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Optimization Algorithms for Medical Image Quality Improvement

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***Abstract*— This paper proposes four optimization algorithms: BAT algorithm, Firefly algorithm (FFA), Gases Brownian movement optimization (GBMO), Wind driven optimization (WDO) for tuning image parameters a, b, c and k of image. For algorithms brief description, main equations for solution are given. Three objective functions are formulated and performance of images is tested with three objective functions. The simulation results of algorithms are compared by performance parameters such as mean square error, root mean square error, peak signal to noise ratio and entropy.**

Keywords BAT algorithm, Gases Brownian movement optimization, Firefly algorithm, Wind driven optimization, Entropy

I. Introduction

Optimization Algorithms are the powerful tools to obtain suitable parameters for design aspects and accurate set of operating conditions. Optimization Algorithms reduce the complexity and risk in operation. These algorithms can assist workers in operation and design. Optimization Algorithms finds applications in medical field for enhancing the quality of medical images like X-ray, CT and MRI images [2].

Image enhancement entails making adjustments to digital images to make them more acceptable for display or additional image analysis. Sharpening, contrast adjustment, filtering, interpolation, magnification, and other techniques for improving images are available. Quantifying the enhancement criterion is the most difficult aspect of image enhancement. As a result, a lot of image enhancing approaches are empirical and involve interaction to produce good results. However, due to its applicability in almost all image processing scenarios, image improvement continues to be of utmost importance. Enhancing a colour image could call for enhancing the colour balance or contrast in the image [3].

Human image datasets, most frequently derived from MRI or CT scanners, are used and explored as part of image processing in the medical field. It helps radiologists and physicians diagnose or carry out research by giving them a better grasp of the anatomy of certain individuals or groups of patients. One can non-invasively and in great detail investigate internal anatomy using medical image processing. Making and analysing 3D anatomical models may improve patient outcomes or more precisely diagnose medical conditions. Medical images frequently contain uncertainties, which can be seen as erroneous grey levels, a lack of homogeneity between image segments, or a lack of contrast between an object and its surroundings. Because of this, it is challenging to segment or identify the boundaries of abnormal structures or lesions in the images, which leads to a wrong diagnosis. Therefore, these medical images need to be enhanced. The objective of enhancement is to change an image's format so that it is better suited for subsequent processing, like segmentation.

II. IMAGE QUALITY PARAMETERS

A. Mean Square Error (MSE)

The MSE, which is determined by the equation, stands for the mean square error between two images ‘P’ and ‘Q’ of size M x N.A smaller value of MSE indicates better performance of an algorithm.

$$MSE = \frac{\sum_{i,j}(P_{i,j} - Q_{i,j})^2}{MN} \quad (1).$$

B. Root Mean Square Error (RMSE):

The RMSE is obtained by taking the square root of MSE and is given in equation (2.5). A smaller value of RMSE indicates better performance of an algorithm.

$$RMSE = \sqrt{\frac{\sum_{i,j}(P_{i,j} - Q_{i,j})^2}{MN}} \quad (2)$$

C.Peak Signal to Noise Ratio

The PSNR value is calculated by dividing the maximum possible signal power by the power of the distorting noise that affects the quality of its representation. The PSNR value is calculated using an equation 2.6 and is represented in decibels.

$$PSNR = 10log_{10}(\frac{L^2}{MSE}) \quad (3)$$

D. Structural Similarity Index Measure

A measure of similarity between two images that is congruent with human visual perception is the Structural Similarity Index Measure ((SSIM)). Luminance, contrast, and structural comparisons can all be used to determine how similar two objects are. One of the complete reference image quality metrics, the SSIM index, calls for a distortion-free, fully complete reference image. In order to determine the SSIM value, windows a and b of size N x N must be defined in both the reference image (P) and the deformed image (Q), respectively.

$$SSIM = \frac{(2\mu_a\mu_b + C1)(2\sigma_{ab} + C2)}{({\mu_a}^2 + {\mu_b}^2 + C1)({\sigma_a}^2 + {\sigma_b}^2 + C2)} \quad (4)$$

E. Mean SSIM

The Mean SSIM (MSSIM) index value is calculated using equation 2.8 after statistical measures are locally computed due to the non-stationary nature of image signals.

$$MSSIM(P,Q) = \frac{1}{W}\sum_{i=1}^{M} SSIM(a_i, b_i) \quad (5)$$

F.Entropy

Any pixel in an image can be thought of as a random variable. The equation 2.9 yields the entropy (H), a measurement of the average information content of an image. A large value of entropy indicates more information content.

$$H = -\sum_{i=0}^{L-1} P(r_i)log_2P(r_i) \quad (6)$$

III. OBJECTIVE FUNCTION

An objective function is required to evaluate the quality of an enhanced image without human intervention. There are numerous objective functions available in the literature. It is observed that a good contrast enhanced image has more edgels than the original image, and the enhanced version should have a higher intensity of the edges. In this study, an objective function is created by combining two performance measures: the sum of the number of edgels (edge pixels) and the PSNR. The formulation of objective functions for this research study is presented below.

$$Objective\ function\ OF_1 = F(I_e) = \log(\log(E(I_S))) \times \frac{n_{edgels(I_S)}}{M \times N} \times H(I_e) \quad (7)$$

$$Objective\ function\ OF_2 = PSNRI(I_e) \quad (8)$$

$$Objective\ function\ OF_3 = W_1 \times OF_1 + W_2 \times OF_2 \quad (9)$$

The optimization techniques used in this study are designed to find the best solution (a, b, c, and k) that maximises the objective function based on the objectives in the objective function.Three scenarios for image enhancement problems are tested using optimization algorithms in this work to assess the importance of objective function.

The three scenarios are listed as follows:

Case 1: Considering OF_1 to find the best solution (a, b, c & k)
Case 2: Considering OF_2 to find the best solution (a, b, c, & k)
Case 3: Considering OF_3 to find the best solution (a, b, c & k)

IV. BAT ALGORITHM

Another population-based algorithm developed by Xin-She-Xang in 2010 for solving global optimization challenges is the Bat algorithm [1-4]. The echolocation behaviour of bats inspired this algorithm. They are the second biggest order of mammals, and they migrate hundreds of kilometres to find prey from various types of insects, even in complete darkness, using a property known as echolocation. Each bat flies at a different velocity and with a different wavelength and loudness. The bat uses sonar-type echolocation to distinguish between preys and avoid obstacles. It changes its wavelength, loudness, and pulse emission rate as it hunts for prey. For measuring algorithm performance, optimal parameter setting is critical. As shown in Figure 5.1, the bat emits a loud sound pulse and waits for an echo to bounce back from the surrounding objects. Each sound pulse contains both loudness and frequency. The loudness decreases as the bat moves closer to the prey, and the sound pulse emitted by the bat lasts only a short time. Most bat species have a frequency range of 25 KHz to 100 KHz, with some reaching up to 150 KHz. Normally, bats emit 10-20 sound bursts per second, but when hunting for prey, they emit 200 sound bursts per second.

The wave length of a constant frequency ‘f’ sound burst is given by

$$\lambda = v/f \quad (10)$$

Where is the velocity of light and wavelength ranges from 2mm to 14mm for frequencies ranging from 25 KHz to 150 KHz.Xin-She-Xang established rules and made some assumptions for implementation of Bat Algorithm :

Assumption 1: Using echolocation, bats can detect distance as well as the difference between prey and barriers.

Assumption 2: To find prey, bats fly at a random velocity at a position with a fixed frequency and varying wavelength and loudness A_0.

Assumption 3: Bats automatically adjust the wavelength of the emitted pulse, and depending on the proximity of the target, they also tweak the rate of pulse emission r ϵ [0,1], where 0 relates to no pulses and 1 refers to the maximum rate of pulse emission. A_0's loudness ranges from a large positive value to a small constant value.

A.Implementation steps of BA

Step 1: Set the problem and algorithm parameters.
The algorithm parameters, such as population size, problem dimension, the maximum number of iterations, and limits, must be initialized in the first step.
Step 2: Random generation of a, b, c and k gains

$$X = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{d-1}^1 & x_d^1 \\ x_1^2 & x_2^2 & \cdots & x_{d-1}^2 & x_d^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{pop-1} & x_2^{pop-1} & \cdots & x_{d-1}^{pop-1} & x_d^{pop-1} \\ x_1^{pop} & x_2^{pop} & \cdots & x_{d-1}^{pop} & x_d^{pop} \end{bmatrix} \tag{11}$$

$$x_i^j = x_{min,i} + (x_{max,i} - x_{min}$$

Where d is the set of decision variables, $\mathbf{x}_i^j$ represents the j[th] population of the i[th] particle, which is usually generated in between limits as $\mathbf{x}_{max,i}$ and $\mathbf{x}_{min,i}$, and rand() is an arbitrary number between 0 and 1.

$$Soln = [X] \tag{12}$$

Step 3: Fitness evaluation: calculate the fitness values for each initial solution and record the best solution.

Step 4: Begin the BAT algorithm's evolution procedure. Assign a frequency to each Bat at random.

$$f_i = f_{min} \tag{13}$$

Where β ϵ [0, 1] is a random vector drawn from a uniform distribution
Initially, each bat is assigned a frequency at random, drawn uniformly from the range [ ].

Step 5: Randomly generate Bat positions (a, b, c and k parameters)

Step 6: Fitness assessment (objective function): Determine the fitness values for each solution.

Step 7: Selection: In this step, compare each new bat solution to the corresponding initial solution and replace the better solution with the initial bat to find the best bat and best solution among the initial bats.

Step 8: Stopping criterion: If the maximum number of iterations is reached during this step, the computation is terminated. Otherwise, steps 4 through 7 are repeated.

V. Firefly Algorithm

Bioluminescence is caused by a chemical reaction within a living organism that makes them glow. Most bioluminescent organisms are found in the ocean. Some-including fireflies and fungi are found on the land. Fireflies are famous for their spectacular bioluminescent courtship displays. They are the world's most efficient light producers. An average electric bulb gives 90 percent of its energy as heat and only 10 percent as light. Fireflies produce light through an efficient chemical reaction that allows them to glow without wasting heat energy, all the 100 percentage of the energy goes into making light. They talk each other using these light signals. Each species has its own pattern of light flashing. Firefly algorithm is a nature-inspired algorithm [1-3] inspired by the mating and flashing behaviour of fireflies. The intensity of the light decreases with increase in distance between two fireflies, therefore fireflies can communicate to a limited distance. The number of fireflies in the space always moves towards brighter firefly, if no one is brighter they move randomly in the space [3]. Inspired by the behaviour of firefly Xin-She Yang developed firefly algorithm by the following assumptions[7]:

- Any firefly moves towards brighter firefly irrespective of their gender.
- The attractiveness and brightness between any two flies decrease with the increase in the distance between them.
- The brightness of a firefly resembles the objective function.

A. Light intensity and Attractiveness

The Attractiveness (β) is proportional to the light intensity (L) and decreases with distance (r). Flash light is formulated as objective function to be optimized. Attractiveness differs with the difference in the distance r_{ij} between firefly i and firefly j.

The intensity of light follows the inverse square law as:

$$L(r) = L_s / r^2 \tag{14}$$

where L_S is intensity at source

with the known medium, the coefficient of absorption γ is constant and the light intensity L varies with the distance r as:

$$L(r) = L_0 \; e^{-\gamma r^2} \tag{15}$$

where L_0 is the initial intensity at r = 0

Since attractiveness and light intensity are directly proportional between adjacent fireflies, the attractiveness can be written as:

$$\beta = \beta_0 e^{-\gamma r^m} \qquad (m \geq 1) \tag{16}$$

B. Distance between fireflies

The distance between two fireflies i and j at x_i and x_j respectively is the Cartesian distance written as:

$$r_{ij} = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{17}$$

where $x_{i,k}$ is the K^{th} component of spatial coordinate x_i of the i^{th} firefly and d is the number of dimensions.

C. Position Update

When the firefly i is attracted to more attractive firefly j, the updated position can be determined by the following equation

$$x_i = x_i + \beta_0 e^{-\gamma r_{ij}^2} (x_j - x_i) + \alpha\epsilon \quad (18)$$

where the second term is due to attraction and third term is randomization with α being randomization parameter and ϵ being the vector of the random numbers drawn from the Gaussian distribution. For n number of flies distributed uniformly in the entire search space, as the iterations of the algorithm continues firefly converges into all local optimum and by comparing best solution among these local optima, global optima can be reached.

VI. GBMO ALGORITHM

To find the best solution, the GBMO algorithm employs the law of motion, gases Movement, and turbulent rotational movement. In the proposed method, the agents are molecules, and their effectiveness is determined by their positions [9].Each of these molecules start moving in the solution space, allowing all molecules to move towards to the solution. T = 0 ensures the convergence of the GBMO algorithm. A molecule in GBMO has four performance requirements: mass, position, turbulence radius and velocity.

The Gases brownian motion optimization algorithm is used to optimise the a, b, c, and k parameters. Individual performance is evaluated using three objective functions, OF1, OF2, and OF3,

A.Implementation steps of GBMO

The GBMO algorithm is described in this section for optimising the a, b, c, and k parameters for MRI image enhancement. The following are the steps of the proposed algorithm:

Step 1: Initialization at random. The GBMO algorithm gets started with a population (Molecules in the space). In fact, it generates a swarm of molecules with erratic positions and speeds.

$$x_i^d = x_{min,i} + (x_{max,i} - x_{min,i}) * rand() \quad (19)$$

$$v_i^d = v_{min,i} + (v_{max,i} - v_{min,i}) * rand() \quad (20)$$

where *i* is the number of populations and *d* is the number of decision variables, x_i^d represents threshold levels, i.e., i^{th} population of d^{th} threshold level generated randomly in between limits as $x_{max,i}$ and $x_{min,i}$, and *rand()* is random number between 0 and 1.

Where, $x_i = (x_i^1, x_i^2 \dots\dots x_i^d)$ and $v_i = (v_i^1, v_i^2 \dots\dots v_i^d)$ represent the i^{th} molecule's position and velocity.

$$x_i^d = [Th_i^1, Th_i^2, Th_i^3 \dots\dots Th_i^d] \quad (21)$$

Step 2: Each molecule will be assigned a random turbulence radius between [0, 1].

Step 3: A temperature will be assigned to the system. The GBMO algorithm's convergence is guaranteed by temperature. Temperature can influence the velocity of molecules. The temperature has a significant impact on the algorithm's exploitation and exploration abilities.

Step 4: Velocity and position update: In GBMO algorithm, x_i^d and v_i^d would be computed as follows:

$$v_i^d(t+1) = v_i^d(t) + \sqrt{3KT/m} \quad (22)$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t) \quad (23)$$

Step 5: Fitness evaluation of agents: The fitness function values for the molecules will be evaluated at this stage. The fitness information obtained from the individuals is used to update the population of molecules in this optimization approach.

Step 6: Aside from Brownian motion, every molecule has turbulent rotational motion, which is vibration in a specific radius with a radius that is a random number in the interval [0, 1]. The turbulent rotational motion is represented by equation and modelled by a chaotic sequence generator called Circle map.

$$x_i^d(t+1) = x_i^d(t) + b - \left(\frac{a}{2\pi}\right) \sin\left(2\pi x_i^d(t)\right) mod(1) \quad (24)$$

Step 7: Evaluate and compare the objective function values to the new molecule positions.

Step 8: Mass and temperature values are being updated.

A lighter molecule with a higher velocity is more efficient. The fitness evaluations are used to calculate the mass values. The following equations are used to update the molecule's mass:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (25)$$

Step 9: Repeat steps 3-7 of the search until the stopping criteria is met.

VII. WDO ALGORITHM

The wind blows in the atmosphere with the goal of producing pneumatic force. In general, the air parcel is used to move from high to low weight at a relative speed to the weight inclination [10]. Furthermore, the induction of the WDO algorithm includes a few suspicions and disentanglements. WDO's initial stride is supported by Newton's second law of motion, which is used to determine precise results, particularly for the examination of climatic movement. The WDO algorithm relies on two mathematical equations to update the velocity and position of an air parcel. Equation based on ideal gas law can be used to determine the velocity update equation for an infinitesimal air parcel moving with the wind. The velocity update equation is expressed as:

$$\vec{u}_{new} = ((1-\alpha)\vec{u}_{old}) + g(-\vec{x}_{old}) + \left[\left|\frac{P_{max}}{P_{old}} - 1\right| RT(x_{max} - x_{old})\right] + \left[\frac{-C_{old}^{otherdim}}{P_{old}}\right] \quad (26)$$

After updating the velocity of the parcel using equation (), the position of the air parcel can be updated using Below equation.

$$\vec{x}_{new} = \vec{x}_{old} + (\vec{u}_{new} \times \Delta t) \tag{27}$$

Step 1: Parameterization of the problem and the algorithm

The algorithm parameters such as population size (POP), problem dimension, and maximum number of iterations (Itermax), *RT, g, α, c* and V_{max} must be initialised for WDO in the first step. The problem parameters, such as the number of thresholds and the limits of threshold levels, must be set.

Step 2: The initial velocities of each air particle are generated at random (thresholds).

$$V = \begin{bmatrix} v_1^1 & v_2^1 & \cdots & v_{d-1}^1 & v_d^1 \\ v_1^2 & v_2^2 & \cdots & v_{d-1}^2 & v_d^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ v_1^{pop-1} & v_2^{pop-1} & \cdots & v_{d-1}^{pop-1} & v_d^{pop-1} \\ v_1^{pop} & v_2^{pop} & \cdots & v_{d-1}^{pop} & v_d^{pop} \end{bmatrix} \tag{28}$$

Step 3: Air particles are generated at random (thresholds)

$$x = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{d-1}^1 & x_d^1 \\ x_1^2 & x_2^2 & \cdots & x_{d-1}^2 & x_d^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{pop-1} & x_2^{pop-1} & \cdots & x_{d-1}^{pop-1} & x_d^{pop-1} \\ x_1^{pop} & x_2^{pop} & \cdots & x_{d-1}^{pop} & x_d^{pop} \end{bmatrix} \tag{29}$$

$$x_i^j = x_{min,i} + (x_{max,i} - x_{min,i}) * rand() \tag{30}$$

where *i* is the set of decision variables and *j* is the number of populations, x_i^j represents threshold levels, i.e., the j[th] population of the i[th] threshold level randomly generated between the limits $x_{max,i}$ and $x_{min,i}$, and rand() is a random number between 0 and 1.

$$x_i^j = [Th_1^1, Th_2^1, Th_3^1 \dots \dots Th_i^1\ ] \tag{31}$$

In the WDO algorithm, x_i represents a collection of air particles (solutions), with each air particle assigned a random position and velocity in the search space. An air particle is a solution with thresholds.

Step 4: Evaluation of each air particle in the initial population Determine the fitness value for each of the initial solutions. Keep track of the best solution so far.

Step 5: Begin the WDO algorithm's evolution procedure by setting iter=0 to the iteration counter.

Update the velocity of the each air particle in the current population using the best available for the subsequent iteration.

Step 6: Evaluate each new air particle population.

Step 7: Update the most effective solution (gbest).

Compare each new solution to the previous solution; if the new solution is better, record the best solution; otherwise, discard the new solution and keep the previous solution as it is.

Step 8: Stopping criterion

VIII. Results and Discussion

A.Simulation Results of BA

BA's convergence characteristics are depicted in Figure 1. The Table 1 displays the fitness value, computation time, and tuned a, b, c, and k parameters. Optimization with OF3 converges faster than OF1 and OF2.The performance parameters of BA with OF1, OF2 and OF3 are given in Table 2.The enhanced images with BA is shown in Figure 2.

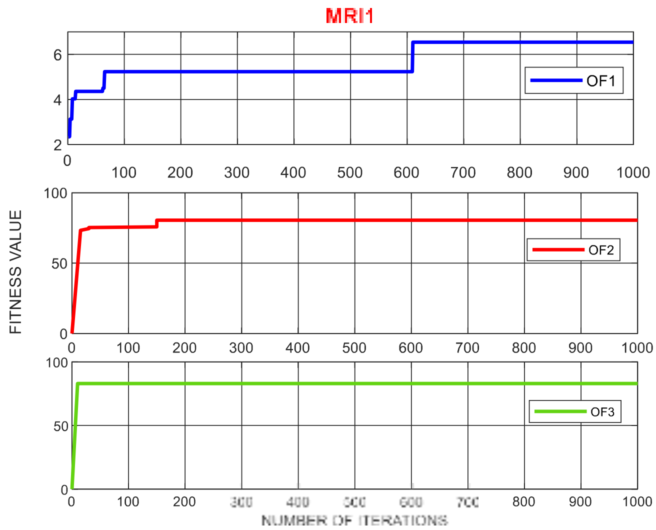

Fig.1 Convergence characteristics of BA

TABLE 1 TUNED PARAMETERS OF BA

Image Name	Objective function	a	b	c	k	Fitness value	Computation time
MRI1	OF1	0.11	0.239	0.588	1.278	6.11	250.875
	OF2	1.019	0.239	1.000	1.500	80.52	208.671
	OF3	1.022	0.239	1.000	1.500	81.25	22.731

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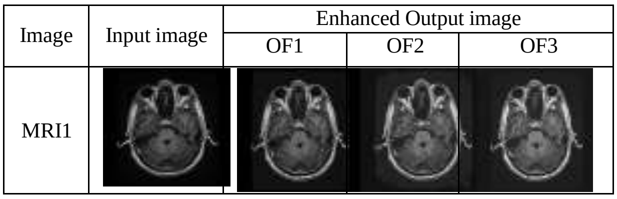


Fig.2 Enhanced images with BA

TABLE 2 PERFORMANCE PARAMETERS OF BA

Image Name	Method	Edge pixels		Entropy		PSNR	RMSE	MSSIM
		Init.	Final	Init.	Final			
MRI1	OF1	4513	4676	5.758	6.11	68.5	0.123	0.724
	OF2	4513	4434	5.758	6.42	80.52	0.03	0.98
	OF3	4513	4609	5.758	6.53	81.25	0.029	0.983

A. *Simulation Results of FFA*

FFA's convergence characteristics are depicted in Figure 3. The Table 3 displays the fitness value, computation time, and tuned a, b, c, and k parameters. Optimization with OF3 converges faster than OF1 and OF2.The performance parameters of FFA with OF1, OF2 and OF3 are given in Table 4.The enhanced images with FFA is shown in Figure 4.

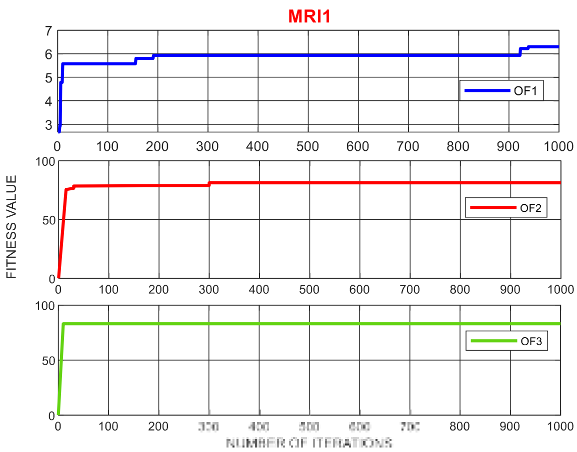


Fig. 3 Convergence characteristics of FFA

TABLE 3 TUNED PARAMETERS OF FFA

Image Name	Objective function	a	b	c	k	Fitness value	Computation time
MRI1	OF1	0.150	0.069	0.182	0.964	6.14	409.68
	OF2	1.019	0.239	1.000	1.500	81.02	205.969
	OF3	1.022	0.239	1.000	1.500	81.09	22.998

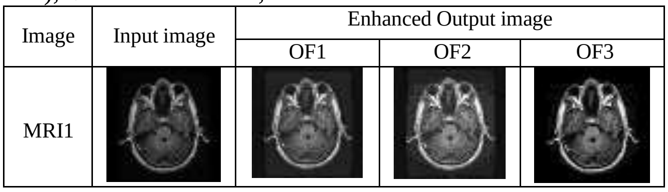


Fig.4 Enhanced images with FFA

TABLE 4 PERFORMANCE PARAMETERS OF FFA

Image Name	Method	Edge pixels		Entropy		PSNR	RMSE	MSSIM
		Init.	Final	Init.	Final			
MRI1	OF1	4513	4680	5.758	6.14	69.1	0.121	0.729
	OF2	4513	4439	5.758	6.45	81.2	0.029	0.987
	OF3	4513	4603	5.758	6.57	81.9	0.028	0.99

B. *Simulation Results of GBMO*

GBMO's convergence characteristics are depicted in Figure 5. The Table 5 displays the fitness value, computation time, and tuned a, b, c, and k parameters. Optimization with OF3 converges faster than OF1 and OF2.The performance parameters with OF1, OF2 and OF3 are given in Table 6.The enhanced images with GBMO is shown in Figure 6.

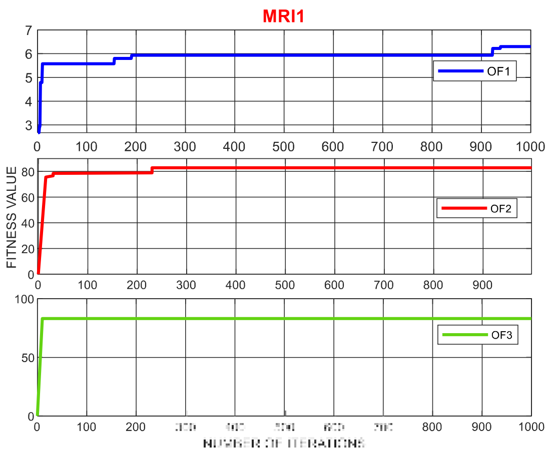


Fig. 5 Convergence characteristics of GBMO

TABLE 5 TUNED PARAMETERS OF GBMO

Image Name	Objective function	a	b	c	k	Fitness value	Computation time
MRI1	OF1	0.153	0.239	0.206	0.712	6.26	249.364
	OF2	1.019	0.239	1.000	1.500	82.82	211.416
	OF3	1.019	0.239	1.000	1.500	83.53	21..997

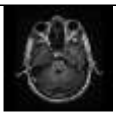
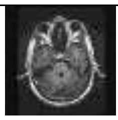
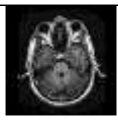
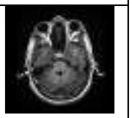
Image	Input image	Enhanced Output image		
		OF1	OF2	OF3
MRI1				

Fig.6 Enhanced images with GBMO

TABLE 6 PERFORMANCE PARAMETERS OF GBMO

Image Name	Method	Edge pixels		Entropy		PSNR	RMSE	MSSIM
		Init.	Final	Init.	Final			
MRI1	OF1	4513	4726	5.758	6.26	70.48	0.119	0.73
	OF2	4513	4583	5.758	6.57	82.82	0.028	0.989
	OF3	4513	4649	5.758	6.7	83.53	0.027	0.992

C. Simulation Results of WDO

WDO's convergence characteristics are depicted in Figure 7. The Table 7 displays the fitness value, computation time, and tuned a, b, c, and k parameters. Optimization with OF3 converges faster than OF1 and OF2.The performance parameters with OF1, OF2 and OF3 are given in Table 8.The enhanced images with WDO is shown in Figure 8.

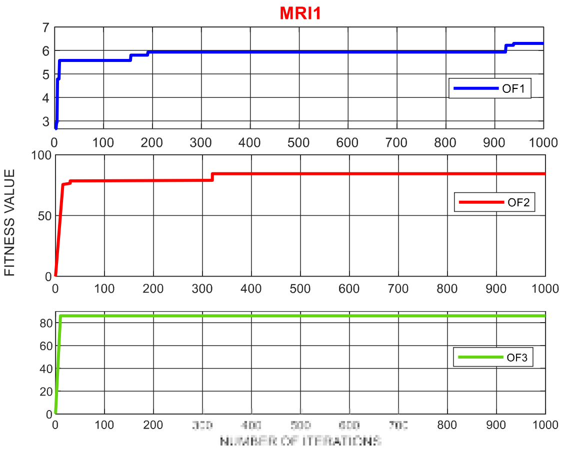


Fig. 7 Convergence characteristics of WDO

TABLE 7 TUNED PARAMETERS OF WDO

Image Name	Objective function	a	b	c	k	Fitness value	Computation time
MRI1	OF1	0.142	1.000	0.352	0.900	6.38	208.979
	OF2	1.019	0.239	1.000	1.500	84.48	205.499
	OF3	1.021	0.239	1.000	1.500	85.02	20.950

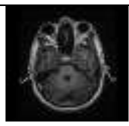
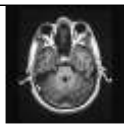
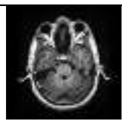
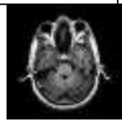
Image	Input image	Enhanced Output images		
		OF1	OF2	OF3
MRI1				

Fig.8 Enhanced images with WDO

TABLE 8 PERFORMANCE PARAMETERS OF WDO

Image Name	Method	Edge pixels		Entropy		PSNR	RMSE	MSSIM
		Init.	final	Init.	final			
MRI1	OF1	4513	4774	5.758	6.38	71.89	0.116	0.732
	OF2	4513	4628	5.758	6.71	84.48	0.028	0.991
	OF3	4513	4695	5.758	6.83	85.2	0.027	0.994

CONCLUSION

In this paper, the proposed model has four tuning parameters that control the degree of enhancement of the given input image. Optimization algorithms are used to obtain optimal values of these tuning parameters, resulting in a better enhanced image. Furthermore, these tuning parameters are optimized using three different objective functions: based on edge strength (OF1), based on PSNR (OF2), and based on a weighted combination of OF1 and OF2, which is labelled as OF3. A total of four optimization algorithms are applied to the proposed image improvement model using three objective functions to obtain optimal tuning parameter values that can yield a better image than the input image. The methods are qualitatively analyzed for MRI image using image quality performance evaluation metrics such as edge pixel count, entropy, PSNR, RMSE, and MSSIM. According to the result analysis, the proposed novel objective function (OF3), which is a weighted combination of the first and second objective functions, performed well in improving the quality of MRI image by providing more information in the enhanced image along with improved peak signal to noise ratio and improved structural similarity than each of the input images considered for evaluation. Furthermore, when compared to the other optimization algorithms proposed in this paper, the WDO optimization algorithm provided better tuning parameter values. As a result, the WDO-based image enhancement model outperformed the other three algorithms in terms of both quantitative and qualitative analysis of the enhanced images.

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