



A fusion approach based on black hole algorithm and particle swarm optimization for image enhancement

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Abstract

The main objective of this paper is to present a new 2-stage hybrid optimization algorithm based scheme named PSO-BHA for image enhancement. A parameterized mapping function and a novel objective function are utilized in this paper to achieve the best-enhanced images. The suggested scheme combines the merits of particle swarm optimization (PSO) with the black hole algorithm (BHA) in two sequential stages to find the best parameters for the mapping function with the aid of the proposed objective function. The objective function uses contrast, edge, entropy, and universal quality index (UQI) for measuring contrast, and different improved information in the enhanced image. In the proposed scheme, PSO is applied first to adjust the tunable parameters of the mapping function and as a result, new pixel intensities are produced. Then, in the second stage, the obtained pixel intensities are again passed through the mapping function whose parameters are tuned by the use of the BHA. The suggested framework overcomes the limitations of the traditional histogram equalization (HE) based enhancement techniques in which excessive contrast enhancement and image information loss can occur. The suggested method is evaluated on several test images and compared with different state-of-the-art methods. The results indicate that the proposed framework provides superior performance to all existing methods in terms of various metrics. The proposed scheme also contributes to substantial feature enhancement and contrast boosting in the enhanced image, while retaining the natural feel of the original image.

Keywords Contrast enhancement · Particle swarm optimization · Black hole algorithm · Histogram equalization · Evolutionary algorithm

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1 Introduction

Image enhancement plays a significant role in many real-world applications such as medical image processing [30], satellite image analysis [6], remote sensing [40], and video processing [28]. The principal objective of image enhancement is to improve the features, contrast, and visual perception of the images as several ill factors such as noise, aperture size, and shutter speed during the image acquisition process adversely affect image quality. Contrast enhancement improves the visual quality of the images by expanding the intensity range of the grayscale image. Region of interest (ROI) can be easily observed in a good contrast image. The major challenge in image quality improvement is to maintain the basic features of the image and preserve its brightness while performing contrast enhancement operations [7].

The histogram equalization (HE) [22] technique is one of the most common approaches of the spatial domain for enhancing the image qualities due to its effectiveness and simpler implementation. HE utilizes the histogram of the input image and the cumulative density function (CDF) to map the gray levels of the image to new gray levels. The main problem with the traditional HE method is that it tends to change the brightness of the image, leading to undesirable visual artifacts in the enhanced image. Various extensions of HE [10, 35, 37, 63] have been suggested to overcome the HEs drawbacks, but with limited success.

In addition to these HE-based approaches, image enhancement can also be conducted by other techniques such as contrast stretching [36, 57], low-pass, high-pass filters [42], the Retinex model [4], and swift algorithm [3]. However, for a large range of low-contrast images, such techniques have often struggled to produce satisfactory results. Recently, deep learning methods [9] have been used to enhance image contrast. Although deep learning-based methods could produce promising results when considering human preference, the decomposition of the image is typically difficult to estimate and their implementation time is unsatisfactory.

It is important to highlight that contrast enhancement can not be implemented automatically without human intervention in the abovementioned methods [29]. One of the key challenges is the choice of an objective function that increases the contrast of the input image while maintaining its basic and detailed features. The second major challenge confronting most contrast enhancement techniques is the adjustment of the parameters for generating a high-quality image [7]. In this regard, nature-inspired optimization algorithms (NIOAs) have been utilized to enhance the image contrast automatically. Various optimization-based contrast enhancement methods have been proposed such as krill herd optimization algorithm (KH) [30], social spider optimization (SSO) [7], cuckoo search (CS) [29], particle swarm optimization (PSO) [24, 45], black hole algorithm (BHA) [56], genetic algorithm (GA) [49], differential evolution (DE) [19], bat algorithm [20], artificial bee colony (ABC) [11], ant colony optimization (ACO) [25], and salp swarm algorithm (SSA) [8].

Despite the rapid development of the NIOAs, their success, and widespread application, the research is still open to new designs and improvements to existing ones due to the duality between exploitation and exploration capabilities of optimization algorithms. To boost the capability of the NIOAs, hybridization between different NIOAs is one of the most common and effective strategies [21]. Several different hybrid metaheuristics have been developed for image contrast enhancement such as the hybrid of GA, ACO, and simulated annealing (SA) [27], the hybrid of DE with SA [5], the hybrid of GA with PSO [43], the hybrid of CS with PSO [58], the hybrid of PSO and artificial immune system [39], the hybrid of PSO with ABC [41], and the hybrid of KH with PSO [47].

There is no unique image enhancement technique and its measurement criterion which satisfies all the necessity and quantitatively judge given image quality [21]. Moreover, according to the No Free Lunch theorem, no optimization method can beat every other NIOAs to solve all problems. Motivated by these reasons, a new hybrid scheme based on PSO and BHA is introduced for image enhancement, as an alternative to existing approaches, aims to provide better-enhanced images.

PSO is widely used in practical applications due to its simple structure, fast convergence speed, and high efficiency. However, the PSO easily gets trapped in locally optimal solutions. To overcome this challenge and increase PSO performance, BHA is selected to combine with PSO. The primary reason for the use of BHA is that it has remarkable advantages over other NIOAs such as its ability to avoid local optima, rapid convergence, and its simple and parameter-free structure [55]. In various optimization concerns, BHA demonstrates superior performance, but in some datasets, it lacks exploration capabilities. BHA's hybrid with PSO is implemented to combine the strengths of two algorithms in order to provide a more powerful algorithm for image enhancement by striking a good balance between exploration and exploitation.

This paper provides insight into the development of a hybrid PSO–BHA scheme for image enhancement. The proposed approach utilizes a global/local transformation function to produce enhanced images. The transformation function includes several parameters that heavily affect its performance. The suggested scheme first uses PSO to find optimal values for the mapping function parameters with the help of a novel fitness function. Then, new pixel intensity values from the previous stage are passed through the mapping function once again (remapping), where BHA is explored to find the tunable parameter. The performance of the suggested framework is verified by 7 test images, and the experimental results are compared with HE [22], contrast-limited adaptive HE (CLAHE) [10], the adaptive double plateaus HE (ADPE) [35], piecewise affine HE (PAE or PE) [37], linear contrast stretching (LCS) [57], the simplest color balanced algorithm (SCB) [36], the screened Poisson equation (SPE) [42], tuned brightness controlled single-scale retinex (TBCSSR) [4], Swift [3], PSO [24], BHA [56], and DE-SA [5]. The outcome indicates that the proposed framework has better performance, both qualitatively and quantitatively, compared to all existing methods in term of contrast, fitness value, edge details, entropy, peak signal to noise ratio (PSNR), the universal quality index (UQI), structural similarity index (SSIM), and mean square error (MSE).

The contribution of this paper is two-fold. First, a two-stage framework based on the hybrid of two powerful NIOAs (PSO and BHA) is proposed to enhance the images' quality and contrast. The suggested approach automatically adjusts the transformation function's parameters and is suitable for both gray-scale and color images. Second, a novel fitness function is introduced which is related to contrast, edges, entropy, and UQI. It allows PSO and BHA to look for the best-enhanced image while providing a good trade-off between the feature enhancement, contrast boosting and the naturalness of the image.

The remainder of the study is structured as follows. Section 2 presents an overview of the related works. Brief overviews of the PSO and BHA are presented in Section 3. In Section 4, the proposed hybrid PSO-BHA scheme and related modules are discussed. Section 5 provides the experimental results to illustrate the efficiency of the suggested scheme as compared to other existing methods. Finally, Section 6 demonstrates the conclusion.

2 Literature review

Image enhancement techniques improve the appearance of images for better visual interpretation. They also increase the performance of subsequent tasks, such as computer vision [12, 61], image segmentation [2, 16, 31–34, 44, 50], image processing [13, 18, 38, 51, 52], and object detection and tracking [14, 15, 17, 62].

Among the various types of contrast enhancement methods, HE based algorithms have attracted the attention of many researchers. Zuiderveld [63] proposed CLAHE, as a generalization of adaptive HE (AHE), to improve low contrast images. CLAHE is one of the most well-known and powerful techniques that has been applied to a variety of image types. CLAHE emphasizes the local contrast enhancement, in which the image is divided into small regions (non-coinciding blocks), and histogram equalization is performed on each block. CLAHE avoids the problem of large peaks in the histogram by clipping a small portion of the peak and redistributing the clipped portion uniformly in the other histogram bin. However, the main drawback of CLAHE is the selection of its parameters, including clip-limit (CL), block-size, and distribution function. The quality of the enhanced image in CLAHE depends most on the CL hyperparameter. The improper selection of CL significantly reduces the quality of the image toward its degradation. Campos et al. [10] used a learning-based hyperparameter selection method for tuning the CLAHE parameters automatically.

Liang et al. [35] designed an adaptive contrast enhancement technique for infrared images using double plateaus histogram equalization (ADPE). Double-plateau HE utilizes a lower threshold value to protect and enhance the details and an upper threshold value to constrain background noise. A critical issue of double-plateau HE is how to correctly pick these upper and lower thresholds. ADPE approach calculates and updates these threshold values in real-time by searching and predicting local maximum and minimum gray intervals according to the histogram of the infrared image. Lisani et al. [37] used piecewise affine histogram equalization to enhance the contrast of images. The technique is an optimization of traditional HE, in which the cumulative histogram is segmented. Then, a piecewise linear transform of the intensity levels is performed and the segmented cumulative histogram basically changes linearly. To suppress the noise, the slope of the local affine contrast change is controlled by local information. Inappropriate adjustment of slope parameter may introduce undesirable artifacts in the output image. Yang [57] suggested a modified contrast-stretching technique (LCS) to enhance a non-uniformly illuminated image. The lower frequency and upper-frequency information are considered for intensity transformation, where lower frequency information is processed by the conventional manipulation, and the high-frequency information is overstated by the log transformation. Limare [36] introduced the simplest color balance algorithm (SCB) to correct the color contrast of the underexposed images or images taken in artificial lights. The assumption underlying this algorithm is that white should correspond to the highest Red (R), Green (G), and Blue (B) values observed in the image, and obscurity to the lowest values. The algorithm simply stretches, as much as it can, the values of the three channels R, G, and B, so that they occupy the maximal possible range [0, 255], by applying an affine transform $ax + b$ to each channel. Pixel saturation should be performed before applying the affine transformation. However, the level of pixel saturation in SCB should be set precisely in order to prevent the appearance of visual artifacts in the output image. Morel et al. [42] proposed the screened Poisson equation (SPE) based approach for eliminating the effect of non-uniform illumination and at the same time retaining the image data. The output of the algorithm is an image which is the result of applying the screened Poisson equation to each

color channel separately, followed by an SCB. Al-Ameen and Sulong [4] provided an improved version of the single-scale Retinex (SSR) algorithm named tuned brightness controlled single-scale Retinex (TBCSSR), which can be used to process the low-contrast CT images efficiently and overcome the common problems of its standard version. Al-Ameen [3] also designed a new swift algorithm to enhance the quality of the images. Initially, a non-complex logarithmic function is applied to attenuate immoderate pixel values as a preprocessing phase. In order to adjust the brightness and contrast, a new non-linear enhancement function is then applied, which is experimentally developed based on mathematical, statistical, and spatial knowledge. Finally, to rearrange the image pixels into their natural dynamic range, a regularization function is applied as a post-processing stage.

Gorai and Ghosh [24] considered image enhancement as an optimization problem and utilized PSO to solve it. A global/local transformation and objective function based on entropy and edge information are employed in methodology. The best-enhanced image is achieved according to fitness function by optimizing the parameter of transformation function with the help of PSO. In comparison to LCS, HE, and GA, PSO has shown better performance. Yaghoobi et al. [56] suggested BHA to find the optimal parameter values for the transformation function. The fitness function again is composed of entropy and edge information. BHA was selected due to its simplicity, ease of implementation, and also its invincibility against the parameter tuning issues, and showed better performance than LCS, HE, GA, and PSO. Anupriya and Akashtayal [5] combined several NIOAs into one optimization mechanism to provide a more effective search methodology for image enhancement. The comparison between the three hybrid algorithms including GA-SA, PSO-SA, and DE-SA is made based on the objective evaluation of the resultant image. It is also shown that the hybrid approach performs better than individual GA, PSO, and DE.

3 Algorithms background

This section provides background concerning the optimization algorithms.

3.1 Particle swarm optimization (PSO)

PSO [60] is one of the strong global search methods focused on swarm intelligence that is derived from the behavior of birds swarming. A single individual in PSO is called a particle and the particle combination constitutes the whole swarm. Each particle in the swarm has its velocity and position and can fly in the search space. To find an optimal solution in the swarm, the algorithm looks at each particle to determine the best one in the current swarm using a fitness function. Then, the whole swarm moves to the best global position. At each iteration, each particle changes its position according to its new velocity using the following equations:

$$v^j(t+1) = w^j x^j(t) + c_1 r_1 (x_{pbest}^j - x^j(t)) + c_2 r_2 (x_{gbest} - x^j(t)) \quad (1)$$

$$x^j(t+1) = x^j(t) + v^j(t+1) \quad (2)$$

where c_1 and c_2 are cognitive and social parameters respectively, which are usually set to 2. r_1 and r_2 are random values between 0 and 1. w^i denotes the selected weighting factor, and $x^i(t)$ and $x^i(t+1)$ represent the locations of the i th particle at iterations t and $t+1$, respectively. x_{pbest}^i and x_{gbest} are symbolized the i th particle's own best position and the best solution of the entire swarm. Figure 1 shows a general flowchart of the PSO.

Compared to other NIOAs, PSO has advantages, including simplicity in implementation, a few numbers of parameters to adjust, fast convergence, and effectiveness in finding global optima. However, it still suffers from the problem of easy-to-fall-into local convergence, which motivates us to look for a hybrid technique to further improve the PSO performance.

3.2 Black hole optimization algorithm (BHA)

The BHA [26] is a population-based search method that emulates the phenomenon of the black holes in the universe. A black hole (BH) is a region of space that hosts an extensive volume of mass. All the mass of the BH falls into its center, known as the singularity. There is a strong gravitational force around the BHs singularity, called an event horizon that prevents any nearby object from escaping [1].

A solution in the BHA is called a star, and the algorithm begins with a random generating of the stars in the search space. Then, it looks at the all-stars to find the best solution, called BH. The stars begin moving towards the BH and, consequently, BH starts to absorb them. The stars' movement is carried out through the following equation:

$$x^i(t+1) = x^i(t) + r[x_{BH} - x^i(t)] \quad (3)$$

where $x^i(t)$ and $x^i(t+1)$ represent the positions of the i th star at iterations t and $t+1$, respectively. r is a random value between 0 and 1, and x_{BH} denotes the position of the BH in search space.

In the BHA, if a star reaches a better position when it moves towards the BH, the position of the star will be chosen as BH. In other words, the BH updates its position and moves to the location of the star. Moreover, if a star crosses the event horizon of the BH during its movement, the BH swallows the star and a new star is born randomly. The star disappears

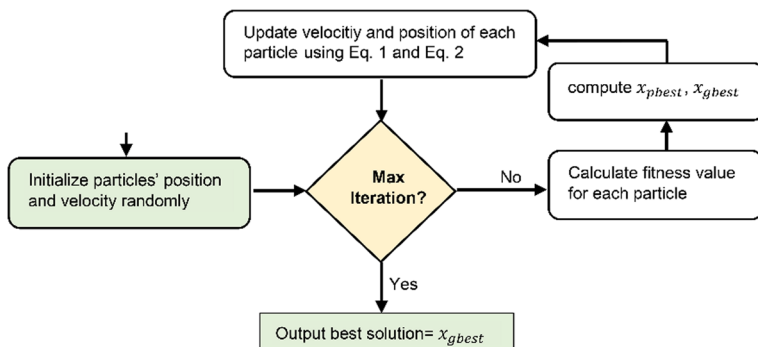


Fig. 1 A flowchart of the PSO algorithm

from the space solution when its distance from the BH is less than the event horizon radius. The event horizon radius (R) is calculated by the following equation:

$$R = \frac{f_{BH}}{\sum_{i=1}^{popsize} f_i} \quad (4)$$

where f_{BH} represents the fitness value of the BH, f_i denotes the fitness value of the i th star, and $popsize$ is the total number of stars.

The algorithm continues until a predefined number of iterations. Figure 2 displays a BHA general flowchart. It is worth noting that we slightly modified the BHA to improve its performance in this study. In the original algorithm, when a solution falls into BH and disappears, a new star is generated randomly and the algorithm goes to the position updating phase. However, in the modified version, when a new star is born in the search space, the algorithm checks its fitness value immediately. If the newborn star has a better fitness value than the BH, the algorithm replaces the BH with the new star before going to the position updating phase. For more details refer to [46].

We were inspired to use the BHA for image enhancement by its remarkable advantages over other NIOAs including its capability in escaping local optima, fast convergence, simple and parameter-free structure [55]. BHA shows superior results in different optimization problems, but it lacks exploration capabilities in some datasets. BHA's hybrid with PSO is implemented to boost the strengths of the BHA.

4 The proposed enhancement method

The main objective of this research is to utilize the proposed 2-stage hybrid NIOAs-based framework as an image enhancement system to find optimal parameter values for an intensity transformation function using a proposed fitness function. The proposed technique transforms an image into a visually pleasing one by maximizing the detailed information without incurring any visual artifact. The complete framework of the proposed method is presented in Fig. 3.

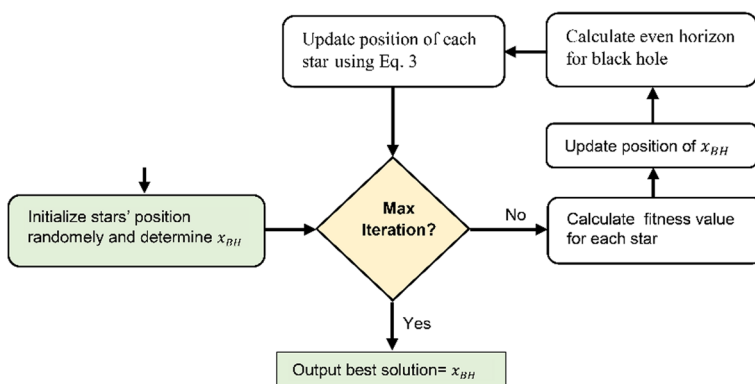


Fig. 2 A flowchart of the BHA approach

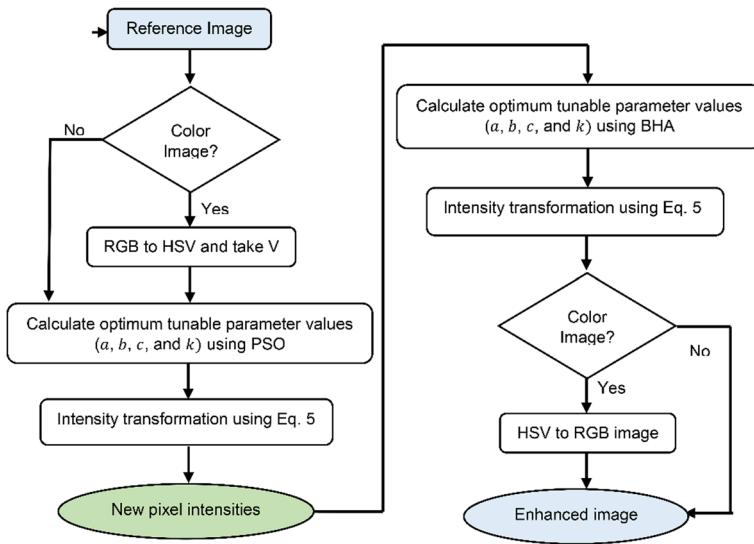


Fig. 3 Functional block diagram of the proposed technique

In this section, the proposed PSO-BHA enhancement scheme is discussed in detail. The scheme consists of three important components which are the transformation function, the fitness function, and the search process. The detail of each component is described in the following.

4.1 Transformation function

For the image quality enhancement task, a transformation function is required to produce a new intensity value for each pixel of the original image to generate an improved image. The mapping function considered in this paper employs both the local and global information of the image, and is defined as:

$$e(i, j) = \frac{k \cdot D}{(\sigma(i, j) + b)} [r(i, j) - c \times \mu(i, j)] + \mu(i, j)^a \quad (5)$$

$$D = \frac{1}{M \times N} \sum_{i=0}^{M-1} \cdot \sum_{j=0}^{n-1} r(i, j) \quad (6)$$

$$\mu(i, j) = \frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} r(i, j) \quad (7)$$

$$\sigma(i, j) = \sqrt{\frac{1}{n \times n} \sum_{i=0}^{n-1} \sum_{j=0}^{n-1} (r(i, j) - \mu(i, j))^2} \quad (8)$$

where $r(i,j)$ and $e(i,j)$ denote the intensity values of the $(i,j)^{th}$ pixels in the reference image (r) and enhanced image (e), respectively. $M \times N$ represents the size of the reference image. D , $\mu(i,j)$ and $\sigma(i,j)$ denote global mean, local mean, and local standard deviation of $(i,j)^{th}$ pixel of reference image over a $n \times n$ window, respectively [47, 59].

In the transformation function, four parameters a, b, c , and k need to be optimized. They strongly influence the performance of the transformation function in producing enhanced images. The ranges of these parameters are set to $a \in [0, 1.5]$, $b \in [0, 0.5]$, $c \in [0, 1]$ and $k \in [0.5, 1.5]$ in this study. In order to obtain an improved image with minimal computation, NIOAs can be adopted to search for the optimal values of the transformation parameters. In the following subsections, the process of setting these parameters using the PSO–BHA scheme is described.

4.2 Fitness function

In order to solve the NIOAs-based image enhancement problem, a fitness function is essential to measure the level of improvement in an image without any human intervention. A Fitness function is a mathematical expression used to evaluate the relative effectiveness of potential solutions. In optimization-based enhancement, the design of the fitness function is very critical as the desired performance depends heavily on the fitness function.

In this paper, a new fitness function is proposed to aid optimization algorithms in finding the optimum values for tunable parameters and thus providing better-enhanced images. Four objective parameters, including contrast (C), entropy (H), edge information (E), and UQI , are involved in the proposed fitness function (F). The fitness function for the given problem is defined as

$$F(e) = 0.5 \times UQI(e) \times (E(e) + H(I_e)) \times C(e) \quad (9)$$

where r and e denote reference (original) image and enhanced image, respectively.

The gray level co-occurrence matrix (GLCM) is one of the statistical approaches which is used for texture analysis in order to identify regions of interest in an image [30]. The GLCM is generated in the horizontal and vertical directions and $(i,j)^{th}$ entry of this matrix is expressed as:

$$G(i,j) = \sum_{i=0}^{X-1} \sum_{j=0}^{Y-1} \partial(x,y) \partial(x,y) = \begin{cases} 1, & \text{if } e(x,y) = i \text{ and } e(x,y+1) = j \\ & \text{and } e(x,y) = i \text{ and } e(x+1,y) = j \\ 0, & \text{otherwise} \end{cases} \quad (10)$$

where (x,y) represents the pixel coordinate in enhanced image e . The Contrast property can be derived from GLCM using the following equation:

$$C = \sum_{i,j} |i-j|^2 \times \frac{G(i,j)}{\sum_{i=0}^{X-1} \sum_{j=0}^{Y-1} G(i,j)} \quad (11)$$

In Eq. 9, $E(e)$ denotes the number of edge pixels in the enhanced image. This value is expected to be high in high-quality images. In this study, the Sobel edge detector was used to calculate the corner intensities. The number of the edge pixels in the obtained Sobel edge image is determined by counting the number of pixels whose intensity value is equal to one.

$$E(e) = \sum_{ij=1} (\sqrt{g_x^2 + g_y^2}) \quad (12)$$

where

$$g_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} * e, g_y = \begin{bmatrix} +1 & +2 & +1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} * e$$

The third term in the fitness function is $H(e)$ which represents the entropy of the enhanced image and define as follows:

$$H(e) = - \sum_{\forall i} p_e(i) \log_2(p_e(i)) \quad (13)$$

The UQI , the fourth term of the suggested fitness function, is used as an image quality distortion measure. It is characterized mathematically by modeling the distortion of the image relative to the reference image as a combination of three factors: correlation loss, distortion of luminance, and distortion of contrast [54]. Considering reference and enhanced images as r and e , the UQI can be calculated as a product of three components, which is formulated as

$$\begin{aligned} UQI(r, e) &= \left(\frac{\sigma_{re}}{\sigma_r \sigma_e} \right) \times \left(\frac{2\mu_r \mu_e}{(\mu_r)^2 + (\mu_e)^2} \right) \times \left(\frac{2\sigma_r \sigma_e}{\sigma_r^2 + \sigma_e^2} \right) \\ &= \frac{4\mu_r \mu_e \sigma_{re}}{(\mu_r^2 + \mu_e^2)(\sigma_r^2 + \sigma_e^2)} \end{aligned} \quad (14)$$

where

$$\begin{aligned} \mu_r &= \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} r(i, j), \mu_e = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} e(i, j) \\ \sigma_r^2 &= \frac{1}{M+N-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (r(i, j) - \mu_r)^2, \sigma_e^2 = \frac{1}{M+N-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (e(i, j) - \mu_e)^2 \\ \sigma_{re} &= \frac{1}{M+N-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (r(i, j) - \mu_r)(e(i, j) - \mu_e) \end{aligned}$$

We apply the sliding window technique across local regions to use this quality index to 2D images. Beginning from the image's top-left corner, the window $n \times n$ slides through all rows and columns until it hits the image's bottom right corner. The calculated local quality index

UQI_j is then combined to form the whole image UQI . If the total number of sliding steps is M , the overall UQI is determined using Eq. 15.

$$UQI = \frac{1}{M} \sum_{j=1}^M UQI_j \quad (15)$$

It is worth noting that the 0.5 value is used to balance the impact of UQI on the fitness function formula

4.3 Detailed steps of the proposed PSO/BHA-based scheme

The proposed scheme for image enhancement is composed of two stages: the PSO-based enhancement stage and the BHA-based enhancement stage, as depicted in Fig. 3. A step-by-step procedure of the suggested scheme is summarized as follows, pseudo-code is given in Algorithm 1.

Stage I PSO-based enhancement

Step 1 An input image r with low contrast is taken. If r is a grayscale image, it is directly used, whereas if it is a color image, HSV color space is adapted. HSV separates the information of the image into hue (H), saturation (S), and value (V) channels. V channel is considered since enhancing the V-channel does not change the original color of pixels [48]. The size of the input image is $M \times N$.

Step 2 A random set of values for 4 parameters (a, b, c, k) of the transformation function be generated, following uniform probability distribution. The parameters are under boundary constraints which were mentioned in the 4.1 section. These random values are used to initialize the particle's position in the search space.

Step 3 Each particle generates an enhanced image by putting these candidate values in the mapping function (Eq. 5). The quality of the enhanced image is evaluated by the fitness function (Eq. 9).

Step 4 According to Eqs. 1 and 2 the position and velocity of particles are updated at each iteration. The algorithm is terminated after reaching a predefined number of iterations, and the best value for a, b, c , and k is reported.

Step 5 Using the best solution, final pixel intensity values are obtained.

Stage II BHA-based enhancement

Step 1 The enhanced image obtained from the first stage is considered for processing in the second stage.

Step 2 Again, random values for parameters a, b, c , and k from uniform distribution will be generated, which are utilized to initialize the position of the stars in the population.

Step 3 Each star provides candidate parameter values for the mapping function (Eq. 5) which gives an enhanced image. To assess the quality of the enhanced image, the fitness function (Eq. 9) is used.

Step 4 The positions of the stars are updated at each iteration according to Eq. 3. Upon completing a predefined number of iterations, the algorithm is finished, and the best values for a, b, c , and k is provided.

Step 5 The final enhanced image is given using the best-reported solution.

Algorithm 1 PSO-BHA based image enhancement scheme

Stage I: PSO

```

01 Initialize the particle's position  $x_i$  ( $i = 1, 2, \dots, n$ ) and corresponding velocities randomly. The position of
    each particle has four components  $a, b, c$ , and  $k$ , which are initialized with random values within their
    range.
02 While ( $t < \text{maximum iteration}$ ) do
03   for  $i = 1$ : population size do
04     Generate enhanced image using Eq. 5 and  $x_i$ 
05     Compute the fitness value of the particle  $x_i$  using Eq. 9
06     if the fitness value of  $x_i > \text{fitness value of } x_{pbest\ i}$  then
07        $x_{pbest\ i} = x_i$ 
08     end if
09   end for
10   compute the best solution in the population as  $b$ 
11   if the fitness value of  $b > \text{fitness value of } x_{gbest}$  then
12      $x_{gbest} = b$ 
13   end if
14   for  $i = 1$ : population size do
15     Update the velocity of each particle using Eq. 1
16     Update the position of each particle using Eq. 2
17   end for
18 end while
19 Output:  $x_{gbest}$  (best values for parameters  $a, b, c$ , and  $k$ )
    Generate improved image using Eq. 5 and  $x_{gbest}$ . Then, utilize it as the input image of BHA

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Stage II: BHA

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20 Initialize the stars population  $x_i$  ( $i = 1, 2, \dots, n$ ) randomly and
21 for  $i = 1$ : population size do
22   Generate enhanced image using Eq. 5 and  $x_i$ 
23   Compute the fitness value of the star  $x_i$  using Eq. 9
24 end for
25 set the best solution in the population as the Black Hole  $x_{BH}$ 
26 While ( $t < \text{maximum iteration}$ ) do
27   for  $i = 1$ : population size do
28     Update the position of each star  $x_i$  using Eq. 3
29     Generate enhanced image using Eq. 5 and  $x_i$ 
30     Compute the fitness value of the star  $x_i$  using Eq. 9
31     if the fitness value of  $x_i > \text{fitness value of } x_{BH}$  then
32        $x_{BH} = x_i$ 
33     end if
34     Calculate the radius of the event horizon ( $R$ ) using Eq. 4
35     if  $\sqrt{(x_{BH} - x_i)^2} < R$  Then
36       Remove the star  $x_i$  and generate a new star
37       if the fitness value of new  $x_i > \text{fitness value of } x_{BH}$  then
38          $x_{BH} = x_i$ 
39       end if
40     end if
41   end for
42 end while
43 Output:  $x_{BH}$  (best values for parameters  $a, b, c$ , and  $k$ )
    Generate final enhanced image using Eq. 5 and  $x_{BH}$ 

```

5 Experimental results

Five grayscale and two color test images from the Kodak dataset [53], named “Pirate”, “Jet Plane”, “Walkbridge”, “lake”, “Woman blonde”, “Kodim21”, and “Kodim9” were used to evaluate the efficiency of the suggested framework. The proposed approach is tested against twelve well-known conventional and state-of-the-art image enhancement techniques including HE [22], CLAHE [10], ADPE [35], PAE [37], LCS [57], SCB [36], SPE [42], TBCSSR [4],

Swift [3], PSO [24], BHA [56], and DE-SA [5]. The suggested algorithm was implemented using MATLAB 2019a and all the experiments were conducted on a system having a 2.4 GHz Intel Core i5 processor with 8 GB RAM. The parameter setting for different techniques is provided in Table 1.

5.1 Quality evaluation metrics

To compare the quantitative results of state-of-the-art algorithms with the proposed scheme, eight image quality assessment (IQA) metrics are used, whose details are given in Table 2. These standard and well-known metrics for comparison purposes are contrast, fitness value, Edge details, entropy, PSNR, UQI, SSIM, and MSE, which provide support to qualitative analysis. A higher value of entropy, PNSR, SSIM, and UQI implies richer details and better performance, while a lower value of MSE means the image quality is better. For more details on IQA metrics refer to [23].

Table 1 Parameter setting of different enhancement techniques

Algorithm	parameter	Assigned values
Equalize Piecewise	N	10
PSO-BHA	Number of solutions, Maximum number of iterations c1 and c2	35, 35 0.5
DE-SA	Number of solutions, Maximum number of iterations, Initial Weighting Factor (F), crossover rate (CR)	35,35 0.5,0.2
Balance Simplest saturates	Sleft, Sright	3
Swift	r	1.5
TBCSS-Retinex	beta	4

Table 2 Different IQA metrics to evaluate the efficiency of the proposed method

Parameters	Formula	Remarks
Contrast	$C = \sum_{i,j} i - j ^2 \times \frac{G(i,j)}{\sum_{i=0}^{x-1} \sum_{j=0}^{y-1} G(i,j)}$	Contrast computed by Gray-Level Co-Occurrence Matrix (GLCM)
Entropy	$H(e) = -\sum_{i=1}^N p_e(i) \log_2(p_e(i))$	Quantifies the information contained in the image.
Edges details	$E(e) = \sum_{i,j=1}^M (\sqrt{g_x^2 + g_y^2})$	Sobel edge detection is utilized to count edge pixels
MSE	$MSE(r, e) = \frac{1}{MN} \sum_{i=1}^{M-1} \sum_{j=1}^{N-1} (r(i, j) - e(i, j))^2$	r and e denote the reference and enhanced images respectively, MN is the size of the image.
SNPR	$PSNR(r, e) = 10 \log_{10} \left(\frac{(L-1)^2}{MSE(r, e)} \right)$	L is a dynamic range of pixel values (256 for 8-bit grayscale images).
SSIM	$SSIM(r, e) = \frac{(2\mu_r\mu_e + C_1)(2\sigma_{re} + C_2)}{(\mu_r^2 + \mu_e^2 + C_1)(\sigma_r^2 + \sigma_e^2 + C_2)}$	Compare the enhanced image(e) structures with the reference image (r).
UQI	$UQI(r, e) = \frac{4\mu_r\mu_e\sigma_{re}}{(\mu_r^2 + \mu_e^2)(\sigma_r^2 + \sigma_e^2)}$ where $\bullet \mu_r = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} r(i, j)$, $\mu_e = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} e(i, j)$ $\bullet \sigma_r^2 = \frac{1}{M+N-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (r(i, j) - \mu_r)^2$, $\sigma_e^2 = \frac{1}{M+N-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (e(i, j) - \mu_e)^2$ $\bullet \sigma_{re} = \frac{1}{MN-1} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} (r(i, j) - \mu_r)(e(i, j) - \mu_e)$	Measure image similarity across distortion

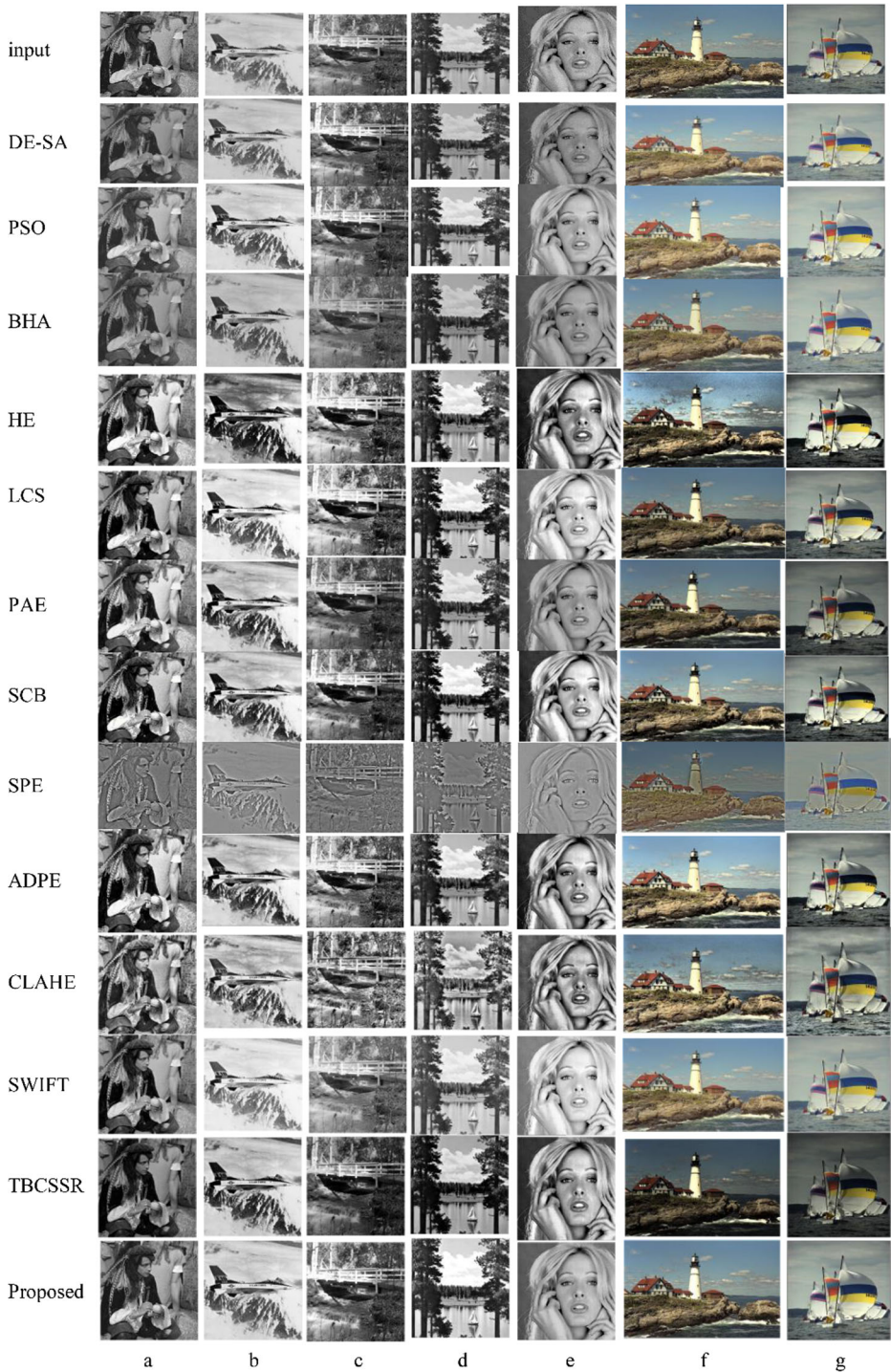


Fig. 4 Simulation result for (a) Priate, (b) Jet Plane, (c) Walkbridge, (d) lake, (e) Woman blonde, (f) Kodim21, and (g) Kodim9 images using HE [22], CLAHE [10], ADPE [35], PAE [37], LCS [57], SCB [36], SPE [42], TBCSSR [4], Swift [3], PSO [24], BHA [56], DE-SA [5], and the proposed scheme

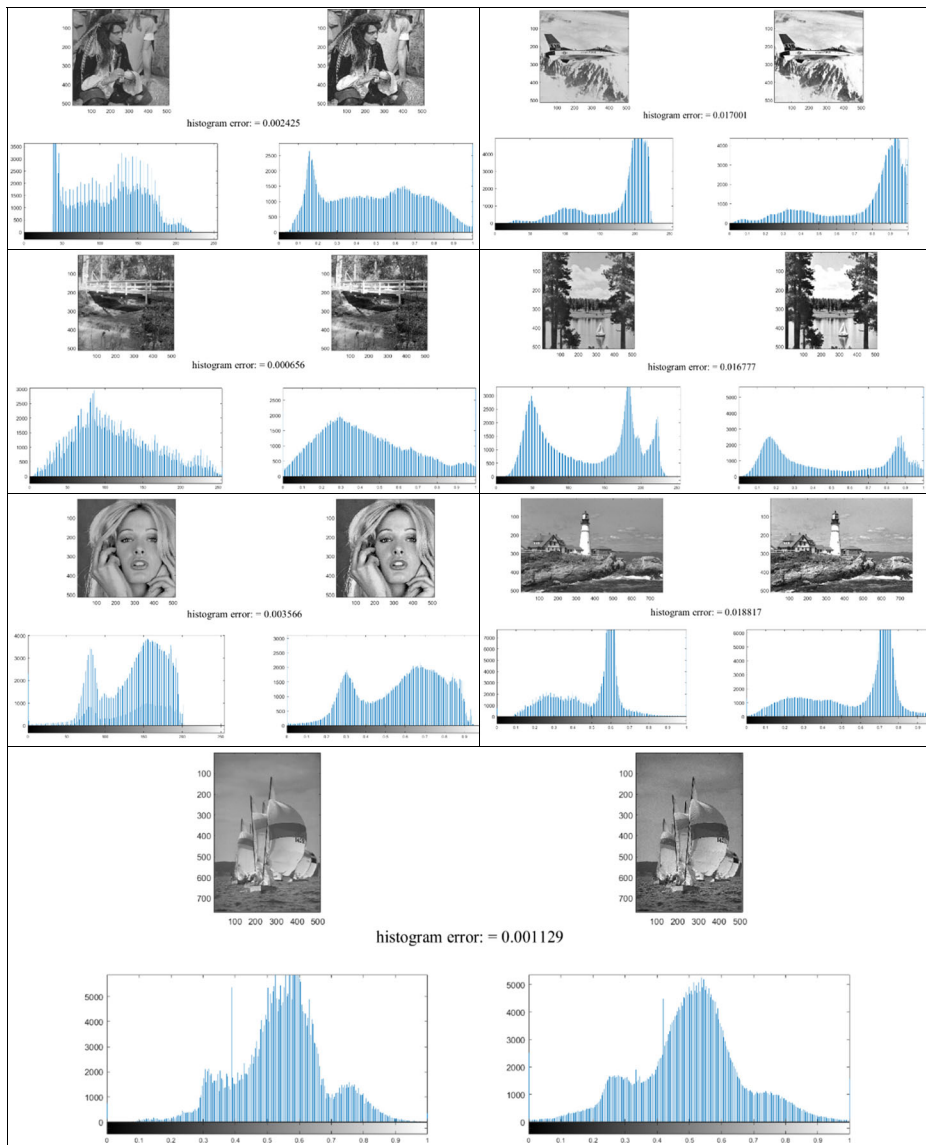


Fig. 5 Result of proposed PSO-BHA enhancement technique: (Left) histogram of original image, (right) histogram of enhanced image

5.2 Qualitative and quantitative analysis

The illustration from Fig. 4 is representing the result of the seven test images processed by different state-of-art techniques and the proposed PSO-BHA-based scheme. As can be seen from this figure, the suggested method outperforms existing image enhancement methods by obtaining the best visual image quality.

Figure 5 presents the original images (left), their corresponding histogram, and the enhanced images obtained for each test image (right) by using our proposed scheme. In Fig. 5, we can see

Table 3 Comparison of contrast for experimental images

image	original	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	0.46	0.64	0.90	0.68	0.97	0.88	0.99	0.93	0.97	1.03	1.43	0.71	0.61	1.03
Jet Plane	0.44	0.65	0.71	0.62	1.10	0.75	0.78	0.99	0.60	0.90	0.89	0.51	0.85	0.85
Walk bridge	0.87	1.55	1.18	1.07	1.65	1.05	0.99	1.20	1.48	1.40	2.87	0.85	0.95	2.02
lake	0.61	0.73	0.91	0.88	0.78	0.93	0.82	0.98	0.82	0.78	1.29	0.66	0.78	1.03
Woman blonde	0.43	0.71	0.90	0.61	1.10	0.68	0.88	1.04	0.66	1.04	1.15	0.58	0.86	1.15
Kodim21	0.65	0.68	0.87	0.89	2.03	0.78	0.83	1.18	0.80	1.38	1.68	0.59	0.69	1.45
Kodim09	0.40	0.45	0.48	0.41	1.00	0.64	0.53	0.80	0.47	0.82	1.11	0.87	0.42	0.97

The best results are highlighted in bold font

that the contrast of the input image is improved. This figure also demonstrates the distinction between the input image and the enhanced image histograms. There is a flat (ideally uniform) histogram in the high contrast image. Compared to the original image, the histogram of all the enhanced images is much flatter (denoting a more uniform distribution of the intensity).

Quantitative evaluation of the enhancement is required in addition to subjective visual quality assessment. Table 3 demonstrates the contrast values obtained from the various methods. It enables us to assess the proposed method from an objective point of view. Contrast is a co-occurrence matrix descriptor, and in enhanced images, high contrast value is a required feature. It is observed that the suggested technique meets this feature. The repeatability and reliability of the proposed algorithm can be seen in Table 4, which shows the average fitness and standard deviation (STD) values for five independent runs. The suggested algorithm yields a low standard deviation which means that our proposed method is stable.

Table 5 demonstrates an increase in edges and visual understanding of the enhanced images. The process of increasing fitness for different test images over 35 iterations has been included in Fig. 6. This figure shows the robustness of the algorithm during the set optimization cycle in increasing fitness. Entropy is also used to assess the content of the image, and a higher value provides a more comprehensive image. The entropy values for distinct techniques of all sample images are represented in Table 6. From this table, we can see that the suggested technique can improve the information in images by increasing the entropy and ranked second after CLAHE.

The other objective quantitative measurements that we used in this study are the PSNR and SSIM. The PSNR and SSIM results are presented in Tables 7 and 8, respectively. The enhancement techniques should generate higher values for PSNR and SSIM than with respect to the input image. A higher PSNR and SSIM value indicates a higher quality image. Considering these two metrics, the quality of the processed image is well enhanced with regard to the original image using the proposed framework. The measured UQI, an extremely suitable metric for evaluating the efficiency of an algorithm, is illustrated in Table 9. The UQI values show that the suggested PSO-BHA algorithm has a good upper hand over the other enhancement techniques consistent with all the test images taken into account.

The MSE in Table 10 gives so small value to the proposed PSO-BHA approach, indicating its effectiveness in optimizing the parameters used in the intensity transformation process. The repeatability of the suggested algorithm can be observed in Fig. 7. This figure shows the obtained average transformation function results for every 35 algorithm runs for each sample image. As demonstrated, in separate runs, the resulting transfer functions have almost the same shapes.

In the term of computational running time, the suggested technique required more execution time than conventional techniques, since the processing time for NIOA based techniques is expected to be high due to iterations required for global convergence. The calculation times of our trials and their respective characteristics have been reported in Table 11.

Overall, it is clear that the result of the proposed 2-stage hybrid scheme based on BHA and PSO is better since the overall performance of numerical parameters like PSNR, SSIM, UQI, entropy, and contrast produce higher values, while MSE produces lower values when

Table 4 Average fitness and STD values obtained using the proposed algorithm

image	Pirate	Jet Plane	Walk bridge	lake	Woman blonde	Kodim21	Kodim09
AVG	278.73	318.61	237.05	319.02	294.27	422.36	468.82
STD	1.26	2.22	1.54	3.65	1.00	1.49	0.93

Table 5 Comparison of edge details for experimental images

image	original	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	9511	109,218	10,772	11,161	9539	9548	9596	9569	10,014	9622	11,115	9436	9624	10,784
Jet Plane	8998	9823	9747	9677	8685	9035	9468	9243	9368	9428	9620	8627	9431	9845
Walk bridge	10,025	10,243	10,109	11,272	11,128	10,015	9948	10,013	10,590	10,534	11,636	10,315	9845	10,661
lake	10,496	11,348	11,355	11,321	9943	10,517	10,558	10,537	10,993	10,080	10,387	10,414	10,469	11,500
woman blonde	8910	10,182	10,718	10,147	8904	8975	8973	9178	9319	9022	10,013	8426	8910	11,326
Kodim21	1770	1992	1991	1990	1762	1753	1740	1840	1826	1901	1965	1780	1514	1995
Kodim09	1189	1294	1357	1320	1283	1308	1295	1400	1232	1389	1838	1137	1108	1413

The best results are highlighted in bold font

Table 6 Comparison of Entropy for experimental images

image	original	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	7.23	7.51	7.48	7.25	5.92	7.18	7.10	7.13	6.99	7.16	7.88	7.23	7.23	7.53
Jet Plane	6.71	6.80	6.70	6.81	5.71	6.65	6.62	6.46	6.42	6.57	7.54	6.63	6.27	6.83
Walk bridge	7.68	7.77	7.77	7.48	5.98	7.60	7.60	7.41	7.22	7.53	7.96	7.55	7.21	7.81
lake	7.48	7.36	7.38	7.48	5.97	7.40	7.42	7.25	6.94	7.19	7.89	7.35	6.93	7.66
woman blonde	6.95	7.12	7.23	6.94	5.95	6.92	6.88	6.69	6.41	6.88	7.81	6.94	6.72	7.58
Kodim21	6.79	6.68	6.76	6.73	5.60	6.75	6.68	6.56	6.26	6.69	7.50	6.60	6.08	6.90
Kodim09	7.10	6.88	7.06	6.90	5.96	7.00	6.97	6.78	5.81	7.00	7.54	6.87	6.50	7.42

The best results are highlighted in bold font

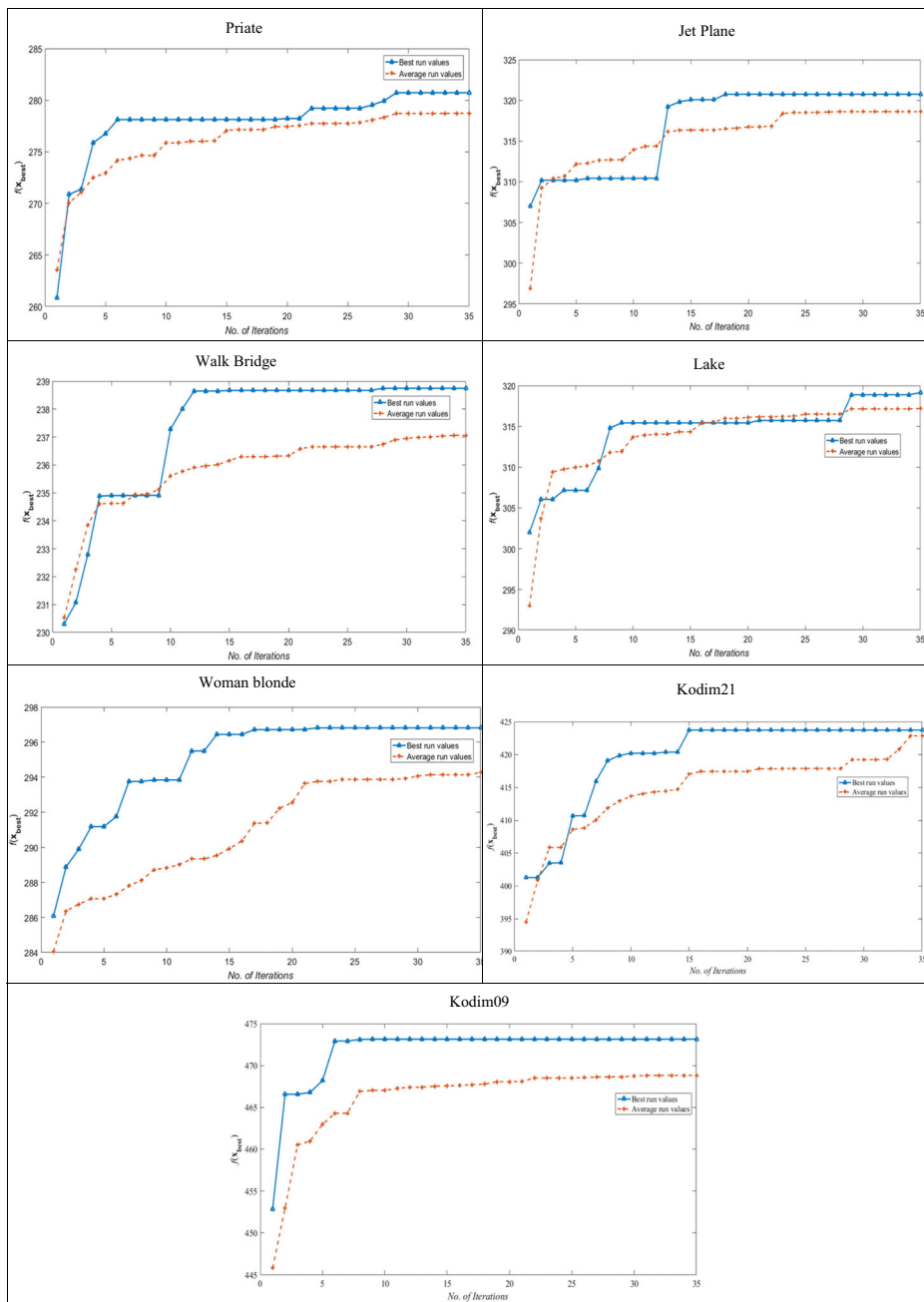


Fig. 6 Fitness evaluation of test images during the progress of the proposed scheme

compared with other techniques. This can be confirmed by observing Fig. 5, illustrating the overall performance of the enhancement techniques on each image. Figure 8 is a graphical representation of the experimental results shown in Tables 2, 5, 6, 7, 8 and 9. The proposed scheme also shows preservation of the natural feel of the original images without introducing undesired artifacts on enhanced images.

Table 7 Comparison of image quality using PSNR for experimental images. A larger value indicates a better image quality

image	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	28.30	27.26	31.00	18.06	20.77	18.61	19.79	16.70	18.44	18.22	24.09	18.13	31.25
Jet Plane	36.13	21.08	25.35	11.84	20.60	20.84	18.57	14.11	19.63	20.64	20.18	19.83	36.18
Walk bridge	25.75	30.22	25.28	19.33	28.77	24.76	24.64	15.65	22.80	15.13	21.91	17.99	32.20
lake	26.90	30.35	25.31	24.37	23.05	28.20	21.25	13.55	26.87	17.82	20.77	19.28	33.00
woman blonde	31.11	22.69	26.30	16.98	15.93	19.46	16.85	17.27	18.08	19.26	13.96	20.09	28.07
Kodim21	17.58	16.30	24.86	16.63	22.89	21.34	22.11	16.85	16.77	19.27	21.66	12.69	28.34
Kodim09	21.63	17.04	17.80	15.43	23.65	16.34	18.37	19.11	19.21	20.32	21.34	12.13	26.22

The best results are highlighted in bold font

Table 8 Comparison of image quality using SSIM for experimental images. A larger value indicates a better image quality

image	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	0.9522	0.9341	0.9393	0.8480	0.8300	0.8733	0.8041	0.8400	0.8200	0.7497	0.8949	0.8055	0.9718
Jet Plane	0.9761	0.9685	0.9736	0.5415	0.9589	0.9050	0.8863	0.9122	0.8510	0.7967	0.9878	0.8890	0.9758
Walk bridge	0.9628	0.9755	0.9606	0.8645	0.9735	0.9661	0.9306	0.8755	0.9301	0.7365	0.9706	0.8573	0.9920
lake	0.9692	0.9598	0.9371	0.8559	0.9324	0.9760	0.8780	0.8516	0.9393	0.7484	0.9652	0.8072	0.9835
woman blonde	0.9324	0.8574	0.9344	0.7400	0.9475	0.8904	0.8267	0.9110	0.8068	0.7508	0.9374	0.8681	0.9425
Kodim21	0.9457	0.9330	0.9638	0.5820	0.9572	0.9474	0.9063	0.9350	0.8730	0.7637	0.9792	0.7456	0.9718
Kodim09	0.9816	0.9469	0.9637	0.7200	0.9490	0.8963	0.8475	0.9549	0.8646	0.7650	0.9831	0.7765	0.9842

The best results are highlighted in bold font

Table 9 Comparison of image quality using UQI value for experimental images. A larger value indicates a better image quality

image	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHE	Swift	TBCSSR	Proposed method
Pirate	0.9335	0.9105	0.9129	0.8104	0.8241	0.8357	0.7836	0.7864	0.7982	0.6960	0.8914	0.8063	0.9676
Jet Plane	0.9391	0.9317	0.9509	0.4440	0.9369	0.8319	0.8309	0.8388	0.7473	0.6675	0.9862	0.8171	0.9521
Walk bridge	0.9634	0.9746	0.9574	0.8575	0.9742	0.9652	0.9291	0.8588	0.9256	0.7262	0.9692	0.8613	0.9927
lake	0.9562	0.9421	0.9139	0.8207	0.9284	0.9727	0.8691	0.8023	0.9205	0.6938	0.9612	0.8001	0.9782
woman blonde	0.9044	0.8170	0.9043	0.6948	0.9333	0.8575	0.7848	0.8534	0.7675	0.6898	0.9359	0.8359	0.9609
Kodim21	0.9246	0.9081	0.9385	0.5309	0.9578	0.9421	0.8762	0.9060	0.8100	0.6681	0.9747	0.7365	0.9579
Kodim09	0.9717	0.9030	0.9450	0.6130	0.9159	0.8743	0.7760	0.8886	0.7888	0.6301	0.9771	0.7636	0.9792

The best results are highlighted in bold font

Table 10 Comparison of image quality using MSE for experimental images. A lower value indicates a better image quality

image	PSO	BHA	DE-SA	HE	LCS	PAE	SCB	SPE	ADPE	CLAHF	Swift	TBCSSR	Proposed method
Pirate	0.0016	0.0032	0.0007	0.0156	0.0084	0.0137	0.0133	0.0213	0.0143	0.0150	0.0038	0.0153	0.0007
Jet Plane	0.0002	0.0078	0.0029	0.0654	0.0087	0.0082	0.0139	0.0387	0.0109	0.0086	0.0095	0.0103	0.0012
Walk bridge	0.0029	0.0007	0.0030	0.0110	0.0013	0.0033	0.0034	0.0270	0.0052	0.0306	0.0064	0.0158	0.0006
lake	0.0020	0.0009	0.0029	0.0036	0.0040	0.0015	0.0075	0.0441	0.0021	0.0164	0.0083	0.0117	0.0005
woman blonde	0.0007	0.0054	0.0023	0.0200	0.0250	0.0113	0.0206	0.0187	0.0150	0.0118	0.0401	0.0097	0.0003
Kodim21	0.0174	0.0234	0.0030	0.0217	0.0050	0.0073	0.0060	0.0200	0.0210	0.0118	0.0068	0.0537	0.0015
Kodim09	0.0060	0.0190	0.0160	0.0280	0.0040	0.0230	0.0140	0.0120	0.0120	0.0092	0.0073	0.0612	0.0040

The best results are highlighted in bold font

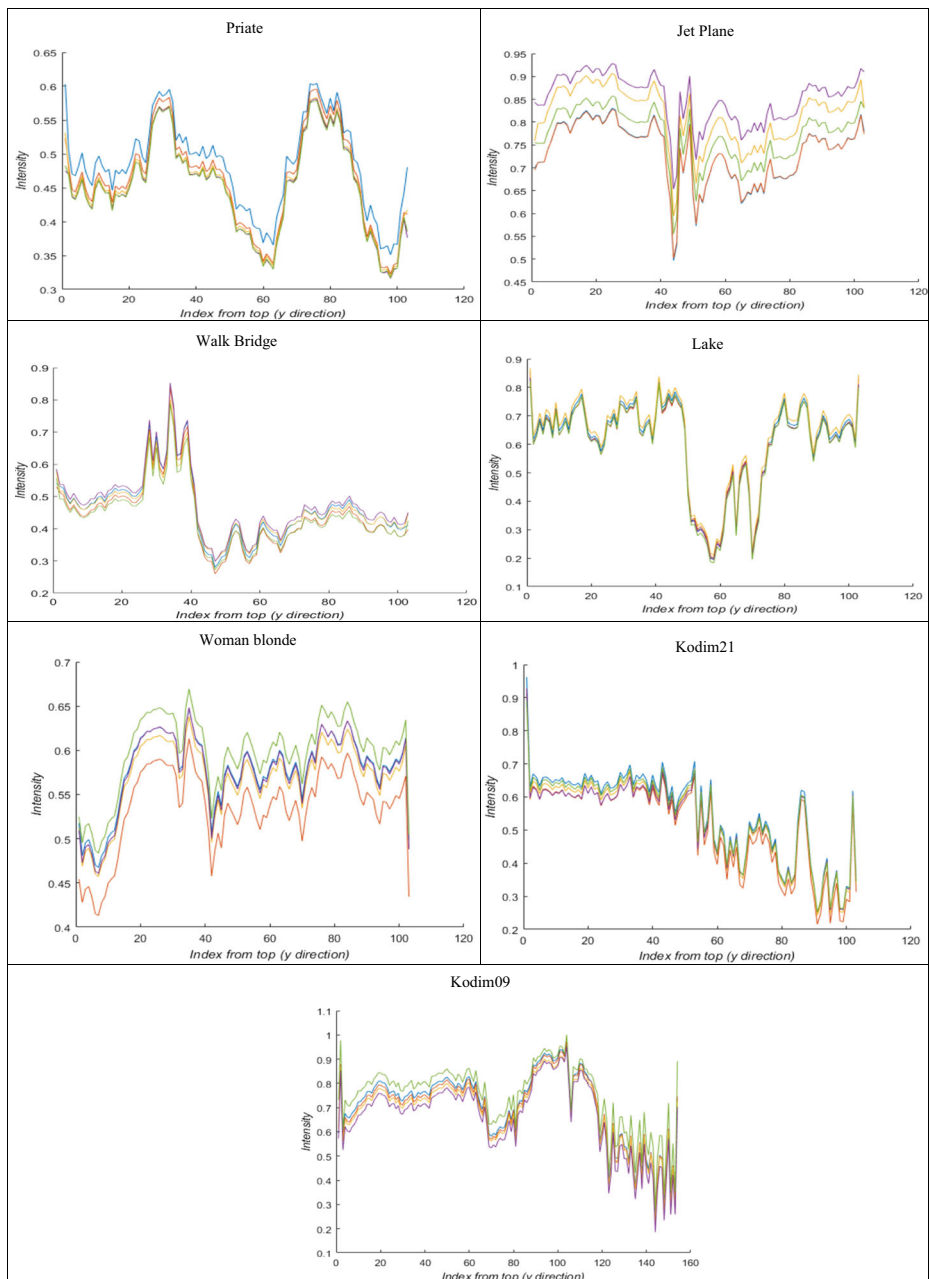


Fig. 7 Average transformed function obtained from each of the 35 times run of the suggested algorithm

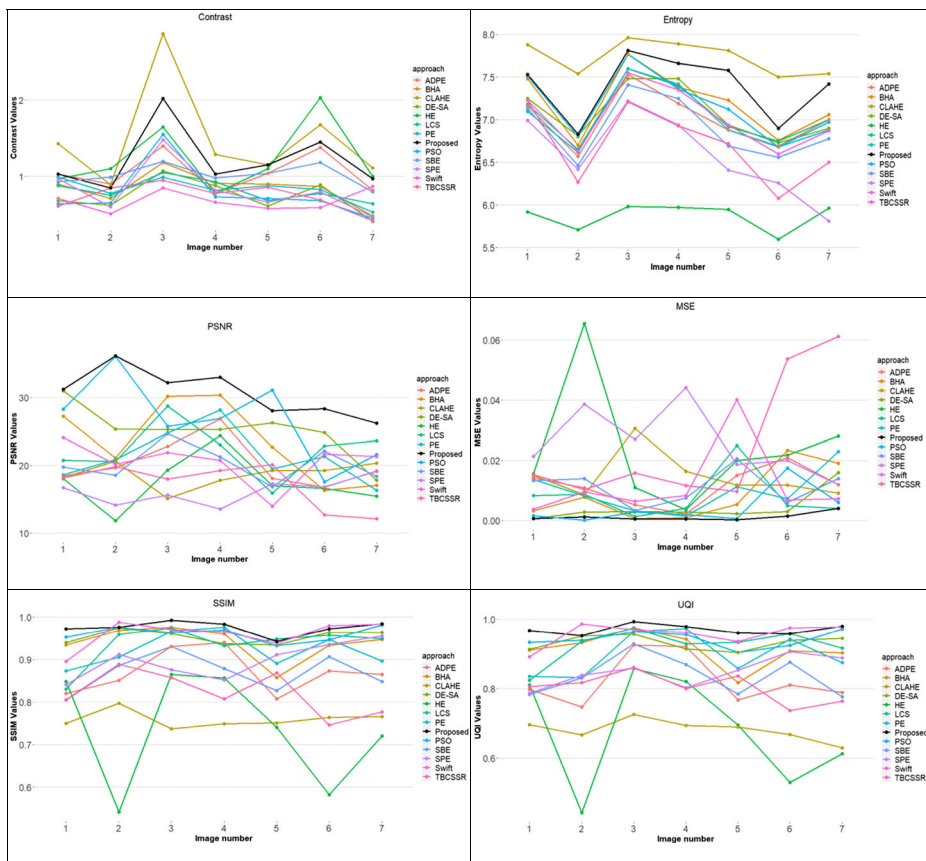
6 Conclusions

In this paper, the gray level image enhancement problem has been considered and solved through a 2-stage hybrid NIOAs-based framework. The central idea of the framework is to explore PSO and BHA in two sequential phases to adjust the parameters of a local/global

Table 11 Processing time for each resized test image (0.2)

image	Size	BHA Duration(seconds)	PSO Duration(seconds)	Hybrid PSO-BHA Duration(seconds)	Iterations
Pirate	512×512	59.84	89	140	35
Jet Plane	512×512×2	63.34	97.11	164.59	35
Walk bridge	512×512×2	62.76	98.99	153.88	35
lake	512×512×2	62.53	94.84	154.39	35
woman blonde	512×512	62.27	100.60	166.59	35
Kodim21	512×768	93.53	177.31	212.57	35
Kodim09	768×512	90.36	139.53	217.79	35

enhancement mapping function in order to improve image quality and increase contrast. In the first stage, PSO uses a new fitness function to find the optimal parameter values for the mapping function. The proposed fitness function considers contrast, edge, entropy, and UQI of the enhanced images to measure the level of improvement. The suggested fitness function provides a good trade-off between feature enhancement, contrast boosting, brightness preservation, and the naturalness of the image. Then in the second stage, those intensities from the previous stage are again passed through the mapping function, in which BHA is used to tune the mapping function's parameters. To illustrate the effectiveness of the suggested scheme, it is

**Fig. 8** Quality performance graphs for each image using different methods

compared with well-known different HE-based, NIOA-based, and standard enhancement techniques: HE, CLAHE, ADPE, PAE, PSO, BHA, DE-SA, LCS, SCB, SPE, TBCSSR, and Swift. From the analysis of the experimental results, it is concluded that the proposed optimization-based technique achieves better enhancement results as compared with all existing methods for almost all test images with respect to various image quality assessment metrics: edge details, contrast, entropy, PSNR, UQI, SSIM, and MSE.

We remark that unlike traditional HE-based approaches that suffer from the presence of excessive contrast, offset intensity artifacts, and degraded visual quality in the enhanced image, the proposed hybrid scheme provides better-enhanced images without introducing artifacts. Although the proposed scheme overcomes the drawbacks of conventional HE-based approaches, it can lead to over-enhanced images if the number of iteration in optimization algorithms are not precisely adjusted.

As future works, the first stage of the hybrid system can be replaced by different filter methods to achieve better enhancement performance. The suggested scheme's performance can also be examined on various types of images such as medical images, satellite images, underwater images, and infrared images using different fitness functions. Moreover, the gamma coefficient in the Gamma correction enhancement method or constraint parameters in HE-based methods can be optimized using the hybrid PSO/BHA approach.

Declarations

Conflict of interest There is no conflict of interest between the authors to publish this manuscript.

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