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Artificial Bee Colony Optimized Multi-Histogram Equalization for Contrast Enhancement and Brightness Preservation of Color Images

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Abstract: This study proposes an optimized Multi-Histogram Equalization (OMHE) technique for contrast enhancement while preserving the brightness of an input image. The objective of this study is to improve the visual interpretability or perception of information among color images. In this technique, input image histogram is partitioned into multiple sub-histograms and then classical histogram equalization process is applied to each one. Values of t threshold points for dividing the image histogram into t+1 sub-histograms are optimized using Artificial Bee Colony, a swarm intelligence-based optimization algorithm. A new fitness function for evaluating the contrast of enhanced image is proposed here that will guide the Artificial Bee Colony algorithm into finding the optimal threshold values. AMBE (Absolute Mean Brightness Error), PSNR (Peak signal to noise ratio), SSIM (Structural Similarity Index) and Entropy are computed for quantitative analysis of the performance of the proposed method with existing methods. Comparisons show that proposed method performs better than other present approaches by enhancing the contrast well while preserving the brightness of the input image.

Index Terms: Contrast enhancement; multi-histogram equalization; artificial bee colony optimization

1. Introduction

Contrast enhancement and brightness preservation are the basic preprocessing steps applied on experimented images by almost all the algorithms in the realm of digital image processing. The basic objective behind the application of contrast enhancement techniques is to improve the visual interpretability or perception of information among images. Most contrast enhancement techniques used Histogram modification as the key strategy. Global Histogram Equalization (HE) is the simple and widely used technique for enhancing image contrast [1]. This method uses the cumulative density function (CDF) of the Image's histogram as the intensity remapping function to achieve uniform distribution among pixel intensities. It works well in the field of medical and radar image processing as well as texture analysis. Mean shifting problem of this method make it less commonly used in the field of consumer electronics. This method shifts the mean brightness of the histogram equalized image from the actual mean to the middle gray level of the input image. It may lead to annoying artifacts and excessive brightness change in the output image which is not desirable for consumer electronic products. To overcome the limitations of GHE, many researchers have proposed many useful variants of it. Most of these techniques can be broadly classified into two groups namely Bi-Histogram Equalization and Multi-Histogram Equalization [2]. The objective of this study is to develop a multi-HE based contrast enhancement method for color images that produces better contrast enhanced images while preserving their brightness level. Most of the existing Multi-Histogram Equalization based methods are suffered from the limitation of deciding threshold levels for dividing the image Histogram into multiple sub-histograms. Various criteria like mean, median, local maxima/minima, kapur's entropy, otsu's method, interclass and intra class variance have been used by different researchers to segment the image histogram into multiple sub-histograms. Some researchers used local maxima/minima as threshold levels. The proposed study used a population based metaheuristic to optimize these threshold levels.

2. Related Works

Brightness preserving Bi-Histogram Equalization (BBHE) [3] technique divides the input histogram into two sub-histograms based on the mean brightness of the image and independently equalizes these sub-histograms. It has been clearly proved that this method preserves the mean brightness while reducing unnatural enhancement as well as unwanted artifacts in contrast to the GHE. The equal area Dualistic Sub-Image Histogram Equalization (DSIHE) [4], an extension of BBHE, separates the histogram based on median instead of mean. This method works well in case of images having non-uniform intensity distribution. MMBEBHE [5] is another extension of BBHE which separate the histogram of input image into two sub-histograms using a threshold level that provides maximal brightness preservation by yielding minimum Absolute Mean Brightness Error (AMBE). Though these methods can perform good contrast enhancement, they also cause more annoying side effects depending on the variation of gray level distribution in the histogram. Range Limited Bi-histogram Equalization (RLBHE) [6] is another bi-histogram equalization based technique which used the Otsu's method to automatically find a histogram shape based threshold for dividing the input histogram into two independent sub-histograms that minimized the intra-class variance. This method assumes that image contains two classes of pixels i.e. foreground and background. An optimum threshold is calculated to minimize the intra-class variance between these two classes of pixels. Output images produced by this technique achieves more visually pleasing contrast enhancement and maintains the input mean brightness.

Multi-HE (Multi-Histogram Equalization) decomposes the image histogram into large number of sub-histograms and then equalize each sub-histogram individually by applying classical HE processes. Multi-HE based methods are supposed to preserve the natural appearance and mean brightness in the enhanced image as each sub-histogram yields lesser shift in brightness when equalized independently [2]. Recursive Mean-Separate Histogram Equalization (RMSHE) [7] and Recursive Sub-image Histogram Equalization (RSIHE) [8] are Multi-HE based methods. RMSHE and RSIHE methods are the recursive variants of BBHE and DSIHE respectively, which recursively divides the input histogram to generate multiple sub-histograms based on the mean and median intensity values respectively. The objective of higher brightness preservation is well achieved by these methods as compared to Bi-HE and other conventional HE methods. The common disadvantage of RMSHE and RSIHE is the difficulty of defining the optimal limit of recursion. Minimum Within-Class Variance MHE (MWCVMHE) and Minimum Middle Level Squared Error MHE (MMLSEMHE) are proposed in [9]. The optimal number of sub-images is automatically decided using a cost function. Results of this method show that it produces more natural looking images with more brightness preservation as compared to other HE methods. DHE (Dynamic Histogram Equalization) [10] is a smart local contrast enhancement technique which partitions the image histogram into sub-histograms based on local minima and assigns specific gray level ranges for each partition. To ensure that there is no dominating portion in the sub-histograms, each partition is further gone through a repartitioning test. This simple and computationally effective method achieved the better overall contrast enhancement without making any loss in image details. MPHEBP [11] is the method which partitions the image histogram into multiple sub-histograms based on each detected peak in the original histogram

RSWHE (Recursively separated and weighted Histogram Equalization) is another multi-histogram equalization based method for brightness preservation and image contrast enhancement proposed in [12]. RSWHE is based on the idea of recursively segmenting the input image histogram into two or more sub-histograms. These sub-histograms are modified by applying a weighting process. Histogram Equalization is then independently performed on these weighted sub-histograms. Researchers shows that RSWHE produces images with better contrast enhancement and preserve brightness more accurately as compared to other similar recursive methods such as RSIHE and RMSHE.

BPDHE (Brightness Preserving Dynamic Histogram Equalization) [13] is an extension method of MPHEBP [11] and DHE [10]. In this method, image histogram is first preprocessed for covering the disappeared brightness levels and its smoothness before partitioning it using local maxima as proposed in MPHEBP. Like DHE, this method assigns new dynamic range to each partition before equalizing these partitions separately. Finally, normalization of output intensity is achieved so that the average intensity of input and output images remains almost same. In another study [14], authors present an overview of different possibilities for using BPDHE method for contrast enhancement of color images.

BPDFHE (Brightness Preserving Dynamic Fuzzy Histogram Equalization) [15] is a modified version of BPDHE [13]. In this modified technique, researchers use fuzzy statistics for representation and processing of digital images for contrast enhancement. In order to handle inexactness of grey values in a better way, a Fuzzy Histogram is computed using the triangular fuzzy membership function. That fuzzy histogram is then partitioned into multiple sub-histograms using local maxima. Every partition formed between two consecutive local maxima is then equalized dynamically. For better preservation of mean brightness, peaks of the image histogram didn't get remapped.

3. Histogram Equalization

In Transformation Function *f(k)* for Global Histogram Equalization of a given digital image X, $x(i,j)$ represents intensity level of the pixel at (i,j) location. The total number of image pixels is N and the image intensity is digitized into L levels that are $\{x_0, x_1, x_2, \dots, x_{L-1}\}$. The histogram h_k for intensity k, is defined as:

$$h(k) = n_k,\ for\ k = 0,1,2...,L-1 \tag{1}$$

where n_k is the number of occurrences of intensity k in the image. The probability density function, $pdf(k)$ is defined as:

$$pdf(k) = \frac{h(k)}{N},\ \ for\ k = 0,1,2...,L-1 \tag{2}$$

The cumulative density function, cdf(k) is defined as:

$$cdf(k) = \sum_{l=0}^{k} pdf(l),\ \ for\ k = 0,1,2...,L-1 \tag{3}$$

The transformation function *f(k)* based on cumulative density function for histogram equalization is defined as:

$$f(k) = x_0 + (x_{L-1} - x_0).cdf(k) \tag{4}$$

Then, the output image, Y, after applying the transformation function can be expressed as:

$$Y = \{y(i,j)\} = \{f(x(i,j) \mid \forall x(i,j) \in X\} \tag{5}$$

where (i,j) are spatial coordinates of the pixel in the image.

In Multi-Histogram Equalization (MHE), histogram of an image is partitioned into several segments called sub-histograms and then applying histogram equalization individually on each sub-histogram. Local contrast stretching and local adaptability can be achieved by using MHE. Moreover, it reduces the level of compression caused by high frequency histogram segments in global HE [16]. To partition the histogram of an image into $t+1$ segments, a set of t thresholds is determined. This can be defined as:

$$TH = \{th_1, th_2, ..., th_t\} \tag{6}$$

By using these thresholds, input image $X[x^{low}, x^{high}]$ is decomposed into $t+1$ sub-images as $\{X_1[x^{low}, th_1],\ X_2[th_1+1, th_2], \dots, X_{t+1}[th_t+1, x^{high}]\}$.

After partitioning, the input image can be defined as:

$$X[x^{low}, x^{high}] = \bigcup_{i=1}^{t+1} X_i[x_i^{low}, x_i^{high}] \tag{7}$$

where, X_i represents i^{th} sub-image of X. x_i^{low}, x_i^{high} represents the lower and uppermost boundaries of i^{th} out of $t+1$ sub-images respectively. It should be noted that lower boundary of first sub-image i.e. x_1^{low} is equal to x^{low} and uppermost boundary of last sub-image i.e. x_{t+1}^{high} is equal to x^{high}. In literature, application of histogram equalization (HE) after segmented an image into two sub-images (number of thresholds i.e. t = 1) and more than two sub-images (number of thresholds i.e. t > 1) are referred to as Bi-Histogram Equalization and Multi-Histogram Equalization respectively.

The method for equalizing the histogram of each sub-image is similar as used in global histogram equalization. For each sub-image X_i, with the range of $[x_i^{low}, x_i^{high}]$, the transformation function *f(k)* is defined as:

$$f_i(k) = x_i^{low} + (x_i^{high} - x_i^{low}).\sum_{j=x_i^{low}}^{k} \frac{h(j)}{M_i} \qquad for\ i = 1...t+1\ and\ \ k = x_i^{low}, ... x_i^{high} \tag{8}$$

where $f_i(k)$ represents the new intensity level corresponding to the k^{th} intensity level in the original image, $h(j)$ is the number of pixels with intensity j, and M_i is the total pixels contained in the sub-image X_i.

4. Artificial Bee Colony (ABC) Algorithm

During literature study, it has been found that swarm intelligence based algorithms can be successfully applied in solving wide variety of problems [14,15]. These algorithms can also be applied for finding the optimal thresholds for partitioning an image histogram into multiple sub-histograms. In this study, we used Artificial Bee Colony (ABC), a swarm intelligence based global optimization algorithm for finding the optimal multilevel thresholds.

ABC is a stochastic algorithm developed by Karaboga in 2005. The motivation behind ABC algorithm is the smart foraging behavior of natural honeybees. This algorithm follows a population-based search procedure, in which possible food sources (solutions) are discovered and evaluated iteratively by the artificial bees with the aim to discover the optimal food sources[19]. In this algorithm, three kinds of honeybees (the employed bees, the onlookers and the scouts) worked collectively in search of food sources which corresponds to the possible solutions. Each bee selects a food source and try to exploit the neighborhood of it in search of better food source (solution). Classification of bees in three categories are based on how they select the possible solution to exploit. The employed bee considers various food sources around the food sources in her memory and update her memory if found a better solution. The employed bees share the information about the newly found food sources with the onlooker bees. The onlooker bees evaluate the food sources and select better quality food sources among those found by the employed bees. The scout bees would search for new possible food sources randomly after some food sources are rejected due to low quality[20,21]. The primary phases of ABC algorithm is briefly described as:

Initialization: In ABC algorithm, each possible food source position for the bee colony corresponds to a solution vector x_i with n values, $x_{ij}, j = 1 \dots n$. The problem in question is to search an optimal vector x which maximize/minimize the objective fitness function. Population of m solution vectors is initialized, and the fitness of each solution is quantized. Initialization of population is done randomly within the search space using the following equation:

$$x_{ij} = l_j + rand(0,1) \times (u_j - l_j) \tag{9}$$

where, u_j and l_j are upper and lower bounds of jth parameter in solution vector x.
Iteratively perform the following steps until the maximum number of iterations is reached or the stop condition is satisfied.

Employed bee stage: Each employed bee tries to find a better new solution y_i by moving randomly in the neighbor of its current solution x_i. If the new solution selected by the employed bee has the better fitness value than that of its currently associated solution, then employed bee will replace the old solution with this new solution otherwise it keeps its old solution. Equation for selecting/generating new solution is given below:

$$y_{ij} = x_{ij} + rand(-1,1) \times (x_{ij} - x_{kj}) \tag{10}$$

where k is the randomly chosen index.

Onlooker bee stage: After all employed bees have completed their search for better solution, they share this information about possible solutions with onlookers. Each onlooker bee probabilistically selects a solution according to its fitness value using the roulette wheel selection method. The fitness-based probability Pr_i for each solution is assigned using the following equation.

$$\mathrm{Pr}_i = \frac{fitness_i}{\sum_{k=1}^{n} fitness_k} \tag{11}$$

where $fitness_i$ is the fitness of solution i and n is the total number of solutions. After selecting a solution, onlooker bee tries to find a better new solution corresponding to the selected solution just like employed bee using equation (10). A greedy selection is used to keep among the probabilistic solution and the new solution.

Scout bee stage: A solution will be abandoned if its fitness value has not been improved for a given number of generations. Then a new solution is re-generated using the initialization method. The solutions are updated using the greedy criteria, and the best solution and its corresponding fitness value are recorded.

The implementation of ABC algorithm is relatively simple and straightforward to solve optimization problems. In various studies, ABC algorithm has been proved its effectiveness at low computational cost. Many researchers in their studies [22,23,24] have evaluated and compared the performance of the ABC algorithm with other well-known evolutionary algorithms like GA, PSO, ACO & DE to show the effectiveness of ABC algorithm.

5. Methodology

As mentioned above, the proposed work uses an ABC approach for optimizing the thresholds levels for multi-histogram equalization. A set of threshold levels is substituted by a new set in the search of a solution that produce a better contrast enhanced image after applying multi-histogram equalization. The new set of threshold levels is optimized using ABC algorithm. While applying optimization algorithm in the field of image contrast enhancement, there is a need of: (i) a transformation function that will produce new pixel intensities for the enhanced image from the old pixel intensities of the original image; and (ii) design of an objective fitness function by which quality of the enhanced image is measured [21]. Design of these two important functions highly influenced the quality of the output image.

In our proposed technique, the transformation function is described in equation (8). This transformation function is applied to each sub-histogram achieved after segmentation of the original histogram using t thresholds levels. The ABC algorithm is used in the proposed technique to optimize the t threshold levels for partitioning the original histogram into t+1 sub-histograms. In the search of optimal solutions, there is a need to evaluate the quality of solutions developed by our ABC algorithm. The objective fitness function is used to guide the artificial bees moving in search for optimal solutions.

We used a fitness function based on the number of edge pixels, their intensity values, Entropy, PSNR and Contrast of the whole image. With the application of these measures, Objective Fitness Function (OFF) is defined in two parts:

$$OFF1 = (\log(\log(E(I_s)))\frac{n(edges(I_s))}{m.n}.H(I_e).PSNR(I_e) \tag{12}$$

$$OFF2 = 10\log_{10} C_{contrast}(I_e) \tag{13}$$

$$OFF = 0.75 \times OFF1 + 0.25 \times OFF2 \tag{14}$$

In the above formula, I_e is the enhanced image, $E(I_s)$ is the sum of edge intensities of the Sobel edge image [1] obtained after applying the Sobel filter on the enhanced image I_e, $n\big(edges(I_s)\big)$ is the number of the edges in the Sobel edge image, $H(I_e)$ is the entropy and $PSNR(I_e)$ is the peak signal to noise ratio of the enhanced image. m and n are the dimensions in terms of horizontal and vertical pixels of the image respectively. $C_{contrast}$ [25] is used here to evaluate the contrast improvement. Its formula is:

$$C_{contrast} = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} I_e^{\,2}(m,n) - \left|\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N} I_e(m,n)\right| \tag{15}$$

where M and N represents the width and height of the image, $I_e(m,n)$ is the intensity value at (m,n) location in the enhanced image I_e. $C_{contrast}$ represents the deviation of intensity levels. Its higher value implies more informative image having good contrast because of larger dynamic range of intensity levels. The proposed methodology helps in finding the optimal thresholds for segmenting the input histogram into multiple sub-histograms by which more local details can be preserved after applying histogram equalization to these sub-histograms.

In this paper, we have performed color image enhancement using Optimized Multi-Histogram Equalization. First, input image in RGB color space is converted into HSV color space. Enhancement is done on the V Channel of the HSV image using Multi-Histogram Equalization (MHE). The threshold levels used for partitioning the image histogram are optimized using Artificial Bee Colony (ABC) algorithm. The number of threshold levels used here are equal to the number of peaks found in input image histogram but maximum upto 5, as a greater number of thresholds decreases the level of contrast enhancement. The number of artificial bees used in ABC optimizer is set to be 30 and the number of maximum iterations is set to be 50. The proposed method is implemented using Matlab programming language on a PC with Intel Core^{TM} i3 CPU 2.3 GHz and 4 GB RAM.

6. Experimental Results and Discussion

It is very difficult to determine the quality of the output image produced after applying any contrast enhancement technique. We use both qualitative and quantitative measures to compare the results of the proposed approach with some conventional as well as soft computing based contrast enhancement techniques.

To do the comparative evaluation of the effectiveness and robustness of proposed method, we selected 20 color images with diverse features from Kodak Lossless True Color Image Suite. With the expectations to achieve better contrast enhancement and preservation of mean brightness, we compared the results of the proposed method with some traditional contrast enhancement techniques (BBHE[3], DSIHE[4], MMBBHE[5], RMSHE[7], DHE[13]) as well as with some state-of-the-art metaheuristic based enhancement techniques (Artificial Bee Colony Algorithm[20], Particle

Swarm Optimization[26], Genetic Algorithm[27]). The performance of all these methods is measured qualitatively in terms of human visual perception and quantitatively using AMBE, PSNR, Entropy and SSIM. For visual analysis of the results, output images and their histogram plots produced by applying proposed and existing contrast enhancement techniques for six sample images are shown in Fig. 1 to 12. Brief explanation about image quality measures used for quantitatively evaluate the results is also given here.

A. Absolute Mean Brightness Error (AMBE)

It is defined as the absolute difference between the mean intensity values of input and output images

$$AMBE = |m_i - m_o| \tag{16}$$

where m_i and m_o are the mean intensities of the input and output images as defined in the following equation

$$m = \frac{\sum_{k=0}^{L-1} i_k \times n_k}{N} \tag{17}$$

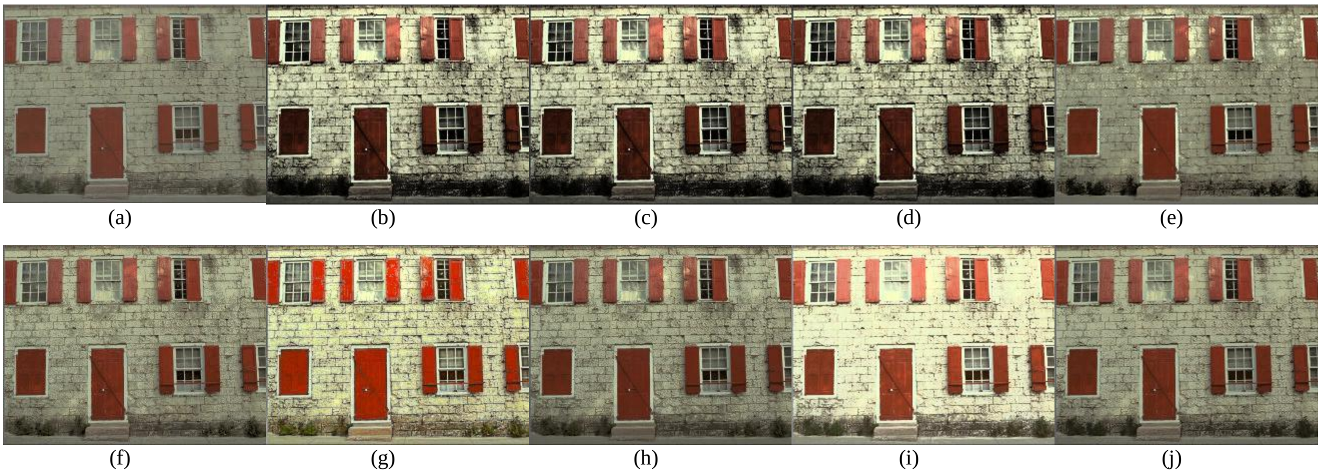


Fig. 1. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

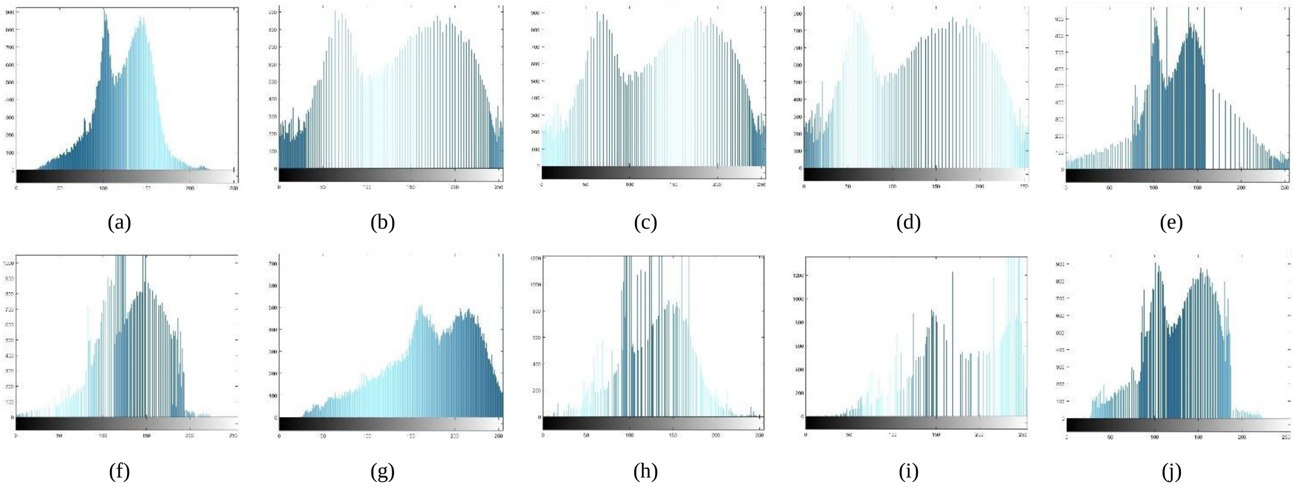


Fig. 2. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

where i_k is the kth intensity value and n_k is the number of pixels at that intensity value. L is the maximum intensity value and N is the total number of pixels in the image. Smaller value of AMBE represents that there is small difference between the average intensity of the input and the average intensity of the output image. So, the method which gives small value of AMBE is preserve the mean brightness of the image[16].

B. Mean Square Error (MSE)

MSE is the average of squared differences of input and enhanced image intensities. It measures the pixel differences

$$MSE(X,Y) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}(X(m,n)-Y(m,n))^2 \tag{18}$$

where X and Y are the input and enhanced image respectively. M and N are the numbers of rows and columns of the images. Therefore, the minimum MSE means better image enhancement.

C. Peak Signal-to-Noise Ratio (PSNR)

PSNR is a very popular metric for evaluating the performance of contrast enhancement techniques. It is a ratio between the maximum possible power of the signal and the power of noise. It is distortion metric which crucially depends on Mean-Squared Error (MSE). PSNR is defined as

$$PSNR(X,Y) = 10\log_{10}\frac{(L-1)^2}{MSE(X,Y)} \tag{19}$$

L is number of possible discrete grey levels in the images. The maximum PSNR represents better quality of the enhanced image.

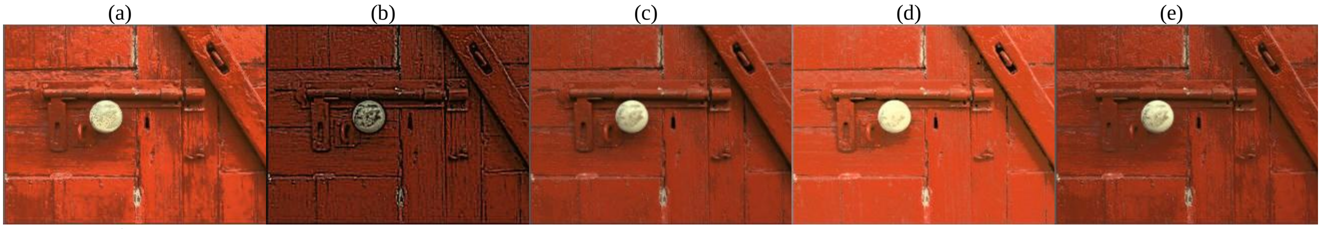
D. Structural Similarity Index (SSIM)

The structural similarity index is a method for measuring the visual similarity between two images. It evaluates the luminance, contrast and correlation factors of the image [28]. Higher value of SSIM indicates the greater similarity between the images. It is computed as

$$SSIM = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY} + C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)} \tag{20}$$

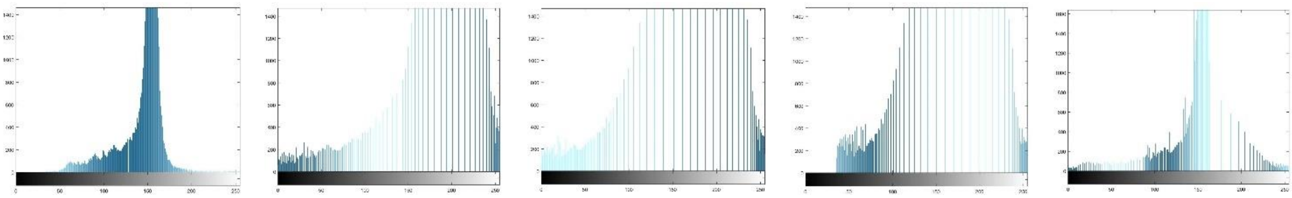
Here $\mu_X, \mu_Y, \sigma_X^2, \sigma_Y^2$ are mean and variance of image X and Y respectively. σ_{XY} is covariance of X and Y.

(a) (b) (c) (d) (e)



(f) (g) (h) (i) (j)

Fig. 3. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach



(a) (b) (c) (d) (e)

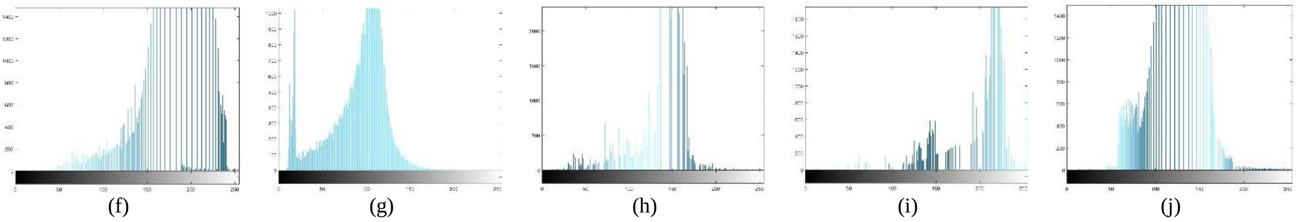


Fig. 4. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

E. Entropy

Entropy is a tool used to measure the richness of information content in an image. It is defined as:

$$H = -\sum_{i=0}^{N-1} p(i)\log_2 p(i) \tag{21}$$

where $p(i)$ denotes the probability of intensity i and N is the number of intensity levels in the considered image. Higher value of entropy means, more information content is preserved in the output image. If the entropy of the enhanced image is very close to the original image then we can say that the enhancement method has the capability to preserve the information content of the image [29]

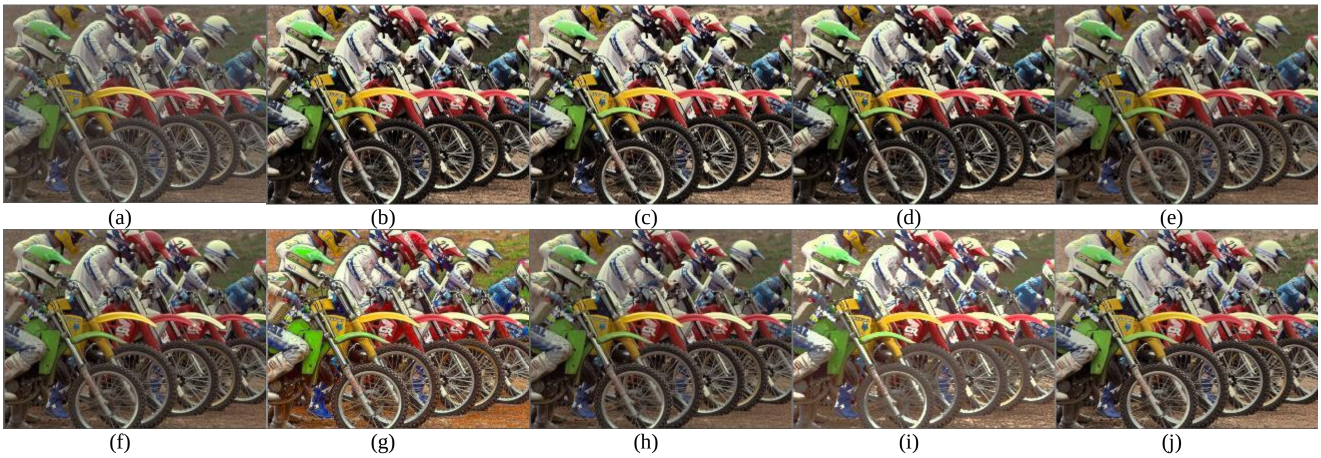


Fig. 5. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

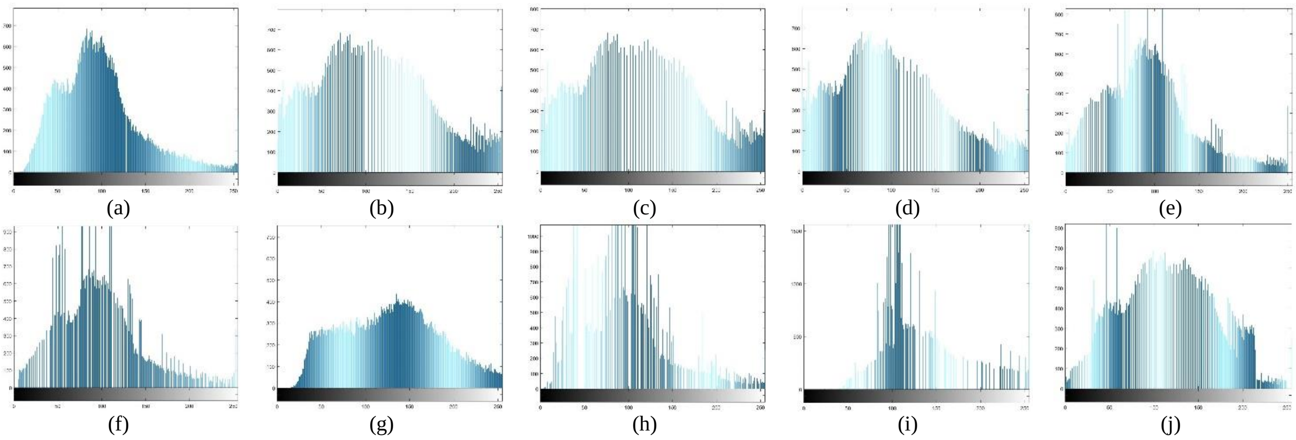


Fig. 6. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

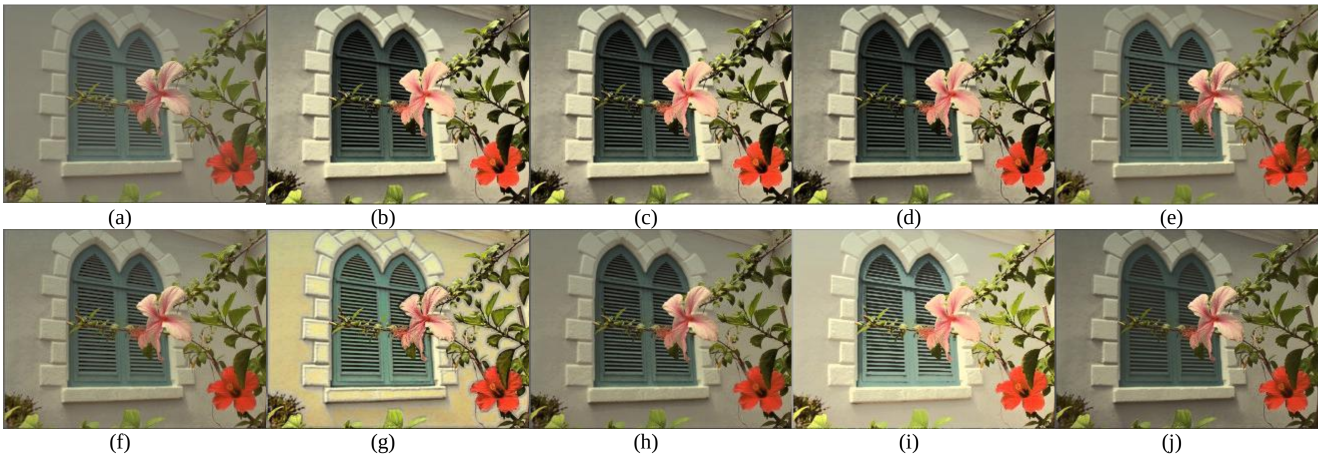


Fig. 7. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

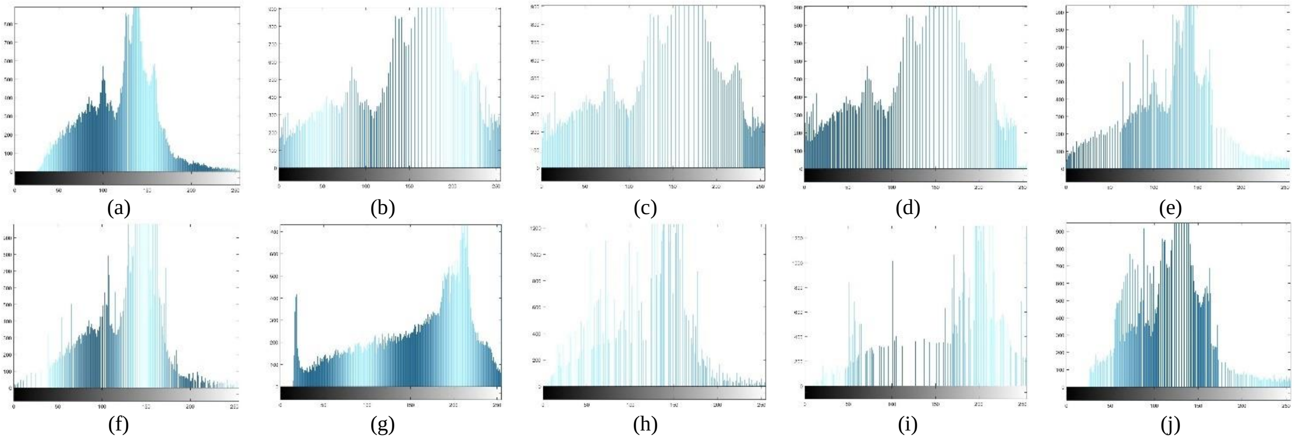


Fig. 8. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

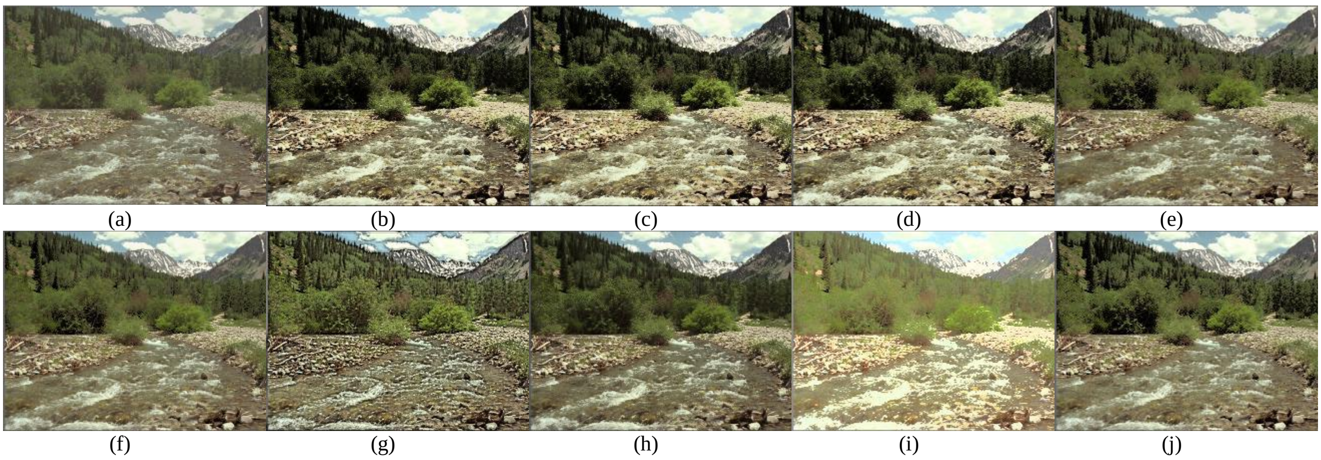
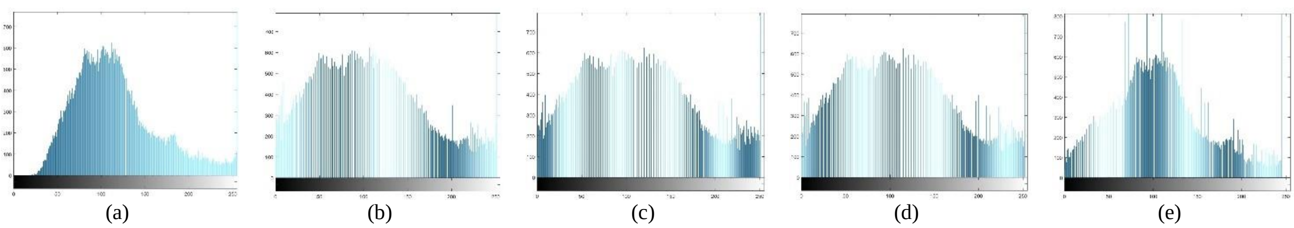


Fig. 9. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach



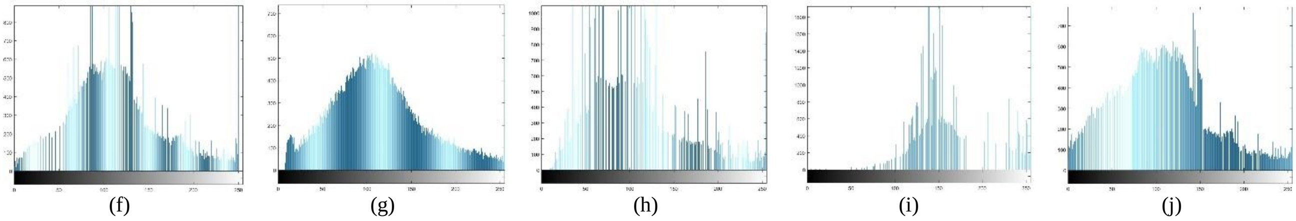


Fig. 10. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

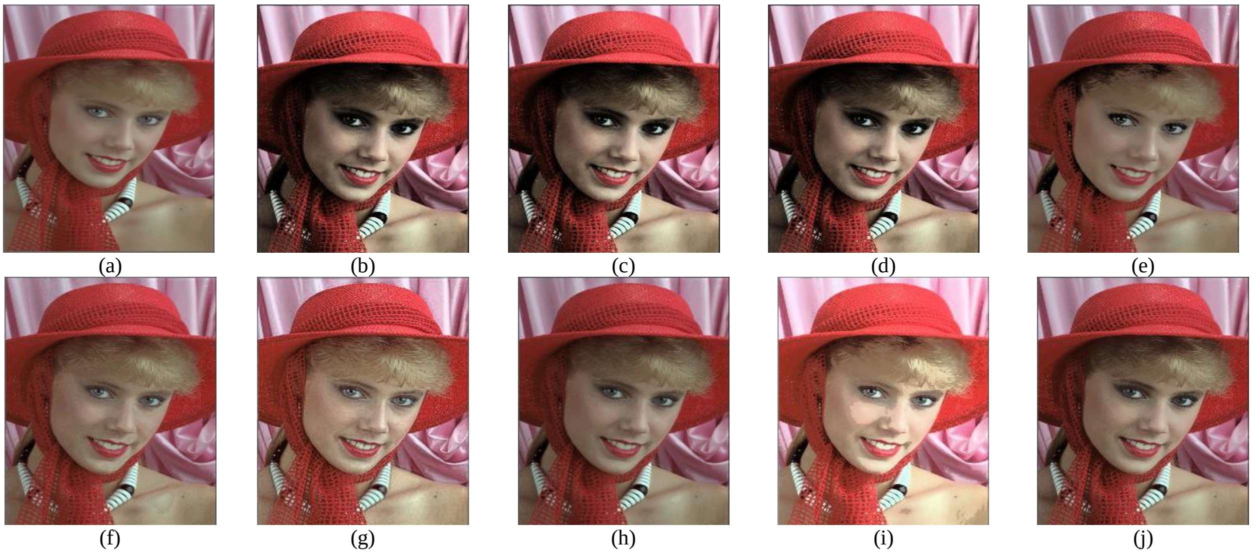


Fig. 11. (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

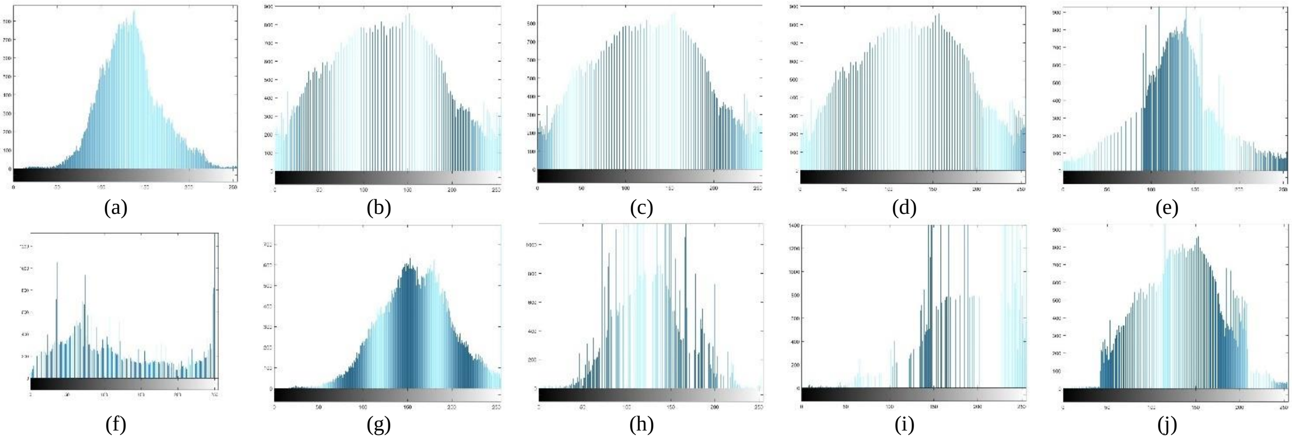


Fig. 12. Histogram image of (a) Original Image (b) BBHE (c) DSIHE (d) MMBBHE (e) RMSHE (f) DHE (g) PSO (h) GA (i) ABC (j) Proposed Approach

Output images shows that the proposed technique is robust for contrast enhancement of color images as compared to other conventional techniques as well as some state-of the-art metaheuristic techniques. In the figures numbered 1, 3 and 5, it is clearly visible that methods (b), (c) and (d) produced over-enhanced images. Method (e) produced well contrast enhanced images but some of these are not natural looking. Output images produced by method (g) looks having inappropriate colors. The resulted images produced by methods (f) and (h) are good looking but not well enhanced in all the cases. Most of the resulted images produced by method (i) are overexposed. This method fails to preserve the mean brightness of input images. By inspecting all the results visually, it can be noticed that the proposed technique produced good results for almost all tested images. It also preserves the details of the input images and suppress over enhancement.

Table 1. Comparison of AMBE values computed for enhanced images by different methods and proposed approach

Te3st Images	AMBE								
	BBHE	DSIHE	MMBBHE	RMSHE	DHE	PSO	GA	ABC	Proposed Approach
1	7.1653	5.3508	**0.6877**	2.4883	26.8787	49.1756	1.5050	71.0442	6.0643
2	20.3462	1.3370	4.2023	1.9919	47.2814	53.8975	4.9676	58.3056	**0.6555**
3	3.8719	2.0839	1.7222	1.2384	1.1324	47.3326	15.1608	1.8955	**0.1432**
4	17.2633	10.5228	3.6070	0.9349	32.8091	42.5360	8.5028	59.2225	**0.3230**
5	7.8455	13.1321	0.3953	**0.0632**	1.5899	36.4035	3.3187	40.7789	5.5078
6	18.5536	14.1462	0.5841	3.6417	0.7036	15.2509	6.8113	23.9731	**0.5301**
7	14.3216	8.9293	1.8487	**0.7181**	9.6255	38.2545	3.0206	54.5937	11.2985
8	11.2725	10.2093	0.3093	1.5022	3.7980	15.0755	8.8109	9.1188	**0.1053**
9	30.6540	6.8906	4.8724	0.8416	0.2236	11.4203	**0.0335**	2.3118	2.1042
10	10.6658	10.4114	1.6737	0.7610	2.8660	23.3900	6.2967	62.4729	**0.6311**
11	25.3177	20.0333	2.4059	1.3082	7.9915	37.9853	12.1357	33.1453	**0.0744**
12	12.2175	17.5283	1.8107	2.0923	7.9765	8.8010	14.3247	13.9527	**1.3735**
13	5.5060	1.4211	0.4690	1.8243	13.1115	1.3997	8.9254	53.7677	**0.3726**
14	3.7511	6.3012	**0.3004**	0.7181	11.6280	26.6062	5.2243	36.0602	2.1191
15	11.7137	14.2982	0.2617	1.0324	0.4016	10.3357	2.1753	18.6796	**0.0755**
16	4.5124	2.3804	1.0993	**0.3363**	2.7562	27.2756	5.3511	59.1117	9.4799
17	2.0223	3.6173	2.4263	0.2721	3.8976	14.1589	8.8083	57.7668	**0.1363**
18	5.2592	0.6498	2.6698	0.4530	1.2452	8.1939	2.7382	50.2032	**0.4453**
19	19.0640	20.8040	4.7252	2.6062	6.3958	37.3881	5.3848	46.3261	**0.6906**
20	13.9092	3.1921	1.4708	1.6776	3.6391	20.3255	5.1448	0.5017	**0.4293**

Table 2. Comparison of PSNR values computed for enhanced images by different methods and proposed approach

Test Images	PSNR								
	BBHE	DSIHE	MMBBHE	RMSHE	DHE	PSO	GA	ABC	Proposed Approach
1	15.9641	16.0619	16.1380	25.9235	16.0508	14.6956	27.4851	11.3269	**28.8463**
2	17.8432	17.2304	18.7818	28.8661	16.7587	16.6061	32.7712	16.5554	**37.7312**
3	19.2170	18.9633	19.9929	31.8812	35.0477	14.0977	24.8845	26.1347	**39.0723**
4	17.1944	17.1992	17.7196	**32.8831**	15.4420	14.7745	26.9077	12.8257	23.4336
5	19.2569	18.4331	20.9243	**35.6834**	33.9194	17.6872	34.3218	16.0869	27.6974
6	20.4820	20.9035	21.8338	28.0328	29.4827	20.9044	29.4119	19.9683	**29.4927**
7	17.0442	17.3160	18.3439	30.9253	27.7100	15.7442	29.8455	13.4179	**31.0185**
8	22.5853	22.6617	23.1706	32.8072	33.2718	21.1605	28.4746	28.2609	**42.6148**
9	15.2340	22.8238	20.5602	36.1028	0.2236	16.4370	36.1147	**36.6162**	34.5820
10	17.4679	17.5491	20.6918	31.0329	**33.8006**	16.6051	29.2478	12.4422	31.0447
11	16.0735	16.5229	20.7686	32.2137	27.4446	16.2745	27.4086	17.1888	**32.2686**
12	17.6138	16.8894	23.4926	29.6272	27.2805	17.8226	24.6998	24.3414	**29.9015**
13	20.4109	19.8100	19.9437	31.5067	24.4427	21.0284	28.0784	14.1134	**41.6261**
14	22.9377	22.4726	23.8312	36.0404	26.1309	18.2353	30.1218	16.6377	**36.8576**
15	23.4163	22.9607	24.5190	37.1430	35.3592	24.9003	34.4605	22.4297	**40.5194**
16	17.7963	17.8506	17.7933	29.7926	**34.8085**	20.3294	31.9646	13.9956	23.6869
17	16.3427	16.3513	17.9523	27.2294	**29.2212**	17.4037	27.8182	12.8373	15.6392
18	16.7145	16.7561	16.9558	31.9129	**33.3225**	22.9361	29.4938	14.2782	27.8975
19	17.9115	17.6150	25.2781	27.8122	24.6780	16.3887	33.8302	14.4448	**36.2535**
20	19.4811	19.2988	19.1742	30.9175	31.1638	15.8649	29.6040	**37.9143**	32.2727

Table 3. Comparison of ENTROPY values computed for enhanced images by different methods and proposed approach

Test Images	ENTROPY									
	Original Image	BBHE	DSIHE	MMBBHE	RMSHE	DHE	PSO	GA	ABC	Proposed Approach
1	7.2026	7.8200	7.8103	7.7871	7.4049	7.5873	7.7040	7.3351	7.4662	7.3399
2	6.7571	7.0416	6.9437	6.8985	6.7548	6.9072	6.6029	6.4483	6.8984	6.7336
3	7.4653	7.7179	7.7540	7.7297	7.4856	7.4703	7.7714	7.3337	7.5134	7.8215
4	7.2057	7.7459	7.7429	7.7118	7.2592	7.5110	7.8800	7.1812	7.4800	7.4551
5	7.4254	7.7235	7.7647	7.6376	7.4831	7.4960	7.7987	7.4089	7.3318	7.5140
6	7.5322	7.7264	7.7303	7.7416	7.6226	7.5112	7.6576	7.5320	7.3843	7.7715
7	7.2816	7.8455	7.8293	7.7626	7.3565	6.2969	7.8255	7.2957	7.4242	7.5904
8	7.7037	7.8931	7.8973	7.9052	7.7402	7.7013	7.6884	7.7102	7.6337	7.9159
9	6.2761	5.9560	6.2442	6.1356	6.2441	0.2236	6.0556	6.1792	6.1256	6.2670
10	7.3012	7.8566	7.8531	7.7411	7.4497	7.3444	7.7708	7.2968	7.2115	7.4457
11	7.1336	7.7378	7.7157	7.5255	7.1878	7.3501	7.7105	6.9727	7.5076	7.8081
12	7.3261	7.7042	7.7252	7.5708	7.3400	7.4152	7.5804	7.3315	7.2193	7.7314
13	7.5572	7.8125	7.8550	7.8478	7.6349	6.6659	7.6946	7.5449	7.2561	7.5747
14	7.5520	7.7862	7.8018	7.7581	7.6314	6.5427	7.7998	7.5171	7.6861	7.5896
15	7.5891	7.5164	7.4836	7.5760	7.5354	7.5037	7.4356	7.5273	7.5596	7.6298
16	7.4795	7.7559	7.7618	7.7728	7.5612	7.5070	7.7321	7.4053	7.6721	7.8852
17	7.1376	7.8602	7.8514	7.7890	7.2919	7.2745	7.6304	7.1983	6.8984	7.6577
18	7.1871	7.8513	7.8553	7.8477	7.2725	7.2657	7.2382	7.3243	7.2359	7.3678
19	7.3821	7.7566	7.7699	7.5808	7.5448	7.5721	7.8491	7.2284	7.5108	7.4579
20	7.5019	7.8020	7.8230	7.8277	7.5759	7.5338	7.7903	7.3507	7.4460	7.5693

Table 4. Comparison of SSIM values computed for enhanced images by different methods and proposed approach

Test Images	SSIM								
	BBHE	DSIHE	MMBBHE	RMSHE	DHE	PSO	GA	ABC	Proposed Approach
1	0.7131	0.7108	0.6956	0.9527	0.8039	0.7528	0.9740	0.7725	0.9795
2	0.8501	0.7897	0.8736	0.9831	0.8992	0.7720	0.9910	0.8888	0.9977
3	0.8031	0.8101	0.8324	0.9707	0.9881	0.6272	0.9471	0.9439	0.9944
4	0.8231	0.8006	0.7959	0.9800	0.8240	0.6844	0.9681	0.8552	0.9389
5	0.8499	0.8395	0.8740	0.9884	0.9866	0.7982	0.9912	0.8344	0.9777
6	0.8640	0.8671	0.8887	0.9489	0.9889	0.8922	0.9846	0.9484	0.9916
7	0.8394	0.8298	0.8368	0.9816	0.9635	0.7435	0.9789	0.8268	0.9522
8	0.9040	0.9034	0.9076	0.9822	0.9899	0.9040	0.9818	0.9830	0.9979
9	0.9190	0.9463	0.9391	0.9879	0.2236	0.7254	0.9936	0.9961	0.9887
10	0.8262	0.8272	0.8672	0.9547	0.9859	0.5704	0.9588	0.7761	0.9649
11	0.7500	0.7332	0.7906	0.9767	0.9586	0.7396	0.9495	0.8972	0.8459
12	0.8004	0.7794	0.9352	0.9720	0.9753	0.8364	0.9678	0.9580	0.9796
13	0.8405	0.8397	0.8393	0.9711	0.8998	0.8450	0.9746	0.7989	0.9983
14	0.9071	0.9066	0.9125	0.9850	0.8867	0.7926	0.9703	0.8952	0.9957
15	0.9601	0.9577	0.9553	0.9840	0.9964	0.9232	0.9827	0.9307	0.9976
16	0.7886	0.7946	0.7963	0.9715	0.9933	0.9304	0.9871	0.8515	0.9678
17	0.7855	0.7838	0.8594	0.9562	0.9831	0.7940	0.9766	0.8432	0.7774
18	0.7601	0.7636	0.7803	0.9764	0.9791	0.8574	0.9762	0.8685	0.9506
19	0.8840	0.8810	0.9389	0.9527	0.9495	0.6926	0.9746	0.7798	0.9759
20	0.7959	0.7990	0.8007	0.9714	0.9781	0.7464	0.9794	0.9936	0.9843

Table 1-4 shows the comparison of results yielded by quantitative measures applied on the output images produced by different enhancement methods. Comparison of AMBE values in Table 1 shows that the proposed approach outperforms the other enhancement methods by producing minimum values in 14 out of 20 sample images. It proved that the proposed OMHE method succeeded in better preserving the mean brightness of input images as compared to other methods. Table 2 shows that the OMHE enhanced images have higher PSNR values as compared to other methods in 12 out of 20 experiments. This means that OMHE approach proves its superiority in achieving better contrast enhancement. Entropy values of enhanced images using different methods are shown in Table 3. Upon analyzing these values, it is clear that Entropy values computed for OMHE enhanced images are very close to the Entropy values of their respective input images. It proves that proposed method is capable to preserve the information content of input images. Higher SSIM values (Table 4) in 10 out of 20 enhanced images certified that OMHE enhanced images are much similar with input images.

Generally, a particular technique gives best result for a special kind of images only and may not be useful for other images. Robustness toward different kind of images provides an additional quality of the proposed approach. Experiments proved that proposed method remain successful in achieving its main aim to preserve the mean brightness and quality enhancement of low-contrast images.

7. Conclusion

In this work, we proposed and tested a hybrid method for contrast enhancement of color images called Optimized Multi-Histogram Equalization. Experiments showed that in most of the cases, our method generated more natural looking contrast enhanced images as compared to other traditional as well as some state-of-the-art metaheuristic methods while preserving the brightness and other details of input images. The proposed method produced maximum PSNR, SSIM and minimum AMBE values in most of the cases. This shows that the proposed fitness function works well in guiding the Artificial Bee Colony algorithm to find the optimal threshold values. This method can be useful for contrast enhancement of medical images, weakly illuminated images as well as remote sensing images for various applications. However due to use of optimization technique in finding the best solutions, time complexity is marginally increased. So, there is a scope of reducing the computational time complexity of the proposed method, other optimization techniques can be tried as a future scope of work.

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