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Solve Cocktail Party Problem Based on Hybrid Method

Hussein M. Salman[1], Ali Kadhum M. Al-Qurabat*[2,3] and Abd alnasir Riyadh Finjan[4]

[1]*College of Material Engineering, University of Babylon, Babylon Iraq*
[2]*Cyber Security Science Department, College of Science, Al-Mustaqbal University, 51001, Babylon, Iraq*
[3]*Department of Computer Science, College of Science for Women, University of Babylon, Babylon, Iraq*
[4]*Supreme Commision for Hajj and Umrah, Baghdad, Iraq*

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Abstract: One of the most intractable issues in contemporary digital signal processing, particularly with regards to blind source separation methods, is known as the cocktail party dilemma. This problem suppose there are many sensors record many signals at same time to produce many mixed signals. To solve this problem, one of an important methods used for this purpose is an Independent Component Analysis method. This method abbreviates in how separate mixed signals without any pre-knowledge about the mixing signals?. It treats on the statistical features of a mixing signals. This work introduces a novel method to solve the cocktail party problem, by using hybrid method from the Quantum Particle Swarm Optimization method and the Bell- Sejnowski neural method to enhance the performance of the Independent Component Analysis. In addition, the proposed method uses the Negentropy function to be the objective function of the optimization process. The proposed algorithm has been implemented on two cases of three really signals, with 8-KHz frequencies. The results of the separating process measured in two directions: firstly by comparing the results with other methods as Particle Swarm Optimization and the Quantum Particle Swarm Optimization, where the results appear that the proposed method appears very high results than other methods. Secondly, by using standard metrics as Absolute Value Correlation Coefficient, Signal to Distortion Ratio, and Signal to Noise Ratio.

Keywords: Cocktail-Party Problem, BSS, ICA, QPSO, Bell-Sejnowski (InfoMax) method

1 Introduction and Overview

There is a phenomenon when one or many sensors sense one or many signals at the same time. The received (observed) signals will be mixed. This phenomenon is called the “cocktail party problem”. Examples of this problem are: many persons or songs talking in many microphones at the same, or MEG, EEG sensors, or camera capturing many interesting objects; etc. Figure 1 illustrates this problem. The Cocktail-Party issue is a well-known example of a digital signal processing (DSP) challenge. To solve this problem and separate the mixed signals, a technique called a Blind Source Separation (BSS) is used. The BSS is one of a number of influential and great methods in DSP introduced in the 1980s [1], [2].

The key purpose of the BSS is to separate mixture signals and re-building the original components from the observed (received) signals. The mixture signals (components) can be treated as a sequence of sensor outputs. To mix number signals (sources), it must be based on some criteria, such as the Gaussianity and a condition number of the mixture matrix. These conditions are defaults in some DSP problems, similar to the problem of cocktail party, which includes a typical example for the Blind Source Separation [1], [2], [3], [4]. Figure 1 illustrates in detail the sketching of the Cocktail-Party problem.

There are many approaches of BSS, as Independent Component Analysis (ICA), Non-negative Matrix Factorization (NMF), and Sparse Component Analysis (SCA) [4]. The ICA approaches are mostly trusted methods of the BSS. The BSS techniques are examples of unsupervised learning approaches that use either a priori knowledge or a theoretically derived goal function, therefore; both post-processing and pre-processing of the signal vector are very necessary [1].

In this study, we provide a new hybrid strategy to enhance the ICA’s capabilities. The proposed method depends on the Bell-Sejnowski neural approach (InfoMax method) [5] with the Quantum Particle Swarm Optimization (QPSO). The model given here employs the QPSO method to enhance the efficiency of an InfoMax-based ICA technique. The InfoMax (BS) approach has speed convergence features

E-mail address:Hus12ms@uobabylon.edu.iq;ali.kadhum.mohammed@uomus.edu.iq;Naserreyadh@gmail.com

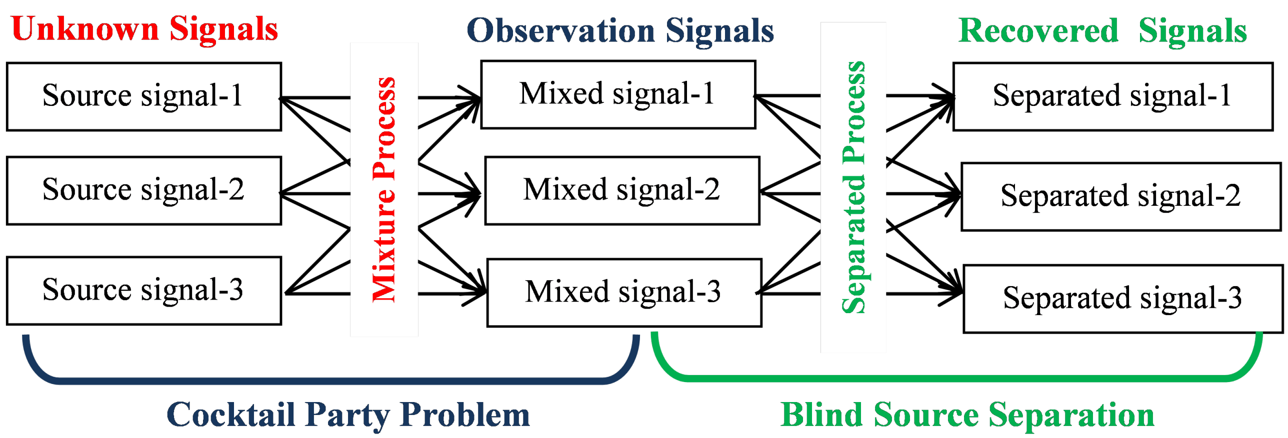

Figure 1. Cocktail Party Problem.

but is poor in the separation accuracy process. The QPSO is using Infomax as a contrast model for ICA method optimization.

Comparisons were made between the results obtained using the suggested approach and those obtained using the "Quantum Particle Swarm Optimization-based ICA" described in [6] and the "PSO-based ICA method" described in [7]. A number of objective measures, including the Absolute Value of Correlation Coefficient (AVCC) [8], Signal-to-Distortion Ratio (SDR) [9], and the Signal-to-Noise Ratio (SNR) [10], will be used to assess the performance of the provided approach.

A rest of this work is arranged as follows: section two gives a background for ICA, QPSO and InfoMax algorithms. Related works state in section three. Section four describe in details the suggested technique. The experiential outcomes and discussion presented in section five. The conclusions came in section six.

2 Background

In this section, a detailed description is given for the algorithms used in this paper, namely the ICA algorithm, the QPSO algorithm, and the InfoMax (BS) algorithm.

- The ICA is a statistical-based computation approach. It was used to separate and recover the mixture of source signals (observation signals) based on the statistical analysis of the components of the received signals. This mostly occurs by applying higher-order statistics to those components. The ICA can be written as a mathematical model as in the below model:

$$x(t) = As(t) \tag{1}$$

Note that $x(t) = [x_1, x_2, \ldots, x_n]^T$ represents the $n \times 1$ mixture vector, $(t) = [s_1, s_2, \ldots, s_n]^T$ represent $n \times 1$ unfamiliar source signal vector and non-Gaussian zero-mean components are s_i, last, A is an unfamiliar $n \times n$ non-singular mixture matrix. Generally, the mathematical model in (1) represents the ICA linear model [2], [11], [12].

In the linearity formula, the procedure includes establishing the separated matrix, which stands for the opposite of the mixture matrix. In addition, to attempt to find the source signals from equation (1), one must find another model for that purpose as soon as possible in the mathematical model as in equation (2), which represents the separation process [1], as follows:

$$y(t) = Wx(t) \approx s(t) \tag{2}$$

Note that $y(t) = [y_1, y_2, \ldots, y_n]^T$ is $n \times 1$ separated signal, and W is a $n \times n$ separated square matrix. Before executing the separation process, one must do some operations such as centering and whitening [1], [3], [12].

Each method of ICA is based on two main, non-sequentially related parts: the objective function and the optimization. The first part focuses on the effects of the statistical features. The second part has effects on the algorithmic features. Therefore, the ICA is stronger when it includes a strong objective function, which means a fast and simple computation [11], [13].

At first, the ICA method used traditional neural network methods as an optimization approach for instance, Newton-like methods, gradient methods, and others [1], after that it (ICA) depends on the swarm intelligence method and the genetic algorithms [11]. The FastICA method [14], [15] is the most familiar and popular method in the ICA [1].

Secondly, the other part of the ICA approach, the contrast (objective) functions, are done according to one of the Gaussianity measurements, such as the Mutual Information, the Negentropy function, and the Kurtosis function. The mathematical model of the Kurtosis is shown in equation (3), and equation

(4) represents the Negentropy function based on the kurtosis. Both of these equations (3 and 4) are mostly used in most research.

$$kurt = E(x^4) - 3[E(x^2)]^2 \tag{3}$$

$$J(x) \approx \frac{1}{12} \times k_3(x)^2 + \frac{1}{48} \times k_4(x)^2 \tag{4}$$

The k_i is the i^{th} cumulant, E represents an expectation parameter, and x represents mixed signals [1], [6]. In addition, many ICA methods use a number of linear functions that achieve the best separation of signals under some considerations and the nature of the problem, or using some learning rules as in the neural network-based ICA methods (for example, Gradient functions, self organization map (SOM) and Radial Basis Function (RBF)) [1], [3].

- There are a number of computer optimization methods that simulate the nature of animals such as birds and fish. These methods are called metaheuristic optimization techniques, which are based on the quantum base of the animals. These methods are used for learning in the algorithm of an information structure. One of these categories is swarm intelligence, which includes particle swarm optimization, quantum particle swarm optimization (QPSO), and others. The QPSO is the last version of the PSO, where it depends on the quantum principle of the received data [16], [7].
The QPSO algorithm depends on the search area of the article in a particular dimension. The main parameter is the so-called δ potential, which represents the gain of search to be near the point p_{ij}. In general, the particle will be represented in a particular dimension in the workspace with a center p. In order to calculate the *delta* potential, the $Schrodinger$ equation is used. Depending on the $Schrodinger$ model, the distribution function F and the pdf Q can be formulated as in equations 5 and 6.

$$Q(X_{ij}(t+1)) = \frac{1}{L_{ij}(t)} e^{-2|p_{ij}(t) - x_{ij}(t+1)|} / L_{ij}(t) \tag{5}$$

$$f(X_{ij}(t+1)) = \frac{e^{-2|p_{ij}(t) - x_{ij}(t+1)|}}{L_{ij}(t)} \tag{6}$$

Where $L_{ij}(t)$ computed by Monte Carlo estimated formula, which represents the standard deviation, additionally, the location of the particles can be determined using equation (7).

$$X_{ij}(t+1) = P_{ij}(t) \pm \frac{L_{ij}(t)}{2} \times ln(\frac{1}{u}), \quad u = rand(0,1) \tag{7}$$

To evaluate the $L_{ij}(t)$, the method employs a global point of the population is m (mean best position), also is denoted as *pbest* of all particles, as in the equation (8).

$$m(t) = \left(\frac{1}{M} \sum_{i=1}^{M} P_{i,1}(t), \frac{1}{M} \sum_{i=1}^{M} P_{i,2}(t), \frac{1}{M} \sum_{i=1}^{M} P_{i,n}(t) \right) \tag{8}$$

M denotes the population size and P_i is the *pbest* of the particle i. The $L_{ij}(t)$ is given in equation (9)

$$L_{ij}(t) = 2\beta * |m_j(t) - X_{ij}(t)| \tag{9}$$

In addition, equation (10) provides the location for the particle i

$$X_{ij}(t+1) = P_{ij}(t) \pm \beta * |m_j(t) - X_{ij}(t)| * ln(\frac{1}{u}) \tag{10}$$

Note that β denote the contraction–expansion parameter, represents the control parameter of the model convergence [7], [17].

- An Information Maximization approach is introduced by the two scientists (A. Bell and T. Sejnowski) in 1995 - sometimes abbreviate as BS algorithm - as a self-organizing learning algorithm in neural network to solve the cocktail party problem [5].
Generally, this approach used an unsupervised learning rules of an information theory for the neural network methods, leveraging signal processing's higher-order statistics for blind source separation scenarios like the cocktail party issue, whereby mixed signals must be disentangled. This method, in the BSS, can be summarized as:
Assumption there are two signals, y_1 and y_2 (two inputs and two outputs) in the separation case or two time points in the de-convolution case. Also, based on the information theory, the joint entropy of y_1 and y_2 (here, the two signals considers, statistically, as two variables) may be:

$$H(y_1, y_2) = H(y_1) + H(y_2) - I(y_1, y_2) \tag{11}$$

Where $H(y_1, y_2)$ is the joint entropy of the output, $H(y_1)$ represents the entropy of the variable (y_1), $H(y_2)$ represents the entropy of the variable (y_2), and $I(y_1, y_2)$ denotes to the mutual information between the variables (y_1) and $H(y_2)$.
The above equation (11), includes maximizing the individual entropies of y1 and y2, while reducing the pair's mutual information, denoted by $I(y_1, y_2)$. In the limit when $H(y_1, y_2)$ equals zero or is very close to zero, this indicates to the independence of two variables, statistically. The goal of the ICA is to minimize the mutual information between the observation variables. The algorithm used a stochastic ascent algorithm to maximize the joint entropy.
To perform the Independent Component Analysis, Bell and Sejnowski suggested in the Info-Max method two main stages: firstly, is the nonlinearity defined by the relation (12) as follow:

$$y' = \frac{dy}{du} = y^p(1-y)^r \quad (12)$$

This equation represents differential form of the generalized *sigmoid* function of the approximate cumulative distribution function (CDF). The variables p and r in this equation are both real, positive values. This equation may be numerically integrated to get a *sigmoid* that is both flat and unit-like when p is extremely high and r is very small, also $p \neq r$, as shown in details in [4]. When $p = r = 1$ the figure of function will be fits distribution of the Kurtosis, whereas, $p = r = 5$ the figure of function will be fits distribution of the Skew. The equation in (12) represent the nonlinear.
Second stage include applying the nonlinearity formula of the CDF function of the sigmoid function, in the network by using the weighted matrix and bias vector as in the following equations respectively:

$$\triangle W \propto [W^T]^{-1} + [p(1-y) - ry]x^T \quad (13)$$

$$\triangle W_0 \propto p(1-y) - ry \quad (14)$$

Where $\triangle W$ denote to weighted matrix , W^T is initial weighted matrix , x and y are two variable vectors (two components), and $\triangle W_0$ represent the bias weight.
As a result, the linear form of the Bell-Sejnowski (InfoMax) algorithm can be written as:

$$W = \sum u \times w^T + (1 - 2 \times g(y) \times y^T) \times w \quad (15)$$

Where $g(y) = (1 + e^{-u})^{-1}$ represent the logistic function, and w is initial separated matrix, and u is learning rate (range 0 to 1).

3 Related Works

To review most recently papers that nearby used the ICA with InfoMax method, and the QPSO method, this section for this purpose.

The authors of [5] introduced first version of the InfoMax method to recover the signals from mixed signals and blind deconvolution. This method depends on the information theory concepts and the mutual information between the signals. It used the neural network and sigmoid function with these networks, where concerned on minimizing the mutual information between the observation (blind) signals and maximizing joint entropy between them, so on separate the signals be easy. This method was new novel method to solve cocktail party problem.

In [18], the researcher improved the InfoMax method by using the maximum likelihood principle with the InfoMax approach. The maximum likelihood idea is associated with an objective (contrast) function. This principle used to the signal (source) separation issue. This method depends on the Kullback divergence principle by minimizing this parameter between the observed (mixed) sources to result separated matrix that lead to perform the separation process.

The researchers in [6] introduced a method dependent on the QPSO algorithm to improve the efficiency of the ICA algorithm. Negentropy function is the objective function that used in the algorithm. The algorithm produced respectable separation results, although it was noticeably slower than the standard FastICA technique. The researchers used the SNR and the SDR metrics as an evaluation measurements.

In [19], the authors presented a comparative study between the QPSO method and other methods as the PSO algorithm and FastICA algorithm, that used to improve the performance of the ICA. The comparative does under some subjective measures as the signals plotting and some objective measures as SNR and SDR measures. The study shows that the QPSO method could improve ICA's performance more than other methods.

The authors of [20] proposed new algorithm for improving the performance of the ICA algorithm by hybrid the Bigradient neural approach with the QPSO algorithm. The authors sum between the features of two methods as the speed of the Bigradient method and the accuracy of the QPSO method to produce fast and accuracy method. The method implemented on real sound and speeches under some evaluation measures as the SNR, the SDR, and the AVCC.

In [21], the author introduced a framework depends on the information-theoretic view for nonnegative factorization and polytopic matrix factorization, two structured matrix factorization methods that maximize determinants. To perform this idea, the author as known Log-Determinant (LD) entropy. This concept depends on the alternative joint entropy measure between the observation (blind) signals based on log-determinant of covariance.

According to the works mentioned above, it turns out that the limitations of existing works are summarised in an inefficient and unreliable manner in most cases of independent component analysis, especially when the sources increase. Also, they do not use a hybrid approach and do not use the Negentropy function as an objective function.

4 Research Methodology

This section focuses on the presented algorithm, which comprises two stages: first, the steps of the algorithm and its equations. The second part includes a detailed description of the algorithm.

A. The presented algorithm

The presented algorithm uses one of the information theory models, the InfoMax (BS) method, as an improvement approach for the BSS methods as an ICA approach. Also, this paper uses the QPSO algorithm as a method for optimizing the ICA method in a hybrid approach. As a result, the proposed algorithm is:

At first, the algorithm deals with at least two source signals for building the super vector [1], which denote the mixture signals. Two pre-processes performed as preliminary steps of the ICA algorithm are [1], [2], [3]:

Centering process: comprise calculate the mean attribute of the mixture vector signal, then it subtracted from the mixture vector, ($x' = x - E[x]$). After that, the mean is summated with the estimation source signal vector, ($s = s' + A - 1E[x]$).

Whitening process: this process includes orthogonal for the mixing matrix. This can be done by uncorrelating the source signals and obtaining the unit variance during linear transformation model ($x \sim= \Lambda D \Lambda^{-1} x^T$), the Λ is an eigenvector of $E[xx^T]$, and D is an eigenvalue of $E[xx^T]$.

After the pre-processes, according to the objective (contrast) function, the whitening source signals will be separated. The presented algorithm uses the negentropy based on Kurtosis (3) and (4) as a contrast model. Negentropy measures the difference in entropy between a given distribution and the Gaussian distribution with the same mean and variance.

In this paper, we use the QPSO method for enhancing the performance of the ICA algorithm. To find the initial state of the objective function, it uses the Kurtosis equation (a fourth-order statistic). After that, start the main iteration of the optimization algorithm; in the method, and based on the pre-iterated loops, find the mean best factor of the global dimension state in the search workspace. The proposed algorithm used the InfoMax (BS) learning model to compute the fitness value for every loop in the QPSO method.

In the second stage, by using the InfoMax model, which has speed convergence, the algorithm has been improved. Also the presented algorithm calculates the fitness function in the QPSO and uses the following equation to compute the function of learning g, as in (16).

$$g = x \times e^x \tag{16}$$

The x is the received mixed vector.

However, the proposed method used the InfoMax (BS) model inside the QPSO algorithm to optimize the performance of the ICA. Where BS has more speed convergence than QPSO, therefore the hybrid between BS and QPSO can give separation results with more accuracy than others. Also, this is due to some features such as fewer parameters and a lower execution time.

B. Hybrid Presented Algorithm Steps

The presented algorithm is a hybrid of InfoMax and QPSO for separating the mono-speech observation signals. The steps of the proposed method could be ordered as two stages: firstly includes all pre-processing steps and the essential steps of the ICA method. The second stage include the optimized steps for the first stage. These steps show how to use the hybrid method (QPSO and InfoMax) to optimized the performance of the ICA and also include the post-processing steps of the method. Both two-stage systems will be illustrated in detail as follows:

- First stage - Pre-processing steps and ICA steps :
  1) Initialize three speeches under some metrics as: noiseless, monochrome, 8000Hz frequency, and equalized length. Also statistically, the speeches must be Independent and Identically Distributed (i.i.d.) random variables.
  2) To simulate the mixing process as in equation (1), must find mixture matrix achieves the statistical condition known as the well-condition criteria. Best mixture matrix when it's well-condition is 1 (plus or minus something).
  3) Now, the algorithm receives mixed signals. Main two preprocessing for the separation process done on the mixed signals are the Centering process and the whitening process. These two processes may be repeated many times.
  4) As mentioned in section 1.1, the ICA consist of two processes: optimization method and objective function. In this paper, the Negentropy function based on kurtosis will be used as an objective function as shown in equation (4).

- Second stage – optimizing the ICA This stage includes main steps in the proposed method that concerned to improve the performance of the ICA Method.
  1) Initialize the QPSO's parameters and at same time initialize the InfoMax method. The step take some sub-steps to set all the parameters and coefficients of those methods, to achieve best results in the optimization process under some evaluation measures.
  2) Before login the repetition of the QPSO algorithm, the algorithm needs to find initial fitness value necessary in the fitness (objective) function.
  3) New objective (fitness) value and objective function are calculated starting from this step. The objective function that used in this paper is an Negentropy based on kurtosis as in equation (4).
  4) After login the loop of the method, it will compute the centering and whitening processes in each iteration.
  5) Main parameter in the QPSO is calculated depending on the equation (8).

6) To correct and update the fitness value of the optimization algorithm, InfoMax formula is used for that purpose according to the equation (15). The experiences prove that this formula under some setting of its parameters gave best and accurate separating results.
7) In each iteration, the parameters of the optimization method will updated and exchanged into new scales, and improved by InfoMax periodically. This updating enhances the results of the current loop, which effect affirmative on next loop.
8) The steps 5 to 7 repeated to N times under parameter called MaxIter, that set to maximum iteration number of the optimization process.
9) Last step in the algorithm is the performance evaluation of the results of the optimization process and the accuracy of the separation results. Two types of the evaluation metrics used are: subjective measures (plotting the separation signals), and objective measures (SNR, SDR, and AVCC).

5 Results and Discussion

This section will discuss the performance of the presented algorithm by stating the investigational results of the recovering process, and recovering the original signals. Also, this section will compare these results with other algorithms as the QPSO-based ICA algorithm.

A. *Set the Initial Parameters of Mixture process*

The proposed algorithm uses the cocktail party idea to illustrate the separation process. First, collect speech signals from many datasets on the websites of the databank of the International Telecommunication Union (ITU), and the University of Dallas [22]. All the signals are clear of any noise and $8000Hz$ frequencies. Second, check all the speeches and sound signals under i.i.d. condition, and the gaussainity by the Kurtosis measure, as in the preliminaries of the ICA method [1], [5].

The paper assumes there are two sources and two sensors. The speeches are mixed in an instantaneous linear model (equation 1), and the 3×3 mixture matrix A will be built by a normal (Gaussian) distribution, with domain $[-20, 20]$, as in equation (17):

$$A = a + (b - a) \times randn(3, 3) \tag{17}$$

Note that a is the minimum and b is the maximum boundary of the distribution domain. The matrix achieves a conditional number feature. After that, select two mixture cases from the available speeches as shown in Table I.

The proposed algorithm's primary parameters may be set to values such as 10 for population size, 60 for the maximum range iteration, and 0.75 for the inertia weight (*beta* in equation 10).

The QPSO-based ICA (as in reference [6]) factors are maximum range iteration is 50, population=10, and inertia weight (β in equation 10) is 0.75. Whereas the main parameters of the PSO method are: the convergence speed parameter called an "inertia weight" $w = 0.8$, the acceleration constants ($c_1 = c_2 = 1$), and randomized parameters (r_1, r_2) are in slope $(0-1)$. The InfoMax algorithm parameters are $\mu = 0.01$, $p = 0.5$, and $r = 0.1$, also $p, r < 1$, and $p \neq r$ as mentioned in the equation 12.

B. *Evaluation Measurements*

The presented method uses some objective measurements as SNR, SDR, and AVCC. These metrics are famous used in the signals evaluation DSP researches. These measures state as follows: The reestablishment metric is formulated as a SNR measure of the error [10], that is:

$$SNR = 10log\left(\frac{\sum_t^T (v_i(t))^2}{\sum_{t=1}^N (v_i(t) - z_i(t))^2}\right)(dB) \tag{18}$$

Note that $v_i(t)$ represents the original signals, $z_i(t)$ represents the separated signals, N represents the interval of the signals, and t represents the period index. The SNR metric scales between the range $[0 - 1]$ between a specific signals. If it was nearby to 1, that means the two signals have the highest correlation, and vice versa. Depending on SNR measure, the separated components must be nearby to the energy level of the original component. In addition, SDR [9], is formulated as:

$$SDR = 10log\left(\frac{\sum_{t=1}^N (v_i(t) - z_i(t))^2}{\sum_t^T (v_i(t))^2}\right)(dB) \tag{19}$$

As well as, the AVCC [8], is used to detects the similarity level between source components and separated components. The AVCC defined as follow:

$$AVCC = \left|\frac{\sum_{t=1}^N (z_i(t) v_k(t))}{\sqrt{\sum_{t=1}^N v_i^2(t) \sum_{t=1}^N z_k^2(t)}}\right| \tag{20}$$

Higher AVCC and SDR, and lower SNR denoted to similarity index between the separation components and source components.

C. *Experimental Results and Analysis*

The introduced work is implemented under the technical language MATLAB R2017b. The computer utilized has a processor speed of 2.5 GHz (Intel Core i5) and 12 GB of RAM. The results of the proposed method are evaluated in two ways: the first way is to represent the signals (source

TABLE I. The Speech Signals and Mixing Matrix

Case No.	Source Signals	Length (samples)	Kurtosis (Gaussian Value)	Kurtosis of Recovered Signals	a	b	Mixing Matrix
	source-1		7.3709	7.5246			2.5981 1.6145 1.7437
1	source-2	50000	4.2686	4.2678	0	1	-1.5430 2.9281 1.7149
	source-3		6.1309	6.1296			1.5557 2.2052 -2.4348
	source-1		7.3709	7.3503			-2.9349 2.8909 -0.2048
2	source-2	61038	7.2118	7.2267	-1	1	2.5983 -1.1030 -2.3122
	source-3		7.4982	7.4981			-2.6364 -1.7024 -2.3940

signals, mixed signals, and separated signals) as shown in Table II. This is called a subjective measure for the evaluation.

With waves, two methods will be used for assessing and analyzing the suggested procedure and separation outcomes: When comparing the suggested approach to others, the wave shape of the source signals, mixed signals, and separated signals is used as an indicator. Figure (3) shows the sources and the mixture signals, Figure (4) shows the separated signals in the proposed method, the QPSO-based ICA method, the Bigradient-based ICA method, and the separate signals in the FastICA method. All these methods deal with four mixture cases, each case formulate by two mono-speech signals from eight signals.

As shown in Table II, the figures clearly describe the wave plots of the source signals, the mixture signals and the separated signals for all cases studies with three signals, implemented under three methods of the ICA, (PSO, QPSO, and the proposed method). According to these depictions, the presented algorithm gave best accuracy results in the separated process than other methods (PSO and QPSO).

Second idea used for measuring the separation method are so called objective measures that depend on the statistical features of the signals. This paper uses some famous measures of signals metrics such as the AVCC (Absolute Value Correlation Coefficient), the SDR (Signal–to–Distortion Ratio), and the SNR (Signal–to–Noise Ratio), as shown in Tables III, IV, and V.

Based on Tables III, IV,and V can plotting the analysis data of the used measurements as an illustrating for the proposed methods and compared with other methods. The figures 2, 3, and 4 are representing of the depicting of measures.

As shown in the above figures which represent the analysis of the performance measurements used to evaluate the separation results of the presented methods and comparative with other algorithms as PSO and QPSO. The figures and the correspondence tables illustrate that the proposed method (ICA based on hybrid QPSO and InfoMax method), that used to solve the cocktail party problem in the Blind Signal Separation, improve the method and gave better results than other methods according to the AVCC, the SDR and the SNR indexes.

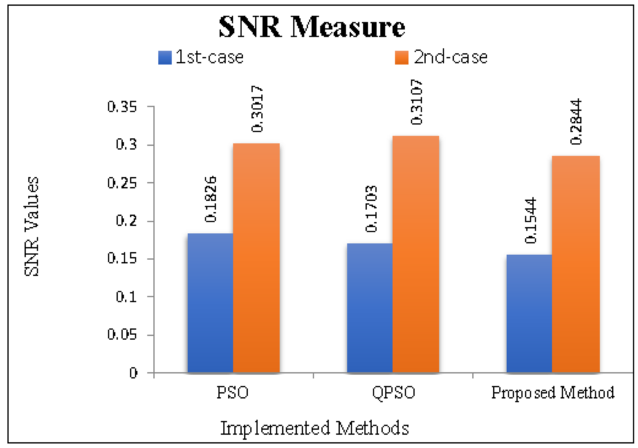

Figure 2. The SNR Measurement.

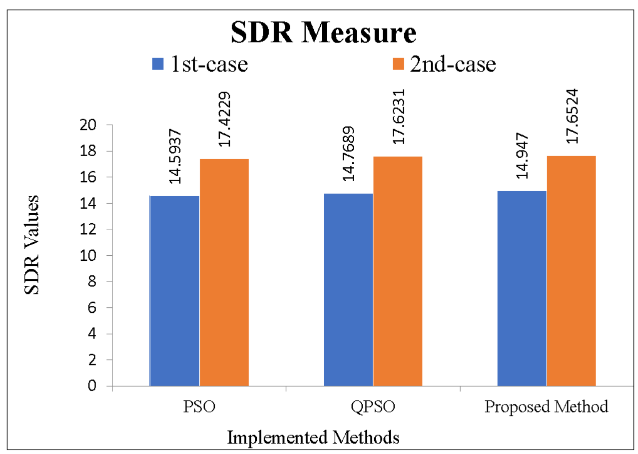

Figure 3. The SDR Measurement.

The limitations of this study can be summarized as follows:

- At least one of the source sounds / speeches must have a Gaussian distribution.
- The mixture process is instantaneous.

TABLE II. Plot Original, Mixed and Separated Speech Signals

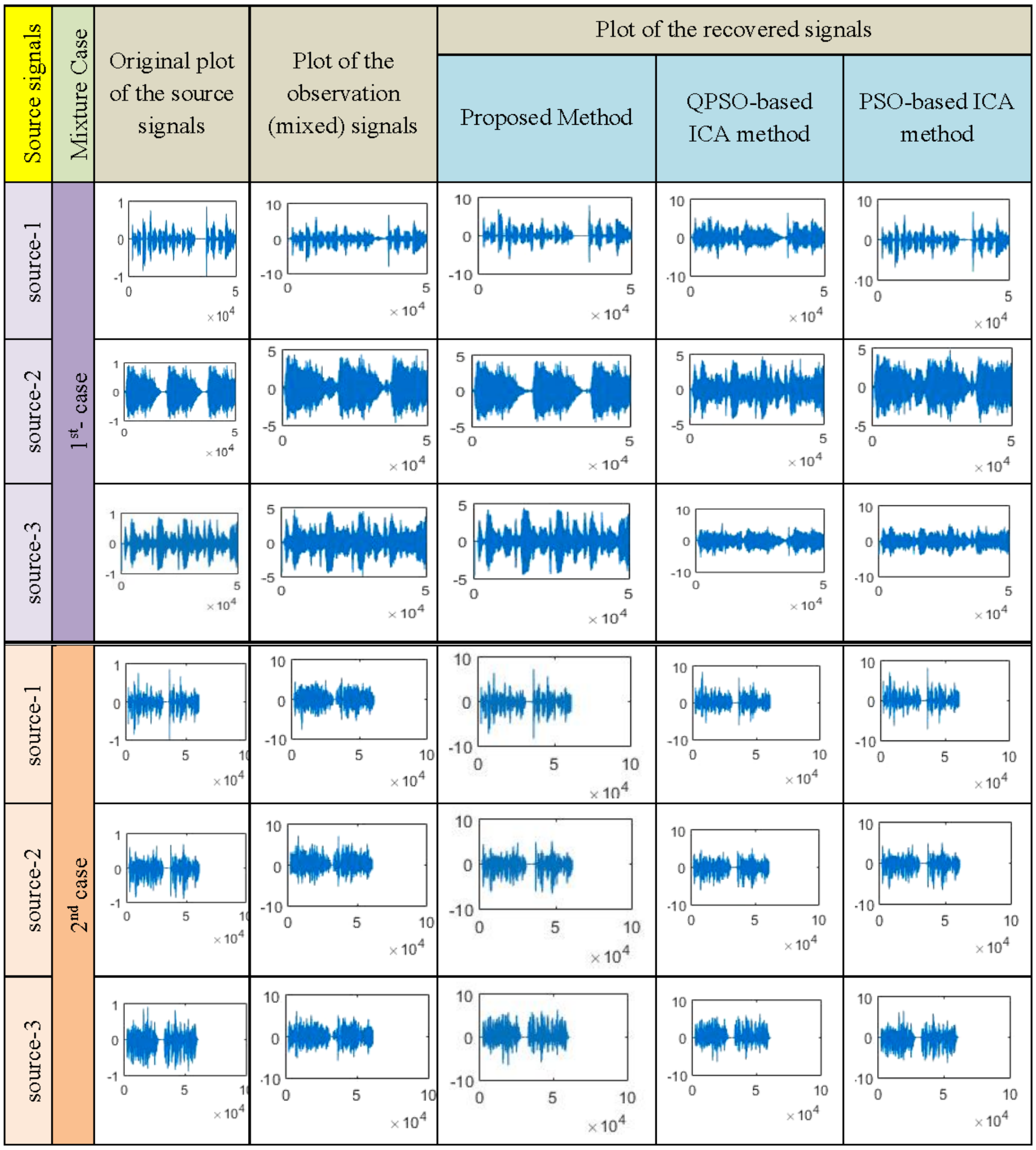

TABLE III. SNR Measurement (dB)

	PSO	QPSO	Proposed Method
1	0.1826	0.1703	0.1544
2	0.3017	0.3107	0.2844

TABLE IV. SDR Measurement (dB)

	PSO	QPSO	Proposed Method
1	14.5937	14.7689	14.947
2	17.4229	17.6231	17.6524

- The distribution of the sources is an independent identical distribution (i.i.d.).

TABLE V. AVCC Measurement (dB)

	PSO	QPSO	Proposed Method
1	0.0715	0.0436	0.0025
2	0.0586	0.0679	0.0402

In this work, we chose the QPSO method because it has many general advantages such as speed, lower parameters, lower computation time, more efficiency, and more reliability than other swarm optimization methods, especially the PSO method. In this work, this method gave very good results in the mixture source separation process compared to other methods.

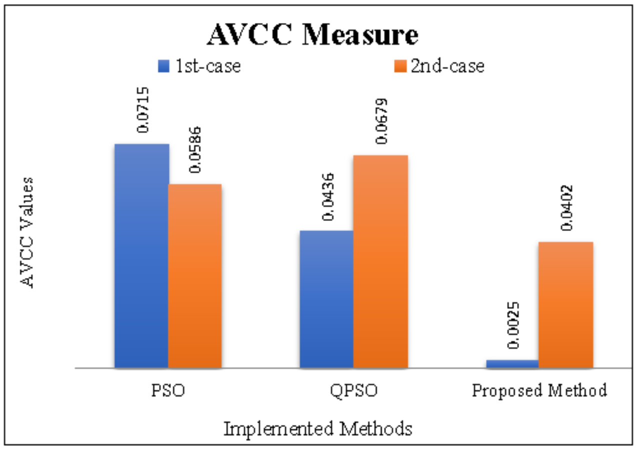

Figure 4. The AVCC Measurement.

6 Conclusions

When there are many signals recorded by many sensors simultaneously, where each sensor records all signals, the channel of these recorded signals will travel the mixture of signals at the same time. This problem is called the cocktail party problem. The cocktail party problem is one of the still problems in the DSP. The field of this problem is called Blind Source Separation. There are many methods to solve the BSS, such as the ICA method. The ICA method depends on the statistical features of the received signals. Traditional ICA methods offer some non-accuracy, especially when increasing the mixing signals. This paper introduces a new hybrid method to enhance the performance of the ICA using the hybrid InfoMax and QPSO methods. The proposed algorithm used the *Negentropy* as an objective (contrast) function.

The proposed hybrid algorithm is implemented with three mono-speech signals mixed in an instantaneous mixture method. The presented algorithm gave good results based on some evaluation metrics such as SNR, SDR, and AVCC. Also compared with other algorithms such as PSO and QPSO.

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Hussein M. Salman received his Ph.D. in Software (Machine Learning) in 2019 from the College of Information Technology at the University of Babylon, Iraq. He received the B.Sc. and M.Sc. degrees in Computer Science from the College of Science at the University of Babylon, Iraq in 2001 and 2011 respectively. He joined the College of Material Engineering, University of Babylon, Iraq, in 2001, where he is currently a Lecturer. His research interests include Machine Learning, Artificial Intelligence, Optimization, IoT.

Ali Kadhum M. Al-Qurabat received his Ph.D. in Software (Wireless Sensor Networks) in 2018 from the University of Babylon, Iraq. He received the M.Sc. degree in Information Technology from Universiti Tenaga Nasional (UNITEN), Malaysia, in 2012. He received the B.Sc. degree in computer science from the University of Babylon, Iraq, in 2002. He joined the Department of Computer Science, University of Babylon, Iraq, in 2006, where he is currently an Assistant Professor. His research interests include WSN, Data Aggregation, IoT, Data Mining, Data Compression and E-Procurement. Dr. Al-Qurabat has been a TPC Member of several national and international networking conferences and a Reviewer for several international journals. He is the author of a great deal of research studies published in national and international journals, and at conference proceedings.

Abd alnasir R. Finjan received his Ph.D. in Software (Wireless Sensor Networks) in 2018 from the College of Information Technology at the University of Babylon, Iraq. He received the higher diploma and M.Sc. degrees in Computer Science from the Iraqi Commission for Computers and Informatics in 2002 and 2006 respectively. He received a B.Sc. degree in Computer Science from the Al-Rafidain University College, Iraq in 2001. His research interests include Networks, Wireless Networks.