ORIGINAL RESEARCH

A logarithmic law based histogram modification scheme for naturalness image contrast enhancement

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Abstract

In this paper, a new logarithmic histogram modification technique for image contrast enhancement with naturalness preservation has been proposed. Traditional histogram equalization scheme usually causes extreme contrast enhancement, which results in unnatural look and artifacts. The proposed technique first enhances the contrast of the image globally through addition and logarithmic law based modification scheme, thereafter the local details of the image are emphasized through the coefficient scaling directly in the compressed domain using discrete cosine transformation. The proposed method can enhance the image contrast uniformly with less number of parameters without losing its basic features. Experimental results show that the proposed method preserves the natural appearance of the image and yields better perceptual quality as compared to the state-of-the-art techniques.

1 Introduction

Image enhancement is an important and attractive field of image processing, where the subjective quality of the image is essential for human interpretation. Contrast enhancement is an image enhancement technique used for both computer vision and human perception. Image quality improvement is a renovation applied to the raw input image to produce enhanced image with selectively emphasized region of interest. The contrast enhancement techniques are very diverse, broadly classified into two categories: direct enhancement method and indirect enhancement method (Gonzalez and Woods 2002; Goyal et al. 2018; Malik et al. 2018; Bhandari et al. 2018; Arici et al. 2009). Histogram equalization (HE) is most commonly used histogram processing technique, which aims to equalize the probability density function so that it can match uniform distribution approximately (Gonzalez and Woods 2002). HE has mean shift problem, which implies that the mean brightness is often very far from the input image mean brightness, which is not desirable in many

cases or different application-oriented images such as satellite and medical images. To overcome these limitations, numerous researchers have offered different approaches to improve the enhancement quality of the HE-based approaches. Brightness preserving bi-histogram equalization (BBHE) (Kim 1997) was the earliest work on preserving the brightness of the original input image in the enhanced output image.

Furthermore, dualistic sub-image histogram equalization (DSIHE) (Wang et al. 1999) has been proposed to overcome the enhancement limitations. Although, these techniques are visually pleasing than the convention HE technique but they do not offer any controllability for over enhancement and are not very robust to noise. Afterward, a relatively new technique named as image contrast enhancement method for preserving mean brightness (ICEPMB) (Huang and Yeh 2013) was proposed which employed an automatic histogram separation block using PSNR based segmentation followed by intensity transformation block. Another new approach has been proposed towards the histogram modification framework using gamma correction methods. Adaptive gamma correction with weighting distribution (AGCWD) (Chiu et al. 2011; Rani and Kumar 2014) uses the idea of defining a separate gamma for every bin available in the histogram. The value of gamma is obtained from the

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modified cumulative distribution function (CDF) value and it is adaptive to the image.

Recently, a simple histogram modification scheme (SHMS) is proposed (Chang and Chang 2010) to solve the patchiness effect and washed-out appearance in the image through the application of conventional HE method. 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 non-zero bins to combat patchiness effect. This technique can be applied to the single threshold as well as multi-threshold histograms such as BBHE and DSIHE methods. However, for the case of multiple thresholds, relatively higher degree of brightness preservation is required to avoid generation of artifacts in the enhanced images. Consequently, quadrants dynamic histogram equalization (QDHE) (Ooi and Isa 2010) enhances the image by dividing the original image histogram into four sub-histograms, which are based on the median brightness of the input image.

Unlike the above methods, the weighted histogram approximation method (WAHE) (Arici et al. 2009) does not modify the original histogram directly by transformation function. Only the pixels having sufficient contrast with respect to their neighbors are counted in the histogram to avoid extreme change of smooth areas. Then, a weighted histogram approximation method is applied for further smoothing of the histogram. Finally, contrast stretching is performed to exploit the dynamic range of gray-levels method which is effective on the histogram pits only. Furthermore, gamma correction and addition based histogram modification (GCAHM) (Wang and Chen 2017) has been proposed through the combination of gamma correction and WAHE method to get more improvement which makes it suitable for the pits as well as spikes in the histogram.

Histogram equalization is a simple image contrast enhancement (CE) method but it produces excessive enhancement and creates unnatural artifacts on images with high peaks in their histograms. Therefore, many advancement have been reported in the literature towards the image contrast and brightness preservation related issues. In 2013, a novel scheme to enhance the image and video contrast has been presented through Bezier curve (Cheng and Huang 2013). In 2014, for real time image processing applications, a new hardware-based CE method has been proposed which have simple design to implement on hardware. In this paper, approximation concepts are considered to minimize the time complexity (Huang and Chen 2014). In 2015, a histogram-based locality-preserving contrast enhancement (CE) algorithm has been introduced (Shin and Park 2015), which aims to preserve locality of the input image histogram while enhancing the global contrast. Recently, an adaptive CE method has been proposed by considering both the shape of a 1D histogram and statistical detail on the gray-level differences among neighboring pixels computed by a 2D

histogram (Kim and Kim 2017). Thereafter, a CE technique termed stratified parametric-oriented histogram equalization (SPOHE) is presented to efficiently produce a district and improved outcome without introducing any visual distortion such as halo or blocking effects, which is usually present in the previous streamlined image enhancement techniques (Liu et al. 2017a, b).

Due to significant performance in contrast and brightness enhancement areas, histogram based method continuously attracts many researchers to solve image enhancement related problems. Kumar et al. (2012) proposed a new method for low-contrast satellite image enhancement based on the singular value decomposition (SVD) and discrete cosine transform (DCT), which is obtained after processing through the traditional HE method. Subsequently, in 2014, they have introduced another two new approaches by exploiting the concept of the cuckoo search algorithm and artificial bee colony to get the optimum contrast and brightness enhancement using DWT–SVD for satellite image, which is also first processed by traditional HE. Later, in 2016, an improved knee transfer function and gamma correction based algorithm has been developed to realize the contrast and brightness enhancement of satellite images (Bhandari et al. 2016). Although various methods have been proposed to formulate the specific problem of contrast enhancement, these approaches have improved image qualities in a miscellaneous way especially by exploiting histogram-based methods. Enhancement of many natural images poses special challenges, because there may be less spectral variation from pixel to pixel and most importantly, there may be a high degree of correlation among the data from different sources. Therefore, to overcome these drawbacks, this paper addresses problems of quality enhancement, which is mainly focused to obtain a good trade-off between mean brightness preservation and contrast enhancement along with other basic parameters. In this paper, an effective histogram modification framework using DCT-μ, and DCT-A techniques for brightness preserved color satellite image enhancement has been proposed.

The rest of the paper is organized as follows. Section 2 gives an overview of discrete cosine transform. Section 3 provides a detailed discussion of the traditional histogram equalization and histogram modification technique. The proposed method is discussed in Sect. 4. Section 5 provides experimental results and discussion. Section 6 concludes the paper.

2 Motivation and overview of DCT

To overcome the problem of over and under area improvement issues, a group of researchers proposed many new techniques to achieve brightness preserving contrast

enhancement. Celik and Tjahjadi (2011) have proposed a contextual information and variational model based image contrast enhancement algorithm. Further, they have proposed an automatic image contrast improvement scheme via histogram equalization and gaussian mixture modeling theory to perform nonlinear data mapping for producing visually pleasant enhanced images (Celik and Tjahjadi 2012). Likewise, a two-dimensional histogram equalization based image contrast enhancement method has been introduced which exploits the contextual detail nearby each gray level value (Celik 2012). In 2016, he has proposed a new method for global contrast enrichment through spatial mutual information (SMI) of gray scale information of an input image and PageRank algorithm

$$\alpha_k = \left\{ \begin{array}{ll} \frac{1}{\sqrt{2}} & k = 0 \\ 1 & else \end{array} \right\} \qquad (2)$$

It can be assumed that the component corresponding to (0, 0) i.e. y (0, 0) is the largest energy component or DC component which contain average value of sample image. The DCT helps to separate the image into spectral sub-bands of differing importance. The contrast enhancement using DCT is based upon the fact that lower absolute value of $y (k, l)$ represents a lower energy component means lesser spatial details.

Inverse discrete cosine transform is used to obtain image back from the frequency domain which is defined as:

$$x(m, n) = \sqrt{\frac{2}{M}} \sqrt{\frac{2}{N}} \sum_{k=0}^{M-1} \sum_{l=0}^{N-1} \alpha_k \alpha_l \, y(k, l) \times \cos \frac{(2m+1)k\pi}{2M} \cos \frac{(2n+1)l\pi}{2N} \qquad (3)$$

((Celik 2016). Recently, a simple and proficient fusion-based methodology have been developed through the combination of different image processing concepts to improve the contrast of the weakly illumination images (Fu et al. 2016). In order to overcome the shortcoming of the above methods, another brightness preserving adaptive contrast enhancement scheme has been proposed which uses 1D and 2D histogram models (Kim and Kim 2017).

The foremost reason behind proposing this scheme is to mainly overcome the problem of over and under enhancement that can be seen in many histogram based methods. The proposed algorithm can well enhanced the low contrast images with more naturalnesss, color preservation ability, and also prevents the artificial colors in the enhanced image unlike the other approaches. Furthermore, the proposed algorithm can well maintain the details of the image while sustaining the natural presence of the image. In this scheme, the local details of the image are emphasized through the coefficient scaling directly in the compressed domain using DCT. The computational time of the proposed method is also very less as compared to other methods.

The DCT is a technique to obtain frequency information from the signal. DCT works by representing the signal as the sum of weighted *cosine basis functions, which* are *orthogonal* in nature (Khayam 2003). For M × N image the 2-D cosine basis functions are computed by multiplying the horizontally oriented 1D cosine basis with a vertically oriented set of same functions. Thus, the transform can be given as:

$$y(k, l) = \sqrt{\frac{2}{M}} \sqrt{\frac{2}{N}} \alpha_k \alpha_l \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} x(m, n) \\ \times \cos \frac{(2m+1)k\pi}{2M} \cos \frac{(2n+1)l\pi}{2N} \qquad (1)$$

3 Histogram equalization and modification

Several image contrast improvement approaches compute mapping function from the traditional HE technique or the modified type. Traditional histogram equalization method tries to determine a enhance image with a histogram which is as close to an identical allocation as possible.

3.1 Histogram equalization

The traditional histogram equalization offers exploitation of original histogram to obtain mapping function and attempts to achieve an image with histogram close to a uniform distribution.

Let I be an input image with a gray level range $[0, K - 1]$. The probability density function can be defined as:

$$p(k) = \frac{h_i(k)}{N} \qquad \text{for } k = 0, 1, \ldots, K - 1, \qquad (4)$$

where h_i is input image histogram and N is the number of pixels in the image.

Based on probability density function (PDF) the cumulative distribution function (CDF) can be defined as:

$$C(k) = \sum_{l=0}^{k} p(l) \qquad \text{for } k = 0, 1, \ldots, K - 1 \qquad (5)$$

Conventional HE maps the input intensity k to output intensity $T(k)$ using the following transformation function:

$$T(k) = \lfloor (K - 1) \times C(k) + 0.5 \rfloor \qquad (6)$$

The mapping function is directly affected by the rate of increment of CDF function, which is directly proportional to PDF function value. Hence, if PDF has very high value

at some instant, then the rate of increment of CDF will be more and vice versa. This dependence will cause excessive brightness change for very high rate and patchiness effect for the very slow rate.

3.2 Addition based histogram modification (AHM)

To overcome the problem underlined in conventional HE, a suitable solution is to modify the histogram to the extent so that histogram peaks and pits are no more a problem in equalization and shape of the histogram i.e. ascending and descending pattern, is maintained. Let h be an input histogram and u be a uniform histogram then a complementary set of requirements i.e. pits and peaks are less and histogram shape is maintained, which can be obtained by objective function as defined in (Arici et al. 2009).

$$\tilde{h} = arg\,\min_{h} ||h - h_i||_2^2 + \lambda ||h - u||_2^2 \tag{7}$$

where $\tilde{h}, h, h_i$ and $u \in R^{K \times 1}$, and $\lambda \in [0, +\infty)$ is an adjustable parameter.

The solution to Eq. (7) can be given as:

$$\tilde{h} = \left(\frac{1}{1 + \lambda}\right) \times \left(h_i + \lambda u\right) \tag{8}$$

The modified histogram is thus a weighted average of original and uniform histograms. The level of enhancement can be varied by tuning the parameters. As the adjustable parameter is increased, the mapping function goes towards original one. As pointed out by (Arici et al. 2009) the AHM is effective on the pits in the histogram but it is not robust for histogram peaks.

4 Proposed method

In this section, the proposed scheme has been discussed in detail that is followed by comprehensive steps and an overall flowchart routine.

4.1 Global contrast enhancement

4.1.1 Logarithmic law based histogram modification

Since, the addition based contrast enhancement method is not very effective to overcome the spikes in the histogram of the image (Arici et al. 2009). Therefore, a logarithmic law based approach has been exploited to overcome such kind of problem for quality image enhancement. From the communication systems, we know that during speech coding to suppress the high-frequency components a phenomenon called companding (compressing–expanding) is utilized. In companding the higher frequency components are relatively

mapped to the smaller area over the amplitude axis, thus the number of bits used to represent the data is reduced. When data is received at receiver end it is expanded using the inverse law of the function utilized to compress it. In this paper, two forms of compander are used which are A-law and μ-law companders. Only compressing operation is required from the combined operation of compressing and expanding. To suppress peaks in the histogram of the image, a modified form of compander can be used which only affect the peaks and leaves the pits untouched.

For A-law

$$h_m(x) = \begin{cases} -Ah(x)/(1 + ln(A)) & h(x) < 1/A \\ -(1 + ln(Ah(x)))/(1 + ln(A)) & \text{otherwise} \end{cases} \tag{9}$$

For μ-law

$$h_m(x) = \begin{cases} \mu h(x)/(ln(1 + \mu)) & h(x) < 1/\mu \\ (ln(1 + \mu h(x)))/((ln(1 + \mu)) \times \ln(2)) & \text{otherwise} \end{cases} \tag{10}$$

where A is a parameter defined for companding. h_m is modified histogram and h is input histogram. Various levels of enhancement are obtained using the values of A or μ in corresponding laws.

4.1.2 Logarithmic law and addition based histogram modification

For suitable contrast enhancement without excessive brightness and patchiness effect a combination of addition and logarithmic law-based histogram modification is utilized.

Addition based histogram modification mentioned in Eq. (8) can be further simplified to represent it as the sum of the original histogram and weighted uniform histogram. Therefore, the logarithmic law based modifications are applied to the modified histogram. Hence, the resulting histogram can be given as:

$$h_f = CP\left(h_i + \delta\right) \tag{11}$$

where $CP(\cdot)$ is defined as compressing operation and h_f is the final modified histogram.

4.1.3 Selection of parameters

The effectiveness of the presented algorithm depends upon the value of the parameters used to control the level of enhancement. There are two tuning parameters in each case of compressor utilized in this paper. To choose optimum tuning parameter, in case of A-law, the value of A and δ, whereas in case of μ-law, values of μ and δ should be selected according to the fluctuant curve of the histogram.

4.1.3.1 The value of δ Addition of some value to the histogram can modify the histogram to make it nearer to the uniform histogram. Thus, the value of δ should be such that it improvises the varying nature of histogram. If the histogram is varying too much the value of δ should be higher to compensate and vice versa.

The standard deviation is the factor, which models the variability of the histogram. Thus, the parameter δ can be assumed to have a value equal to some fraction which depends upon the level of enhancement required. In this work, the value of δ is taken to be equal to the value of standard deviation:

$$\delta = \sqrt{\frac{1}{K}\sum_{k=0}^{K-1}\left[h_i(k) - \tilde{u}\right]^2} \tag{12}$$

where h_i is input histogram and $\tilde{u}$ is average of h_i.

4.1.3.2 The value of A/δ The parameters A/δ can overcome spikes in the histogram. A bigger value of parameter A/δ means more enhancements in the contrast. The value of the parameter A/δ should be related to the contrast of the image. Roughly, the contrast of the image is related to the standard deviation of the image. Hence, the value of A/δ is assumed to be a multiple of standard deviation. In this paper, the value of A/δ is taken to be 3/4th of the standard deviation.

4.2 Local detail enhancement

This paper is focused to achieve feature preserved image contrast enhancement. Therefore, with regards to enhancing the contrast of the image both globally and locally, we adopt the procedure defines in (Fu et al. 2015) for scaling the coefficients directly in the compressed domain. As defined above, the DCT is used to obtain coefficients in the frequency domain. For further improvement of the image contrast, DCT components are exploited in the compressed domain. The coefficients of the frequency domain having lower values are scaled up with factor alpha (α) if they are under certain limit as defined in (Khayam 2003):

$$\acute{y}(k,l) = \begin{cases} y(k,l) & if \ |y(k,l)| > 0.01 \times y(k,l) \\ \alpha y(k,l) & otherwise \end{cases} \tag{13}$$

The value of scaling factor $\alpha > 1$ controls the level of enhancement. Automatic selection of parameter alpha can be defined as below:

$$\alpha = 1 + \sqrt{\left|H(\tilde{I}) - H(I)\right|} \tag{14}$$

where $H(\cdot)$ is entropy of the image and $\tilde{I}$ is the image after global image contrast enhancement.

At last, the final output image is reconstructed back from the compressed domain using inverse DCT (IDCT). A very large value of parameter would cause over enhancement in terms of edges and details losses. Automatic parameter setting provides a good trade-off between the level of enhancement and detail preservation. The flowchart of the proposed algorithm is given in Fig. 1.

An overall detailed methodology with steps is given as below:

Step 1: As a first step, an input image with low contrast has been taken for processing.

Step 2: Separate out luminance and chrominance component of input image. Only luminance component is further processed for enhancement purpose.

Step 3: Histogram of the luminance component is obtained from the input image.

Step 4: Histogram of input image is modified sequentially, first by using addition based modification then compressing based operation. The parameter chosen for AHM and compressing are δ and A/δ, which are equal to standard deviation and 3/4th of standard deviation respectively.
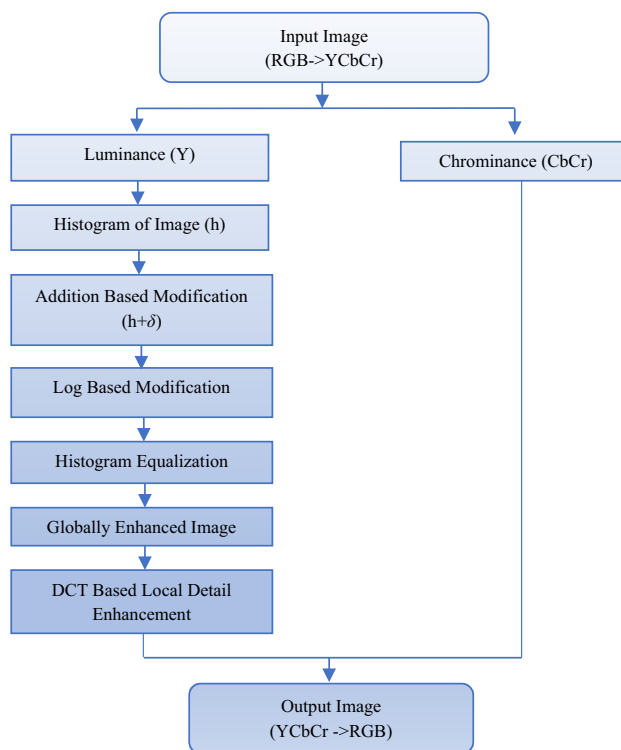

Fig. 1 Flow chart of DCT based method

Step 5: The luminance layer is equalized using the mapping function obtained from modified histogram.

Step 6: To improve local details, scaled value of DC component is utilized from the transformation matrix as in Eq. (13) with the parameter alpha (α), which is related to entropy of the image.

Step 7: The AC component of DCT of luminance component are modified according to Eq. (13). Then the image is reconstructed back to spatial domain by applying inverse operation.

Step 8: The original chrominance and modified luminance component are layered together to construct the final enhanced image.

5 Experiments and discussion

In this section, the experimental results are presented. Therefore, the performance of the proposed algorithm is evaluated using well-known image quality checking fidelity parameters such as SSIM, CPP, DE, PSNR, AMBE EME and MEME. Table 1 represents the fidelity parameter considered to test the efficiency of proposed method. The definition of different objective assessment parameters can be described as given below.

5.1 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:

$$\text{SSIM}(I, \tilde{I}) = \frac{(2\mu_I \mu_{\tilde{I}} + C1)(2\sigma_{I\tilde{I}} + C2)}{(\mu_I^2 + \mu_{\tilde{I}}^2 + C1)(\sigma_I^2 + \sigma_{\tilde{I}}^2 + C2)} \quad (15)$$

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

$$\mu_I = \frac{1}{N} \sum_{i=1}^{N} I_i \quad (16)$$

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

$$\sigma_{I\tilde{I}} = \frac{1}{(N-1)} \sum_{i=1}^{N} (I_i - \mu_I)(\tilde{I}_i - \mu_{\tilde{I}}) \quad (17)$$

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.

5.2 Constant per pixel (CPP)

Contrast per pixel (CPP) (Santhi and Banu 2015) 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:

$$C = \frac{\sum_{i=0}^{N} \sum_{j=0}^{M} (\sum_{(m,n) \in R_3^{(i,j)}} |\gamma(i,j) - \gamma(m,n)|)}{MN} \quad (18)$$

The higher value of CPP means better contrast.

Table 1 Comparison of MEME values computed by different algorithm and proposed method

Test images	MEME										
	Input Image	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT *A*-law	Proposed DCT μ-law
1	4.0414	20.6987	13.8031	14.8221	5.4065	20.6987	4.6935	8.2238	20.3152	7.1602	7.4274
2	70.3391	126.612	126.638	123.768	80.585	126.59	91.0251	90.0003	122.322	92.3825	93.8021
3	3.0821	6.1944	5.2959	5.9521	3.5769	6.2026	3.8246	4.7984	8.0089	4.3317	4.4023
4	0.49639	6.8779	1.8614	3.8254	1.0939	6.8453	0.94326	1.723	7.6230	0.88816	0.90934
5	46.5771	178.1799	180.1044	178.5406	58.8835	179.463	58.6403	79.4467	166.1089	62.6567	63.5696
6	2.4369	69.1601	28.4079	52.7304	3.0366	69.3153	5.392	12.686	34.6413	4.8622	4.9587
7	21.5231	43.6646	49.2197	46.2644	28.0038	43.6646	30.7686	30.8256	42.0011	30.0525	29.8827
8	13.5984	59.9118	43.5837	49.3200	23.9409	59.9118	25.1449	24.3028	64.7403	20.8203	21.8162
9	26.6582	57.3534	54.924	56.6179	37.884	57.3534	38.2738	38.0684	58.355	37.4902	35.4934
10	21.3189	53.537	50.6916	51.6654	30.9847	53.537	33.5825	33.3731	52.7613	34.7997	35.6038

5.3 Discrete entropy (DE)

Discrete entropy (DE) quantifies the information present in the image (Celik 2014). More is the information content more will be the entropy. The entropy is defined as:

$$DE(I) = - \sum_{\forall k} P(k) log(P(k)) \tag{19}$$

where $p(k)$ is PDF as defined in Eq. (4). A higher value of DE implies richer details.

5.4 Peak signal to noise ratio (PSNR)

Peak signal to noise ratio (PSNR) (Bhandari et al. 2014a, b) is performance metric used for the evaluation of the quality of the enhanced image. It represents 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:

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

where the RMSE can be defined as:

$$RMSE = \left(\frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \left| \tilde{I}_{xy} - I_{xy} \right|^2 \right)^{1/2} \tag{21}$$

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

5.5 Absolute mean brightness error (AMBE)

Absolute mean brightness error (AMBE) (Wang and Chen 2017) is defined as the difference between the mean intensity values of input and enhanced image.

$$AMBE = \left| \mu_{\tilde{I}} - \mu_I \right| \tag{22}$$

where μ_I is average intensity of image as defined in Eq. (16).

Smaller the AMBE value means the average intensity of input image is better preserved.

5.6 Modified measure of enhancement (MEME)

The parameter measure of enhancement (EME) is prone to noise and it does not mix with inter-block contrast, since it depends only upon the maximum and minimum value in a block, not on the distribution of the other values and there is no mixing of contrast measure blockwise. Hence, a modified version of the EME called MEME is given by (Wang and Chen 2017) as:

$$MEME = \alpha \times \frac{C_{I_{DC}}}{k_1 \times k_2} \times \frac{1}{k_1 \times k_2} \sum_{i=1}^{k1} \sum_{j=1}^{k2} C_{i,j}^w \tag{23}$$

where $k_1 \times k_2$ is number of sub-images. I_{DC} is a thumbnail image of I. $C_{i,j}^w$ and $C_{I_{DC}}$ are intra block and inter block contrast. C is defined as:

$$C = \sqrt{\frac{1}{L \times M} \sum_{m=1}^{L} \sum_{n=1}^{M} \left(I_{m,n} - mean(I_{m,n}) \right)^2} \tag{24}$$

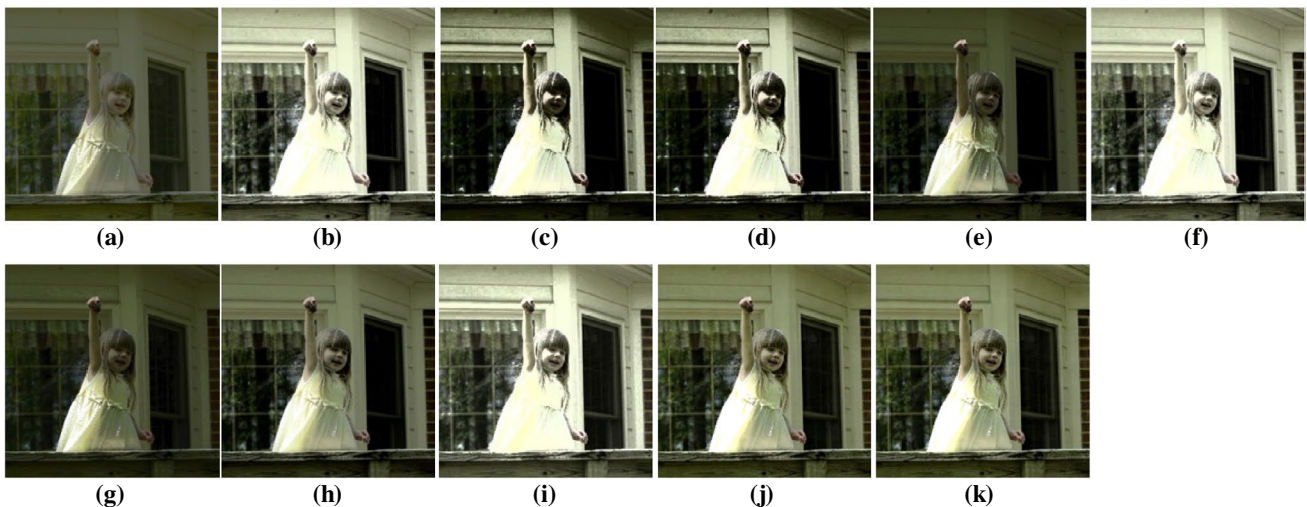where $M \times N$ is the size of the image I of interest.

Fig. 2 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A
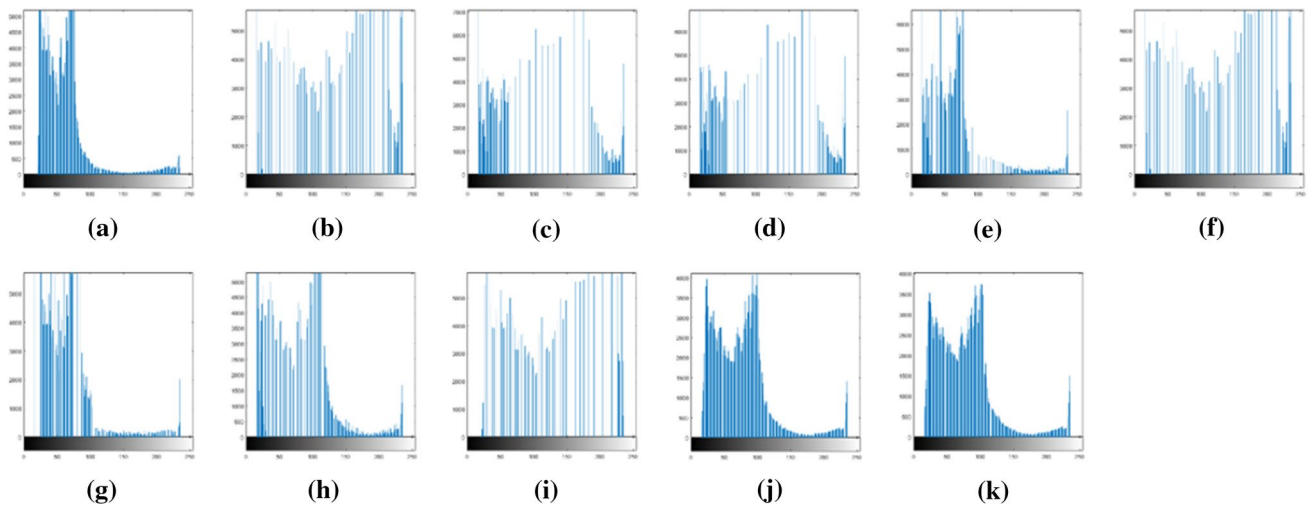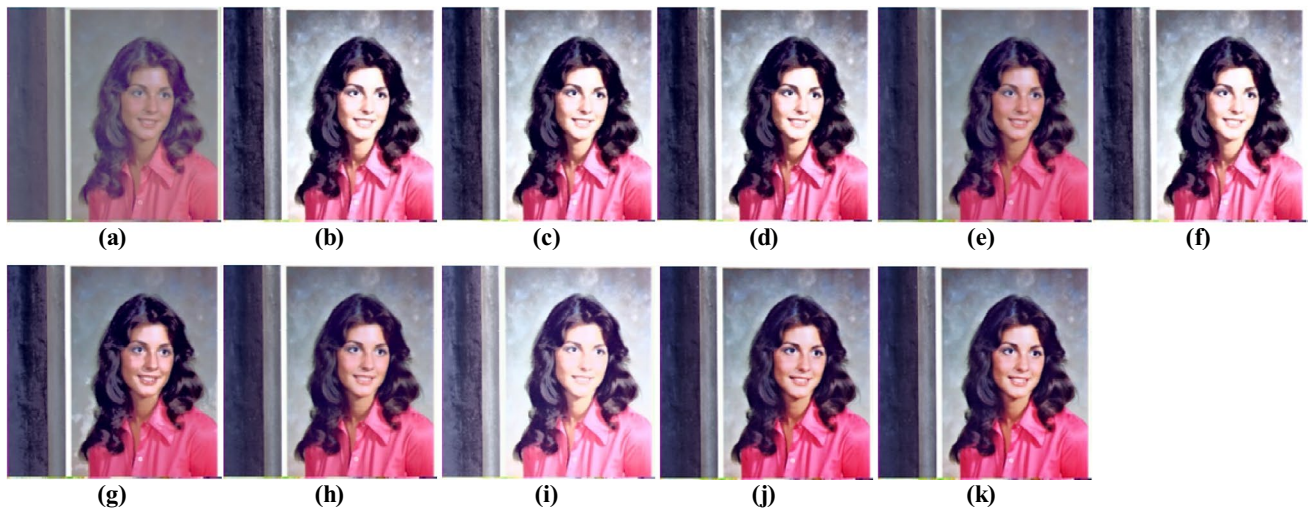
Fig. 3 Histogram image of **a** Original image, **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

Fig. 4 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

5.7 Subjective analysis

Ten images with diverse image feature are examined in this section for performance evaluation and enhancement quality checking. Generally, a particular state-of-the-art technique works best for a special kind of image only and may not be useful in a very wide sense for the different purpose. Towards robustness for different kind of images provides an additional quality of the proposed approach. Enhancement results and histogram plots of the proposed and existing methods are shown in Figs. 2 and 3, respectively. In each case, the proposed algorithm provides a better result as compared to other methods. It can be observed in Fig. 3 that

the histogram plots of the proposed approach preserve the original shape of the histogram in a better way. For example, the resultant image in Fig. 2j, k for the first test image has the highest contrast enhancement and the histogram of that image is best matched with the original histogram among all compared methods. The color appearance of the proposed output image is very similar to the concern input test image. The first test image is a dark image, still, the output image using the proposed scheme produces a homogeneous and smooth texture.

In the case of Fig. 4a, a background is close to a plain color and there is a probability of degradation in methods which are not controlling the rate of CDF function prior to
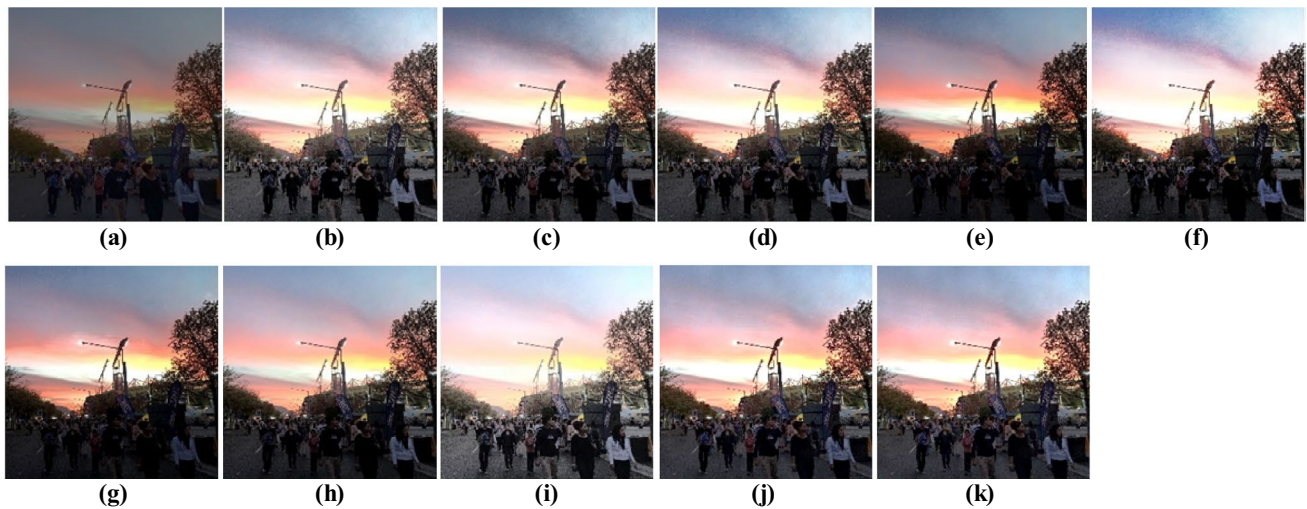
Fig. 5 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

Fig. 6 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

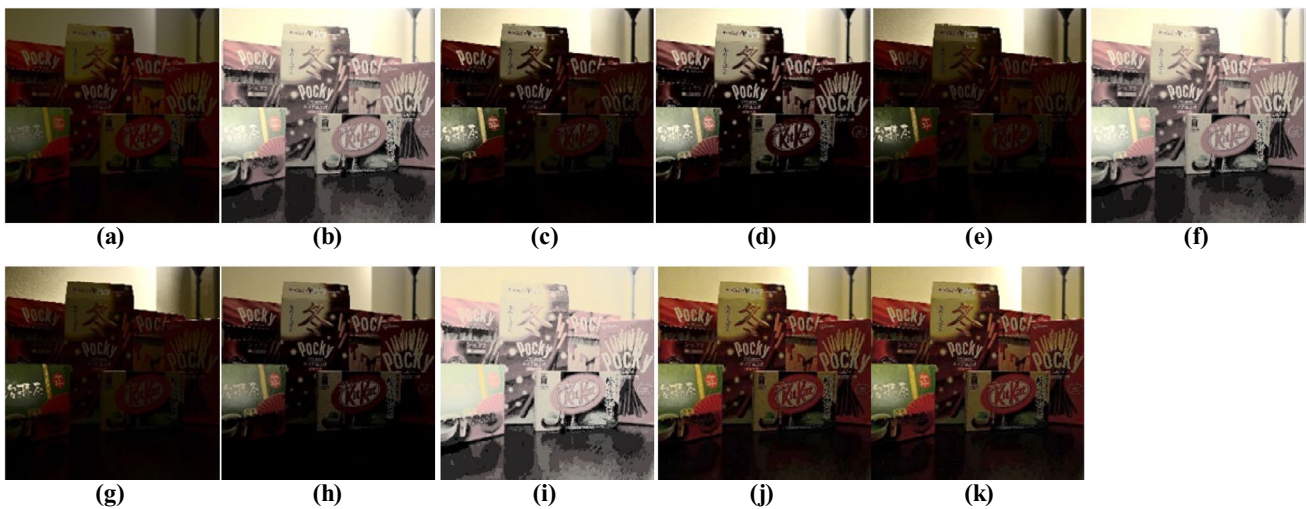applying histogram equalization such as BBHE, DSIHE and ICEPMB. Both *A*-law and *μ*-law methods provide comparable performances as seen from the histogram of the images. The proposed algorithm is very effective in preserving the mean brightness and yet providing good results even in the case of dark images also as seen from the Figs. 5 and 6. Likewise, Figs. 7 and 8 show optimum as well as balance level of enhancement provided by the proposed algorithm. Consequently, the input image in Fig. 7a shows the same trends in the enhancement level as in the image in Fig. 4a. It can be easily remarked from the enhancement quality of Figs. 4j, k and 7j, k that there is no loss of any feature or information. Similarly, in case of satellite images considered

in Figs. 9, 10, 11 and 12, proposed algorithm provides the optimum level of enhancement without degrading the quality of the image. Figures 13, 14 and 15 validate the superiority of the proposed method.

Global and local enhancement results using proposed method have been demonstrated in Fig. 16 for girl and lady image. In Fig. 16c, f, the color and detail improvement can be easily identified in the background and object region of the girl and lady image. On the other hand, illustrations provided in the Figs. 17, 18, 19, 20, 21, 22, 23, 24, 25 and 26 represent the enhanced images processed by different closely related techniques such as Fuzzy-Contextual Contrast Enhancement (FCCE) (Parihar et al. 2017), Exposure
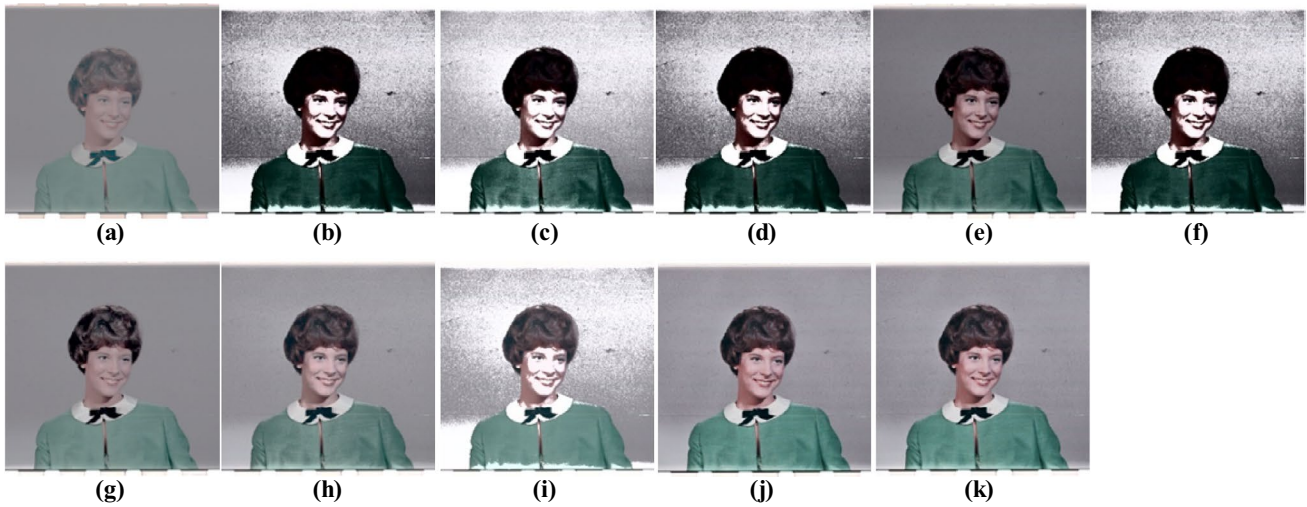
Fig. 7 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

Fig. 8 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

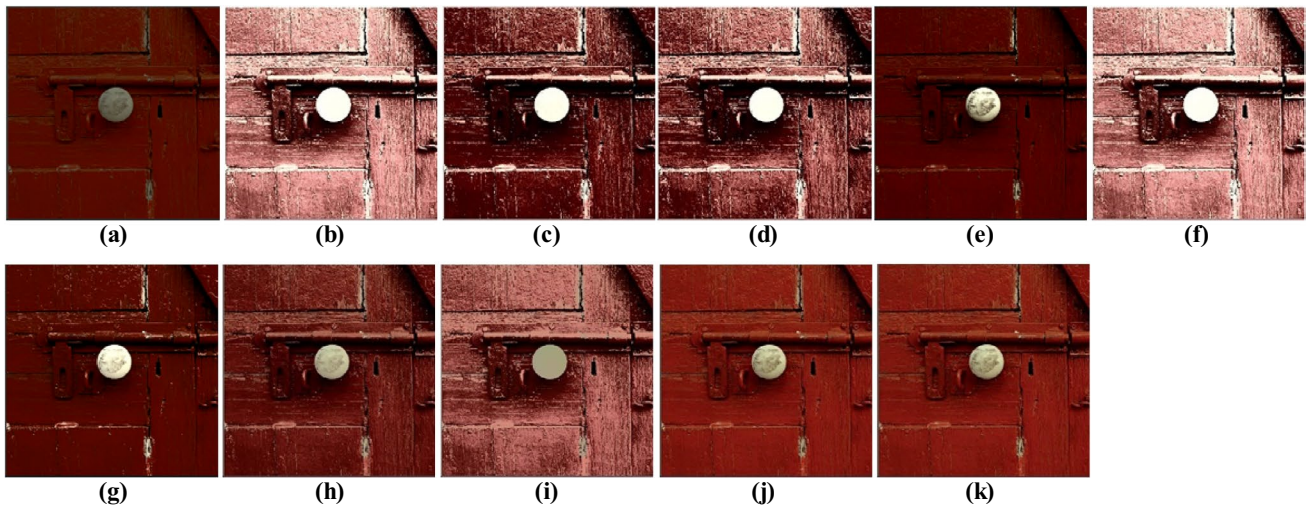Based Sub Image Histogram Equalization (ETHE) (Singh and Kapoor 2014), Dominant Orientation-based Texture Histogram Equalization (DOTHE) (Singh et al. 2016), Multiscale Retinex (MSR) (Liu et al. 2017a, b), and Dong's method (Dong et al. 2011). Furthermore, Fig. 27 depicts the original and corresponding output image using proposed scheme for five more satellite images. The satellite images demonstrated that the proposed method could well preserved the brightness and contrast of the original image without introducing artifacts.

5.8 Objective analysis

The proposed algorithm is compared to different well-known state-of-the-art techniques and results are arranged in form of separate tables for fair comparison of each parameter. In this paper, numerous famous enhancement techniques are included for better comparison of the proposed methodology, which are HE (Gonzalez and Woods 2002), BBHE (Kim 1997), DSIHE (Wang et al. 1999), QDHE (Ooi and Isa 2010), SHSM (Chang and Chang 2010), WAHE (Arici et al. 2009), ICEPMB (Huang and Yeh 2013) and AGCWD (Chiu et al. 2011). The reason behind selecting these methods is the exploitation of traditional histogram-based approach. These
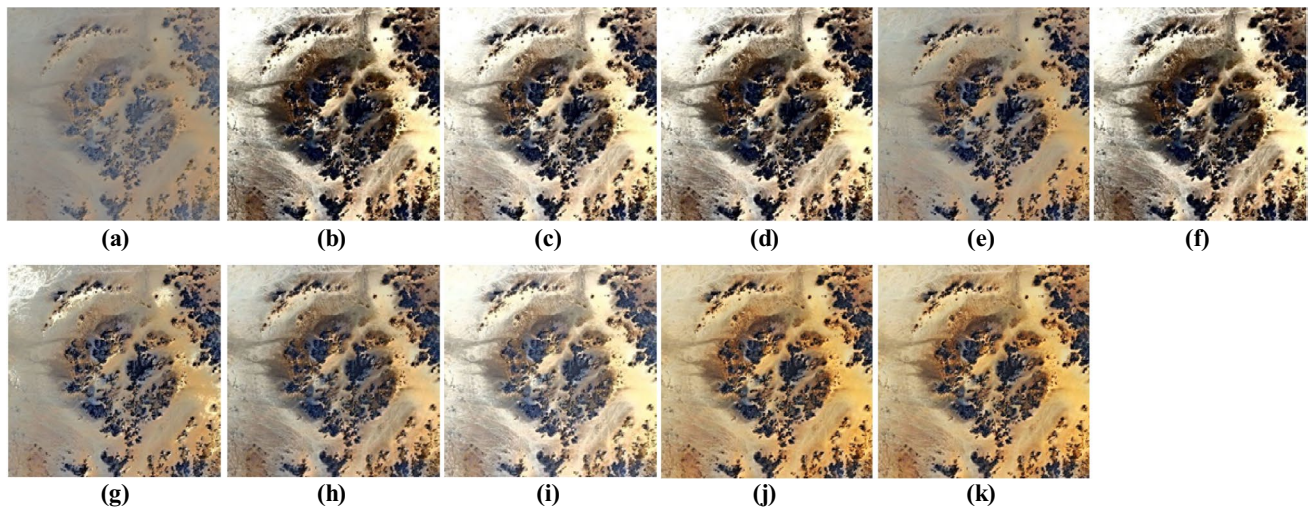
Fig. 9 **a** Original image processed by **b**HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

Fig. 10 **a** Original image processed by **b**HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-μ, **k** Proposed DCT-A

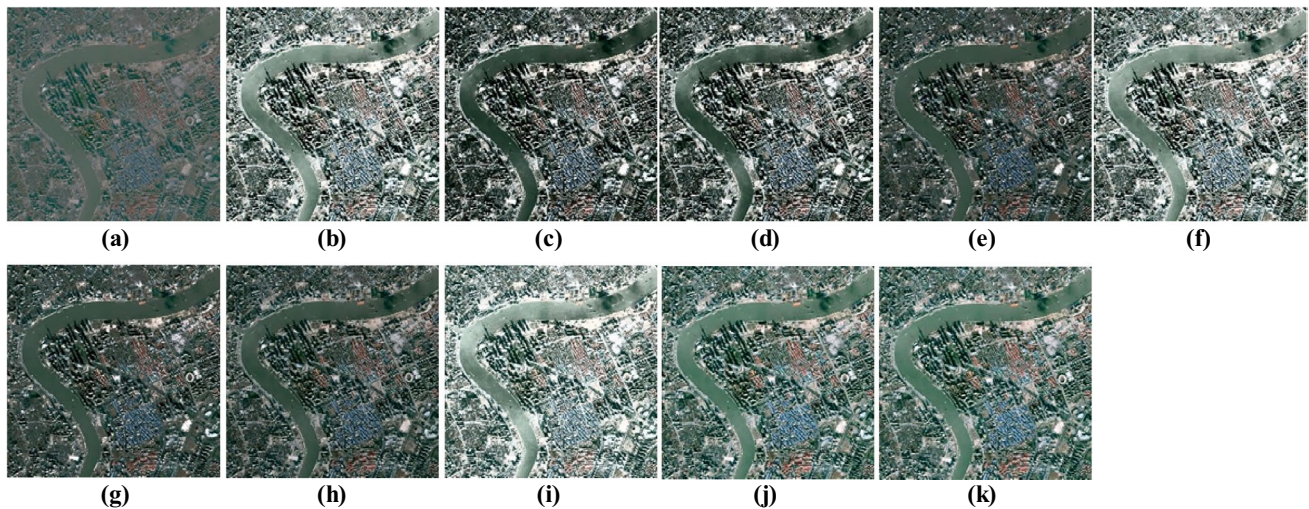methods are focused on sub-histogram, histogram clipping or dynamic histogram equalization schemes. Some of the techniques such as HE, BBHE, DSIHE, QDHE, SHSM, are related to histogram equalization, whereas WAHE is related to histogram modification-based techniques. Other compared techniques are ICEPMB and AGCWD, which are related to PSNR based segmentation and adaptive gamma correction respectively. In addition, the two versions of the proposed method is also presented with the parameters as described above in the proposed methodology section.

Figures 13, 14 and 15 report the graphical representation of the data presented in the tabular format from Tables 2, 3, 4, 5, 6 and 7, which provide a comprehensive study of each method along with the proposed approach. The discrete entropy is calculated over the intensity component of the image only and in case of discrete entropy, the proposed algorithm provides the best value in all the cases studied in this paper without any exception. Tables 2, 3, 4, 5, 6 and 7 report the performance metrics for each method. Since from the subjective evaluation, we can clearly see that ICEPMB lacks in the enhancement criteria, hence this is an expected result. SSIM (Wang et al. 2004; Bhandari et al. 2014a, b), presented in Fig. 15a, which measures the structural similarity between input and output images. It can be seen that the proposed algorithm provides a better trade-off between enhancement and preservation for the dark images too as
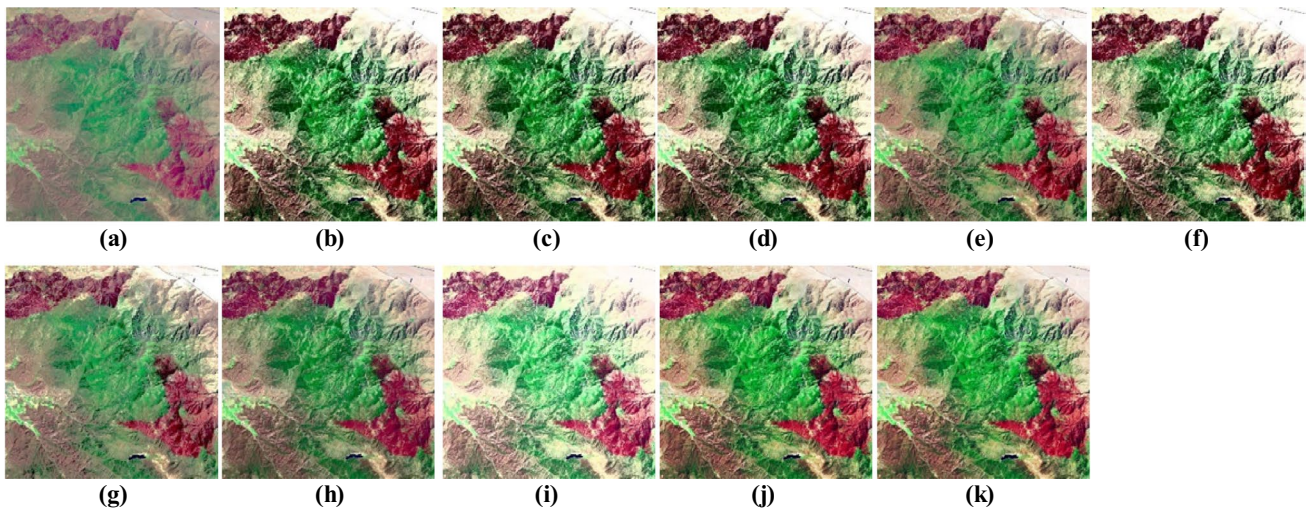
Fig. 11 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-µ, **k** Proposed DCT-A
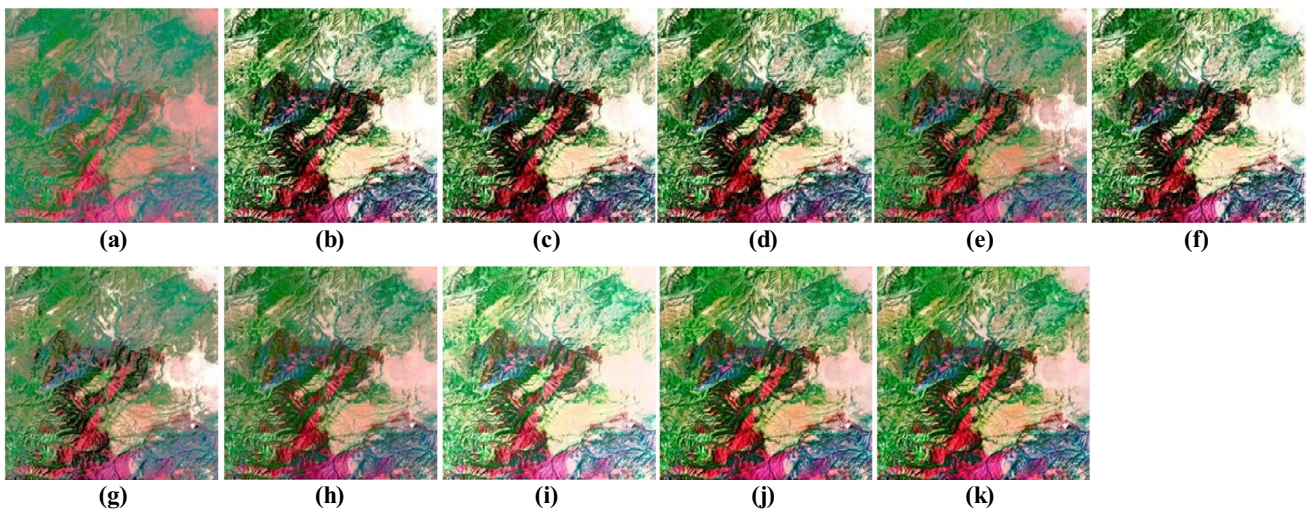
Fig. 12 **a** Original image processed by **b** HE, **c** BBHE, **d** DSIHE, **e** QDHE, **f** SHMS, **g** ICEPMB, **h** WAHE, **i** AGCWD, **j** Proposed DCT-µ, **k** Proposed DCT-A

compared to HE, BBHE, DSIHE, QDHE, SHSM, WAHE, ICEPMB and AGCWD methods.

The other parameters such as MEME (Wang and Chen 2017) and CPP (Santhi and Banu 2015) are related to the level of enhancement. MEME yields optimum values that is close to the MEME value of input image as shown in Fig. 13a. CPP provides higher values for almost each case as seen from the Fig. 15b. Since the proposed algorithm makes a tradeoff between the level of enhancement and structural similarity which is depending upon values of parameters employed in the proposed algorithm and can be tuned to get better performance. Moreover, the proposed techniques give the flexibility to adopt a suitable tuning parameter according to the need of enhancement, which may increase or decrease on the basis of the level of distortion level in an image. Thus, from the validated output enhancement results and histogram plots perspective, it can be concluded that the proposed method outperforms and it also overcomes the drawbacks of traditional HE method which possesses over enhancement and under enhancement properties. However, histogram based existing methods such as HE, BBHE, DSIHE, QDHE, SHSM, WAHE, ICEPMB and AGCWD introduce major changes in the image gray level when the image is low contrast or spread of the histogram is not significant.

From Figs. 28, 29, 30, 31, 32 and 33, it is clear that the proposed method produces the superior scores for MEME,
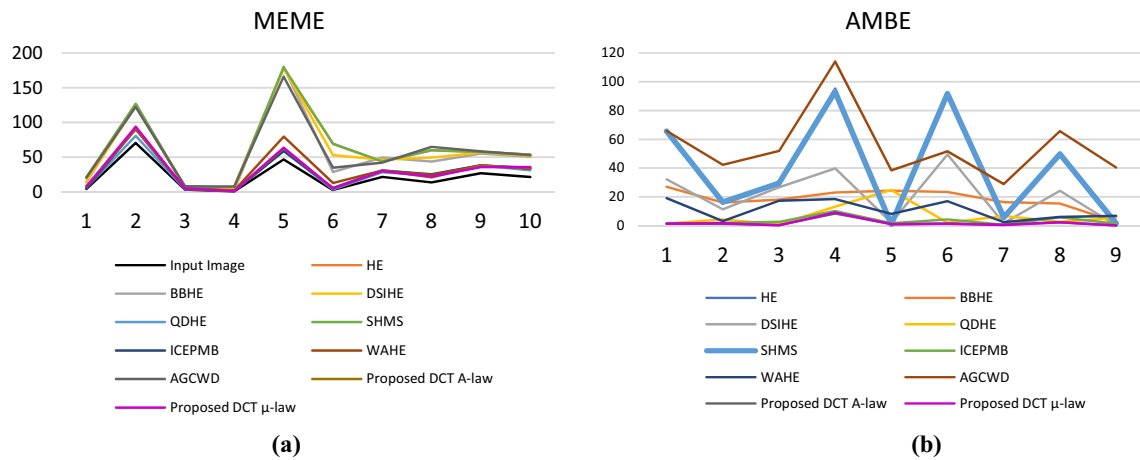
Fig. 13 a, b MEME and AMBE performance graphs for each test images using traditional and proposed method respectively

Fig. 14 a, b DE and PSNR performance graphs for each test images using traditional and proposed method respectively
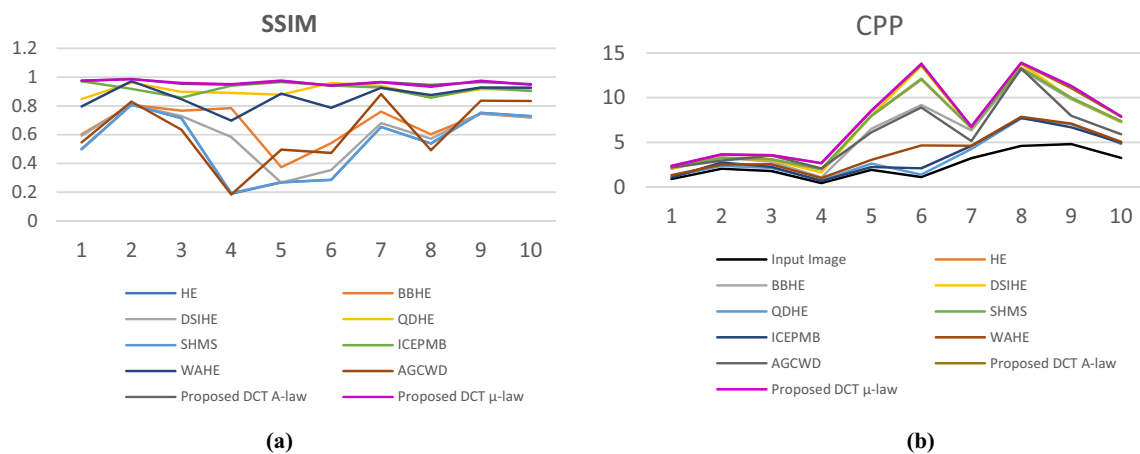
Fig. 15 a, b SSIM and CPP performance graphs for each test images using traditional and proposed method respectively

Fig. 16 **a, d** The local enhanced image, **b, e** denote global enhanced image, and **c, f** indicate the proposed method respectively

Fig. 17 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

Fig. 18 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

Fig. 19 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

Fig. 20 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*
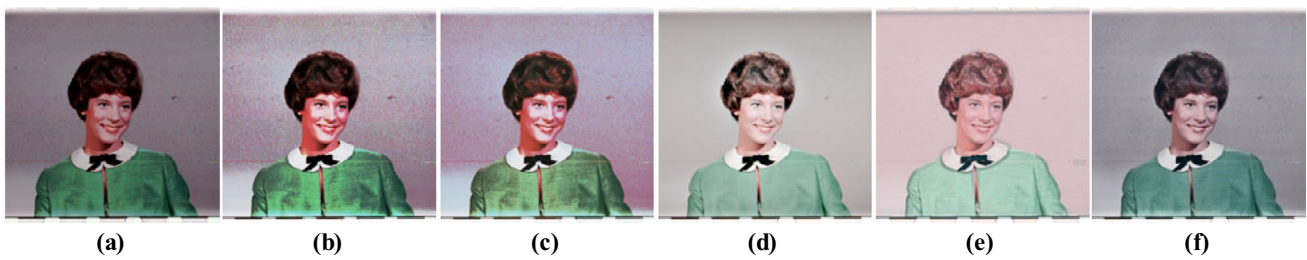
Fig. 21 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

Fig. 22 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

AMBE, DE, PSNR, SSIM, and CPP parameter as compared to the FCCE, ETHE, DOTHE, MSR, and Dong's methods in almost every case. Table 8 reports computational complexity in terms of running time where proposed method offers fast processing speed as compared to FCCE, ETHE, DOTHE, MSR, and Dong's method. Furthermore, the graph pattern of computation complexity has been given in Fig. 34 to examine the time complexity for each method. Hence, it may be concluded that the proposed method shows better enhancement performance against other methods.

Furthermore, histogram and retinex based existing methods such as FCCE, ETHE, DOTHE, MSR, and Dong's
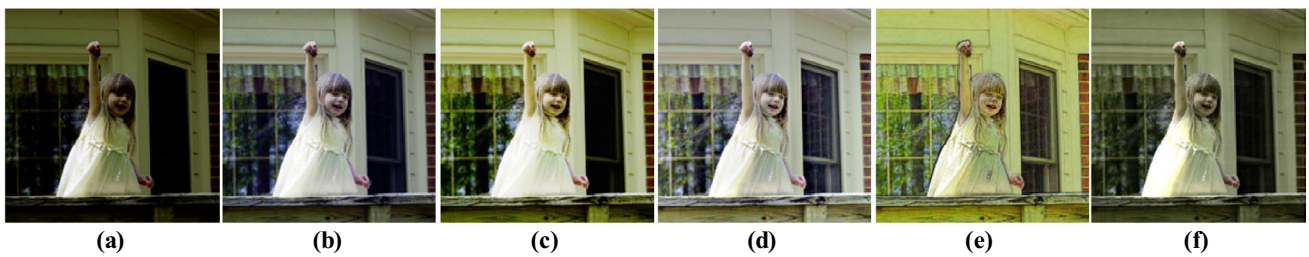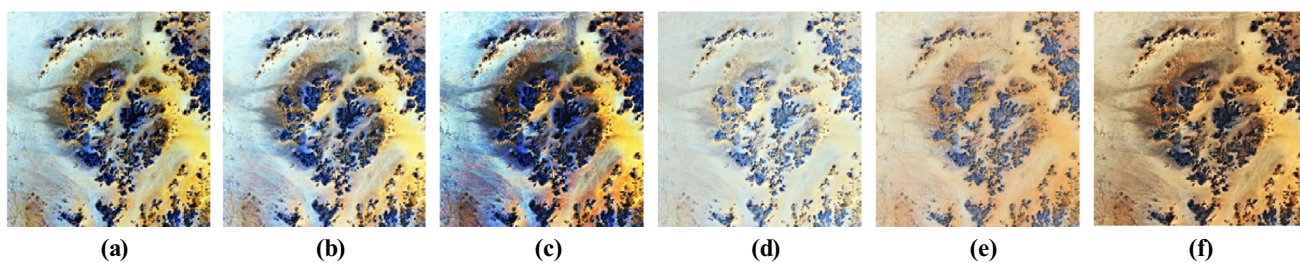
Fig. 23 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*
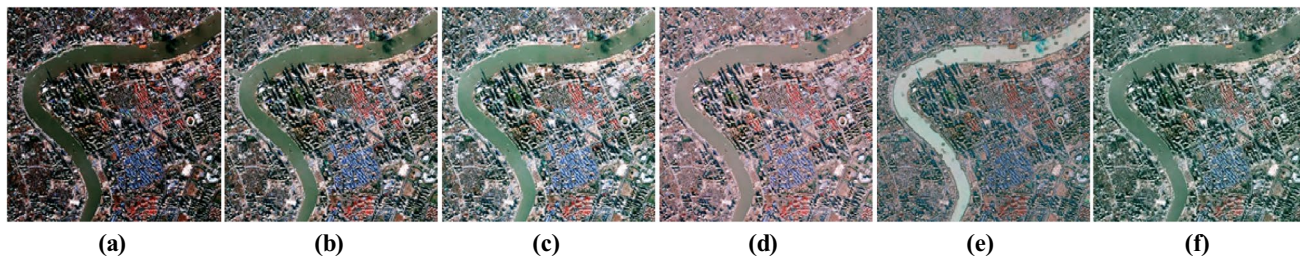
Fig. 24 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*
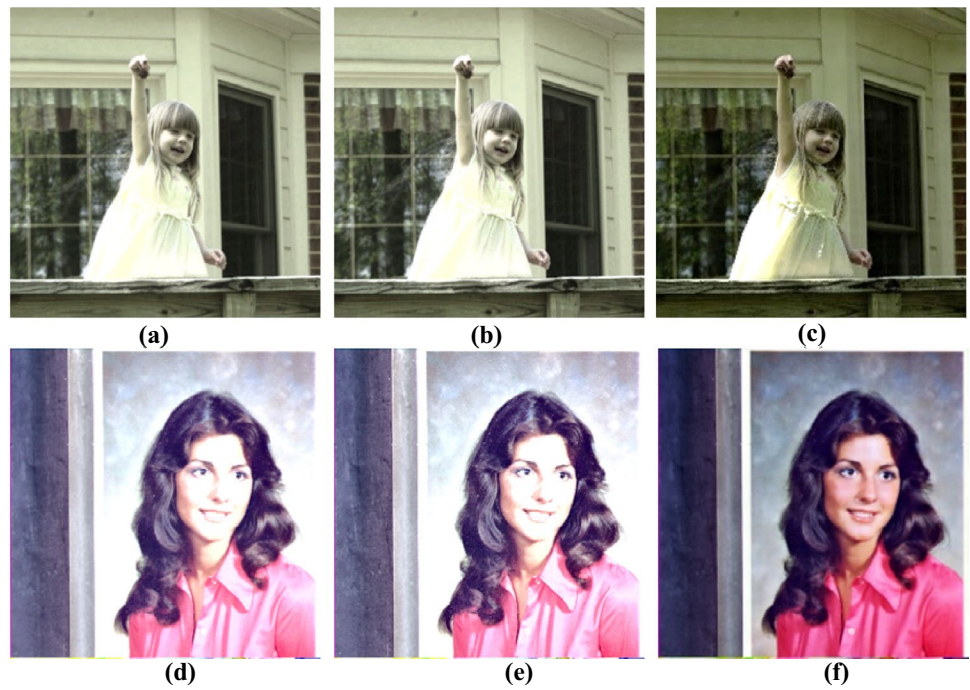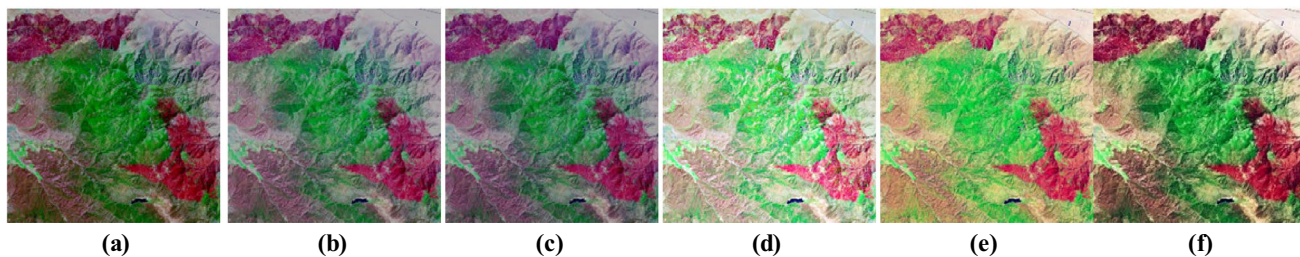

Fig. 25 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*
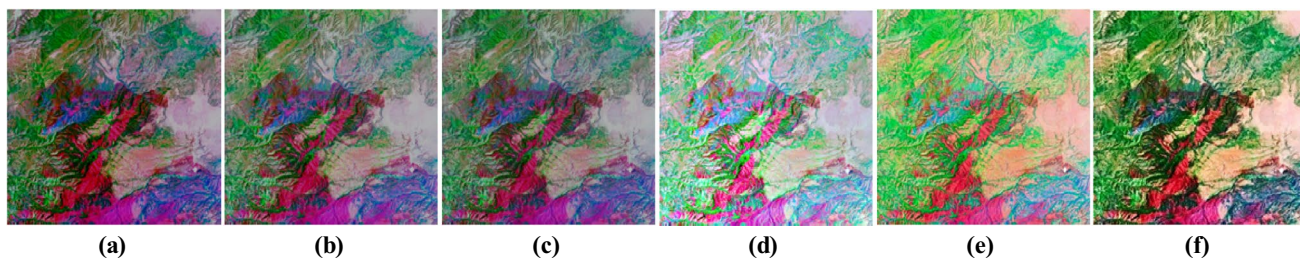
Fig. 26 **a** FCCE, **b** ETHE, **c** DOTHE, **d** MSR, **e** Dong, and **f** proposed DCT-*A*

method introduce major changes in the image gray level when the image is low contrast or spread of the histogram is not significant. These methods cannot preserve the mean image-brightness which is critical to many applications. The comparison of MEME, AMBE, DE, PSNR, SSIM, and CPP value for each method has been shown in Tables 7,

Fig. 27 **a–e** The original satellite images and **f–j** denote the enhanced images by the proposed method, respectively

Table 2 Comparison of AMBE values computed by different algorithm and proposed method

Test images	AMBE									
	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT A-law	Proposed DCT μ-law
1	65.63	26.9194	32.1193	1.4183	65.63	1.5149	19.0249	65.7616	1.3173	1.308
2	16.1956	16.018	11.3099	4.2679	16.1913	1.796	3.055	42.2403	1.3055	1.6023
3	29.5247	18.0047	26.6039	0.79478	29.408	2.5322	17.2661	51.8445	0.3677	0.139
4	95.2849	22.983	39.7615	13.0488	93.0812	10.1225	18.4294	114.1771	8.3155	9.1064
5	1.2459	24.2593	1.9910	24.716	0.9281	1.6359	8.064	38.4554	1.0894	0.87054
6	92.2152	23.2784	49.3666	1.9301	91.7214	4.3123	16.9767	51.663	1.3953	1.2314
7	5.6684	16.3411	1.6197	6.7182	5.6684	0.53432	2.3918	28.9013	0.6649	0.3302
8	49.833	15.3773	24.2097	2.5461	49.833	5.7216	5.9951	65.737	2.2829	2.2039
9	1.6	2.6134	0.0994	5.3679	1.600	1.2598	6.678	40.4095	0.0434	0.0812
10	8.611	2.9955	4.7189	5.0298	8.611	1.6917	2.7647	43.0014	1.5571	1.4427

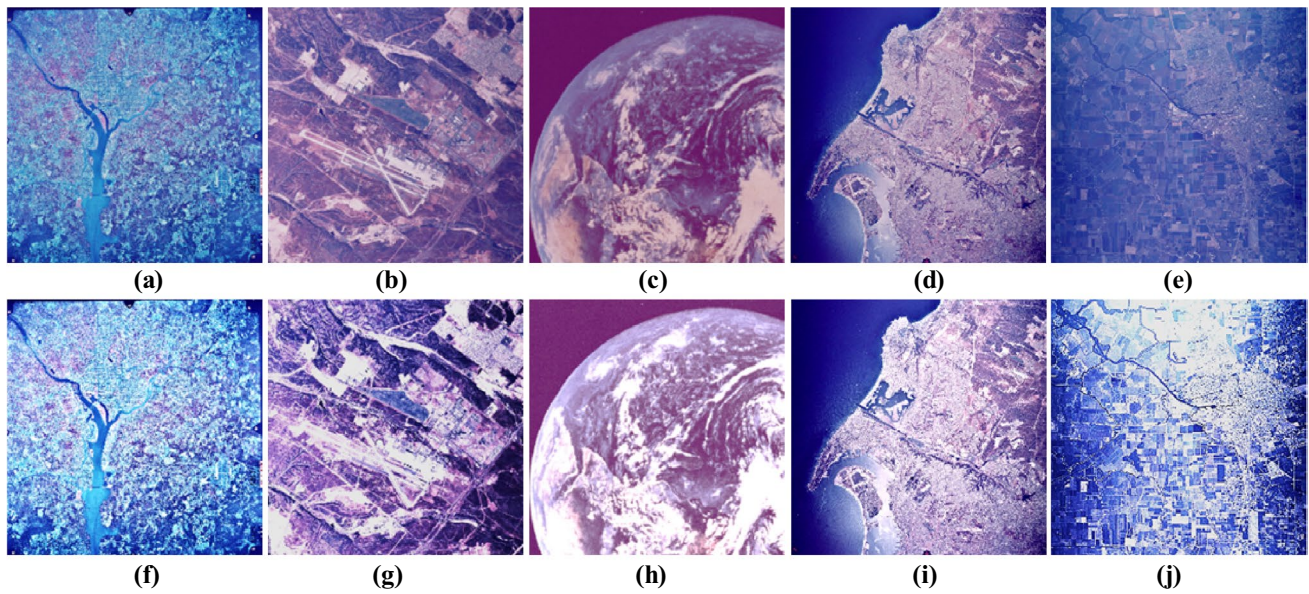**Table 3** Comparison of DE values computed by different algorithm and proposed method

Test images	DE										
	Input image	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT A-law	Proposed DCT μ-law
1	4.4648	4.1359	4.105	4.105	4.2563	4.1359	4.2596	4.4242	4.0451	4.8449	4.8713
2	4.8606	4.7056	4.7039	4.6836	4.7758	4.7104	4.6273	4.8358	4.7477	5.1291	5.1438
3	4.8348	4.5736	4.5542	4.5739	4.5773	4.5686	4.4899	4.635	4.4643	5.0109	5.0323
4	3.8407	3.5848	3.5508	3.5388	3.6229	3.5925	3.6512	3.5397	3.2057	4.2142	4.2148
5	3.7094	3.2321	3.2103	3.2327	3.6105	3.2343	3.5087	3.6689	3.332	4.2888	4.3282
6	3.3415	3.4356	3.5426	3.4424	3.3538	3.4245	3.0971	3.3344	2.9863	3.7622	3.7366
7	4.6234	4.4292	4.4869	4.4512	4.511	4.4292	4.3954	4.5932	4.6088	4.9811	4.9971
8	4.563	4.3072	4.2689	4.2801	4.4867	4.3072	4.3603	4.5155	4.2363	4.6491	4.8325
9	4.8849	4.7896	4.7942	4.7911	4.8704	4.7896	4.7415	4.8566	4.6088	5.1509	4.9696
10	4.7733	4.8426	4.8439	4.8436	4.8762	4.8426	4.7704	4.7921	4.5741	5.1089	5.1218

Table 4 Comparison of PSNR values computed by different algorithm and proposed method

Test images	PSNR									
	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT *A*-law	Proposed DCT *μ*-law
1	8.5666	12.1745	11.4674	26.2063	8.5666	34.3474	18.3181	8.6445	34.7893	34.9297
2	15.7259	15.7169	16.1441	27.2417	15.7261	24.6134	24.5166	13.0154	26.3948	25.8899
3	15.7869	18.3795	16.4494	**29.313**	15.8039	26.687	20.2361	11.5394	27.798	27.1843
4	6.2574	13.5206	10.5947	16.6913	6.382	17.9763	16.9675	4.9307	26.5679	25.9534
5	11.5786	11.6438	11.5472	17.7395	11.5376	27.9775	22.3226	12.5268	31.14	30.7392
6	5.9299	11.5883	8.6455	25.6073	5.9472	21.1439	18.0762	10.5196	26.49	26.2111
7	13.7847	14.3473	13.9752	23.0158	13.7847	23.0371	21.718	15.4735	25.8436	25.6786
8	10.0833	13.0879	12.1723	20.2789	10.0833	19.5308	21.2855	8.7583	23.7774	22.9108
9	15.2535	15.2473	15.2263	21.7268	15.2535	22.2301	21.081	13.4362	25.3192	26.0985
10	14.6879	14.8739	14.808	21.8818	14.6879	20.8297	21.2835	12.8954	23.621	23.1144

Table 5 Comparison of SSIM values computed by different algorithm and proposed method

Test images	SSIM									
	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT *A*-law	Proposed DCT *μ*-law
1	0.49913	0.60279	0.5934	0.84719	0.49913	0.97156	0.79641	0.54637	0.97333	0.97484
2	0.80803	0.80682	0.80567	0.96168	0.80807	0.91764	0.97057	0.82933	0.98721	0.98444
3	0.71408	0.76668	0.72927	0.89747	0.71417	0.85768	0.84609	0.63431	0.9528	0.95966
4	0.18928	0.7842	0.58367	0.8898	0.1935	0.94057	0.69785	0.18439	0.94676	0.95091
5	0.26931	0.37426	0.26635	0.8775	0.26825	0.9661	0.88513	0.49593	0.97139	0.97558
6	0.2867	0.54124	0.35476	0.9598	0.28501	0.94136	0.78707	0.47254	0.94352	0.94059
7	0.65432	0.76023	0.68074	0.93956	0.65432	0.9271	0.92507	0.88216	0.96535	0.96315
8	0.53899	0.60219	0.57151	0.86145	0.53899	0.85747	0.87498	0.492	0.94519	0.93243
9	0.75134	0.74538	0.74785	0.91608	0.75134	0.92525	0.92715	0.83638	0.96606	0.97449
10	0.72864	0.71908	0.72132	0.91416	0.72864	0.90263	0.92596	0.83341	0.95222	0.94703

Table 6 Comparison of CPP values computed by different algorithm and proposed method

Test images	CPP										
	Input image	HE	BBHE	DSIHE	QDHE	SHMS	ICEPMB	WAHE	AGCWD	Proposed DCT *A*-law	Proposed DCT *μ*-law
1	0.91738	2.199	2.0595	2.0744	1.1939	2.199	1.0883	1.361	2.2032	2.3459	2.3758
2	2.0566	3.2821	3.2879	3.2812	2.3888	3.2812	2.7661	2.5159	2.9688	3.6249	3.6632
3	1.8052	3.1008	2.8422	3.0314	2.1359	3.1094	2.2651	2.5556	3.5404	3.5464	3.5759
4	0.44283	2.0012	1.0869	1.651	0.7613	2.0064	0.70144	1.0216	2.0909	2.6758	2.6845
5	1.9335	7.9488	6.5233	8.0202	2.6363	7.9912	2.2506	3.0492	6.1379	8.5083	8.5494
6	1.1324	12.0303	9.1794	13.548	1.4057	12.1117	2.104	4.664	8.9134	13.6907	13.8128
7	3.2401	6.6224	6.3383	6.6298	4.262	6.6224	4.6087	4.6329	5.1575	6.7782	6.7797
8	4.6115	13.3137	13.1414	13.7749	7.6712	13.3137	7.7467	7.8711	13.257	13.8448	13.910
9	4.8121	9.9849	9.8525	9.9605	7.048	9.9849	6.6895	7.1034	7.9865	11.0695	11.325
10	3.2738	7.3642	7.267	7.3101	4.8389	7.3642	4.9779	5.0705	5.9121	7.8597	7.9191

Table 7 Comparison of MEME values computed by different algorithm and proposed method

| Test images	MEME							
	Input image	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	4.0414	9.5243	14.2089	19.5537	8.6493	8.2614	7.1602	7.4274
2	70.3391	104.6720	117.816	127.828	95.019	99.024	92.3825	93.8021
3	3.0821	5.0120	6.7718	7.1064	5.8603	5.4744	4.3317	4.4023
4	0.49639	1.9663	5.5778	2.8437	1.8759	6.6025	0.88816	0.90934
5	46.5771	69.8433	130.908	119.2689	68.775	66.015	62.6567	63.5696
6	2.4369	7.6101	35.6045	17.5352	4.9842	5.3474	4.8622	4.9587
7	21.5231	41.9409	54.5506	45.8841	37.9735	36.376	30.0525	29.8827
8	13.5984	28.1235	47.3261	45.8841	27.4139	25.374	20.8203	21.8162
9	26.6582	36.3533	53.6361	57.5237	38.6502	36.9203	37.4902	35.4934
10	21.3189	34.4051	51.3758	49.0752	37.0757	35.9519	34.7997	35.6038
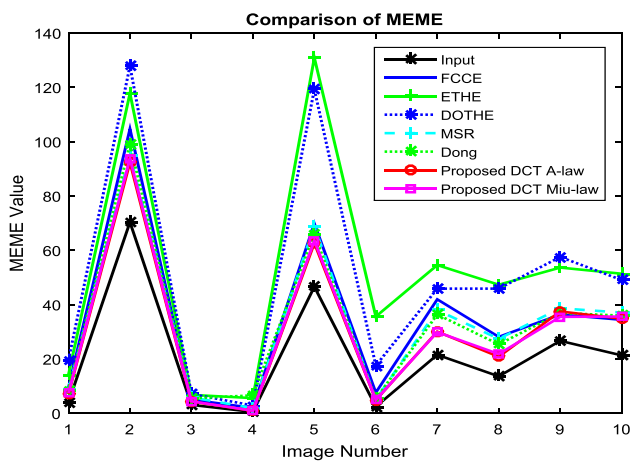
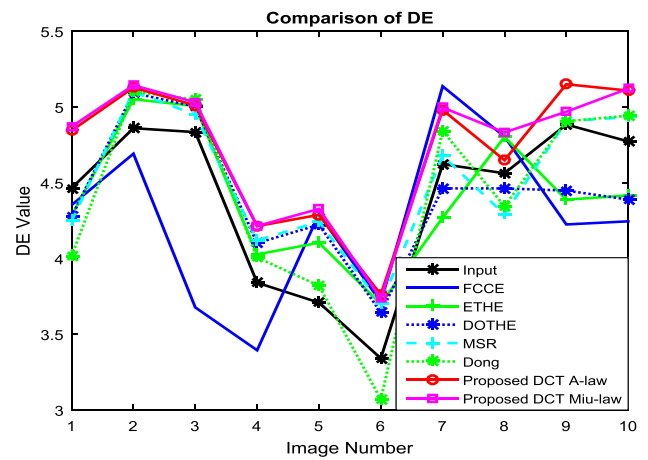**Fig. 28** MEME performance graph for each method

Fig. 30 DE performance graph for each method
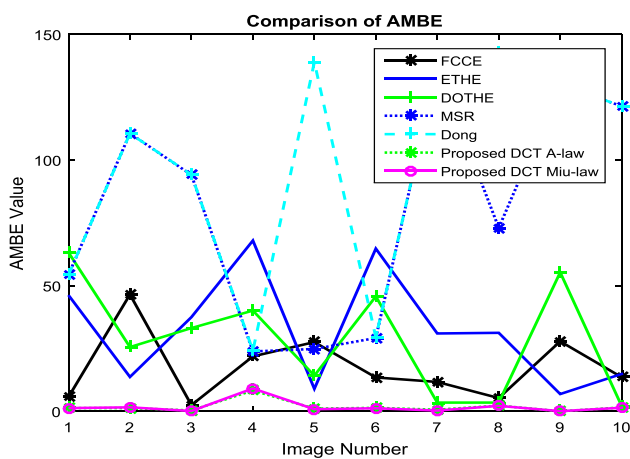

Fig. 29 AMBE performance graph for each method
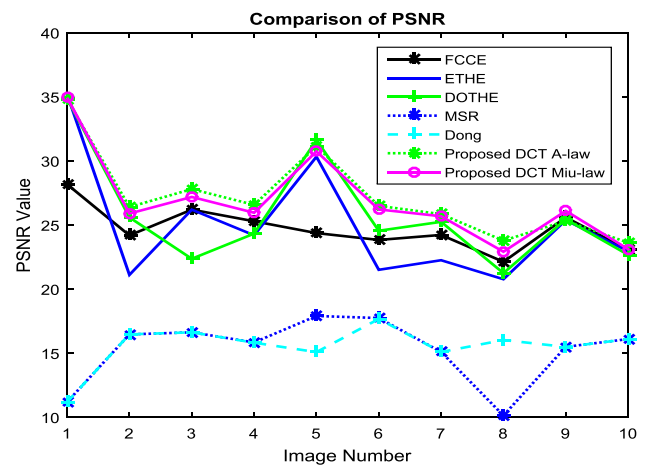

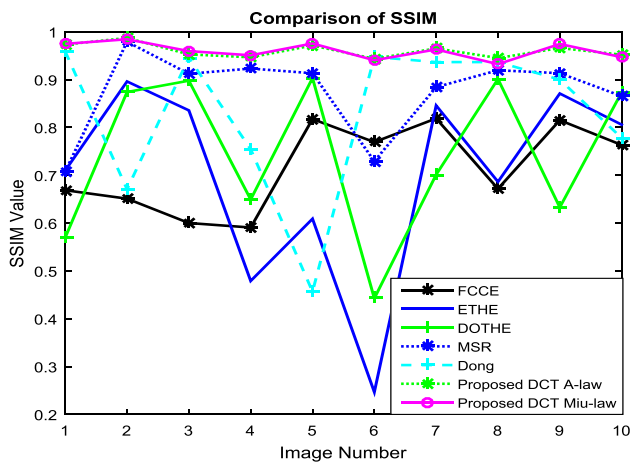**Fig. 31** PSNR performance graph for each method

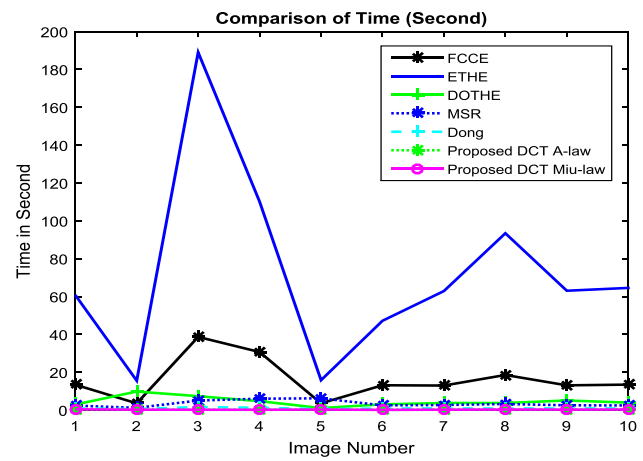**Fig. 32** SSIM performance graph for each method
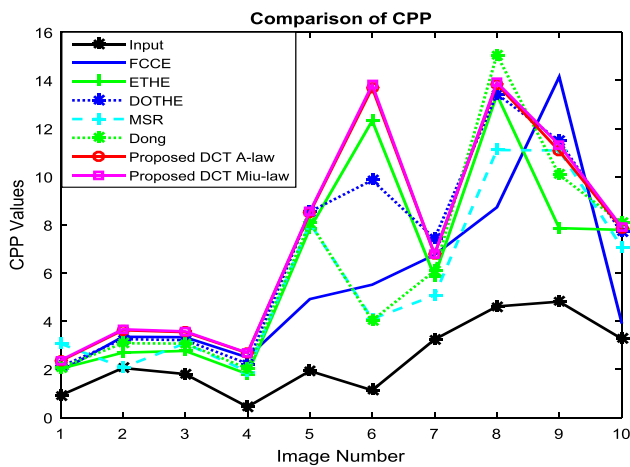

Fig. 34 Time analysis graph for each method

Fig. 33 CPP performance graph for each method

9, 10, 11, 12 and 13. From the evaluation of experimental outcomes, it can be concluded that the proposed DCT A-law and μ-law methods produce images that are not only quantitatively superior but also well in terms of quality as compared to HE, BBHE, DSIHE, QDHE, SHMS, ICEPMB, WAHE, AGCWD, FCCE, ETHE, DOTHE, MSR, and Dong's methods. These methods cannot preserve the mean image-brightness which is critical to many image processing applications. The proposed method significantly reduces the amplified noise and low-light distortion without affecting original color and detail of the input image, therefore, it can be used for many visual imaging devices, which requires image enhancement with naturalness and brightness preservation. The limitation of the proposed architecture is that it will not work effectively work for medical images or very dark images. Other demerit of the proposed method could be considered that it may introduced some color artifacts when the contrast level of input image is highly distorted.

Table 8 Comparison of CPU time (s) computed by different algorithm and proposed method

test images	Time						
	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	13.433	60.817	2.9389	2.3619	0.8675	0.4231	0.4271
2	3.5684	15.557	9.8118	1.2047	0.5596	0.2342	0.2340
3	38.677	189.02	7.3594	5.0377	1.6311	0.1955	0.1923
4	30.687	110.13	4.7308	6.0327	1.2533	0.1826	0.1852
5	3.5877	15.810	1.0918	6.2227	0.5897	0.2878	0.2832
6	13.132	47.198	3.0398	2.5094	0.8354	0.1229	0.12554
7	12.976	62.915	3.7475	2.7047	0.8853	0.2280	0.2213
8	18.563	93.437	3.7475	3.2263	0.8451	0.3198	0.3142
9	13.088	63.077	5.0923	2.5517	0.91127	0.2526	0.2552
10	13.467	64.568	3.9542	2.4462	0.88549	0.3145	0.3131

Table 9 Comparison of AMBE values computed by different algorithm and proposed method

Test images	AMBE						
	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	5.7303	46.2439	63.2397	54.3561	54.3408	1.3173	1.308
2	46.5042	13.6956	25.5813	110.6081	110.550	1.3055	1.6023
3	2.4849	37.4966	33.1464	94.0897	94.1767	0.3677	0.139
4	21.8805	67.9669	40.0995	23.8512	24.1233	8.3155	9.1064
5	27.5668	8.9885	14.2126	24.8332	138.971	1.0894	0.87054
6	13.4969	64.7613	45.7472	29.1868	29.4805	1.3953	1.2314
7	11.7010	30.9966	3.4904	136.829	136.913	0.6649	0.3302
8	5.2999	31.2530	3.4904	73.0171	142.913	2.2829	2.2039
9	27.8635	6.8868	55.3181	129.789	129.870	0.0434	0.0812
10	13.5910	14.8890	2.1200	121.479	121.532	1.5571	1.4427

Table 10 Comparison of DE values computed by different algorithm and proposed method

Test images	DE							
	Input image	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	4.4648	4.3530	4.2820	4.2764	4.2481	4.0155	4.8449	4.8713
2	4.8606	4.6921	5.0521	5.0927	5.1021	5.1018	5.1291	5.1438
3	4.8348	3.6777	5.0068	5.0038	4.9502	5.0505	5.0109	5.0323
4	3.8407	3.3949	4.0273	4.1023	4.1204	4.0073	4.2142	4.2148
5	3.7094	4.2944	4.1047	4.2237	4.2436	3.8211	4.2888	4.3282
6	3.3415	3.7126	3.7001	3.6462	3.7020	3.0715	3.7622	3.7366
7	4.6234	5.1373	4.2704	4.4632	4.6786	4.8425	4.9811	4.9971
8	4.563	4.8051	4.8029	4.4632	4.2917	4.3455	4.6491	4.8325
9	4.8849	4.2253	4.3890	4.4491	4.9076	4.9066	5.1509	4.9696
10	4.7733	4.2459	4.4168	4.3895	4.9329	4.9433	5.1089	5.1218

Table 11 Comparison of PSNR values computed by different algorithm and proposed method

Test images	PSNR						
	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	28.1740	35.1941	34.9007	11.1881	11.1874	34.7893	34.9297
2	24.1855	21.1074	25.5906	16.4630	16.4657	26.3948	25.8899
3	26.1954	26.1954	22.3619	16.6257	16.6244	27.798	27.1843
4	25.2874	24.1954	24.3239	15.8373	15.8162	26.5679	25.9534
5	24.3665	30.3208	31.6281	17.8990	15.0799	31.14	30.7392
6	23.8306	21.5020	24.5482	17.7387	17.6676	26.49	26.2111
7	24.2217	22.2489	25.2430	15.0968	15.0918	25.8436	25.6786
8	22.1235	20.7664	21.2430	10.1340	16.024	23.7774	22.9108
9	25.5904	25.3745	25.4405	15.4912	15.4866	25.3192	26.0985
10	23.0675	22.9535	22.6717	16.0994	16.0961	23.621	23.1144

Table 12 Comparison of SSIM values computed by different algorithm and proposed method

Test images	SSIM						
	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	0.6688	0.7099	0.5698	0.7077	0.9588	0.97333	0.97484
2	0.6511	0.8962	0.8741	0.9792	0.6707	0.98721	0.98444
3	0.6002	0.8357	0.8978	0.9123	0.9458	0.9528	0.95966
4	0.5908	0.4791	0.6494	0.9232	0.7545	0.94676	0.95091
5	0.8176	0.6090	0.9034	0.9134	0.4567	0.97139	0.97558
6	0.7694	0.2467	0.4426	0.7294	0.9475	0.94352	0.94059
7	0.8189	0.8459	0.7013	0.8844	0.9367	0.96535	0.96315
8	0.6718	0.6864	0.9013	0.9196	0.9367	0.94519	0.93243
9	0.8152	0.8710	0.6329	0.9135	0.9001	0.96606	0.97449
10	0.7634	0.8059	0.8734	0.8655	0.7781	0.95222	0.94703

Table 13 Comparison of CPP values computed by different algorithm and proposed method

Test images	CPP							
	Input image	FCCE	ETHE	DOTHE	MSR	Dong	Proposed DCT A-law	Proposed DCT μ-law
1	0.91738	1.9280	2.0285	2.1114	3.0684	2.0703	2.3459	2.3758
2	2.0566	3.3522	2.6938	3.2551	2.0769	3.0829	3.6249	3.6632
3	1.8052	3.3349	2.7658	3.2141	3.0814	3.0703	3.5464	3.5759
4	0.44283	2.4948	1.8040	2.2377	1.9036	2.0373	2.6758	2.6845
5	1.9335	4.9184	7.8483	8.5469	8.0720	8.1000	8.5083	8.5494
6	1.1324	5.5155	12.3234	9.8537	4.0930	4.0321	13.6907	13.8128
7	3.2401	6.7530	5.8578	7.4337	5.0698	6.0893	6.7782	6.7797
8	4.6115	8.7288	13.3974	13.4337	11.106	15.056	13.8448	13.910
9	4.8121	14.1461	7.8632	11.4832	11.0895	10.079	11.0695	11.325
10	3.2738	3.9544	7.7919	7.6999	7.0842	8.0774	7.8597	7.9191

6 Conclusion

In this paper, a novel logarithmic histogram modification scheme has been proposed for image enhancement with naturalness and brightness preservation. The proposed algorithm is composed of global and local enhancement process to produce overall good results. At first, to compute global enhancement, addition and logarithmic law based modifications have been applied to the histogram and then histogram equalization is applied to calculate mapping function. Thereafter, to enhance the local details, a coefficient scaling method using DCT has been applied. A number of experiments were performed over proposed method to find out its robustness and it is concluded that proposed algorithm produces a very high quality of image enhancement for different type of images such as satellite images, dark image or low illumination image. The enhanced images produced by the proposed methodology generally keep its naturalness intact in spite of histogram equalization steps. The proposed method is simple in complexity due to straightforward operations like addition and logarithmic. Experimental results

demonstrate that the proposed scheme produces highest SSIM, PSNR, entropy and optimum MSE, MEME, AMBE, CPP values for almost all the cases for each method.

As a scope of future work, the proposed algorithm can be used as an objective function for various evolutionary optimizing techniques to get optimum enhancement results. Furthermore, different combinations of the presented method can be used through the multi-objective optimization based problems to improve the quality of poor quality images. 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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