{s}(t))^2} \right) \text{ (dB)}$$  \hspace{1cm} (19)

The parameter $s$ denote the vector of the original signal, and $\hat{s}$ denote the recovered signal.

### 3. Related Works

There are many researchers adapt the PSO and QPSO to solve the Blind Source Separation by the Independent Component Analysis (ICA), in both directions Linear ICA and Nonlinear ICA.

J. Cheng *et al* (2005), present method to use the PSO in the BSS based on the Kullback-Leibler divergence theory in Independent Component Analysis, one can derive an approximation function that is represented as the fitness function in Optimization algorithm. By minimizing the Kullback-Leibler divergence via Optimization algorithm. After that can generate the separation matrix, which can used to recover source signals [18].

F. Nian *et al* (2009) introduced enhance the ICA via the improvement of the PSO algorithm by the dynamic inertia weight which is based on evolution speed and aggregation degree is introduced into PSO. And then, Based on the analysis of ICA, a fitness function of PSO was defined. Finally, the detailed algorithm was given by using improved PSO [19].

Cai and Tian (2011), used the Higher Order Odd Polynomial (HOOP) to set the inverse nonlinear function, where the parameters of HOOP optimized by the PSO. This paper used the joint entropy estimation to convert Mutual Information (MI), because of the MI is unstable when the finite sample length and the separated signals may be unsatisfactory. They used the Gaussian Mixture Model (GMM) to set the pdf of separated sources. The Correlation Coefficient measurement is used as the evaluation metric [20].

Kurihara and Jin’no (2013), proposed a method for nonlinear ICA by using the RBF (Radial Bases Function) network. The author employed the PSO to optimize the parameters of the RBF. They used the Gaussian distribution function as the cost function in the RBF. In addition, they show that the RBF method can use other function as a linear function, a cubic function, thin plate function, multi-quadratic function, or inverse multi-quadratic function. This paper used the MSE (mean square error) as an evaluation metric [21].

### 4. Comparative Study

This study include mainly two parts: first part include solve the ICA problem using QPSO as an optimization method [5,17]. Second part, include a comparative study among some the ICA methods and the QPSO based ICA proposed method.

**First part:** by employing the QPSO algorithm to optimize the linear ICA to solve the cocktail-party idea that concentrate on separate number of mixed signals observed by number of sensor. The method in this paper summarized in the following steps:

1. Preparing at least two noiseless mono-speech signals with same length and same frequencies under IID metric.
2. Preparing the mixture coefficient, which achieve the condition number parameter, then mixing the signals, based on the equation (1).
3. Applying the centering and whitening operations as the preprocessing steps of ICA.
4. Implement the function (Negentropy based on Kurtosis) as an objective (contrast functions) with ICA.

**Second part:**

1. Set the parameters of the QPSO algorithm: Maxitr=50 (maximum number of iteration), Population=15 and alpha parameter, which generally, take range (0.5-2.0) so-called Contrast-Expansion (CE). In this study, alpha (β in equation 17) parameter set as 0.75 depending on the experiments that gave best optimizing results.
2. Initialize the fitness value by using the negentropy based on kurtosis function as the fitness function.
3. Applying the pre-processing operations of the ICA method (centering and whitening).
4. Initialize the mbest coefficient of the particles, as stated in equation (15).
5. In each iteration, update the fitness value, by taken best value, based on the fitness function used. Up to the Maxitr parameter.
6. In end of QPSO algorithm, evaluate the results based on particular measurements (as mentioned in section 2-4).

Secondly, the comparative part include studying the behavior of the specified three methods (QPSO based ICA, PSO based ICA, and standard FastICA) and the performance of each method according many measurements (SNR and SDR), as in the section 4.

5. Simulation Result and Analysis

During the proposed study, we examine many pairs speeches signals. These speeches token from the database, which achieve the required sound properties (as the IID.), these speeches noiseless and in different conditions. The method simulate cocktailing by two different speeches, and inject them to the proposed method. All algorithms in this study were programmed in MATLAB R2017b under process Intel® Core ™ i5, CPU 2.50GHz, RAM 12.0GB, and Windows7 64-bit. Original signals and mixed signals shown in table (1), and the separated signals showed in table (2).

| Signals Name | Length (sample) | Source Signals | Mixed Signals |
|--------------|-----------------|----------------|---------------|
| Source-A1    | 50000           |                |               |
| Source-A2    | 50000           |                |               |
| Source-B1    | 23323           |                |               |
| Source-B2    | 23323           |                |               |
| Source-C1    | 21582           |                |               |
| Source-C2    | 21582           |                |               |

According to the evaluation metrics (SNR and SDR), the proposed method (QPSO based ICA) give, in most cases, give the best separation results, more accuracy in less elapsed time than other methods, as shown in table (3) for SNR and table (4) for SDR. Also shown in analyzed figure (1) for the SNR measurement and figure (2) for the SDR measurement.
The measurement map between the source speeches signals and the recovered speeches signals for each specified method separately. The good values of SNR measurement is in the range [0 to 1], good value is nearby to 0. The best values of the SDR measurement, a good value is the highest.

Table 2. the separated signals depending the selected methods

| Signals Name | Separated Signals |
|--------------|------------------|
| Source-A1    | FastICA          |
| Source-A2    | PSO              |
| Source-B1    | QPSO             |
| Source-B2    |                 |
| Source-C1    |                 |
| Source-C2    |                 |

Table 3. The SNR measurement of the selected signals under the specified methods

| Signals Name       | Length of Signal (sample) | QPSO  | PSO   | FastICA |
|--------------------|---------------------------|-------|-------|---------|
| Source-A1, Source-A2 | 50000                     | **0.09** | 0.1992 | 0.0949  |
| Source-B1, Source-B2 | 23323                     | **0.0156** | 0.1031 | 0.016   |
| Source-C1, Source-C2 | 21582                     | **0.0165** | 0.0179 | 0.0772  |

Figure 1. The SNR metric for the specified methods
Table 4. The SDR measurement of the selected signals under the specified methods

| Signal Names      | Length of Signal (sample) | QPSO   | PSO    | FastICA |
|------------------|---------------------------|--------|--------|---------|
| Source-A1, Source-A2 | 50000                     | 13.9695 | 13.7693 | 13.6689 |
| Source-B1, Source-B2 | 23323                     | 27.4347 | 20.1893 | 27.0463 |
| Source-C1, Source-C2 | 21582                     | 21.259  | 20.0863 | 26.6643 |

Figure 2. The SDR metric for the specified methods

6. Conclusions

There are number of strategies used to solve the Blind Source Separation problem, one of these strategies is so name Independent Component Analysis (ICA). Furthermore, the ICA algorithm used in many scientific fields (feature extraction, signals separation, image encryption, image compression, .., etc.). In addition, in optimization studies, many modern issues introduced in the swarm intelligence especially on the Quantum Particle Swarm Optimization (QPSO) algorithm. This paper introduced study to employing the features of QPSO to enhance the performance of the ICA methods as modern method employed in signal separation, so comparing results of QPSO based ICA and the results of other methods. We studied the cocktail-party idea of real mono-speech signals with sampling frequency 8KHz. The results appeared excellent results, depending on the evaluation gauges: SNR, SDR and plot signals.

References

[1] P. Comon, and C. Jutten, “Handbook of Blind Source Separation , independent component analysis and applications”, academic press, oxford 2010.
[2] A. Hyvarinen, J. Karhunen ,and F. Oja ,”independent component analysis”, john wily & son, 2001.
[3] S. Makino, T. W. Lee , and H. Sawada , “ Blind Speech Separation”, springer, 2007.
[4] N. A. Muhsin ,”A comparison among adaptive ICA algorithms for blind speech signals separation: cocktail party problem”, Ph.D. thesis, university of technology, Iraq, 2006.
[5] Hussein M. Salman, “Mono Speech Signal Separation Using Optimize Independent Component Analysis Algorithm”, Ph.D. thesis, University of Babylon, Iraq, 2019.
[6] K. Zhang , G. Tian ,and L. Tian ,” Blind source separation based on JADE algorithm and application “, 3rd international conference on mechatronics, robotics, and automation (ICMRA 2015).
[7] A. Hyvarinen, “Independent Component Analysis: recent advances”, royal society publishing, December 2016.
[8] R. Mutihac, and M.M. Van Hulle, “A comparative survey on adaptive neural network algorithms for independent component analysis “, Faculty of physics, university of Bucharest, 76900
Romania.

[9] V. Krishnaveeni et al., “Comparison of independent component analysis algorithms for removal of ocular artifacts from electroencephalogram”, Measurement Science Review, Volume 5 Section 2, 2005.

[10] J. Sun, C. Lai and X. Wu, “Particle swarm optimization classical and quantum perspectives”, CRC Press, 2012.

[11] J. Sun, B. Feng and W. Xu, “Particle swarm optimization with particles having quantum behavior”, IEEE-2004.

[12] J. Kennedy and R. Eberhart, “Particle swarm optimization”, Proceedings of the IEEE international conference on neural networks, Perth, Australia, pp. 1942-1948, 1995.

[13] M. Xi, J. Sun and W. Xu, “An improved quantum-behaved particle swarm optimization with weighted mean best position”, Applied Mathematics and Computation, Elsevier Inc., Vol. 11, No. 2 (2016), pp. 121-132.

[14] N. A. Abbas, “Image encryption based on Independent Component Analysis and Arnold’s Cat Map”, Egyptian Informatics Journal, 2015, http://dx.doi.org/10.1016/j.eij.2015.10.001.

[15] E. Vincent et al., “Performance measurement in blind audio source separation”, IEEE Transactions on Audio, Speech and Language Processing, Institute of Electrical and Electronics Engineers, 2006, 14 (4), pp. 1462-1469.

[16] A. Hyvarinen, "Survey on Independent Component Analysis", Neural Computing Surveys 2, 94-128, 1999.

[17] Hussein M. Salman and Nidaa A. Abbas, “Independent component analysis based on quantum particle swarm optimization”, Egyptian Informatics Journal 19 (2018) 101–105, Elsevier 2018, https://doi.org/10.1016/j.eij.2017.11.001.

[18] J. Cheng, T. Su, and Y. Ni, “Blind Signal Separation Using Modified Particle Swarm Optimization”, Department of Electronic Engineering, National Kaohsiung University of Applied Sciences, 2005.

[19] F. Nian, W. Li, X. Sun, and M. Li, “An Improved Particle Swarm Optimization Application to Independent Component Analysis”, IEEE-2009.

[20] L. Cai and X. Tian, “Improved post-nonlinear independent component analysis method based on Gaussian mixture model”, IEEE, 2011.

[21] T. Kurihara and K. Jin’no, “A Nonlinear blind source separation system using particle swarm optimization algorithm”, Journal of Signal Processing, Japan, 2013.