

Bigradient neural network-based quantum particle swarm optimization for blind source separation

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ABSTRACT

An independent component analysis (ICA) is one of the solutions of a blind source separation problem. ICA is a statistical approach that depends on the statistical properties of the mixed signals. The purpose of the ICA method is to demix the mixed source signals (observation signals) and recovering those signals. The abbreviation of the problem is that the ICA needs for optimizing by using one of the optimization approaches as swarm intelligent, neural networks, and genetic algorithms. This paper presents a hybrid method to optimize the ICA method by using the quantum particle swarm optimization method (QPSO) to optimize the Bigradient neural network method that applies to separate mixed signals and recover sources signals. The results of an implement this work prove that this method gave good results comparing with other methods such as the Bigradient neural network and the QPSO method, based on several evaluation measures as signal-to-noise ratio, signal-to-distortion ratio, absolute value correlation coefficient, and the computation time.

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1. INTRODUCTION

Blind source separation (BSS) is a powerful signal processing method proposed in the late 1980s. As the product of artificial neural networks, statistical signal processing, and information theory. After then BSS becomes an important topic in research and development in many areas [1].

The main task of the BSS is extracting and recovering the underlying source signals from multivariable statistical data (observation signals). The observation signals can be manipulated as the mixing of source signals, that is, the observed mixed signal is a series of sensor outputs. The mixing process is done under some conditions as the well-condition of the mixing matrix and the gaussianity of the source signals, as in the cocktail party problem, that represents the typical example of the BSS [1]-[4]. Figure 1 sketching the cocktail-party problem.

In this paper, we proposed a new hybrid method of the ICA based on the quantum particle swarm optimization (QPSO) and Bigradient neural network method. The proposed method includes enhancing the performance of the Bigradient-based ICA method by using the QPSO optimization method. The Bigradient neural network method characterizes with the speed convergence but not accurate in the separation process. By using the QPSO method to optimize the ICA method based on the Bigradient neural network method. The

QPSO is using the Bigradient function as an objective function with two learning parameters, to adjust the convergence of the ICA algorithm and to accurate of the separation process.

The results of the proposed method compared with other methods as the FastICA [5], [6], and “the ICA based on quantum particle swarm optimization” as in [7]. In addition, evaluate the proposed method by number of measurements as the signal-to-noise ratio (SNR) [8], the signal-to-distortion ratio (SDR) [9], the absolute value of correlation coefficient (AVCC) [10], and the computation time.

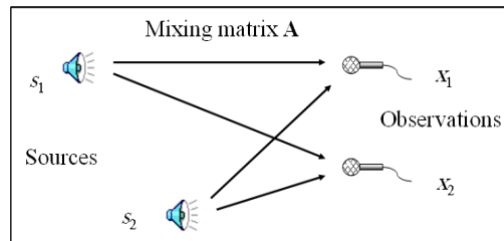


Figure 1. Cocktail party problem

The rest of this paper is organized as: section 2 described ICA in detail. The QPSO and Bigradient neural networks are introduced in sections 3 and 4 respectively. Section 5 states the related works. Section 6 described the proposed method. The experimental results described in section 7. The conclusion came in section 8.

1.1. Independent component analysis (ICA)

It is a statistical computation method and base on the statistical properties of the observation signals. Main task of ICA is recovering and finding the original sources from the observation signal. The mathematical representation of the observation signals can done as in the (1):

$$x(t) = As(t) \quad (1)$$

Where $x(t) = [x_1, x_2, \dots, x_n]^T$ represents $n \times 1$ observations vector, $(t) = [s_1, s_2, \dots, s_n]^T$ is a $n \times 1$ unknown source vector and zero-mean non-Gaussian elements s_i , and A is an unknown $n \times n$ non-singular mixing matrix. Above model is the general linear model of the ICA methods [2], [3], [7].

In the linear schema, the process consists of finding the inverse of the mixing matrix A . Also, to solve the observation model – as in (1), to recover the sources and separate them, must assume found matrix, so-called a separation matrix- to be in new formula in mathematical representation as:

$$y(t) = Wx(t) \approx s(t) \quad (2)$$

Where $y(t) = [y_1, y_2, \dots, y_n]^T$ represent $n \times 1$ recovered signal, and W is $n \times n$ separated matrix. The model in (2) represent the separation process in the ICA methods [1]. There are some preprocesses must do on the observation signals as the centering and whitening [1], [2], [5].

Any algorithm of the ICA methods depends on two extremely dependence axioms are the optimization method and the objective (contrast) function. The optimization method affects with the algorithmic properties of the ICA method; and the objective (contrast) function affect with the statistical properties of the ICA method. In addition, the powerful of the ICA depends on the choosing of the objective function, which must be simple and fast computation [3].

Firstly, the ICA used some of the classical neural network as an optimization method for example, gradient methods, Newton-like methods, and others [1], [11], [12] then the genetic algorithms and evolutionary algorithms as the swarm intelligence optimization methods [3], [13]. Linearly, FastICA method [5], [6] is a most popular linear ICA methods which depends on the fixed-point iteration method also can be consider as an approximative Newton iteration method, also there are number of adapted and proposed methods that depends on number of linear functions [1].

In order, the second part of the ICA methods -objective function- done by using one of the gaussian measuring functions as Kurtosis function, Negentropy function, mutual information (MI) function and maximum likelihood (ML) function [1]. Most researchers adapt the kurtosis function as in (3) and the negentropy based on kurtosis function as in (4).

$$kurt = E(x^4) - 3[E(x^2)]^2 \quad (3)$$

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

Where k_i represents the i -th cumulant, E is an expectation operation, and x is data vector of the signals [1], [7], [14], [15].

1.2. Quantum particle swarm optimization (QPSO)

QPSO is one of most popular meta-heuristic optimization methods based on the quantum principle of the animal nature as fishes and birds. To find the efficient solution, the meta-heuristic algorithms use the learning algorithms for an information structuring [14], [16].

This method assumes that each particle looks in the search area with a δ potential on a certain dimension, nearby the point p_{ij} . Generally, the particle swarm can be represented in a certain dimensional area, with a center p . To solve the dimensional δ potential, the Schrödinger formula used for this purpose. Based on this formula, the pdf Q and the distribution function F can be defined as in (5) and (6) respectively.

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

$$F(X_{ij}(t+1)) = e^{-2|p_{ij}(t)-x_{ij}(t+1)|/L_{ij}(t)} \quad (6)$$

Where $L_{ij}(t)$ calculated using Monte Carlo estimation approach, where denote a standard deviation, also the particle position can be calculated as in (7).

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

For evaluating the $L_{ij}(t)$, the algorithm uses the mean best position m , which is a global point of the population, is pbest of all particles, as given in the (8).

$$m(t) = (m_1(t), m_2(t), \dots, m_n(t)) = \left(\frac{1}{M} \sum_{i=1}^M P_{i,1}(t), \frac{1}{M} \sum_{i=1}^M P_{i,2}(t), \dots, \frac{1}{M} \sum_{i=1}^M P_{i,n}(t) \right) \quad (8)$$

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

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

Also, the position of the particle i is given in (10)

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

Where β represents the contraction-expansion factor, is the control parameter of the algorithm convergent [17], [18].

1.3. Bigradient neural network algorithm

There are various methods depend on the neural networks to solve the ICA algorithm in both linear mixture and nonlinear mixture. Neural PCA and ICA architectures and learning algorithms can be divided into two main groups: hierarchic approaches, which estimate the principal components or eigenvectors themselves; and symmetric subspace type approaches, which estimate the ICA subspace only [19], [20]. The Bigradient algorithm is learning algorithm for separating matrix W after pre-whitening [21], [22], as:

$$W_{k+1} = W_k + \mu_k v_k g(y_k^T) - \gamma_k W_k (I - W_k^T W_k) \quad (11)$$

In (11), the learning parameter μ_k decreased linearly from 0.01 to 0.00001 with the number of iteration steps k , and γ_k is another positive learning parameter, usually about 0.5 [23]. The first update term $\mu_k v_k g(y_k^T)$ is essentially a nonlinear Hebbian term, and the second term $\gamma_k W_k (I - W_k^T W_k)$ keeps the weight matrix W_k roughly orthogonal. One of its best features is flexibility. The (11) can be applied with slightly different forms and choices to separating either sub-Gaussian or super-Gaussian sources. It is also

easy to modify the (11) so that the weight vectors of the neurons are computed sequentially in a hierarchic order [12].

2. LITERATURE REVIEW

In this section, we will review some recently related works about the blind source separation problem and the neural networks algorithms.

Pehlevan *et al.* [23] introduced a method for the blind signal separation problem to solve the nonnegative similarity matching problem depending on deep learning of neurons in the neural networks, through designing three-layers neural network under feedforward architecture. In the second layer, all neurons were learned with deep learning using the backpropagation. The last layer recovered the hidden sources. In this work, objective function was used to derive the learning rules and the architecture of the designed network. The authors compared those work with five ICA methods are projected gradient descent algorithm, FastICA, Infomax ICA, Linsker' Network, and Nonnegative PCA. So implement all these methods with natural images.

Salman and Abbas [7] introduced new method to optimize the ICA method by using quantum particle swarm optimization method. This method used a Negentropy function as an objective function in the ICA. The method yields good results in the separation process, but it something slow compared with standard FastICA method. The authors evaluated the performance of this method using a number of metrics as signal-to-noise ratio index and signal-to-distortion ratio index.

Isomura and Toyozumi [24] proposed a method in neural networks depends on error gated hebbian rule (EGHR) to extract the mixed sounds in the BSS. The EGHR learning rule benefits in reducing the sensor inputs especially in recording animal sounds. In addition, the EGHR can operate with multi context of the BSS. Other benefits of the EGHR is extract sources with low dimensional context. The authors applied the proposed method to extract the animal sounds.

Abbas and Salman [15] introduced some methods to enhance the performance of the linear ICA depending on the quantum particle swarm optimization (QPSO) and the gloworm swarm optimization (GSO) with three objective functions are Entropy, Negentropy, and Mutual Information. So, the author proposed new Nonlinear ICA method depends on some nonlinear methods. The proposed nonlinear ICA method compared with commonly standard nonlinear ICA methods as SOM based ICA and RBF based ICA methods. The results proved that the proposed method gave good results according to some evaluation measurements as SNR, SIR, log-Likelihood ratio, and perceptual evaluation speech quality (PESQ). All the proposed methods (linear ICA and nonlinear ICA) implemented with dataset of real speeches taken from the international telecommunication union (ITU), under 8 KHz frequencies.

Brendel, and Kellermann [25], introduced an algorithm to enhance the independent vector analysis (IVA), which is one of the BSS methods depended on the data-driven scheme to the acoustic mechanisms. The authors proposed fast convergence rules based on eigenvalue extraction and the majorize-minimize (MM) concepts with the Negentropy objective function. The updated rules could be efficient optimization approach of independent low rank matrix analysis (ILRMA) methods. The authors applied their proposed method with data recorded in real world sounds.

3. RESEARCH METHODOLOGY

As mentioned in the previous sections, one of still problems in the digital signal processing (DSP) is blind source (Signal) separation (BSS). The BSS problem emerging in many real-world fields as sound (speech) signal processing, natural image processing, MRI, fMRI, EEG and MEG. The ICA approach is most efficient method to solve the BSS problem. The ICA needs to use and implement some optimization methods as a part of its work. Therefore, in many standard and proposed methods of the ICA, it used neural networks, genetic algorithms, and/or swarm intelligence methods. Most ICA methods confront some difficulties in efficient, accuracy, and speed.

This section concentrates on the proposed method that contain two parts, firstly walk about the method inline steps and its equations and stages. Second part contains the flowchart and the algorithm of the proposed method.

3.1. Proposed method

In the proposed method, we used one of the neural network methods is the Bigradient method as an ICA strategy to solve BSS problem. At same time, we used the quantum particle swarm optimization as an optimization method for the ICA in a hybrid manner. The BSS method will be as:

Firstly, the method assumes that there are, at least, two mixed mono-speech signals to formulate so-called super vector with two vectors [1], this super vector represent the observation signals. Before execute the ICA steps, must performing main two pre-processes [1], [2]:

Centering: include compute the mean of the observation signal and then subtract this mean from the observation source itself, ($x' = x - E[x]$) and then add the mean vector to the estimated source vector, ($s = s' + A^{-1}E[x]$).

Whitening: whiten the mixed signal x . To obtain the observation signals uncorrelated and have unit variance, applying the linear model transformation ($x \sim = ADA^{\frac{1}{2}} x^T$), where A represent eigenvector of $E[xx^T]$, and D denote the eigenvalues of $E[xx^T]$. The aim of whitening process is to orthogonal the mixing matrix.

After then, separate these whitened signals based on the objective function. The proposed method used the approximation negentropy function based on Kurtosis (3) and (4) as an objective function.

To optimize the results of the ICA, we used the QPSO optimization algorithm: in this algorithm, we used the fourth-order statistic degree equation (Kurtosis) to find the initial value of the fitness function. Then, intrmission into main loop of the algorithm; inside the algorithm and under predefined iterations, find mean best state of the global state in the search space of the problem. To find the value of the fitness value for each iteration inside the QPSO algorithm, we used Bigradient neural learning for this purpose.

Secondly, while the Bigradient neural network characterized with high speed convergence – as mentioned in section 1.3 in this paper - it used in the proposed method as in (11); to compute the fitness value of the QPSO algorithm; where the learning function g is defined as in (12).

$$g = x * e^x \quad (12)$$

Where x represents the observation signal vector.

Nevertheless, this algorithm has important limitation is unable to get good result in the separation process. Therefore, in the third part, the proposed method tends to optimize the Bigradient algorithm by using the quantum particle swarm optimization method because this method have some features as an accurate results in the separation process, few parameters, and lower computation requirements, but this method slower than Bigradient method. For specific iterations, the proposed hybrid method get good results collect between the Bigradient method and the QPSO method.

3.2. Extremely steps of the proposed method

The proposed method hybrid between QPSO and Bigradient to separate the mono-speech mixed signals. The flowchart order as flow: first step, receiving observation (mixture signals), the signals mixed in instantunous manner and include at least two speeches. Second step performs the extreme preprocesses (centering and whitening), step three includes calculating initial fitness value by using the objective functio “Kurtosis function” as in (3). From step 4 the core of the proposed method will started, where in predefine iteration, the QPSO implemented and optimized using the Bigradient function until terminate the iteration. The Bigradient function consider as the objective function of the proposed ICA method. At the end of the flowchart, recovering the source signals and evaluating of the performance of the proposed method. The Figure 2 illustare the flowchart of the proposed method.

In addition, the algorithm of the proposed method contains nine main steps. These steps ordered as flow: steps (1, 2) include performing the preprocesses of the ICA (centering and whitening), step 3, find the initial maximum value of the fitness function. From step 4 to step 7, the QPSO performed and inside it the Bigradient function is used. The step 8 includes separating the mixed signals and recovering the sources. In step 9, performing the evaluation process of the performance of the proposed method. This algorithm illustrated following in Algorithm 1.

Algorithm (1): Bigradient based on QPSO ICA algorithm

Input: *white-x* % whitened vectors

Output: *z*; % separated vectors (recovered sources)

Algorithm Steps

1. Initializing set of diagonal separated matrices.
 $x_1 = \text{randomly}(K, K, \text{population});$
 2. Calculate initially fitness values of the current positions of particles using the objective function
 3. For $i=1$ to *population*
 $y = x_1 * \text{white-}x;$
Centering and Whitening y;
 Perform the objective function based on the system in (3 and 4)
 $\text{fit}(i) = \text{sum}(\text{proposed fun.});$ % compute current fitness value
End_for
 4. Find the initial maximum value of the fitness value
-

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    pgmax = maximum (fit)
5.   Main loop iteration of the QPSO algorithm
    d=1; % iteration index
Do
mbest=sum(fit) / population; % mean of the best local positions
for i=1 to population
for j=1 to K
for s=1 to K
phi = random();
p=phi * pmaxj,s,i + (1-phi) * pgmaxj,s ;
u=random();
xj,s,i=p± (alpha * ||mbest- xj,s,i || * ln(1/u));
end_for(s)
end_for(j)
end_for(i)
6.   Calculate new values of the positions of particles
    For m=1 to population
    y= xi* x;
    Centering and Whitening y;
    Perform Bigradient rule -as an objective function- with two parameters ( $\mu_k, \gamma_k$ ) to find new fitness value as in (11)
    fitnew(m)=  $W_k + \mu_k v_k g(y_k^T) - \gamma_k W_k(I-W_k^T W_k)$  % find new fitness value
    End_for(m)
7.   Find the new maximum value of the fitness values.
    pgmax = maximum (fitnew)
8.   Increment the iteration, and stopped
    d=d+1; % iteration index.
Until d= maxiter; % terminate the loop of QPSO algorithm.
9.   z = y; % recovered sources
10.  SNR, SDR, AVCC; % Evaluation process.
End Algorithm.

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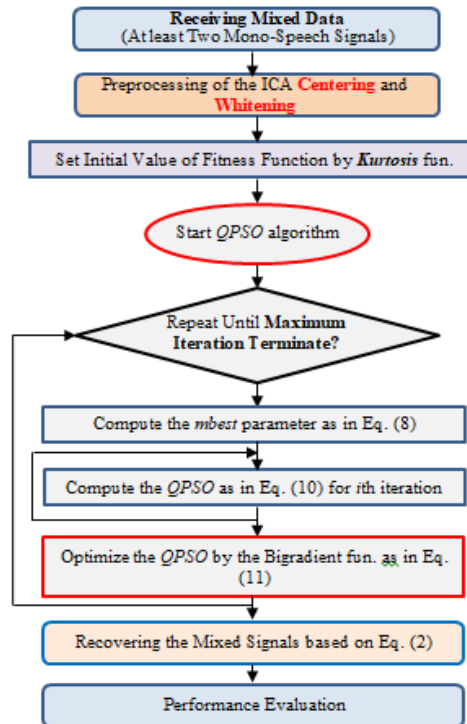


Figure 2. Flowchart of the proposed method

4. RESULTS AND DISCUSSION

After implement the proposed method with a specified speeches, the results of the separation process was novel and more speed convergence than other compared methods. Additionally, to illustrate the performance of the proposed Hybrid ICA method, we report the experimental results on the separation

signals. We compared the results with three ICA methods, QPSO-based ICA method [7] introduced in section 1.2, Bigradient-based ICA method [21] illustrated in section 1.3, and standard FastICA method [5].

The proposed method (hybrid method) collect some of the QPSO advantages in the accuracy and some of the Bigradient neural network advantages in the speed convergence. These properties made the proposed method gave good results better than QPSO and Bigradient, also better than standard FastICA method.

4.1. Source signals and parameters setting

this paper adapts the cocktail-party issue to illustrate the proposed method in the separation process. Firstly, the speech signals are selected from the website of the database of the international telecommunication union (ITU) (https://github.com/denniguse/ITU-T_pesq/tree/master/comform), and the database of the University of Dallas (<http://www.utdallas.edu/~loizou/speech/noizeus/>). Different eight speech signals selected from those websites and remaned by the authors are source11, source22, source4, source7, julia8, 22m, ray8, are rich8. All these signals are noiseless and 8KHz frequency. Secondly, all these signals achieve the super-gaussianity principle, and independent identical distribution (i.i.d) conditions according Kurtosis measurement in (3), as the ICA conditions [1], [6].

The paper assumes a cocktail party problem with two sources and two sensors as an application of the BSS. The sources mixed in instantaneous linear method in (1), and the 2×2 mixing matrix A is generated in randomly distributed normal, in the closed range $[-20, 20]$, as in (13):

$$A = a + (b - a) * rand(2,2) \quad (13)$$

Where a, and b are the minimum and maximum range of signals distribution respectively. This matrix achieves the well-condition number. As result, from the selected speech signals formulate four mixture cases. The mixture cases are case1 (source11, source22), case2 (source4, source7), case3 (julia8, 22m), and case4 (ray8, rich8) under the same mixing conditions. The Table 1 views all the initial parameters of the mixture process.

Table 1. Speeches files and mixing matrices

Mixed case	Sources names	Kurtosis of source signals	Length (samples)	A	b	Mixed matrix	Condition number
1	source11	4.2686	50000	-20	20	-43.3496 -35.8895	1.5189
	source22	6.1309				-26.8210 19.2581	
2	Source4	5.4201	50000	-12	12	8.8056 -13.3578	1.4703
	Source7	3.8568				-14.3396 -21.1326	
3	Julia8	6.3970	21582	-1	1	0.7338 -1.1131	1.2703
	22m	7.9978				-1.1950 -1.7611	
4	Ray8	7.4982	61038	-3	2	-1.2118 1.6230	1.2558
	Rich8	6.5054				-1.2055 -1.1720	

In additional, main parameters of the proposed method set as population=10, maximum iteration is 60, and contraction-expansion factor (β in (10)) is 0.75, (parameters of Bigradient in (11) are $\mu=0.00001$, $\gamma=0.5$).

The QPSO-based ICA as in [7] parameters are maximum iteration is 35, population=10, and contraction-expansion factor (β in 10) is 0.75. The Bigradient-based ICA algorithm parameters are $\mu=0.00001$, $\gamma=0.5$ as in (11).

4.2. Performance evaluation

In order to measure the accuracy of the proposed algorithm, we evaluate it using three performance indexes: signal-to-noise ratio (SNR), signal-to-distortion ratio (SDR), and absolute value of correlation coefficient (AVCC). They are, respectively, defined as follows.

The reconstruction measure is stated as a signal-to-noise ratio index of the error [8], that is:

$$SNR = 10 \log \left(\frac{\sum_t (v_i(t))^2}{\sum_{t=1}^N (v_i(t) - z_i(t))^2} \right) (dB) \quad (14)$$

Where $v_i(t)$ is the source signals, $z_i(t)$ denote the recovered signals, N is length of the signals (number of samples), t is time index, and i signal index. The SNR measurement place in the range $[0, 1]$ between two signals. It nearby to 0, when both signals nearby to have same energy level. Based on the SNR

index, the recovered signals should be rescaled to the same energy level as their corresponding original signals. Also, signal-to-distortion ratio (SDR) [9], is defined as:

$$\text{SDR} = 10 \log \left(\frac{\sum_{t=1}^N (v_i(t) - z_i(t))^2}{\sum_{t=1}^T (v_i(t))^2} \right) \text{ (dB)} \quad (15)$$

In additional, the absolute value of correlation coefficient (AVCC) [10], is exploit to determine the similarity degree between original signals and recovered signals. The AVCC described in (16):

$$\text{AVCC} = \left| \frac{\sum_{t=1}^N z_i(t) v_k(t)}{\sqrt{\sum_{t=1}^N v_i^2(t) \sum_{t=1}^N z_k^2(t)}} \right| \quad (16)$$

Lower SNR, and higher SDR and AVCC represent that the separated and recovered signals are near similar to the source signals. Furthermore, the computation time is used as evaluation index for all methods under same device and equipment conditions.

4.3. Performance analysis of separation results

The proposed method and other methods are simulated and programmed with MATLAB R2017b. They are executed on PC under Intel Core i5, CPU 2.5 GHz, and RAM 12 GB.

To evaluate and analysis the performance of the proposed method by using the performance measurements: SNR, SDR, AVCC and computation time. The Tables 2-5 describe the results of the proposed method in separation process under these evaluation indexes, and same separation conditions for all separation cases.

Table 2 illustrates the accuracy of the proposed method versus other methods under the SNR measurement, where lower results are evidence on higher accuracy separation. In this table, the proposed method (Hybrid) appear more accuracy than other method in two separation cases as indicated in red color. So, same index observed in Table 3, under the SDR measurement, the proposed method (Hybrid) gave better accuracy result in one separation case indicated in red color. Also, in the Table 4, the proposed method (Hybrid) gave best results in one case as indicated in red color, under the AVCC measurement. In the SDR and AVCC measurments, better results (higher accuracy) are higher values. Table 5, the computation time measurement, appears that the Bigradient method is faster than other methods but the proposed method (hybrid) was faster than QPSO method as indicated in green color.

As a results, the QPSO method was better than Bigradient method in the accuracy measurements (SNR, SDR, and AVCC), but the Bigradient method was better than the QPSO method in computation time measurement. Whereas the proposed method collects best accuracy properties of the QPSO method with the speed of the Bigradient method.

Table 2. SNR measurement (dB)

	QPSO	Hybrid	FastICA	BiGradient
1	0.1916	0.2013	0.2003	0.2395
2	0.2234	0.0813	0.2517	0.1413
3	0.1032	0.1032	0.1125	0.0416
4	0.1182	0.102	0.2748	0.3032

Table 3. SDR measurement (dB)

	QPSO	Hybrid	FastICA	BiGradient
1	14.0401	13.9585	13.9598	13.087
2	19.2094	18.0378	18.6442	18.6747
3	20.1899	20.1919	19.8358	20.1905
4	16.964	16.649	18.1005	17.0802

Table 4. AVCC measurement

	QPSO	Hybrid	FastICA	BiGradient
1	0.761	0.8741	0.6567	0.6532
2	12.4493	1.0372	12.6557	5.9844
3	3.011	3.0069	3.1057	0.0684
4	1.5409	0.4259	11.9029	11.2008

Table 5. Computation time (second)

	QPSO	Hybrid	FastICA	BiGradient
1	8.5599	4.497	0.3988	0.1078
2	8.545	4.3368	0.1582	0.0831
3	3.8416	1.9454	0.1603	0.0565
4	10.4473	5.4693	0.2105	0.0876

From these tables, we can clearly observe that the proposed method behave well than other methods in most cases according to all measurements. Based on SNR index and AVCC index, the proposed (hybrid) method better than the Bigradient and QPSO methods in most cases. Also, in the SDR index, the hybrid (proposed) method better than Bigradient method. Whereas, the time computation index clearly demonstrates that the hybrid method faster than QPSO method. Therefore, the hybrid method (QPSO and Bigradient) consider as a novel method of the BSS problem.

5. CONCLUSION

The ICA approaches are one of the solutions of the BSS problem. It depends on the objective function and the optimization method. One of the ICA methods is the QPSO-based ICA, which gave good accuracy results but it suffer the low speed convergence in the separation process. Another method of the ICA is Bigradient neural network method, which was faster than QPSO and FastICA methods in the separation process, but it lower accuracy than QPSO-based ICA method. In this paper, the author proposed new hybrid method collect the advantages of both QPSO and Bigradient methods. The proposed hybrid method gave good accuracy separation results, at same time it consumed low computation time under same separation conditions. All methods (proposed method and other method) evaluated under some objective measurements as SNR, SDR, AVCC, and computation time. Also, the proposed hybrid method compared with other methods as QPSO-based ICA, standard FastICA, and Bigradient neural network. All these methods operate with linear instantaneous mixture of mono-speech signals, and executes with eight signals under gaussian distribution and 8-KHz frequency.

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