International Journal of Computing and Digital Systems
2025, VOL. 17, NO. 1, 1–11

http://dx.doi.org/10.12785/ijcds/1571032872

Blind Image Separation based on Meta-heuristic Optimization Methods and Mutual Information

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, 51002, Babylon, Iraq*
[2]*Department of Cyber Security, College of Sciences, Al-Mustaqbal University, Babylon, Hillah, 51001, Iraq*
[3]*Department of Computer Science, College of Science for Women, University of Babylon, 51002, Babylon, Iraq*
[4]*Supreme Commission for Hajj and Umrah, Baghdad, Iraq*

Received 24 May 2024, Revised 15 September 2024, Accepted 19 September 2024

Abstract: There are a number of modern disciplines in digital signal processing (DSP) that deal with so-called blind images. The core of this problem is that there are two images mixed into one image, which requires separating these images and recovering the original images. There are many methods and strategies used to solve this problem. One of these solutions is unsupervised machine learning mechanisms, as in Independent Component Analysis (ICA), which uses the statistical properties of the latent images. This method is essentially dependent upon the statistical characteristics of observation signals and the non-Gaussian limitations between the mixed image conditions. For all applications, the ICA needs to be enhanced; therefore many optimization methods used for that purpose. The swarm intelligence methods are one of many techniques utilized to enhance the ICA's efficiency. For this purpose, in this paper, three swarm optimization methods used are Quantum Particle Swarm Optimization (QPSO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC). These methods implemented, on nine gray-scale images with seven nixing cases, separately. The results are been evaluated under three metrics for assessment are Structural Similarity Index Measurement, Peak Signal to Noise Ratio, and Normalized Cross Correlation. The applying of this system gave optimal results under the specified measurements.

Keywords: Blind Image Separation, BSS, ICA, Cocktail Party problem

1. INTRODUCTION

One of a signal processing mechanism is so-called a Blind Source Separation (BSS) which emerged in the late '1980s [1], [2]. The BSS represents process of separating to unknown mixed signals and recovering original signals. The latent signals are mixing in unknown method. It becomes very significant topic in several areas of signal processing, as speech processing, medical imaging, image processing, communication systems, and others [1], [3], [4]. At the 20 years ago, the BSS researches were widely concentrated on speeches and sounds signal separation. That due to the simplicity of speech signal representation and easily recovering the original signals form the observations. After the developing in the BSS algorithms, it become able to process all data types as blind images.

In general, there is a novel method of the BSS present successfully solutions of the blind image separation is called the Independent Component Analysis (ICA). This method essentially is dependent upon the statistical characteristics of an observation signals and the non-Gaussian limitations between the mixed images conditions [5], [6].

In the ICA method, there are some limitations, such as: there should be not less than one regularly distributed (Gaussian) source and a number of sensors that is higher than or equivalent to the number of sources, and other limits [1], [3], [7], [8]. For these reasons, the ICA viewed some drawbacks as an attenuation and a distortion in the recovering signals. Additionally, the fitness (objective) function and the optimization approach are the two primary components that the ICA rely on [1], [3]. In order, it very necessary to use an active either the objective function or the optimization technique for improving the performance of the ICA results.

In past years, most researches which dealing with the ICA concerned on the blind sounds and speeches signals [1], [3], [7], [9]. In the current time, the researchers goes to treat blind text and blind images [5], [10], and other types of signals according to a particular application. For all applications, the ICA needs to enhancing, therefore many optimization methods used for that purpose as neural

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

networks, genetic algorithm particle swarms, and other methods.

In this work, three meta-heuristic optimization methods used in order to enhance the ICA algorithm's performance, these methods are PSO [11], [12], [13], ABC [14], [15], and QPSO [12], [16]. These methods applied under nine separation cases, comes from fourteen images, ten gray-scale images mixed to produce seven mixture images and four-color images mixed to produce two mixture cases. The results of the separation process shows that the recovering image match or very nearby to match original images determined by a few objective and subjective metrics, as Normalized Cross-Correlation (NCC) [17], [18], Structural Similarity Index Measure (SSIM) [19], [20] and Peak Signal to Noise Ratio (PSNR) [21], [19], [22].

This section views research focuses which are the Blind Image Separation and ICA also some methods of Meta-heuristic Optimization Methods as the QPSO, PSO and ABC.

A. Blind Image Separation and ICA

The BSS is one of the many contemporary applications of Digital Signal Processing (DSP). It found for solving number of problems as a radial test in medical fields, music, sound treatments, and speeches processes. To standard BSS mechanism, there is more famous reality example called "cocktail party problem" [1], [7], [9], [23]. The cocktail party problem assumes there are number of conversations inside room and number of sensors (microphones) recording the speeches of all the conversations simultaneously, as shown in Figure 1.

Number of sensors and number of the conversations mostly equivalent, equal N. The conversations called "sources" denoted by $s = [s_1, s_2, \ldots, s_N]^T$ and each sensor receives all the signals in mixture form.

These mixed signals called "observations" represented by $x = [x_1, x_2, \ldots, x_N]^T$. Mixing system defined as in equation (1):

$$x = As \tag{1}$$

A is the $N \times N$ mixing matrix and depends on unknown coefficients called mixing matrix, mostly represent the distances between the sensors (observations) and the speakers (sources). The mixing matrix must be square invertible matrix.

As a consequence, generally, the BSS separates and recovers the mixed signals into original sources, to achieve this aim it assume there separating matrix ($W = A^{-1}$) which used in the separated process to recover the sources or independent components, $y = [y_1, y_2, \ldots, y_N]^T$. Equation (2) provides a representation of the separation process:

$$y = Wx \tag{2}$$

All methods that used to solve the BSS problem estimate the separated matrix, to achieve best approximation of the sources, based on an optimization method and an objective function used with that method.

The BSS problem can be resolved in a variety of ways: ICA has turn into surely utmost popular method applied for the BSS, Sparse Component Analysis (SCA) method, Non-negative Matrix Factorization (NMF) method [23], [24], [25]. ICA is an analytical technique that breaks out the independent components based on the statistical characteristics of the mixed sources [1], [3], [9].

$$MI(x) \approx C + \frac{1}{48} \sum_{i=1}^{m} [4k_3(x_i)^2 + k_4(x_i)^2 + 7k_4(x_i)^4 - 6k_3(x_i)^2 k_4(x_i)] \tag{3}$$

The constant C is parameter for adjusting an approximation.

The method which implemented to improve the behavior of ICA method is an optimization algorithm. The algorithmic features of the ICA method, as the convergence, stability, and the storage requirements depend on the optimization method [25], [26], [27], [28], [29].

Oldest methods of the ICA were using the neural networks as an optimization techniques. It depending on gradient idea as a fitness function for estimating the latent constructions. The nature of the gradients ideas faced from trap the local minima in the search area, and the long time in the learning and training operations. Moreover, the ICA methods depends on neural networks may uses an entropy, but it needs to the learning and training operations and also trapped in the local minima [1], [2], [23].

There is other scope of the methods to solve the BSS problem based on meta-heuristic optimization methods as a Genetic Algorithms [30], Particle Swarm Optimization [11], [12], and simulated annealing method [31]. The ICA uses some functions in the informatics theory as the Entropy, the Mutual Information, the Negentropy, and the Maximum Likelihood as a fitness (objective) function [1], [27].

B. Meta-heuristic Optimization

Techniques for finding solutions that arrange how higher-level tactics and local improvement processes interact to build a process that can break out of local optima and conduct a thorough search of the solution space. Three primary goals of meta-heuristic techniques are meant to tackle difficult issues more quickly, produce resilient algorithms, and solve problems more thoroughly [27], [32], [33]. Every meta-heuristic technique trades off local search

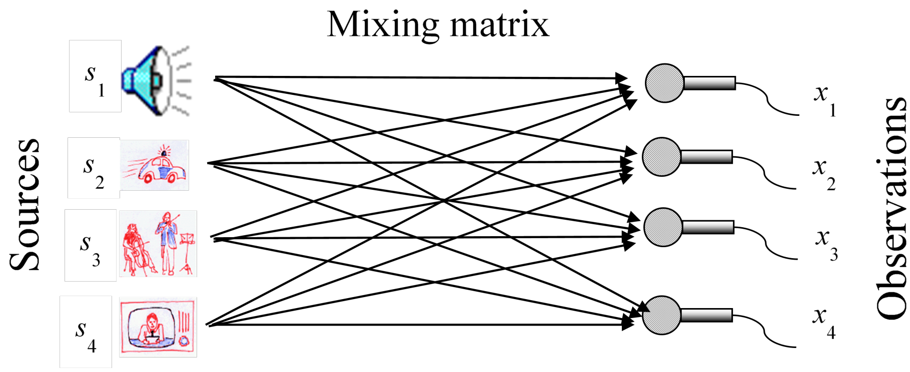

Figure 1. Cocktail Party Problem [3,7]

and randomization. Although there is no assurance that the meta-heuristic algorithms will arrive at the best answers, they are capable of locating high-quality solutions for challenging optimization issues.

Using learning algorithms for information structure, the meta-heuristic algorithms identify the optimal solution [12]. The exploration problem represents the global search in these algorithms, whereas the exploitation notion represents the local search. In addition, the BSS and ICA methods unsupervised machine learning approaches where they not require any knowledge about the output. Therefore, the meta-heuristic methods more appropriate than the neural networks which require knowledge about the output for the training operations.

1) Particle Swarm Optimization

Kennedy and Eberhart [11] introduced the PSO method in 1995. This is a search technique that relies on population search heuristics. The velocity and location are the two primary parameters for each search phrase in this approach, which is termed Particle. Each particle keeps all of its locations in its memory and searches for the best place inside the local search region known as the local best position. These placements are described as the present particle's experience inside the present dimension. The particle finds new locations in other dimensions during the search process; these new locations are referred to as new experiences, and so on. The essential task for each swarm is to detect the best position in the global space through the iteration of search operations. Among the local locations in n-spaces of the current local swarm, the final position is the best one [12]. Each swarm's location and velocity were calculated using equations (4) and (5), respectively [11].

$$v_i(t+1) = wv_i(t) + c_1r_1(t)(pbest_i(t) - x_i(t)) + c_2r_2(t)(gbest_i(t) - x_i(t)) \quad (4)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (5)$$

The v is a particle velocity P, and its position is x, For every P in the search region in n-spaces, the $pbest$ indicates the ideal local location and the $gbest$ the best global position. Moreover, the inertia weight, or w, is a convergence-related metric. In addition, there are two random parameters scaled between [0 and 1], r_1 and r_2, and the constants c_1 and c_2, which represent acceleration parameters.

2) Quantum Particle Swarm Optimization

The QPSO method is an upgraded form of the PSO optimization method introduced by Sun et. al. (2004). QPSO is not have the velocity parameter and used a little argument, and easy in an implementation [16]. It introduces a good optimizing for many issues in wide scientific and engineering areas [12]. This method can be described as:

It is assumed that, around the point p_{ij}, each particle swarm searches in the work space with a δ potential on a certain dimension. Generally, each dimension represents an individual particle. To solve the δ potential for each dimension, the Schrödinger equation can be implemented for this purpose. According to the Schrödinger, the pdf Q and the function F (distribution function) represented in the equations (6) and (7) respectively.

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

$$F(X_{ij}(t+1)) = e^{-2|p_{ij}(t) - x_{ij}(t+1)|} / L_{ij}(t) \quad (7)$$

Where $L_{ij}(t)$ represent the standard deviation and computed by Monte Carlo method, therefore using equation (8), the particle location may be calculated.

$$X_{ij}(t+1) = P_{ij} \pm \frac{L_{ij}(t)}{2} ln(1/u), \quad u = rand(0,1) \quad (8)$$

The mean optimal position m is used in the procedure to assess the $L_{ij}(t)$. that represents a global point for all particles in the population.

$$m(t) = (m_1(t), m_2(t), ..., m_n(t)) = \left(\frac{1}{M} \sum_{i=1}^{M} P_{i,1}(t), \frac{1}{M} \sum_{i=1}^{M} P_{i,2}(t), ..., \frac{1}{M} \sum_{i=1}^{M} P_{i,n}(t), \right) \quad (9)$$

The population size is shown by M, and the $pbest$ of a particle i is represented by P_i. The $L_{ij}(t)$ is given in the following equation (10):

$$L_{ij}(t) = 2\beta \times |m_j(t) - X_{ij}(t)| \quad (10)$$

Also, Equation (11) provides the particle i's location.

$$X_{ij}(t+1) = P_{ij} \pm \beta \times |m_j(t) - X_{ij}(t)| \times ln(1/u) \quad (11)$$

The parameter β denote to the contraction–expansion, is a convergence factor of the method [32].

3) Artificial Bee Colony algorithm

ABC is one of BIO type methods presented by Karaboga (2007). It mimics a bee colony's rummaging habit [14], [15]. It has been different than other bio methods where it modest than others, as the ant colony method, genetic algorithm (GA), and PSO method [15].

A food supply is seen to be a potential solution in the ABC technique, which optimizes the problem. There are two groups of the artificial bee colonies: onlooker and employed bees. In this algorithm denote to the employed bees by N_e, and N_u the onlooker bees, $N_e = N_u$.

In initial case of the ABC, let $X_i = \{X_i^1, X_i^2, X_i^3, \ldots, X_i^D\}$ denote to the i^{th} food source in the colony.

Next, the following is a representation of each food source:

$$X_i^j = X_{min}^j + rand(0,1)(X_{max}^j - X_{min}^j) \quad (12)$$

where $j \in \{1, 2, ..., D\}$ and $i \in \{1, 2, ..., SN\}$. The worker bees are apportioned at random onto different food sources in order to assess the quantity of nectar present. The amount of nectar that the food source at position i has is proportionate to the fitness value of the solution i. Bees on the job will look for potential food locations V_i close to the last one. Here is a representation of the position search equation:

$$v_i^j = X_i^j + \phi_i^j (X_i^j - X_k^j) \quad (13)$$

Since $k \in \{1, 2, ..., SN\}$, k must differ from i in this case. Through the use of a greedy selection process, V_i will replace X_i if its fitness value is equal to or greater than X_i; if not, X_i is kept.

Each spectator bee will select a food source based on the likelihood value attached to it once all employed bees have finished searching their neighborhoods. It is possible to compute the chance value p_i that an observer bee would select X_i using the following formula:

$$P_i = \frac{f(X_i)}{\sum_{m=1}^{N_e} f(X_m)} \quad (14)$$

where the fitness value of solution i is denoted by $f(X_i)$. It is obvious that the roulette detection approach is applied. The spectator bee will provide a new version based on (13), when it has chosen a food source based on the probability value p_i. If the new food source has a quantity of nectar that is better than or equal to X_i, then X_i will be updated by the new food source.

In the ABC approach, an employed bee will turn into a scout bee and start introducing a food source at random based on (12) if a position corresponding to one employed bee cannot be strengthened further during a pre-defined number of rotations. In contrast, the new food supply replaces the old one.

In summary, the ABC method comprises three stages: assigning the employed bees to the food sources and measuring their nectar yields; following the announcement of the food sources' nectar yields, observers search the area for new food sources; diagnosing the scout bees and assigning them to new food sources.

2. Related Works

There are many of papers processing the blind image separation problem with the ICA based on some optimization methods and some objective functions. In this section will view recently proposed methods in this field.

In [34], 2018, the authors presented a method to separate a blind image based on ICA using the Pyramid Technique and Ridgelet transform concepts. The method depend on regard the image as multiple components and by applying pyramid processing can obtain the components of the target image, where works throughout the different domains and then separate the image into its components. The method deployed many methods for above purpose as Discrete Wavelet Transformation, Time Domain, Discrete Sine Transformation, and Discrete Cosine Transformation, these transformations used with pyramid operations and non-pyramid operations. The authors used number of objective metrics to evaluate their work, such as SNR, RMSE, PSNR, and NCC as an evaluation measurements.

In [10], 2020, the proposed method used to remove or reduce the degradation in digital documents images as noise and blur. The authors introduced new BSS method based on

Copulas Theory to separate the front-ground / back-ground of target image. The method aims to optimize the readability of text and OCR efficiency.

In [35], 2020, the authors introduced a separation method for the blind images based on one of neural network types is Generative Adversarial Network (GAN). The GAN method is unrestricted with statistical limitations and samples. This feature make the separation process more reliability than other neural network methods. In [5], 2022, the proposed method used one of the ICA strategies is the Joint Approximate Diagonalization of Eigenmatrices (JADE) mechanism. This mechanism (JADE) analyze the observation signals to produce the eigenmatrices and find an approximate of the diagonal matrices. Both them used for recovering an original images. The method used the forth-order cumulants as an objective function.

In [36], 2022, the writers suggested a way to separate the blind images based on a hybrid PSO and firefly algorithms. The method's outcomes in comparison to other swarm optimization methods as standard PSO, ABC, and RobustICA methods. For the evaluation, the authors used number of objective measures as SNR, SSIM, and PSNR metrics.

3. Research Methodology

A. *Mixed Images Initialization*

In this stage, initialize a mixed images under a specification conditions: as grayscale images (8-bit), clean (noiseless), and with 512×512 pixels; so attain the independent, identical distribution (i.i.d.) as possible.

Some of images files downloaded from dataset of standard 512×512 grayscale test images from University of Granada – Department of computer science and artificial intelligence – computer vision group. From this dataset, we spotted different nine nature images for the mixing process, these images shown in Figure 2.

After determining the images to mixing, normalizing these images separately. Then, randomly, the images - in Figure 2 - mixed to get seven mixture cases after determine mixing matrix under well-condition. The mixing matrix created by using the formula $A = a - 2 * a * rand\ n(k, k)$ where k represent number of sources (images) and a is ending of distribution range. Generally, by experience, this formula gave mixing matrix achieve best Gaussian mixture observations under some considerations as the i.i.d. condition and kurtosis metric, where the images have sub-Gaussian statistical distribution.

Table I includes the mixed images, and the mixing matrix and its condition number for the cases studies which are seven cases. The mixing process is linear instantaneous mixing as mentioned in the mathematical model in equation (1). Also, the table showed the kurtosis (Gaussian distribution measurement) for the selected images (sources) and for the mixed cases of same images. Obviously, according to the kurtosis, the spotted images attaining an iid condition. So the estimated mixed matrix give well condition for the signal vector of the studying images which were sub gaussian distribution.

B. *Proposed System (Separation Process)*

To understand the mechanism of proposed system, there are main four stages in sequential ordering. Firstly, stage includes simulation of the mixing routine. Next stage (second) is an ICA process. The core step (third stage) in the system is selection and applying the optimization technique to improve the performance of ICA algorithm. Last stage (forth stage) include the evaluation process of the results under some metrics. Below, the detailing steps of these stages.

- First stage: mixing process simulation
  1) Initialize raw data (at least two images), under some conditions.
  2) Normalizing the images.
  3) Initializing mixing matrix that achieve the invertible matrix and conditional number.
  4) Perform the mixing process depending on the equation (1).
- Second stage: implementing the ICA method
  1) Performing main two pre-processing actions of the ICA (Centering and whitening) on received mixing images.
  2) The Mutual Information function is applied as the objective function in ICA as mentioned in equation (3). This function is used as completed factor in the separation process additionally with the optimization technique.
- Third stage: optimizing the performance of the ICA:
  1) Select one of the proposed optimization methods (PSO, QPSO, and ABC).
  2) Initialize the parameters of the selected method under assumption conditions.
  3) Set a particular objective (contrast) function. This work used the Mutual Information function as the contrast function. At same time initialize the cost value and the parameters of objective function.
  4) Determine number of the iteration for the selected optimization method, so determine the population number.
  5) In each epoch of an optimization technique, execute the centering and whitening and all equations of this method.
  6) Update the cost value and the parameters of the optimization method.
  7) Select best value of the cost function which give best results in the separation process, and set it as new cost function. Also update the

(a) #1 (b) #2 (c) #3

(d) #4 (e) #5 (f) #6

(g) #7 (h) #8 (i) #9

Figure 2. Samples of Selected Images for Mixing Process

TABLE I. Source Images Information and Mixture Matrix.

Mixed Case No.	Spotted Images Names	Kurtosis of Original Images	Kurtosis of Estimated Images	Mixing Matrix	Condition Number	Mixed Image
1	#4	2.3667	2.5255	0.4462 0.8057	1.2	
	#5	2.3618	2.7193	0.9077 -0.6469		
2	#7	3.0235	2.8844	0.3927 0.6090	1.4	
	#8	1.4434	1.9401	0.9076 -0.4403		
3	#3	3.1243	2.3184	0.7014 -0.6814	1.4	
	#1	1.9934	2.3621	0.4850 0.4914		
4	#3	3.1243	3.1626	0.4942 0.6074	1.3	
	#7	3.0235	3.1144	-0.7679 0.7573		
5	#4	2.3667	2.5972	0.4462 0.8057	1.2	
	#1	1.9934	2.1686	0.9077 -0.6469		
6	#6	3.4346	3.1782	0.3927 0.6090	1.4	
	#7	3.0235	2.6187	0.9076 -0.4403		
7	#2	2.9405	2.7193	-0.6424 0.9140	1.0	
	#9	2.6589	2.6385	0.9692 0.6620		

population range depends on new results of the objective function.

8) Repeat steps 5-6, until terminate all the iterations.
9) Normalizing (post-processing) the resulting images to be suitable to viewing.

- Fourth stage:

1) Evaluate the results of each selected optimization method by using number of standard metrics as PSNR, SSIM, and NCC.

4. Results Analysis and Discussion

All the preliminaries of the research as the raw data and the initial parameters of the proposed methods, and it's results will discussed in this section.

A. *Set the Initial Parameters*

It is very necessary and important to illustrate the initialization of all parameters in the suggested procedure. The proposed procedure uses number of raw images to simulate the cocktail party idea and separation process. Firstly, get the images from standard dataset in the University of Granada [33]. They are checked and normalized to suitable under some mixing conditions.

This work suppose there are two images mixed in an instantaneous linear manner as mentioned in equation 1.

Secondly, the parameters of metaheuristic used methods. The PSO method parameters are: population=10, alpha=0.9019, iteration number is 50, inertia weight (w) =0.8, and c1=c2=1 (acceleration constants). The QPSO method parameters are :CE (Contrast-Expansion) coefficient alpha=0.7500, population=10, iteration number = 20, phi=0.2937 (randomized), u=0.4306 (random factor for convergence), mBest=0.2162, and (r_1, r_2) randomized parameters are in slope (0-1). The ABC method parameters are: population=5, var_min=-1, and var_max=1, maximum iteration=10.

B. Evaluation Measurements

Objective metrics like SNR, PSNR, SSIM, and NCC are used in the approach that is being given. These measures are well-known for being utilized in Blind picture Separation to assess picture quality. These actions specify the following:

The formula used to create the reestablishment metric is the metric Peak Signal to Noise Ration is used in this work to assess the suggested approaches' performance. Because it used to detect and determine the noise amount carefully between two signal components [35], it is employed in this work. The mathematical formula of this metric typed below, as in equation (16)

$$PSNR = 20\ log_{10}\left(\frac{HW\ max\ X_t(i,j)^2}{\sum_{i=1}^{H}\sum_{j=1}^{W}\left(X_t(i,j) - Z_t(i,j)\right)^2}\right) \tag{15}$$

Where X_t and Z_t are represent the original images and the separated (recovered) images respectively, also H and W denote to the height and the width of an images respectively too. The dB is a unit of the PSNR. If the value of PSNR is large , this means that the distortion between the source image and separation image, small and the last closer to the first [21], [19], [35].

The other metric used in this work to evaluate an image quality is SSIM metric. This measurements depending on the computing of the standard deviation (square root of variance) as an estimate of signal components (separated images) [20]. It is an index of the quality of the separation process. The general form of this metric is :

$$SSIM(x,z) = \frac{(2\mu_x\mu_z + C_1)(2\sigma_{xz} + C_2)}{(\mu_x^2 + \mu_z^2 + C_1)(\sigma_x^2 + \sigma_z^2 + C_2)} \tag{16}$$

Where x and z are an original image and estimated image respectively. The μ is the mean and σ is the standard deviation (variance for one component and covariance for two components). C_1 and C_2 are two computed constants used for avoiding the instability if $(\mu_x^2 + \mu_z^2)$ is very close to zero [19], [20]. They could computed as $C_1 = (k_1 * L)^2$ and $C_2 = (k_2 * L)^2$, k_1 and k_2 are two constants scaled as suitability with problem nature. So, L represents the dynamic range of the pixel-value computed as ($L = 2^{bitsperpixel} - 1$) [35]. Note that the SSIM measurement applying the similarity concept, therefore it gives higher values nearby to 1 when there is high separation and the reconstruction images similar the original images, and vice versa.

To obtain more reliability, we used new metric for evaluation process is so-called Normalized Cross Correlation (NCC) [18], it is used to find the similarity between the original image and estimated image. As known as, the covariance used as a measure of the strength of the correlation between two sets of time series (or numbers). The cosine of the angle θ between two components (or two vectors) is simplest form of the NCC.

The NCC is one of those quantities with application in variety of research fields as diverse as signal processing, statistical finance, medical image,..., etc. [18], [34]. The general form of the NCC is shown in equation (18).

$$NCC = \frac{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(X * Z)}{\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}(X)^2} \qquad -1 \leq NCC \geq 1 \tag{17}$$

Where X is an original image, Z is an estimated image, $N \times M$ is size of an individual images, and i, j are the period indexes. The NCC is very useful to compare the estimation image with the source image. It is between closed period [-1,1], and if it nearby to $-/+$ zero this meaning that the estimation image more same the original image.

C. Results and Analysis of the Experiment

The work that has been introduced is implemented using MATLAB R2017b as the technical language. The computer in use also has an Intel Core i5 processor running at 2.5 GHz and 12 GB of RAM. Two methods are used to assess the outcomes of the suggested method: The first method is an subjective manner which represented the showing of the images in three views; original, mixed and separated (recovered) images, as shown and observed in Figure 2 and Table I.

Another way to evaluate the results is by using the objective measurements that uses some statistical features as mean, variance, covariance, and standard deviation. In this work, some more important and sufficient metrics in this field are used as PSNR, SSIM, and NCC. After applying this metrics, the results were very nearby to the optimality of the standard scales for each measure. Table II shows the scales of all these measurements for all the mixing states.

As observing in the above table, for each evaluation metric overall proposed methods, the metric implemented between the original and separated images. So, note that the PSNR occupies high scales, more than 8 and less than 18 for each image separately, this mean that all separated

TABLE II. Evaluation measurements used in the proposed system.

Separated Cases	Images	PSNR (dB)	SSIM	NCC
1	#5	12.7	0.85	0.004
	#8	17.5	0.91	-0.007
2	#41	11.8	0.8	0.003
	#45	9.15	0.78	-0.003
3	#4	11.14	0.9	0.004
	#1	9.15	0.8	0.003
4	#4	14.5	0.9	-1.50E-04
	#41	11.79	0.8	-7.32E-05
5	#5	14.75	0.85	-8.41E-05
	#1	11.09	0.81	-2.25E-04
6	#30	16.03	0.88	0.003
	#41	11.7	0.8	-9.20E-04
7	#2	11.37	0.82	-6.63E-04
	#48	8.62	0.76	-2.07E-05

images are more similarity to the original images and they are suffer lowest from distortions.

As well as, in the SSIM metric and based on the standardized of it, all the results were very nearby to 1, this meaning that the separation process progress according to it planning and the proposed optimization methods enhance the performance of the ICA approach.

Another evaluation metric used in this work is the Normalized Cross Coefficient (NCC). The key function of this measurement is find the similarity between two images, and it scaled between -1 to 1, where the higher similarity nearby to 0, also this very observe in above table. The scales of NCC are very near to 0, this refer to high similarity between the images in each separation process. That led to tell us, the results of the proposed system are as required and the estimation of all mixed images gave excellent results. All this description appear clearly in Figure 3.

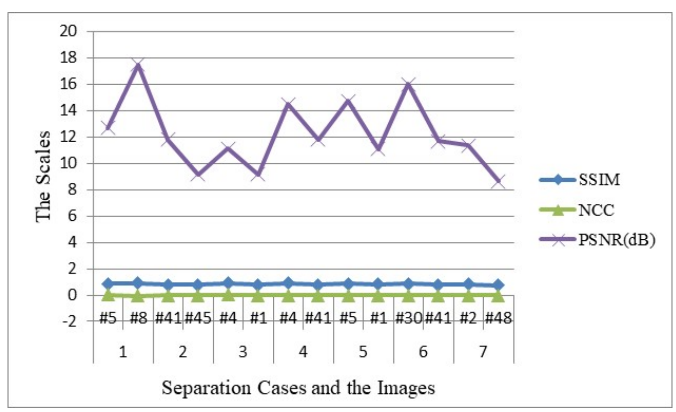

Figure 3. Evaluation measurements used in the Proposed System

The limitations of the proposed method: - The work implemented the grayscale images only, of course , can extend the study to comprehend other formats of images. - The proposed method assume the mixing method is an instantaneous mixing manner. - The proposed method uses the linear ICA, it can use non-linear ICA under some considerations.

5. Conclusions

There are many problems in the DSP represented in the BSS problem. One of these problems is a mixture images as in the medical images. To solve these problems, there are many methods as ICA and its versions. To optimize these methods, the scientists used many methods as neural networks, genetic algorithms and swarm optimization. In this paper, three intelligence swarm optimization proposed to enhance the ICA's efficiency. These methods are Particle Swarm Optimization, Quantum Particle Swarm Optimization, and Artificial Bee Colony Algorithm. Cocktail Party problem used as a standard problem state with images mixtures where simulate seven mixture cases from nine grayscale images getting from different websites. The simulation process applied under standard conditions and then to manipulate the ICA algorithm applying the proposed optimization methods. After then evaluate the results by using three metrics, PSNR, SSIM, and NCC. Evaluation results of the estimation (covered) images were very optimal and very nearby to source images before the mixing process.

References

[1] A. Hyvärinen, "Independent component analysis: recent advances," *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 371, no. 1984, p. 20110534, 2013.

[2] A. Hyvärinen and E. Oja, "Independent component analysis: algorithms and applications," *Neural networks*, vol. 13, no. 4-5, pp. 411–430, 2000.

[3] H. M. Salman, "Mono speech signal separation using optimize independent component analysis algorithm," Ph.D. dissertation, Ph. D. dissertation, University of Babylon, Iraq, 2019.

[4] A. L. N. Al-Hajjar, "An overview of machine learning methods in enabling iomt-based epileptic seizure detection," *The Journal of Supercomputing*, vol. 79, no. 14, pp. 16 017–16 064, 2023.

[5] K. Ali, A. Nourredine, and K. Elhadi, "Blind image separation using the jade method," *Engineering Proceedings*, vol. 14, no. 1, p. 20, 2022.

[6] P. Comon, "Independent component analysis, a new concept?" *Signal processing*, vol. 36, no. 3, pp. 287–314, 1994.

[7] N. A. Abbas and H. M. Salman, "Independent component analysis based on quantum particle swarm optimization," *Egyptian Informatics Journal*, vol. 19, no. 2, pp. 101–105, 2018.

[8] A. Idrees and A. SA, "Two-level energy-efficient data reduction strategies based on sax-lzw and hierarchical clustering for minimizing the huge data conveyed on the internet of things networks," *J Supercomput*, vol. 78, no. 16, p. 17844, 2022.

[9] H. M. Salman and N. A. Abbas, "Comparative study of qpso and other methods in blind source separation," in *Journal of Physics: Conference Series*, vol. 1804, no. 1. IOP Publishing, 2021, p. 012097.

[10] A. Ourdou, A. Ghazdali, A. Metrane, and M. Hakim, "Digital document image restoration using a blind source separation method based on copulas," in *Journal of Physics: Conference Series*, vol. 1743, no. 1. IOP Publishing, 2021, p. 012034.

[11] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95-international conference on neural networks*, vol. 4. ieee, 1995, pp. 1942–1948.

[12] J. Sun, C.-H. Lai, and X.-J. Wu, *Particle swarm optimisation: classical and quantum perspectives*. Crc Press, 2016.

[13] A. Idrees, "Distributed data aggregation and selective forwarding protocol for improving lifetime of wireless sensor networks," *Journal of Engineering and Applied Sciences*, vol. 13, no. 5, pp. 4644–4653, 2018.

[14] D. Karaboga and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (abc) algorithm," *Journal of global optimization*, vol. 39, pp. 459–471, 2007.

[15] L. Chen, L. Zhang, Y. Guo, Y. Huang, J. Liang *et al.*, "Blind source separation based on covariance ratio and artificial bee colony algorithm," *Mathematical Problems in Engineering*, vol. 2014, 2014.

[16] J. Sun, B. Feng, and W. Xu, "Particle swarm optimization with particles having quantum behavior," in *Proceedings of the 2004 congress on evolutionary computation (IEEE Cat. No. 04TH8753)*, vol. 1. IEEE, 2004, pp. 325–331.

[17] K. Kondo, *Subjective quality measurement of speech: its evaluation, estimation and applications*. Springer Science & Business Media, 2012.

[18] A. Kaso, "Computation of the normalized cross-correlation by fast fourier transform," *PloS one*, vol. 13, no. 9, p. e0203434, 2018.

[19] A. Hore and D. Ziou, "Image quality metrics: Psnr vs. ssim," in *2010 20th international conference on pattern recognition*. IEEE, 2010, pp. 2366–2369.

[20] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: from error visibility to structural similarity," *IEEE transactions on image processing*, vol. 13, no. 4, pp. 600–612, 2004.

[21] S. Wolf and M. Pinson, "Reference algorithm for computing peak signal to noise ratio (psnr) of a video sequence with a constant delay," *ITU-T Contribution COM9-C6-E*, 2009.

[22] M. K. Jabar and A. K. M. Al-Qurabat, "Human activity diagnosis system based on the internet of things," in *Journal of Physics: Conference Series*, vol. 1879, no. 2. IOP Publishing, 2021, p. 022079.

[23] H. M. Salman, A. K. M. Al-Qurabat *et al.*, "Bigradient neural network-based quantum particle swarm optimization for blind source separation," *IAES International Journal of Artificial Intelligence*, vol. 10, no. 2, p. 355, 2021.

[24] Y. Deville, "Blind source separation and blind mixture identification

methods," *Wiley Encyclopedia of Electrical and Electronics Engineering*, pp. 1–33, 1999.

[25] X. Yu, D. Hu, and J. Xu, *Blind source separation: theory and applications*. John Wiley & Sons, 2013.

[26] A. Hyvarinen, "Survey of independent component analysis," *Neural Computing Surveys*, vol. 2, 1999.

[27] N. A. M. Abbas and H. M. Salman, "Enhancing linear independent component analysis: Comparison of various metaheuristic methods." *Iraqi Journal for Electrical & Electronic Engineering*, vol. 16, no. 1, 2020.

[28] H. M. Salman, "Speech signals separation using optimized independent component analysis and mutual information," *Science*, vol. 2, no. 1, pp. 1–6, 2021.

[29] H. M. Salman, A. K. M. Al-Qurabat, and A. R. Finjan, "Solve cocktail party problem based on hybrid method," *International Journal of Computing and Digital Systems*, vol. 15, no. 1, pp. 1–9, 2024.

[30] F. Rojas, C. G. Puntonet, I. Rojas, J. Ortega, and A. Prieto, "Genetic algorithm approach to nonlinear blind source separation," in *Proceedings of the 2002 Congress on Evolutionary Computation. CEC'02 (Cat. No. 02TH8600)*, vol. 2. IEEE, 2002, pp. 1098–1102.

[31] C. G. Puntonet, A. Mansour, C. Bauer, and E. Lang, "Separation of sources using simulated annealing and competitive learning," *Neurocomputing*, vol. 49, no. 1-4, pp. 39–60, 2002.

[32] E.-G. Talbi, *Metaheuristics: from design to implementation*. John Wiley & Sons, 2009.

[33] W. Fang, J. Sun, Y. Ding, X. Wu, and W. Xu, "A review of quantum-behaved particle swarm optimization," *IETE Technical Review*, vol. 27, no. 4, pp. 336–348, 2010.

[34] M. Y. Abbass and H. Kim, "Blind image separation using pyramid technique," *EURASIP Journal on Image and Video Processing*, vol. 2018, pp. 1–16, 2018.

[35] X. Sun, J. Xu, Y. Ma, T. Zhao, S. Ou, and L. Peng, "Blind image separation based on attentional generative adversarial network," *Journal of Ambient Intelligence and Humanized Computing*, vol. 13, no. 3, pp. 1397–1404, 2022.

[36] A. Khalfa, M. Sahed, E. Kenane, and N. Amardjia, "A novel blind image source separation using hybrid firefly particle swarm optimization algorithm," *Engineering, Technology & Applied Science Research*, vol. 12, no. 6, pp. 9680–9686, 2022.