Check for updates

Directed searching optimized texture based adaptive gamma correction (DSOTAGC) technique for medical image enhancement

Upendra Kumar Acharya[1,2,3] · Sandeep Kumar[2]

Abstract
Because of complexity and low contrast in medical images, few enhancement techniques result unwanted artifacts and information loss by affecting the structure similarity and peak signal to noise ratio. To meet these challenges, a Directed searching optimized texture-based adaptive gamma correction technique is proposed in this article. This proposed technique utilizes the textured regions of the image and suppresses the effect of non-textured regions for eliminating the artifacts. An adaptive clipping threshold is used in the textured image to control the enhancement rate. For improving the contrast, the transfer function of the enhanced image is evaluated using the modified weighted probability density function and adaptive gamma parameter. To make the algorithm more adaptive, parameters like clipped threshold, gamma parameter, and textural threshold are to be optimized using directed searching optimization algorithm. For improving the information contents and noise suppression capability, the proposed technique incorporated a fitness function which is a combination of entropy and peak signal to noise ratio. Equal weightage has been given to each parameter in the fitness function for obtaining a balanced optimal result. Then, the performance of the proposed technique is evaluated in terms of visual quality, information contents, average mean brightness error, noise suppression, and structural similarity. Experimental results show the proposed technique results in better visual effects without information loss. It effectively suppresses the effect of artifacts and significantly improves the contrast by making edges clearer and textures richer over other algorithms.

Keywords Image enhancement · Magnetic resonance imaging · Computed tomography · Directed searching optimization · Histogram equalization · Adaptive gamma correction

✉ Sandeep Kumar
  sandeep@nitdelhi.ac.in

1 Department of Electronics and Communication Engineering, Galgotias College of Engineering and Technology, Greater Noida, Uttar Pradesh, India

2 Department of Electronics and Communication Engineering, National Institute of Technology, Delhi, India

3 Department of Electronics and Communication Engineering, KIET Group of Institutions, Ghaziabad, Uttar Pradesh, India

1 Introduction

In medical science, proper monitoring of body function, physiological sign and diagnosis with better accuracy is a challenging task. Medical image processing plays a major role in early diagnosis of different disease. Medical imaging techniques like computed tomography (CT), magnetic resonance imaging (MRI) techniques are used by doctors for analyzing the pathological changes in the human body. The accuracy of the diagnosis and treatment depends on the quality of such images. But during acquisition and transmission, the image becomes blurred and has low contrast, [22] and complex due to presence of several overlapped objects. So, understanding of such images are difficult. This low contrast in the medical images allows the doctors to provide inaccurate judgment. But, for the reduction of deaths, the abnormality should be identified with accuracy. So, contrast improvement agents can be injected for enhancing such images, but these are not good for patients every time. So, before abnormality identification [24], it is important to make the image quality, features, and details more significant. To achieve this, medical image enhancement techniques are used by the Doctors for disease diagnosis, tumor detection and any type of abnormal detection.

Histogram Equalization (HE), [14] is a common technique for improving the contrast, by directly changing the pixel values. As the medical image has a large low gray background, So, the HE technique makes the entire image more bright [33]. As, the gray value changes to a large extent, it leads over enhancement and information loss. It causes artifacts in the enhanced images. It is also tough to improve the texture region using the HE technique alone. To modify the histogram and to find the better-enhanced image, Huang et al., [16] proposed an adaptive gamma correction technique with weighting distribution (AGCWD) function. But this technique is unable to preserve the edge details. The unclearness and low contrast is found in the medical image due to interference, noise, and low light environment. So an image enhancement method has been presented in the article, [22] by combining the both spatial domain and wavelet domain. In this method, after blurring (Sharpening), the upper-frequency part of the image is de-noised with the help of median filtering and the output image is formed by fusing all sub-images.

Another technique is proposed by Liu et al., [23] by partitioning the image into different frequency band sub-images. Then linear transformation is used in the low-frequency band and thresholding is used for de-noising the high-frequency bands. After that, all bands are reconstructed in spatial domains with the help of inverse transformation, and performance is measured in terms of entropy, and PSNR. The paper [21] presents an enhancement technique that adjusts the fractional-order as per the gradient feature of the image. It uses Otsu technique and fractional differential algorithm to enhance the image adaptively. A simple and adaptive enhancement technique is proposed by Kallel et al., [17] for dark medical images by using the concept of decomposition of image and correction factor. The author of this article claims supremacy over other techniques in terms of overall quality and visibility of local details. In modern diagnosis, medical images suffer from low-luminance and non-uniformity problems which affect the diagnosis process.

To generate a clear view of the images, a technique is presented in [36], which first enhances the visual perception with the help of luminance-level modulation and then improves the details using gradient modulation. Small and important details of the image may hide or distort because of blurring and noise in medical images. To restore the images, a new gradient-based plug-and-play algorithm has been presented in, [10]. The external denoiser is used in this paper with the help of a deep CNN, trained on

gradient domain. A directional sparsely-sampled sinogram interpolation is implemented for the enhancement of the CT images in [20]. To minimize the radiation does in CT scanning, a sparsely-sampled sinogram is used in this article. For the reduction of artifact and to enhance image quality, an effective approach of sinogram interpolation method has been used which is based on directional information. The enhanced medical image suffers the problems of noise, over enhancement and information loss. So diagnosis is ineffective for diseases like a tumor. So a weighted constrained HE technique is proposed in [7] for the contrast enhancement of medical images which incorporates with Otsu's threshold, Particle Swarm Optimization (PSO) and AGC. This algorithm focuses on preserving the information by selecting the proper threshold.

A method of enhancement technique is discussed in [34] to enhance the segmented liver image with the help of HE. This technique utilizes the segmentation concept with gray stretching to achieve the best result. For brightness preservation along with improving the contrast of brain images, an adaptive HE and fuzzy logic-based technique is proposed by Subramani et al. [32]. Initially, the method of fuzzy is applied to the input image and then the output image is associated with AHE technique. A memory augmented autoencoder approach is presented in [11] for detecting anomalies in IoT data, by using reconstruction errors. For suppressing the generalization ability of this model, a memory mechanism is used in this paper. And, time series data anomaly detection has been done with the help of memory-augmented autoencoder. Kandhway et al. [18] introduced a krill herd (KH) optimization-based framework for medical images which utilizes the fitness function and plateau limits to produce the best-enhanced image.

Many other enhancement techniques [1–6, 12, 13, 15, 27, 29–31] have also been developed to improve the contrast, to preserve the brightness, entropy, edge and reduce the artifacts. But few techniques are able to improve the contrast of the image but they don't produce better result in terms of information contents. Few algorithms result better entropy but cannot produce satisfactory brightness preservation, peak signal to noise ratio, and structure similarity. Few techniques are not adaptive and results artifacts. But an enhancement technique is said to be effective, if the technique is adaptive and proper balance possible among these parameters in the enhanced images, better information content, AMBE, PSNR and SSIM. So, to achieve an adaptive and effective enhancement technique for medical images, following are the main contributions and novelty, which are discussed below.

1) This technique presents an optimal approach to find the texture region from medical images for suppressing the effect of artifacts in the enhanced image. Its main purpose is to preserve the edge details and eliminate artifacts effectively. The threshold for finding the texture region varies from image to image. So, threshold value is optimized using Directed Searching optimization (DSO) algorithm.
2) The main problem associated with image enhancement techniques is over enhancement. So, it is required to control the enhancement rates, else it causes more information loss. To resolve these issues, few authors utilize the parameters like mean, median [29, 30, 35] of the histogram for clipping the histogram.

But in this paper, an adaptive clipped threshold is used to clip the histogram for controlling the enhancement rate. This technique avoids the over enhancement and preserves the details during enhancement. The appropriate optimized threshold (V_{th}) is selected using DSO algorithm.

3) In AGCWD [16] technique, the exponential parameter (ϕ) is fixed for all the images. So it may or may not result better enhancement in all types of medical images. But, to make it more adaptive and to enhance the image quality more effectively, a tunable parameter(ϕ) is used in this paper along with a weighted probability density function (PDF). The value of ϕ is not fixed in this paper and it depends on type of images. The value of ϕ is optimized in such a way that it will improve the visual quality.

4) The thresholds parameters like textural threshold, clipping threshold, and gamma parameters are optimized using DSO algorithm for which, the fitness function is maximized automatically without human intervention. It will make the algorithm more adaptive.

5) The transfer function of the enhanced image is evaluated using modified optimal weighted PDF and optimal gamma parameters.

6) Performance of the proposed DSOTAGC technique is measured and compared with state-of-the-art techniques in terms of visual quality, information contents (entropy), AMBE, PSNR, and SSIM.

The remaining part of the paper is arranged as follows. Section 2 describes the details of the proposed technique including edge detection, clipping technique, AGC, DSO, fitness function, threshold selection. Section 3 represents the comparative analysis of the DSOTAGC technique with respect to existing technique. The paper is concluded in Section 4.

2 Proposed DSOTAGC technique

To improve the image quality such as visibility, information contents, brightness preservation and to reduce the artifacts, an adaptive enhancement technique is proposed in this article named as DSOTAGC technique. The proposed method is based on adaptive gamma correction (AGC) technique, adaptive clipping technique and DSO algorithm. As it is required to improve such parameters in the enhanced image, so the enhancement problem is presented as an optimization (maximization) problem in this article. So, an optimal algorithm like DSO is used in this paper. As DSO utilizes the benefit of both position updating and mutation, so it can produce better optimal results by preventing premature convergence in complex medical images. For improving the contrast, AGCWD is used with an adaptive gamma parameter. The rate of enhancement is controlled with the help of an adaptive clipped threshold. The proposed framework for image enhancement is shown in Fig. 1 and discussed below.
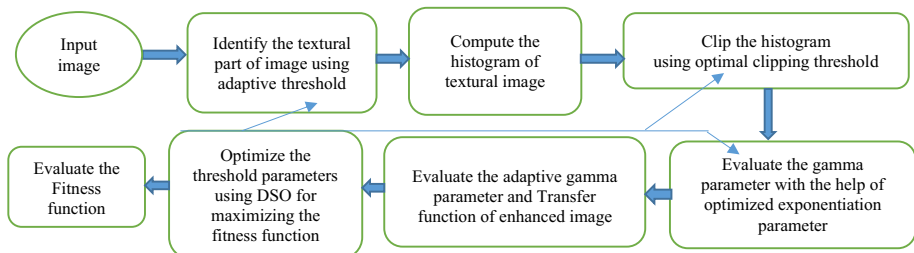

Fig. 1 Proposed framework of DSOTAGC technique

a) As medical images are textural images, so, Sobel operator with an optimal textural threshold is used to find out the texture region.
b) Compute the textured histogram.
c) Clip the histogram using the adaptive clipping threshold.
d) Find the transfer function of the enhanced image with the help of adaptive gamma parameter and modified PDF.
e) Define the fitness function.
f) Optimize the texture threshold, clipping threshold, gamma parameter using DSO algorithm to maximize the fitness function automatically.

2.1 Input the image and detect the texture region

The MRI and CT scan images are taken from Medpix [9, 25] and MRTIP [26] data base to improve their quality for early diagnosis. In general, medical images contain both non-texture and texture region. But the pixels of the non-texture region biased the enhanced images and produce artifacts in the enhanced image. So, the effect of the non-texture region should be minimized. For which, the texture region of each image is 1st identified in this article. For identifying the texture region, edge pixels of such images should be detected. This has been done with the help of Sobel operator and a textural threshold (T_{sp}) in this paper. It evaluates the gradient of each pixel. Here, the input image is represented by I. Intensity value of pixel at coordinate (x, y) is depicted by $I(x, y)$. Two 3×3 masks have been used for measuring gradient at each pixels. The gradient (G_x) in the x direction as,

$$G_x = \begin{bmatrix} +1 & 0 & -1 \\ +2 & 0 & -2 \\ +1 & 0 & -1 \end{bmatrix} \times I_{x,\ y}^{3\times3} \tag{1}$$

Gradient (G_y) in y-direction as,

$$G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{bmatrix} \times I_{x,\ y}^{3\times3} \tag{2}$$

The gradient ($G_{x,\ y}$) at each pixel as,

$$G_{x,y} = \left(G_x^2 + G_y^2 \right)^{0.5} \tag{3}$$

Then, an image edge map $I_s(x, y)$ is constructed using the measured gradient at each pixel and a particular threshold T_{sp}.

$$I_s(x, y) = \begin{cases} 1, & G_{x,y} \geq T_{sp} \\ 0, & G_{x,y} < T_{sp} \end{cases} \tag{4}$$

It is considered as the reference image for finding the texture region. If the gradients value of that image is greater than that of the threshold, then these values are considered for texture histogram computation. The threshold for finding the texture region varies from image to image. So, after performing a lot of experiments, the range of threshold is considered in between 0 to 9, and the threshold is optimized with the help of DSO algorithm.

2.2 Histogram computing and clipping

After extracting the textural region, the histogram of the textural image is computed. Then an adaptive clipped threshold is evaluated for clipping the histogram. The main purpose of clipping threshold is to control the enhancement rate. This technique avoids over enhancement and preserves the details during enhancement. The appropriate optimized threshold (V_{th}) is selected using DSO algorithm. The value of this parameter is taken in between 0 to 1. The clipped normalized histogram is formed using Eq. (5).

$$Pd(k) = \begin{cases} V_{th}, & if \ X(k) \geq V_{th} \\ X(k), & if \ X(k) < \ V_{th} \end{cases} \tag{5}$$

In Eq. (5), the variables *Pd* and *X* represent the PDF of clipped histogram and *PDF* of the textured image respectively, whereas *k* is the index, varies up to maximum gray level of the image.

2.3 Evaluation of adaptive gamma parameter and transfer function of enhanced image

A weighting distribution function is used in this article to modify the statistical histogram and to form a weighted histogram. To enhance the image quality, a tunable parameter (ϕ) is used along with a weighted PDF function. The value of ϕ is not fixed in this paper and it depends on type of the images. The value of ϕ is selected within the range [0, 1] for maximizing the objective function. The weighted PDF (pd_w) is computed as,

$$pd_w(i) = \max(Pd) \times \left(\frac{Pd(i) - \min(Pd)}{\max(Pd) - \min(Pd)} \right)^{\phi} \tag{6}$$

In Eq. (6), *Pd* represents the PDF which is computed using the clipped histogram of textured image. Then, the weighted cumulative density function (CDF) is calculated using in Eq. (7). The adaptive gamma (Y) is evaluated using weighted CDF and presented in Eq. (8).

$$cd_w(i) = \sum_{i=0}^{i_{max}} \frac{pd_w(i)}{\sum pd_w} \tag{7}$$

$$Y = 1 - cd_w(i) \tag{8}$$

Then the enhanced image is constructed using the adaptive gamma parameter (Y), intensity value of the image (*i*) and maximum gray level (i_{max}) of the image. The transfer function ($T(i)$) of the enhanced image is represented as,

$$T(i) = i_{max}(i/i_{max})^{Y} \tag{9}$$

2.4 Directed searching optimization (DSO) algorithm

Zou et al., [37] introduced DSO algorithm for solving constrained optimization problems. It is performed in two main steps, such as position updating and genetic mutation. Position

updating is required for the convergence of the DSO. Mutation enhances the diversity of the individual and is a benefit for preventing premature convergence. A penalty function is adapted for balancing the constraint and objective and violations. It includes the parameters like, population size (*PS*), forward probability (P_α), iterations (*iter*), forward co-efficient (α), mutation probability (P_m), and backward co-efficient (β). Initialize the population matrix (*PM*), where the variable (*DM*) represents the dimension (*DM*) of the problem space.

$$PM = \begin{bmatrix} P_1^1 & P_2^1 & \cdots & P_{DM}^1 \\ P_1^2 & P_2^2 & \cdots & P_{DM}^2 \\ \vdots & \vdots & \ddots & \vdots \\ P_1^{PS} & P_2^{PS} & \cdots & P_{DM}^{PS} \end{bmatrix} \tag{10}$$

The position updation using DSO algorithm is shown in Fig. 2. In this figure, the ith component of jth solution vector of kth iteration is depicted by $P_i^j(k)$. The variable $P_i^{j_g}(k)$ represents i^{th} component of j_g^{th} global solution vector of kth iteration and j_g is the index of global solution vector. As per this strategy, P_i^j is inclined to reach $P_i^{j_g}$, so the main searching region is considered as the region nearer to $P_i^{j_g}$. So the forward region is represented by *PF*. The backward region is shown by *PB*. Here, P_{iL} and P_{iU} are the lower and upper bound of ith component.

To update the position of solution vector, the following conditions must be verified. The variable *j* lies in the range [1, *PS*] and $j \neq j_g$ and *i* must vary in between [1 *DM*]. Then, the condition (rand () $< P_\alpha$) must be checked. If this is satisfied then the position updating is carried out as per Eq. (11).

$$P_V = P_i^j(k) + (1 + \alpha)\left(P_i^{j_g}(k) - P_i^j(k)\right) \tag{11}$$

In Eq. (11), the adaptive step size is represented by $P_i^{j_g}(k) - P_i^j(k)$. This step size becomes small when the solution vectors are nearer to each other and it is benefit for local search. But at first, the solution vectors are far away from each other in solution space, so the step size is more and is required for global search. Then the following conditions is required to check.

$$\text{If } P_V > P_{iU} => P_V = P_{iU} \tag{12}$$

$$\text{If } P_V < P_{iL} => P_V = P_{iL} \tag{13}$$
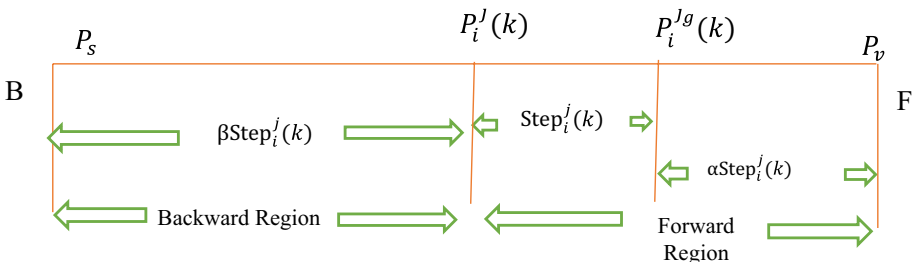
Then the new updated position is,

Fig. 2 Position updating strategy of DSO

$$P_i^j(k+1) = P_i^j(k) + r \times \left(P_V - P_i^j(k)\right) \tag{14}$$

If, rand $() < P_\alpha$ is not satisfied, then position is updated in backward direction.

$$P_s = P_j^i(k) - (\beta) \times \left(P_i^{j_s}(k) - P_i^j(k)\right) \tag{15}$$

Again the following conditions are checked in backward direction

$$\text{If } P_S > P_{iU} => P_S = P_{iU} \tag{16}$$

$$\text{If } P_S < P_{iL} => P_S = P_{iL} \tag{17}$$

Then the position in backward direction is updated using the equation,

$$P_j^i(k+1) = P_i^j(k) + r \times \left(P_s - P_i^j(k)\right) \tag{18}$$

For improving the performance of the DSO algorithm, mutation operator is used after position updating. Then the mutation probability condition is checked. If rand $() < P_m$ then the new updated position is,

$$P_i^j(k+1) = P_{iL} + r \times \left(P_{iU} - P_{iL}\right) \tag{19}$$

If the population size is too small, DSO has few possibilities to find the optimal solution, as only a small part of the search space is explored. If the population size is more, then DSO slows down the convergence rate. So, it cannot be faster than a moderate sized population and results in wastage of resources. So, moderate size of iterations and population are taken and each of size 50 to reduce the complexity, to reduce the wastage of resources, and to find the best convergence performance.

Mutation enhances the diversity of individuals and exploits the unseen location of the searching space. But, a higher value of mutation probability may lead the solution to more diverge. So the probability of mutation is taken as 0.01. As the forward region is nearer the global position, so the forward coefficient and forward probability are considered as 1 and 0.8 respectively. The variable r is a random number that lies in between 0 to 1. The backward region is used for slowing down the convergence rate and backward co-efficient (β) is taken as 10. The upper and lower bound of ith component P_{iU} and P_{iL} depends on the threshold values taken in this paper.

2.5 Fitness function

In this paper, a fitness function is defined to select the optimum value of the tunable parameters using a heuristic optimization approach. It creates fitness criterions [7, 8, 18, 19] for the enhanced image. The diagnosis process becomes more complicated if the image is having less information contents and signal strength. So it is required to improve the entropy and PSNR. So, the fitness function taken in this paper, is a multi-objective function and represented as the summation of both entropy and PSNR. It depends on the constraint parameters used in this paper such as textural threshold, clipping threshold and optimal value of ϕ which are required for constructing the enhanced image. The defined fitness function is.

$$f = \beta_1 f_1 + \beta_2 f_2 \tag{20}$$

Whereas, β_1 and β_2 are the constants and their values represents the significance of individual objective function. Both objective functions are considered with equal importance, so the value of β_1, β_2 are taken as 0.5. As in the enhanced medical image, both entropy and PSNR are required to be improved, so the fitness function should be maximized and shown in Eq. (21).

$$J = \arg\left(\max(f)\right) \tag{21}$$

In Eq. (20), f_1 represents the entropy or the average information contents and measured using Eq. (22). f_2 is the PSNR of the enhanced image and evaluated using Eq. (23–24).

$$f_1 = H\left(I_e\right) = -\sum_{l=0}^{L-1} P(l)\log_2 P(l) \tag{22}$$

$$f_2 = PSNR = 10\log_{10}\left(\frac{(L-1)^2}{MSE}\right) \tag{23}$$

In Eq. (22), $P(l)$ represents the PDF at intensity level l and the maximum gray level is presented by variable L. Whereas, the mean square error (MSE) is represented as,

$$MSE = \frac{1}{r*c}\sum_{i=1}^{r}\sum_{j=1}^{c}\left(I_o(i,j) - I_e(i,j)\right)^2 \tag{24}$$

Whereas, $I_o(i,j)$, and $I_e(i,j)$ represents the original and enhanced image respectively.

3 Results and discussions

To verify the feasibility and robustness, the proposed method is applied to medical images (200 MRI and CT images) collected from various databases [9, 25, 26]. Then the performance of this method is investigated in both qualitative and quantitative approaches by comparing with existing methods including HE [14], Dualistic sub-image histogram equalization (DSIHE) [33], median mean based sub-image clipped histogram equalization (MMSICHE) [30], Exposure based sub-image histogram equalization (ESIHE) [29], AGCWD [16], dominant-orientation based texture histogram equalization (DOTHE) [31], triple clipped dynamic histogram equalization based on standard deviation (TCDHE-SD) [35] and Particle swarm optimization based enhancement technique [19]. MATLAB R2018a is used to perform the simulation work.

3.1 Performance Parameter

To evaluate the performance of the proposed DSOTAGC technique, parameters like entropy, PSNR, absolute mean brightness error (AMBE), and structure similarity index measure (SSIM) are taken into consideration.

Entropy is used to evaluate the information contents and the richness of the details within the image [8]. More value of the entropy [8] indicates better information contents within the images. It is measured using Eq. (22). As medical images are associated with noise, so it is required to suppress the noise. The performance index PSNR [1] is measured

in this article to show the noise suppression quality. It is defined by the ratio of maximum signal power to distorted noise power, It is inversely proportional to MSE and measured using Eq. (23). Higher PSNR presents the better noise suppression capability.

The parameter SSIM [28] provides consistent image visual quality in terms of structural information. The SSIM value ranges from 0 to 1. Better is the similarity in enhanced image with respect to input image, when SSIM is nearer to 1. It considers three terms, related to luminance, contrast, and structure. It is measured using Eq. (25).

$$SSIM(x, y) = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left(\mu_x{}^2 + \mu_y{}^2 + C_1\right)\left(\sigma_x{}^2 + \sigma_y{}^2 + C_2\right)} \tag{25}$$

Whereas μ_x, μ_y are the mean intensity, σ_x, σ_y are the standard deviations of gray-scale images x and y respectively. The sample correlation coefficient between x and y is represented by σ_{xy} . And $c1$ and $c2$ indicate the constant and are used here to avoid instability. Again to measure the brightness preservation, AMBE is measured using Eq. (26). It represents mean intensity difference between input and enhanced images. Minimum value of AMBE indicates better enhancement and brightness preservation [30]. Whereas, in Eq. (26), $mean(I_o)$ and $mean((I_e)$ represent the mean intensity value of the input and enhanced image.

$$AMBE = \left| mean\left(I_o\right) - mean\left(\left(I_e\right)\right)\right| \tag{26}$$

3.2 Performance analysis

Because of the complexity problem in medical imaging, few existing techniques cannot produce satisfactory results. The rate of change of information is very rapid from region to region because of the overlapping of tissues in medical imaging. So the proper processing with satisfactory results is a challenging task in medical imaging. So, to achieve better enhancement effect, DSOTAGC technique is presented in this paper, whose simulated results are shown in Figs. 3, 4, 5, 6, 7, 8, 9 and 10 Then, qualitative and quantitative approaches are used to evaluate its performance. The qualitative approach comprises visual quality and histogram analysis, whereas quantitative approach involves the performance parameters like entropy, PSNR, SSIM, and AMBE.

The original medical images are shown in Figs. 3, 4, 5, 6, 7 and 8, in which organs are not clearly visible. HE and DSIHE technique improves the contrast, but some details are over-enhanced and look worse than the original image. Figure 9 represents the histogram of image-1 and its enhanced image. It indicates, how the shape of enhanced image is similar with input image. From these figures, it is cleared that, by HE, DSIHE, ESIHE, techniques, the gray distribution of the images is fully changed, which affects the visual quality of the resultant image. MMSICHE technique results a better enhanced image in terms of AMBE which indicates better brightness preservation. But it cannot produce satisfactory information contents within the enhanced image. And the resultant image is not much clear.

DOTHE technique enhances the edges but produces noise in the enhanced image. In DOTHE algorithm, some objects can be easily observed, but quality of the image is not good. AGCWD technique enhances image but the edge contents is not preserved. As it is not adaptive and results information loss, So it is not suitable for all types of medical images. TCDHE-SD technique also produces better quality image but not perform better
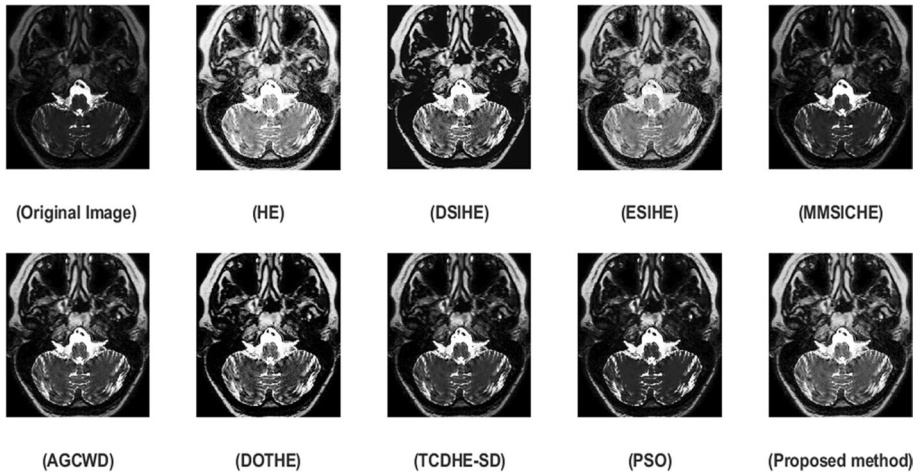
Fig. 3 Image-1 and enhanced by enhancement techniques

in terms of similarity with respect to original image. TCDHE-SD technique is only based on histogram division and doesn't use any parameter to improve the edge contents in the enhancement image. PSO-based technique improves the edge details and entropy better as compared to other techniques as it utilizes the fitness function as the summation of entropy and edge contents.

But the proposed DSOTAGC method preserves the image edges and produces better enhancement effect than other existing methods. It also produce optimal results by making a balance among information contents and PSNR. It is because of the equal weightage of each objective function defined in the fitness function (Eq. (20)). The
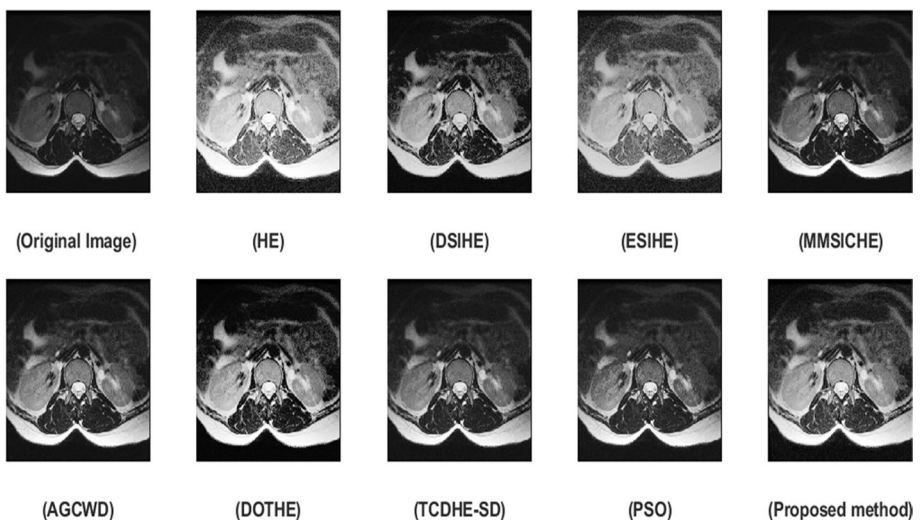

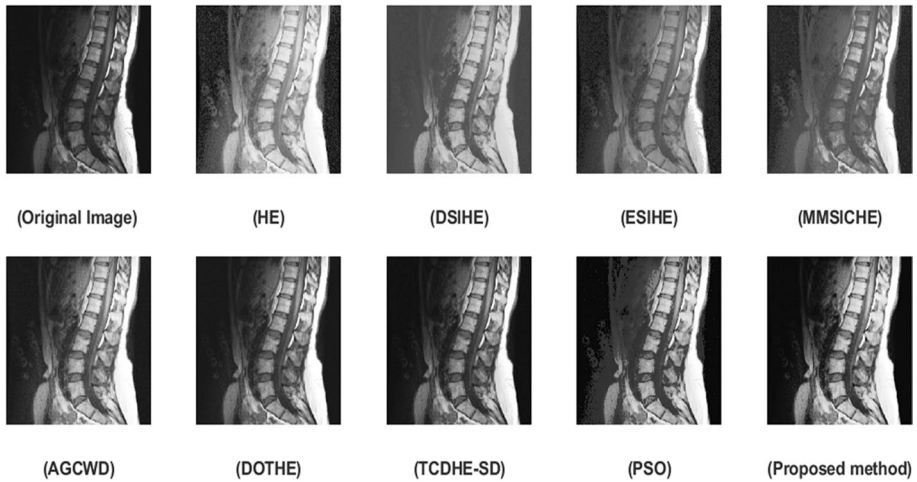**Fig. 4** Image-2 and enhanced by enhancement techniques

Fig. 5 Image-3 and enhanced by enhancement techniques

enhancement of the contrast, preservation of brightness, and entropy is also better in the proposed technique over other techniques. The better contrast in the enhancement image is because of the adaptive gamma parameter. As initially, Sobel operator is used to determine the edges, then the non-texture effect is suppressed, so it results better preservation of edges in the enhanced images.

Existing methods like DOTHE, AGCWD show the effect of over-enhancement and are evident from Figs. 3, 4, 5, 6, 7, 8 and 9. But, an adaptive clipped threshold is proposed in this paper for controlling the enhancement rate. So, proposed technique results better in terms of over enhancement and controlling the enhancement rate. Proposed
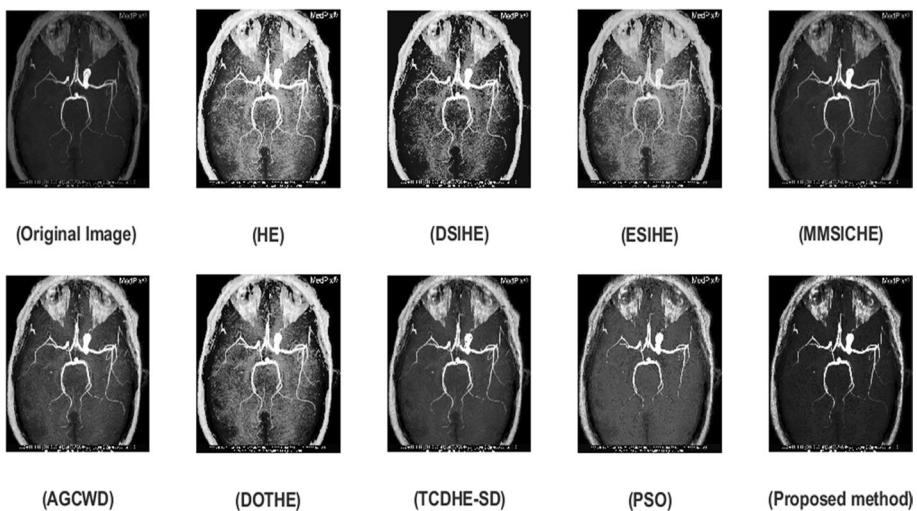

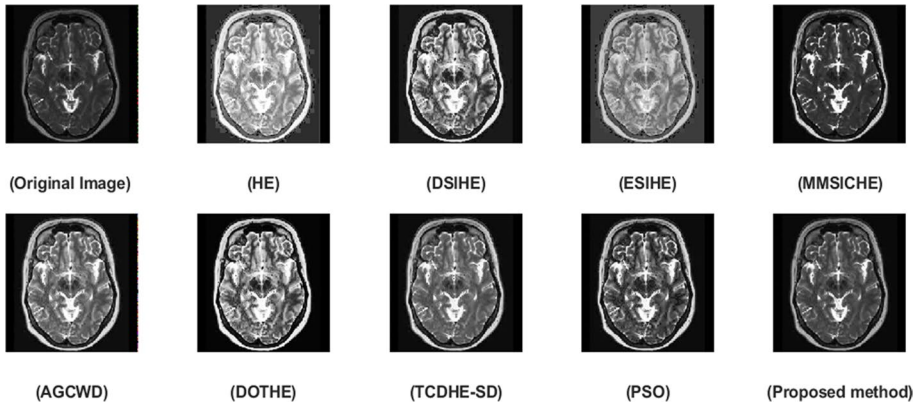**Fig. 6** Image-4 and enhanced by enhancement techniques

Fig. 7 Image-5 and enhanced by enhancement techniques

method is adaptive because the textural threshold, clipped threshold, and adaptive gamma value have been optimized with the help of DSO algorithm.

This proposed algorithm results better adaptive-ness because of both position updating strategy and mutation of DSO algorithm. So the pre-matured convergence has been prevented and produces the best optimal result. From Figs. 3, 4, 5, 6, 7 and 8, it is also observed that, the artifact content is more in HE, DSIHE, ESIHE, AGCWD, DOTHE, TCDHE-SD, and PSO based technique. It is because of non-texture pixels to the enhanced image and over enhancement. As over enhancement is controlled and non-texture effect is minimized, so proposed technique results artifact free images.

The measured entropy and PSNR values are presented in Table 1 and 2 respectively. It is observed that the proposed DSOTAGC method results better information content and PSNR over other methods. Low entropy is observed in HE technique, as it loses much
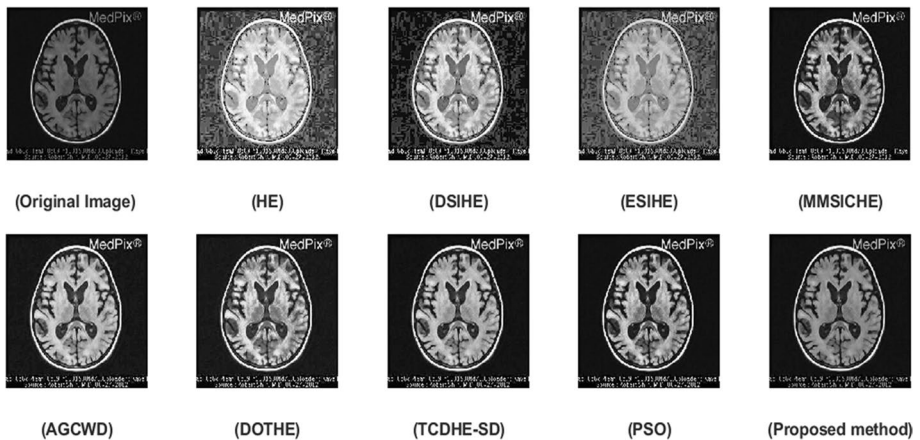

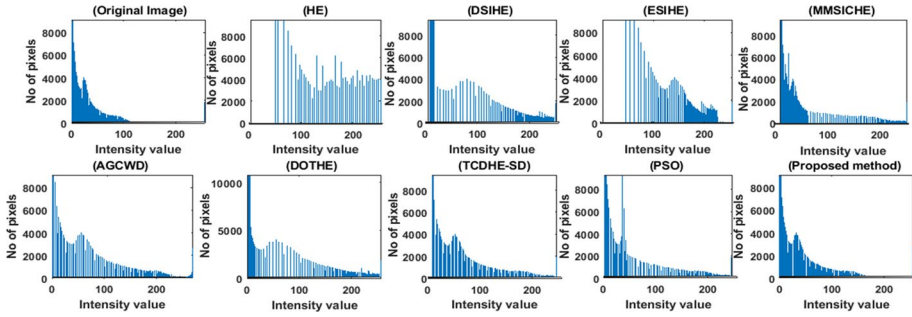**Fig. 8** Image-6 and enhanced by enhancement techniques

Fig. 9 Histogram of input and enhanced image-1

information because of over enhancement. The proposed DSOTAGC technique yields entropy, nearly equal to that of input images shown in Table 1. It indicates, information content is preserved by the proposed method.

Higher PSNR obtained by DSOTAGC method results reduction in noise components and produce an artifacts free images. So, the resultant image is of pleasant quality with improved contrast. The measured AMBE value is shown in Table 2 and it is noticed that the brightness error is less in the proposed method over other discussed techniques. It represents, the brightness is better preserved by our proposed technique, and over enhancement is also controlled. The enhancement technique is more suitable, if SSIM is very close to one. From Table 2, it is noticed that proposed DSOTAGC technique results better SSIM as compared to existing techniques. So shape of the histogram of the enhanced image obtained by proposed method is very similar to the histogram of the original image, shown in Fig. 9. It is because of better contrast, texture as well as edge enhancement.

To verify the performance of the enhancement techniques, the experiment has been performed using MRI and CT images, but only few images are shown in this paper. The average values of entropy, PSNR, AMBE, and SSIM have been measured using all two hundred medical images and shown in Fig. 10a-d. After performing this experiment, it
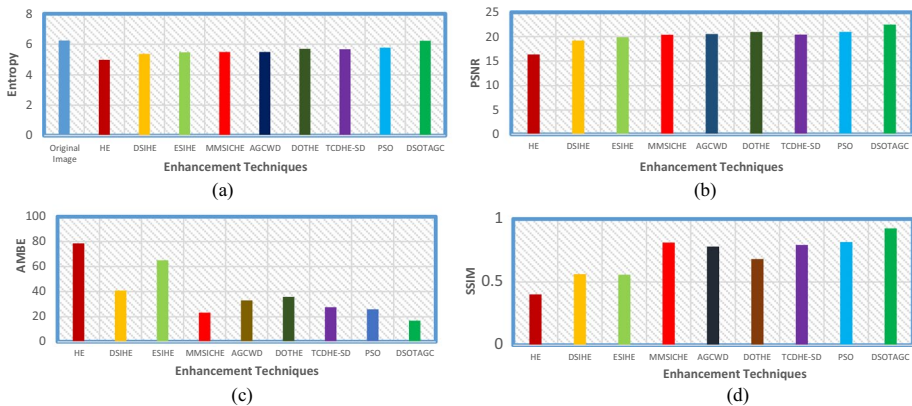

Fig. 10 Average plot (**a**) Entropy, (**b**) PSNR (**c**) AMBE, (**d**) SSIM

Table 1 Measured Entropy

Parameter	Image /Technique	Original image	HE	DSIHE	ESIHE	MMSICHE	AGCWD	DOTHE	TCDHE-SD	PSO	DSOTAGC
Entropy	1	5.89	5.10	5.60	5.67	5.73	5.82	5.51	5.75	5.70	5.85
	2	6.23	5.39	6.04	5.97	6.15	6.19	5.92	6.20	6.08	6.21
	3	6.13	5.33	5.89	5.96	5.99	6.00	5.99	6.01	5.99	6.04
	4	5.96	5.00	5.69	5.74	5.79	5.70	5.77	5.68	5.77	5.93
	5	6.00	4.98	5.67	5.75	5.93	5.93	5.74	5.71	5.66	5.98
	6	5.81	4.76	5.55	5.55	5.62	5.71	5.71	5.53	5.57	5.78
	7	5.83	4.44	5.45	5.52	5.63	5.65	5.63	5.42	5.68	5.72
	8	6.27	4.67	5.92	5.87	5.93	5.96	6.09	6.05	6.14	6.23
	9	6.27	5.25	5.92	5.97	6.15	6.18	6.07	6.02	6.03	6.24
	10	6.24	4.80	5.87	5.94	6.04	6.00	5.99	5.99	6.05	6.12

Table 2 Measured PSNR, AMBE, SSIM

Parameters	Image/Technique	HE	DSIHE	ESIHE	MMSICHE	AGCWD	DOTHE	TCDHE-SD	PSO	DSOTAGC
PSNR	1	22.18	26.84	24.12	26.44	26.79	27.67	27.11	27.23	29.39
	2	24.66	24.82	24.36	25.65	25.84	26.86	25.71	26.15	28.35
	3	16.35	17.06	18.24	19.34	17.06	18.59	17.45	18.68	20.19
	4	14.06	18.70	18.06	20.02	18.01	18.57	20.29	21.08	22.61
	5	20.97	22.20	23.10	24.54	24.25	24.20	23.41	24.32	26.98
	6	12.61	17.63	18.19	19.59	18.91	18.17	17.76	18.10	20.67
	7	14.24	18.06	18.06	18.21	17.21	18.93	18.81	18.43	19.80
	8	16.73	17.13	17.12	17.72	17.97	18.28	17.40	16.04	18.27
	9	12.44	19.35	19.21	16.40	19.59	18.01	19.09	18.58	20.84
	10	15.96	17.17	17.16	17.94	17.62	17.10	17.32	17.09	18.47
AMBE	1	104.07	45.46	92.25	11.35	28.87	36.88	24.23	21.94	10.57
	2	93.05	37.92	78.22	20.71	33.83	40.09	28.63	24.29	20.95
	3	25.805	26.69	28.22	24.11	33.28	21.57	25.10	23.98	19.96
	4	93.703	51.51	77.64	12.96	38.91	57.60	33.75	42.78	12.77
	5	88.09	44.18	73.23	18.86	36.20	38.13	31.29	25.02	14.96
	6	89.00	51.43	75.67	17.01	33.17	39.28	27.76	21.71	14.45
	7	90.47	39.06	68.74	21.65	29.46	33.33	19.26	17.09	18.14
	8	54.89	28.86	43.19	25.56	27.84	24.06	28.78	23.43	21.60
	9	83.68	46.58	66.45	17.31	36.59	46.42	31.66	34.03	16.51
	10	62.28	35.77	46.69	23.83	32.87	21.93	26.44	25.52	21.87
SSIM	1	0.33	0.62	0.36	0.90	0.72	0.65	0.78	0.79	0.93
	2	0.29	0.56	0.33	0.90	0.71	0.49	0.76	0.67	0.86
	3	0.61	0.89	0.76	0.80	0.87	0.77	0.63	0.56	0.94
	4	0.25	0.36	0.63	0.78	0.66	0.79	0.75	0.53	0.93

Table 2 (continued)

Parameters	Image/Technique	HE	DSIHE	ESIHE	MMSICHE	AGCWD	DOTHE	TCDHE-SD	PSO	DSOTAGC
	5	0.45	0.61	0.51	0.90	0.75	0.64	0.81	0.77	0.93
	6	0.30	0.42	0.65	0.84	0.75	0.58	0.84	0.85	0.93
	7	0.40	0.46	0.66	0.92	0.84	0.71	0.91	0.88	0.92
	8	0.50	0.64	0.64	0.93	0.88	0.78	0.86	0.88	0.93
	9	0.35	0.45	0.42	0.87	0.74	0.53	0.80	0.83	0.92
	10	0.52	0.58	0.58	0.95	0.85	0.84	0.89	0.91	0.92

has been observed that, the proposed DSOTAGC technique results better average entropy, PSNR, AMBE, and SSIM, over other existing techniques. So, from the qualitative analysis (Figs. 3, 4, 5, 6, 7, 8 and 9) and quantitative analysis (Table 1 and 2), average plot (Fig. 10), it is observed that, proposed DSOTAGC based technique outperforms in terms of the visual quality, brightness, information, edge preservation, noise suppression, and structure similarity.

Because of its adaptive-ness and better performance, the proposed DSOTAGC technique can be used as a preprocessing technique for medical imaging applications such as coronavirus detection, brain tumor detection, brain tissue segmentation and monitoring the disease in the human body.

4 Conclusions

In this paper, a novel medical image enhancement technique is proposed with the objectives of improving the contrast, entropy, PSNR and making the image artifacts free. The most challenging task in the image enhancement technique is removing the artifacts along with preserving image texture. So, initially, texture region from the image has been identified using Sobel operator and suppressed the non-texture effect. The problem of the over enhancement in medical images is eliminated using adaptive clipping technique. To make the algorithm adaptive, the texture threshold, clipping threshold, and exponent parameters have been optimized using DSO algorithm. As, the fitness function is a combination of entropy and PSNR and each having equal importance, so DSOTAGC technique produces a balanced adaptive optimal result with better entropy and PSNR value. Contrast is improved with the help of adaptive gamma parameters. Further, the proposed approach is not only good for artifact suppression but also better for structure similarity. After performing more number of experiments, it is found that the DSOTAGC technique achieves the best enhancement effect by enhancing the details of the non-contrast medical images, improving the contrast and avoiding artifacts. Overall quality of the image and visibility of the local details by the proposed DSOTAGC technique is better than the other discussed techniques.

Declarations

References

1. Acharya UK, Kumar S (2020) Particle swarm optimized texture based histogram equalization (PSOTHE) for MRI brain image enhancement Optik 224:165760.
2. Acharya UK, Kumar S (2021) Genetic algorithm based adaptive histogram equalization (GAAHE) technique for medical image enhancement. Optik 230:166273.

3. Acharya UK, Kumar S (2021) Image Enhancement Using Exposure and Standard Deviation-Based Sub-image Histogram Equalization for Night-time Images. In: Proceedings of International Conference on Artificial Intelligence and Applications. Springer, Singapore, pp 607–615

4. Acharya UK, Kumar S (2021) Directed searching optimized mean-exposure based sub-image histogram equalization for grayscale image enhancement. Multimed Tools Appl 80(16):24005–24025

5. Acharya UK, Kumar S (2021) Swarm intelligence based adaptive gamma corrected (SIAGC) retinal image enhancement technique for early detection of Diabetic Retinopathy. Optik 247:167904.

6. Acharya UK, Kumar S (2023) Image sub-division and quadruple clipped adaptive histogram equalization (ISQCAHE) for low exposure image enhancement. Multidim Syst Sign Process 34(1):25–45

7. Agarwal M, Rani G, Dhaka VS (2020) Optimized contrast enhancement for tumor detection. Int J Imaging Syst Technol 30(3):687–703

8. Bhandari AK, Pankaj K, Maurya S (2020) Salp swarm algorithm-based optimally weighted histogram framework for image enhancement. IEEE Trans Instrum Meas 69(9):6807–6815

9. Biomedical Image Search Engine (n.d.) https://openi.nlm.nih.gov.

10. Cascarano P, Piccolomini EL, Morotti E, and Sebastiani A (2021) Plug-and-Play gradient-based denoisers applied to CT image enhancement. arXiv preprint arXiv:2102.07510

11. Gao, H, Qiu, B, Barroso, RJD, Hussain, W, Xu, Y, Wang, X (2022) Tsmae: a novel anomaly detection approach for internet of things time series data using memory-augmented autoencoder. IEEE Transactions on network science and engineering

12. Gao, H, Xiao, J, Yin, Y, Liu, T, Shi, J (2022) A mutually supervised graph attention network for few-shot segmentation: the perspective of fully utilizing limited samples. IEEE Transactions on neural networks and learning systems

13. Gao H, Huang J, Tao Y, Hussain W, Huang Y (2022) The joint method of triple attention and novel loss function for entity relation extraction in small data-driven computational social systems. IEEE Transac Comput Soc Syst 9(6):1725–1735

14. Gonzalez RC, Woods RE (2002) Digital image processing. Prentice Hall Press, Upper Saddle River, NJ, USA

15. He K, Jian G, Xie L, Zhang X, Xu D (2021) Regions Preserving Edge Enhancement for Multisensor-Based Medical Image Fusion. IEEE Trans Instrum Meas 70:1–13

16. Huang SC, Cheng FC, Chiu YS (2012) Efficient contrast enhancement using adaptive gamma correction with weighting distribution. IEEE Trans Image Process 22(3):1032–1041

17. Kallel F, Hamida AB (2017) A new adaptive gamma correction based algorithm using DWT-SVD for non-contrast CT image enhancement. IEEE Transac Nano Biosci 16(8):666–675

18. Kandhway P, Bhandari AK, Singh A (2020) A novel reformed histogram equalization based medical image contrast enhancement using krill herd optimization. Biomed Sig Proc Control 56:101677.

19. Kanmani M, Narsimhan V (2018) An image contrast enhancement algorithm for grayscale images using particle swarm optimization. Multimed Tools Appl 77(18):23371–23387

20. Kim HG, Yoo H (2018) Image enhancement for computed tomography using directional interpolation for sparsely-sampled sonogram. Optik 166:227–235

21. Li B, Xie W (2015) Adaptive fractional differential approach and its application to medical image enhancement. Comput Electr Eng 45:324–335

22. Li Z, Jia Z, Yang J, Kasabov N (2020) An efficient and high quality medical CT image enhancement algorithm. Int J Imaging Syst Technol 30(4):939–949

23. Liu L, Jia Z, Yang J, Kasabov N (2015) A medical image enhancement method using adaptive thresholding in NSCT domain combined unsharp masking. Int J Imaging Syst Technol 25(3):199–205

24. Magudeeswaran V, Singh JF (2017) Contrast limited fuzzy adaptive histogram equalization for enhancement of brain images. Int J Imaging Syst Technol 27(1):98–103

25. Medical image database (n.d.) https://medpix.nlm.nih.gov.

26. MRTIP Data base (n.d.) https://www.mr-tip.com/serv1.php

27. Shoaib M, Mohsin M, Ansari IK, Maddhesiya H, Acharya UK (2020) Single image haze removal using variable fog-weight. In Journal of Physics: Conference Series, IOP Pub, 1706(1): 012091.

28. Singh N, Bhandari AK (2021) Principal Component Analysis-Based Low-Light Image Enhancement Using Reflection Model. IEEE Trans Instrum Meas 70:1–10

29. Singh K, Kumar R (2014) Image enhancement using exposure based sub image histogram equalization. Pattern Recogn Lett 36:10–14

30. Singh K, Kumar R (2014) Image enhancement via median-mean based sub-image-clipped histogram equalization. Optik 125(17):4646–4651

31. Singh K, Vishwakarma DK, Walia GS, Kapoor R (2016) Contrast enhancement via texture region based histogram equalization. J Mod Opt 63(15):1444–1450

32. Subramani B, Veluchamy M (2018) MRI brain image enhancement using brightness preserving adaptive fuzzy histogram equalization. Int J Imaging Syst Technol 28(3):217–222
33. Wang Y, Chen Q, Zhang B (1999) Image enhancement based on equal area dualistic sub-image histogram equalization. IEEE Trans Consum Electron 45:68–75
34. Yang L, Liang Y, Fan H (2010) Study on the methods of image enhancement for liver CT images. Optik 121(19):1752–1755
35. Zarie M, Pourmohammad A, Hajghassem H (2019) Image contrast enhancement using triple clipped dynamic histogram equalisation based on standard deviation. IET Image Process 13(7):1081–1089
36. Zhao C, Wang Z, Li H, Wu X, Qiao S, Sun J (2019) A new approach for medical image enhancement based on luminance-level modulation and gradient modulation. Biomed Sign Proc Contr 48:189–196
37. Zou D, Liu H, Gao L, Li S (2011) Directed searching optimization algorithm for constrained optimization problems. Expert Syst Appl 38(7):8716–8723