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New contrast enhancement approach for dark images with non-uniform illumination☆

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ABSTRACT

Contrast enhancement of dark images with non-uniform illumination is a difficult task, as these images have both dark and bright regions. Hence, we cannot use many of the widely accepted methods of contrast enhancement, which rely on enhancing the contrast of the both of dark and bright regions at equal level, which results in over enhancement and disappearance of the finer details in brighter regions. This motivated us to design an approach for contrast enhancement of dark images with non-uniformly illumination without affecting the details in the bright regions. We are proposing a method which deals with 'YCbCr' model, as by using this color model we can separately use luminance part 'Y'. Then, we enhance the luminance part 'Y' of the image by using a newly developed sigmoid function.

1. Introduction

In many situations an image is taken in extreme light conditions, such as excessive bright or dark environmental conditions the result is low contrast, which produces low dynamic range of intensities in the dark and bright regions. Due to this non-uniform illumination, the details in both dark region as well as in bright region disappear. In such cases, if we use contrast enhancement tools in order to enhance the contrast of dark regions, the bright regions become over enhanced and the details in the bright regions disappear. This situation motivated us to develop a new approach by which we can enhance the contrast in both the regions of the image without affecting the details.

Many techniques are used for image enhancement; histogram equalization (HE) is one of the simplest and widely accepted technique [1]. A number of variations of HE are also available in the literature [2–7], these variants of HE are having their own benefits and drawbacks. Later, various 'adaptive histogram equalization' (AHE) approaches were proposed by Hummel [8], Ketcham [9], and Pizer [10] to overcome the drawbacks of HE. These adaptive approach use a mapping function on each pixel in the histogram to increase the local contrast. Although AHE produces good results, but it suffers with the problem of slow speed and over enhancement of noise in image. The enhancement in the noise causes appearance of the artifacts in the processed image. In [11], K. Zuiderveld proposed 'contrast limited adaptive histogram equalization' (CLAHE) to deal with the drawback of AHE and to remove the artifacts in the processed image. Later, various authors proposed variants of CLAHE, few of them are discussed in [12,13]. The main problem of CLAHE is that it does not use whole dynamic range of histogram.

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To overcome the drawback of HE, Yang et al., [14] proposed 'bin underflow bin overflow histogram equalization' (BUBO-HE). This approach use two frequency thresholds, to control the level of enhancement. The main drawback of BUBO-HE method is that it does not address the decreased local contrast problem.

Later, Chiu et al., [15] proposed another approach for dimmed light images based on adaptive gamma correction (AGC). In this approach, image is enhanced by using weight distribution to modify the pixel intensity of the input image. This approach suffers by over enhancement in bright areas of input image.

In 2011, Kang et al., [16] proposed an approach 'adaptive height-modified histogram equalization' (AHMHE) for enhancing the contrast of images with back-light affect. This approach firstly converts the RGB color image into YCbCr color image and generates a mapping function for Y component based on adaptively height-modified histogram. After that, a local contrast map is defined by difference operation of Y component with blurred Y and then a new chroma correction method is applied. This approach also have the same drawback as all the previous approaches of over enhancement in brighter areas of input image.

In [17] a new enhancement approach is suggested by authors, using the fuzzy methods for enhancing the contrast, of low contrast non-uniform illumination images. They employed modified Gaussian membership function in the enhancement process on gray-scale. Recently few other methods [18,19] have been proposed for contrast enhancement and brightness preservation of all type of images (including dark images with non-uniformly illumination). These methods are able to enhance contrast of all type of images without affecting their original features. But, sometimes these methods preserve mean brightness in the processed image so accurately that it is not possible to measure contrast enhancement by viewing the image.

The drawbacks motivate us to design a new approach by which we can enhance contrast of dark region without affecting the mean brightness of the image and color information of brighter region. In this paper, we propose a new approach for handling dark images with non-uniform illumination using modified sigmoid function. In proposed approach, we deal with the YCbCr color model instead of RGB color model, as our main objective is to archive uniform illumination and hence the contrast enhancement. For this we use modified sigmoid function on the base layer of the luminance component of the input image and obtained new base layer and detail layer of illuminance component Y. Finally, we get the output image after converting new YCbCr image into RGB image. The results of proposed approach are compared with above described approaches used for dimmed light images (AHMHE, BUBO, CLAHE and AGC) and proposed approach overcomes the drawbacks of these approaches.

The organization of this paper is as follows: Section 2 describes proposed method in detail. Experimental results and comparison with other methods are shown in Section 3 and a short concluding remark is given in Section 4.

2. Proposed method

In this section we describe the proposed approach in detail. The block diagram of the proposed algorithm is as given in Fig. 1:

2.1. RGB to YCbCr color space conversion

There are number of color space models available in digital image processing. Some of important models are HSV, YCbCr, YUV, YIQ etc. Every color space model has its own properties and importance. Since we want to enhance the contrast of the image with non-uniformly illumination, it is logical to use YCbCr color model model, as in this model, its Y part contains the detailed information of luminance component and C_b and C_r are the blue-difference and red-difference chroma components. The main advantage of using YCbCr color space model is that we can enhance the luminance by enhancing the Y part only, without affecting the color information contained in Cb and Cr part.

In proposed approach, we initially convert RGB color image into YCbCr color space. To convert RGB color model into YCbCr color model [16] we are using following equation:

$$\begin{pmatrix} Y \\ Cb \\ Cr \end{pmatrix} = \begin{pmatrix} 16 \\ 128 \\ 128 \end{pmatrix} + A \cdot \begin{pmatrix} R \\ G \\ B \end{pmatrix}, \tag{1}$$

where,

$$A = \begin{pmatrix} 65.481 & 128.553 & 24.966 \\ -37.797 & -74.203 & 112.000 \\ 112.000 & -93.786 & -18.241 \end{pmatrix}$$

and Y: [16,235], Cb: [16,240], Cr: [16,240].

2.2. Decomposition of Y component

Once, we convert the given RGB image into YCbCr image and get the illuminance component Y. We are interested in decomposing the luminance component Y into its base layer and detailed layer. Base layer contains the smooth part of the

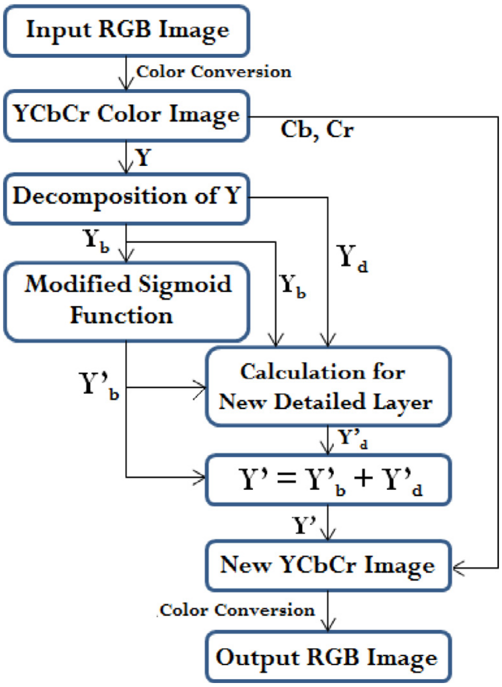

Fig. 1. Functional block diagram of proposed method.

luminance layer and detailed layer contains geometrical edges of the illuminance component. For decomposing luminance component Y into base layer and detailed layer we use a 3×3 low pass filter (LPF).

$$LPF = \begin{pmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{pmatrix}. \tag{2}$$

As we apply 3×3 low pass filter (LPF) on the luminance component Y, we get a base layer Y_b. To get the detailed layer Y_d we subtract the base layer Y_b from the luminance component (Y) i.e.,

$$Y_d = Y - Y_b, \tag{3}$$

where, Y_d shows the detailed layer which is the difference between Y and Y_b and contains the image details.

Fig. 2(a) shows the original luminance Y image and its histogram is shown in Fig. 2(b). Base layer Y_b and detailed layer Y_d are shown in Fig. 2(c) and (d), respectively.

2.3. Use of sigmoid function for contrast enhancement.

Sigmoid function is the continuous nonlinear 'S' shaped mathematical function, which is a the special case of the logistic function and defined in Eq. (4) and shown in Fig. 3.

$$y(x) = \frac{1}{(1 + e^{-t(x)})}. \tag{4}$$

In image processing, we can use sigmoid function as a histogram transformation function for enhancing the contrast in the low contrast images.

In [20], Watanabe et.al., proposed a new sigmoid function. In this newly proposed sigmoid function the output value $out(x, y)$ for each pixel (x, y) is obtained by:

$$out(x, y) = 255F(A'(x, y)), \tag{5}$$

and

$$A'(x, y) = \frac{A(x, y)}{255}, \tag{6}$$

where, $A(x, y)$ shows a pixel value of an input image and $A'(x, y)$ shows a normalized pixel value. The sigmoid function F varying 0 to 1, and define as:

$$F(z) = \begin{cases} b^{1-\gamma} z^{\gamma}, & 0 \le z \le b \\ 1 - (1-b)^{1-\gamma}(1-z)^{\gamma}, & b < z \le 1, \end{cases} \tag{7}$$

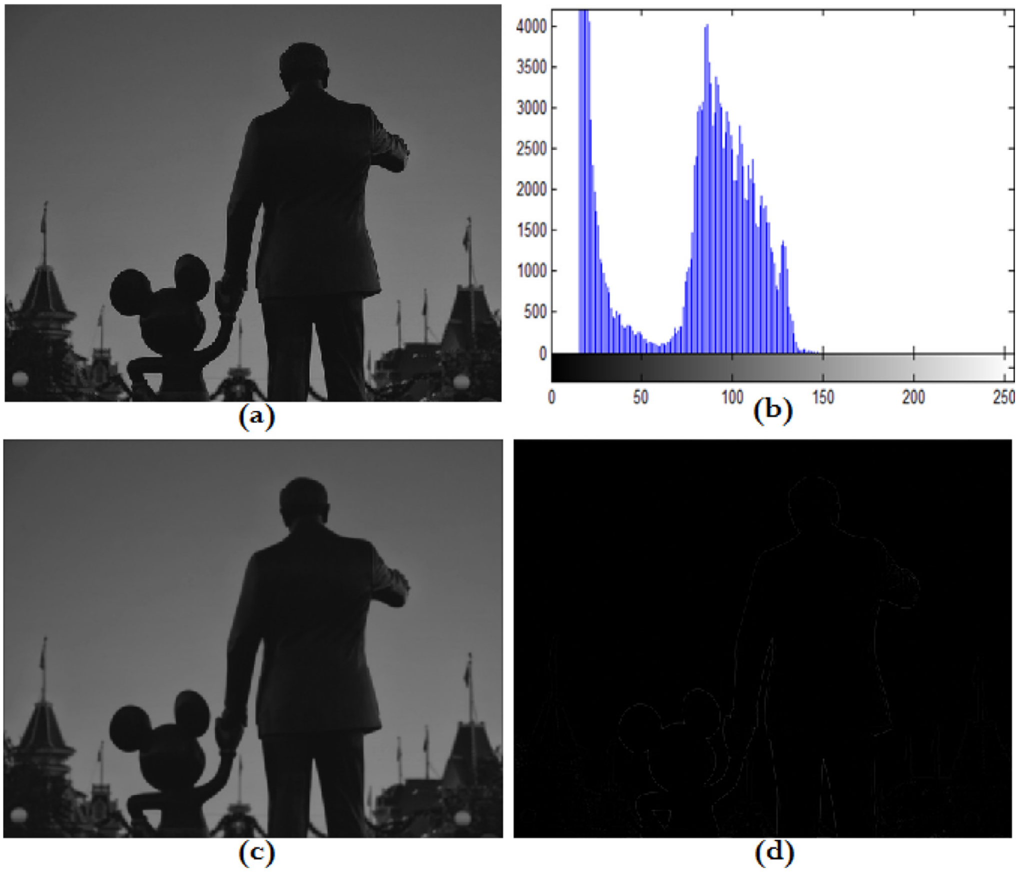

Fig. 2. (a) The original Y image, (b) The original Y histogram, (c) The base layer Y_b and (d) The detailed layer Y_d.

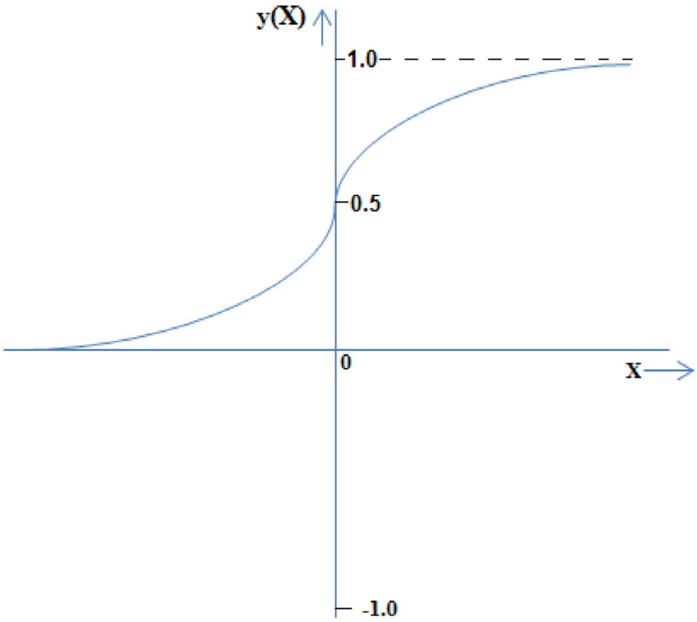

Fig. 3. Sigmoid function.

where, γ is a parameter concerning the degree of inclination of F, $b \in [o, 1]$. The value of γ is always great than equal to 1, for $\gamma = 1$, we have $F(z)$ identical to z.

Watanabe et al., in [20], fixed $\gamma = 1.4$ and consider b as the average intensity of input image. Later, Tanaka et al., [21] suggested another sigmoid function by making slight changes in Watanabe's sigmoid function.

2.4. Modified base layer $\mathrm{Y_b}$.

In this step, initially we normalise the base layer Y_b using following expression:

$$Y_b^{norm}(x, y) = \frac{Y_b(x, y)}{255}, \tag{8}$$

where, Y_b^{norm} is the normalized base layer. After normalization, we convolved this normalized base layer with a Gaussian function g such that:

$$P(x, y) = (g * Y_b^{norm})(x, y), \tag{9}$$

where, g is the Gaussian function and defined as:

$$g(x, y) = k\ \mathbf{exp}\left(\frac{-(x^2 + y^2)}{2\sigma^2}\right), \tag{10}$$

where, σ is the standard deviation of the Gaussian function g and k is a constant for the normalization of g, which is calculated as:

$$\sum_x \sum_y g(x, y) = 1. \tag{11}$$

Now we define the modified sigmoid function $F_{(x,\ y)}$ which is as follows:

$$F_{(x,y)}(Y_b^{norm}) = \begin{cases} P(x, y)^{1-\gamma} Y_b^{norm\,\gamma}, & 0 \le Y_b^{norm} \le P(x, y) \\ 1 - (1 - P(x, y))^{1-\gamma}(1 - Y_b^{norm})^{\gamma}, & \\ & P(x, y) < Y_b^{norm} \le 1, \end{cases} \tag{12}$$

where, γ is a contrast adjustment parameter.

The output of the modified sigmoid function is denoted by $O(x, y)$ and defined as follows:

$$O(x, y) = 255 \times F_{(x,y)}(Y_b^{norm}(x, y)).$$

At last, the enhanced intensity of the pixel (x, y) in the base layer $Y_b^{'}(x, y)$ is given by,

$$Y_b^{'}(x, y) = w \cdot O(x, y), \tag{13}$$

where, w is a normalizing parameter to control the mean illumination of the output image and calculated as:

$$w = \frac{[\mathbf{max}\{O(x, y)\} - \mathbf{min}\{O(x, y)\}]}{\alpha \cdot [\mathbf{max}\{Y_b(x, y)\} - \mathbf{min}\{Y_b(x, y)\}]}, \tag{14}$$

where, $0 < \alpha < 1$. It is clear from above Eq. (14) that w is the ratio between the difference of maximum and minimum pixel value of O and Y_b and used as the mean illumination controller in the output image. Illumination control is necessary as output image with high illumination lost its natural appearance. We can adjust the illumination in the output image using α and w.

Fig. 4(a) and (b) show the cumulative distribution function (CDF) of original base layer Y_b and enhanced base layer $Y_b^{'}$, respectively and Fig. 4(c) shows the enhanced base layer $Y_b^{'}$. It is clear from Fig. 4, that CDF of enhanced base layer $Y_b^{'}$ is less steep as compare to the CDF of Y_b this shows that the distribution of $Y_b^{'}$ is more flatter and close to uniform CFD.

2.5. Modified new detailed layer and enhanced luminance component.

Once we get enhanced base layer $Y_b^{'}$, our next task is to archive the enhance in detailed layer. Let the intensity of pixel (i, j) in the detail layer $Y_d(i, j)$ and $Y_b(i, j)$ is the intensity of the pixel (i, j) in the base layer. After applying the modified sigmoid function $Y_b(i, j)$ is adjusted to $Y_b^{'}(i, j)$. Now the intensity of enhanced detailed layer image at pixel (i, j) is the $Y_d^{'}(i, j)$ is defined by the following relationship:

$$\frac{Y_d(i, j)}{Y_b(i, j)} = \frac{Y_d^{'}(i, j)}{Y_b^{'}(i, j)}, \tag{15}$$

where, $Y_d^{'}(i, j)$ is the new detailed layer at (i, j)th pixel. Since, $Y_b(i, j)$, $Y_b^{'}(i, j)$ and $Y_d(i, j)$ are known then $Y_d^{'}(i, j)$ can be easily obtained by using following equation:

$$Y_d^{'}(i, j) = \frac{Y_d(i, j)}{Y_b(i, j)} \cdot Y_b^{'}(i, j). \tag{16}$$

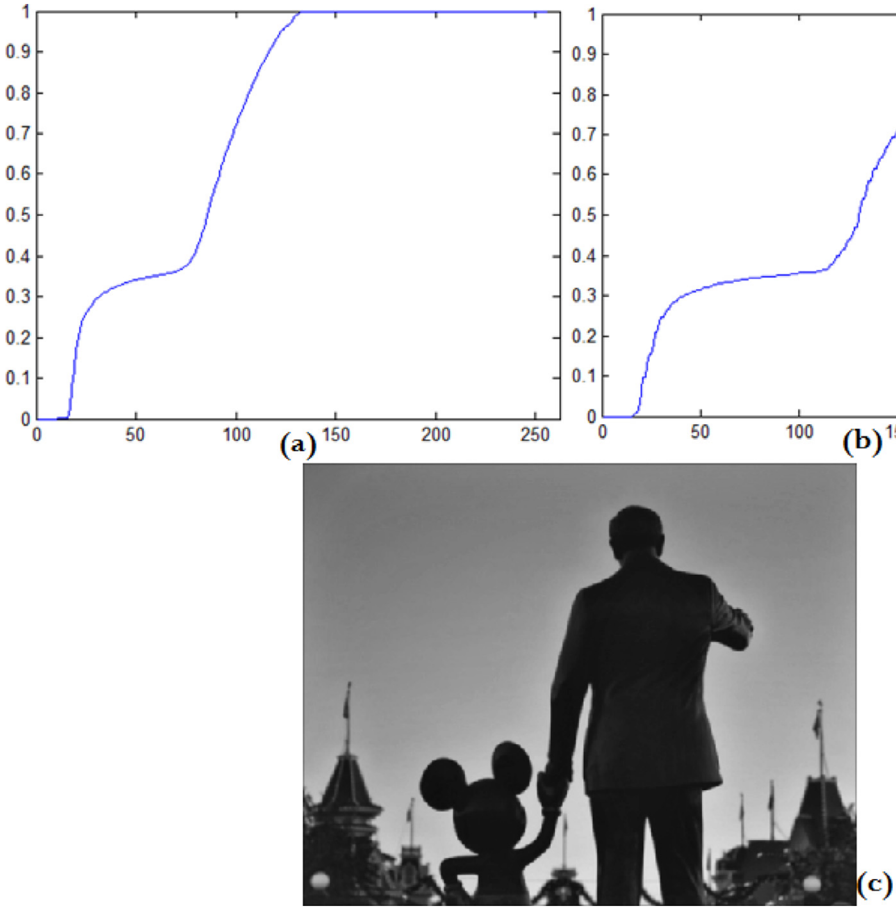

Fig. 4. (a) Shows the cumulative distribution function (CDF) of Y_b, (b) Shows the CDF of $Y_b^{'}$ and (c) Shows output base layer $Y_b^{'}$.

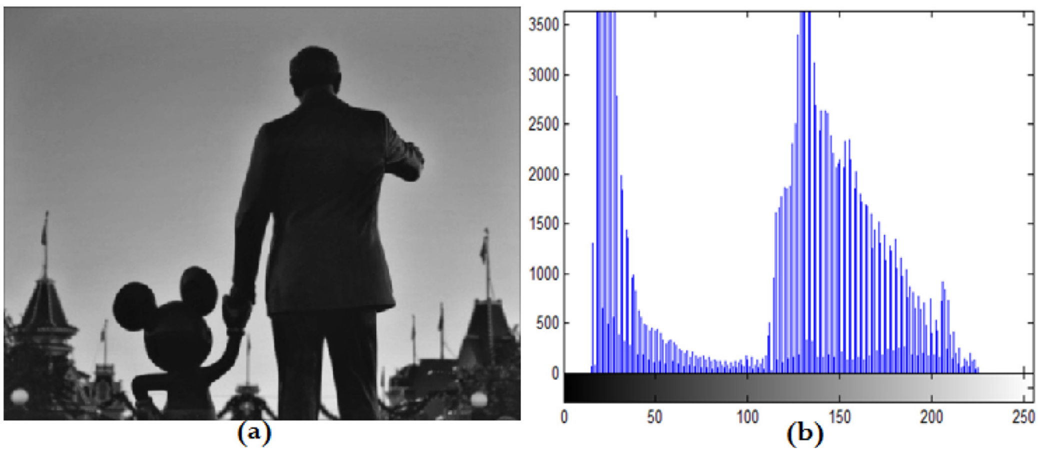

Fig. 5. (a) Shows output $Y^{'}$ image and (b) Shows histogram of output $Y^{'}$.

After getting enhanced base layer $Y_b^{'}$ and detailed layer $Y_d^{'}$, our task is to calculate the enhanced luminance image $Y^{'}(i, j)$, which is summation of base layer $Y_b^{'}$ and detailed layer $Y_d^{'}$:

$$Y^{'}(i, j) = Y_b^{'}(i, j) + Y_d^{'}(i, j). \tag{17}$$

The output luminance image $Y^{'}$ and its histogram is shown in Fig. 5(a) and (b), respectively.

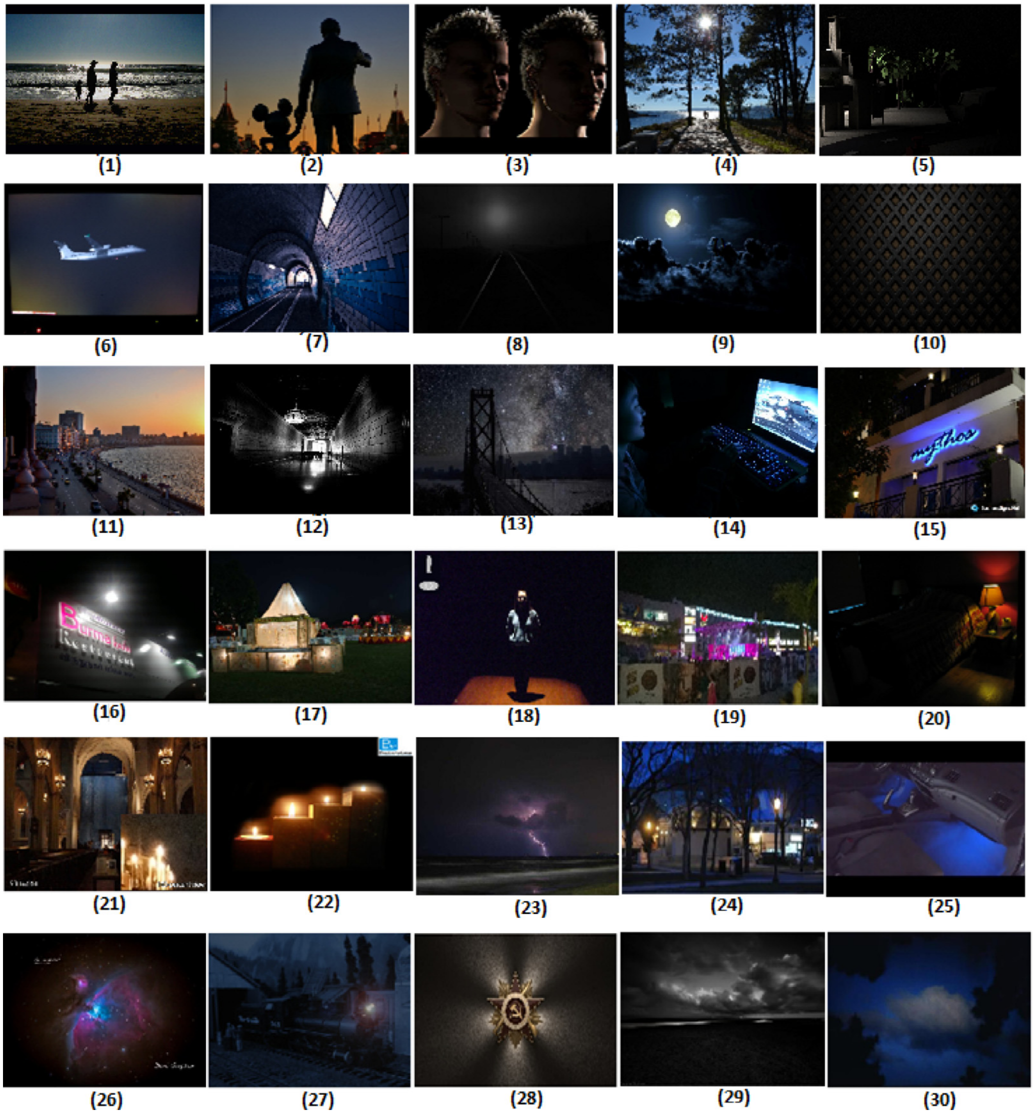

Fig. 6. Test images, (1) Couple, (2) Men, (3) Face, (4) Tree, (5) Flower, (6) Plane, (7) Wall, (8) Track, (9) Cloud, (10) Square, (11) Sea, (12) Gallery, (13) Bridge, (14) Laptop, (15) House, (16) Board, (17) Tent, (18) Lady, (19) Mall, (20) Bed, (21) Hall, (22) Candle, (23) Rain, (24) Forest, (25) Car, (26) Light, (27) Train, (28) Logo, (29) Plain and (30) Sky.

2.6. YCbCr to RGB color conversion

Finally, we convert the $Y_nCb_nCr_n$ color image (value of Y_n, Cb_n and Cr_n are Y', Cb and Cr, respectively) into $R_nG_nB_n$ color image by using following equations [22]:

$$R_n = 1.164(Y_n - 16) + 1.596(Cr_n - 128)$$

$$G_n = 1.164(Y_n - 16) - 0.391(Cb_n - 128) - 0.813(Cr_n - 128)$$

$$B_n = 1.164(Y_n - 16) + 2.018(Cb_n - 128). \tag{18}$$

3. Experimental result

In this section we compare the performance of the proposed approach with the few well known approaches like AHMHE [16], BUBO [14], CLAHE [11] and Adaptive Gamma Correction (AGC) [15]. For this comparison we use 30 test images shown in Fig. 6. For this comparison purpose we use both quantitative and qualitative measures.

Table 1
Results of PQM for 30 images.

Images	AHMHE	BUBO	CLAHE	AGC	Proposed
Couple	8.341	9.302	8.539	8.722	8.987
Men	8.933	10.384	9.921	10.009	10.357
Face	5.619	7.845	6.504	6.433	8.910
Tree	7.792	8.983	8.197	8.224	8.667
Flower	8.643	12.857	10.959	10.918	11.809
Plane	6.024	8.691	7.008	5.593	8.625
Wall	7.878	10.066	8.538	8.790	9.900
Track	10.025	12.200	12.172	11.508	12.876
Cloud	8.789	10.667	9.625	9.525	10.124
Square	7.479	8.643	8.821	8.239	10.375
Sea	8.654	9.931	8.732	8.976	9.816
Gallery	8.467	9.785	8.823	8.809	9.331
Bridge	8.072	9.786	8.497	8.827	10.616
Laptop	7.873	9.573	8.785	8.929	9.091
House	8.666	10.340	9.172	9.443	9.757
Board	9.046	9.658	9.073	8.995	9.247
Tent	5.754	8.233	6.566	6.852	8.778
Lady	5.173	9.879	7.953	7.725	10.221
Mall	8.944	11.159	9.449	9.891	10.312
Bed	7.226	9.619	8.619	8.406	9.661
Hall	8.017	9.565	8.273	8.585	9.528
Candle	8.877	9.419	9.082	8.979	9.492
Rain	4.273	6.273	5.038	4.373	8.643
Forest	6.347	8.943	7.350	7.534	9.206
Car	5.852	6.837	6.903	5.790	7.597
Light	8.395	10.343	9.182	9.056	10.298
Train	7.427	9.418	8.525	8.256	10.043
Logo	8.548	10.649	9.270	9.488	10.383
Plain	8.925	11.007	9.557	9.823	10.748
Sky	5.520	6.189	6.485	5.604	8.439
Average	7.653	9.541	8.521	8.410	9.728

Table 2
Results of entropy for 30 images.

Images	Original	AHMHE	BUBO	CLAHE	AGC	Proposed
Couple	7.099	7.156	7.099	7.382	7.286	7.535
Men	6.640	7.374	7.162	7.018	7.053	7.146
Face	4.409	5.323	4.409	4.961	5.159	5.646
Tree	7.360	7.092	7.357	7.805	7.459	7.377
Flower	4.103	4.634	4.103	4.640	4.793	4.804
Plane	5.579	5.666	5.578	6.068	6.001	6.061
Wall	6.839	7.325	6.831	7.509	7.231	7.180
Track	4.541	5.930	4.541	5.107	4.537	4.881
Cloud	4.667	5.541	4.696	5.196	5.391	5.768
Square	5.272	6.630	5.666	6.241	6.176	6.066
Sea	7.486	7.414	7.591	7.541	7.522	7.615
Gallery	4.087	4.148	4.084	4.430	3.961	5.362
Bridge	6.644	7.575	6.916	7.512	7.375	7.177
Laptop	4.402	5.484	4.389	4.819	5.062	5.312
House	6.610	7.189	6.612	7.159	6.954	7.071
Board	6.330	6.528	6.325	6.768	6.628	6.831
Tent	6.245	6.457	6.244	6.777	6.662	6.815
Lady	5.521	7.371	5.520	6.401	6.058	5.824
Mall	6.733	7.312	6.726	7.554	7.159	6.841
Bed	4.379	5.350	4.817	5.117	5.319	5.431
Hall	7.038	7.368	7.031	7.587	7.413	7.640
Candle	3.744	4.171	3.738	4.109	3.868	5.219
Rain	5.816	7.049	6.129	6.709	6.736	6.886
Forest	6.626	7.382	6.652	7.349	7.164	7.409
Car	5.553	6.456	5.989	6.224	5.976	6.531
Light	5.235	5.989	5.331	5.767	5.623	6.072
Train	6.247	7.159	6.775	7.091	7.038	7.156
Logo	6.218	6.513	6.505	7.141	6.846	6.936
Plain	6.221	6.702	6.280	7.078	6.208	6.908
Sky	5.792	6.547	6.112	6.690	6.442	6.787
Average	5.781	6.428	5.907	6.392	6.237	6.476

Table 3
Results of RMSC for 30 images.

Images	Original	AHMHE	BUBO	CLAHE	AGC	Proposed
Couple	0.217	0.322	0.217	0.249	0.324	0.296
Men	0.177	0.309	0.275	0.194	0.330	0.286
Face	0.137	0.246	0.137	0.180	0.233	0.193
Tree	0.238	0.332	0.237	0.280	0.338	0.319
Flower	0.091	0.214	0.091	0.140	0.188	0.133
Plane	0.122	0.245	0.122	0.144	0.224	0.161
Wall	0.183	0.285	0.183	0.227	0.275	0.217
Track	0.064	0.240	0.161	0.108	0.216	0.096
Cloud	0.125	0.260	0.131	0.188	0.238	0.163
Square	0.059	0.316	0.199	0.160	0.255	0.090
Sea	0.244	0.328	0.274	0.243	0.343	0.340
Gallery	0.189	0.271	0.189	0.252	0.283	0.243
Bridge	0.111	0.298	0.164	0.200	0.265	0.162
Laptop	0.223	0.260	0.223	0.225	0.281	0.261
House	0.183	0.289	0.184	0.229	0.297	0.251
Board	0.227	0.302	0.226	0.244	0.320	0.287
Tent	0.214	0.276	0.214	0.226	0.288	0.267
Lady	0.122	0.205	0.122	0.146	0.205	0.164
Mall	0.184	0.273	0.184	0.213	0.268	0.219
Bed	0.084	0.213	0.099	0.125	0.188	0.123
Hall	0.199	0.274	0.199	0.231	0.275	0.246
Candle	0.187	0.240	0.187	0.213	0.252	0.233
Rain	0.068	0.247	0.086	0.142	0.207	0.146
Forest	0.146	0.263	0.148	0.219	0.238	0.221
Car	0.101	0.279	0.149	0.169	0.244	0.186
Light	0.099	0.271	0.113	0.161	0.239	0.178
Train	0.074	0.273	0.120	0.146	0.245	0.151
Logo	0.114	0.265	0.133	0.198	0.230	0.193
Plain	0.114	0.268	0.147	0.185	0.254	0.190
Sky	0.070	0.268	0.178	0.133	0.230	0.131
Average	0.145	0.271	0.170	0.192	0.259	0.205

Table 4
Results of MOS for 30 images by 10 subjects.

Images	Original	AHMHE	BUBO	CLAHE	AGC	Proposed
Couple	4.0	3.0	4.5	4.5	6.5	7.5
Men	4.4	2.5	4.3	4.9	5.5	7.6
Face	3.2	3.9	3.5	3.8	4.0	6.4
Tree	4.3	4.6	5.0	5.9	6.6	8.0
Flower	3.5	3.0	4.4	5.3	6.0	7.2
Plane	4.8	2.9	4.7	4.5	4.2	6.1
Wall	4.5	3.5	5.1	6.0	6.6	7.9
Track	3.0	2.8	5.2	5.5	5.4	6.5
Cloud	4.5	3.3	3.9	4.9	5.5	6.6
Square	4.3	5.1	4.8	5.8	5.6	6.9
Sea	4.7	4.5	5.2	6.1	5.0	6.5
Gallery	3.4	4.0	3.5	4.0	4.1	4.4
Bridge	3.9	3.6	4.0	4.4	5.2	6.7
Laptop	3.7	3.4	4.1	5.5	4.9	5.8
House	4.4	4.5	5.3	5.6	5.1	7.5
Board	4.6	5.2	4.8	5.5	5.1	6.0
Tent	5.1	3.8	5.3	4.5	5.5	6.2
Lady	4.8	4.2	4.9	4.6	4.5	5.3
Mall	4.9	3.5	5.0	4.6	4.5	5.5
Bed	4.2	3.3	4.0	5.5	5.2	5.9
Hall	4.9	3.5	4.5	5.2	5.0	6.1
Candle	5.0	3.8	4.8	5.6	5.5	6.2
Rain	4.6	3.4	4.8	4.9	4.9	5.8
Forest	4.2	3.7	4.4	5.5	5.3	5.9
Car	4.5	4.1	4.7	5.8	5.3	6.3
Light	4.8	3.8	4.9	5.6	5.3	6.2
Train	4.1	4.3	4.6	5.1	5.0	5.6
Logo	4.7	4.4	4.8	5.5	5.3	6.4
Plain	4.3	3.9	4.5	5.7	5.4	6.5
Sky	4.5	4.3	4.8	5.3	5.1	6.1

Fig. 7. Shows visual quality results for Cloud image.

3.1. Quantitative assessment

To evaluate the effectiveness of proposed approach, we choose three metrics, i.e. perceptual quality metric (PQM), entropy and root mean square contrast (RMSC). The description about these metrics are given below:

3.1.1. Perceptual quality metric (PQM)

PQM is a no-reference metric for judging the image quality and proposed by Wang et al. [23] to judge visible blocking and blurring artefacts in the image. We have used code available at their website [23] to compute the PQM. According to Mukherjee and Mitra [24], the value of PQM should close to 10. Digression away from 10 in any direction shows decrease in perceptual quality.

Table 1 shows comparison among different method for PQM values. It is clear from Table 1 that the average value of PQM of proposed method is very close to 10 but for other methods average value of PQM is very much less than 10 which shows decrease in perceptual quality.

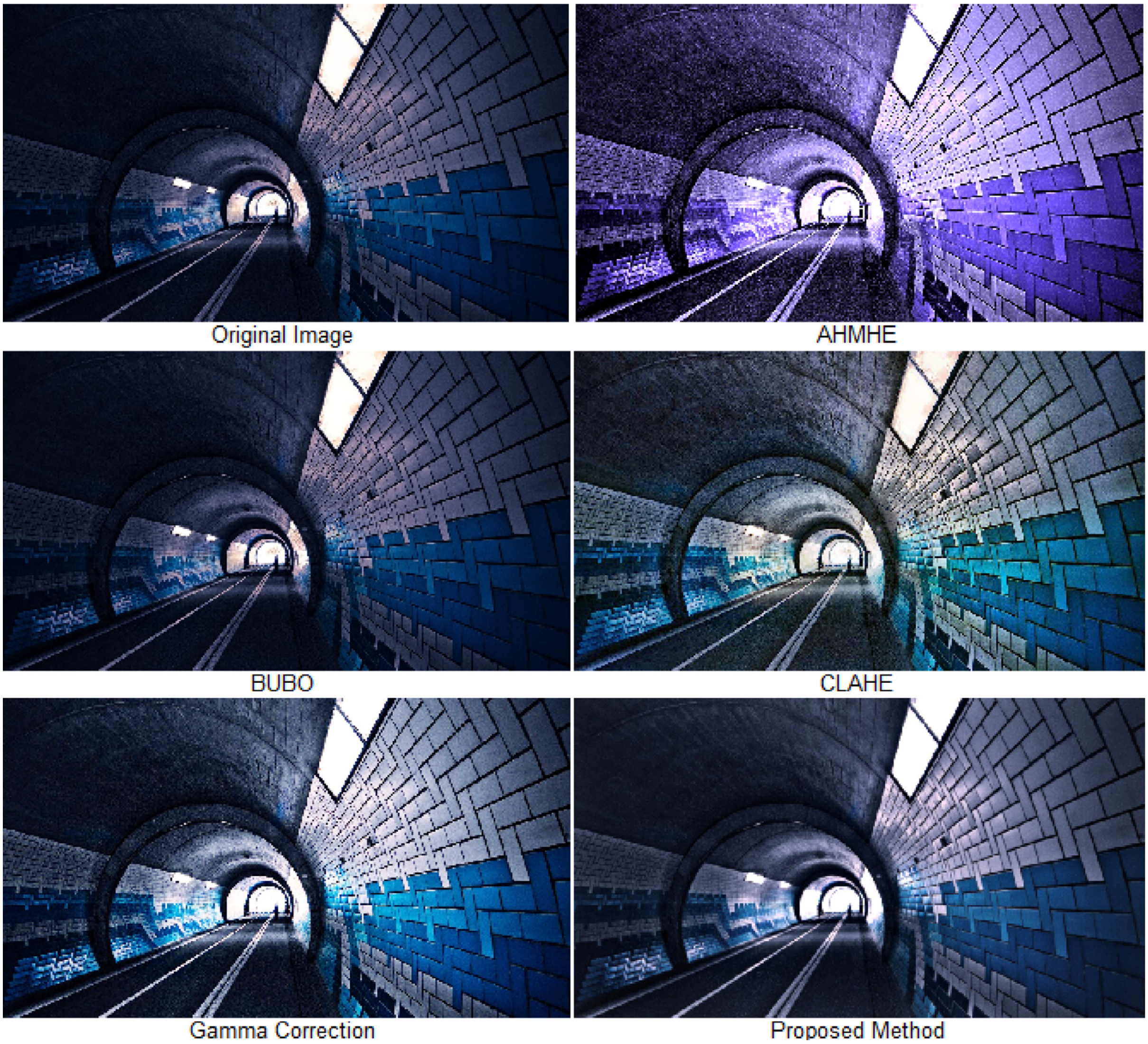

Fig. 8. Shows visual quality results for Wall image.

3.1.2. Entropy

Entropy shows the richness of the details in the processed image [7]. In general, higher entropy means that image holds higher details and information. The mathematical expression for calculating the entropy is given below:

$$Entropy[p] = -\sum_{i=0}^{L-1} p(i)\mathbf{log}_2 p(i), \tag{19}$$

where, $p(i)$ is probability of ith gray level and L is total number of gray levels.

Table 2 shows the results of entropy for the different methods. It is clear from Table 2 that average entropy for proposed method are better as compare to other methods which show that the processed image, we obtain after applying proposed method contains higher details and information.

3.1.3. Root mean square contrast

RMSC is used to calculate the overall luminance contrast in an image. RMSC is defined as the standard deviation of the pixel intensities [25]:

$$RMSC = \sqrt{\frac{1}{PQ}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1}(I_{ij} - \bar{I})^2}, \tag{20}$$

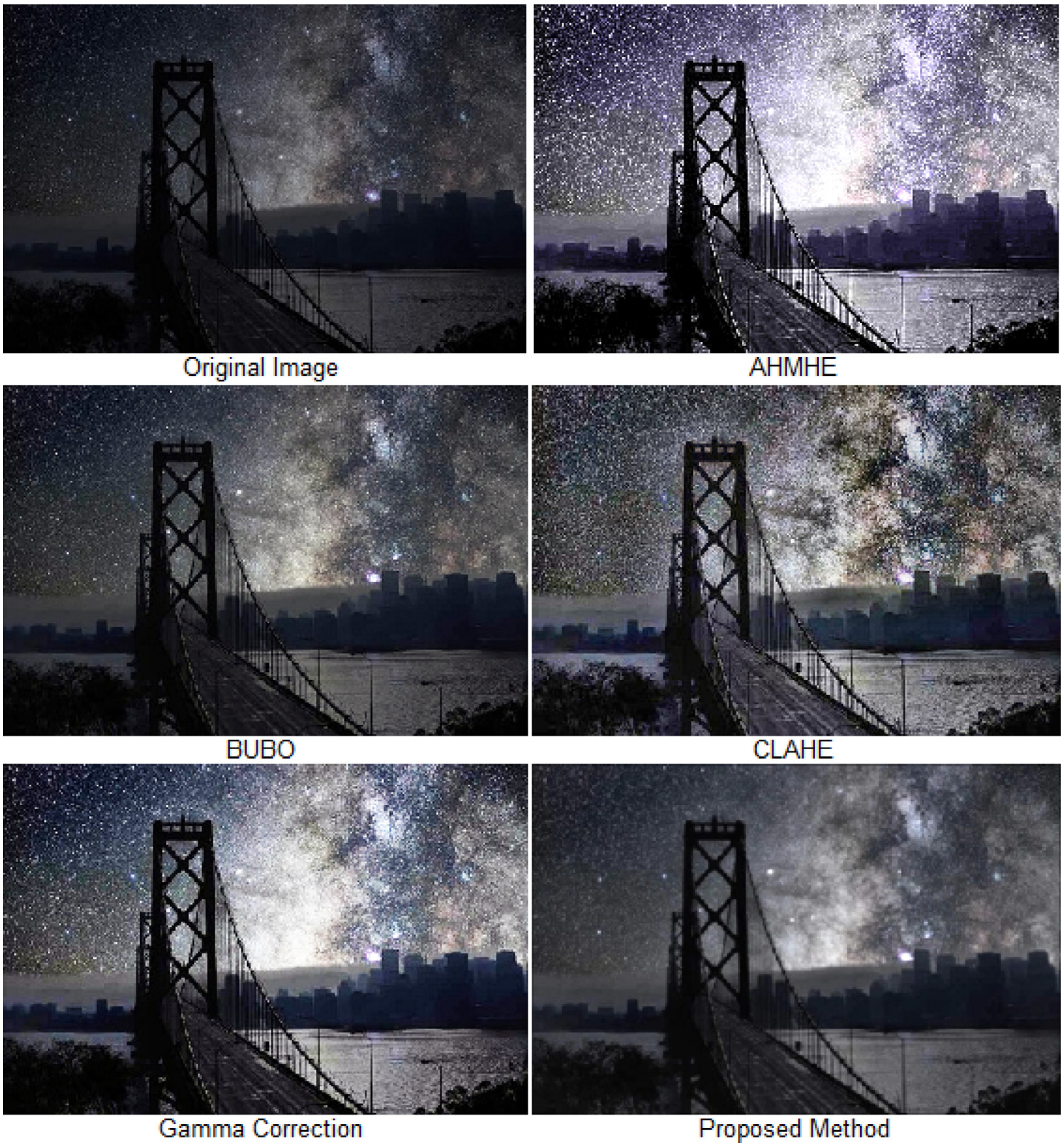

Fig. 9. Shows visual quality results for Bridge image.

where, intensities I_{ij} are the (i, j)th element of the two dimensional image of size P by Q. $\bar{I}$ is the average intensity of all pixel values in the image. The image I is assumed to have its pixel intensities normalized within the range [0,1].

Table 3 shows the results of RMSC. It is clear from Table 3 that average results of RMSC of proposed method are better than the BUBO and CLAHE methods and lesser than the AHMHE and AGC methods. Although AHMHE and AGC approaches score better than proposed approach, it is clear from the visual results that AHMHE and AGC methods show over enhancement and unnatural artefact in the output image and proposed method overcomes these drawbacks of AHMHE and AGC methods after providing sufficient contrast in the output image.

3.2. Quality assessment

In this section, we compare the visual quality results of proposed method with the results of other methods.

Figs. 7–11 show the visual quality assessment for Cloud, Wall, Bridge, Bed, Rain and Logo images, respectively. It is clear from images shown in Figs. 7–11 that AHMHE shows some additional colors in its output image, whereas, CLAHE and AGC show over enhancement in bright areas of images and BUBO gives image which is very similar to the original image, but the processed image obtain by using proposed method appears natural without any artefacts and human eyes also perceived

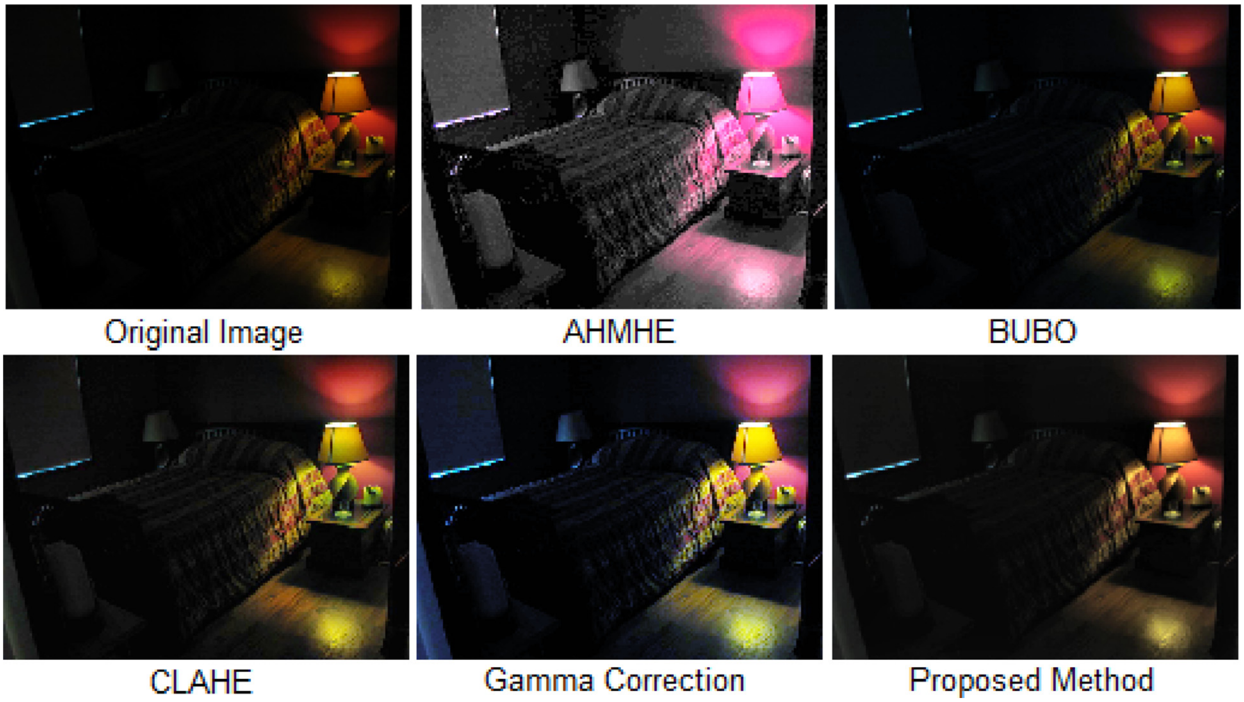

Fig. 10. Shows visual quality results for Bed image.

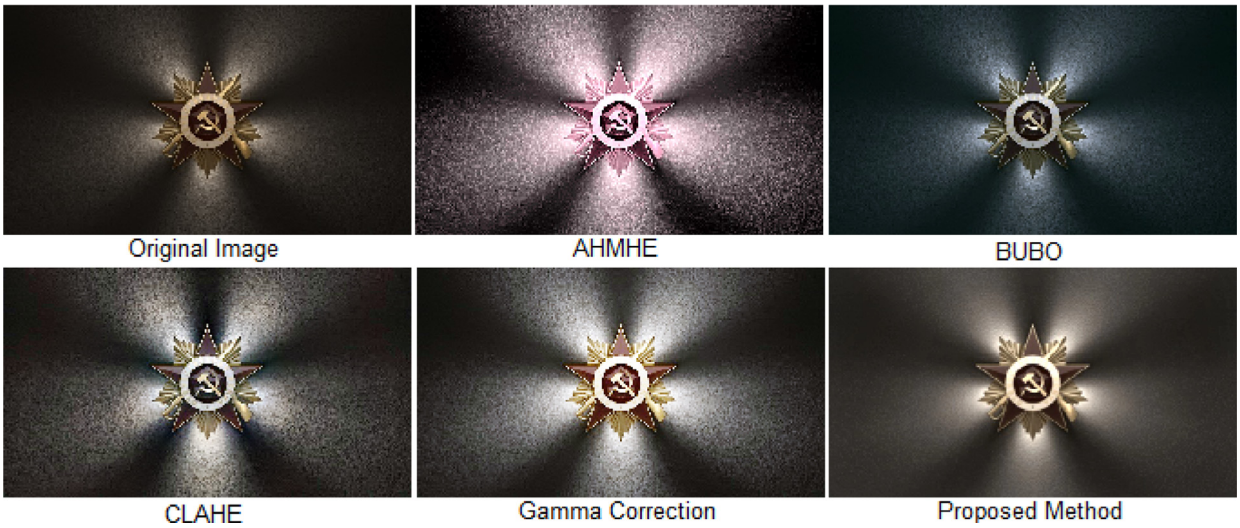

Fig. 11. Shows visual quality results for Logo image.

these images as a good image. The results of proposed method also show that the proposed method overcome the over enhancement drawback of other approaches.

To confirm its effectiveness with respect to human subject's perspective, we include a Mean Opinion Score (MOS) of subjective evaluation of each image by ten subjects [16]. This evaluated the processed images in terms of their overall sharpness, contrast and colorfulness by scores ranging from 0 (bad) to 10 (best), for each image.

Table 4 shows the results of MOS and it is clear that proposed method scored better as compare to other methods for each image. The only limitation of the proposed approach is that we empirically fixed the values of few parameters such as b and γ. Although these empirical values work efficiently for all types of images. It might be possible that for some particular types of images the results are not so efficient. In future we would like to extend this approach to the extent where the values of these parameters will also be image specific.

4. Conclusion

In the proposed approach we used luminance part to enhance the contrast of the image and hence the resultant images have better contrast enhancement without affecting the color information of the input image. Also, it is very clear that the results of the proposed method are free from noise enhancement and there are no artifacts due to enhancement process. Another advantage of the proposed method is that the enhancement is at different level in the darker region and brighter region. Thus bright regions are not over enhanced, while the details of the dark regions are enhanced significantly. We made a comparison of the efficiency of the proposed method with the various other important methods, using the various quantitative and qualitative measures. On the basis of the results of the measures, we can say that the overall performance of the proposed approach is significantly better as compared to the other methods.

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References

[1] Jain AK. Fundamentals of digital image processing. Prentice-Hall: Englewood Cliffs, NJ; 1989.
[2] Kim JY, Kim LS, Hwang SH. An advanced contrast enhancement using partially overlapped sub-block histogram equalization. IEEE Trans Circuits Syst Video Technol 2001;11(4):475–84.
[3] Kim Y. Contrast enhancement using brightness preserving bi-histogram equalization. IEEE Trans Consumer Electron 1997;43(1):1–8.
[4] Wan Y, Chen Q, Zhang B. Image enhancement based on equal area dualistic sub-image histogram equalization method. IEEE Trans Consumer Electron 1999;45(1):68–75.
[5] Chen S, Ramli AR. Contrast enhancement using recursive mean-separate histogram equalization for scalable brightness preservation. IEEE Trans Consumer Electron 2003;49(4):1301–9.
[6] Sim KS, Tso CP, Tan YY. Recursive sub-image histogram equalization applied to gray scale images. Pattern Recognit Lett 2007;28(10):1209–21.
[7] Kim M, Chung MG. Recursively separated and weighted histogram equalization for brightness preservation and contrast enhancement. IEEE Trans Consumer Electron 2008;54(3):1389–97.
[8] Hummel RA. Image enhancement by histogram transformation. Comput Graphics Image Process 1977;6:184–95.
[9] Ketcham DJ, Lowe RW, Weber JW. Real time image enhancement techniques. Hughes Aircraft, Pacific Grove, California: in Seminar on Image Processing; 1976. p. 1–6.
[10] Pizer SM. Intensity mapping for the display of medical images, in functional mapping of organ systems and other computer topoics. Soc Nuclear Med; 1981.
[11] Zuiderveld K. Contrast limited adaptive histogram equalization, chapter VIII, graphics gems IV. Cambridge, MA: Academic Press; 1994. p. 474–85.
[12] Reza AM. Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement. J VLSI Sig Proc 2004;38:35–44.
[13] Arigela S, Asari VK. Adaptive and nonlinear techniques for visibility improvement of hazy images. In: Proceedings of the 7th international conference on advances in visual computing, 2; 2011. p. 75–84.
[14] Yang S, Oh JH, Park Y. Contrast enhancement using histogram equalization with bin underflow and bin overflow. In: Proceedings of international conference on image processing, 1; 2003. p. 881–4.
[15] Chiu YS, Cheng FC, Huang SC. Efficient contrast enhancement using adaptive gamma correction and cumulative intensity distribution. IEEE Int Conf Syst Man Cybern 2011;22(3):2946–50.
[16] Kang B, Jeon C, Han DK, Ko H. Adaptive height-modified histogram equalization and chroma correction in YCbcr color space for fast backlight image compensation. Image Vis Comput 2011;29(8):557–68.
[17] Hasikin K, Isa NAM. Adaptive fuzzy contrast factor enhancement technique for low contrast and nonuniform illumination images. Signal Image Video Process 2014;8(8):1591–603.
[18] Tiwari M, Gupta B, Shrivastava M. High-speed quantile-based histogram equalisation for brightness preservation and contrast enhancement. Image Process, IET 2015;9(1):80–9.
[19] Gupta B, Agarwal TK. Linearly quantile separated weighted dynamic histogram equalization for contrast enhancement. Comput Electr Eng 2017. ISSN 0045–7906, https://doi.org/10.1016/j.compeleceng.2017.01.010.
[20] Watanabe T, Konnai K, Hoshino Y. γ transformation by sigmoid function in digital camera printing system. NIHON GAZO GAKKAISHI 2002;41(1):3–10.
[21] Tanaka G, Suetake N, Uchino E. Image enhancement based on multiple parametric sigmoid functions. In: Proceedings of 2007 international symposium on intelligent signal processing and communication systems. China: Xiamen; 2007.
[22] YCbcr color spacean intro and its applications. 2017. http://www.roman10.net/2011/08/18/ycbcr-color-spacean-intro-and-its-applications/, Accessed on 1 May.
[23] Wang Z, Sheikh HR, Bovik AC. No-reference perceptual quality assessment of JPEG compressed images. Proc IEEE Int Conf Image Process 2002;1:477–80.
[24] Mukherjee J, Mitra SK. Enhancement of color images by scaling the DCT coefficients. IEEE Trans Image Process 2008;17(10):1783–94.
[25] Peli E. Contrast in complex images (PDF). J Opt Soc Am A 1990;7(10):2032–40. doi:10.1364/JOSAA.7.002032.

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