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Directed searching optimized mean-exposure based sub-image histogram equalization for grayscale image enhancement

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Abstract
This paper presents a novel enhancement technique for low light grayscale images. The main goal of this work is to enhance the visual quality and improve the information contents (entropy) of the images using a novel Directed Searching Optimized mean-exposure based sub-image histogram equalization technique. Initially, the proposed method clips the original histogram to prevent over enhancement. The clipped histogram is divided into two sub-histograms, based on mean intensity value. A further division of the lower sub-histogram is carried out, based on an exposure threshold to avoid unnatural artifacts. Then, each sub-histogram is equalized independently followed by a modified transfer function. Two optimal constraint parameters are used in this paper, to reduce the information loss during histogram equalization. The Directed Searching Optimization algorithm is employed in this paper for automatic selection of the constraint parameters in order to maximize the fitness function. It makes the proposed technique more adaptive. Finally, the proposed method is compared with other existing histogram equalization based image enhancement techniques. Simulation results show that, the proposed method is able to maximize the information contents effectively and preserves the natural appearance of the image. It also results better visual quality image with improved PSNR, SSIM, FSIM and reduced MSE as compared to other state-of-the-art methods.

Keywords Image enhancement · Histogram equalization · Directed searching optimization · Histogram sub-division

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1 Introduction

In this technological world, images are being captured by different camera sensors for different applications, but manipulation of these images without any information loss is an arduous task. The process of transformation of a degraded low quality input image to the image with better qualityis known as image enhancement technique. This technique is used for improving the interpretability of information contents for viewers with better quality image. The degradation in an image is due to non-uniform environmental illumination, imperfect image acquisition, noise, aperture size, shutter speed, low quality camera sensor, poor light environment [28]. Quality of the image is also degraded due to the distance between camera sensor and target. This effect can be observed while taking the images of the earth's surface from satellite or aircraft. So to improve the quality of such images, the image enhancement technique is used in image processing.

The method of image enhancement can be performed either in spatial domain or in the frequency domain. Spatial domain is directly associated with the pixel value of an image. Histograms are considered as the basis for a number of spatial domain techniques. It describes the frequency of the intensity values that occur in an image. Its shape predicts the possibility of contrast enhancement. To set the image statistics in a clarified visual format, histograms are also used.The most commonly used spatial domain technique is histogram equalization [12]. The frequency domain method is associated with fourier transform of an image. In frequency domain, fourier transform of image is multiplied with filter transfer function. Then,an enhanced image is obtained by taking the inverse transform of the product term. It modify the distribution of pixel values. The frequency domain method is based on convolution theorem. Computation complexity is less in frequency domain techniques, but simultaneously, it cannot enhance every part of an image [19].

An image which is captured in low light environment is not clearly visible. So, to enhance such image, many histogram equalization (HE) based methods have been proposed. Histogram equalization is a technique for improving the quality of image by modifying the intensity distribution of Histogram [6]. It is based on input gray level probability distribution. By the method of the histogram equalization, the image's histogram becomes flattened and stretched [12]. So the overall brightness of the image is to be improved. The most widely used areas of HE are medical and radar image processing. But the main shortcoming of HE is that, it generates some unnatural enhancement in output image and due to such excessive change in brightness, image becomes brighter. So this method is not suitable for consumer electronics such as TV because of its flattening property [17].

To mitigate such limitation observed in HE, Y. T. Kim [17] introduced a new algorithm named as Brightness Preserving Bi-Histogram Equalization (BBHE), for contrast enhancement. The main focus of this algorithm is to preserve the mean brightness of the given image and enhancing the contrast. As per this algorithm, the input image is decomposed into two sub-images depending on the mean of the input image. Then the sub-images are equalized independently depending on corresponding Histogram of the sub-image. Again to avoid the artifacts and over enhancement, another histogram equalization based technique known as equal area Dualistic Sub-image Histogram Equalization (DSIHE) was introduced [32]. In this method, the image is divided into sub-images of two equal areas depending upon the probability density function. Then the individual sub-images are equalized differently. Finally the enhanced image is obtained by combining these equalized sub-images. Also, it has been observed that, this method enhances the image as well as preserves the original image luminance.

In [7], Soong-Der Chen et al. proposed an enhancement method which is an extension of BBHE and is known as Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE). The main goal of this method is to provide maximum brightness preservation. But in MMBEBHE, the separation of image is based on the threshold level, at which, Absolute Mean Brightness Error (AMBE) is minimum. This AMBE is the absolute separation between input mean and output mean. MMBEBHE can enhance the contrast of the image and preserve the mean brightness which may or may not be handled well by HE, BBHE and DSIHE. Chen et al. [8] proposed a technique for image enhancement, which recursively performs the BBHE. This method performs the image subdivision based on mean intensity value in a recursive way. Then in [25], a new algorithm was proposed for image enhancement, which recursively performs the division of histogram, based on the median value of brightness instead of mean brightness.

The above discussed techniques are not able to provide any mechanism for controlling the level of enhancement with preserving brightness and entropy. In [26], the author proposed another technique for contrast enhancement of low exposure image known as Exposure based Sub-Image Histogram Equalization (ESIHE). In this paper the author has given more focus for contrast enhancement and Maximizing the entropy. The work in [27] is mainly associated with enhancement of low light, or night vision images. It includes two methods such as, Recursive Exposure based Sub-image histogram equalization (R-ESIHE) and Recursively Separated Exposure based sub-image histogram equalization (RS-ESIHE). The method R-ESIHE recursively performs ESIHE [26] method till the exposure among successive iteration is less than a predefined threshold. RS-ESIHE performs the image histogram subdivision recursively. Each histogram is divided into sub-Histogram based on respective exposure thresholds and equalizes each sub histogram independently and finally integrates into one image.

Another approach for image contrast enhancement and entropy restoration is presented in [28] which is based on swarm intelligence, Histogram equalization and gamma correction. In 2018, M. Kanmani [16] proposed a new technique for enhancing the information contents and improving the visual quality of the grayscale image by using particle swarm optimization algorithm and adaptive gamma correction technique. Then, A. K. Bhandari [5] proposed an image enhancement technique which produces a higher contrast image with minimum change in entropy with respect to the original image by using Social Spider Optimization algorithm. In 2019, M. Zarie suggested a robust contrast enhancement technique [36] named as image contrast enhancement using triple clipped histogram equalization based on standard deviation. In the last few years, different approaches [1–4, 9–11, 13–15, 18, 20–24, 30, 31, 33–35, 37–39] have been developed to improve the quality of images and to handle the challenges of image enhancement.

From literature survey [2, 5, 7–9, 12, 13, 16–18, 24–27, 30, 32, 33, 36], it has been observed that most of the existing methods have the following drawback.

i. More Information loss
ii. Over enhanced image
iii. No control on enhancement rate
iv. Result artifacts in the enhanced image.
v. Not adaptive
vi. Loss of the natural appearance of the image by affecting the structure, feature similarity.

In this work, our proposed method emphasizes to meet the challenges like maximization of entropy, improving the visual quality of the image, controlling the enhancement rate, reducing the artifacts and natural appearance of the image without much affecting the basic structure, feature. By taking the following parameters into mind, a novel image enhancement technique is proposed in this paper. The main contributions of this proposed work is

i. Subdivision of the histogram based on mean and exposure threshold in order to preserve the brightness and improve the natural appearance of the image.
ii. Construct a new transfer function (mapping function) for the enhanced image using CDF of each sub-image and constraint parameters.
iii. Automatic Selection of the constraint parameters as per the fitness function, using DSO algorithm. Selection of these parameters takes place without human intervention which makes the proposed method more adaptive.

The rest part of this paper is arranged as follows. Section 2 addresses the proposed method, which includes the description of clipping technique, image sub-division, HE, DSO algorithm with mathematical expression. In Section 3 includes result analysis and comparison of the proposed method with different existing methods by taking different parameters. Section 4 concludes the paper by justifying the objective.

2 Proposed method

The proposed method is an extension of histogram equalization technique. The enhancement problem is represented as an optimization problem in this paper. The main objective of this paper is to avoid the shortcomings found in HE based technique. The histogram equalization technique improves the contrast of the image at the cost of more information loss. There is no controlling parameter used to control the enhancement rate. There is no specific method used in histogram equalization method to maximize the information contents of enhanced image. It also creates some unnatural artifacts and over enhancement problems. So, a novel image enhancement technique is proposed in this paper to improve the information content, enhance the quality of the image and controlling the enhancement rate. This proposed algorithm consists of following main steps named as histogram clipping technique, histogram sub-division with equalization and maximization of entropy.

2.1 Histogram clipping technique

To eliminate the problem of over enhancement observed in histogram equalization and to control the enhancement rate, clipping technique is used in this paper. This technique is used to clip the original histogram $h(k)$ and to form a new histogram $h_c(k)$. In this technique, a clipping threshold is formed by using (1). The bin of the histogram, whose value is greater than the clipping threshold, is limited to the threshold level. The formula used to calculate clipping threshold [26] is

$$T_c = \frac{1}{l} \sum_{k=0}^{l-1} h(k) \tag{1}$$

The new clipped Histogram is represented as,

$$h_c(k) = \begin{cases} h(k), & h(k) < T_c \\ T_c, & h(k) \geq T_c \end{cases} \tag{2}$$

2.2 Histogram sub-division with equalization and maximization of entropy

To improve the natural appearance of the image and to avoid unnatural enhancement, the clipped histogram is bisected into two sub-histograms, based on mean intensity value. Two sub-Histograms are generated named as lower histogram and upper histogram. Again, to avoid unnatural artifacts, the lower histogram is divided into two sub-histograms known as extremely low exposure histogram and low exposure histogram. Then each sub-histogram performs histogram equalization independently. The transfer function used for both extremely low exposure and low exposure image contains two different constraint parameters which controls the information content of the image during HE in each sub-image.

To maximize the information contents, an efficient optimization technique known as Directed Searching Optimization (DSO) [40] algorithm. Has been used in this paper. DSO algorithm performs two most important operations which are needed to find the best optimal solution in a solution space and prevent the premature convergence of DSO. It includes two operations such as position updating and genetic mutation. Position updating is used to find the best solution vector among the set of randomly generated solution vectors and it takes the major role for convergence of DSO. Genetic mutation takes the active role to increase the diversity of solution vectors and prevent the premature convergence.

To solve any optimization problem, a cost function or fitness function is necessary to compute the fitness of each solution vector. It has been observed that the entropy of enhanced image is very less as compared to input image which indicate the information loss is more in HE [12]. So naturalness is loosed in enhanced image. So to minimize the entropy difference between the input image and enhanced image, an objective function is used in this paper which indicates maximization of information content of enhanced image. The information content (entropy) is to be maximized by using Directed Searching Optimization algorithm (DSO). The fitness function is represented in (3)

$$arg\ Max\ H = -\sum_{i=0}^{l-1} p(i) log_2 p(i) \tag{3}$$

Where H represents the entropy of image and $p_i = \frac{n_i}{s \times t}$ is the probability of occurrence of i^{th} intensity level and $(s \times t)$ is the total number of pixels present in the image.

2.3 Steps involved in proposed method

Here, Fig. 1 represents the flowchart of our proposed method. To simulate the proposed method, the following steps are taken into consideration.

Step 1: Compute the Histogram of the input image
Step 2: Calculate the mean of the image intensity value.
Step 3: Evaluate the clipping threshold using (1) and clip the original Histogram using (2) to avoid over saturation.
Step 4: The clipped histogram is decomposed into two sub-Histogram based on the mean intensity value X_m [8]. Where the lower sub-histogram contain intensity value, up to mean intensity and upper sub-Histogram having intensity value lies in between mean and max gray level.

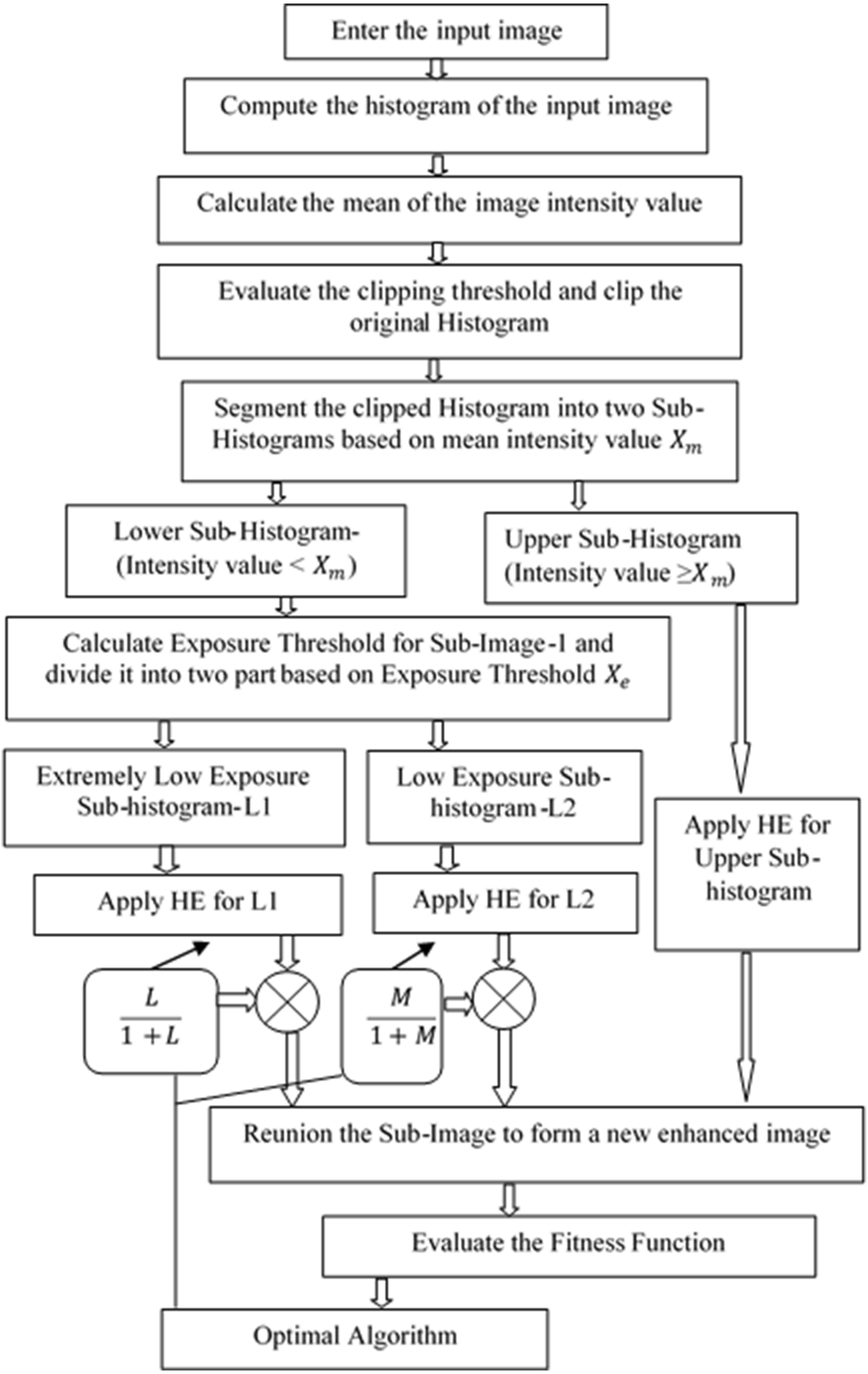

Fig. 1 Flowchart of the proposed method

Step 5: Again the lower sub-histogram is sub-divided into two sub-histograms by using exposure threshold X_e [26]. So, two sub-Histograms are formed, extremely low exposure sub-histogram and low exposure sub-histogram. Finally, these histogram sub-divisions result three sub-images named as sub-image-1, sub-image-2, and sub-image-3.

Step 6: The probability density functions (PDF) of sub-image-1, sub-image-2, sub-image-3 are calculated using Eqs. (4), (5) and (6) respectively.

$$P_{Ll}(k) = \frac{h_c(k)}{N_{Ll}}, for\ 0 \le k \le X_e - \mathbf{1} \tag{4}$$

$$P_{Lu}(k) = \frac{h_c(k)}{N_{Lu}}, for\ X_e \le k \le X_m - \mathbf{1} \tag{5}$$

$$P_U(k) = \frac{h_c(k)}{N_U}, for\ X_m \le k \le l - 1 \tag{6}$$

The variables N_{Ll}, N_{Lu}, *and* N_U represent the number of pixels in sub-image-1, sub-image-2, and sub-image-3 respectively.

Step 7: The cumulative density function (CDF) of sub-image-1, sub-image-2, sub-image-3 are evaluated using (7–9).

$$C_{Ll}(k) = \sum_{k=0}^{k=X_e-1} P_{Ll}(k) \tag{7}$$

$$C_{Lu}(k) = \sum_{k=X_e}^{k=X_m-1} P_{Lu}(k) \tag{8}$$

$$C_U(k) = \sum_{k=X_m}^{k=l-1} P_U(k) \tag{9}$$

Step 8: The transfer function (mapping function) of individual sub-image is determined using (10–12).

Transfer function for sub-image-1,

$$F_{Ll} = \left(\frac{L}{1+L}\right)[(X_e - X_{min})C_{Ll}] \tag{10}$$

Transfer function for sub-image-2,

$$F_{Lu} = \left(\frac{M}{1+M}\right)\left[(X_e+1) + \left(\left(X_m-(X_e+1)\right)C_{Lu}\right)\right] \tag{11}$$

Transfer function for sub-image-3,

$$F_U = (X_m+1) + (l-(X_m+1))C_U \tag{12}$$

A complete image Y,(13**)** is formed by integrating all three sub-images.

$$Y(\boldsymbol{s},\boldsymbol{t}) = \boldsymbol{F_{Ll}} \cup \boldsymbol{F_{Lu}} \cup \boldsymbol{F_U} \tag{13}$$

In (6), l represents the maximum gray level and in (10), X_{min} represents the minimum gray level. Two constraint parameters L and M are used in the above transfer function (10), (11). The values of these parameters are taken in the range [0, 1]. The DSO algorithm is used to search the most optimal values of L and M in a two dimensional searching space for which it give the maximum fitness value.

Step 9: Initialize all the parameters for the DSO algorithm [40].

i. Population Size or number of solution vector (*PS*).
ii. Maximum number of iterations (*iter*)
iii. Forward probability (P_α)
iv. Forward co-efficient (α)
v. Backward co-efficient (β)
vi. Genetic Mutation Probability (P_m)

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

Initialize the population matrix *PM*, where i varies from 1,2,3,…..,Dimension (*DM*) of the problem space and j varies from 1,2,3,……, Population Size (*PS*). Figure 2 represents the position updating strategy of DSO algorithm [40]. In Fig. 2, the region between P and V is named as forward region and the region between P and S is named as backward region. Here $P_i^j(k)$ is the i^{th} component of j^{th} solution vector of k^{th} iteration,$P_i^j(k+1)$ is the corresponding

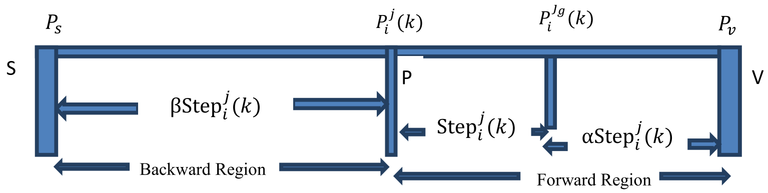

Fig. 2 Position updating strategy using DSO

updated component. Here j_g is the index of the global solution vector. $P_i^{j_g}(k)$ is the i$^{\text{th}}$ component of $j_g{}^{\text{th}}$ global solution vector of k^{th} iteration. P_{iU} and P_{iL} are the upper and lower bound of i^{th} component of position vector. P_V,P_s are forward and backward extension of $P_i^j(k)$. The variable r represents the random number which lies in between [0, 1]. After initializing the parameters, position updating and genetic mutation operators [40] are used to search the optimal solution.

To update the position of each solution vector, it must follow the following conditions. These conditions are $j \in [1, PS]$ and $j \neq j_g$, $i \in [1\ DM]$. Then, a random number is generated and check the forward probability condition (Rand () < P_α). If, the forward probability condition is satisfied then the position is updated in forward direction using (14).

$$P_V = \mathrm{P_i^j(k)} + (1+\alpha)\left(\mathrm{P}_i^{\mathrm{j_g}}(\mathrm{k}) - \mathrm{P_i^j(k)}\right) \tag{14}$$

In (14), $P_i^{j_g}(k) - P_i^j(k)$represents the adaptive step size. Initially solution vectors are sporadic in solution space, so this adaptive size is beneficial for global search. But in later stage, solution vectors are close to each other, so step size is small which is helpful for local search of the DSO algorithm If, P_V is greater than the upper bound of i^{th} position component, then limited it, to upper bound P_{iU}. If P_v is less than lower bound, then limited it to lower bound P_{iL}Thenthe new updated position is shown in (15)

$$P_i^j(k+1) = P_i^j(k) + r \times \left(P_V - P_i^j(k)\right) \tag{15}$$

If, the forward probability condition is not satisfied, then position is updated (16) in backward direction.

$$P_s = P_j^i(k) - (\beta) \times \left(P_i^{j_g}(k) - P_i^j(k)\right) \tag{16}$$

If, P_s is greater than the upper bound of i^{th} position component, then it is limited to the upper bound P_{iU}. If P_s is less than lower bound, then limited it to lower bound P_{iL}. Then the new updated Position (17) in backward direction,

$$P_j^i(k+1) = P_i^j(k) + r \times \left(P_s - P_i^j(k)\right) \tag{17}$$

This Backward region is the auxiliary region and it is used to slow down the convergence of DSO. After position updating, the genetic mutation operator is being used to improve the DSO performance. To apply genetic mutation, it will check the genetic mutation probability condition. If that satisfied the genetic mutation probability (Rand() <P_m) then the new updated component (18) is,

$$P_i^j(k+1) = P_{iL} + r \times (P_{iU} - P_{iL}) \tag{18}$$

3 Results and discussions

In this section, the simulation result of the proposed method is compared with some of the existing image enhancement techniques like HE [12], BBHE [17], DSIHE [32], MMBEBHE [7], ESIHE [26], Particle Swarm Optimization (PSO) based technique [24], by considering the following performance parameters such as entropy, MSE, PSNR, SSIM, FSIM and execution time. To perform the simulation work, hundred low light images are taken from USC-SIPI database [29] and few randomly selected images are presented in this paper. All these analysis were performed on Intel(R), core (TM), i3-4005U CPU @1.70 GHz, 4.00 GB RAM, 64 bit operating System, Matlab-2018.

3.1 Parameter selection for experiment setup

The parameters taken to perform the simulation work of our proposed method are presented in Table 1.The parameters should be keenly selected, so that the optimal or globally best solution can be achieved with proper avoidance of excessive complexity up to a certain extent. Larger population size may leads to less number of iterations for similar time bounded convergence for a given optimization problem. Very large as well as very low population size should be avoided, as they may lead to unnecessary complex behavior and premature result respectively. Various experiment works have been conducted and it has been observed that a population of moderate size will results the best optimal solution with less number of iteration without wastage of resources**.** So, in this paper the population size and number of iterations are taken as 50 and 30 respectively. Genetic mutation works in a random manner and is used to enhance the diversity of individuals. It is required for improving the DSO performance by preventing the premature convergence to local minima through exploiting the unseen areas of the search space. But a higher value of mutation probability may lead the solution to diverge. So the mutation probability is considered as 0.01. Like the PSO algorithm, a new position updating strategy has been used in DSO algorithm. As per this strategy, the current position is inclined to mimic the global best position. The forward region is considered as the main searching region which is actually a region near the global position. So the forward probability and forward coefficient are taken as 0.8 and 1 respectively. The backward region is an auxiliary region, and it is used to slow down the rapid convergence of the DSO algorithm, which is beneficial to prevent the premature convergence of the DSO. So the backward coefficient is taken as ten. After performing many experimentations, finally the value of the constraint parameters have been taken in the range of [0, 1] for proper balanced weighted summation.

3.2 Performance evaluation based on visual quality

To show the supremacy of the proposed method, both visual and quantitative analysis are carried out in this paper. Figs. 3, 5, 6, 7, 8 and 9 represent the input images and their corresponding enhanced images obtained by using different enhancement techniques. Figure 4

Table 1 Parameters taken for simulation work

Parameters	Values
Population Size or number of solution vector (*PS*)	50
Max number of iteration (*iter*)	30
Forward probability (P_α)	0.8
Forward coefficient (α)	1
Backward coefficient (β)	10
Genetic Mutation Probability (P_m)	0.01
Constraint Parameters (*L, M*) range	[0,1]

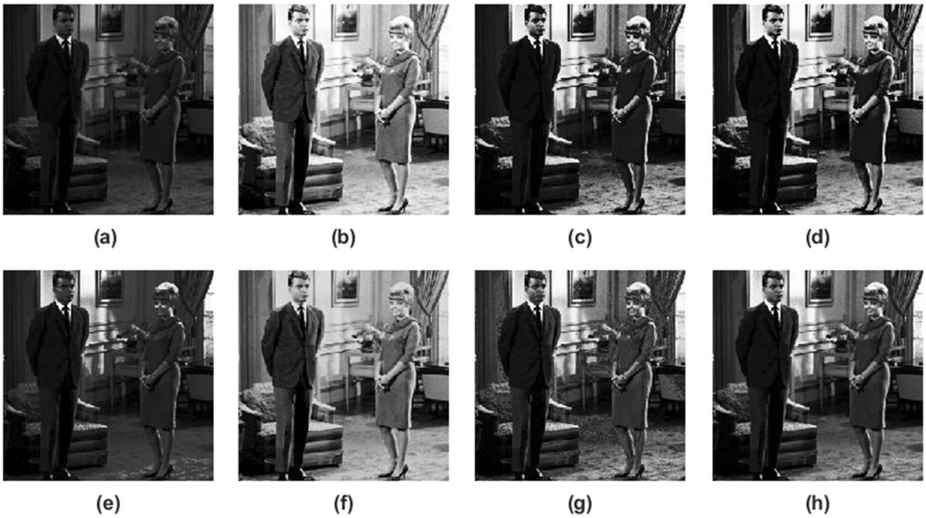

Fig. 3 Enhanced result of image-1, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (**h**) Proposed method

represents the histogram or the intensity distribution at different pixels of above mentioned images. From these histograms of Fig. 4, it is noticed that, the process of the intensity distribution of our proposed method is completely different from other techniques. From the histogram equalized images (Figs. 3b, 5b and 9b) and histogram of HE image (Fig. 4b), it is observed that HE introduced a significant change in brightness. Due to the stretching and flattening property of the histogram equalization, the dynamic range of the original image is expanded, which is shown in Fig. 4b. So that image obtained by the histogram equalization is much brighter than the input image. It is because; HE mapped the gray level proportionally with cumulative density function (CDF). It has also been observed that the histogram of the histogram equalized image does not follow the pattern of the input image histogram. The HE technique enhances the contrast of the image, but produces some artifacts. There is no mechanism used in HE, BBHE, DSIHE and MMBEBHE methods to avoid over enhancement.

So these methods result over enhancement images. The ESIHE technique produce better enhanced images, but the information loss is more in such images. The enhanced image produced by PSO based technique contain so many noise points which are shown in Figs. 3, 5,

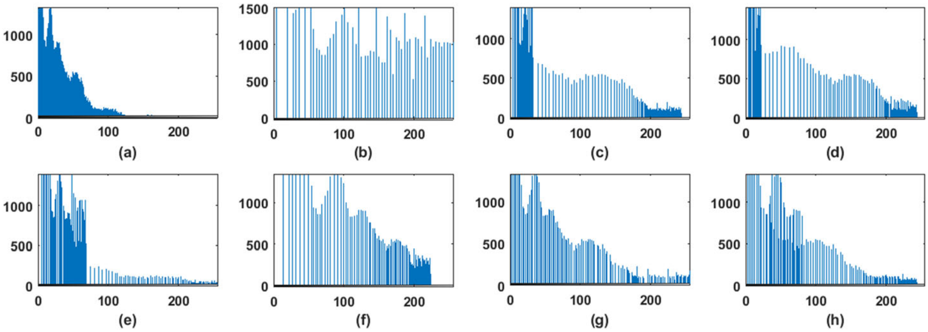

Fig. 4 Histogram of Enhanced result of image-1, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (h) Proposed method

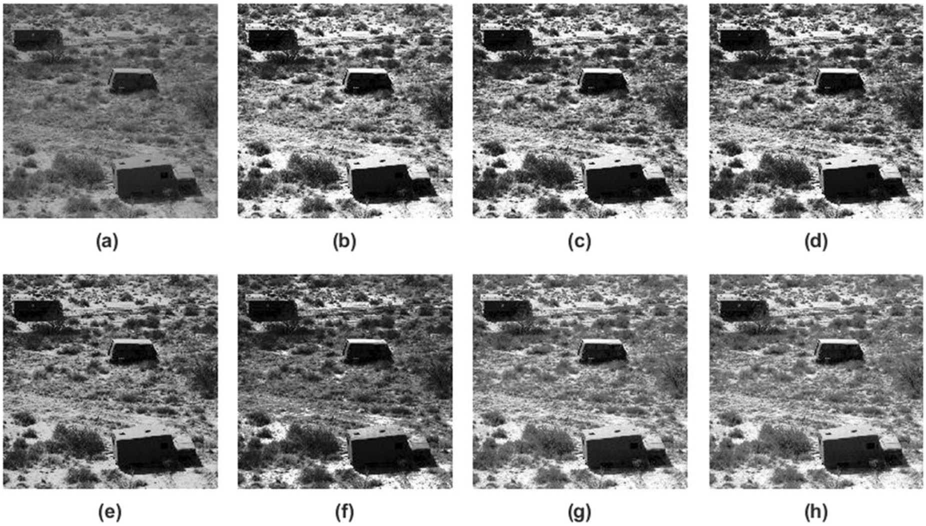

Fig. 5 Enhanced result of image-2, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (**h**) Proposed method

6, 7, 8 and 9. But, the over enhancement problem is eliminated in our proposed method, by using clipping technique.

Some unnatural artifacts has also been noticed in the background part of HE, BBHE, DSIHE, MMBEBHE, ESIHE, PSO based techniques based enhanced images in Figs. 3, 6 and 8. From Fig. 8h, it has been observed that all three vehicles are clearly visible in the image which is produced by our proposed method. But the third vehicle in Fig. 8, is not visible in the enhanced image produced by other state of the art techniques. No such unnatural enhancement

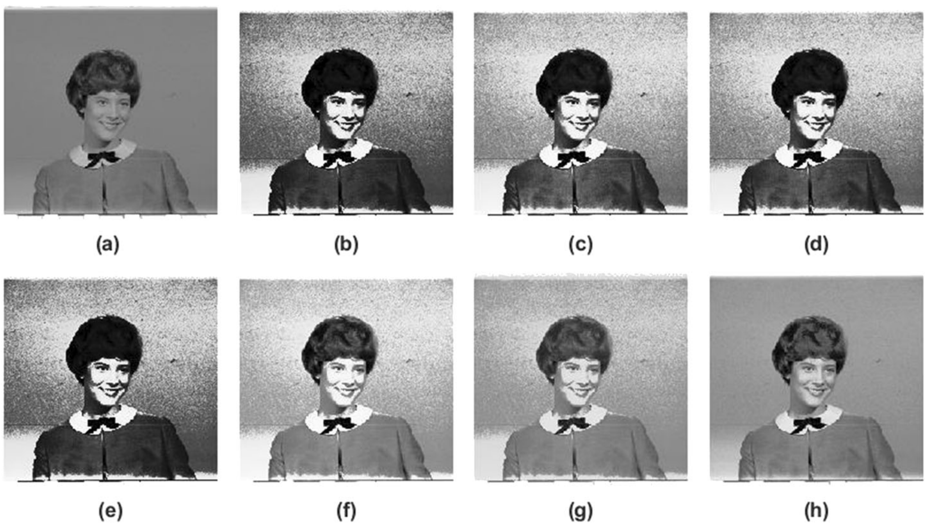

Fig. 6 Enhanced result of image-3, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (**h**) Proposed method

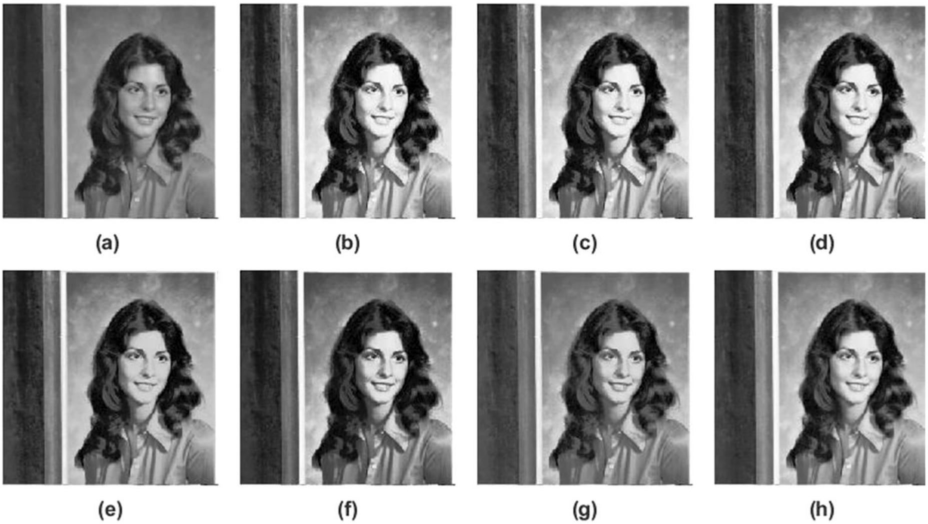

Fig. 7 Enhanced result of image-4, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO, (h) Proposed method

or artifacts found in the enhanced image obtained by our proposed method because of such novel histogram sub-division technique. The histogram of the proposed method also follows the pattern of the histogram of the input image, shown in Fig. 4a and 4h. So the enhanced image obtained by the proposed method is more similar with input image as compare to other methods. From the above simulation results, it has been observed that, proposed method yields the images of more natural looking by enhancing the contrast.

Extraction of a highly improved Image from low quality image is the main target of image enhancement. So, visual quality of the image is not only the criteria to measure the performance of different enhancement technique, but also some quantitative analyses are required to

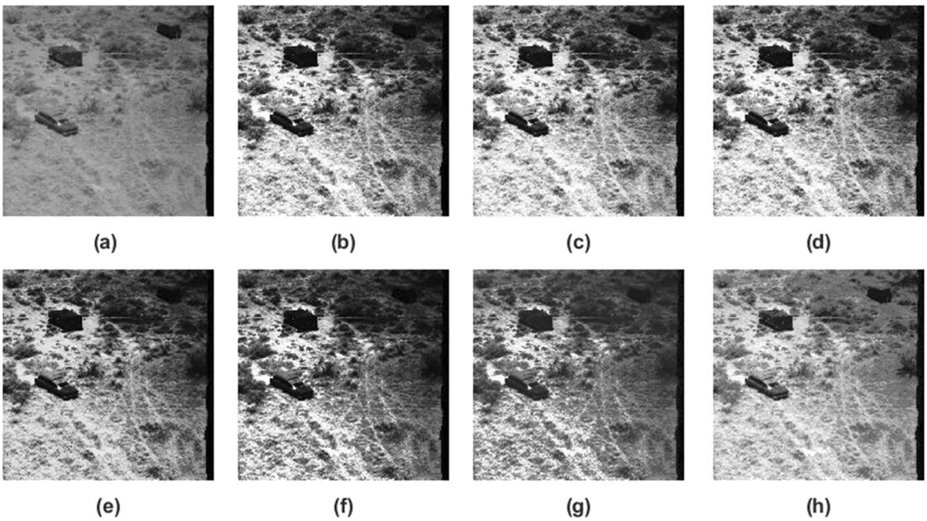

Fig. 8 Enhanced result of image-5, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (**h**) Proposed method

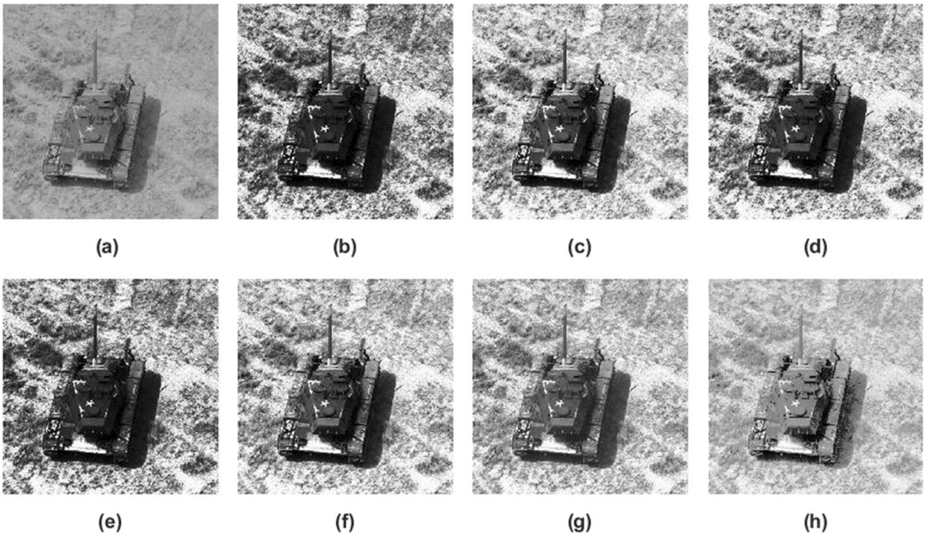

Fig. 9 Enhanced result of image-6, (**a**) Original, (**b**) HE, (**c**) BBHE, (**d**) DSIHE, (**e**) MMBEBHE, (**f**) ESIHE, (**g**) PSO (**h**) Proposed method

evaluate the same. So following parameters are also taken to measure the performance of enhanced image.

3.3 Performance evaluation based on entropy

Entropy represents the average information content of the image. Then Entropy of each enhanced image is calculated using (19).

$$H = -\sum_{i=0}^{l-1} p(i) log_2 p(i) \tag{19}$$

Here, p(i) represents the normalized histogram value of the image. Here H represents the entropy of enhanced image. The higher value of H indicates the image contain more information. From Table 2 and Fig. 10a, it has been noticed that the average information content of enhanced image by the method of BBHE is better as compared to HE and DSIHE and MMBEBHE but worse than the other techniques used in this paper. Information loss is more in Histogram Equalization technique and it also produces some unusual enhancement. But our proposed method gives better entropy preservation as compared to other methods. Because, the DSO algorithm used to search the optimal constraint parameters in such a way that, it will maximize the entropy.

3.4 Performance evaluation based on mean square error (MSE)

It is the mean of the square of the error between the input image and enhanced image [14]. Mean Square Error between original image and enhanced image is calculated using (20). From Table 3 and Fig. 10b, it has been observed that the mean square error between the input image and histogram equalized image is very high as compare to the other HE based algorithm and the MSE value is very less in our proposed method.

Table 2 Performance analysis of enhancement techniques based on entropy value

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	5.6764	6.2248	6.1905	6.1791	6.2257	6.2428	6.3583
Image-2	5.9559	6.4425	6.4567	6.4707	6.4158	6.5290	6.5472
Image-3	4.6755	5.2535	5.2438	5.2420	5.3449	5.3389	5.4935
Image-4	5.9612	7.0051	6.9964	7.0433	7.0211	7.0304	7.1577
Image-5	5.5353	5.9749	5.9661	5.9417	5.9048	5.9164	6.0625
Image-6	4.9660	5.4142	5.3803	5.3724	5.4260	5.4330	5.4774
Image-7	5.5771	6.1274	6.1160	6.1272	6.1171	6.1168	6.1689
Image-8	5.9591	7.0031	7.0100	7.0019	7.0036	7.1083	7.1237
Image-9	5.5211	5.8575	5.8575	5.8517	5.8210	5.8245	5.9424
Average entropy	5.5364	6.1448	6.1353	6.1367	6.1422	6.1711	6.2591

$$MSE = \left(\frac{1}{m \times n} \sum_{s=0}^{m-1} \sum_{t=0}^{n-1} \left(I_{enha}(s,t) - I(s,t) \right)^2 \right) \tag{20}$$

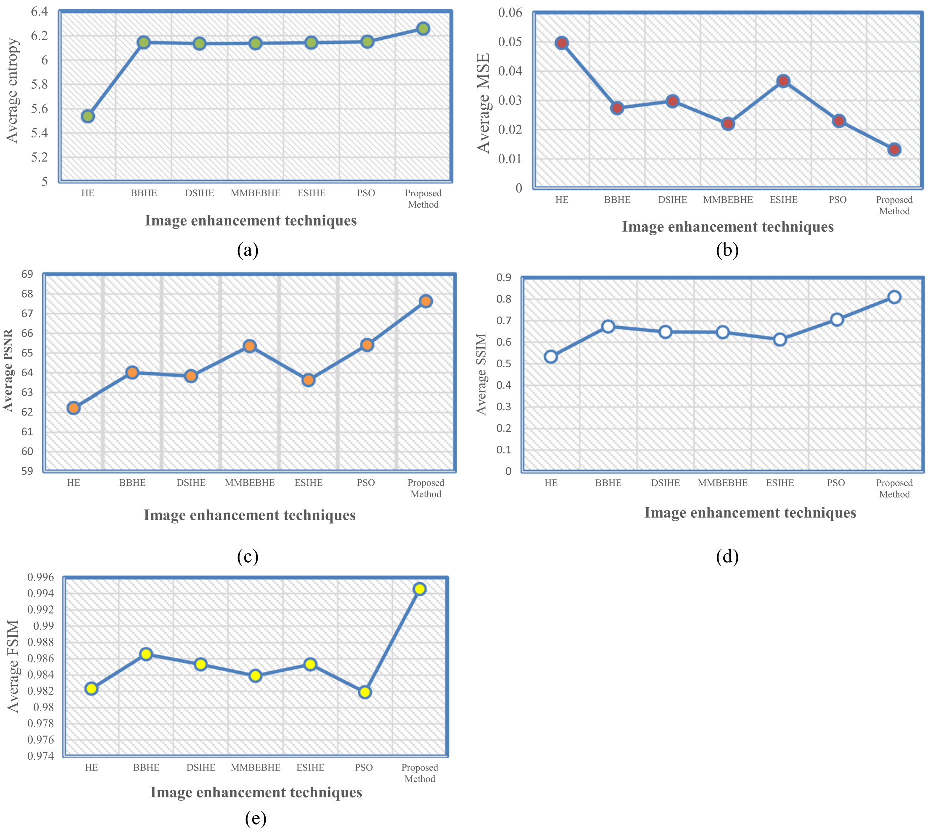

Fig. 10 Average value of the measured performance parameters obtained by different enhancement techniques (**a**) Average entropy, (**b**) Average MSE, (**c**) Average PSNR, (**d**) Average SSIM, (**e**) Average FSIM

Table 3 Performance analysis of enhancement techniques based on MSE value

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	0.1726	0.0413	0.0639	0.0101	0.1198	0.0733	0.0305
Image-2	0.0322	0.0240	0.0234	0.0121	0.0151	0.0140	0.0143
Image-3	0.0500	0.0416	0.0403	0.0389	0.0412	0.0142	0.0039
Image-4	0.0178	0.0144	0.0130	0.0061	0.0084	0.0075	0.0059
Image-5	0.0341	0.0275	0.0275	0.0237	0.0312	0.0258	0.0163
Image-6	0.0418	0.0196	0.0222	0.0383	0.0405	0.0170	0.0099
Image-7	0.0251	0.0192	0.0188	0.0235	0.0261	0.0218	0.0165
Image-8	0.0238	0.0234	0.0231	0.0197	0.0225	0.0091	0.0066
Image-9	0.0484	0.0353	0.0353	0.0257	0.0242	0.0241	0.0151
Average MSE	0.0496	0.02741	0.0297	0.0220	0.0366	0.0230	0.0132

3.5 Performance evaluation based on peak signal to noise ratio (PSNR)

It is one of the performance measurement techniques to evaluate the quality of the output image [14]. It is defined as the ratio between maximum powers of signal to power of distorting noise and is calculated using (21). The PSNR is inversly related to the Mean Square Error (MSE). If, higher is the value of PSNR, more is the image quality. From Table 4 and Fig. 10c, it has been found that proposed method results better PSNR value as compared to other existing methods.

$$PSNR = 20log_{10}\frac{255}{Root\ Mean\ Square\ Error} \tag{21}$$

3.6 Performance evaluation based on structural similarity index measure (SSIM)

It measures the structural similarity between input and output image [9]. It is computed using (22).

$$SSIM = \frac{\left(2\mu_x\mu_y + C_1\right)\left(2\sigma_{xy} + C_2\right)}{\left({\mu_x}^2 + {\mu_y}^2 + C_1\right)\left({\sigma_x}^2 + {\sigma_y}^2 + C_2\right)} \tag{22}$$

Table 4 Performance analysis of enhancement techniques based on PSNR value

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	55.7580	61.9694	60.0734	68.068	57.3429	59.4775	63.2752
Image-2	63.0434	64.3189	64.4329	67.2845	66.3227	66.5653	66.5725
Image-3	61.1343	61.9376	62.0713	62.2262	61.9803	66.6003	72.1857
Image-4	65.6227	66.5339	66.9744	70.2522	68.8576	69.7225	70.3564
Image-5	62.7932	63.7234	63.7355	64.3720	63.1856	64.1440	65.9879
Image-6	61.9092	65.2072	64.6525	62.2930	62.0512	65.8046	68.1344
Image-7	64.1175	65.2826	65.3739	64.4023	63.9541	63.5987	65.9374
Image-8	64.3486	64.4245	64.4801	65.1746	64.5988	68.5396	69.9057
Image-9	61.2807	62.6506	62.6506	64.0258	64.2810	64.2283	66.3220
Average PSNR	62.223	64.0054	63.8272	65.3443	63.6193	65.4089	67.6308

Where, μ_x, μ_y are the mean and σ_x, σ_y are the standard deviation of the input image and enhanced image respectively. Here, the sample correlation coefficient between these two images is represented by σ_{xy}. C_1, C_2 are the constants used to eliminate the instability. From Table 5 and Fig. 10d, it has been noticed that the average structural similarity between the input image and enhanced image obtained by using our proposed method is far better as compared to the other HE based method used in this paper. A very poor SSIM is generated by using HE.

3.7 Performance evaluation based on feature similarity index measure (FSIM)

The feature similarity between original image and enhanced image is measured by FSIM [39]. The formula used to measure FSIM (23) is

$$FSIM = \frac{\sum_{x\in X} S_L(x) PC_m(x)}{\sum_{x\in X} PC_m(x)} \tag{23}$$

Here X represents the whole image, $S_L(x)$ is the similarity between the input image and enhanced image, $PC_m$is the phasecongruency map Feature Similarity Index Measure (FSIM) between enhanced image and original image is calculated using (23). Table 6 and Fig. 10e represent the average FSIM obtained by different enhancement techniques. From these results, it has observed that the feature similarity between original image and enhanced image is less in Histogram Equalization and more in our proposed method.

3.8 Execution time

Table 7 represents the execution time of the different algorithms. It indicates the computational time complexity of enhancement techniques [15]. All the experiments were performed on a computer with Intel i3, 1.7 GHz processors, 4 GB RAM and Matlab 2018a. From this table, it has been observed that the HE and ESIHE techniques take very less time to process the images among all these existing techniques. BBHE, DSIHE and MMBEBHE algorithms require all most similar time to generate the enhanced images. But these techniques are not adaptive in nature. They don't use any of the optimization techniques to find the optimal parameters. So

Table 5 Performance analysis of enhancement techniques based on SSIM value

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	0.2976	0.6867	0.5960	0.8023	0.3437	0.4173	0.5285
Image-2	0.6824	0.7446	0.7440	0.7640	0.7413	0.8521	0.8612
Image-3	0.3174	0.4695	0.4541	0.4018	0.5389	0.6412	0.9047
Image-4	0.7809	0.8456	0.8466	0.8421	0.8217	0.8107	0.9156
Image-5	0.5985	0.6652	0.6475	0.6383	0.5720	0.6953	0.8123
Image-6	0.4240	0.6612	0.5878	0.4750	0.5617	0.7029	0.7625
Image-7	0.6707	0.7763	0.7690	0.6886	0.7008	0.7114	0.8209
Image-8	0.6986	0.7202	0.7180	0.7241	0.6971	0.8125	0.8901
Image-9	0.4899	0.5375	0.5375	0.5648	0.6229	0.7107	0.8782
Average SSIM	0.5327	0.6733	0.6478	0.6471	0.61292	0.7060	0.8105

Table 6 Performance Analysis of the enhancement techniques based on FSIM value

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	0.9840	0.9867	0.9910	0.9935	0.9851	0.9752	0.9850
Image-2	0.9962	0.9947	0.9944	0.9962	0.9943	0.9965	0.9985
Image-3	0.9540	0.9622	0.9603	0.9544	0.9667	0.9683	0.9920
Image-4	0.9874	0.9867	0.9867	0.9903	0.9917	0.9821	0.9953
Image-5	0.9793	0.9851	0.9825	0.9794	0.9681	0.9693	0.9947
Image-6	0.9703	0.9906	0.9816	0.9710	0.9909	0.9805	0.9957
Image-7	0.9903	0.9926	0.9910	0.9906	0.9936	0.9933	0.9963
Image-8	0.9893	0.9898	0.9896	0.9894	0.9877	0.9881	0.9966
Image-9	0.9896	0.9902	0.9902	0.9901	0.9893	0.9831	0.9964
Average FSIM	0.9823	0.9865	0.9853	0.9839	0.9853	0.9818	0.9945

the execution time of such techniques is very less over other optimized based techniques like PSO and DSO. Finally the execution time of the proposed technique is compared with one of the PSO based image enhancement technique. It has been found that the time taken by the proposed method is less as compared to the PSO based technique. It is because of the new position updating strategy of the DSO algorithm and the simplicity in proposed methodology.

3.9 Convergence performance

The Fig. 11a-d represents the convergence performance of proposed method for image-1-4. The convergence performance shows, how fast the global optimum is reached i.e., the minimum number of iteration required to reach the best value which is nothing but the maximum entropy value. In each iteration, this fitness value or entropy value is measured by using (3). From these convergences plot, It has been observed that DSO required very less iterations to converge and for reaching the maximum fitness value as compared to PSO for the application of image enhancement. In PSO, only position and velocity updating strategies are used to search the most optimal solutions. Mutation operator is not used in PSO. It is because of the simplicity in methodology, new position updating strategy and mutation of DSO algorithm.

Table 7 Performance analysis of enhancement techniques based on execution time

Image/ Algorithm	HE	BBHE	DSIHE	MMBEBHE	ESIHE	PSO based technique	Proposed Method
Image-1	0.5901	1.8170	1.8939	2.1929	0.2987	150.6324	134.6735
Image-2	1.1561	2.4738	2.2348	2.4779	0.5563	262.4896	248.9994
Image-3	0.6082	1.8214	1.5960	1.6941	0.8480	148.2183	137.0434
Image-4	0.6130	1.7249	1.7694	2.3714	0.7835	158.4350	144.4434
Image-5	0.6223	4.3653	2.8196	2.2880	0.4807	245.9708	232.6591
Image-6	0.6168	2.2789	2.0823	2.2985	1.0809	238.6088	233.8544
Image-7	0.6193	3.7881	2.0786	2.2633	1.1275	258.2361	247.0894
Image-8	0.8296	2.2446	2.4498	2.2524	2.0124	284.4805	260.9814
Image-9	1.4392	2.1117	2.1357	2.2063	1.0912	254.9629	229.6334
Average Execution time	0.7883	2.5140	2.1178	2.2272	0.9199	222.4483	207.7086

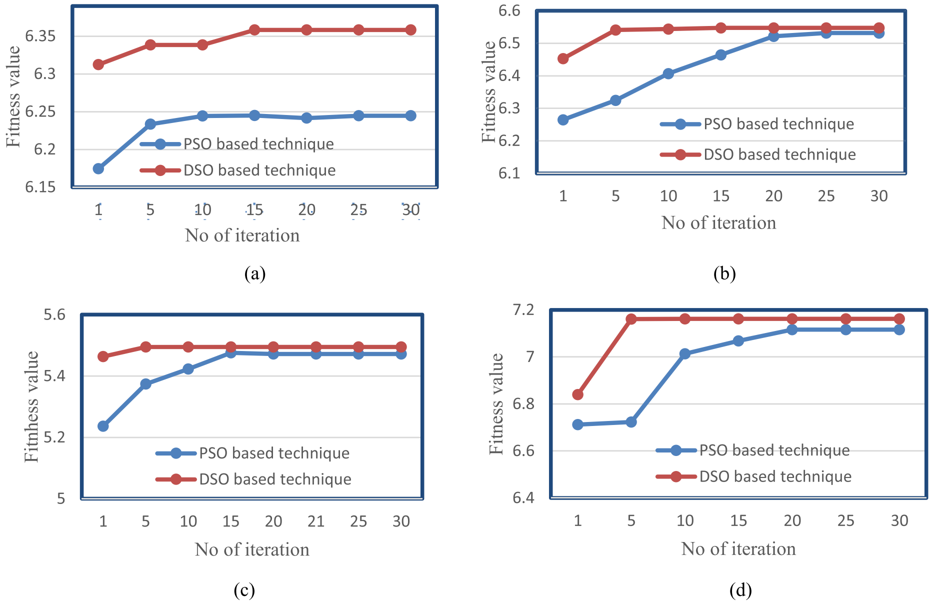

Fig. 11 Convergence plot of proposed method for (**a**) image-1, (**b**) image-2, (**c**) image-3, (**d**) image-4

From the above analysis, it is noticed that HE method enhances the contrast of the image, but not able to produce a quality image in terms of entropy, SSIM, PSNR, naturalness, FSIM and adaptiveness. But the execution time of HE technique is very less. The other HE based methods like BBHE, DSIHE, MMBEBHE, ESIHE, enhances the low illuminated image and somehow preserve the above discussed performance parameters. The above simulation results show the excellency of the proposed method. The excellency of this method is due to the novel way of sub-division of image, modified transfer function and the dynamic searching nature of the Directed Searching Optimization technique. By observing the above simulated results shown in figures (Figs. 3, 4, 5, 6, 7, 8, 9, 10 and 11) and Table (Tables 2**,** 3**,** 4**,** 5 and 6), it can be concluded that our proposed method performs superior in terms of visual quality, entropy, SSIM, MSE, PSNR, FSIM, naturalness and adaptiveness over other existing methods.

4 Conclusions

In this paper, a novel mean and exposure based sub-image histogram equalization method is proposed in which, an optimization technique named as DSO algorithm has been implemented for harvesting more and more information contents in low light grayscale images. To prevent the over enhancement, clipping technique is implemented along with HE. The method of sub-division of histogram takes the major role in preserving the natural appearance of the image. The Optimization technique, DSO is used in this paper for finding the optimal constraint parameters for improving the information content of enhanced image. As searching of these parameters is carried out without human intervention, so proposed method is more adaptive. This method takes less execution time as compared to PSO and more time as compared to other discussed method. But it generates best optimal results over other techniques. The visual quality of the enhanced images shows the robustness of the proposed method. The supremacy of the proposed method is also proved by taking the performance parameters like entropy, SSIM, FSIM, PSNR, and MSE. From the simulation results, it has been observed that Directed Searching Optimized Mean-Exposure based sub-image histogram equalization technique performs better as compared to most of the state-of-the-art techniques.

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