A Novel Blind Image Source Separation Using Hybrid Firefly Particle Swarm Optimization Algorithm

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Abstract-Signal and image separation are extensively used in numerous imaging applications and communication systems. In this paper, a novel Blind Source Separation (BSS) approach, based on the Hybrid Firefly Particle Swarm Optimization (HFPSO), is proposed for separating mixed images. This approach processes the observed source without any prior knowledge about the model and the statistics of the source signal. The proposed method presents high robustness against local minima and converges quickly to the global minimum. Via numerical simulations, the proposed approach is tested and validated in comparison with standard Particle Swarm Optimization (PSO), Robust Independent Component Analysis (RobustICA), and Artificial Bee Colony (ABC) algorithms. The obtained results show that the presented technique outperforms the existing ones in terms of quality of image separation, the Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). Moreover, the obtained results demonstrate that our approach provides also promising results in image separation from noisy mixtures.

Keywords-blind image separation; hybrid firefly particle swarm optimization; PSNR; SSIM

I. INTRODUCTION

Blind Source Separation (BSS) is a signal processing approach that was first proposed in the late '80s [1]. The BSS refers to the separation of unknown signals that are mixed in an unknown manner. It has been an important topic in many applications of signal processing, such as medical imaging, communication systems, speech processing, image processing, etc. [2, 3]. Unlike speech signals, it is well known that images cannot easily satisfy the constraints of the BSS method. During the past three decades, most research studies on the BSS problem have been focused on speech separation. Nowadays, researchers are more interested in blind image separation due to its importance in many real-world applications.

Generally, the Independent Component Analysis (ICA) approach has been considered as a solution to many BSS problems [4]. This approach lies in the fact that the assumption of statistical independence and the non-Gaussian restraint among the sources does not hold in image mixing conditions. However, the ICA approach faces some limitations and drawbacks, i.e. it is not able to separate the signals if the number of sensors is less than the number of sources. Furthermore, the local minima problem is another limitation of the ICA method in many applications. In order to overcome the drawbacks of ICA approach, many optimization methods have been developed, based on evolutionary algorithms. These algorithms have been extensively used for tackling BSS problems [5-8]. By using Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), a blind separation method based on reducing mutual information has been introduced in [5]. Using GA, the blind separation problem is also investigated in [6] based on high order statistics of kurtosis. In the same context, a cost function based on the feature distance and kurtosis was proposed to solve BSS problems using PSO and GA [7]. Besides, the Artificial Bee Colony (ABC) algorithm was applied in [8] to solve BSS problem using a combination of many types of the cost function.

Most previous studies have discussed blind speech separation. However, in this study, a novel separation approach using a modified version of the Hybrid Firefly Particle Swarm Optimization (HFPSO) algorithm will be used to separate image mixtures. To evaluate the performance of the proposed

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hybrid method, we present a fair comparison with other works where four examples are illustrated under noisy and noiseless conditions.

II. ONE-DIMENSIONAL BLIND SIGNAL SEPARATION PROBLEM DESCRIPTION

Assume that $S_i, i = 1, 2, \dots, n$ are unknown signals that are independent and feasible. The source signals are linearly blinded with each other by the mixing matrix A as:

$$X = A.S \quad (1)$$

A linear instantaneous blind image separation algorithm is the one suggested in this paper for image separation. This indicates that the constant random coefficients are present in the mixing model. This relation in a noisy environment will be:

$$X = A.S + n \quad (2)$$

where the additive noise signal is denoted by n. The objective separation is to estimate the unmixing matrix W without any knowledge about the mixing matrix A. The unmixing matrix is used to approximate the original source signals using the following equation.

$$Y = W.X \quad (3)$$

where Y represents an estimate of source signal S. It is obvious that the estimated signals involved in Y assuming $W = A^{-1}$ are the exact same as the original sources S.

III. PREPROCESSING PROCEDURES OF THE SEPARATION PROBLEM

To prevent using a difficult optimization approach, the preprocessing phase should be completed in the first step of the separation procedure. The signals are centered and whitened during the preprocessing stage. In order to produce the observed signals with zero mean value, centering is conducted by subtracting the average values $M_i = E_i(X_i)$ from the observed signals. With a linear transmission, whitening transforms the mixed signals into white uncorrelated and with unit variance signals. The identity matrix of the whitened covariance matrix X is given by [9]:

$$E\{\tilde{X}.\tilde{X}^T\} = I \quad (4)$$

To obtain the whitened mixed signals, the Principal Component Analysis (PCA) algorithm is used. The eigenvectors of the covariance matrix of the observed signals are employed as follows:

$$\tilde{X} = UV^{-\frac{1}{2}}U^T X = UV^{-\frac{1}{2}}U^T A.S = diag\left(V_1^{-\frac{1}{2}} \dots V_m^{-\frac{1}{2}}\right) \quad (5)$$

where V is a diagonal eigenvalue matrix and U is the orthogonal eigenvector matrix. It is important to note that applying the whitening stage will result in an orthogonal new mixing matrix and a reduction in the number of parameters that must be evaluated throughout the optimization phase.

IV. OVERVIEW OF PSO AND FIREFLY ALGORITHMS

A. *Partical Swarm Optimization (PSO)*

PSO was proposed in [10]. The motions of bird and fish swarms in pursuit of food or fleeing from perceived threats served as the model's inspiration. PSO algorithm has outperformed many other search methods due to its ability to find results quickly, requiring fewer parameters, while being less likely to become trapped at local optima. PSO begins with a collection of random solutions known as particles, with a group of particles being referred to as a crowd or flock. Mathematically, initialization of the ith particle is determined by $x_i = l_b + rand(u_b - l_b)$, were l_b and u_b are the lower and upper bounds. Each particle in the solution space is first assigned a random value as part of the search process. Each particle's position will be modified at each iteration based on its best position p_1 and the best positions of the other particles in its topological neighborhood $gbest$. The velocity vector v_i^t will be added to find the new position. PSO is an iterative process, and at each iteration v_i^t and x_i are defined respectively according to the following rules:

$$v_i^t = wv_i^{t-1} + R_1C_1(pbset_i - x_i) + R_2C_2(gbest - x_i) \quad (6)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (7)$$

were w represents the inertia weight which is significant in the exploration/exploitation process, v_i^t and x_i^t indicate the velocity and the position of the *i*th particle at iteration t, $pbset_i$ and $gbest$ stand for the location of the best solution so far discovered by the *i*th particle and the best overall solution respectively. Two random numbers, R_1 and R_2, were produced from a uniformly distributed range $[0, 1]$ Since C_1 is multiplied by the distance to each particle's optimal position and C_2 is multiplied by the distance to the optimal position for all particles, C_1 and C_2 are the cognition and social learning components respectively.

B. *Firefly Algorithm (FA)*

FA was first developed in [11, 12]. FA is known as a metaheuristic optimization technique which is inspired by the natural behavior of fireflies [11-14]. The algorithm considers randomly generated solutions as fireflies, and brightness is assigned based upon their performance on the objective function. One of the rules used to construct the algorithm is that a firefly will be attracted to a brighter firefly, and if there is no brighter firefly, it will move randomly. The inverse square law is used to calculate the amount of light (I) at a given distance (r) from a light source. As a result, as distance rises, light intensity diminishes. In addition, light weakens and loses intensity as distance rises due to absorption by the air. Due to these factors, fireflies can typically be seen from only a few hundred meters away, which is a sufficient range for them to communicate. As a result, flashing light may be expressed as the objective function to be improved, which offers a new population-based optimization method [11, 12]. According to the inverse square law, a light intensity $I(r)$ at r distance from a light source I_s can be estimated by:

$$I\,(r) = \frac{I_s}{r^2} \quad (8)$$

Light is absorbed in an environment with a constant light absorption coefficient $\gamma \epsilon [0, \infty]$. As a result, one can use the following equation to build a Gaussian:

$$B\,(r) = B_0 e^{-\gamma r^2} \quad (9)$$

A firefly's attraction at a distance r is $B\,(r)$, while its attractiveness at $r = 0$ is B_0. Suppose i and j are two fireflies with positions $X_i(x_i, y_i)$ and $X_j(x_j, y_j)$ respectively. The Euclidean distance r_{ij} between two fireflies is computed by:

$$r_{ij} = \left\|X_i - X_j\right\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \quad (10)$$

The new position X_i of the less brilliant firefly i and its migration toward the more brilliant firefly j, is calculated by:

$$X_i = X_i + B_0 e^{-\gamma r_{ij}{}^2}\left(x_j - x_i\right) + \alpha\epsilon_i \quad (11)$$

where ϵ_i is a vector of random variables drawn from the Gaussian distribution and $\alpha \in [0, 1]$ is a randomization parameter [15, 16].

$$w = w_i - \left(\frac{w_i - w_f}{iteration_{max}}\right) \times iteration \quad (12)$$

$$f(i,t) = \begin{Bmatrix} \text{true, if } fiteness(particle_i^t \leq gbest^{t-1} \\ \text{true, if } fiteness(particle_i^t > gbest^{t-1} \end{Bmatrix} \quad (13)$$

$$V_i(t+1) = X_i(t+1) - X_{i\_temp} \quad (14)$$

where:

$$X_i(t+1) = X_i(t) + B_0 e^{-\gamma r_{ij}{}^2}(X_i(t)\text{-}gbest^{t-1}) + \alpha\epsilon_i,$$

w is the inertia weight, w_i and w_f are the initial and final values of the linear decreasing inertia weight respectively.

V. THE PROPOSED SEPARATION APPROACH

The proposed separation approach is presented in this section. The newly developed BSS system is used here in order to solve issues with multiple image source separation. Our technique is based on the HFPSO algorithm [17]. This hybridization makes allow combining the search power PSO with the optimization capabilities of FA. This approach makes use of both algorithms' characteristics and seeks to find a balance between exploration and exploitation [17]. Basically, our approach has been implemented in 4 stages (See Figure 1): In the first stage, the input image sources decomposed into 1-D signals are mixed. After that, HFPSO algorithm is used to unmix the output signals. Then, (3) is used to estimate the output signals and the estimated output signals were transformed into images. In the last stage, the effectiveness of the BSS system is assessed.

A. Hybrid Firefly and PSO (HFPSO)

PSO is typically utilized in the global search in the proposed hybrid combination of two algorithms because it offers quick convergence in exploration. Furthermore, FA is frequently employed in local search since it offers exploitation fine-tuning. Studies on inertia weight that are dynamically modified and take improvements over prior personal bests have been successful [16]. The main objective of HFPSO is to benefit from the advantages of FA and PSO algorithms [17]. Exploration will benefit from the PSO algorithm, and the FA will look after local search. The inertia weight will be dynamically updated. The initialization of all the parameters is the first step in the HFSPO algorithm. Particle locations and velocities are initialized to random values in the predetermined ranges. Fitness, global best ($gbest$), and individual best ($pbest_i$) will then be computed. The particle's fitness in the current stage and in the previous iteration will be compared according to (13). The FA will assume control and local search will begin if the particle fitness value is the same or improved; otherwise, the PSO algorithm proceeds in accordance with (6). If the FA algorithm is in use, then (11) and (14) will be used to determine position and the velocity. The ranges of position and velocity for each firefly and each particle are checked in the following step. The process will be stopped if the maximum number of iterations is reached and the output will be $gbest$ and its fitness value.

B. Evaluation of the Objective Function

The fitness function suggested in this paper is based upon mutual information and kurtosis. Kurtosis is a crucial component of BSS. It is used here to sort the independent components and to measure the non-Gaussianity of signals. The degree of dependence between the components is measured with mutual information. The later must be kept to a minimum in order to have independent components. The definition of the mutual information is:

$$I(y_1, y_2, \dots, y_n) = \sum_{i=1}^{n} H(y_i) - H(Y) \quad (15)$$

where$H(y_i) = -E \cdot log(p_{Yi}(y_i))$ and $H(Y) = -E \cdot log(p_Y(y))$ are the entropies of the estimated original signals, E denotes the expectation operator, and $p_Y(y)$ the density of the kurtosis y. By using the following formula, the kurtosis of the estimated original signals can be calculated:

$$Kurt(y) = \sum_{i=1}^{n} |E(y_i^4) - 3E^2(y_i^2)| \quad (16)$$

The fitness function can be expressed by:

$$J = I(y_1, y_2, \dots, y_n) + Kurt(y) \quad (17)$$

When the fitness function J is maximized, the estimated signals are mutually independent.

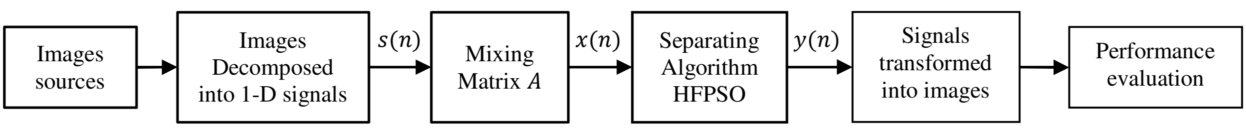

Fig. 1. Diagram of the proposed method.

C. BSS using HFPSO Algorithm

In this part, the HFPSO algorithm will be used to determine the coefficient for the separating matrix W. By maximizing the objective function given in (17), the optimization technique seeks to identify the coefficients that will result in estimated signals that are independent. The dimension D of the optimization procedure is the same as the number of coefficients in the separation matrix. The iterative process of Figure 2 can be used to implement the HFPSO-based BSS algorithm.

01: Initialize $t = 0$;
02: A random initial set of parameters is used to construct an initial population of size using the parameters $\{W_{i=1}^{pop}\}$ and $\{v_{i=1}^{pop}\}$;
03: Each fitness particle, $\{W_{i=1}^{pop}\}$ evaluated using (17);
04: if fitness$\{W_{i=1}^{pop}\} > pbest_i$ according to (13) then
05: $\quad W_{i\_temp} = W_i$;
06: $\quad W_i = W_i + B_0 e^{-\gamma r_{ij}^2}(W_j - W_i) + \alpha\epsilon_i$;
07: $\quad V_i(t+1) = W_i(t+1) - W_{i\_temp}$
08: else
09: Update w using (12);
10: $v_i^t = wv_i^{t-1} + R_1C_1(pbset_i - W_i) + R_2C_2(gbest - W_i)$;
11: $W_i = W_i + v_i^t$;
12: $t = t + 1$;
13: Repeat steps 2 until convergence is reached;
14: Output the panicle W with the best fitness value and compute the separated signals $y = W.X$.
15: Separated signals transformed into images.

Fig. 2. Pseudocode of the HFPSO BSS algorithm.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

In this section, some computer simulations were carried out in order to assess the effectiveness and compare the performance of the proposed approach against PSO, ABC, and RobustICA [18]. In all the conducted experiments, four benchmark images ("Ily", "Parrot", "Barbara" and "Einstein") were used. During initialization, the sensors and sources are set to 2 elements each. The 2×2 mixing matrix A is randomly chosen as follows:

$$A = \begin{bmatrix} 0.6 & -0.4 \\ -0.4 & 0.6 \end{bmatrix}$$

A. Parameters Settings

The different parameter initialization values for the proposed HFPSO approach are: The population pop size is fixed to 50, the problem has a dimension of 4 ($D = 4$), minimum velocity $v_{min} = -v_{max}$, maximum velocity $v_{max} = 0.1$, search range $(x_{max} - x_{\min})$, inertia weight $w_i = 0.9$, and $w_f = 0.5$, $C_1 = 1.49$, $C_2 = 1.495$, $\beta_0 = 0$, $\gamma = 1$, and $\alpha_0 = 0.5$.

B. Performance Evaluation

In this paper, two performance indices have been used to assess the effectiveness of the propped method, the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index Measure (SSIM). The PSNR is defined by [19]:

$$\text{PNSR}(f,g) = 10log_{10}\left(\frac{255^2}{\text{MSE}(f,g)}\right) \quad (18)$$

where MSE is the mean squared error which is calculated by

$$\text{MSE}(f,g) = \frac{1}{M\times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(f_{ij} - g_{ij})^2 \quad (19)$$

where f is the original image, g is the reconstructed image and the size of the images is $M \times N$.

The SSIM index is defined as [20, 21]:

$$\text{SSIM}(f,g) = \frac{(2\mu_i\mu_{rec}+c_1)(2\sigma_{i,rec}+c_2)}{(\mu_i^2+\mu_{rec}^2+c_1)(\sigma_i^2+\sigma_{rec}^2+c_1)} \quad (20)$$

where rec and i for the reconstructed and original images, respectively, and σ_{rec} and σ_i are the mean standard deviations of the original and reconstructed images. The positive constants c_1 and c_2 are used to avoid a null denominator. We choose specifically in this paper $c_1 = (K_1L)^2$ and $c_2 = (K_2L)^2$, where $K_1 = 0.01$, $K_2 = 0.03$ and $L = 255$.

In order to assess the performance of the proposed approach, three different simulations were conducted. The obtained results are presented in Figures 3 and 4 for the noise-free case and in Figure 5 for the noisy case. For noisy mixtures, we assumed that the mixed images are corrupted by an additive white Gaussian noise with SNR equal to 5dB. We list in the upper-left part of each Figure the used grayscale benchmark images ("Bear Lake Lighthouse" and "Henry David Thoreau" images for Figure 3, "Charlie Chaplin" and "Albert Einstein" images for Figures 4 and 5). These test images were marked as Public Domain or CC0 and are free to use [22]. The sizes of all test images are 256×256. The mixtures of each pair of images appear always in the upper-right part of the presented Figures. As a result of the experiments, the separated images from RobustICA, PSO, ABC, and the proposed approach are listed in the second and third rows of these Figures. For the noise-free case, Figure 3 shows the experimental results with "Bear Lake Lighthouse" and "Henry David Thoreau" images, while the obtained results for "Charlie Chaplin" and "Albert Einstein" images are presented in Figures 4 and 5.

It is illustrated in Figures 3 and 4 and can be seen from the obtained results for the noise-free scenario, that the proposed approach performs better than RobustICA, PSO, and ABC. In fact, we can observe that the separated images using our method have a better quality compared to those separated by other methods. PSO and ABC provide acceptable results as well (see Figures 3(d), 3(e), 4(d) and 4(e)). It can be observed also that the separation quality of the RobustICA method is relatively poor. In order to evaluate quantitatively the effectiveness of the introduced approach and compare its separation performance against RobustICA, PSO, and ABC methods, the PSNR and SSIMindices were used. For instance, the numerical metrics obtained from different separation methods are reported below subfigures (c), (d), (e) and (f) of Figures 3 and 4. From this, we can observe that the visual improvements of the proposed separation method are consistent with the reported numerical results.

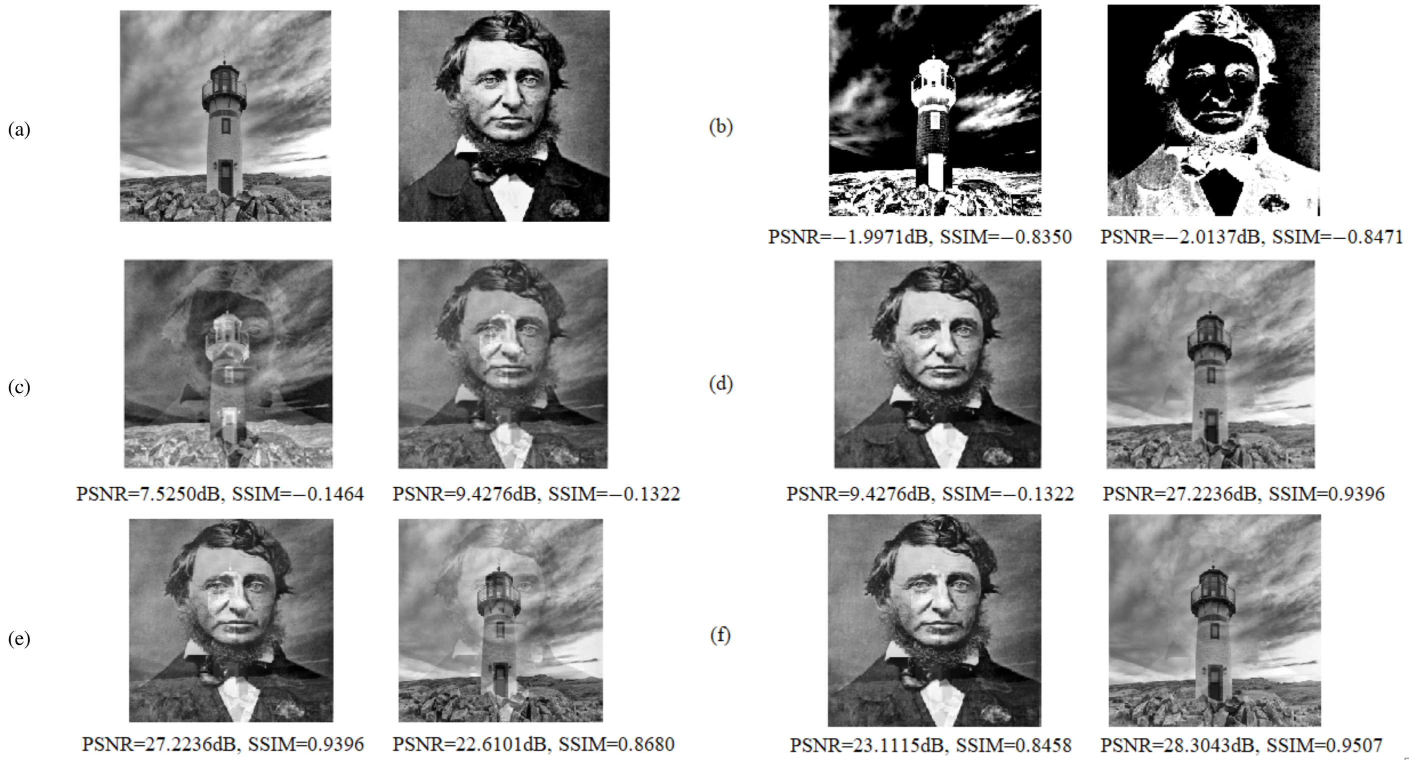

Fig. 3. Results of separating mixtures of noise-free images (a) original images. From left to right: "Bear Lake Lighthouse" and "Henry David Thoreau", (b) mixed images, (c) RobustICA, (d) PSO, (e) ABC, (f) proposed.

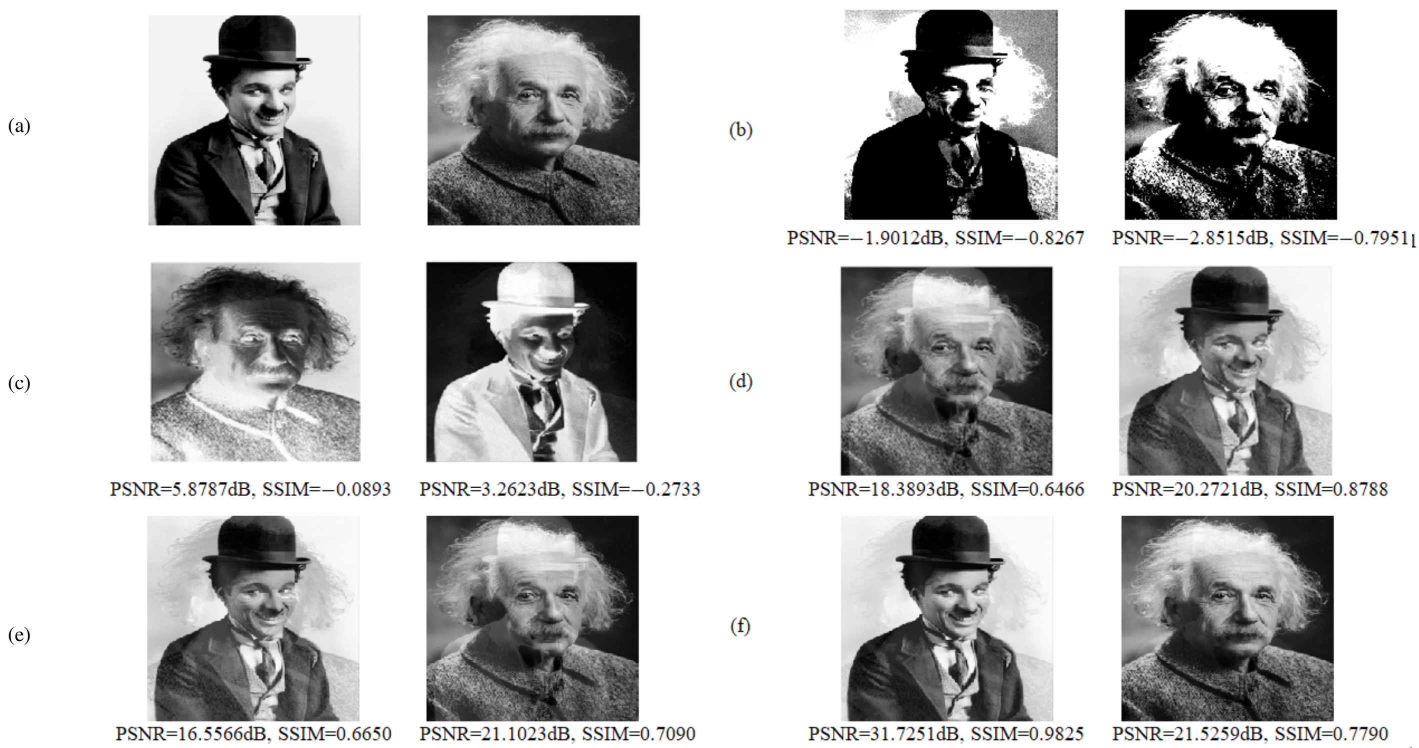

Fig. 4. Results of separating mixtures of noise-free images: (a) Original images. From left to right:"Charlie Chaplin" and "Albert Einstein",(b) mixed images (c) RobustICA, (d) PSO, (e) ABC, (f) proposed.

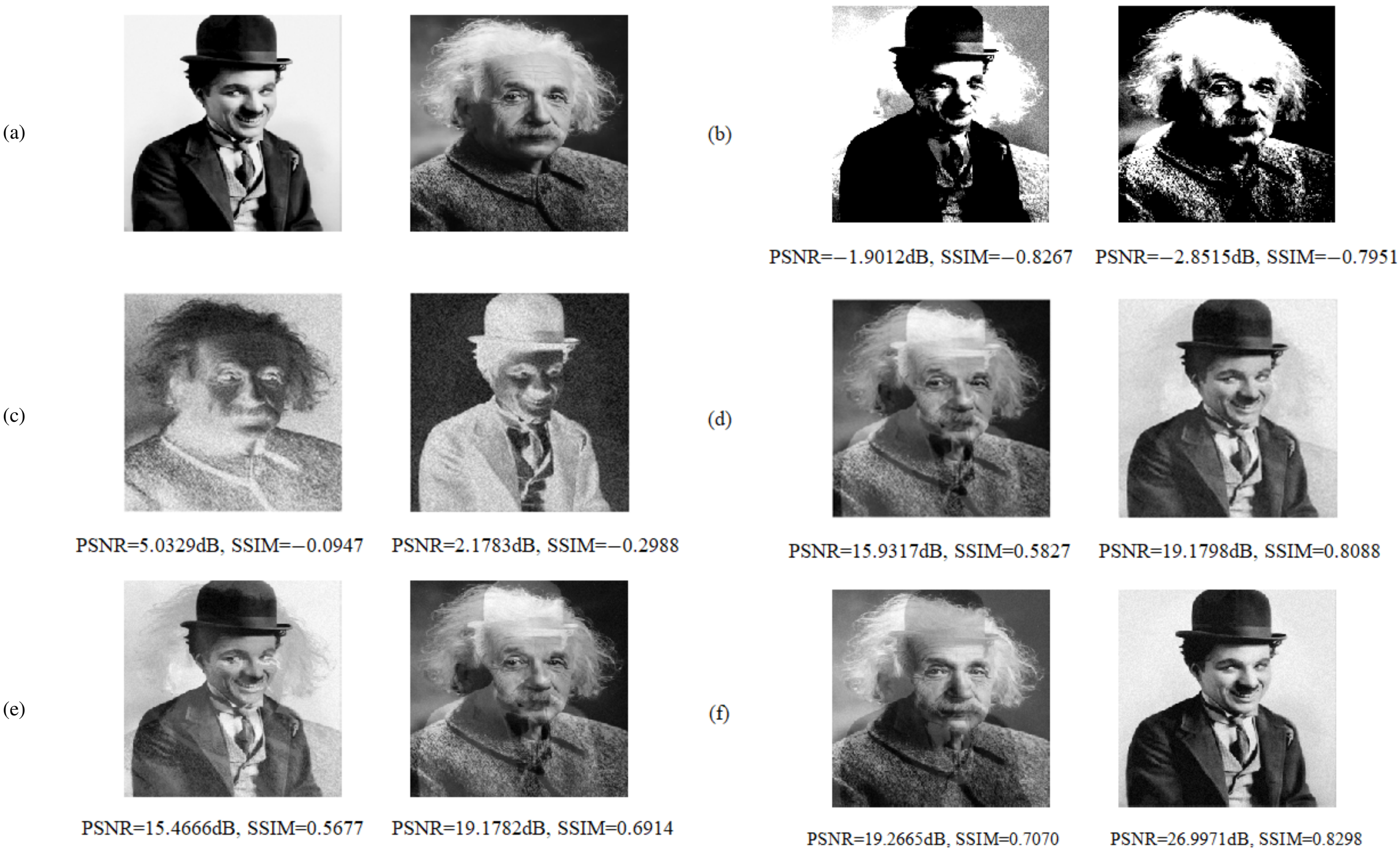

Fig. 5. Results of separating mixtures at noise level 5dB (a) Original images, (b) mixed images, (c) RobustICA, (d) PSO, (e) ABC, (f) proposed.

TABLE I. PSNR (DB) FOR THE PROPOSED APPROACH, ABC, PSO AND ROBUSTICA ALGORITHMS AT DIFFERENT NOISE LEVELS

Separation method	Proposed	ABC	PSO	RobustICA
SNR = ∞				
Charlie Chaplin	31.7251	16.5566	20.2721	3.2623
Albert Einstein	21.5259	21.1023	18.3893	5.8787
SNR = 5dB				
Charlie Chaplin	26.9971	15.4666	19.1798	2.1783
Albert Einstein	19.2665	19.1782	15.9317	5.0329
SNR = 0dB				
Charlie Chaplin	21.5486	12.5340	17.2280	2.744
Albert Einstein	14.9109	13.8784	12.7259	5.6871
SNR = -5dB				
Charlie Chaplin	17.1398	13.3876	17.0051	2.3869
Albert Einstein	11.0998	11.0006	11.0156	5.1287

Now, we will show the results of separation process at different noise levels (SNR = ∞, 5, 0, and -5 dB). According to Figure 5, for noisy images at SNR=5dB, it can be observed that our method still provides acceptable separation quality despite the presence of additive white Gaussian noise (See Figure 5(f)). However, the RobustICA is highly affected by noise and provides therefore much poorer quality than PSO and ABC. This is well illustrated in Figure 5(c)-(e). Further numerical results are summarized in Tables I and II. Here the test images are only "Charlie Chaplin" and "Albert Einstein", since the other cases give similar conclusions. For all noise levels, Table I indicates that the PSNR of the resulting images by the proposed method is the best. In addition, as illustrated in Table II, our approach achieves also the highest SSIM results for the considered noise levels. In summary, it can be shown that the proposed method produces higher quality and efficiency compared to the RobustICA, PSO, and ABC approaches in terms of PSNR and SSIM indices. This indicates that our approach has strong separation capability.

TABLE II. SSIM FOR THE PROPOSED APPROACH, ABC, PSO AND ROBUSTICA ALGORITHMS AT DIFFERENT NOISE LEVELS

Separation method	Proposed approach	ABC algorithm	PSO	RobustICA
SNR = ∞				
Charlie Chaplin	0.9825	0.6650	0.8788	-0.2733
Albert Einstein	0.7790	0.7090	0.6466	-0.0893
SNR = 5dB				
Charlie Chaplin	0.8298	0.5677	0.8088	-0.2988
Albert Einstein	0.7070	0.6914	0.5827	-0.0947
SNR = 0dB				
Charlie Chaplin	0.6514	0.4402	0.6276	-0.2923
Albert Einstein	0.6109	0.5502	0.4453	-0.0767
SNR = -5dB				
Charlie Chaplin	0.6084	0.5464	0.5938	-0.2994
Albert Einstein	0.3049	0.3008	0.3036	-0.0898

VII. CONCLUSION

This paper addressed the blind source separation problem by introducing a novel image separation approach based on a hybrid firefly and particle swarm optimization algorithm. The performance of the proposed approach has been assessed and tested against PSO, RobustICA, and ABC methods using different benchmark images. The simulation results demonstrate that our approach is more effective at separating noiseless source images from their observed mixture than other methods. In addition, the proposed technique still provides acceptable separation quality in noisy situation. As a future perspective, it will be good to examine multi-objective optimization for more than two sources.

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REFERENCES

[1] J. Herault, C. Jutten, and B. Ans, "Detection de grandeurs primitives dans un message composite par une architeture de calcul neuromimetique en apprentissage non supervise," in *10° Colloque sur le traitement du signal et des images*, Nice, France, Jan. 1985, pp. 1017–1022.

[2] G. D. Pelegrina, L. T. Duarte, and C. Jutten, "Blind source separation and feature extraction in concurrent control charts pattern recognition: Novel analyses and a comparison of different methods," *Computers & Industrial Engineering*, vol. 92, pp. 105–114, Feb. 2016, https://doi.org/10.1016/j.cie.2015.12.017.

[3] H. Buchner, E. Petersen, M. Eger, and P. Rostalski, "Convolutive blind source separation on surface EMG signals for respiratory diagnostics and medical ventilation control," in *2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, Orlando, FL, USA, Dec. 2016, pp. 3626–3629, https://doi.org/10.1109/EMBC.2016.7591513.

[4] F. J. Theis, "Uniqueness of complex and multidimensional independent component analysis," *Signal Processing*, vol. 84, no. 5, pp. 951–956, May 2004, https://doi.org/10.1016/j.sigpro.2004.01.008.

[5] S. Mavaddaty and A. Ebrahimzadeh, "Blind signals separation with genetic algorithm and particle swarm optimization based on mutual information," *Radioelectronics and Communications Systems*, vol. 54, no. 6, Jul. 2011, Art. no. 315, https://doi.org/10.3103/S0735272711060045.

[6] S. Mavaddaty and A. Ebrahimzadeh, "Evaluation of Performance of Genetic Algorithm for Speech Signals Separation," in *2009 International Conference on Advances in Computing, Control, and Telecommunication Technologies*, Bangalore, India, Sep. 2009, pp. 681–683, https://doi.org/10.1109/ACT.2009.173.

[7] Y. Yang, X. Wang, and D. Zhang, "Blind Source Separation Research Based on the Feature Distance Using Evolutionary Algorithms," *International Journal of Acoustics and Vibrations*, vol. 19, no. 4, pp. 276–281, Dec. 2014, https://doi.org/10.20855/ijav.2014.19.4360.

[8] L. Chen, L. Y. Zhang, and Y. J. Guo, "Blind Image Separation Method Based on Artificial Bee Colony Algorithm," *Advanced Materials Research*, vol. 468–471, pp. 583–586, 2012, https://doi.org/10.4028/www.scientific.net/AMR.468-471.583.

[9] S. Mavaddati, "Blind Voice Separation Based on Empirical Mode Decomposition and Grey Wolf Optimizer Algorithm," *Iranian Journal of Electrical and Electronic Engineering*, vol. 15, no. 3, pp. 330–342, Sep. 2019, https://doi.org/10.22068/IJEEE.15.3.330.

[10] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of ICNN'95 - International Conference on Neural Networks*, Aug. 1995, vol. 4, pp. 1942–1948, https://doi.org/10.1109/ICNN.1995.488968.

[11] X.-S. Yang, "Firefly Algorithms for Multimodal Optimization," in *Stochastic Algorithms: Foundations and Applications*, Berlin, Heidelberg, 2009, pp. 169–178, https://doi.org/10.1007/978-3-642-04944-6_14.

[12] X.-S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *International Journal of Bio-Inspired Computation*, vol. 2, no. 2, pp. 78–84, Nov. 2010, https://doi.org/10.1504/IJBIC.2010.032124.

[13] N. M. Okasha, "Reliability-Based Design Optimization of Trusses with Linked-Discrete Design Variables using the Improved Firefly Algorithm," *Engineering, Technology & Applied Science Research*, vol. 6, no. 2, pp. 964–971, Apr. 2016, https://doi.org/10.48084/etasr.675.

[14] M. F. Masouleh, M. A. A. Kazemi, M. Alborzi, and A. T. Eshlaghy, "A Genetic-Firefly Hybrid Algorithm to Find the Best Data Location in a Data Cube," *Engineering, Technology & Applied Science Research*, vol. 6, no. 5, pp. 1187–1194, Oct. 2016, https://doi.org/10.48084/etasr.702.

[15] A. Nickabadi, M. M. Ebadzadeh, and R. Safabakhsh, "A novel particle swarm optimization algorithm with adaptive inertia weight," *Applied Soft Computing*, vol. 11, no. 4, pp. 3658–3670, Jun. 2011, https://doi.org/10.1016/j.asoc.2011.01.037.

[16] M. Taherkhani and R. Safabakhsh, "A novel stability-based adaptive inertia weight for particle swarm optimization," *Applied Soft Computing*, vol. 38, pp. 281–295, Jan. 2016, https://doi.org/10.1016/j.asoc.2015.10.004.

[17] İ. B. Aydilek, "A hybrid firefly and particle swarm optimization algorithm for computationally expensive numerical problems," *Applied Soft Computing*, vol. 66, pp. 232–249, May 2018, https://doi.org/10.1016/j.asoc.2018.02.025.

[18] V. Zarzoso and P. Comon, "Robust Independent Component Analysis by Iterative Maximization of the Kurtosis Contrast With Algebraic Optimal Step Size," *IEEE Transactions on Neural Networks*, vol. 21, no. 2, pp. 248–261, Oct. 2010, https://doi.org/10.1109/TNN.2009.2035920.

[19] L. C. Chan and P. Whiteman, "Hardware-Constrained Hybrid Coding of Video Imagery," *IEEE Transactions on Aerospace and Electronic Systems*, vol. AES-19, no. 1, pp. 71–84, Jan. 1983, https://doi.org/10.1109/TAES.1983.309421.

[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, Apr. 2004, https://doi.org/10.1109/TIP.2003.819861.

[21] N. Diffellah, Z. E. Baarir, F. Derraz, and A. Taleb-Ahmed, "A Global Variational Filter for Restoring Noised Images with Gamma Multiplicative Noise," *Engineering, Technology & Applied Science Research*, vol. 9, no. 3, pp. 4188–4195, Jun. 2019, https://doi.org/10.48084/etasr.2737.

[22] "Free-Images.com - Free Public Domain Images." https://free-images.com.