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Image Enhancement using Gray Wolf and Whale optimization algorithms

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Abstract

Image enhancement is one of the preprocessing phases in image processing. Image enhancement can effectively improve the appearance of the image for the realization purpose so that the image can be utilized for analytics and the human visual system. The central aim of image enhancement is to induce detail that is concealed in an image or to escalate contrast in a low-contrast image. The contrast enhancement aims to mend the quality of an image to turn it into a more appropriate one for a specific presentation. Till today, many image enhancement methods have been suggested for several presentations and lots of attempts have been made to find a way to further intensify the quality of the enhancement results and reduce the computational intricacy and memory usage. In this paper, image contrast enhancement has been regarded as an optimization problem and a parameterized transformation function, which contains the local and global information of the image was applied to increase the contrast of an image. Two meta-heuristic algorithms i.e. Whale Optimization Algorithm (WOA) and Grey Wolf Optimization algorithm (GWO) were utilized to find the optimal amount of the parameters while maximizing the objective function. The objective function was made up of entropy, edge information of the image, and the structural similarity index measure (SSIM). The outcomes of the suggested method were matched with PSO and with two classic enhancement techniques, including histogram equalization, and contrast stretching. The experimental findings demonstrate that the suggested method outperforms the others.

Keywords: Image enhancement, Particle swarm optimization, Whale optimization algorithm, Histogram equalization, Contrast stretching.

1. Introduction

Image enhancement is a crucial phase in all image processing applications such as image segmentation, image reconstruction, object detection, object classification, and image analysis that can convert an image to another one to increase the interpretability or sensitivity of information for human spectators or to create an excellent input image for other computerized image processing techniques.

Al-Samaraie and Al Saiyd [1], utilized image information in several image processing applications and expanded a vibrant variety of particular characteristics in the image. When an image is altered from one form to a new one via the processes like imaging, scanning, or transmitting, the quality of the produced image can be decreased and become lower than the original one; consequently, image enhancement is vital. Gorai and Ghosh [2], attained worthy segmentation consequences with an enhancing filter. Kumar Rai *et al.* [3], made use of three image enhancement techniques including Contrast stretching [4], Histogram equalization [4], and Contrast partial adaptive histogram equalization.

Image enhancement procedures can be separated into four categories: point operations (for instance contrast stretching, histogram equalization), spatial operations (for instance median filtering, noise smoothing), transform operations (for instance homomorphic filtering), and pseudo-coloring [5]. In this paper, spatial processes were taken into consideration.

Histogram equalization [4] has been the most widespread technique for contrast enhancement of grayscale images [6]. Assume if an image is generally dark, then its histogram would be skewed towards the lower end of the greyscale, and all the image parts would be compacted into the dark end of the histogram [7]. Two methods including Pixel-Based Texture Synthesis and Patch-Based Texture Synthesis were used to uncontaminated the gray-scale image [8].

Mittal *et al.* [9] utilized the fuzzy method in image enhancement, and separated the fuzzy sphere-based enhancement into three stages: fuzzification, amendment of membership values, and defuzzification; and stated that their technique could work on both gray-scale and colored images.

In [10-12], some novel and groundbreaking struggles based on histogram and contrast enhancement techniques have been carried out.

Linear contrast stretching uses a linear alteration that maps the gray scales in a given image to load the complete range of criteria.

Pseudo-coloring is an enhancement method that affectedly colors the gray-scale image constructed on a color mapping, with the widespread collaborative trials needed to regulate a satisfactory mapping [13]. Color images can be developed by dividing the image into the quality of color or light and intensity constitutes [14].

The image enhancement's greatest complexity is providing a criterion for enrichment [15]. The aim of color enhancement will possibly either expand the brightness or raise the saturation [16]. Image Enhancement has been one of the expanded research fields in image processing as it is more promising in several uses such as satellite image processing, medicine, army, print mass media, etc [17]. The majority of the image enhancement work usually manipulates the image histogram by some transformation function to obtain the required contrast enhancement. Consequently, this operation also

International Journal of Innovation in Computer Science and Information Technology
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delivers the maximum information contained in the image.

The key disadvantage of traditional image enhancement methods is the demand for human mediation in determining whether the image is processed for the favorite goal or not, and this is due to the absence of detailed or programmed standards for measuring the amount of image enhancement. Consequently, after refining the image, it is essential to evaluate and assess the processed image to control whether the obtained image satisfies the preferred goal or not [18]. Therefore, widespread efforts have been made to substitute human meddling with meta-heuristic algorithms [19].

Meta-heuristic algorithms play a significant role in substituting human assessments and construing processed images. The meta-heuristic algorithms further improve images and have the maximum level of effectiveness on the equations that are restricted by the user to gain the best results.

Anupriya [20] made a comparison between the enactment of hybrid meta-heuristic and classical meta-heuristic algorithms in the area of image enhancement and determined that the hybrid method overall creates better consequences as compared to the classical meta-heuristic techniques. Similarly, the outcomes of both hybrid and classical meta-heuristic are better than traditional methods such as histogram equalization.

Babu and Sunitha [21] suggested an image enhancement method employing Cuckoo search optimization (CS) [22] algorithms and morphological operation [4]. In their method at first, the color image was transformed into a gray-scale image and then, the finest contrast value was attained by calculating the fitness through the CS algorithm. Then, the morphological operation was done by altering the intensity parameters to develop the quality of the image. As a final point, the gray-scale image was transformed into the original color image once more.

Gorai and Ghosh [23] suggested a PSO [24] based automatic image enhancement method for grayscale images. Their method was matched with several other image enhancement techniques, such as linear contrast stretching, histogram equalization, and genetic algorithm-based image enhancement [25], and it was found that their technique often gave a superior consequence equated to other techniques that they have stated.

Xuanhua *et al.* [26]suggested a hybrid intelligent algorithm that joined bacterial foraging algorithm and particle swarm optimization to improve the contrast of an image and ensured that in their technique, not only the general image contrast was enhanced, but also the minutiae information about the goal image was efficiently improved, and noise intensification was controlled.

Jebril and Al-Haija [27, 28] converted the full-colored input image into a gray-scale image and calculated the image-contrast parameter by using the fitness function of the CS [22] algorithm. The key aim of applying the CS algorithm was to improve the quality of the image to gain the most actual and vigorous amount of contrast factor, also, the morphological procedures which were achieved by regulating the intensity parameters, and they concluded that the CS algorithm was better proficient for optimizing the enhancement functions in comparison with genetic algorithms (GA) [29] and particle swarm optimization(PSO).

In this paper, a parameterized transformation function that had local and global information of an image was utilized to improve the contrast of grayscale images and then assess it by a fitness function. The key aim of the optimization methods such as PSO, GWO [30], and WOA [31] is to take full advantage of the fitness function by defining the ideal amount of the parameters in the transformation function. The fitness function contains the entropy, edge information of the image, and the similarity index measure. The enhanced grayscale images which resulted from WOA and GWO algorithms were matched with PSO-based image enhancement of Gorai and Ghosh [23] and other contrast enhancement techniques. Gorai and Ghosh [23] optimized the parameters of the transformation function by maximizing the fitness function [32]which consisted of the edge information and entropy of the image. When the objective function that contained the edge and entropy information of the image is increased, its structural similarity to the original image may be lost, so both criteria were considered in the proposed method. In fact in the proposed method, the parameters of the transformation function were optimized by maximizing the weighted sum of two functions. The first function contains the entropy and edge information of the image and the second function contains the similarity index measure.

It was seen that meta-heuristic algorithms resulted in superior outcomes in comparison with other automatic image contrast enhancement methods and the GWO and WOA had somewhat similar results and performed better than PSO based enhancement method. As the fitness function was based on entropy and edge information of the image, the algorithm managed to save image information and confine noise intensification.

The remainder of the paper is organized as follows: Section 2, explains the functions used in the suggested work (transformation function and objective functions). In Section 3, the theory of GWO, WOA algorithms, and suggested methodology has been explained. In Section 4, results and discussion have been represented. And, finally, Section 5 includes the conclusion part.

2. Image enhancement functions

The transformation function for the contrast enhancement acquired the input image intensity value of every pixel and created a novel equivalent intensity value. A fitness function was utilized to assess the quality of the enhanced image produced by the transformation function and SSIM [33] value. In this section, the transformation function and objective functions have been defined.

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
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2.1. Transformation function

Input image contrast can be improved by using the transformation function that contemplates the The classical local enhancement transformation function [28, 34] has been given in Eq. (2.1):

$$O_I(x,y)=\frac{\mu_G(x,y)}{\sigma_l(x,y)}\left(I_I(x,y)-\mu_l(x,y)\right) \quad (2.1)$$

where $\mu_l(x,y),\sigma_l(x,y)$ are the grayscale local mean and standard deviation; respectively which are mutually computed in an operator-defined window with radius n and focused at the location (x,y), μ_G is the global mean of the original image, and intensity of each pixel of $P\times Q$ image, where P,Q indicates the rows and columns; respectively.

$I_I(x,y),O_I(x,y)$ are the gray-scale intensities of the input and output images, respectively. One of the prevalent techniques for contrast enhancement is the global intensity transformation [34] which developed from Eq. (2.1) and is used for any pixel that is located at (x, y) of the image as in the next equation:

$$O_I(x,y)=\frac{\varphi.\mu_G(x,y)}{\sigma_l(x,y)+\gamma}\left(I_I(x,y)-\tau.\mu_l(x,y)\right)+(\mu_l(x,y))^{\rho}$$

$$\rho,\gamma,\tau,\varphi \in \mathrm{R}\geq 0 \quad (2.2)$$

$\mu_G(x,y),\mu_l(x,y),\sigma_l(x,y)$ are the global mean, local mean, and local standard deviation; respectively, that can be abridged as [34]:

$$\mu_G(x,y)=\frac{1}{PQ}\sum_{x=1}^{n}\sum_{y=1}^{n}I_I(x,y) \quad (2.3)$$

$$.\,\mu_l(x,y)=\frac{1}{nn}\sum_{x=1}^{n}\sum_{y=1}^{n}I_I(x,y). \quad (2.4)$$

$$\sigma_l(x,y)=\sqrt{\frac{1}{nn}\sum_{x=1}^{n}\sum_{y=1}^{n}(I_I(x,y)-\mu_l(x,y))^2} \quad (2.5)$$

$\rho,\gamma,\tau\,and\,\varphi$ are parameters in the Eq. (2.2) which for diverse values take several intensities for each pixel. The foremost purpose was to optimize these four parameters by meta-heuristic algorithms in which the value of the achieved image was assessed by the fitness function. The parameter ranges were the same as [35].

$$\rho\in[0,1.5],\gamma\in[0,0.5],\tau\in[0,1],\varphi\in[0.5,1.5] \quad (2.6)$$

However, different quantities of γ [28] would have a fundamental effect on image intensity; small values would expand the intensity of the image. Therefore, after intensity normalization, the original image vanished. Consequently, to overwhelm this issue, the range of γ was augmented and set out in $\left[1,\frac{\mu_G}{2}\right]$.

2.2. Objective functions

The objective function was required to assess the quality of an enhanced image devoid of human meddling. There have been many objective functions in the literature [36] [37] [38]. Since, in most papers, only a transformation function is used to evaluate the image quality in meta-heuristic algorithms, a multi-objective problem has been considered here. The objectives were the weighted sum of two functions. The first one contained three procedures, specifically the entropy value, the sum of edge intensities, and the number of edges. The Entropy value exposed the information content in the image and was computed based on a histogram which was described as follows

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Received: 21 March 2022
Accepted: 10 June 2022

$$Entropy\left(I_E\right)=-\sum_{i=0}^{255}E_i \tag{2.7}$$

$$E_i=\begin{cases} h_i\log_2 h_i & h_i\neq 0\\ 0 & h_i=0\end{cases} \tag{2.8}$$

Where E_I is the enhanced image and h_i is the i^th intensity probability.
The first objective function was described as follows:

$$F_1\left(E_I\right)=\log(\log\left(N\left(S_I\right)\right))\times\frac{N\_E\_P\left(S_I\right)}{PQ}\times Entropy\left(E_I\right) \tag{2.9}$$

S_I , $N\_E\_P\left(S_I\right)$, and $N\left(S_I\right)$ are a Sobel edge detector [6], the number of edge pixels, and the amount of Sobel edge pixel intensities, respectively. The edges could be perceived by numerous effectual edge indicator algorithms such as Sobel, Laplacian [6], Canny [39], etc.

$$S_I=\sqrt{(\partial u_{E_I}\left(x,y\right))^2+(\partial v_{E_I}\left(x,y\right))^2} \tag{2.10}$$

$$\begin{aligned}\partial u_{E_I}\left(x,y\right)&=E_I\left(x+1,y-1\right)+2E_I\left(x+1,y\right)+E_I\left(x+1,y+1\right)-E_I\left(x-1,y-1\right)\\&-2E_I\left(x-1,y\right)-E_I\left(x-1,y+1\right)\end{aligned} \tag{2.11}$$

$$\begin{aligned}\partial v_{E_I}\left(x,y\right)&=E_I\left(x-1,y+1\right)+2E_I\left(x,y+1\right)+E_I\left(x+1,y+1\right)-E_I\left(x-1,y-1\right)\\&-2E_I\left(x,y-1\right)-E_I\left(x+1,y-1\right)\end{aligned} \tag{2.12}$$

The second objective function which could clarify the enhanced image quality was the similarity index measure (SSIM) [33] as follows:

$$F_2\left(E_I\right)=SSIM=\frac{\left(2\mu_I\mu_{E_I}+c_1\right)\left(2\sigma_{I,E_I}+c_2\right)}{\left(\mu_I^2+\mu_{E_I}^2+c_1\right)\left(\sigma_I^2+\sigma_{E_I}^2+c_2\right)} \tag{2.13}$$

Where, μ_I,μ_{E_I} and $\sigma_I^2,\sigma_{E_I}^2$ are the mean value and variance value of the corresponding original and enhanced images, and σ_{I,E_I} is the covariance between original and enhanced images. $c_1=(0.01\times 255)^2, c_2=(0.03\times 255)^2$ are two constants.

The fitness function was defined as follows:

$$Fitness=w_1F_1\left(E_I\right)+w_2F_2\left(E_I\right) \tag{2.14}$$

where $w_1,w_2\geq 0$ are weights and $w_1+w_2=1$.

3. Metaheuristic Algorithms and the main method

In this section, the used meta-heuristic algorithms that have been used and the suggested methodology are discussed.

3.1. Whale optimization algorithm (WOA)

The whale optimization algorithm (WOA) has been a newly presented nature-inspired algorithm suggested by Mirjalili and Lewis [31]which imitates the hunting behavior of humpback whales [41]. One of the hunting behaviors of whales is that they dive about 12 meters under the prey and begin to form bubbles in a twisting form around the prey then come to the water surface to catch the prey. The mathematical modeling of the WOA algorithm has been clarified as follows. For more information refer to [31].

3.1.1. Surrounding prey

Humpback whales can detect the position of the prey and can surround it. Since the exact location of the prey (optimal solution) is not known, the whale algorithm considers the best current solution as the target or close to the target, and other whales update their position according to the current solution. This act has been exemplified as follows in Eqs. (3.1) and (3.2).

$$\vec{R}=\left|\vec{W}.\vec{L}^*\left(t\right)-\vec{L}\left(t\right)\right| \tag{3.1}$$

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
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$$\vec{L}^{*}(t+1)=\vec{L}^{*}(t)-\vec{V}.\vec{R} \quad (3.2)$$

where "t", $\vec{L}^{*}$ and $\vec{L}$ signify the current iteration, the current finest solution, and the location vector respectively,"| | " is the absolute value, and"." is elementwise multiplication. If there is a superior solution, $\vec{L}^{*}$ should be updated. The vectors $\vec{V},\vec{W}$ have been figured as follows.

$$\vec{V}=2\vec{m}.\vec{n}-\vec{m} \quad (3.3)$$

$$\vec{W}=2\vec{n} \quad (3.4)$$

In the exploration and exploitation phases $\vec{m}$ is reduced from 2 to 0 through the iterations, and $\vec{n}$ is a random value in [0, 1].

3.1.2. Bubble-net attacking method (exploitation phase):

The bubble-net attacking of humpback whales contains two methods, the first approach is the shrinking surrounding technique which is accomplished by reducing the value of $\vec{m}$ in Eq. (3.3) Correspondingly, the amount of $\vec{V}$ is also decreased. The second approach is the spiral updating position technique in which whales try to imitate the helix-shaped movement around the best solution (prey) as follows:

$$\vec{L}(t+1)=\vec{R}.e^{cf}.\cos(2\pi f)+\vec{L}^{*}(t) \quad (3.5)$$

The distance between the prey and i^{th} whale is designated by $\vec{R}$, c and f are constant and arbitrary numbers in [-1, 1] respectively. The humpback whales swim around the prey within a shrinking circle and along a spiral-shaped route at the same time. Therefore, this conduct has been modeled by giving the identical likelihood of happening to both of the methods as follows:

$$\vec{L}(t+1)=\begin{cases}\vec{L}^{*}(t)-\vec{V}.\vec{R} & p<0.5\\ \vec{R}.e^{cf}.\cos(2\pi f)+\vec{L}^{*}(t) & p\geq 0.5\end{cases} \quad (3.6)$$

where *p* is considered a random number in [0, 1].

3.1.3. Search for prey (exploration phase)

Changes in $\vec{V}$ values are considered as exploration phase. In this phase, the humpback whales search arbitrarily according to the location of each one. The arbitrary values for $\vec{V}$ is greater than -1 or less than 1 to force the whale to travel far away from the reference whale. In the exploration phase, the position of the whales is updated according to the randomly selected whale. The mechanism $|\vec{V}|$ highlighted the exploration and made it possible for the WOA algorithm to conduct a global search. The mathematical model was as follows :

$$\vec{R}=\left|\vec{W}.\vec{L}_{rand}(t)-\vec{L}(t)\right| \quad (3.7)$$

$$\vec{L}(t+1)=\vec{L}_{rand}(t)-\vec{V}.\vec{R} \quad (3.8)$$

$\vec{L}_{rand}$ is an arbitrarily selected whale in a group of existing whales. The WOA algorithm starts to find the best solution by arbitrarily tracing the whales in the search space. In each repetition, the whales update their location according to either the finest whale or an arbitrarily selected whale. The value of p reveals that the whales should have a spiral or circular movement. The WOA algorithm ends when a predetermined termination condition is met.

3.2. Grey wolf optimizer (GWO)

A Grey wolf optimizer (GWO) algorithm was suggested by Mirjalili *et al.* [30] imitated the social hierarchy and hunting conduct of grey wolves. Group hunting is one of the main behavior of wolves. The

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Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
Accepted: 10 June 2022

wolves' hierarchy from the highest to lowest order is considered as α, β, δ *and* ω wolves. The first, second, and third best solutions are considered as α, β, δ respectively, and the rest of the solutions are ω. The hunting process is persuaded by α, β, δ wolves and ω wolves follow them. The mathematical model of the hunting behavior of the grey wolves has been portrayed in Eqs. (3.9) and (3.10).

$$\vec{R} = \left|\vec{W}.\vec{G}_L(t) - \vec{G}(t)\right| \tag{3.9}$$

$$\vec{G}(t+1) = \vec{G}_L(t) - \vec{V}.\vec{R} \tag{3.10}$$

In the above equations t and $\vec{V}$,$\vec{W}$ designate the current iteration and coefficient vectors respectively, also $\vec{G}_L$ and $\vec{G}$ are the location vector of the prey and the location vector of grey wolf respectively, "." is elementwise multiplication.

The vectors $\vec{V}$ and $\vec{W}$ have been figured as follows:

$$\vec{V} = 2\vec{e}.\vec{a_1} - \vec{e} \tag{3.11}$$

$$\vec{W} = 2\vec{a_2} \tag{3.12}$$

During the iterations, the components of $\vec{e}$ are linearly reduced from 2 to 0 and $\vec{a_1}, \vec{a_2}$ are arbitrary vectors in [0, 1].

Since there is no information about the exact location of the prey, for mathematical modeling it is assumed that the α, β , and δ wolves have better information about the location of the prey so each wolf updates its location according to the three best solutions which have been achieved so far, as given in Eqs (3.13)-(3.15).

$$\vec{R_\alpha} = \left|\vec{W}_1.\vec{G}_\alpha - \vec{G}\right|, \quad \vec{R_\beta} = \left|\vec{W}_1.\vec{G}_\beta - \vec{G}\right| \quad , \quad \vec{R_\delta} = \left|\vec{W}_1.\vec{G}_\delta - \vec{G}\right| \tag{3.13}$$

$$\vec{G}_1 = \vec{G}_\alpha - \vec{V}_1.\left(\vec{R_\alpha}\right) \ , \ \vec{G}_2 = \vec{G}_\beta - \vec{V}_2.\left(\vec{R_\beta}\right) \ , \ \vec{G}_3 = \vec{G}_\delta - \vec{V}_3.\left(\vec{R_\delta}\right) \tag{3.14}$$

$$\vec{G}(t+1) = \frac{\vec{G}_1 + \vec{G}_2 + \vec{G}_3}{3} \tag{3.15}$$

3.3. Suggested methodology

To enhance the grayscale input image a transformation function as shown in Eq. (2.2) was utilized. The transformation function considers both global and local information of the image and is comprised of 4 parameters ($\rho, \gamma, \tau, \varphi$) that should be optimized. The parameter varieties have been well-defined in Eq. (2.6). The parameters of the transformation function were optimized by using different meta-heuristic algorithms such as WOA and GWO by considering Eq. (2.14) as a fitness function. In most metaheuristic-based enhancement methods, only the entropy and edge information of the image is used to evaluate the quality of the enhanced image. Increasing these measures may decrease the similarity of the enhanced image to the original image. So in this paper, the SSIM value is also considered in the fitness function and a multi-objective problem has been defined. The process of using metaheuristic algorithms is as follows: Initially, the total number of n search agents was generated, each containing transformation function parameters. Then, these parameters in each search agent were optimized using the fitness function Eq. (2.14), and the best answer was provided. The process of the WOA and GWO was iterated *T* times until the maximum value of the fitness function was gained. Finally, an enhanced image was obtained using the best parameters for the transformation function. The pseudo-code of the proposed WOA and GWO-based methods are exemplified as follows respectively:

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
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Quasi-code of proposed enhancement method using the WOA algorithm

Enter the original image.
Initialize n search agents L_i randomly, which each contain 4 parameters $(\rho,\gamma,\tau,\varphi)$.
Apply Eq (2.2) to all pixels of the image, according to the parameters that have been initialized.
Different enhanced images are obtained.
Iter=1
Calculate the fitness function for each search agent, using Eq (2.14) and consider L^* as the best solution.
while Iter < maxiter
for all search agents
Update $m, V, W, f, and\ p$
if $p < 0.5$
if $\lvert\vec{V}\rvert < 1$.
Update search agents location through Eq (3.1)
else if $\lvert\vec{V}\rvert \geq 1$
Select a search agent randomly. L_{rand}
Update search agents location through Eq (3.8)
end if
elseif $p \geq 0.5$
Update search agents location through Eq (3.5)
end if
end for
If the search agent is out of the search space, return it back
Calculate the fitness function for each search agent
Update L^* if there is a better solution.
Iter=Iter+1
end while
return L^*
The enhanced image is obtained with the maximum fitness function.

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
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Quasi-code of proposed enhancement method using the GWO algorithm

Enter the original image.
Initialize the population of n gray wolf $G_i\left(i=1,2,\ldots,n\right)$ which each contains 4 parameters $\left(\rho,\gamma,\tau,\varphi\right)$
Apply Eq (2.2) to all pixels of the image, according to the parameters that have been initialized.
iter=1
Initialize e, V, and W
Evaluate the fitness of each gray wolf by the Eq.(2.14)
G_α =the best gray wolf
G_β =the second-best gray wolf
G_δ =the third-best gray wolf
while (iter < Max_iter)
for each gray wolf
Update the position of the current gray wolf by equation (3.15)
end for
Update e, V, and W
Evaluate the fitness of all gray wolfs by the Eq.(2.14)
Update G_α, G_β, and G_δ
Iter=iter+1
end while
return G_α
The enhanced image is obtained with the maximum fitness function.

4. Results and discussion

In this paper, several meta-heuristic algorithms were utilized to solve the image quality enhancement problem and were tested on diverse grayscale images. To this end, four grayscale images such as Baboon 256×256, Peppers 256×256, Gold-hill 256×256, and Iris 300×300 are considered. These images are the noiseless test images in the field of image processing. Each resolution is 8 bits per pixel. The proposed methods (WOA, GWO) were compared with other approaches like Histogram Equalization (HE), Linear Contrast Stretching (LCS), and PSO-based (EPSO) image enhancement [23] techniques. HE and LCS algorithms were distinctly assessed by two objective functions (F_1, F_2), and the PSO-based method was evaluated automatically by the first function F_1, after obtaining the maximum value of the objective function, the value of the similarity index was also calculated manually and the defined fitness function in (2.14) was obtained. The proposed WOA-based (EWOA) and GWO-based (EGWO) enhancement algorithms were assessed automatically by the fitness function stated in Eq. (2.14) which was a weighted sum of two functions (F_1, F_2). For different trial images, the values of the F_1 and F_2 for HE and LCS algorithms and PSO-based method were calculated distinctly, and the weighted sums of these functions were calculated and listed in Table 1, also the values of the first and second functions for all methods were calculated and the results were demonstrated in Tables 2 and 3.

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
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Table 1- fitness values for different images

Image	size	HE	LCS	EPSO	EWOA	EGWO
Baboon	256*256	0.6976	0.865	0.928	**0.9388**	**0.938**
Peppers	256*256	0.9993	1.1573	1.1778	**1.1793**	**1.1787**
Gold hill	256*256	0.9069	1.0788	1.0875	**1.1086**	**1.1065**
Iris	300*300	0.7877	1.066	1.0922	**1.1093**	**1.1084**

Table 2- First function values for different images

Image	size	HE- F_1	LCS- F_1	PSO- F_1	WOA- F_1	GWO- F_1
Baboon	256*256	0.5962	0.7656	0.9082	0.9279	0.9236
Peppers	256*256	1.0614	1.3293	1.3869	1.3796	1.372
Gold hill	256*256	0.9374	1.1706	1.2153	1.228	1.2203
Iris	300*300	0.8622	1.1634	1.2836	1.2359	1.2433

Table 3- Second function values for different images

Image	size	HE- F_2	LCS- F_2	PSO- F_2	WOA- F_2	GWO- F_2
Baboon	256*256	0.7989	0.9644	0.9479	0.9525	0.9498
Peppers	256*256	0.9371	0.9854	0.9686	0.9867	0.9779
Gold hill	256*256	0.8765	0.987	0.9598	0.9892	0.9927
Iris	300*300	0.7132	0.9692	0.9009	0.9827	0.9735

As shown in Table 1, the proposed enhancement methods attained higher fitness values than the existing methods, including classical methods and EPSO. The EWOA and EGWO had almost similar values and provided better results than the EPSO. The main reason for the better performance of the proposed methods compared to the EPSO method is that two objective functions are simultaneously maximized in this method. For fair judgment, the number of iterations and search agent size were equal for all algorithms.

In this study, the same preferences were considered for the objective functions, so the weights in Eq. (2.14) were considered 0.5 and 0.5; respectively. The window size was considered 3 to compute the local mean and the local standard division in Eq. (2.2). The algorithms repeatedly were applied until the optimal fitness value was achieved to get an appropriate enhancement on processed images. The particle size and population size of all algorithms were considered 20 and 30; respectively.

In tables 1-3, the presentation of EWOA and EGWO was compared with three renowned algorithms specifically HE, LCS, and EPSO through Eqs. (2.9), (2.13), and (2.14) on diverse images. As seen in Table 2, by considering the first function, metaheuristic algorithms always acted better than the other methods. Table 3 shows that according to the second function, EGWO and EWOA performed almost better than other methods.

Table 4 have indicated the performance of the diverse images (fitness function) concerning EPSO, EWOA, and EGWO and matching optimal parameters ($\rho, \gamma, \tau, \varphi$).

Table.4- Fitness and optimal parameters values

baboon	fitness	ρ	γ	τ	φ
EPSO	0.928	0.7266	64.8197	0	0.5
EWOA	**0.9388**	0.7009	64.794	0	0.5014
EGWO	**0.938**	0.704	64.8197	0.0104	0.5
Peppers					
EPSO	1.1779	0.9479	60.1279	0.7883	1.067
EWOA	**1.1793**	0.9774	27.8808	0.8842	0.5
EGWO	**1.1787**	0.9382	47.5545	0.7367	0.6855
Gold hill					
EPSO	1.0875	0	45.3203	0	0.5
EWOA	**1.1086**	1.0106	56.059	1	1.0523
EGWO	**1.1065**	1.0157	56.059	1	1.0425
Iris					
EPSO	1.0922	1.0648	45.2981	1	0.8449
EWOA	**1.1093**	1.0198	56.0253	1	1.1073
EGWO	**1.1084**	1.026	54.4748	1	1.1572

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
Accepted: 10 June 2022

Figure 1 has clarified the graphical illustration of the comparison results in terms of the fitness function defined in Eq.(2.9). It was realized that all meta-heuristic algorithms delivered superior results than other automatic image contrast enhancement techniques (HE, LCS). As exemplified in Figure 2 for all images, EWOA, and EGWO performance was superior to EPSO in terms of the fitness value. Figure 3 a, b, c, d, e, and f represent the Original, HE, LCS, EPSO, EWOA, and EGWO respectively, on different images. Since there were two phases including exploration and exploitation which were done distinctly and in almost half of the repetitions, the WOA and GWO had high junction speed and optima evasion at the same time during the repetitions. PSO did not allocate particular repetitions to exploration or exploitation. In other words, PSO utilized one formula to keep informed of the location of the particles, which escalated the probability of getting stuck in local optima. All the computation was done in MATLAB with the Core i5 processor.

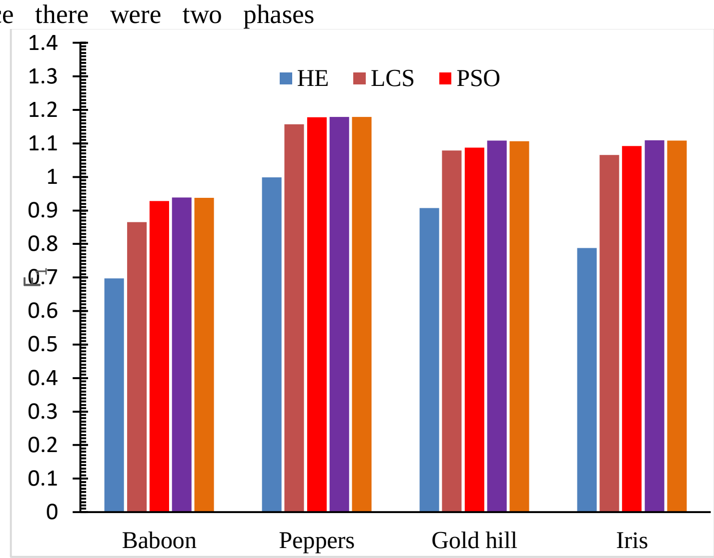
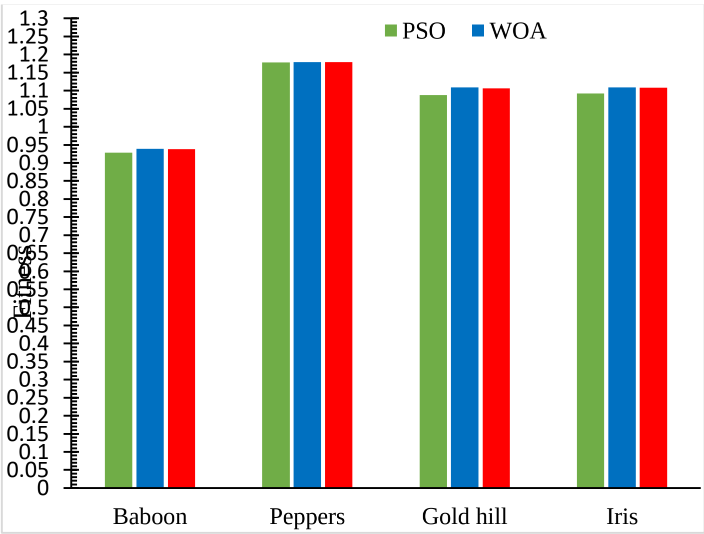


Figure 1. Performance analysis of five algorithms



International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
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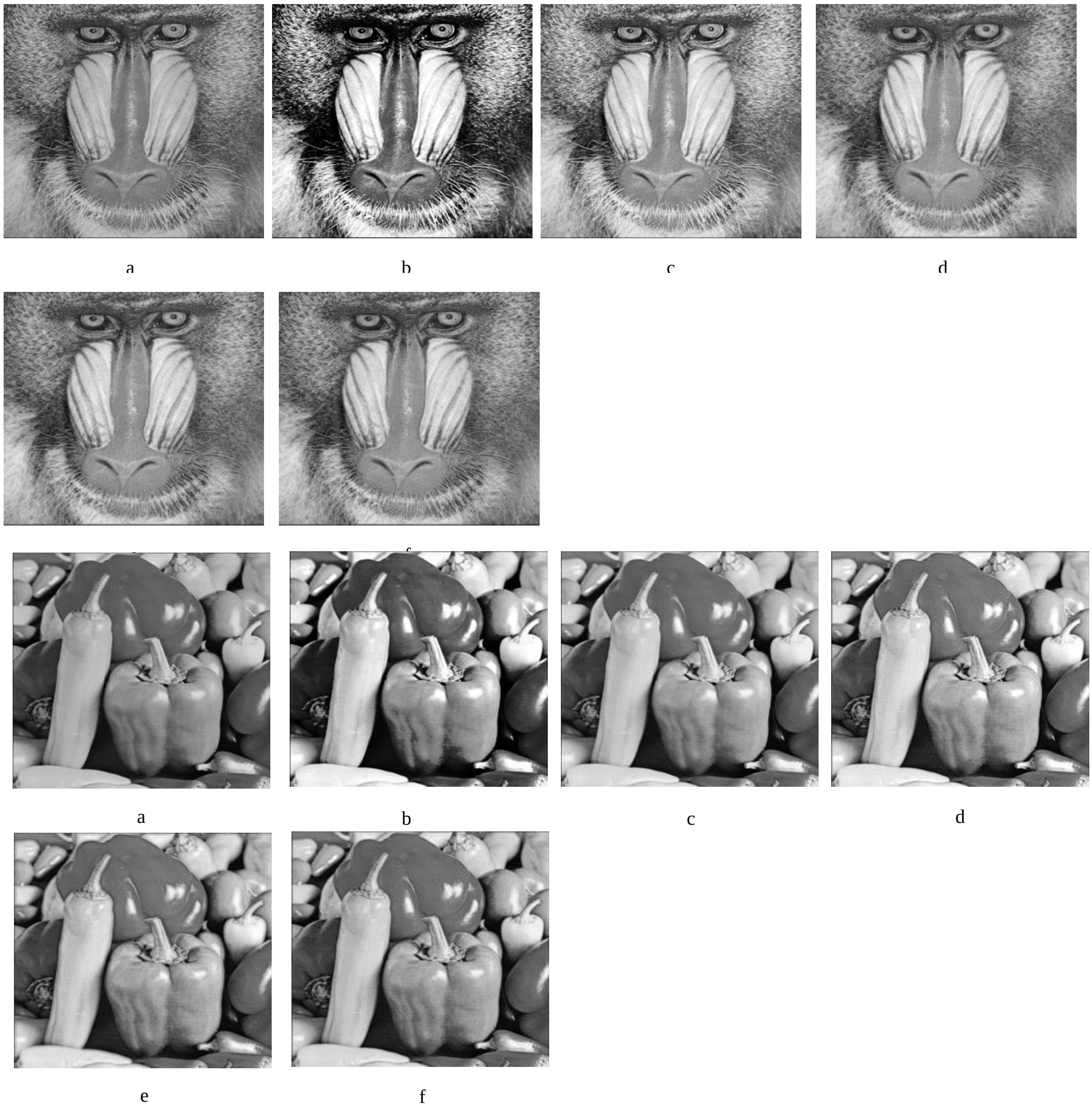
Figure 2. Performance analysis of three metaheuristic algorithms



International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
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Figure 3. Images resulting from enhancement techniques

International Journal of Innovation in Computer Science and Information Technology
Vol.4, NO.1 , P:68 - 81
Received: 21 March 2022
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5. Conclusions

The techniques which improve the contrast of images have been one of the main global subjects of research for a long time. In this paper, two automatic image contrast enhancement techniques [32] for grayscale images that utilized WOA and GWO have been suggested. The results of these methods were compared with other image contrast enhancement techniques i.e. HE, LCS, and a meta-heuristic algorithm, namely, PSO. The results indicated that meta-heuristic algorithms often acted better than other methods, and also the fitness function improved much better with WOA and GWO in comparison with the PSO algorithm because not only does the contrast of the image increase, but also the similarity of the image to the original image increased.

In the future, the window size may also be considered as a parameter for optimization, and the optimal value can be acquired through meta-heuristic algorithms. The combination of WOA or GWO with other meta-heuristic algorithms can also be applied for this purpose. Meanwhile, the proposed technique can be applied to different image applications such as medical and satellite images, etc. For further surveys, color images can also be investigated.

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