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METHODOLOGIES AND APPLICATION

Cuckoo search algorithm-based brightness preserving histogram scheme for low-contrast image enhancement

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Abstract

This paper introduces a novel optimized brightness preserving histogram equalization approach to preserve the mean brightness and to improve the contrast of low-contrast image using cuckoo search algorithm. Traditional histogram equalization scheme induces extreme enhancement and brightness change ensuing abnormal appearance. The proposed method utilizes plateau limits to modify histogram of the image. In this method, histogram is divided into two sub-histograms on which histogram statistics are exploited to obtain the plateau limits. The sub-histograms are equalized and modified based on the calculated plateau limits obtained by cuckoo search optimization technique. To demonstrate the effectiveness of proposed method a comparison of the proposed method with different histogram processing techniques is presented. Proposed method outperforms other state-of-art methods in terms of the objective as well as subjective quality evaluation.

Keywords Cuckoo search algorithm · Histogram equalization · Low-contrast satellite images · Optimized Plateau limit and brightness preservation

1 Introduction

Image enhancement is an important domain of image processing field, in which the pictorial representation of the image is improvised for human perception and machine interpretation. Image contrast enhancement aims to improve the quality of the image by nullifying adverse effect of several factors such as noise, infused in the image during the image acquisition procedure. Contrast enhancement is one of the techniques under image enhancement domain which enhances the overall quality of an input image. Contrast enhancement is a renovation applied to the input image which can emphasize the information content present in the image of interest (Gonzalez et al. 2009). The contrast enhancement technique domain is very diverse but overall, we can classify them into two major categories: direct enhancement methods (Chen et al. 2018; Draa and Bouaziz 2014; Mahapatra et al. 2015) and indirect enhancement method (Bhandari et al. 2017; Celik, and Tjahjadi 2012; Arici et al. 2009). In the first category, the contrast of the image is quantitatively represented by some performance metric and algorithms are developed to improve these metrics for effective quality improvement of the image. In indirect enhancement methods, the contrast of the image is improved through the distribution of the probability distribution function of input image over the dynamic range of the image histogram.

Histogram processing techniques involve various techniques such as histogram equalization, histogram matching, histogram modification. Histogram equalization (HE) (Gonzalez et al. 2009) is used extensively in contrast enhancement process due to its simple and effective nature. It stretches the dynamic range of the image thereby improving overall contrast as per the mapping function obtained from probability distribution function (PDF) of the image.

However, for low-contrast images (with lower dynamic range) histogram equalization (HE) can degenerate the

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quality of the resultant image by introducing washed-out appearance due to excessive brightness change. To overcome this problem different versions of traditional histogram equalization (HE) techniques are proposed in the literature. Some suggests dividing the histogram into several regions based on different statistical parameters to preserve the mean brightness of the image, while others suggest limiting the histogram value in a region where the slope of the cumulative distribution function (CDF) is greater than that of a pre-defined threshold value.

Brightness preserving bi-histogram equalization (BBHE) (Kim 1997) was the pioneer in the field of preserving original input image brightness in the enhanced output image. BBHE technique first divides the original histogram into two sub-histograms depending upon the mean value of the image. Then, traditional HE is applied on these two sub-histograms independently, thereby preserving the mean brightness of the image. However, BBHE scheme suffers from the problem of intensity saturation effect.

Another method to solve the drawbacks of histogram equalization is known as Bi-histogram equalization with plateau limit (BHEPL) (Ooi et al. 2009). BHEPL approach divides the input histogram into two sub-histograms based on the mean of the original histogram. Then clipping process is applied on sub-histograms using a plateau limit followed by application of traditional HE method on individual histograms. Adaptively modified histogram equalization (AMHE) (Santhi and Banu 2015) modifies the magnitudes of the probability density function (PDF) of the input image prior to applying histogram equalization. The scaling factor to modify PDF is adaptively selected and adjusted according to mean (averaged image intensity values) of the input image.

Recently, in 2011, a simple histogram modification scheme (SHMS) (Chang and Chang 2010) is proposed to solve the patchiness effect and washed-out appearance in the image. The histogram is modified before applying HE method. The first nonzero bin is replaced with zero bins to overcome washed-out appearance and last nonzero bin is replaced by a minimum of two last nonzero bins to combat patchiness effect.

Some multiple sub-histogram division-based algorithms were also proposed, which divides the original histogram into 2^r sub-histograms, r being integer. Recursively separated and weighted histogram equalization (RSWHE) (Kim and Chung 2008) method repeatedly separates each sub-histogram until the desired 2^r sub-histograms are obtained. The division into sub-histograms is either based on the mean value or median value of input image. A weighting function is implied over each sub-histogram and thereafter the resulting histogram is equalized conventionally to obtain mapping function. However, higher value of r leads to insignificant enhancement.

The histogram modification using plateau-based clipping methods has been applied to avoid intensity saturation problem. The popular approach for using plateau limits is quadrants dynamic histogram equalization (QDHE) (Ooi and Isa 2010a) and dynamic quadrants histogram equalization plateau limit (DQHEPL) (Ooi and Isa 2010b). In QDHE technique, input image histogram is segmented into four parts using median value along with the mean value-based clipping procedure, which has been applied beforehand to control the rate of enhancement.

In the field of contrast enhancement, various new approaches have been developed to obtain optimum level of enhancement. The optimization techniques like artificial bee colony (ABC) (Karaboga and Akay 2009), bat algorithm (BAT) (Yang 2010) and cuckoo search algorithm (CS) (Yang and Deb 2009) are found very effective in contrast enhancement area. Bhandari et al. (2011) have proposed a new method for low-contrast satellite image enhancement based on singular value decomposition (SVD) and discrete cosine transform (DCT), obtained using traditional HE method. This technique converts the image into the SVD-DCT domain, and after normalizing the singular value matrix, the enhanced image is reconstructed by using inverse DCT. Subsequently, in 2014, the authors have introduced two new approaches by exploiting the concept of the cuckoo search algorithm and artificial bee colony to obtain optimum contrast and brightness enhancement using DWT–SVD for satellite image (Bhandari et al. 2014a, b). Enhancement technique for dark satellite image using knee transfer function and gamma correction through exploitation of DWT–SVD methods is also proposed in the literature (Bhandari et al. 2015a; Bhandari et al. 2016a, b).

However, BHE3PL method does not give satisfactory outcomes in the case of color images and uses a fixed parameter setting depending solely upon the histogram of input image. In contrary, the proposed algorithm utilizes a dynamic parameter, optimized using CS algorithm applied upon histogram of the image. In the Lim et al. paper, a fixed parameter setting has been introduced which makes use of statistical parameter solely on the histogram of the input image, whereas the proposed method utilizes the statistical information from the image histogram and further optimized it to obtain better limits. The CS algorithm provides a good balance between exploration and exploitation and has shown to be the most efficient and the most stable for all kind of images even with the weakly illuminated images such as low-contrast images. These promising properties suggest that the CS algorithm can be effectively considered as an attractive algorithm for the low-contrast image enhancement problem.

The aim of CS algorithm is to use the new and possibly better solutions to take the place of a relatively outdated solution. In CS algorithm, while dealing with single-objective problems, each nest corresponds to only one egg. With this manner, CS can always find better solutions when compared with other bio-inspired algorithms. One of the most important advantages of CS algorithm is its simplicity; therefore, it is very easy to implement. In this paper, a new CS algorithm-based optimal histogram scheme using plateau limits is designed to enhance the quality of the low-contrast image with naturalness and brightness preservation.

In this perspective, this paper introduces a novel optimal histogram scheme for low-contrast satellite image enhancement, aiming, to preserve the features of output image using optimized plateau limits with help of cuckoo search algorithm. The proposed methodology has been examined through different low-contrast test images including low illuminated satellite images and has offered very promising results. Furthermore, proposed scheme is compared with well-known traditional methods such as HE (Gonzalez et al. 2009), BBHE (Kim 1997), QDHE (Ooi and Isa 2010a), BHEPL (Ooi et al. 2009), ACMHE (Santhi and Banu 2015), SHMS (Chang and Chang 2010), RSWHE (Kim and Chung 2008), DQHEPL (Ooi and Isa 2010b), BHE3PL (Lim et al. 2015), ABC and BAT methods.

The rest of the paper is organized as follows. Section 2 provides review of related works. Section 3 gives formulation and overview of optimization technique for contrast enhancement problem. The proposed method for contrast enhancement is discussed in Sect. 4 with detailed methodology and complete flowchart routine. Section 5 provides a look at the comparison of the proposed algorithm with numerous existing methods using different quality measurement parameters. Finally, Sect. 6 concludes the paper by highlighting the merits and demerits of the proposed method with a motivation and future scope.

2 Related works

Inspired by nature, a variety of metaheuristic algorithms have been proposed recently to deal with complicated optimization problems (Wang and Tan 2017). Many of them have solved complex, challenging problems that are difficult to approach using traditional mathematical optimization techniques. These nature-inspired algorithms include hurricane optimization algorithm (Rizk-Allah et al. 2018), multiobjective optimization algorithm (Wang et al. 2017), cuckoo search algorithm (Cui et al. 2017), harmony search algorithm (Wang et al. 2016a), hybrid cuckoo search (Wang et al. 2016b), monarch butterfly optimization (Wang et al. 2015), and binary moth search algorithm (Feng and Wang 2018). Among these approaches, cuckoo search algorithms have become increasingly popular recently. Because cuckoo search algorithm has been exploited in many complicated problems successfully, they have received increased attention in many fields, ranging from academic research to engineering practice. Comparing with other algorithms, one of the advantages of the CS algorithm is that it requires few control variables to regulate. In general, CS algorithm can explore the search space effectively and efficiently. Different from evolutionary algorithm and other swarm optimization, CS algorithm only moves to a better position.

Although numerous methods which have been proposed for image enhancement are developed through the exploitation of the histogram processing, in 2010, an image contrast improvement scheme using genetic algorithm (GA) was introduced (Hashemi et al. 2010). To provide superior image contrast, it exploits the GA to compute the optimal gray level mapping from the input image into new gray levels. These comparatively new metaheuristic algorithms have shown to be very proficient in solving optimization related tasks. These methods have already been more effective than conventional genetic algorithm and the particle swarm optimization (PSO) (Bhandari et al. 2015b). CS algorithm has been presented earlier for solving different optimization problems like multilevel thresholding (Bhandari et al. 2016a, b); however, use of CS algorithm to compute optimal histogram equalization in the context of image enhancement is still untouched. Recently, in 2016, a novel color image segmentation approach using CS algorithm has been proposed, which has outperformed several well-known new optimization algorithms such as differential evolution (DE), wind-driven optimization (WDO) and PSO (Bhandari et al. 2016a, b). The improved performance reported by the authors encouraged us to use a novel metaheuristic algorithm such as ABC (Bhandari et al. 2015c), BAT (Mishra and Panda 2018) and CS algorithm (Pare et al. 2017).

Recently, in the domain of brightness preserving enhancement, a new bi-histogram three plateau limits-based scheme has been introduced which is named as BHE3PL (Lim et al. 2015). In this approach, initially input image is divided into two sub-histograms and are updated using the plateau limits computed on the corresponding sub-histograms. This paper claims to produce better enhanced image when the HE is individually implemented on the two sub-histograms images.

3 Problem formulation and optimization techniques

For contrast enhancement of general-purpose images, histogram clipping is one of the best methods in terms of preservation of features and simplicity in implementation. Histogram clipping is the process in which the histogram of the image is clipped based on the statistical measures of the image.

General histogram clipping process using a threshold value P and input image histogram h_i can be presented as:

$$h_{\mathrm{m}} = \begin{Bmatrix} h_i & h_i \leq T \\ T & h_i > T \end{Bmatrix} \tag{1}$$

where h_{m} is output histogram after clipping operation.

Multilevel clipping value is obtained where the value of T changes from image to image. The clipping process can be applied on the entire histogram or on a part of it, depending upon the requirement of the algorithm. The number of clipping limits can also be varied according to simplicity and level of enhancement required in the particular problem.

Depending upon the mean value of input image, a histogram clipping-based contrast enhancement method BHE3PL (Lim et al. 2015) employs six clipping to clip the sub-histograms. The detailed procedure of the method is discussed below:

3.1 Histogram segmentation

The first step in the BHE3PL method is to separate the input image histogram into two parts based on the mean value of the input image.

$$m_i = \frac{\sum_{k=0}^{L-1} l_k \times n_{\mathrm{k}}}{N} \tag{2}$$

where l_{k} is kth gray level and n_{k} is number of pixels at that gray level, N is the total number of pixels in the image under observation. L is maximum gray level range in the image. For an 8-bit digital image, the value of L is 256.

Using this mean value, the input image histogram is separated into two sub-histograms named as HI_{L} and HI_{H}. The dynamic range of the lower histogram is defined from lowest nonzero gray level $l_{\min}$ to mean value m_i, whereas the dynamic range of upper histogram ranges from m_i+ 1 to highest nonzero gray level value $l_{\max}$.

3.2 Multiple plateau clipping

In this section, a histogram modification framework is utilized using three plateau limits (PL) in each of the segmented histograms, unlike BHEPL (Ooi et al. 2009) and DQHEPL (Ooi and Isa 2010b) which employs only one plateau limit. The general formula utilized to calculate the plateau limits is given below:

$$T = Z \times P_k \tag{3}$$

where Z is a value ranging between 0 and 1. P_k is the highest value in histogram or sub-histogram being considered.

In BHE3PL routine, plateau limits are calculated based on information contained in the segmented histograms. One of the methods to measure local information from the histogram is the gray level criterion. Gray level criterion (GC) or gray level ration (GR) lies between 0 and 1. GC is the percentage of enhancement required to be applied to the particular bin. A lower percentage of enhancement level is required to be applied to bins having lower GC and vice versa.

The plateau limits are calculated on the basis of GCs as given below:

$$T_{L1} = GC_{L1} \times Pk_L \tag{4}$$

$$T_{L2} = GC_{L2} \times Pk_L \tag{5}$$

$$T_{L3} = GC_{L3} \times Pk_L \tag{6}$$

$$T_{H1} = GC_{H1} \times Pk_H \tag{7}$$

$$T_{H2} = GC_{H2} \times Pk_H \tag{8}$$

$$T_{H3} = GC_{H3} \times Pk_H \tag{9}$$

where Pk_L and Pk_H are peak values in the lower and upper sub-histogram, respectively. GC_{Li} and GC_{Hi} are the gray level criterion for ith plateau limit in the lower and upper sub-histograms, respectively. The value of GCs is defined as

$$GC_{L1} = GC_{L2} - D_L \tag{10}$$

$$GC_{L2} = \frac{m_i - m_{\mathrm{L}}}{m_i - l_{\min}} \tag{11}$$

$$GC_{L3} = GC_{L2} + D_L \tag{12}$$

$$GC_{H1} = GC_{L2} - D_{\mathrm{H}} \tag{13}$$

$$GC_{L2} = \frac{l_{\max} - m_{\mathrm{H}}}{l_{\max} - m_i} \tag{14}$$

$$GC_{H3} = GC_{L2} + D_{\mathrm{H}} \tag{15}$$

where m_{L} and m_{H} are the mean values of the lower and higher sub-histograms, respectively. D_{H} and D_{L} are the gray level criterion differences of the higher and lower sub-histograms, respectively. The values of m_{L} and m_{H} are calculated similarly by the procedure defined by Eq. (2) with the limits of summation defined in sub-histogram range and denominator being equal to total number of pixels in sub-histogram.

The values of D_{L} and D_{H} are calculated using following equations:

$$D_L = \begin{cases} \frac{1 - GC_{L2}}{2} & if \quad GC_{L2} > 0.5 \\ \frac{GC_{L2}}{2} & if \quad GC_{L2} \leq 0.5 \end{cases} \tag{16}$$

$$D_H = \begin{cases} \frac{1 - GC_{H2}}{2} & if \quad GC_{H2} > 0.5 \\ \frac{GC_{H2}}{2} & if \quad GC_{H2} \leq 0.5 \end{cases} \tag{17}$$

With the knowledge of plateau limits, the process of histogram clipping is performed. In this sub-histogram procedure, if the value of histogram bin is lower than corresponding first plateau limit, then the value of histogram bin is taken to be the first plateau limit. If the value is located between first and third plateau limit, the value of histogram bin acquires the value of second PL. However, if the value is found above the third limit, then the bin is modified to the third PL. The mathematical expression of above-defined allotment can be given as

$$\mathrm{HI}_L = \begin{cases} T_{L1} & if \quad \mathrm{HI}_L(k) \leq T_{L1} \\ T_{L2} & if \quad T_{L1} < HI_L(k) \leq T_{L3} \\ T_{L3} & if \ \mathrm{HI}_L(k) > T_{L3} \end{cases} \tag{18}$$

$$HI_H = \begin{cases} T_{H1} & if \quad HI_H(k) \leq T_{H1} \\ T_{H2} & if \quad T_{H1} < HI_H(k) \leq T_{H3} \\ T_{H3} & if \quad T_H(k) > T_{H3} \end{cases} \tag{19}$$

An illustration of all the clipping procedure for a hypothetical image is presented in Fig. 1.

3.3 Histogram transformation

Now, traditional histogram equalization is applied on the segmented histograms individually to obtain mapping function. The histogram equalization for the individual sub-histogram is defined as

$$Y = X_{i-1} + (X_i - X_{i-1}).CDF_i \tag{20}$$

where X_{i-1} and X_i are the lower and higher end of the dynamic range of the ith sub-histogram and CDF_i is cumulative distribution function (CDF) of the corresponding ith sub- histogram. The CDF is defined as the accumulation of probability distribution function.

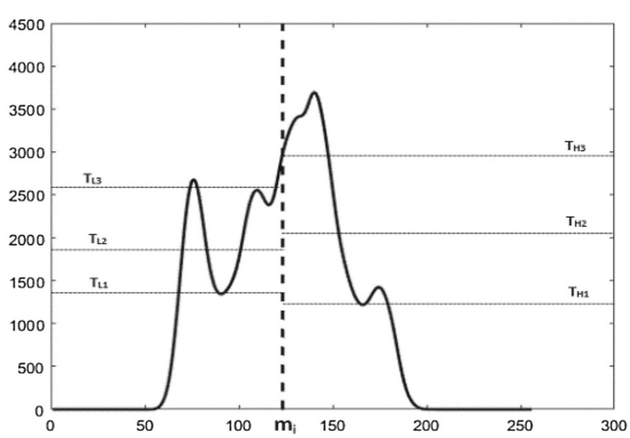

Fig. 1 Histogram modification with plateau limits

$$CDF(k) = \sum_{i=0}^{k} PDF(i) \, k = 0, 1, 2, \ldots, 255 \tag{21}$$

where PDF is probability density function defined as the ratio of histogram bins to the total number of pixels in the image.

$$PDF(i) = h(i)/N \, k = 0, 1, 2, \ldots, 255 \tag{22}$$

where h is histogram of the image and N is total number of pixels in the histogram.

In addition, a brief discussion of ABC, BAT and cuckoo search algorithms has been presented for computation of the optimized brightness preserving sub-histogram scheme for low-contrast image enhancement.

3.4 Bat algorithm

Xin-She Yang proposed the bat algorithm, which is used as a metaheuristic approach for optimization at global scale. This optimization method is stimulated from the echolocation of microbats. The bats use the notion of SONAR echoes to detect their prey and avoid obstacles. The bats transmit the sound waves, and in the presence of an object these waves are reflected back. The time period between the reflection and transmission of the wave impacts the movement of the bats. After the reception of reflected wave, bats use their own pulse to determine the space between them and the prey. The pulse rate ranges from 0 to 1, where 1 represents emission at maximum level and 0 indicates no emission. The loudness of the sound wave and the distance of bat from prey are proportional to each other. Also, the loudness and pulse rate are inversely proportional to one another.

The idealism of the echolocation of microbats can be summarized as follow: Each assumed microbats flies in a random nature by changing the velocity v_i, position x_i, wavelength λ_i or frequency f_i and loudness A_i. As it moves around and searches for its prey, pulse rate r, loudness, and frequency change. Localized random walk intensifies the searching of the prey which halts once the stopping criteria are met. The behavior of microbats is replicated using the frequency tuning technique. The parameters in the bat algorithm balance the exploitation and exploration of the microbats. A detailed overview of the bat algorithm is given in (Yang 2010; Dhar and Kundu 2018).

3.5 Artificial bee colony (ABC)

In ABC, search algorithm is inspired by the foraging behavior of bee colonies. Each food source position in ABC represents a group of possible solutions for the specified optimization task. Once random food sources are generated, employed bees are positioned to locate the food sources and onlooker bees are positioned to compute the quantity of nectar (fitness parameter). Scout bees randomly walk near the complete colony. Equation (23) formulates the neighbor food position

$$SP_i(c+1) = SP_i(c) + \chi_i(SP_i(c) - SP_k(c)) \tag{23}$$

where χ_i is generated randomly in the range -1, to +1, c is number of cycle. If the fitness rate (nectar amount) of the latest food source position $F(SP_i(c+1))$ shows better value as compared to previous food source position $F(SP_i(c))$, then after storing the $SP_i(c+1)$, employed bees provide details about the better food source to onlooker bees, and the $SP_i(c)$ of i is modified through $SP_i(c+1)$, otherwise $SP_i(c)$ remains as it is. A food source i is abandoned, and the concerned bees are affirmed as scout bee if $SP_i(c)$ does not improve after repeated iterations. Scout bees are then assigned to search for new food sources in its vicinity, and a new position $SP_i(c+1)$ is granted if a better food source is located. ABC is elaborated well by Bhandari et al. (2014a) and Bhandari et al. (2015c).

3.6 Cuckoo search algorithm

Cuckoo search algorithm (CS) was proposed in 2009; it is a metaheuristic optimization algorithm, suitable for solving optimization related problems (Yang and Deb 2009). The CS algorithm is based on compelled brood parasitic characteristics of some cuckoo species, which lays their eggs in the nests of other birds called host birds, in accordance with the Lévy flight behavior of fruit flies and some of the birds. In a directive by Lévy flight distribution, it is concluded that the animals and birds fulfill their eating requirement by finding food in a random or quasi-random way. The next step of such distribution depends upon current best and the next best thing (or transition probability) to follow. This behavior is formulated by researchers (Yang and Deb 2009) to design an effective optimization technique called as cuckoo search algorithm with Lévy flight. Each of the egg in cuckoo search algorithm represents a solution under given nest, whereas each of cuckoo egg represents a new solution.

Two statistical distributions are combined to produce the desired results. First one is computed through the Lévy flight distribution to generate new solution or eggs in case of the CS algorithm and another one through the probability of keeping that egg i.e. not being caught by host bird. In case, the host bird discovers foreign eggs; it can get rid of them or abandon the whole nest.

In its simplest form, each nest in CS contains only one egg; however, it can be extended for having more than one egg corresponding to a set of solution for more complex problem statements. The CS is based on three idealized rules:

(a) Each cuckoo lays one egg at a time and dumps it in a randomly chosen nest;
(b) The best nests with high quality of eggs (solutions) will remain active after fitness evaluation and will be carried over to the next generations;
(c) The total number of available host nest is fixed. Hence host bird can find the intruder egg with probability $p_a \in [0,1]$. After finding the foreign egg host bird either can get rid of that or can abandon the whole nest to generate new nests.

Throughout the time many metaheuristic algorithms are introduced for different image processing and image enhancement applications. In the literature, there are various other nature-inspired swarm-based techniques; however, this paper has focused on optimization of plateau limits using cuckoo search algorithm. The reasons behind effectiveness of cuckoo search algorithm over other metaheuristic algorithm are given as

1. CS is a population-based algorithm. The entrywise product is similar to particle swarm optimization (PSO), but random walk for food search via Lévy flight tends to have longer step length as they are scattered through a heavy tail probability distribution.
2. The number of parameters required to tune to obtain optimum performance through CS algorithm is much lesser than that of PSO and genetic algorithms (GA). As a result, CS is more suitable for a general class of optimization problems.
3. Low computational complexity with efficient performance.
4. Fast searching ability to reach optimum solutions for complex problems.
5. Random initialization is more effective due to larger step size.
6. Less number of controlling parameters which are just mutation probability value (p_a) and the scale factor (λ).

Step-by-step procedure for proposed cuckoo search algorithm is given as:

Step 1 To find different solutions, a number of nests (n) are fixed prior to any computation. Discovery rate probability (p_{a}) is fixed. For stopping criteria, either iteration count or tolerance limit-based criteria is used. In this work, a number of nests (n) and p_a are taken to be 50 and 0.25, respectively

Step 2 Dimensionality and boundaries of parameters are also fixed. Dimensionality in this work is 6, and parameter boundaries are fixed by Eqs. (26)–(28)

Step 3 Solutions are randomly initialized by generating n different nest to obtain n different solutions

Step 4 Value of fitness of the solution is evaluated for each nest. The best nest is found corresponding to maximum value of fitness

Step 5 Iteration is initiated and new nests are generated using L′evy flight, but the current best solution is kept. A Levy flight is performed by the equation:

$$x_i(t+1) = x(t)_i + \alpha \oplus L\prime evy(\lambda) \tag{24}$$

where α is step size.

A random walk is provided by above equation. The random step length is chosen from a Lévy distribution, which has an infinite mean with an infinite variance. Lévy distribution is given by

$$L'evy \sim u = t^{-\lambda},\ (1 < \lambda \leq 3) \tag{25}$$

The Lévy function can be modified according to the application. Mantegna's algorithm is one of the Lévy functions.

Step 6 New fitness values are obtained by evaluating this set of solutions. Comparison of the new fitness with the old one is done. If the new one is better than old one, then the current nest is assigned as best nest and corresponding fitness value is considered as the best value up to now

Step 7 Above process is reiterated until some stopping criteria already specified in step 1 is reached

In this paper, recently developed well-known optimizing techniques with new objective function have been exploited to learn feature and brightness preserving enhancement methodology for daily-life and satellite images. Furthermore, pseudocode of BAT, ABC and CS algorithms are provided in Table 1. The specific values of important parameters of each of the optimization algorithm are presented in Table 2.

4 Proposed contrast enhancement methodology

The plateau limits are obtained in the previous section using statistical information from the histogram as a gray level criterion. In this section, an optimization-based technique is introduced to fine tune the plateau limits by maximizing an objective function. It helps in achieving brightness preserved enhancement especially for low-contrast images. In each sub-histograms three plateau limits are to be optimized so minimum dimensionality of the optimization algorithm must be six. In this experiment, the simulations have been executed on MATLAB R2017a on Windows 10 using Intel® Core i7 CPU @ 3.6 GHz processor with 8 GB of RAM. In this paper, proposed scheme is tested with a standard set of benchmark images from the Kodim dataset (http://r0k.us/graphics/kodak/), Image Processing Place (http://www.imageprocessingplace.com/root_files_V3/image_databases.htm) and NASA Earth Observatory (http://earthobservatory.nasa.gov/). This set contains twelve diverse feature color images. All images are in JPEG format with the size of 512 × 512 pixels. Generally, RGB images have three color components: red, green and blue. Therefore, the search for optimal threshold values is carried out on each component of a color image.

4.1 Bound to the Plateau limit values

The effectiveness of the proposed CS algorithm generally depends upon bounds of given parameters. If the bounds are already optimized to produce better results, the convergence rate of the algorithm increases significantly. These bounds help to control the level of enhancement in the feature preserved or brightness conserved image enhancement problems.

In the given problem, for optimization, the bounds on the plateau limits are selected such that the values of the parameter can be always acquired from the values defined by Eqs. (4)–(9). An effective bound can be the regions rendered by the middle point of the different regions generated with Eqs. (4)–(9). A mathematical expression of the bound values in each sub-histogram region can be expressed as

$$\mathrm{T1}/2 < T1' \leq (T1 + T2)/2 \tag{26}$$

$$(\mathrm{T1} + \mathrm{T2})/2 < T2' \leq (T2 + T3)/2 \tag{27}$$

$$(\mathrm{T2} + \mathrm{T3})/2 < T3' \leq (T3 + Pk)/2 \tag{28}$$

where $T1'$, $T2'$, and $T3'$ are new plateau limits to be predicted by optimization. $T1$, $T2$, and $T3$ are older limits specified by Eqs. (4)–(9). Pk is the peak value of bin in corresponding sub-histogram.

Table 1 Pseudocode of BAT, ABC and CS algorithms

<table>
<tr>
<td>
BAT
1. Define objective function $f(x) = \left[x_1, x_2 \ldots x_p\right]^T$
2. Initialize the microbat population v_i and $x_i\,(i = 1,\ 2 \ldots n)$
3. Define A_i, f_i, r_i at x_i
4. While $(t\ <\ \text{max no. of generations})$
Generate new by adjusting frequency
update locations and velocities
4(a). if $(\text{randno.}\ > r_i)$
select a solution among the best solutions
generate a local solution around the selected best solution
end if
4(b). if $\left(\text{randno.}\ < A_i\ \&\ f\left(x_{i+1}\right)\ < f\left(x_{best}\right)\right)$
Accept the new solutions
Increase r_i and reduce A_i
end if
4(c). Rank the microbats and find the current $\text{best}x_{best}$
end while
5. Post process results and visualization
</td>
<td>
ABC
Initialize the population of solution and generate food sources
Evaluate the population
Do
For every employed bee:
Calculate solution using solution search equation below and evaluate
$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j})$
Apply greedy selection process
Calculate probability values P_i for solutions
End
For each onlooker bee:
Compute new solutions from selected solutions based on P_i and
evaluate
Apply greedy selection process
End
Find abandoned solution for scout and replace with new random solutions
Memorize best solution
Until stopping criterion is met
</td>
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<tr>
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CS
Begin
Objective function;
Initialize a population of n host nests, $xi\,(i = 1, 2, \ldots, n)$;
While $(fmin > \ tol)$ or $(t < \ MaxIterations)$;
Generate a cuckoo (k) randomly through Levy flights;
Evaluate its fitness / quality Fk;
Randomly select a nest amongstn$(sayj)$;
if $(Fk\ > Fj)$,
Replace j using new solution;
end
a fraction (pa) of worst nests then abandoned
(And new nests are built at a newlocations through Levy flights);
Keep the nests with quality solutions (best solutions)
Rank the solutions and find the current best;
end while
end
</td>
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4.2 Objective function and fitness criterion

For optimization problem, an objective function is required, which can show the level of enhancement of an image automatically without human intervention. For the enhancement criterion, various objective functions can be proposed considering entropy, peak signal-to-noise ratio (PSNR) and other quality parameters. One of the basic requirements of enhanced image is to have a greater number of edge pixels with higher intensity values than original image (Gonzalez et al. 2009). Using the above measures together, the fitness function is defined in two parts as

$$OF1 = (\log(\log(E(I_S))) \frac{n_{\text{edges}}(I_s)}{m.n} H(I_e) \tag{29}$$

$$OF2 = PSNR(I_e) \tag{30}$$

$$OF = 0.5 * OF1 + 0.5 * OF2 \tag{31}$$

where I_{e} is enhanced image, $I_{S\text{-}}$ is Sobel edge image, and $M \times N$ is the size of the image. For the edge detection, various techniques can be utilized such as Sobel edge detection (Gonzalez et al. 2009) and canny edge detection (Canny 1987). Sobel edge detection is exploited in this paper for better feature preservation scheme. $E(I_S)$ is the sum of intensity values of edge pixels of image, and n_{edges} is number of such edge pixels having greater intensity value than some fixed intensity value. $H(.)$ is the entropy of the enhanced image. $PSNR(.)$ is the peak signal-to-noise ratio of the enhanced image which is predicted in

Table 2 Parameters and their respective values used in optimization algorithms

Algorithms	Parameters	Values
BAT	Frequency max ($Q_{\max}$)	0.2
	Frequency min ($Q_{\min}$)	0
	Loudness (A)	1
	Microbats frequency	50
	Pulse rate (R)	0.5
ABC	Swam size	20
	No. of iteration	300
	lower bound $lb(x_{\min})$ and upper bound $ub(x_{\max})$	1 and 256
	Max trial limit	10
	Value of $F_i(\varphi)$	(0 1)
CS	Number of nests	20
	No. of iterations	300
	Mutation probability value (P_a)	0.25
	Scale factor (β)	1.5

comparison with the original image. Both objective functions *OF1* and *OF2* can be utilized independently or combined as given by Eq. (31).

For optimization problem, an objective function is required without human intervention, which can show the level of enhancement of an image automatically. One of the basic requirements of enhanced image is to have a greater number of edge pixels with higher intensity values than original image (Gu et al. 2015).

However, the presence of noise in the image can blur the boundary and affect the edges in the image. Higher the PSNR means better the signal strength which also indicates better presence of information in an image. The two measures thus are not contradictory in this regard. Thus, averaging them is perfectly good measure as an objective function. In this paper, the main challenge of the proposed scheme is to obtain balance enhanced output which can preserve the basic feature of the input images and maintain good trade-off between contrast and brightness. Visually any image can look not very sharper than other methods, but it may indicate an optimum level of enhancement which preserves brightness and boost contrast in regard with the natural feel of the original image. In addition, the expressions to calculate entropy and PSNR values are given in Sect. 5.

4.3 Detail steps of proposed CS-based enhancement

Details methodology with steps can be given as follows:

Step 1 As a first step, an input image with low contrast has been taken for processing. The size of the image is $M \times N$, and being a color image it has 3 channels R, G, and B

Step 2 Separate the luminance and chrominance component of the input image using conversion from RGB color space to *YCbCr* color space. Only luminance component (Y) is further processed

Step 3 Histogram of the resultant luminance component is evaluated, and separating point of the histogram is computed using Eq. (2)

Step 4 Histograms are segmented into two sub-histograms named as HI_L and HI_H, depending upon the separating point calculated in **step 2**

Step 5 Values of plateau limits for each sub-histogram are calculated using Eqs. (4)–(9)

Step 6 These values of plateau limits are used to calculate lower and upper bound for the parameters required in cuckoo search algorithm. Equations (26)–(28) are utilized for this purpose

Step 7 The plateau limits calculated in **step 5** are now further optimized using CS algorithm with bounds calculated in **step 6** and any one of the objective functions presented in Eqs. (29)–(31)

Step 8 The segmented histograms are now modified with the plateau limits using Eq. (18) and Eq. (19)

Step 9 Resulting modified sub-histograms are individually equalized using Eq. (20) and the mapping function is obtained

Step 10 Now, enhanced luminance component for preserving the brightness is obtained using this mapping function

Step 11 The original chrominance and enhanced luminance components are layered together to obtain an overall feature and brightness preserved enhanced image

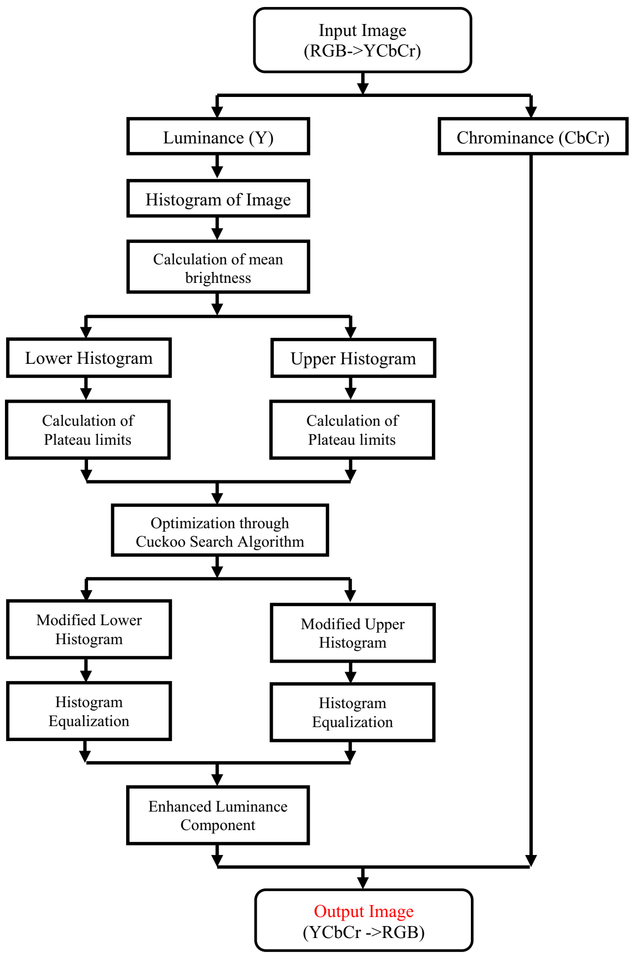

Fig. 2 Flowchart of the proposed cuckoo search algorithm-based approach

In addition, a complete flowchart routine of the proposed algorithm is also shown in Fig. 2.

5 Experiments and discussion

In order to demonstrate the effectiveness of proposed algorithm, several conventional and state-of-the-art techniques are compared, which were discussed in detail in the introduction part. To compare the quantitative results of implemented algorithms with the proposed algorithm, various performance evaluation metrics are required. The performance metric utilized in this paper is lined up in different subsections as

5.1 Quality metric for contrast (QMC)

QMC (a high-performance quality metric for contrast change) (Gu et al. 2018) measures the image visual quality. QMC utilizes saliency preservation as well as incremental entropy to generate a linear function to measure the visual quality of the image. The formula for calculation of the QMC can be given as

$$QMC(\tilde{I}, I) = \Delta D + \gamma \Delta H \tag{32}$$

where I and $\tilde{I}$ are input and enhanced image, respectively.

$\Delta H = \mathrm{H}(I) - H(\tilde{I})$; H(.) is entropy of the image.

$\Delta D = \left\| sign(DCT2(\tilde{I}_D)), sign(DCT2(I_D)) \right\|_0$ $\tilde{I}_D$ and I_D are downsampled version of enhanced and input image, respectively. In this paper, downsampling is done through the bilateral method by a factor of 4.

5.2 Discrete entropy (DE)

Discrete entropy (DE) quantifies the information present in the image (Eramian and Mould 2005). Higher the information content, higher will be the entropy. The entropy is defined as:

$$H(I) = -\sum_{\forall k} P(k) \log(P(k)) \tag{33}$$

where $p(k)$ is PDF as defined in Eq. (22). A higher value of entropy implies richer details. The entropy of image and discrete entropy have been used interchangeably in this paper. In general, entropy or average information of an image is a measure of the degree of randomness in the image. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. In this paper, we used discrete entropy which is an alternative approach to measure the average information that is especially amenable to the methods of discrete mathematics.

5.3 Absolute mean brightness error (AMBE)

Absolute mean brightness error (AMBE) is defined as the difference between the mean intensity values of input and enhanced images.

$$AMBE = \left| m_{\tilde{I}} - m_I \right| \tag{34}$$

where m_{I} is average intensity of image as defined in Eq. (2). Smaller value of AMBE means better preservation of the average intensity of input image.

5.4 Peak signal-to-noise ratio (PSNR)

Peak signal-to-noise ratio is a performance metric which is used for evaluation of the quality of the enhanced image. It is given by the ratio between the maximum possible power of the signal and power of distorting noise that affects the quality of its representation. It is given as:

$$PSNR = 20\log_{10}\frac{255}{RMSE} \tag{35}$$

where the RMSE can be defined as:

$$RMSE = \left(\frac{1}{MN}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1}\left|\tilde{I}_{xy} - I_{xy}\right|^2\right)^{1/2} \tag{36}$$

Higher the value of PSNR means lower the mean square error, hence better is image quality; however, this measure does not include human perspective.

5.5 Structural similarity index (SSIM)

The structural similarity index (Wang et al. 2004) compares the structure of original image with enhanced image. The SSIM is calculated as:

$$\mathrm{SSIM}(I,\tilde{I}) = \frac{(2\mu_I\mu_{\tilde{I}} + C1)(2\sigma_{I\tilde{I}} + C2)}{\left(\mu_I^2 + \mu_{\tilde{I}}^2 + C1\right)\left(\sigma_I^2 + \sigma_{\tilde{I}}^2 + C2\right)} \tag{37}$$

where μ_I is the mean intensity of the image and given as

$$\mu_I = \frac{1}{N}\sum_{i=1}^{N} I_i \tag{38}$$

and $\sigma_{I\tilde{I}}$ is the standard deviation of the image defined as

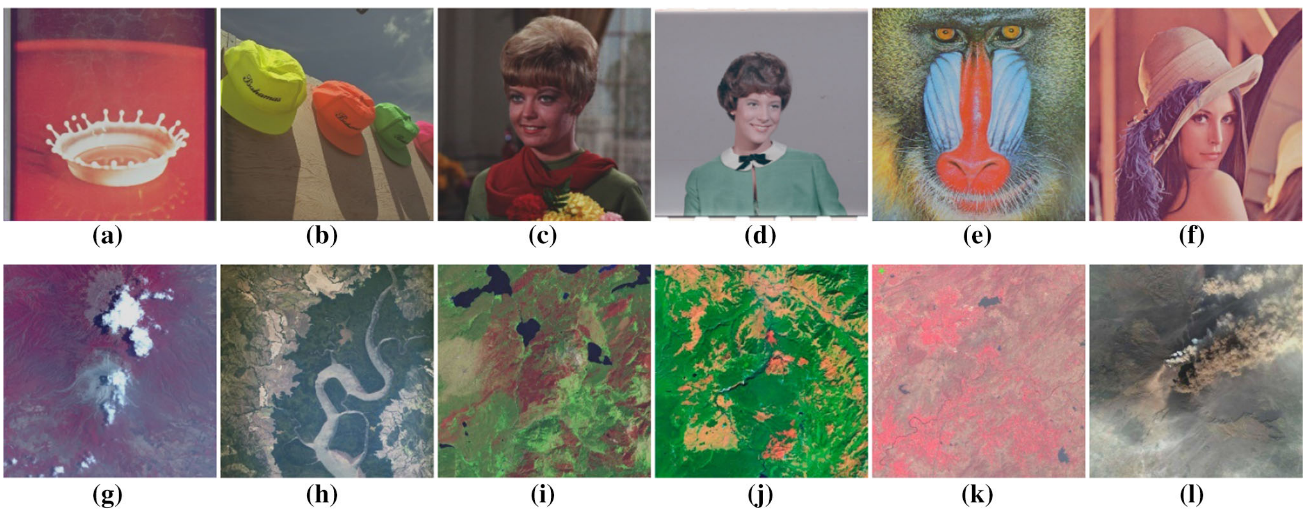

Fig. 3 **a–f** represents low-contrast standard images and **g–l** are low-contrast satellite images

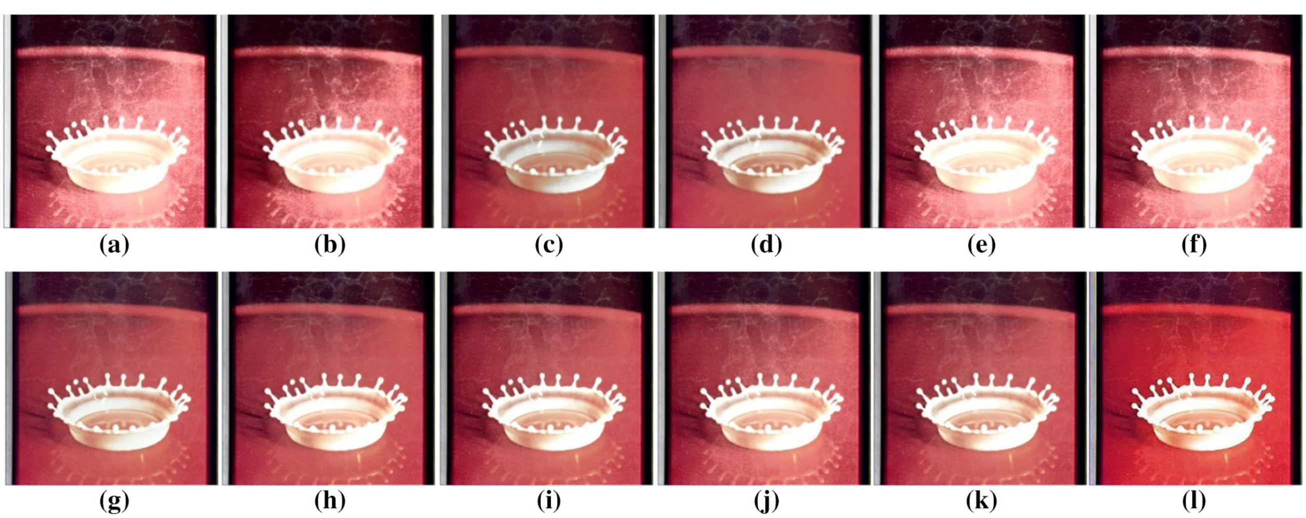

Fig. 4 Simulation results using **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

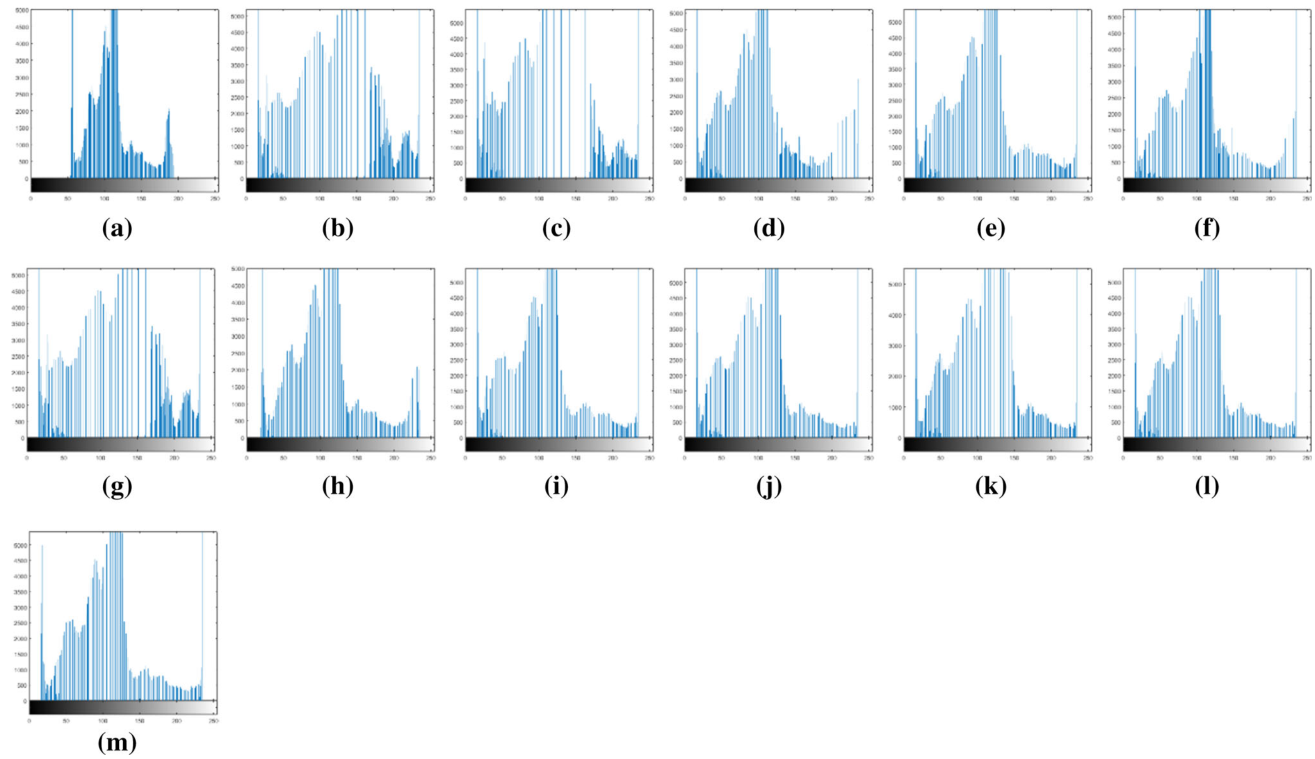

Fig. 5 Histogram image of **a** Original image, **b** HE, **c** BBHE, **d** QDHE, **e** BHEPL, **f** ACMHE, **g** SHMS, **h** RSWHE, **i** DQHEPL, **j** BHE3PL, **k** ABC, **l** BAT, **m** Proposed approach

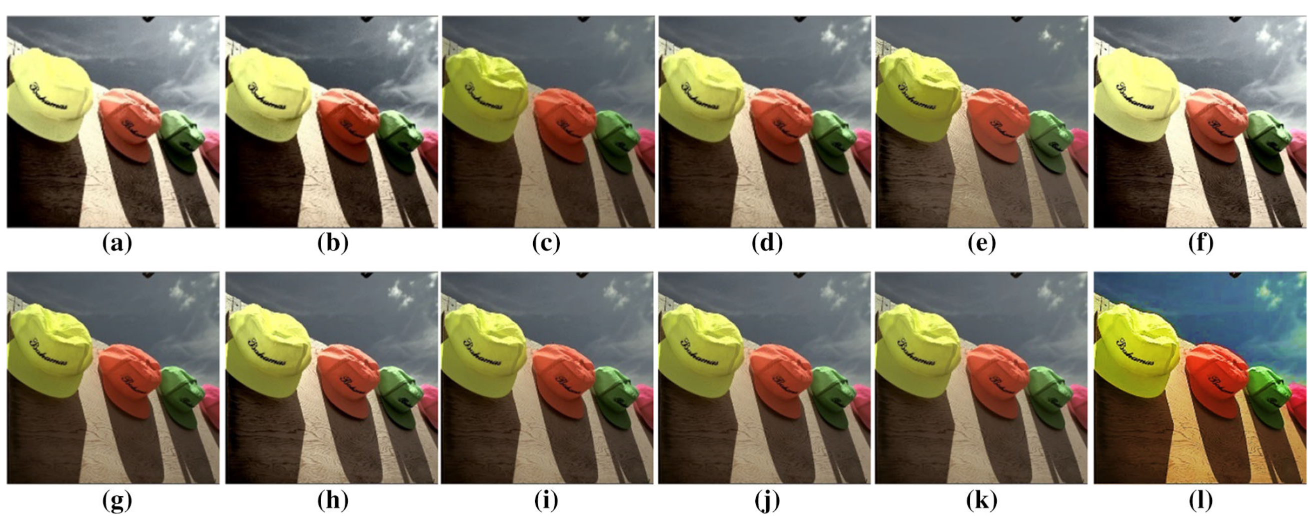

Fig. 6 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

$$\sigma_{I\tilde{I}} = \frac{1}{(N-1)} \sum_{i=1}^{N} (I_i - \mu_I)(\tilde{I}_i - \mu_{\tilde{I}}) \tag{39}$$

C1 and *C2* are the constants and are included to avoid instability when $\mu_I^2 + \mu_{\tilde{I}}^2$ and $\sigma_I^2 + \sigma_{\tilde{I}}^2$ are very close to zero. A higher value of SSIM shows better performance.

5.6 Constant per pixel (CPP)

Contrast per pixel is a performance metric which measures the level of contrast in an image. The contrast of each pixel with respect to the pixels in its neighborhood is calculated and averaged as

Fig. 7 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

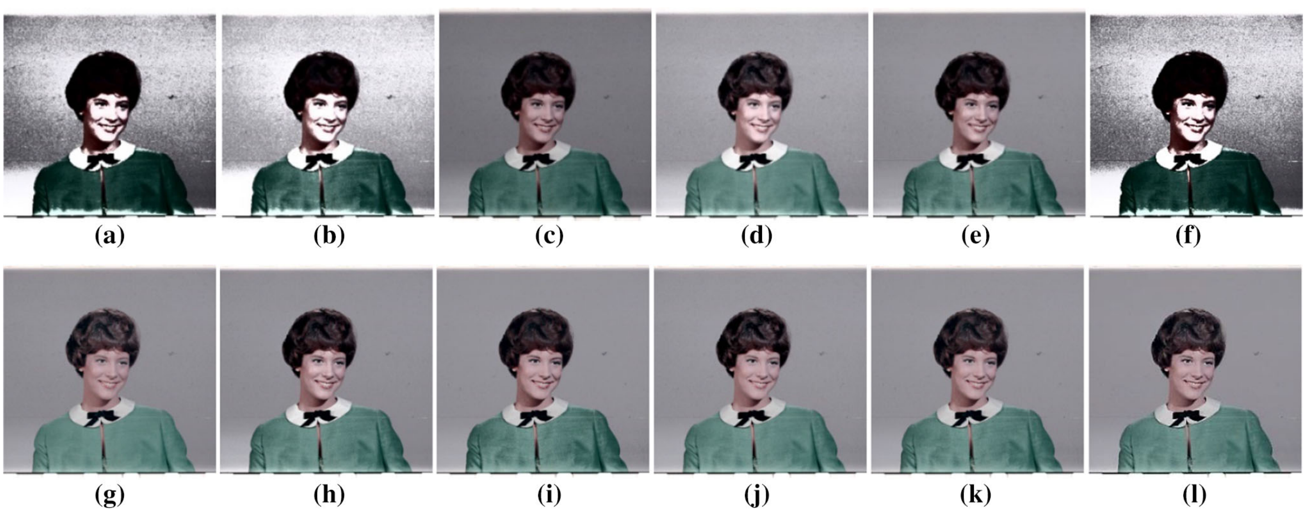

Fig. 8 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

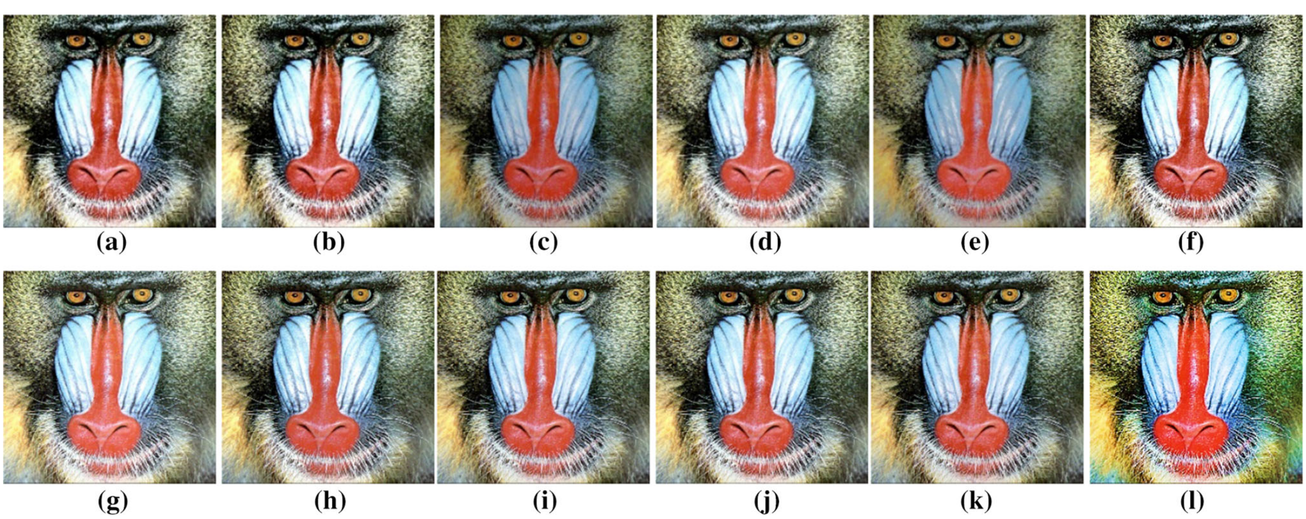

Fig. 9 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

Fig. 10 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

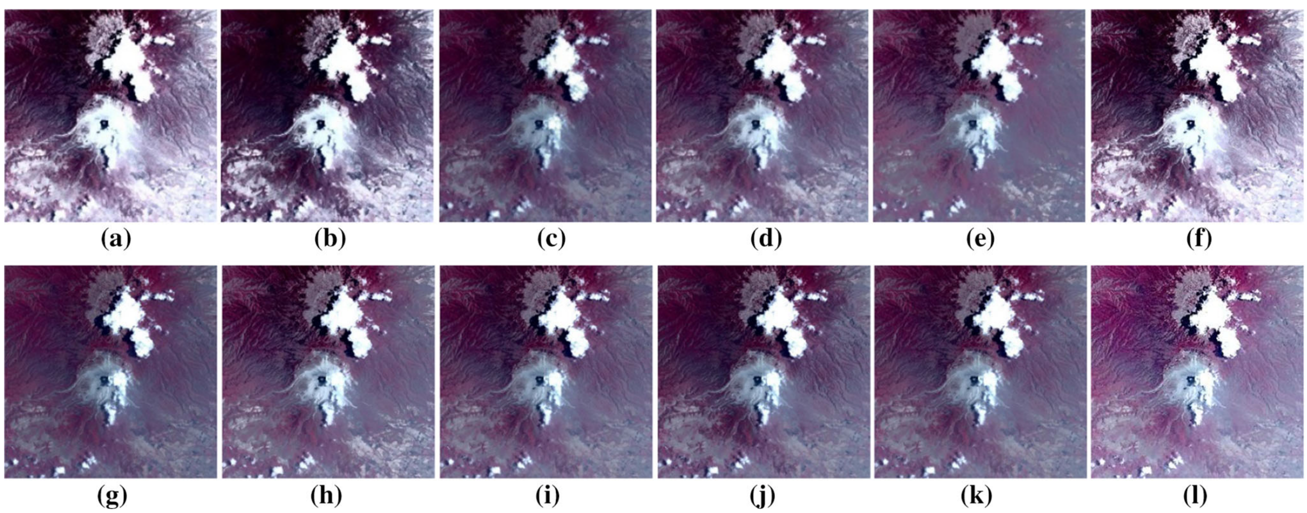

Fig. 11 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

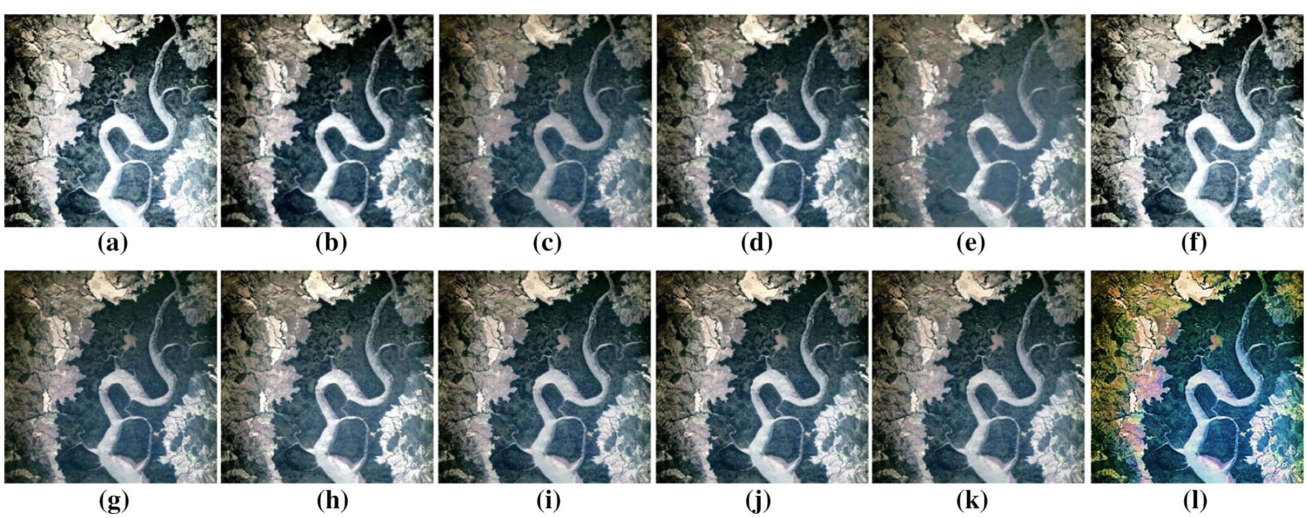

Fig. 12 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

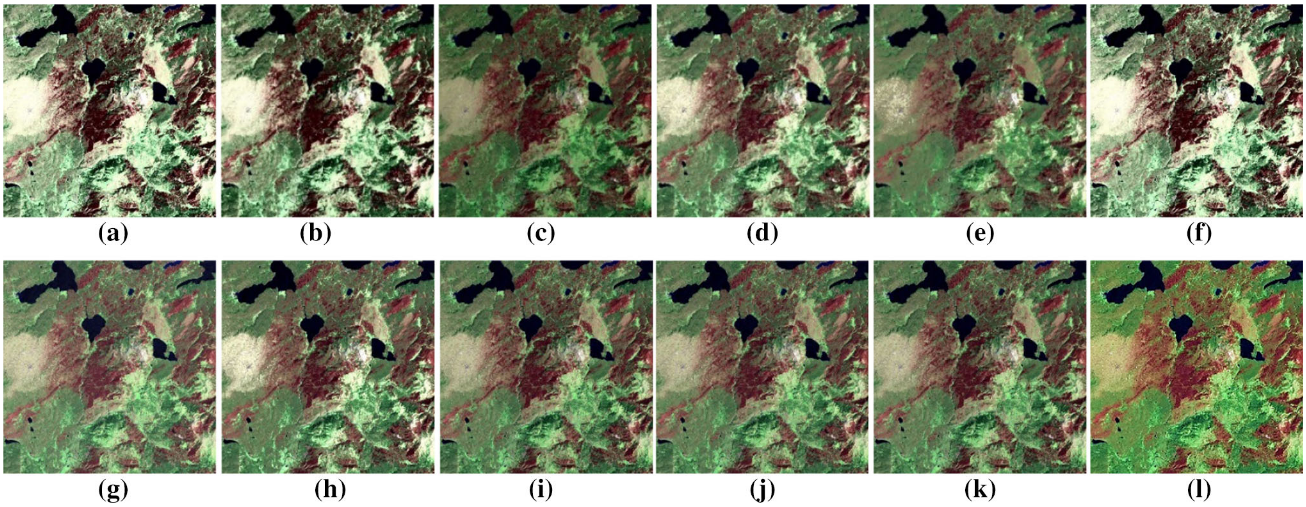

Fig. 13 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

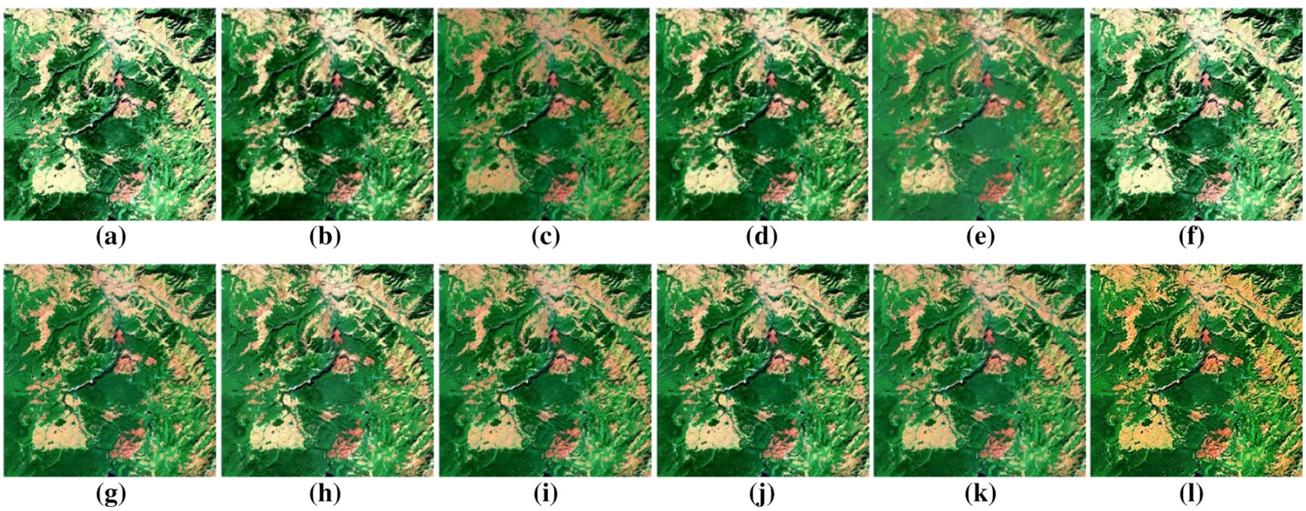

Fig. 14 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

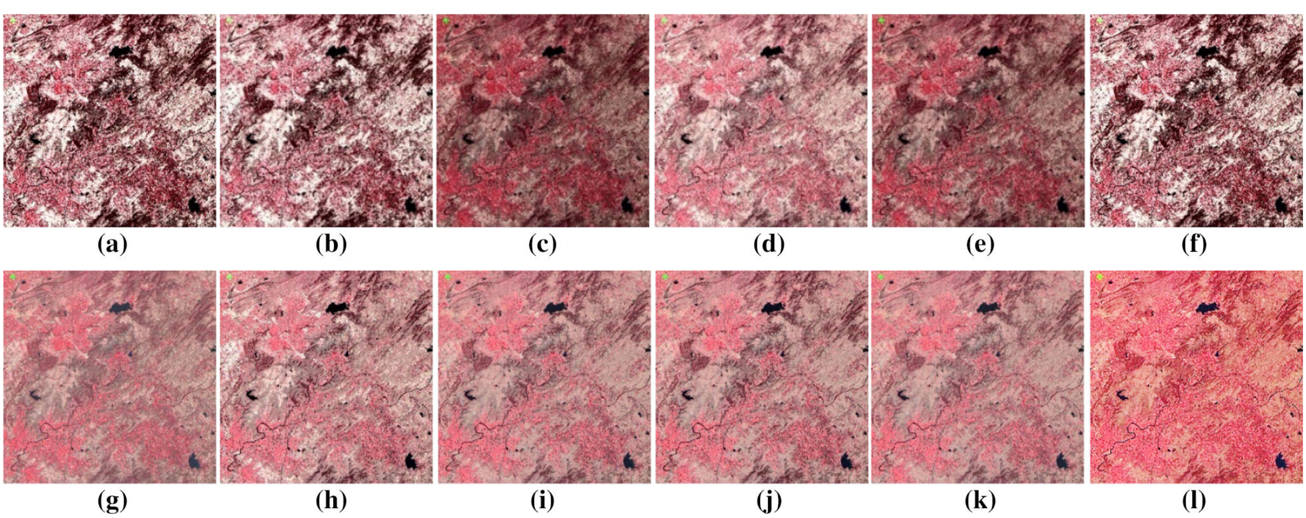

Fig. 15 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

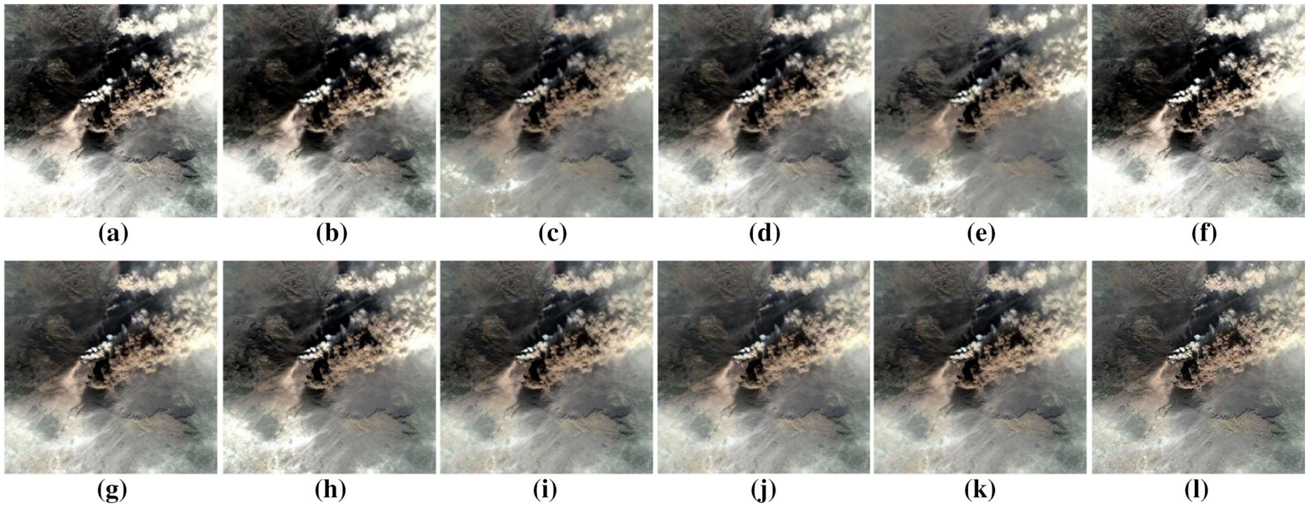

Fig. 16 **a** HE, **b** BBHE, **c** QDHE, **d** BHEPL, **e** ACMHE, **f** SHMS, **g** RSWHE, **h** DQHEPL, **i** BHE3PL, **j** ABC, **k** BAT, **l** Proposed approach

Table 3 Comparison of QMC values computed by different enhancement methods and proposed approach

Test images	QMC											
	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	0.78148	0.78154	0.83722	0.81096	0.85214	0.78097	0.81115	0.83685	0.82926	0.8311	0.81991	0.82595
2	0.74642	0.76826	0.73505	0.75879	0.78752	0.74655	0.75055	0.74594	0.72725	0.75118	0.76699	0.75939
3	0.7752	0.76477	0.74694	0.77492	0.78777	0.76068	0.76563	0.77784	0.77503	0.74108	0.77445	0.75425
4	0.90796	0.97481	0.9729	0.94617	0.94888	0.90751	0.93141	0.97863	0.93229	0.93825	0.93088	0.93022
5	0.70462	0.72018	0.69607	0.69651	0.69538	0.71243	0.66422	0.70093	0.68041	0.6763	0.69611	0.69389
6	0.74125	0.73279	0.71226	0.71868	0.71494	0.74125	0.72262	0.71715	0.7135	0.71237	0.70416	0.72009
7	0.72266	0.72052	0.70138	0.7117	0.72993	0.72262	0.6989	0.69481	0.70412	0.70436	0.69566	0.69615
8	0.72593	0.70577	0.6900	0.67879	0.69596	0.72593	0.67973	0.68075	0.67887	0.68035	0.67951	0.67158
9	0.74178	0.71424	0.72579	0.70209	0.7134	0.74178	0.70291	0.70014	0.70108	0.7152	0.70942	0.70438
10	0.64323	0.6266	0.63916	0.61397	0.67859	0.64323	0.64713	0.66184	0.64759	0.63451	0.6610	0.67271
11	0.62441	0.62976	0.66624	0.63035	0.65971	0.62441	0.66173	0.66078	0.68156	0.6708	0.68159	0.67214
12	0.79524	0.79442	0.75116	0.75887	0.77996	0.79524	0.74833	0.74988	0.73056	0.72941	0.73107	0.72919

$$C = \frac{\sum_{i=0}^{N}\sum_{j=0}^{M}\left(\sum_{(m,n)\in R_3^{(i,j)}}|\gamma(i,j)-\gamma(m,n)|\right)}{MN} \tag{40}$$

where M × N is the size of the input image. The higher value of CPP means better contrast.

5.7 Time complexity (AT)

The processing time is directly related to the complexity of the proposed algorithm. To compute the time required to process an image, independent of size of image, the absolute time (AT) is calculated in megapixels per second (M/s) as given by

$$TPM_k = \frac{T_k}{N_k} \times 10^6 \tag{41}$$

where T_k is the runtime of image k, and N_k is total number of pixels of image k.

5.8 Comparisons with other methods

The proposed approach is compared with other eleven approaches which include (1) conventional histogram-based image enhancement approaches and (2) optimization-based image contrast approaches. The conventional histogram-based contrast enhancement approach presented here includes traditional HE (Gonzalez et al. 2009), mean separated BBHE (Kim 1997), plateau limit-based

Table 4 Comparison of AMBE values computed by different enhancement methods and proposed approach

Test images	AMBE											
	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	17.6259	6.1621	13.2033	0.28951	2.8918	17.6161	2.1765	1.063	3.0671	1.6109	1.7082	1.3082
2	24.1716	5.7572	13.5943	2.2221	0.86393	24.0694	6.3069	1.7615	4.0813	2.3192	1.4811	1.6078
3	48.1307	7.8141	5.8111	3.5069	7.7178	48.0974	1.692	5.1478	4.4249	4.7000	5.5568	4.0033
4	1.2459	24.2593	24.7160	9.1770	7.0950	0.9281	2.4913	3.2823	3.7105	0.76559	2.1463	1.4218
5	1.8905	1.803	19.2805	8.3974	12.1181	1.8692	18.9054	5.7918	4.5567	3.9972	0.48127	5.4426
6	5.5510	7.2817	14.3430	2.8390	8.3779	5.551	1.3065	1.9235	0.0535	2.1765	0.05689	0.83263
7	26.008	0.5332	18.7558	2.2459	2.1126	25.998	15.1523	0.7509	7.0515	10.6592	5.4027	4.0889
8	20.0972	5.1431	14.3137	5.9057	3.5435	20.0972	10.6587	1.8314	7.7077	5.4598	7.5381	6.3841
9	24.3372	8.1841	20.9871	7.6284	5.2516	24.3372	13.2445	6.6051	1.3594	0.09401	1.8591	1.2022
10	19.9458	0.65339	12.5123	1.3121	5.3814	19.9458	0.51177	6.5921	3.2896	0.00853	1.5262	1.7051
11	22.439	15.1663	54.3056	2.9061	44.7514	22.439	12.2692	5.9257	9.5736	10.8319	8.4777	5.3537
12	6.9009	0.8859	9.6306	0.43039	2.4516	6.9009	1.3637	1.7790	3.0507	1.0991	2.7731	1.0633

Table 5 Comparison of DE values computed by different enhancement methods and proposed approach

Test images	DE												
	Original	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	4.5059	4.4656	4.3873	4.4604	4.3964	4.4249	4.4682	4.5126	4.3841	4.383	4.3738	4.3907	4.3996
2	4.3714	4.194	4.202	4.329	4.3274	4.2619	4.1933	4.3686	4.3136	4.3679	4.3655	4.3646	4.3635
3	4.4333	4.2292	4.2813	4.3705	4.3868	4.3226	4.2237	4.4333	4.3723	4.3863	4.3998	4.3892	4.4121
4	3.7094	3.2321	3.2103	3.6105	3.5879	3.4962	3.2343	3.6617	3.5037	3.6573	3.6275	3.6643	3.6676
5	4.6494	4.5638	4.5642	4.5675	4.6825	4.571	4.5639	4.7268	4.6604	4.6849	4.7055	4.6455	4.6566
6	4.7074	4.7121	4.7154	4.6617	4.7078	4.6874	4.7121	4.7271	4.7154	4.7337	4.7393	4.7413	4.7398
7	4.2339	4.0581	4.0688	4.2035	4.1910	4.1389	4.0583	4.2159	4.1973	4.1899	4.1887	4.1931	4.1907
8	4.5807	4.3104	4.3722	4.5291	4.5071	4.4603	4.3104	4.5805	4.4973	4.5848	4.5774	4.5816	4.5822
9	4.3563	4.2021	4.2226	4.282	4.3224	4.2659	4.2021	4.3574	4.3321	4.3275	4.335	4.3248	4.3501
10	4.5602	4.7035	4.8257	4.7238	4.8107	4.5657	4.7035	4.6449	4.6885	4.6816	4.7470	4.6537	4.5951
11	3.6890	3.9956	4.0164	3.6912	3.9182	3.6762	3.9956	3.7137	3.8137	3.7098	3.7160	3.7097	3.7093
12	4.8000	4.4238	4.4279	4.6842	4.6456	4.6602	4.4238	4.7783	4.6906	4.7872	4.7929	4.7846	4.794

enhancement methods like QDHE (Ooi and Isa 2010a), BHEPL (Ooi et al. 2009), ACMHE (Santhi and Banu 2015) and DQHEPL (Ooi and Isa 2010b). Recursive separated RSWHE (Kim and Chung 2008) and a histogram modification technique SHMS (Chang and Chang 2010) also belong to the same class. Furthermore, the proposed scheme is also examined with recently developed BHE3PL (Lim et al. 2015) technique and all the results are arranged in form of separate tables. In addition, graphical plots for each parameter have been included to examine different aspect of the output images. Optimization-based approaches include handling the same problem with other optimization techniques such as bat algorithm and ABC algorithm. All the experiments were performed on an Ubuntu Linux personal computer system having 3.1 GHz Intel Core i7 processor with 6 GB of RAM. The main reasons behind selecting these methods are due to the exploitation of traditional histogram-based approach. These methods are mainly focused on sub-histogram, histogram clipping or dynamic histogram equalization schemes.

Table 6 Comparison of PSNR values computed by different enhancement methods and proposed approach

Test images	PSNR											
	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	13.4111	13.9369	19.2724	18.0893	20.4791	13.4093	20.8137	18.2391	17.9800	17.2952	18.3709	19.0845
2	12.0554	13.0908	19.8303	16.6554	22.0331	12.0551	21.2545	18.6063	20.8993	21.2686	21.8043	22.5092
3	10.1476	13.9008	22.2859	16.5000	18.8509	10.1473	23.8187	17.1800	19.1807	19.4724	19.4928	20.5264
4	11.5786	11.6438	17.7395	19.9242	21.3662	11.5376	29.1567	23.3663	23.6439	24.8966	25.3669	26.6758
5	13.9125	13.8795	18.1872	15.9032	20.0268	13.9091	16.1003	17.2181	17.1808	16.2716	17.0834	18.9539
6	14.6269	14.5609	18.9031	16.504	20.6308	14.6269	17.5862	17.2322	17.6288	16.7115	18.1698	18.9079
7	11.4319	12.8336	18.5107	17.8795	21.5295	11.4298	20.6714	19.7377	20.6828	19.1069	21.4937	22.7715
8	13.0439	14.6422	19.2967	16.6480	21.2993	13.0439	19.4814	18.2134	18.2697	17.5528	18.9340	19.9005
9	11.6876	12.4829	18.5604	16.1733	20.7443	11.6876	19.7772	17.6355	21.0166	21.7987	20.8896	22.6444
10	13.5659	14.9939	20.7806	15.9346	22.0412	13.5659	20.6495	18.7833	20.7758	18.4091	21.3654	23.5919
11	10.6898	10.9204	11.2485	15.9593	12.3925	10.6898	21.359	17.3458	19.8506	18.4739	20.699	23.1277
12	14.3015	14.4337	20.5434	17.1515	21.7283	14.3015	20.2283	19.7655	21.4053	22.3482	21.6758	24.5132

Table 7 Comparison of SSIM values computed by different enhancement methods and proposed approach

Test images	SSIM											
	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	0.80926	0.79426	0.87429	0.88791	0.90272	0.80902	0.93832	0.8845	0.87781	0.88113	0.89372	0.90833
2	0.69437	0.6706	0.86246	0.82793	0.91808	0.69342	0.9185	0.8678	0.9011	0.9159	0.92759	0.94025
3	0.57603	0.63585	0.8463	0.75347	0.8719	0.57546	0.92225	0.77347	0.75798	0.76846	0.75477	0.81788
4	0.26931	0.37426	0.8775	0.84686	0.89464	0.26825	0.97196	0.92838	0.94055	0.94517	0.95592	0.9656
5	0.67523	0.67348	0.85359	0.78491	0.8739	0.67502	0.83427	0.81812	0.8213	0.79155	0.80734	0.87342
6	0.80641	0.80683	0.8869	0.85931	0.91073	0.80641	0.89984	0.8662	0.89222	0.87316	0.90283	0.91572
7	0.57554	0.56347	0.86836	0.81871	0.90513	0.57506	0.93685	0.87027	0.90302	0.86226	0.91836	0.9394
8	0.61207	0.6348	0.80956	0.74615	0.87976	0.61207	0.85304	0.80369	0.78891	0.77348	0.80633	0.85095
9	0.51877	0.51322	0.8247	0.7354	0.8418	0.51877	0.89168	0.80051	0.85129	0.87576	0.84668	0.90003
10	0.74639	0.73974	0.87649	0.79316	0.94577	0.74639	0.92094	0.90151	0.90336	0.86346	0.91875	0.95139
11	0.4204	0.42127	0.69797	0.69361	0.70837	0.4204	0.91555	0.76117	0.85474	0.81609	0.87418	0.91859
12	0.66751	0.65785	0.84488	0.78714	0.87392	0.66751	0.89334	0.85119	0.89669	0.9290	0.90221	0.94872

5.9 Performance evaluation

For the performance evaluation, 12 images contaminated with low contrast are selected from different databases. The input images are represented in Fig. 3. From the visual analysis of the output images, it can be noticed that the proposed technique provides best results for almost all sample images and the presented technique is robust for low-contrast images. Generally, a particular technique gives best result for a special kind of image only and may not be useful for different purpose such as dark or low-contrast images. Robustness toward different kind of images provides an additional quality of the proposed approach. Enhancement results and histogram plots of the proposed and existing methods for sample image 1 are shown in Figs. 4 and 5, respectively.

In this paper, low-contrast images with diverse features are considered to show the effectiveness and robustness of the proposed algorithm over other conventional methods. The main aim of the proposed approach is to preserve the mean brightness and quality enhancement of low-contrast images. The mean brightness preservation criterion is addressed by AMBE parameter. The plot in Fig. 18 shows that proposed algorithm always produces better results in

Table 8 Comparison of CPP values computed by different enhancement methods and proposed approach

Test Images	CPP												
	Org	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	0.8802	2.4031	2.5006	1.3539	1.5737	1.3342	2.4041	1.3971	1.536	1.5709	1.7741	1.5653	1.4769
2	1.0824	2.7995	2.7525	1.6177	2.2288	1.9728	2.802	1.7205	2.2629	1.8095	1.7761	1.7522	1.7006
3	1.4069	3.6956	2.9541	2.1905	2.6269	2.374	3.6975	1.9752	2.6707	2.3300	2.3058	2.3149	2.2129
4	1.9335	7.9488	6.5233	2.6363	3.1932	2.794	7.9912	2.3252	2.6062	2.4985	2.5143	2.4548	2.3449
5	4.0733	10.392	10.416	6.6998	8.9171	6.5701	10.395	8.2004	8.2342	8.3467	8.8513	8.4797	7.5002
6	1.3498	2.6366	2.6509	1.9002	2.3577	1.9133	2.6366	2.2745	2.2644	2.2733	2.3594	2.2698	2.2261
7	1.2749	4.4972	4.1942	2.1857	2.8921	2.2636	4.4985	1.8897	2.6079	2.2933	2.4269	2.2408	2.1136
8	2.2975	6.0354	5.2671	3.9186	4.6109	3.6192	6.0354	3.7796	4.4370	4.2920	4.4725	4.1952	3.9228
9	2.8240	10.095	9.9805	4.8223	7.1626	5.2799	10.095	5.1956	6.2279	5.4541	5.1834	5.503	4.8978
10	3.8209	9.3839	8.5441	5.8893	7.8866	5.7608	9.3839	6.3259	7.0292	6.3400	7.1147	6.2576	5.6807
11	2.5929	16.129	16.216	7.9747	9.9845	8.5349	16.129	5.6467	8.3885	6.6531	7.3969	6.2963	5.3875
12	1.4043	2.7397	2.7004	2.0824	2.4447	2.128	2.7397	2.1445	2.2733	2.0426	1.9808	2.0288	1.8706

terms of mean brightness. QMC measures visual quality and plot of QMC values are shown in Fig. 17. As shown in the plot, the proposed method offers a good balance between visual quality and enhancement parameter. CPP and SSIM values are complementary to each other when the value of one is improved and other one goes below, since CPP measures contrast without any structural similarity consent. CPP and SSIM plots are presented in Figs. 22 and 21, respectively.

The SSIM values of the proposed scheme are always higher than all other methods; thus, the value of CPP is lower, yet it is greater than original image value. Hence, the contrast of the image is boosted but not so much to distort its similarity index from the original image. Discrete entropy is a measure of information content in the image. The values of DE for different images and methods are shown in Fig. 19. The discrete entropy value is lower than other methods and the original image itself. Since, entropy measures information content, higher value means higher information which can be greater than the image itself. PSNR values and DE values are related in this scenario, as entropy value can even increase by the presence of noise component so PSNR value which measures peak signal as compared to noise power is also calculated simultaneously. As shown in Fig. 20, PSNR value is always higher than other implemented methods.

Figure 4 presents simulation results of proposed and existing methods together for the input images in Fig. 3a. The processed image in Fig. 4l is denoting the balance level of enhancement with respect to other methods like HE (Gonzalez et al. 2009), BBHE (Kim 1997) and ACMHE (Santhi and Banu 2015). On comparing the histogram of each enhanced image included in Fig. 5 with respect to the input image histogram, the proposed algorithm is seen to be preserving the original shape of the histogram to a certain extent. The color and brightness appearance of the proposed enhanced images shown in Fig. 4l, Figs. 6l to 16l are very similar to corresponding input test images included in Fig. 3a–l. Test image Fig. 3a, c is slightly darker; still the output image using proposed scheme produces homogeneous and smooth texture which can be noticed from Figs. 4l and 7l, respectively.

The color of the proposed images should be maintained to avoid over enhancement of image. For the effective color preservation, the contrast enhancement methods are applied over intensity component of the image. The color preservation is readily seen from the satellite images presented in Figs. 11, 12, 13, 14, 15, 16. A clear vision of better feature preservation ability using proposed approach can be easily seen from Fig. 8l. For the image Fig. 8, all methods except the proposed, ABC and BAT methods give poor enhancement results, because the shirt of the lady is changing from its natural color to whitish in the lower part

Table 9 Comparison of AT values computed by different enhancement methods and proposed approach

Test images	AT											
	HE	BBHE	BHEPL	QDHE	ACMHE	SHMS	RSWHE	DQHEPL	BHE3PL	ABC	BAT	Proposed approach
1	0.23635	0.43235	1.6311	0.2845	0.42764	0.33642	0.29822	0.28506	0.68742	69.2246	65.539	85.0189
2	0.03623	0.10498	0.12699	0.03773	0.14103	0.03629	0.03864	0.03914	0.0363	68.3566	65.5727	81.1152
3	0.06375	0.12602	0.19749	0.06383	0.20697	0.06383	0.06729	0.07946	0.065925	78.1962	73.3506	90.3114
4	0.05981	0.12558	0.17419	0.06145	0.15121	0.05984	0.06402	0.07422	0.062122	78.5027	73.8722	90.9645
5	0.03857	0.10562	0.12972	0.03497	0.13309	0.03456	0.03518	0.03799	0.033655	69.8305	65.0468	80.4154
6	0.0363	0.09554	0.13819	0.03438	0.12872	0.03383	0.03648	0.03686	0.034324	68.2177	65.9574	84.6606
7	0.03676	0.09568	0.11953	0.0342	0.13387	0.03478	0.0418	0.03668	0.034357	68.3595	65.8173	87.1246
8	0.0361	0.0967	0.13648	0.03424	0.1500	0.03428	0.0375	0.03686	0.033912	69.2358	66.4605	82.3542
9	0.03492	0.09952	0.12466	0.0342	0.13582	0.03425	0.03557	0.03703	0.033914	70.7007	66.5940	82.0538
10	0.03675	0.0979	0.1419	0.03484	0.15412	0.0360	0.03565	0.03745	0.034391	70.0598	66.2806	82.0791
11	0.03963	0.10845	0.11932	0.0401	0.11078	0.04037	0.04098	0.04364	0.039298	67.9170	64.5633	79.7915
12	0.03527	0.09654	0.13875	0.03388	0.14431	0.03553	0.03738	0.03688	0.034489	63.6981	61.0610	75.0071

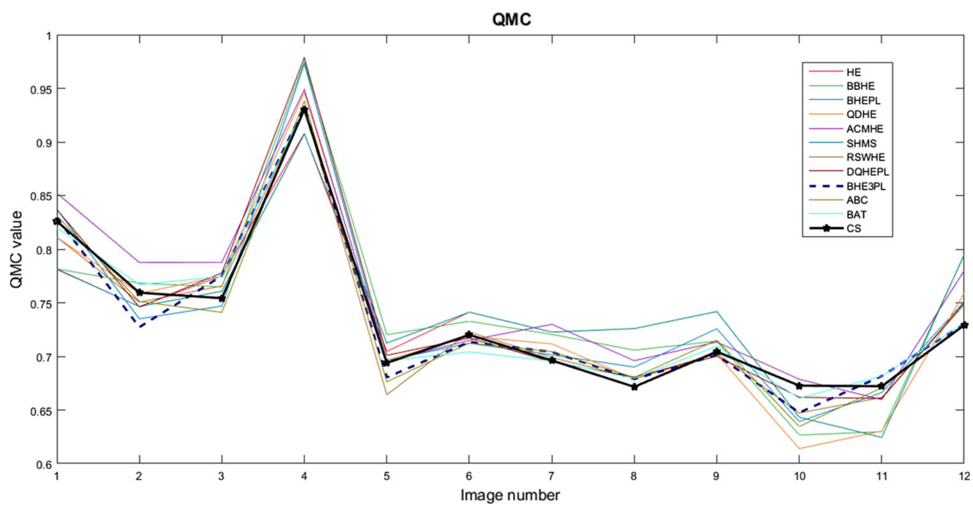

Fig. 17 QMC performance graphs for each test images using different methods

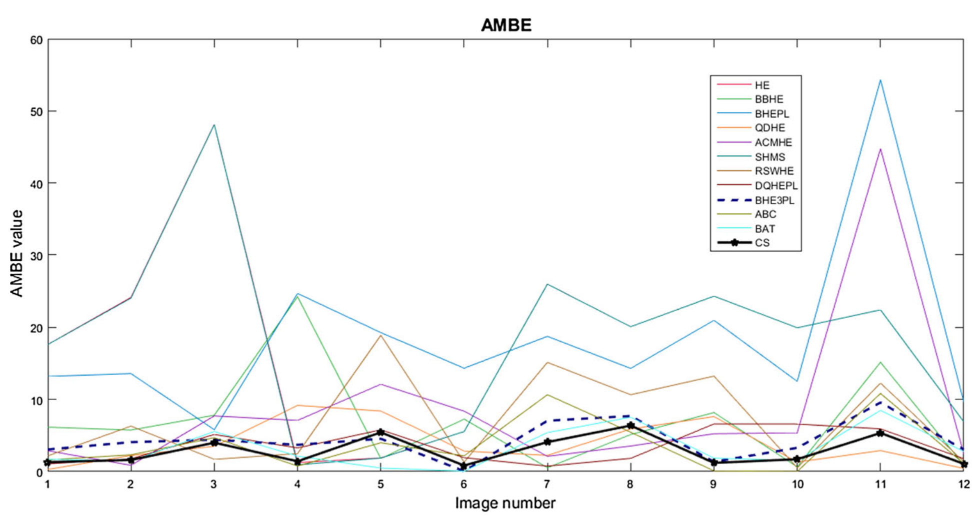

Fig. 18 AMBE performance graphs for each test images using different methods

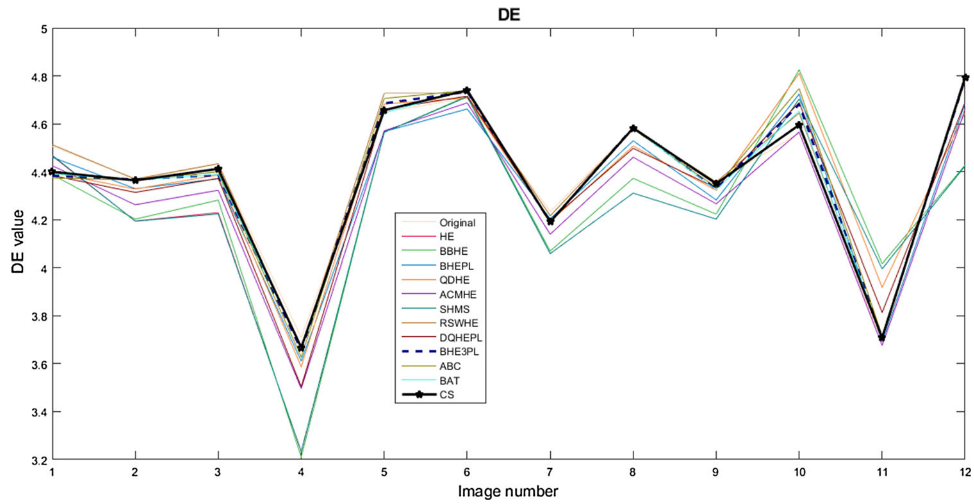

Fig. 19 DE performance graphs for each test images using different methods

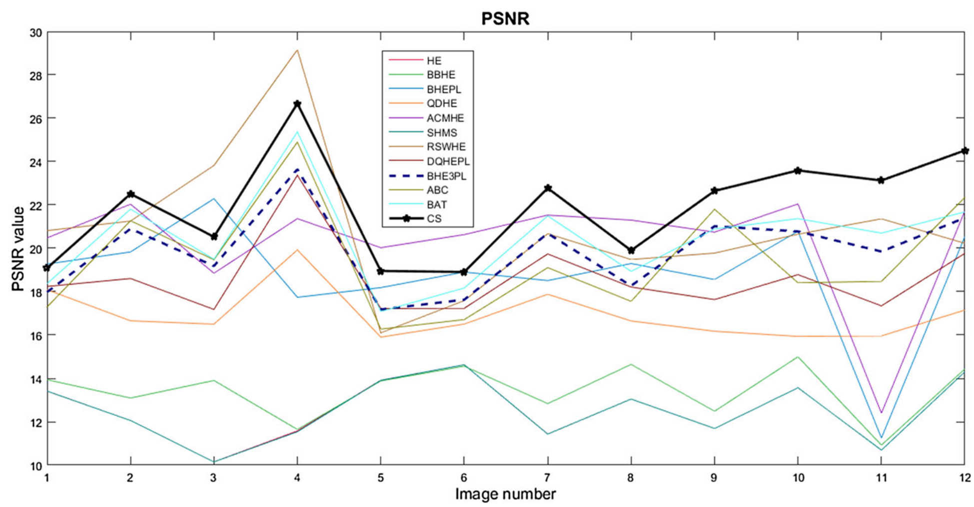

Fig. 20 PSNR performance graphs for each test images using different methods

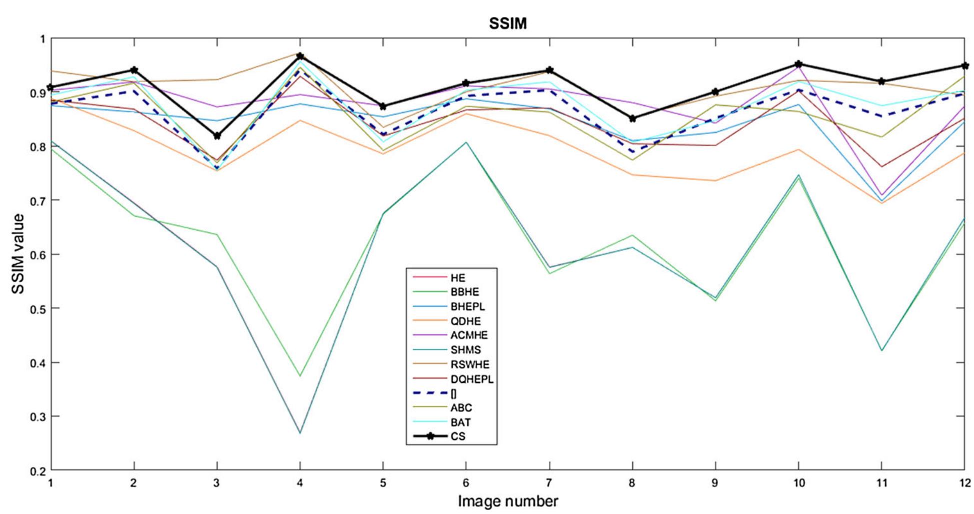

Fig. 21 SSIM performance graphs for each test images using different methods

of the image. Subsequently, few traditional techniques completely fail on this image and produce over enhanced outcomes such as in Fig. 8a, b, f. The proposed algorithm is very effective in preserving the mean brightness and yet providing good results even in case of dark images as seen from Figs. 6 and 7. In case of satellite images considered in

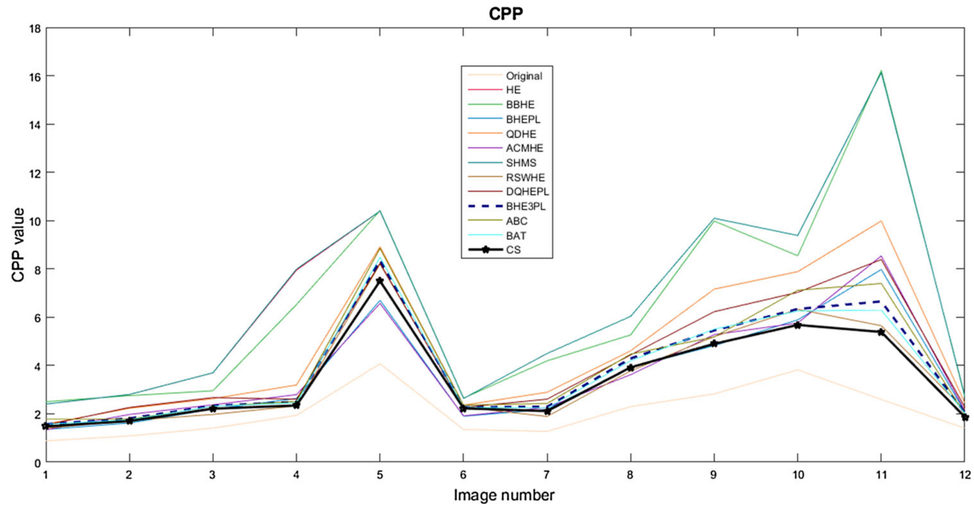

Fig. 22 CPP performance graphs for each test images using different methods

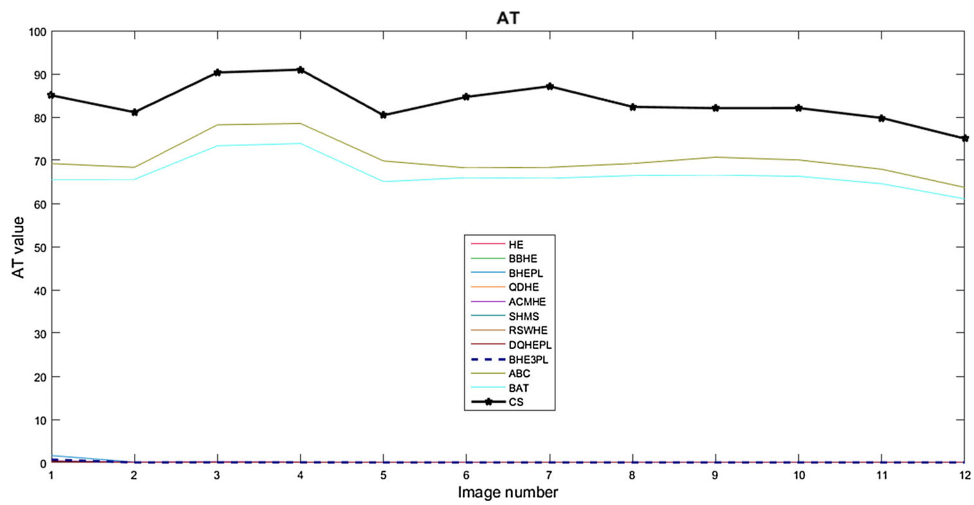

Fig. 23 AT performance graphs for each test images using different methods

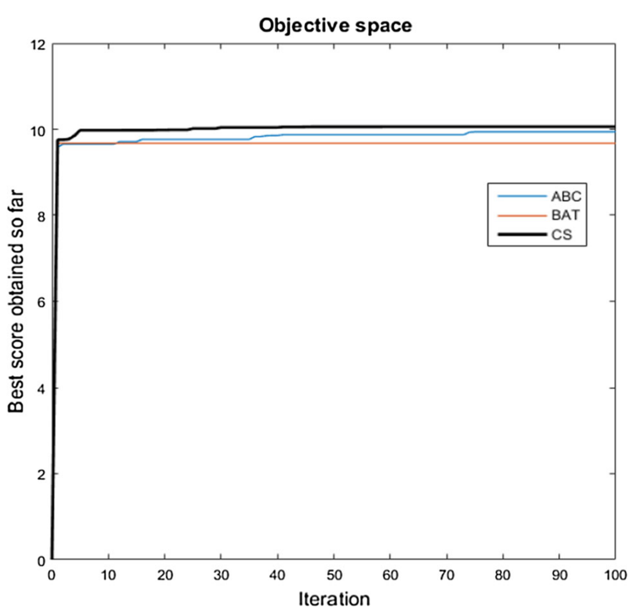

Fig. 24 Convergence plot for Image 1

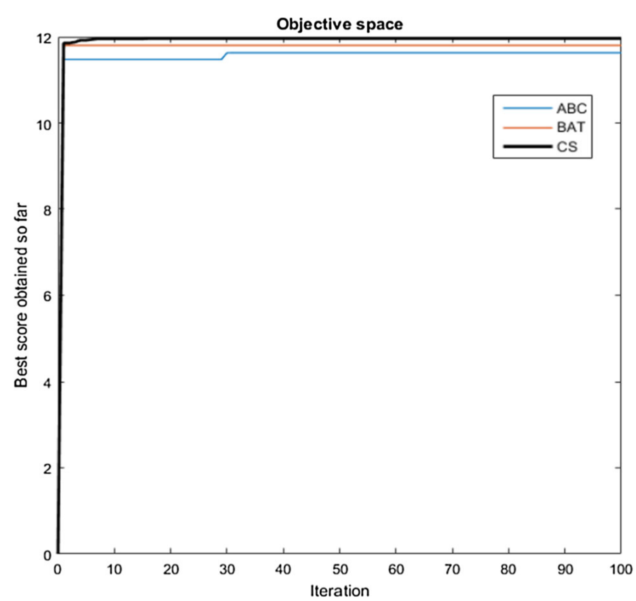

Fig. 25 Convergence plot for Image 2

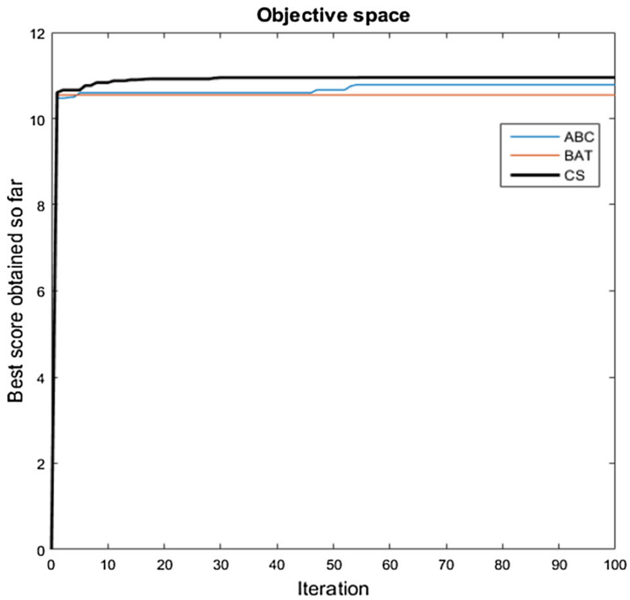

Fig. 26 Convergence plot for Image 3

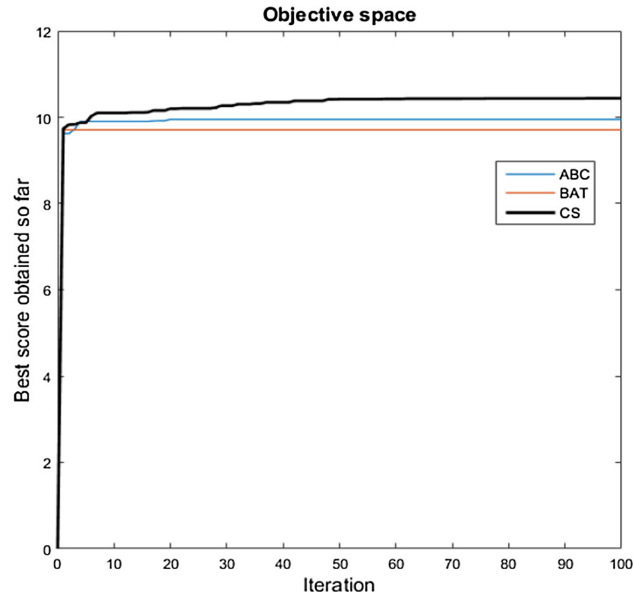

Fig. 28 Convergence plot for Image 5

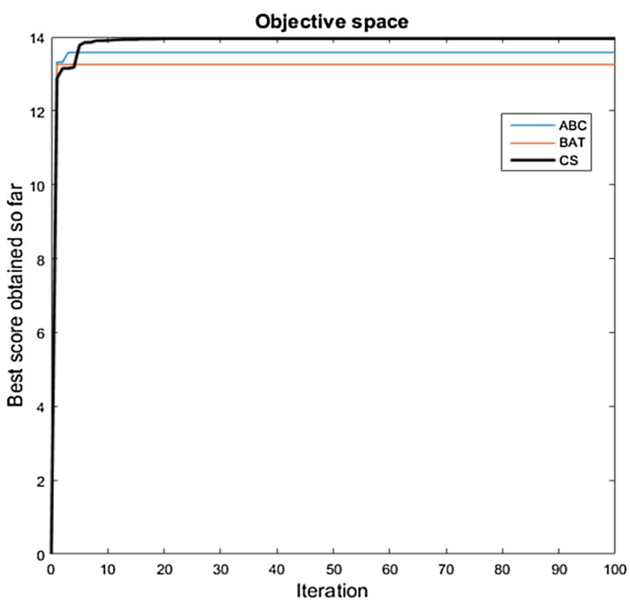

Fig. 27 Convergence plot for Image 4

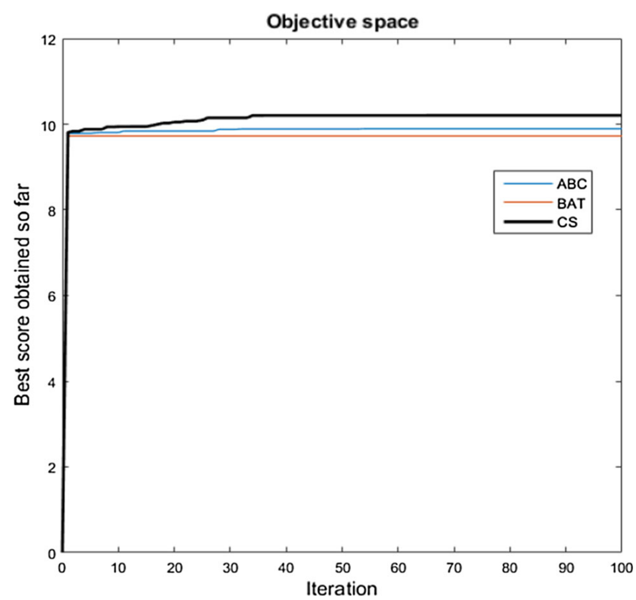

Fig. 29 Convergence plot for Image 6

Figs. 11, 12 and 15, proposed algorithm provides the optimum level of enhancement without degrading the natural quality and actual color of the image.

Images in Fig. 3a–f are standard image processing data set, but in this paper, these images are further converted to low-contrast images to check the robustness of the proposed scheme toward such kind of degradation. The resulting images after enhancement with different approaches are presented in Figs. 4, 6, 7, 8, 9, 10, respectively for standard images. The feature preservation is readily observed in the results of Fig. 3c as the color of the hairs is washed in the algorithms HE, BBHE, QDHE and SHMS. The computed performance parameters have been compared qualitatively from Figs. 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, and are tabulated numerically in Tables 3, 4, 5, 6, 7, 8, 9 for each method. Moreover, the plots presented in Figs. 17, 18, 19, 20, 21, 22 depict the qualitative and quantitative supremacy of the proposed method over well-known methods.

In addition, the complete performance comparison of each approach is presented graphically in Figs. 17, 18, 19, 20, 21, 22, which provides the distinct plots of the QMC, AMBE, DE, PSNR, SSIM and CPP, respectively, where the proposed scheme supersedes the traditional image

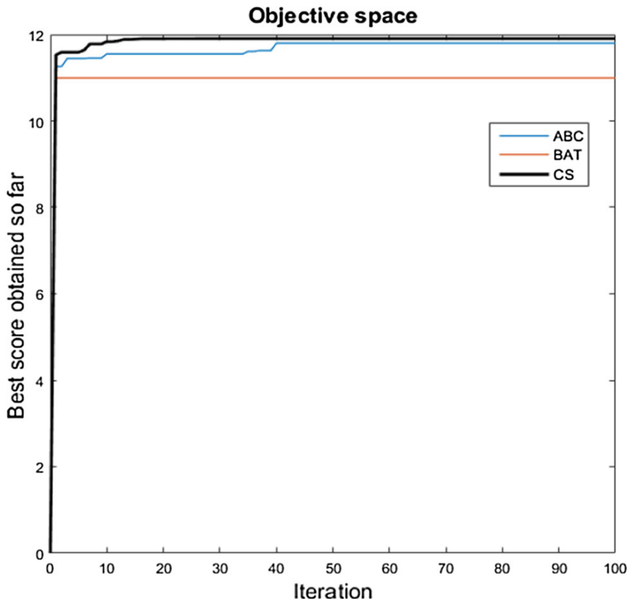

Fig. 30 Convergence plot for Image 7

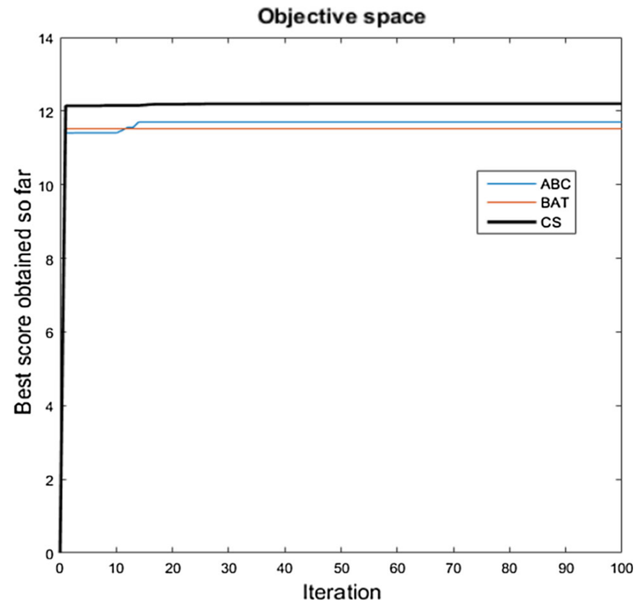

Fig. 32 Convergence plot for Image 9

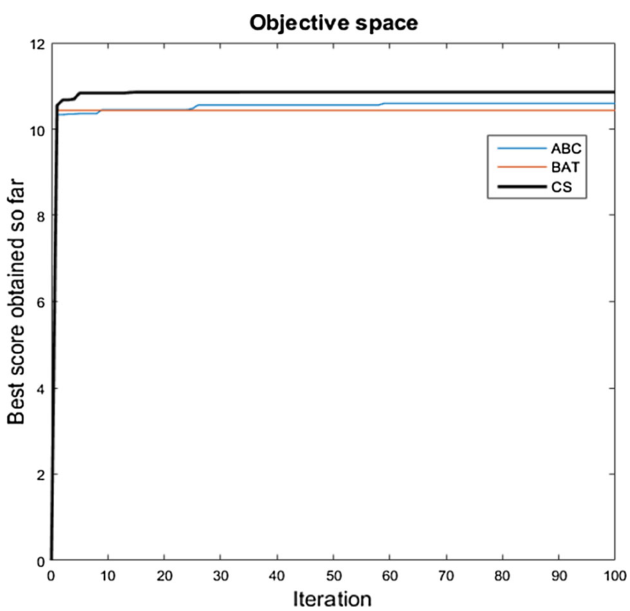

Fig. 31 Convergence plot for Image 8

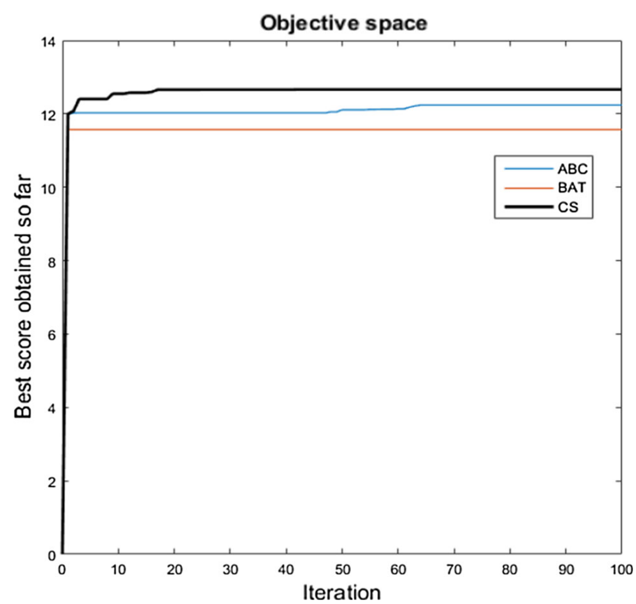

Fig. 33 Convergence plot for Image 10

enhancement systems by realizing the finest image visual features and the optimum brightness performance. The proposed algorithm has a demerit in the terms of computational time complexity due to the presence of optimization algorithm. Therefore, to achieve better contrast and feature preserved enhanced image, time complexity has to be compromised. For clear validation of the proposed CS-based scheme, two new recently introduced metaheuristic techniques, ABC and BAT algorithms, are also implemented in similar way and compared. It is observed that ABC and BAT algorithms outperform existing approaches such as HE (Gonzalez et al. 2009), BBHE (Kim 1997), QDHE (Ooi and Isa 2010a), BHEPL (Ooi et al. 2009), ACMHE (Santhi and Banu 2015), SHMS (Chang and Chang 2010), RSWHE (Kim and Chung 2008), DQHEPL (Ooi and Isa 2010b), and BHE3PL (Lim et al. 2015). However, among all methods, CS-based approach is superior, but ABC and BAT are also producing satisfactory results, and these two algorithms are little faster than the proposed CS-based approach.

Satellite images often need enhancement in the presence of uncertainty, caused due to the factors like highly

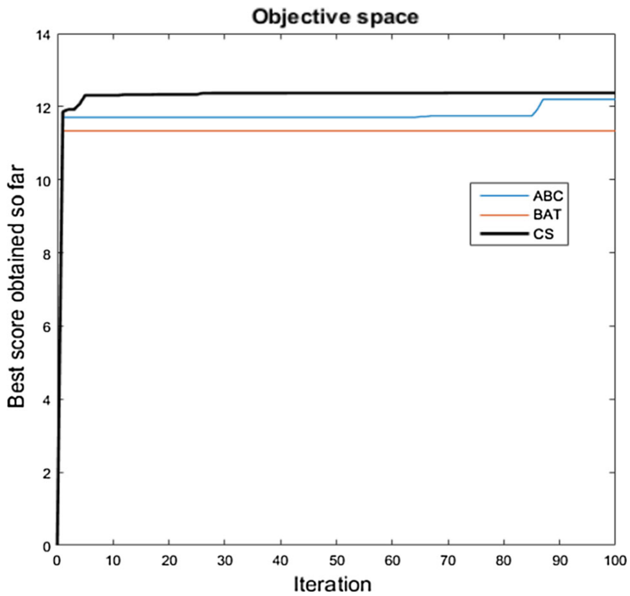

Fig. 34 Convergence plot for Image 11

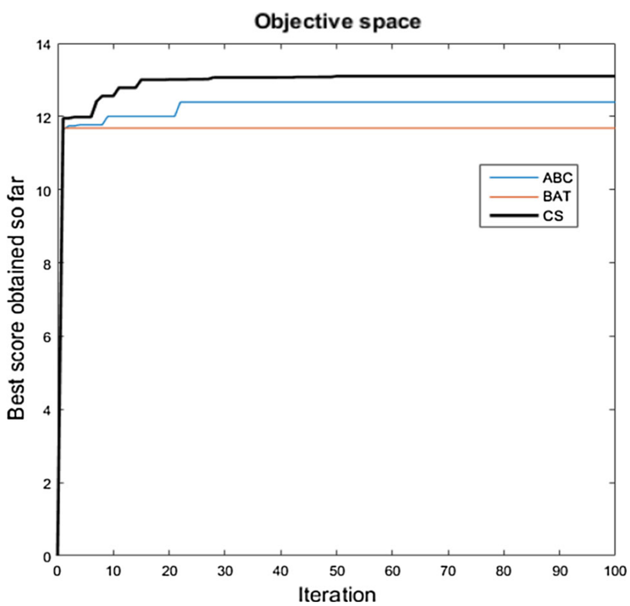

Fig. 35 Convergence plot for Image 12

dependent on environmental conditions, poor resolution and low illumination and have very low spatial resolution. In the proposed approach, the main challenge is the selection of objective function which must enhance the contrast of an input image without effecting its basic feature and detail information such as abrupt improvement in brightness and extreme contrast enhancement. In this paper, three-channel-based optimized enhancement algorithm is designed to get more appropriate naturalness color with brightness preservation for low-contrast satellite images.

Table 10 Wilcoxon test for ABC, BAT and CS algorithm

Test image	CS versus ABC		CS versus BAT	
	h-value	*P*-value	*H*-value	*P*-value
1	1^+	2.50E−04	1^+	6.41E−13
2	1^+	7.05E−05	1^+	5.12E−02
3	0	NaN	0	NaN
4	1^+	1.91E−06	1^+	2.30E −21
5	1^+	4.81E−05	1^+	6.53E−27
6	0	1.59E−02	1^+	2.65E−05
7	1^+	2.30E−12	1^+	3.71E−23
8	1^+	8.42E−23	0	3.24E−05
9	1^+	2.12E−02	1^+	7.20E−03
10	1^+	2.13E−16	1^+	4.02E−02
11	0	NaN	1^-	7.50E−05
12	1^+	4.41E−05	1^+	1.21E−01

Therefore, a distinct study on the application of CS algorithm is made for color image enhancement with naturalness color preservation using optimal plateau limits. For the entire standard test images including satellite images that have been considered, the CS algorithm performs well and is better than HE, BBHE, QDHE, BHEPL, ACMHE, SHMS, RSWHE, DQHEPL, BHE3PL, ABC, and bat algorithms. The experimental results provide the evidence of outstanding performance, accuracy and convergence of the proposed algorithm as compared to other methods. On the other hand, it is found that the computational cost of CS is slightly more as compared to ABC and Bat algorithm. The computational cost of the optimization technique can be further reduced by selecting multiobjective or different variant of CS algorithm in the future works (Figs. 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35).

5.10 Wilcoxon signed-rank test

A new rank-based statistical test has been introduced by the researcher (Derrac et al. 2011) to evaluate the decisions discussed in the experimental study. Wilcoxon signed-rank test is a nonparametric statistical hypothesis test used to assess the performance of the proposed methods with other optimization algorithms. The test has been conducted with a 5% significance level to test the significant difference between algorithms. In the tests, the optimization algorithms are evaluated on the basis of mean value of the objective function computed by each algorithm on different test cases. In Wilcoxon signed-rank test, the null hypothesis is framed as: there is no substantial difference between the means of included algorithms, whereas alternative hypothesis is formulated as: there is noteworthy difference between the means of included algorithms. In order to show the performance of CS algorithm, Table 10 has been included to depict the p value and h-value computed by Wilcoxon test which reports the test of all 100 runs on each test image.

In Table 10, h-value = 1^+ reports significant improvement in the outcomes of CS algorithm as compared to the ABC and BAT algorithms, h-value = 0 represents both optimization techniques are statistically identical results, and h-value = 1^- indicates the significant worst performance of the CS algorithm as to the ABC and BAT algorithms. Furthermore, NaN shows that the data computed by CS versus ABC and CS versus BAT algorithms are equal and therefore, there is no difference between them. The proposed CS-based approach performs significantly better than ABC and BAT algorithms almost each test case. The Wilcoxon rank test results validate the efficacy of the CS heuristic method in improving the performance of employer nature-inspired algorithms.

6 Conclusion

A novel cuckoo search-based image contrast enhancement approach has been proposed with the aim of feature and brightness preservation factors. At first the histogram is divided into two sub-histograms. Then 3 plateau limits are calculated and optimized using a cuckoo search algorithm for each sub-histogram and histogram of the image is modified using those limits. Conventional histogram equalization is applied thereafter. Several experiments were performed to check the effectiveness of the proposed method over other traditional methods, and it is concluded that proposed algorithm not only enhances the low-contrast images but also does not affect the images having higher contrast. Experimental results reveal that the proposed method outperforms other state-of-the-art methods in terms of quantitative as well as qualitative measures. The proposed scheme produces highest SSIM, PSNR, DE and optimum QMC, AMBE, CPP values for almost all the cases. This approach is mainly focused on producing high-quality images with respect to brightness preserved contrast enhancement to reduce maximum artifacts without losing basic image features. However, due to optimization technique being employed to obtain the best solution parameters, the time complexity of the problem is increased marginally.

To reduce time complexity, different optimization algorithms can be tried and best one should be chosen for the appropriate time complexity and convergence rate. As a scope of future work, the proposed algorithm can be used as an objective function for various swarm and evolutionary optimizing techniques to get computationally efficient and more optimum enhancement results. This method can also be useful for enhancement of medical images, weakly illuminated images as well as remote sensing images for various applications.

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Compliance with ethical standards

Conflict of interest All authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with animals performed by any of the authors.

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