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RESEARCH ARTICLE

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Contrast enhancement of digital images using dragonfly algorithm

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ABSTRACT

Contrast enhancement aims to amplify the visual quality of images by modifying the contrast level because digital images may get distorted by casual acquisition. The article deals with contrast enhancement as an optimization problem and uses the Dragonfly Algorithm (DA) to find the optimal grey-level intensity values. The DA for contrast enhancement uses five control parameters (entropy, number of edges, total intensities of edges, the variance of the probability of occurrence of each grey value, and the number of grey levels) to generate an objective function. An ablation study is also performed to understand how different controlling parameter combinations contribute to determining the optimal solution. The proposed approach considers 24 grey-scale images from the Kodak dataset and metrics as Peak Signal-to-Noise Ratio (PSNR), Visual Information Fidelity (VIF), and Structural Similarity Index Measure (SSIM) to verify the output's performance. The PSNR, VIF, and SSIM values in the experiments are 30.87, 0.7451, and 0.9523, respectively. The experimental observations reveal that the proposed DA-based image contrast enhancement produces high-quality images from its low-contrast counterparts. Comparisons with state-of-art methods ensure the superiority of the proposed algorithm. The Python implementation of the proposed approach is available in this Github repository.

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Dragonfly algorithm; image contrast enhancement; Kodak dataset; meta-heuristic

1. Introduction

Image processing is one of the leading research areas in today's world, and it is applied in many domains, such as medical image analysis, real-time object detection, and face recognition. Many complex algorithms are employed to solve these mentioned tasks. However, the researchers generally remark that the images used in such experiments should be informative and of good quality to get the desired outcomes. However, the quality of digital images suffers due to various factors, e.g. contrast, illumination, and noise during image acquisition. Hence, there is a need for image enhancement. Thus, image contrast enhancement is important in the picture, as it plays an important role in different applications. The basic purpose of image contrast enhancement is to improve the readability and interpretability of the information present within the image. It is achieved by suppressing the noise while preserving the connectivity of the edges and other detailed information. Thus, it becomes more suitable for image processing applications. Image enhancement can be expressed as the separation factor between the scene's brightest and darkest spots in the scene [1]. High contrast or low contrast, indicated by this factor, depends on its value. Additionally, images are deblurred with this technique's help; in some cases, it is employed to highlight specific features.

In the related literature, the approaches used to solve the image contrast enhancement problem can be classified into two basic groups: filtering techniques and contrast enhancement methods [2]. In the first approach, each pixel value of the input image is substituted by a value computed by considering the original and its neighbouring pixel values. On the contrary, the second technique maps the grey levels of the input image to newly generated grey levels to improvise an output image with enhanced contrast for a more homogeneous distribution of the corresponding foreground and background pixels [3, 4].

The selection of the image contrast enhancement method is subjective to the observers and the problems they are dealing with. Generally, the solution approaches for image contrast enhancement can be performed in three domains [5]: (a) spatial domain, (b) transform domain, and (c) fuzzy domain [6]. The methods used in the spatial domain operate directly on the image's pixel values to increase the brightness and contrast. In contrast, the methods used in the transform domain correspond to a change in the image frequency. The techniques implemented based on transformations

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commonly employ the Fourier transform. The parts of images with sharp edges and abrupt transitions give rise to high-frequency contents, and smooth areas are responsible for the Fourier transform's low-frequency contents. On the contrary, the methods used in the fuzzy domain have different approaches for image contrast enhancement. Several image-processing functions can be implemented using the concepts of fuzzy logic. The image is first fuzzified, and the moderation of membership functions takes place; finally, the competent outputs are combined to generate a crisp image. Various techniques are available to compare and combine the pixel values with neighbouring pixels. Images can easily be evaluated and understood by properly adjusting brightness and contrast.

Researchers have also applied different meta-heuri stic optimization algorithms for the image contrast enhancement task. Evolutionary algorithms are mainly involved in optimization tasks. Swarm Intelligence (SI) constitutes a significant part of the evolutionary algorithms, and its success in various domains has attracted the attention of researchers worldwide. Some measures that include the count, intensities of edge pixels, and the entropy of the whole image [2] are essential to ensure the image's quality. These measures have been applied for image enhancement using Genetic Algorithm (GA) [7, 8], Artificial Bee Colony (ABC) [9], Particle Swarm Optimization (PSO) [10, 11], and Cuckoo Search (CS) [12–14], where the image contrast enhancement problem is considered as an optimization problem.

The present work employs the Dragonfly Algorithm (DA) as an optimization technique to map the input image's grey levels into a new set of grey-level values. The quality of the resulting image was evaluated by measuring the fitness criteria and considering the five properties of the image. Such properties are the entropy, the number of edges, the total intensities of edges, the variance of each grey value's probability of occurrence, and the number of grey levels having a probability density greater than a certain threshold. According to the research work mentioned in the literature, DA has achieved enormous success in solving different complex problems in different domains [15–17]. Hence, DA was employed in the present experiment to observe this meta-heuristic algorithm's effectiveness for image enhancement purposes.

Highlights of the proposed work are as follows:

(1) In this experiment, the image contrast enhancement problem has been mapped as an optimization problem, i.e. optimizing the input image's grey level intensity values can enhance the image quality that may be used further in different image processing applications.
(2) To the best of our knowledge, DA has been used in image contrast enhancement for the first time.
(3) Input images are taken from standard and open Kodak datasets, which have been enhanced using the DA-based approach.
(4) Without considering the image properties randomly, we have performed an ablation study that reveals how different combinations of controlling parameters used in objective function impact the quality of images produced.
(5) The proposed algorithm used for image contrast enhancement proves its effectiveness compared to many state-of-the-art techniques.

The organization of the paper is as follows. Section 2 provides a brief overview of the past image contrast enhancement methods found in the literature. Section 3 describes the proposed methodology. Section 4 provides a detailed analysis of the results obtained in the work. Finally, Section 5 concludes the work and discusses some future directions.

2. Related work

This section briefly describes a few methods used for image contrast enhancement. Histogram Equalization (HE) is one of the most popular image enhancement techniques in the spatial domain. A histogram plots the pixel intensity frequency at each image pixel, varying from 0 (black) to 255 (white). It spreads the pixel intensity clusters of the image over a dynamic range [18]. A modified version of HE has been proposed by Wang et al. [19], where the probability distribution function of an image is modified by weighting and thresholding before the HE is performed. This method is faster and provides satisfactory results but may create abnormal brightness in images with shallow contrast. To solve this issue, Kim et al. [20] have proposed an alternative bi-histogram equalization method, a modified version of the HE approach that maintains the average brightness of the image. Though the HE technique is useful for contrast enhancement work, its effects are sometimes too drastic. To cope with the associated problems, Stark et al. have proposed a cumulation function to produce grey-level mapping for the local histogram [21]. This function can produce different contrast enhancement degrees by minor variations in the cumulation function and its parameters, making the method flexible and adaptive to several spheres of image enhancement applications. Abdullah-Al-Wadud et al. [22] have proposed modifying conventional HE by partitioning the histograms based on local minima and assigning specific grey level ranges to each partition. After equalization, a repartitioning test is performed to ensure no dominating portions are absent. This helps to avoid the side effects of HE in terms of loss of detail, washed-out appearance, checkerboard effects, etc.

Bhandari et al. [23] have proposed a method where they initially enhanced the image's contrast globally through addition and logarithmic law-based modification scheme. Tao et al. [24] have proposed an image enhancement technique called MLBOHE (Multiple layers block overlapped histogram equalization), where authors have suppressed the noises before BOHE by involving a limited contrast procedure in each layer sub-blocks. Subsequently, a multilayered BOHE image merging process is adaptively performed using an applied image fusion mode. A comprehensive review of different image contrast enhancement methods has been reported by Maini et al. in [25]. Many image contrast enhancement techniques in the literature have shown great success in applications like the medical image diagnosis system [26], enhancement of iris and fingerprint, and palm print images in biometric recognition systems. Considering such applications, fingerprint image enhancement is a significant area where different studies have been conducted to make the ridges and valleys in the image more prominent to improve the performance of fingerprint identification systems [27]. On the other hand, the quality of satellite images is usually poor because they are taken from a long distance and carry an ample amount of noise and distortion due to atmospheric barriers. Various techniques for enhancing contrast, resolution, edge, and density are used to achieve the desired results [28] to deal with such types of problems. Medical image processing is another critical domain where images of different modalities and techniques are used to visualize the inside of the human body for diagnosing and treatment purposes. The challenges faced with these images are low contrast and high noise, which cause distortions in the images, resulting in difficulties in even machine processing [29].

Several methods are available in the domain of image enhancement using SI algorithms. Chen et al. [9] have used the ABC algorithm to enhance image contrast. Their work proposes a new objective fitness function to improve image quality. Also, it introduces a parametric transformation function that guides the ABC algorithm in detecting the optimal parameters for the generation of enhanced intensities of the pixels. Saitoh [7] has employed the GA for image contrast enhancement, which tries to measure the fitness of the input image through the intensity of spatial edges present in the image and increases them, thereby enhancing the quality of the image. The PSO is another popular optimization technique [30, 31] and has also been used by Gorai et al. [10] to present an intensity transformation function. In this work, the function parameters are optimized to enhance the image, and the performance has been assessed by using an objective criterion that uses entropy and edge information. Ant Colony Optimization (ACO) is another swarm-based algorithm [32] that is utilized for contrast and detail enhancement of images by Gupta et al. [33]. Munteanu et al. [8] have attempted to enhance images using a function that calibrates contrast and brightness by transforming adjoining pixel values. Then, image improvement was achieved by employing the GA on a Local Transformation Function (LTF). The performance was measured based on metrics such as the Sobel value, the entropy value, and the number of edges in the image. Recently, LTF was applied by Zhao using the Gravitational Search Algorithm (GSA), CSA by Agrawal et al., and Differential Improvement Algorithm (DIA) by Sarangi et al. [12–14]. Katircioglu et al. [17] have proposed a transformation function called the Regional Similarity Transfer Function (RSTF) for image contrast enhancement, which considers the similarity of density distribution between adjoining pixels.

A novel approach for enhancing the quality of medical images is suggested by Mousania et al.[34]. This involves utilizing a new histogram equalization technique that combines Contrast-limited adaptive HE and Brightness-preserving dynamic fuzzy HE techniques by computing proper weights determined by a fuzzy approach. The aim is to prevent undesirable brightness and intensity saturation effects during the process. The efficacy of the proposed technique was evaluated using five different authenticated medical image databases, and it was found to be advantageous for preserving brightness and enhancing contrast in medical images. This article [35] proposes an image enhancement technique using Grunwald-Letnikov and Riemann-Liouville fractional-order derivatives with GA to optimize the parameters for homomorphic filtering. The method is evaluated on different sizes and types of images and outperforms existing methods by increasing information entropy, average gradient, and contrast improvement index of 6.5%, 52%, and 75%, respectively. The proposed method effectively enhances images with low contrast and non-uniform illumination conditions.

Another method for enhancing low-contrast graytone images has been proposed by Rahman et al. [36]. This procedure divides the image into three sub-images to retain the mean brightness. To control contrast enhancement, a snipping procedure is applied to each histogram. The equalization of the three histograms is carried out separately, and subsequently, these subimages are combined into a single image. The performance of the proposed technique surpasses the conventional histogram equalization-based methods mentioned in the literature across various image quality metrics. Zhang et al. in [37] have shown a colour correction and adaptive contrast enhancement algorithm for underwater images. At first, the author designed the dedicated fractions to compensate for lower colour channels. Then, the proposed algorithm was applied to each colour channel to generate background-stretched and foreground-stretched images. The contrast of the output image improved significantly by combining these background-stretched and foreground-stretched images. Mukhopadhyay et al. in [38] proposed a new gray-scale contrast enhancement algorithm in which the controlling parameters of the Incomplete Beta Function were not tuned, but their near-optimal values are computed through the Artificial Electric Field Algorithm. An image fusion technique that is based on decomposition and division-based strategy has been proposed by Ren et al. [39] for both military and civilian applications. The method improves the guided filter and enhances the contrast of visible images before applying fusion. Two different strategies execute the fusion, resulting in two different sub-fusion results. The proposition of a novel fusion approach termed the ”gradient-brightness criterion” is also put forward. Based on empirical results, it is demonstrated that the performance of the suggested technique surpasses that of preceding fusion methods in both subjective and objective evaluations.

According to Braik, the Incomplete beta function (IBF) has been used as a transformation function for many image contrast enhancement (ICE) works [40]. Authors have shown the limitation of IBF in terms of low parameter selection efficiency and a limited range of mutable parameters to stretch areas with high or low gray levels. They have presented HWOA, a hybrid whale optimization algorithm, along with the Chameleon Swarm algorithm (CSA) to determine the optimal parameters of IBF for ICE. Then, the Bilateral Gamma Correction (BGC) has been employed to produce better contrast and brightness while preserving edge detail. Golabian et al. in [41] have raised the problem of ICE-based work in balancing the contrast and brightness of the images. They have proposed a methodology that implements 2D histogram modification and employed the Krill Herd algorithm to optimize parameters to overcome this issue. Yadav et al. in [42] have proposed an ICE technique for images with low contrast and noise or artifacts. The method has used the image's entropy curve and homomorphic filtering for contrast enhancement purposes. The method enhances the contrast of medical images without increasing the content of noise and artifacts. Jebadass et al. [43] have proposed an interval-valued intuitionistic fuzzy-based algorithm to enhance low-light images. The proposed technique first changed the low-light image to a fuzzy image by using normal fuzzification. The fuzzy image was then converted to an intuitionistic fuzzy image and further to the interval-valued intuitionistic fuzzy image. In the next step, contrast-limited adaptive histogram equalization was employed to produce the resultant image.

3. Proposed methodology

Image contrast enhancement generally considers the techniques that focus on altering the attributes of an image, namely, photometric characteristics; one of them is the contrast [2, 25] of the images. Including observer-centric elements, like the human visual system (HVS) and the observer's expertise, introduces significant subjectivity into the diverse array of image enhancement techniques. In the proposed work, the contrast enhancement method has been considered a "global" intensity transformation performed on all grey level values present in an image. To achieve this goal, the DA has been employed as an optimization technique to map the grey levels of input images to newly generated grey levels for contrast enhancement. The next subsection describes the basic procedure of the DA-based optimization technique.

3.1. *Dragonfly algorithm*

The DA is a meta-heuristic optimization technique designed to simulate the swarming behaviour of dragonflies in nature, with the aim of exploring the search space and determining the best solution for a certain optimization problem [44, 45]. These fundamental behaviours, commonly called exploration and exploitation, serve as the foundational operations of any meta-heuristic optimization algorithm. The algorithm embodies three essential principles, originally proposed by Reynolds et al. [46], which are elucidated as follows:

(1) Separation (S_i): This ensures the avoidance of static collisions between individuals and their neighbours.
(2) Alignment (A_i): It involves matching the velocity of individuals concerning their neighbours.
(3) Cohesion (C_i): It describes the inclination of individuals to approach the centre of mass of the neighbour.

Mathematical representations of these principles are provided by Equations (1)–(3), where M represents dragonfly's current position, M_j denotes jth neighbour's position, V_j denotes the velocity of the jth neighbour, and N signifies the neighbourhood's size.

$$S_i = -\sum_{j=1}^{N} M - M_j \tag{1}$$

$$A_i = \frac{\sum_{j=1}^{N} V_j}{N} \tag{2}$$

$$C_i = \frac{\sum_{j=1}^{N} M_j}{N} - M \tag{3}$$

The natural behaviour of the dragonfly swarm leads to the attraction of each dragonfly towards the food source and the repulsion from enemies. Mathematical representations of these attraction and repulsion effects are given by Equations (4)–(5), where the current positions of the dragonfly, food source, and enemies are denoted by M, M^+, and M^-, respectively [44].

$$F_i = M^+ - M \tag{4}$$

$$E_i = M^- - M \tag{5}$$

The position of each dragonfly in the swarm is updated based on the evaluation of the step vector ΔM and the current position M, as shown in Equation (6).

$$\Delta M_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta M_t \tag{6}$$

In this context, the separation weight, alignment weight, cohesion weight, food factor, enemy factor, inertia weight, and iteration number are denoted by the controlling parameters s, a, c, f, e, w, and t, respectively. The i^{th} dragonfly's separation, alignment, cohesion, food source, and enemy position are represented by the variables S_i, A_i, C_i, F_i, and E_i, respectively. The objective of these factors (s, a, c, f, and e) is to explore and exploit a broad spectrum of search spaces to attain the optimal solution. The position vectors are updated using the equation presented as Equation (7).

$$M_{t+1} = M_t + \Delta M_{t+1} \tag{7}$$

For the current image enhancement work, the following values are considered: $w = 0.9{-}0.2$, $s = 0.1$, $a = 0.1$, $c = 0.7$, $f = 1$, and $e = 1$, as inspired by the work in [44]. Several governing factors undergo dynamic updates throughout the algorithm assessment to offer varied exploratory and exploitative tendencies for the dragonfly algorithm (DA). The optimal solution is considered the nourishment source, while the least favourable solution is deemed a foe.

To introduce stochastic behaviour, randomness, and exploration, a random walk using Lévy flight is employed around the search space when no neighbours are detected within the neighbourhood radius [44]. In this case, the position of the dragonfly is updated following Equation (8).

$$M_{t+1} = M_t - Levy(d) \times \Delta M_t \tag{8}$$

The dimensions of the position vectors are represented by t and d. The Lévy function is defined in Equation (9), where r_1 and r_2 are random numbers between 0 and 1, and β is set to 1.5. ρ is determined using Equation (10).

$$Levy(x) = 0.001 \times \frac{r_1 \times \rho}{r_2^{\frac{1}{\beta}}} \tag{9}$$

$$\rho = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\left(\frac{1}{\beta}\right)}, \quad \text{where,}$$

$$\Gamma(m) = (m-1)! \tag{10}$$

While preserving the core framework of the algorithm, we have made minor adjustments to the DA, introducing feasibility verification before updating the dragonfly's position. This entails that the updated solution set will only be accepted if its fitness value surpasses that of the previous optimal food source. Algorithm 1 describes the steps involved in DA, and Figure 2 illustrates the control flow within DA.

Algorithm 1 The steps employed in DA

INPUT: *Grey scale image*
OUTPUT: *Grey scale image with enhanced contrast*
PARAMETERS: *w = 0.9- -0.2,s = 0.1,a = 0.1,c = 0.7,f = 1,e = 1*
BEGIN
Randomly initialize the dragonflies to create population M_i of size N ($M_i \epsilon$ [0, 255], where N denotes the count of unique grey level values in the input image) Randomly initialize step vectors ΔM_i ($i \epsilon$ [Δ_{lb}, Δ_{ub}], where Δ_{lb} and Δ_{ub} are the lower and upper bounds of the initial step value respectively)
iteration=1
while*(iteration <=Maximum number of iterations)*
Compute the fitness values of the position vectors of the dragonflies
Modify the value of the food source and enemy
Modification of w, s, a, c, f, and e
Compute the S, A, C, F, and E values using Equations (1)--(5)
Modify the neighbouring radius
if*(the dragonfly has at least one dragonfly as a neighbour)*
Modify the velocity vector using Equation (6) and store it in temporary the velocity vector
Modify the position vector using Equation (7) and store it in the temporary position vector
else
Modify the position vector using Equation (8) and store it in the temporary position vector
Modify the velocity vector to 0 and store it in the temporary velocity vector
end if
Examine and rectify the new positions in the temporary vector based on the boundaries of variables
if*(fitness of the temporary position >fitness of the food source)*
Replace the current position vector in the swarm with the temporary position vector
Replace the current velocity vector in the swarm with the temporary velocity vector
end if
end while
END

We have applied DA to map the grey level intensities of the input images (taken from the Kodak dataset)

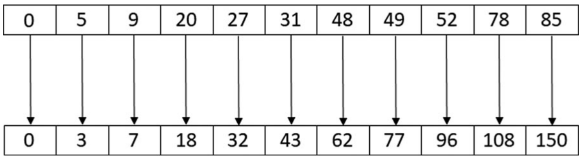

Figure 1. A visual illustration of the mapping of unique grey level intensity values from the input image to the enhanced image.

to newly improvised grey level intensities to enhance the contrast of the considered images. To understand the mapping, we have pictorially presented a sample hypothetical grey level mapping in Figure 1. The steps adopted in the DA procedure are described in detail below.

At the beginning phase of the proposed algorithm, a set of 50 solution vectors was randomly generated. These vectors consisted of unique random values in the range of [0,255] arranged in ascending order and having a length equal to the number of unique grey levels present in the input image, i.e. 256. The values of the step vectors were also randomly initialized between specific upper and lower bounds.

In each iteration of the algorithm, all the solution vectors' fitness values are measured by evaluating the objective function considering different combinations of the controlling parameters. A detailed description of the objective function used in the current experiment is introduced in Section 3.2. The solution vector with the highest and lowest fitness values is considered the food source and the enemy. Accordingly, the values of s, a,c,f,e,w, and t get updated; S_i, A_i, C_i, F_i, and E_i values are measured using Equations (1)–(5) and the radius of the neighbourhood is also updated.

After completing this phase, a validation criterion is established to verify the presence of any neighbouring entities for the current individual. If the criterion is satisfied, the individual dragonfly's velocity and position vectors undergo updates using Equations (6)–(7) and are saved in a temporary position and velocity vectors, respectively. On the other hand, if the criterion is not met, the dragonfly's position vector is updated by applying Lévy flight as defined in Equation (8) and saved in the temporary position vector. If the values in the temporary position vector lie beyond the feature space, they are repositioned within the search space. Before proceeding to the subsequent iteration, the fitness score of the updated position vector is evaluated to determine if it performs better than the existing food source. Upon meeting this condition, the updated solution replaces the one in the swarm, and the velocity vector is updated. Hence, as the algorithm advances, the grey level intensity values are altered based on the fitness until the termination criterion is achieved. The termination criterion, defined as 50 iterations, indicates the maximum number of iterations.

At the end of the algorithm, an optimal solution in the form of improvised grey level values for the input image is obtained, and these values replace the input grey levels index-wise. Thus, the final image turns out to be an enhanced image concerning the contrast by increasing the Peak Signal-to-Noise Ratio (PSNR), Visual Information Fidelity (VIF), and Structural Similarity Index Measure (SSIM) values [47–51]. A detailed flowchart describing the application of DA to image contrast enhancement has been presented in Figure 2.

3.2. Objective function

The primary need of the objective function is to determine the goodness of each newly generated solution vector. As was previously mentioned, this process aims to determine whether it will replace the existing solution vector in the solution set. The objective function has been designed using the metrics used to determine the quality of images. Then, this process validates the image quality produced from newly generated grey-level values. Parametrization has been performed to search for the optimal values guided by the objective function. In the current work, five control parameters have been used in the objective function to measure the fitness of the solution vectors. The five parameters used to formulate the objective functions are listed as follows [52–55]:

- (H): Entropy of the new image resulted from improvised grey level values.
- (ne): The number of edges in the new image resulted from improvised grey level values.
- (E): The total intensities of the edges in the new image resulted from improvised grey level values.
- (Δh): Variance of the probability of occurrence of each grey value in the new image.
- (N_T): The number of grey levels having probability density greater than a certain threshold T

The computational complexity of the DA using the time-dependent transfer function is the same as the original BDA, and it is $O(ISD)$, where I is the iteration number, S is the solution number, and D is the dimension of candidate solutions [56].

The next section describes the performances of the objective function in detail while considering different combinations of controlling parameters. The outcomes observed in the present experiment have also been compared with some standard techniques.

4. Results and discussion

This section describes the detailed observations obtai ned in the experiment. For the performance evaluation, the experimentation has been conducted on the Kodak dataset [54]. There are 24 lossless, true colours

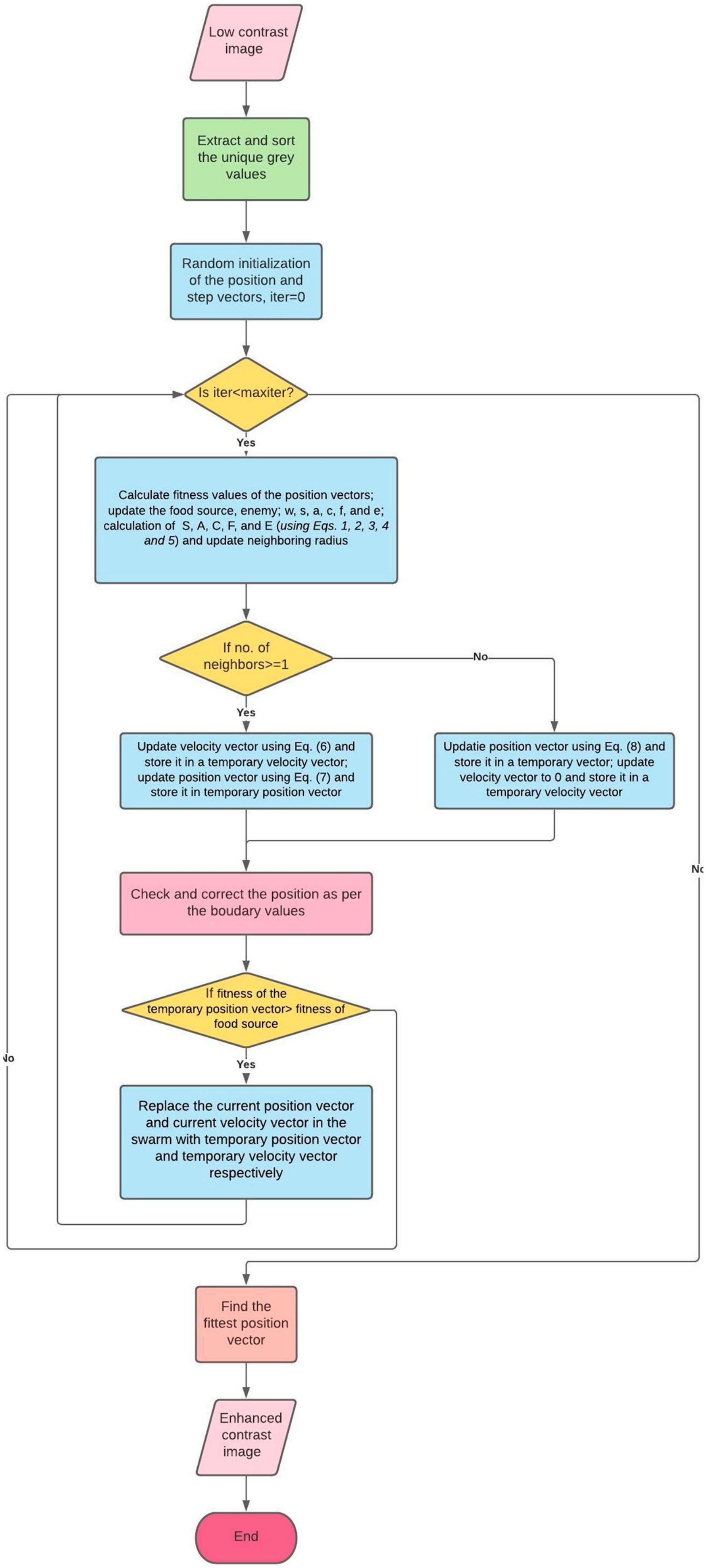

Figure 2. Flowchart of applied DA used for image contrast enhancement task.

(24 bits/pixel) images with a resolution of 756 × 512 in PNG format. These images were converted to grey-scaled images, serving as the Ground Truth (GT) images in our experimental setup. In the current experiment, the contrast of these images has been reduced and served as inputs to our proposed image contrast enhancement technique. For measuring performance, we have considered the three metrics, namely, PSNR [50], SSIM [51], and VIF [49]. A short description of the used metrics is given below.

- PSNR: The metric is expressed as the ratio of the maximum power of the signal to the power of the noise that tends to distort it by modifying its fidelity. It is generally represented in the decibel (dB) scale. In this experiment, it is represented in terms of Mean Square Error (MSE), as defined in Equation (11), where I is a noiseless grey-scale image with dimension $P_H \times P_v$, K is its noisy approximation. P_H and P_v denote the horizontal and vertical dimensions of the images (used in the denominator for all the functions to consider the image size), respectively.

$$MSE = \frac{1}{P_H \times P_v} \sum_{i=1}^{P_H-1} \sum_{j=1}^{P_v-1} \left[I(i,j) - K(i,j)\right]^2 \quad (11)$$

  Accordingly, PSNR is defined as mentioned in Equation (12), where R is the maximum pixel intensity value, and for our case, it is 255.

$$PSNR = 10 \log_{10} \frac{R^2}{MSE} \quad (12)$$

- SSIM: SSIM index is used to calculate how similar two images are. The metric is considered a perception-based model that checks the degradation in image quality as a perceived structural information change, thereby integrating perceptual phenomena, i.e. luminance masking and contrast mask terms. It generally refers to the concept that when pixels are close to each other, they tend to have greater inter-dependencies. It is usually calculated on several windows constituting the image and is defined in Equation (13) as a distance between p and q, where p and q are two windows with common size $N \times N$;μ_p and μ_q denote the mean intensities of p and q respectively; σ_p^2 and σ_q^2 are the variance of p and q respectively;σ_{pq} refers to the covariance of p and q; $c_1 = (K_1 L)^2$ and $c_2 = (K_2 L)^2$, where L denotes the dynamic range of pixel values, and K_1 and K_2 are constants with 0.01 and 0.03 as default values, respectively.

$$SSIM(p,q) = \frac{(2\mu_p \mu_q + c1)(2\sigma_{pq} + c2)}{(\mu_x^2 + \mu_q^2 + c1)(\sigma_p^2 + \sigma_q^2 + c2)} \quad (13)$$

- Sheikh et al. [49] created three separate models: one for statistical analysis of natural scene images, another for image distortions, and an HVS model integrated into an information-theoretic framework. From these three distinct models, they derived a comprehensive full-reference image quality assessment (QA) index. It is defined in Equation (14), where I_R represents the reference image (GT image), and I_{En} represents the enhanced image in the jth sub-band, respectively.

$$\frac{\sum_{j \epsilon subbands} I_R(\overrightarrow{C}^{N,j}; \overrightarrow{F}^{N,j} \| S^{N,j})}{\sum_{j \epsilon subbands} I_{En}(\overrightarrow{C}^{N,j}; \overrightarrow{En}^{N,j} \| S^{N,j})} \quad (14)$$

In the present work, an ablation study has been conducted to show the contribution of the parameters taking part in the objective function individually or in combination with other parameters to determine the fitness value for the solution vectors, thereby enhancing the quality of the output images. The objective function considers all possible combinations of the five parameters [$no.of\ combinations = C(5,1) + C(5,2) + C(5,3) + C(5,4) + C(5,5) = 1 + 5 + 10 + 10 + 5 = 31$]. Table 1 demonstrates the performance of the objective function considering all the combinations of the controlling parameters in terms of the average PSNR, VIF, and SSIM values obtained for all 24 grey-scaled images taken from the Kodak dataset. It has been observed from Table 1 that even though the DA-based approach has been able to produce overall satisfactory results for all the cases with different combinations of parameters, it has produced the best outcome (average PSNR, VIF, and SSIM) for the objective function when it combines the three parameters H, N_T, and Δh with the dimension of the images ($P_H \times P_V$). Again, it has been observed that the model produces the worst result when the objective function considers only the parameter E (total intensities of the edges). For all other combinations, average PSNR values range from 28.33 to 30.47, average VIF values range from 0.6843 to 0.7408, and average SSIM values range from 0.8674 to 0.9519.

In the current experiment, the average PSNR, VIF, and SSIM values are also computed from the proposed DA-based approach for all the grey-scaled images from the Kodak dataset for the best-performing objective function that uses the combination of the three parameters: H, N_T, and Δh. The detailed observations are mentioned in Table 2. This table also provides a better insight into the performance of this objective function used in DA on various images with different distributions of grey-level values. This table shows that the best PSNR, VIF, and SSIM values have been obtained for Kodim22, Kodim02, and Kodim20 images, respectively. The overall average PSNR, VIF, and SSIM results for the dataset are 30.87, 0.7451, and 0.9623, respectively.

Figure 3 highlights the samples of input images, enhanced images, and GT images and their corresponding histogram plots to illustrate the visual effect

Table 1. The average PSNR, VIF, and SSIM values observed from the images in the Kodak dataset [54] for the proposed image contrast enhancement technique using DA when all possible combinations of the control parameters are used in the formation of the objective function to measure the fitness value.

Parameter combination	Avg. PSNR	Avg. VIF	Avg. SSIM
E	28.16	0.6503	0.7934
ne	29.65	0.7201	0.9376
H	30.47	0.6983	0.9469
Δh	30.19	0.7143	0.9405
N_T	29.77	0.6843	0.9273
E and ne	28.91	0.6895	0.8674
E and N_T	28.33	0.7113	0.8837
E and Δh	29.12	0.7347	0.9186
E and H	29.37	0.7298	0.9128
ne and N_T	28.81	0.7060	0.9172
ne and H	30.08	0.7206	0.9406
ne and Δh	30.33	0.7231	0.9519
N_T and Δh	29.62	0.7408	0.9036
N_T and H	29.34	0.7241	0.9357
H and Δh	29.46	0.7077	0.9445
E,ne and H	29.97	0.7395	0.9370
E,N_T and H	29.78	0.706	0.9203
E,H and Δh	30.33	0.7337	0.9394
E,ne and Δh	29.99	0.7311	0.9187
E,ne and N_T	29.57	0.7364	0.9110
E, Δh and N_T	28.72	0.7165	0.8744
ne, Δh and N_T	29.96	0.7114	0.9275
ne,H and N_T	29.63	0.7106	0.9338
ne,H and Δh	29.62	0.7227	0.9064
N_T,H and Δh	**30.87**	**0.7451**	**0.9523**
E,ne, Δh and N_T	28.56	0.7221	0.9008
E,ne,H and N_T	28.97	0.7266	0.9003
ne,H, Δh and N_T	29.63	0.7309	0.9392
E,ne,H and Δh	29.29	0.7266	0.9065
E,Δh,H and N_T	28.74	0.7273	0.8923
E,Δh,H,ne and N_T	29.49	0.7083	0.9356

Table 2. The average PSNR, SSIM, and VIF values observed for all the images from the Kodak dataset for the proposed DA-based image contrast enhancement technique when objective function uses the combination of parameters H, N_T, and Δh.

Image	PSNR	VIF	SSIM
Kodim01	28.07	0.7738	0.9342
Kodim02	28.51	0.8124	0.9216
Kodim03	29.06	0.7186	0.9698
Kodim04	27.43	0.8007	0.9451
Kodim05	33.27	0.7054	0.9534
Kodim06	32.83	0.7515	0.9727
Kodim07	27.68	0.7056	0.9672
Kodim08	27.94	0.7237	0.9852
Kodim09	32.98	0.7261	0.9545
Kodim10	28.53	0.7838	0.9247
Kodim11	27.04	0.7531	0.9542
Kodim12	32.07	0.7218	0.9303
Kodim13	27.65	0.7295	0.9823
Kodim14	28.31	0.7200	0.9159
Kodim15	29.22	0.7563	0.9634
Kodim16	33.22	0.7630	0.9169
Kodim17	30.94	0.7383	0.9632
Kodim18	33.60	0.7445	0.9637
Kodim19	30.52	0.7185	0.9571
Kodim20	34.85	0.7527	0.9727
Kodim21	35.91	0.7391	0.9607
Kodim22	36.77	0.7967	0.9450
Kodim23	34.76	0.7322	0.9577
Kodim24	29.63	0.7173	0.9444
Average	**30.87**	**0.7451**	**0.9523**

of applied DA on the image quality and the distribution of the pixel intensity values. It can also be observed that when the contrast of the input image has been reduced, the pixel intensity distribution in the histogram plot has narrowed its bandwidth. After the enhancement, the bandwidth tends to increase. Intensity values get more evenly distributed, thus enhancing the image contrast. The histogram plots of the enhanced images reflect that the DA-based approach can make the intensity distribution closer to the GT images.

This experiment has also tested the GOA (Grasshopper Optimization Algorithm) [57] and MPA (Marine Predators Algorithm) [58] and reported the outcomes in Table 3. The proposed DA-based methodology has outperformed other algorithms with a significant margin in evaluation metrics. This validates the usability of the proposed technique.

The Wilcoxon signed-rank test [59] has also been performed to test whether the empirical results obtai ned are statistically significant enough to conclude that the proposed DA-based method is better. Since PSNR is the widely accepted metric for evaluating image quality, we have considered it for the statistical test. Here, the input population is the PSNR values of 24 images from the considered Kodak dataset after applying the optimization algorithm for contrast enhancement. The comparison has been done independently for GOA and MPA with DA. Here, the null hypothesis (H_0) is as follows: no significant performance difference exists between the two considered algorithms. The alternate hypothesis (H_1) states that the performance of the two considered algorithms is not the same. The resultant p-value after performing the test can be seen in Table 4. As for both cases, the obtained p-value is less than 0.05 significance level (α), we can reject the null hypothesis and conclude that the proposed DA-based technique is more efficient in the task of image contrast enhancement in comparison with GOA and MPA.

In this section, the efficiency of the proposed DA-based image contrast enhancement technique has been compared with some standard techniques developed in the past. The methods presented in [55, 60, 61] deal with the conventional histogram-based approach. The method explained in [3] applies the GA-based approach, whereas methods mentioned in [12, 13] consider CSA and PSO approaches and the methods proposed in [2, 62, 63] used the ABC-based approach. From the results reported in Table 5, it can be said that the proposed DA-based approach achieves better results compared to other methods in terms of the average PSNR, VIF, and SSIM values for the images taken from the Kodak dataset. The ABC-based approach used in [62] produced VIF and SSIM values almost equal to the proposed method, but the PSNR value obtained is less than the proposed DA-based approach. Compared with other techniques, the proposed DA-based method has given better metric values and proven its applicability to produce better image quality over the past methods.

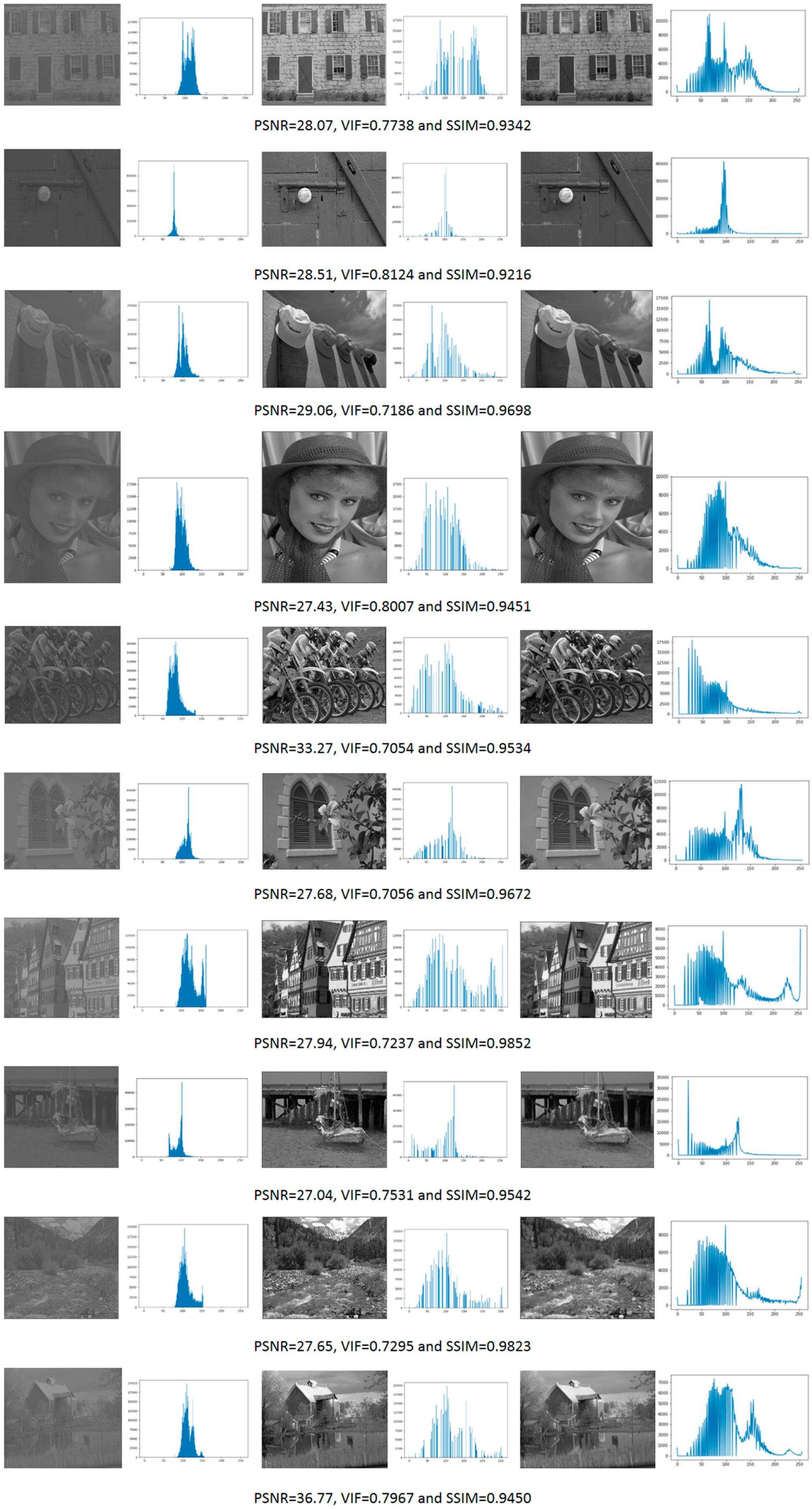

Figure 3. Input, output, GT, and their corresponding histogram plots for sample 10 images from Kodak dataset.

Table 3. Comparison with other optimization algorithms.

Metric	GOA [57] Mean	GOA [57] Standard deviation	MPA [58] Mean	MPA [58] Standard deviation	Proposed Mean	Proposed Standard deviation
PSNR	25.773	1.684	27.437	2.234	30.866	2.946
VIF	0.532	0.033	0.684	0.028	0.745	0.029
SSIM	0.873	0.014	0.835	0.018	0.952	0.019

Table 4. Wilcoxon signed-rank statistical test results using the PSNR scores.

Metric	DA V/s GOA	DA V/s MPA
p-value	0.0247	0.0185

Table 5. Comparative analysis of the proposed DA-based approach with some state-of-the-art methods.

Work Ref.	PSNR	VIF	SSIM
Santhi et al. [61], 2015	16.26	0.41	0.79
Kim et al. [55], 2006	19.88	0.51	0.87
Poddar et al. [60], 2013	17.78	0.63	0.72
Hashemi et al. [3], 2009	18.87	0.51	0.88
Agrawal et al. [13], 2021	15.46	0.52	0.86
Zhao et al. [12], 2011	19.84	0.53	0.91
Gao et al. [62], 2011	24.66	0.75	0.95
Draa et al. [2], 2014	13.56	0.60	0.85
Chen et al. [63], 2018	13.79	0.69	0.86
Mukhopadhyay et al. [38], 2022	25.69	0.81	0.93
Shoda, A. et al. [64], 2023	26.40	–	0.828
Satti, P. et al. [65], 2023	27.80	–	0.89
Proposed, 2024	**30.87**	**0.75**	**0.95**

5. Conclusion and future scope

This paper introduces an image contrast enhancement technique based on DA, a popular meta-heuristic-based optimization algorithm. The current experiments considered five controlling parameters for constructing the objective function used in the DA-based technique that measures the fitness of the candidate solutions. An ablation study has also been conducted to reflect the different combinations of parameters used in the objective function contribute to the fitness evaluation for an improvised solution. The current experimentation considered a sorted vector of unique grey-level values as a candidate solution vector to this maximization problem, which has been optimized using the DA. The evaluation is done on 24 grey-scaled images from the Kodak, publicly available standard dataset. To measure the efficiency of the proposed DA-based image enhancement technique, the contrast of the images was initially reduced to add complexity and fed as the input to the model. The quality of the enhanced images was measured using the metrics PSNR, SSIM, and VIF. It has been observed that the proposed DA-based technique can achieve a good measure of PSNR, SSIM, and VIF with all possible combinations of five parameters but reach the best result for the objective function that makes use of parameters H, N_T, and Δh (PSNR value of 30.87, VIF value of 0.7451, and SSIM value of 0.9523). The best outcome observed through the proposed approach also outperforms some well-known techniques by a significant margin, thus proving DA's robust optimization power and ability to produce better quality images from a low contrast image for better human and machine perception. In the future, the proposed model can also be applied to other datasets. The proposed model can also be used to enhance the image contrast of various image classification applications, where recognition accuracy falls due to the images' poor quality. In the future, other standard optimization techniques can be hybridized with the DA to enhance image contrast.

Author contributions

All authors contributed equally to this work.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

Code availability

The Python implementation of the proposed model is available in this github repository.

Data availability

The current experiment used a publicly available dataset that can be found at https://r0k.us/graphics/kodak/.

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References

[1] Gu K, Zhai G, Lin W, et al. The analysis of image contrast: from quality assessment to automatic enhancement. IEEE Trans Cybern. 2016;46(1):284–297. doi: 10.1109/TCYB.2015.2401732

[2] ”Draa A, Bouaziz A.. An artificial bee colony algorithm for image contrast enhancement. Swarm Evol Comput. 2014;16:69–84. doi: 10.1016/j.swevo.2014.01.003

[3] Hashemi S, Kiani S, Noroozi N, et al. An image enhancement method based on genetic algorithm. In: International Conference on Digital Image Processing. Bangkok, Thailand: IEEE; 2009. p. 167–171. doi: 10.1109/ICDIP.2009.87
[4] Burger W, Burge MJ. Principles of digital image compression. London: Springer; 2009.
[5] Singh LSS, Ahlawat AK, Singh KM, et al. A review on image enhancement methods on different domains. Int J Eng Inventions. 2017;6(1):49–55.
[6] Gonzalez R, Woods R. Digital image processing. London: Prentice-Hall; 2002.
[7] Saitoh F. Image contrast enhancement using genetic algorithm. In: IEEE SMC'99 Conference Proceedings. IEEE International Conference on Systems, Man, and Cybernetics (Cat. No.99CH37028). Tokyo, Japan: IEEE; 1999, p. 899–904. doi: 10.1109/ICSMC.1999.812529
[8] Munteanu C, Rosa A. Towards automatic image enhancement using genetic algorithms. In: Proceedings of the 2000 Congress on Evolutionary Computation. CEC00 (Cat. No.00TH8512). La Jolla, CA: IEEE; 2000. pp. 1535–1542. doi: 10.1109/CEC.2000.870836
[9] Joshi P, Prakash S. An efficient technique for image contrast enhancement using artificial bee colony. In: IEEE International Conference on Identity, Security and Behavior Analysis (ISBA 2015). Hong Kong, China: IEEE; 2015, p. 1–6. doi: 10.1109/ISBA.2015.7126363
[10] Gorai A, Ghosh A. Gray-level image enhancement by particle swarm optimization. In: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC). Coimbatore, India: IEEE; 2009. p. 72–77. doi: 10.1109/NABIC.2009.5393603
[11] Malik R, Dhir R, Mittal SK. Remote sensing and landsat image enhancement using multiobjective pso based local detail enhancement. J Ambient Intell Humaniz Comput. 2018;10:3563–3571. doi: 10.1007/s12652-018-1082-y
[12] Zhao W. Adaptive image enhancement based on gravitational search algorithm. Procedia Eng. 2011;15:3288–3292. doi: 10.1016/j.proeng.2011.08.617
[13] Agrawal S, Panda R. An efficient algorithm for gray level image enhancement using cuckoo search. In: Panigrahi BK, Das S, Suganthan PN, et al., editors. Swarm, evolutionary, and memetic computing. SEMCCO 2012. Lecture Notes in Computer Science. Springer, Berlin, Heidelberg; 2012. doi: 10.1007/978-3-642-35380-2_11
[14] Sarangi PP, Mishra BSP, Majhi B, et al. Gray-level image enhancement using differential evolution optimization algorithm. In: 2014 International Conference on Signal Processing and Integrated Networks (SPIN). Noida, India: IEEE; 2014. p. 95–100. doi: 10.1109/SPIN.2014.6776929
[15] Mirjalili S. Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput Appl. 2015;27(4):1053–1073. doi: 10.1007/s00521-015-1920-1
[16] Rahman CM, Rashid TA. Dragonfly algorithm and its applications in applied science – survey. CoRR abs/2001.02292 (2020). doi: 10.48550/arXiv.2001.02292
[17] Katircioglu F, Cingiz Z. A novel gray image enhancement using the regional similarity transformation function and dragonfly algorithm. El-Cezeri Fen ve Mühendislik Dergisi. 2020;7:1201–1219.
[18] Kaur S, Kaur P. Review and analysis of various image enhancement techniques. Int J Comput Appl Technol Res. 2015;4(5):414–418.
[19] Wang Q, Ward R. Fast image/video contrast enhancement based on weighted thresholded histogram equalization. IEEE Trans Consum Electron. 2007;53(2):757–764. doi: 10.1109/TCE.2007.381756
[20] Kim Y-T. Contrast enhancement using brightness preserving bi-histogram equalization. IEEE Trans Consum Electron. 1997;43(1):1–8. doi: 10.1109/TCE.2002.1010085
[21] Stark JA. Adaptive image contrast enhancement using generalizations of histogram equalization. IEEE Trans Image Process. 2000;9(5):889–896. doi: 10.1109/83.841534
[22] Abdullah-Al-Wadud M, Kabir M, Akber Dewan M, et al. A dynamic histogram equalization for image contrast enhancement. IEEE Trans Consum Electron. 2007;53(2):593–600. doi: 10.1109/TCE.2007.381734
[23] Bhandari AK. A logarithmic law based histogram modification scheme for naturalness image contrast enhancement. J Ambient Intell Humaniz Comput. 2019;11(4):1605–1627. doi: 10.1007/s12652-019-01258-6
[24] Tao P, Pei Y, Celenk M, et al. Adaptive image enhancement method using contrast limitation based on multiple layers bohe. J Ambient Intell Humaniz Comput. 2020;11(11):5031–5043. doi: 10.1007/s12652-020-01810-9
[25] Maini R, Aggarwal H. A comprehensive review of image enhancement techniques. Int J Innov Res Growth. 2019;8(6):593–600.
[26] Raja NSM, Fernandes SL, Dey N, et al. Contrast enhanced medical mri evaluation using tsallis entropy and region growing segmentation. J Ambient Intell Humaniz Comput. 2018;15:961–972.
[27] Hong L, Wan Y, Jain A. Fingerprint image enhancement: algorithm and performance evaluation. IEEE Trans Pattern Anal Mach Intell. 1998;20(8):777–789. doi: 10.1109/34.709565
[28] Pandey P, Dewangan K, Dewangan D. Satellite image enhancement techniques — a comparative study. In: 2017 International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS). Chennai, India: IEEE; 2017. p. 597–602. doi: 10.1109/ICECDS.2017.8389506
[29] Yang Y, Su Z, Sun L. Medical image enhancement algorithm based on wavelet transform. Electron Lett. 2010;46(2):120–212. doi: 10.1049/el.2010.2063
[30] Kennedy J, Eberhart R. Particle swarm optimization. In: Proceedings of ICNN'95 - International Conference on Neural Networks. Perth, WA: IEEE; 1995. p. 1942–1948. doi: 10.1109/ICNN.1995.488968
[31] Zhang Y, Wang S, Ji G. A comprehensive survey on particle swarm optimization algorithm and its applications. Math Prob Eng. 2015;2015:931256.
[32] Dorigo M, Birattari M, Stutzle T. Ant colony optimization. IEEE Comput Intell Mag. 2006;1(4):28–39. doi: 10.1109/MCI.2006.329691
[33] Gupta K, Gupta A. Image enhancement using ant colony optimization. IOSR J VLSI Signal Process. 2012;1(3):38–45. doi: 10.9790/4200
[34] Mousania Y, Karimi S, Farmani A. Optical remote sensing, brightness preserving and contrast enhancement of medical images using histogram equalization with minimum cross-entropy-otsu algorithm. Opt Quant Electron. 2022;55(2):105. doi: 10.1007/s11082-022-04341-z
[35] Gamini S, Kumar SS. Homomorphic filtering for the image enhancement based on fractional-order derivative and genetic algorithm. Comput Electric Eng.

2023;106:108566. doi: 10.1016/j.compeleceng.2022.108566
[36] Rahman H, Paul GC. Tripartite sub-image histogram equalization for slightly low contrast gray-tone image enhancement. Pattern Recognit. 2023;134:109043. doi: 10.1016/j.patcog.2022.109043
[37] Zhang W, Zhuang P, Sun H-H, et al. Underwater image enhancement via minimal color loss and locally adaptive contrast enhancement. IEEE Trans Image Process. 2022;31:3997–4010. doi: 10.1109/TIP.2022.3177129
[38] Mukhopadhyay S, Hossain S, Malakar S, et al. Image contrast improvement through a metaheuristic scheme. Soft Comput. 2022;27(18):13657–13676. doi: 10.1007/s00500-022-07291-6
[39] Ren L, Pan Z, Cao J, et al. Infrared and visible image fusion based on weighted variance guided filter and image contrast enhancement. Infrared Physics and Technology. 2021;114:103662. doi: 10.1016/j.infrared.2021.103662
[40] Braik M. Hybrid enhanced whale optimization algori thm for contrast and detail enhancement of color images. Cluster Comput. 2024;27(1):231–267. doi: 10.1007/s10586-022-03920-9
[41] Golabian M, Mahmoodzadeh A, Agahi H. Image enhancement based on optimized 2D histogram modification by krill herd algorithm. Evolv Syst. 2023;15: 1219–1233.
[42] Yadav PS, Gupta B, Lamba SS. A new approach of contrast enhancement for medical images based on entropy curve. Biomed Signal Process Control. 2024;88:105625. doi: 10.1016/j.bspc.2023.105625
[43] Jebadass JR, Balasubramaniam P. Color image enhancement technique based on interval-valued intuitionistic fuzzy set. Inform Sci. 2024;653:119811. doi: 10.1016/j.ins.2023.119811
[44] Mirjalili S. Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems. Neural Comput Appl. 2016;27(4):1053–1073. doi: 10.1007/s00521-015-1920-1
[45] Saravanan C, Anbalagan P. Multi objective dragonfly algorithm for congestion management in deregulated power systems. J Ambient Intell Humaniz Comput. 2020;12(7):7519–7528. doi: 10.1007/s12652-020-02440-x
[46] Reynolds CW. Flocks, herds, and schools: a distributed behavioral model. In: Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques. New York (NY): Association for Computing Machinery; 1987. p. 25–34. doi: 10.1145/37402.37406
[47] Hore A, Ziou D. Image quality metrics: PSNR vs. SSIM. In: 2010 20th International Conference on Pattern Recognition. Istanbul, Turkey: IEEE; 2010. p. 2366–2369. doi: 10.1109/ICPR.2010.579
[48] Sara U, Akter M, Uddin MS. Image quality assessment through fsim, ssim, mse and psnr–a comparative study. J Comput Commun. 2019;7(3):8–18. doi: 10.4236/jcc.2019.73002
[49] Sheikh HR, Bovik AC. Image information and visual quality. IEEE Trans Image Process. 2006;15(2):430–444. doi: 10.1109/TIP.2005.859378
[50] Poobathy D, Chezian RM. Edge detection operators: peak signal to noise ratio based comparison. Int J Image Graph Signal Process. 2014;6(10):55–61. doi: 10.5815/ijigsp
[51] Wang Z, Bovik AC, Sheikh HR, et al. Image quality assessment: from error visibility to structural similarity. IEEE Trans Image Process. 2004;13(4):600–612. doi: 10.1109/TIP.2003.819861
[52] Munteanu C, Rosa A. Gray-scale image enhancement as an automatic process driven by evolution. IEEE Trans Syst Man Cybern. 2004;34(2):1292–1298. doi: 10.1109/TSMCB.2003.818533
[53] Coelho L.S, Sauer JG, Rudek M. Differential evolution optimization com- bined with chaotic sequences for image contrast enhancement. Chaos Solitons Fract. 2009;42(1):522–529. doi: 10.1016/j.chaos.2009.01.012
[54] Franzen WR. True Color Kodak Images. https://r0k.us/graphics/kodak/.
[55] Kim H-J, Lee J-M, Lee J-A, et al. Contrast enhancement using adaptively modified histogram equalization. In: Chang LW, Lie WN, editors. Advances in image and video technology. PSIVT 2006. Lecture Notes in Computer Science. Springer, Berlin, Heidelberg; 2006. doi: 10.1007/11949534_116
[56] Rahman CM, Rashid TA, Alsadoon A, et al. A survey on dragonfly algorithm and its applications in engineering. Evol Intell. 2023;16(1):1–21. doi: 10.1007/s12065-021-00659-x
[57] Dinh PH. A novel approach based on grasshopper optimization algorithm for medical image fusion. Expert Syst Appl. 2021;171:114576. doi: 10.1016/j.eswa.2021.114576
[58] Dinh PH. An improved medical image synthesis approach based on marine predators algorithm and maximum gabor energy. Neural Comput Appl. 2022;34: 4367–4385. doi: 10.1007/s00521-021-06577-4
[59] Derrac J, García S, Molina D, et al. A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. Swarm Evol Comput. 2011;1(1):3–18. doi: 10.1016/j.swevo.2011.02.002
[60] Poddar S, Tewary S, Sharma D, et al. Non-parametric modified histogram equalisation for contrast enhancement. IET Image Process. 2013;7(7):641–652. doi: 10.1049/ipr2.v7.7
[61] Santhi K, Wahida Banu RSD. Adaptive contrast enhance ment using modified histogram equalization. Optik – Int J Light Electron Optic. 2015;126(19):1809–1814. doi: 10.1016/j.ijleo.2015.05.023
[62] Qinqing G, Dexin C, Guangping Z, et al. Image enhancement technique based on improved PSO algorithm. In: 2011 6th IEEE Conference on Industrial Electronics and Applications. Beijing, China: IEEE; 2011, p. 234–238. doi: 10.1109/ICIEA.2011.5975586
[63] Chen J, Yu W, Tian J, et al. Image contrast enhancement using an artificial bee colony algorithm. Swarm Evol Comput. 2018;38:287–294. doi: 10.1016/j.swevo.2017.09.002
[64] Shoda A, Miyazaki T, Omachi S. JPEG image enhancement with pre-processing of color reduction and smoothing. Sensors. 2023;23(21):8861. doi: 10.3390/s23218861
[65] Satti P, Shrotriya V, Garg B, et al. Intensity bound limit filter for high density impulse noise removal. J Ambient Intell Humaniz Comput. 2023;14:12453–12475. doi: 10.1007/s12652-022-04328-4