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Ambience Retaining Enhancement Algorithm for Uneven Illumination Images using Nonlinear Pixel Level Intensity Transfer Function (AREA)

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Enhancement of uneven illumination images poses serious challenges in image enhancement. This paper presents a simple but effective ambience retaining enhancement algorithm for uneven illumination images based on Retinex theory. The novelty of the method lies in the use of a Nonlinear Pixel level Intensity Transfer function (NPIT) for enhancing the image. Human Vision System (HVS) enhances the scene considering the global and local context of the region. NPIT imitates this functioning of HVS using the parameters prominent luminance level for global information and relative visibility for local information. The image decomposed into illumination image and reflectance image by a Guided Filter. The NPIT mapped illumination image integrate with reflectance image produces the enhanced image. For better visual perception and color reproduction a color balancing is applied as the post processing stage. The algorithm is tested on two publicly available uneven illumination image dataset and a ColorChecker dataset. The empirical results show that the enhanced image of proposed method are naturally looking, artifact free and ambience retaining. The subjective analysis and objective reveal the superiority of the method over other state-of-art methods.

Keywords: ambience, guided filter, nonlinear pixel level intensity transfer function, prominent luminance level, relative visibility

1. INTRODUCTION

The fundamental goal of image enhancement is to produce visually pleasing and naturally looking images along with the improved interpretability of visual information. Due to the richer information of visual perception in color images, the color image enhancement has a rising demand in image processing. The Human Vision System (HVS) has complicated self-adapting ability to perceive the details in both bright and dark regions in a poor illuminated scene. The image acquisition devices are unable to replicate the HVS completely. Hence the captured images contain underexposed, overexposed and mixed exposed regions with poor detail and incorrect color reproductions. The ambience retaining image enhancement algorithm for uneven illumination arises in such situations.

Large number of conventional algorithms [1-4] exists in literature for enhancement of images. In HE based contrast limitation [1], it is difficult to fix an appropriate clip limit for dark and bright regions in an uneven illumination image. Conventional Histogram Equalization (HE) [2] algorithm results over enhancement and color shift in uneven illumination images. HE based brightness preservation [3], the improvement of HE technique,

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brings about enhancement with inappropriate intensity in dark regions of a non-uniformly illuminated images. Large number of algorithms exists in literature which pays attention to contrast enhancement [4] rather than the illumination. These techniques do not work well for uneven illumination images.

The Retinex Theory [5] based enhancement algorithm exists in literature produces naturally looking enhanced images. The Retinex based enhancement algorithms [6-9] based on human perception produce more naturally looking enhanced images. The Single Scale Retinex (SSR) [6] and its improvements uses Gaussian filters to get the ratio of lightness from a central field to extended field. Method proposed in [7] estimates multiple illuminations to improve the enhancement output of non-uniform illumination images. The weighted variational model proposed in [8] fails to enhance the dark regions in non-uniform illumination images. Although Naturalness Preserved Enhancement Algorithm (NPEA) [9] and structure aware illumination map estimation method proposed in [10], works well for non-uniform illumination images, fails to enhance the low light non uniform illumination images. The enhancements methods exist in literature makes drastic change in variation of brightness of the images and results in over enhancement and artifacts and halo effects in over exposed, under exposed and mixed exposed regions of the nonuniform illumination images.

The proposed method fills these gaps by enhancing the uneven illumination images by retaining its ambience. The sense of ambience of the image is the atmosphere or feel of the image. The proposed Nonlinear Pixel level Intensity Transfer function (NPIT) is an adaptive intensity transfer function which enhances the images by considering its global and local context; thus, retains the ambience. In proposed method, the pixels in the over exposed, under exposed and mixed exposed regions are mapped differently according to their characteristics estimated by the parameter prominent luminance level and relative visibility of NPIT. The parameter, prominent luminance level estimates the global ambience of the image and relative visibility estimates the local ambience of the pixel. The effectiveness of Retinex based enhancement algorithms depends on the accuracy of estimation of the illumination image and mapping function. The proposed method uses edge preserving Guided Filter (GF) [11] for estimating illumination component. The filter performs well than traditional filters at extremely low computational effort. Then image decomposed by GF into illumination image and reflectance image. The estimated illumination image mapped by proposed NPIT function, and finally integrated with reflectance image to get the enhanced image. A color balancing is performed as a post processing step for making the output more visually appealing. The experimental results show the better performance of the method for enhancing uneven illumination images by producing naturally looking, ambience conserving enhanced images.

The rest of the paper is organized as follows. The architecture of the proposed method and technical steps are presented in Section 2. Section 3 describes the experimental results for showing the effectiveness of the algorithm. The paper is concluded with a summary in Section 4.

2. PROPOSED METHOD

The proposed method, process the images based on Retinex theory and produces ambience retaining artifact free enhanced images. The illumination image estimated by GF gives better approximation to the illumination image. The adaptive intensity transfer function NPIT, retains ambience of the image by imitating human vision perception. In order to make visibility in local detail, the human eye performs a local processing on the basis global information of the scene. NPIT mimics the HVS by enhancing the image using prominent luminance level and relative visibility. In NPIT, both parameters are used with modified gamma adjustment function, which gives the nonlinear response of HVS, to improve the local detail in the same way as human perception. The integration of NPIT transferred illumination image and reflectance image gives the enhanced image. The experimental results show that the proposed improves the visibility of the over exposed, under exposed and mixed exposed regions without changing the atmosphere of the image. In order to improve the visual pleasantness of the image, a histogram-based color balancing is performed as the last stage. The architecture of the proposed method is given in Fig. 1.

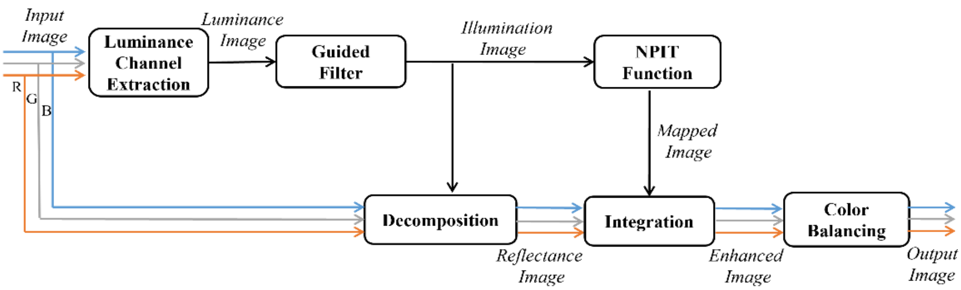


Fig. 1. Architecture of the proposed method.

2.1 Luminance Channel Extraction

The three chromatic channels in color images gives more information than a gray scale image. Processing of the three-color channels separately leads to the loss of interrelations between the channels and introduces artifacts and color shifts. The problem can be solved by transforming three channels to a single channel for further processing. In proposed method, an achromatic channel of RGB image referred as luminance channel is extracted. Here luminance channel is estimated as the maximum value of R, G, and B channels [12]. The luminance is defined by the highest reflectance channel for each pixel and defined as

$$L_u(x, y) = \max(I_c(x, y)) \tag{1}$$

where I_c is the input image and L_u are the luminance channel. Throughout this paper c assumes R, G, and B channels.

2.1 Illumination Image Estimation

The crucial step in Retinex based enhancement approach is the estimation of illumination image. The accuracy of the estimated illumination image affects the quality of enhanced image. The edge preserving low pass filter is used for estimation while illumination changes smoothly across contiguous pixels and have some abrupt transitions along the edges in natural images. The proposed method uses GF, which smoothens homogeneous regions by preserving abrupt variations, for illumination estimation. The estimated illumination image denoted by L_f and defined as

$$L_f(x, y) = \mathrm{GF}(L_u(x, y)) \tag{2}$$

where L_u is the luminance image.

Fig. 2 shows visualization of better performance of GF in preserving the edges than other frequently used filters exists in the literature [9, 18]. The enlargements of marked portion of flower image shown in inset of Fig. 2 (b) demonstrate that Bilateral Filter [13] and Bright Pass Filter [9] in Fig. 2 (c), generates the artificial patterns near edges. Comparing with other filters the GF gives the better edge preserving approximation to input image as in Fig. 2 (d).

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

Fig. 2. Comparison of GF with filtering schemas; (a) Input image; (b) Filtered by bilateral filter [13] with parameters $\sigma_s = 25$ and $\varepsilon = 0.2$; (c) Filtered by bright pass filter [9]; (d) Filtered by GF with parameters $w = 25$ and $\varepsilon = 0.04$.

(a) (b) (c)

Fig. 3. Image decomposition; (a) Input image; (b) Illumination image; (c) Reflectance image.

2.3 Image Decomposition

According to Retinex theory, the intensity perceived by human eye is the product of reflectance and illumination and is defined as

$$I(x, y) = L(x, y)R(x, y) \tag{3}$$

where I is the perceived light intensity of human eyes and L and R are the illumination and reflectance image respectively. In these three variables I is the only known parameter and other two are unknowns. Thus, the reflectance image R_c^l can be estimated as:

$$R_c^l(x,y) = \frac{I_c(x,y)}{L_f(x,y)} \tag{4}$$

where I_c is the input image and L_f is the estimated illumination image. Since processing of reflectance image distorts the detail of the image proposed method leaves the reflectance image unaltered. Fig. 3 shows the image decomposition. Fig. 3 (b) shows the estimated illumination image and Fig. 3 (c) shows the decomposed reflectance image.

2.4 NPIT Mapping and Integration

The global and local context of detail in a scene highly influences the perception of human vision [14]. The sensitivity of retina changes differently for a dark region in a bright scene than dark region in a dark scene. In NPIT this visual perception is adjusted using a modified gamma adjustment function, which maps the pixels based on both global and local context. The gamma value of modified gamma adjustment function is determined from global and local parameters such as prominent luminance level and relative visibility of the image respectively. The modified gamma adjustment function, expressed as

$$\gamma_{(x,y)} = \alpha^{\beta_{(x,y)}} \tag{5}$$

where α is the prominent luminance level and $\beta_{(x,y)}$ is the relative visibility of pixel (x, y). The prominent luminance level of the image estimated by log-average luminance [15].

$$\alpha = \exp\left(\tfrac{1}{N}\sum_{(x,y)} \log(\delta + L_u(x,y))\right) \tag{6}$$

where L_u is the luminance image, N is the number of pixels and δ is used to avoid singularity that occurs if black pixels are present in the image. The adaptive nature of NPIT is obtained by relative visibility and expressed as:

$$\beta_{(x,y)} = \frac{GV - LV_{(x,y)}}{GV} \tag{7}$$

where GV is the global visibility and $LV_{(x,y)}$ is the local visibility of pixel (x, y) in L_f. The relative visibility is estimated by comparing visibility of local region with the global visibility of the image. The global visibility and local visibility are computed by Michelson Visibility [14] measure. According to definition in *e.g.* Eq. (7), the $\beta_{(x,y)}$ becomes high if an object is indistinguishable from background and image enhanced based on prominent luminance level only. The global visibility, GV is defined as

$$GV = \frac{L_f^{\max} - L_f^{\min}}{L_f^{\max} + L_f^{\min}}. \tag{8}$$

$L_f^{\max}$ and $L_f^{\min}$ is the maximum and minimum intensity values in the illumination image L_f.

Local visibility, $LV_{(x,y)}$ measured over neighborhood of (x, y) and defined as

$$LV_{(x,y)} = \frac{WL_f^{\max} - WL_f^{\min}}{WL_f^{\max} + WL_f^{\min}}. \tag{9}$$

where $WL_f^{\max}$ and $WL_f^{\min}$ defines the maximum and minimum values in neighborhood w of illumination image L_f. Here $m/3 \times n/3$ local patch defines the neighborhood, where m and n are the size of the image.

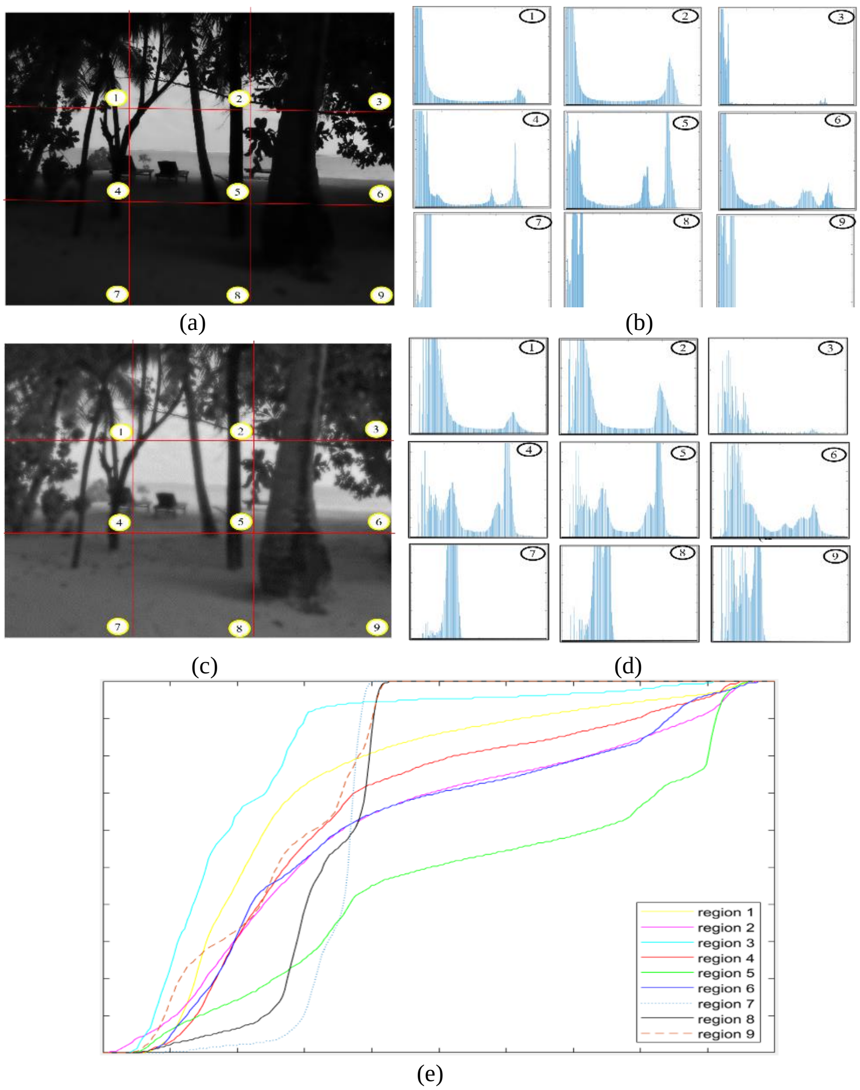


Fig. 4. NPIT function; (a) Illumination image of Fig. 3 (a), prominent luminance Level of the image, $\alpha = 0.0034$; (b) Histogram of each marked region of (a); (c) NPIT mapped image; (d) Histogram of marked region of 4 (c); (e) NPIT mapping function of marked regions of 4 (c).

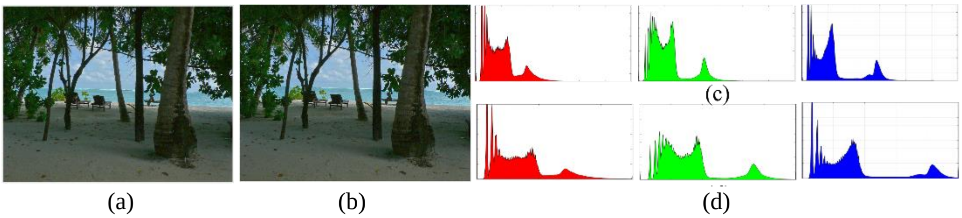


Fig. 5. Color balancing; (a) Enhanced Image of Fig. 3 (a); (b) Color balanced image; (c) RGB histogram of image (a); (d) RGB histogram of (b).

NPIT mapping of illumination image, L_f, produces the mapped image L_m and defined as

$$L_m(x, y) = L_f(x, y)^{\gamma(x, y)}. \tag{10}$$

In order to produce enhanced image, I_c^e, the intensity transferred illumination image, L_m, and reflectance image, R_c^l, are fused together and expressed as

$$I_c^e(x, y) = L_m(x, y) \times R_c^l(x, y). \tag{11}$$

Fig. 4 illustrates the NPIT function. The histogram of over exposed, under exposed and mixed exposed regions of illumination image and NPIT mapped image are shown in Figs. 4 (b) and (d). The NPIT mapping of marked regions are plotted in Fig. 4 (e). The region 5 and region 3 in Fig. 4 (a) are over exposed and under exposed regions respectively. As illustrated in Fig. 4 (e) the NPIT function maps the pixels in under exposed region to higher level than the pixels in over exposed region. As shown in Fig. 4 (e) the mixed exposed regions like region 2, region 4 and region 6 are mapped by NPIT in the same manner according to their characteristics. This property of NPIT produces an ambient preserving enhanced output without any over enhancement and artifacts.

2.4 Color Balancing

Color balancing is performed as a post processing step in the proposed algorithm in order to ensure color saturation. In the proposed method color balancing is performed by clipping the outliers in the histogram of the image and scaling the histogram to a specified range. In proposed method, the outliers are determined using image histogram [16]. The two extreme points in each of the color channels referred as black point and white point of the channel are determined using Cumulative Distribution Function (CDF). Black point of the color channel c is defined as

$$b_c = \min\{v|H_c(v) \leq 0.01\} \tag{12}$$

where $H_c(v)$ is the CDF of color channel c and b_c defines the bin number in which 1% of the data points fall. And the white point of the color channel c defined as

$$w_c = \min\{v|H_c(v) \geq 0.99\} \tag{13}$$

where w_c defines the bin number in which 99% of the data points fall.

The black point of the image, denoted by b, is defined in terms of black point of the channels, and is expressed as

$$b = \min_{c\{R,G,B\}} b_c \tag{14}$$

where b_c is the black point corresponding to R, G, and B channels.

And white point of the image denoted by w and defined as

$$w = \max_{c\{R,G,B\}} w_c \tag{15}$$

where w_c is the white points of R, G, and B channels.

Clipping is performed in the enhanced image and expressed as

$$\bar{I}_c^e(x,y)=\begin{cases}0 & \text{if } I_c^e(x,y)<b\\ 255 & \text{if } I_c^e(x,y)>w\end{cases} \tag{16}$$

where $\bar{I}_c^e$ is the clipped image.

And the color balanced image, denoted by $\bar{I}_c^e$ and defined as

$$\bar{I}_c^b(x,y)=\frac{\bar{I}_c^e(x,y)-\bar{I}_{c_{\min}}^e}{\bar{I}_{c_{\max}}^e-\bar{I}_{c_{\min}}^e} \tag{17}$$

where $\bar{I}_{c\max}^e$ and $\bar{I}_{c\min}^e$ are the maximum and minimum values of $\bar{I}_c^e$.

Fig. 5 depicts the color balancing step. As shown in Fig. 5 (b), color balancing improves the color information of the image and image become more visually pleasing. Figs. 5 (c) and (d) shows the RGB histogram of enhanced image and color balanced image respectively. Fig. 5 (d) shows that for a color balanced image, the histogram of three channels is scaled into complete range and shape of the histogram is preserved as in Fig. 5 (c).

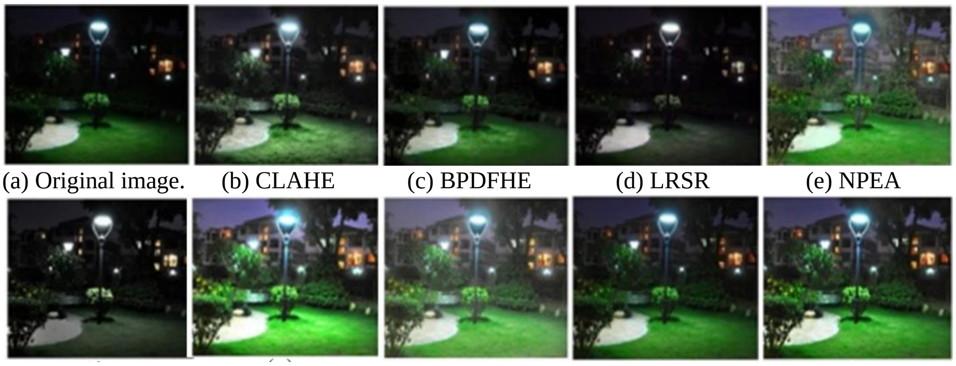
3. RESULTS AND DISCUSSIONS

To demonstrate the performance and effectiveness of proposed method, the method compares with Conventional approaches and Retinex based approaches. And proposed method tested on publicly available datasets [9, 17] and ColorCheker Dataset [18]. The proposed algorithm compares with some Retinex based algorithms like LRSR [19], NPEA [9], NL-Retinex [20], RRM [21] and SDD [22] and with conventional methods like CLAHE [1], and BPDFHE [3] and also compares with low light image enhancement algorithm LIME [10]. For comparison, the implementation codes of the mentioned algorithms available at their websites are used. The parameters of the comparison methods are set default parameters for better performance. In proposed algorithm smoothing parameter of GF, ε, is set as 0.4 and window size, as 25. The experimental result shows that the changes in smoothing parameter, ε and window size, we have less significance in enhancement. However, while calculating complexity of the algorithm the window size, w plays the major role. The computational time complexity of the algorithm can be expressed as $O(w^2)$.

The algorithm tested on the database described in [9] which has 86 uneven illumination images including clear images, rainy images, nightfall images, and nighttime images. The proposed method algorithm is tested with dataset in [18] which contains 23 most challenging non-uniform illumination images. The algorithm also tested with publicly available ColorCheker Dataset [18] which contains 158 RGB images is taken in indoor and outdoor scene and each image contains GretagMacbeth color checker. The enhancement algorithm needs to be assessed both in subjective and objective dimensions. Due to the limitation of space the result of six sample images are displayed in subjective assessment and objective assessment as in [9].

3.1 Subjective Assessment

Subjective assessment, the most challenging task in enhancement, is necessary for judging the pleasantness and quality of output images. The superiority of the proposed method over state of art method is clearly visible in experimental results. Figs. 7-12 (a) are the original images. The Garden test image in Fig. 6 (a) is non-uniformly illuminated night time image with a bright light lamp region and dark building texture background. The enhancement output of the proposed method in Fig. 6 (j) depicts that the method enhances the images without introducing artifacts and halo effects. The competing methods like NPEA, LIME and RRM as shown in Fig. 6 (e), Fig. 6 (g) and Fig. 6 (h) fails to enhance the images by generating artifact around the bright region. The conventional methods CLAHE, BPDFHE and LRSR in Figs. 6 (b)-(d) results in color shift; thus, the ambience of the image lost after enhancement. The Face image in Fig. 7(a) is a backlit image with dark view indoor and bright view outdoor. It is very challenging image to enhance and lots of details in bright background region. The empirical results in Fig. 7 (j) shows that proposed method successfully enhances the image without generating any halo or graying out effect. Figs. 7 (b)-(i) shows that the other state-of-art method generates color shift, artifacts and over enhancement. The nightfall image, Palace in Fig. 8 (a) has a lot of details and multiple light sources. The Fig. 8 (j) shows the ambience preserving capability of the proposed method over other comparing methods. The atmosphere of the image unaltered after the enhancement. As shown in Figs. 8 (b) and (c), CLAHE and BPDFHE generates halo effect and other methods as in Figs. 8 (d)-(i) fails to retain the color information.



(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA

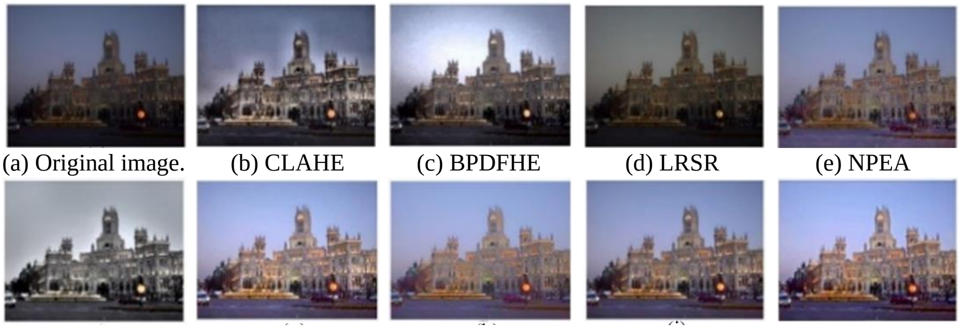
(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

Fig. 6. Comparison of Garden image.

(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA

(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

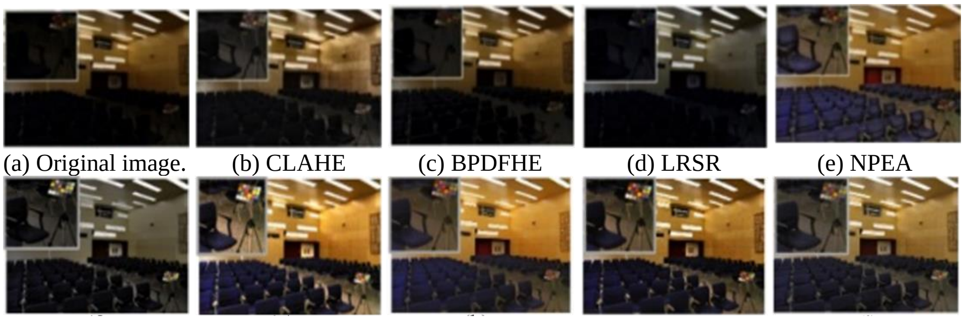
Fig. 7. Comparison of face image.



(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA

(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

Fig. 8. Comparison of palace image.



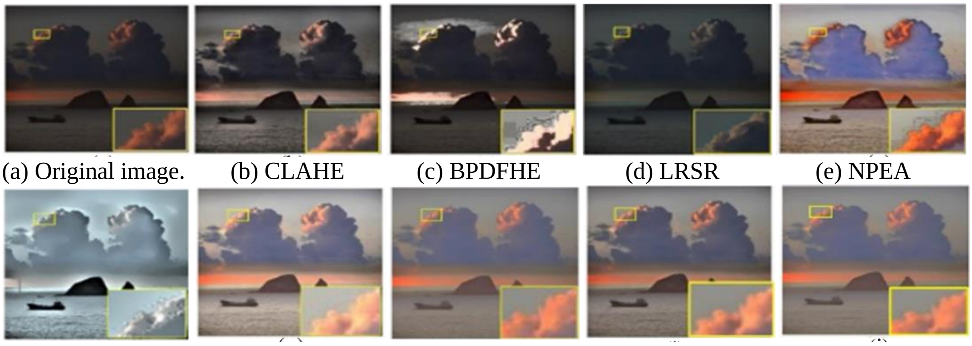
(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA

(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

Fig. 9. Comparison of auditorium image.

The Auditorium image in Fig. 9 (a) is a non-uniformly illuminated indoor image with GretagMacbeth color checker. The color retaining capability of the proposed method demonstrated in Fig. 9 (j). Comparing to other methods as in Figs. 9 (b)-(i), the proposed method enhances the image without any color shift. The GretagMacbeth color checker portion of the image shown in inset of Fig. 9 (j) shows that along with visibility improvement, color information is also retained.

The non-uniform illumination dark image, Sunset as in Fig. 10 (a), is rich with homogeneous regions and heterogeneous regions. The enlargement of marked portion in Figs. 10 (b)-(j) helps to compares the details preserving and color retaining capability of the methods. The enhancement result of proposed method in Fig. 10 (j) depicts improved performance of the proposed method. The Cloudy image as in Fig. 11 (a) contains a lot of details and textures, such as branches, leaves, and building. The enhanced image Fig. 11 (j) shows the capability of the algorithm for preserving the textures and details over competing methods. The ambience retaining capability of the proposed method is clear from the enhanced result of the method. The atmosphere of enhanced nighttime garden image in Fig. 6 (j) and nightfall sunset image in Fig. 10 (j) feels the same images after enhancement. And the enhanced cloudy image in Fig. 11 (j) shows that the enhanced image looks cloudy after enhancement. As demonstrated in Figs. 7-9 (j), the experiments results show the comparable performance of the proposed method over other state of art method by enhancing the image retaining ambience and without making light source confusion or artifacts.



(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA
(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

Fig. 10. Comparison of sunset image.

(a) Original image. (b) CLAHE (c) BPDFHE (d) LRSR (e) NPEA
(f) NL-Retinex. (g) LIME (h) RRM (i) SDD (j) Proposed method.

Fig. 11. Comparison of cloudy image.

3.2 Objective Assessment

The subjective assessment is necessary for evaluation, however, the time and cost involved in it makes a difficult process. Although quantitative metrics evaluate the important characteristics of the image, there is no generally accepted evaluation metric equivalent to subjective assessment. Here, proposed method is assessed using Discrete entropy [23] and Colorfulness Enhancement Factor (CEF) [24]. According to [23], the discrete entropy evaluates the enhancement of detail of the image and highest value for entropy indicates the highest visibility of detail. The improvement of color information by various enhancement algorithms is assessed by CEF metric. CEF is a non-reference metric which predicate the perceived colorfulness. The metric evaluates the colorfulness of the image by finding the ratio between colorfulness metric of enhanced image to original image. The higher CEF indicate the higher colorfulness of the image.

Evaluation result of Discrete Entropy on test images are shown in Table 1. The methods which give the highest three score are highlighted. The higher value in proposed method indicated that the method outperforms other competing methods by improving the detail of the image. Table 2 demonstrate the assessment of quality of image in terms of color enhancement. The NPEA, SDD and Proposed Method are the three methods which gives the highest enhancement value. The CEF values of proposed algorithm in Table 2 shows the comparable performance of proposed method for improving the color information than other algorithms. Table 3 shows the quantitative value of Lightness Order Error (LOE) [9]. LOE evaluates the lightness order error between the original and enhanced images. The evaluation results shown the better performance of proposed algorithm against other state-of-art methods.

Table 1. Quantitative measurement results of discrete entropy.

Images	Garden	Auditorium	Sunset	Face	Palace	Cloudy	Avg.
Org. Image	6.094	6.710	5.707	7.068	6.64	6.012	6.372
CLAHE	6.879	7.124	6.901	7.313	7.264	7.206	7.115
BPDFHE	6.084	6.462	5.811	7.064	6.729	6.453	6.434
LSLR	5.965	6.736	5.716	7.138	6.716	5.919	6.365
NPEA	7.049	7.425	6.819	7.230	6.715	6.648	**6.981**
NL-Retinex	7.051	7.131	5.623	6.074	6.771	6.663	6.553
LIME	7.546	7.546	6.891	6.875	6.334	6.396	6.932
RRM	7.051	7.418	5.948	7.074	6.771	6.663	6.820
SDD	7.076	7.263	6.433	7.067	7.099	7.050	**6.999**
Proposed	7.798	7.254	6.806	7.425	7.455	6.966	**7.284**

Table 2. Quantitative measurement results of Colorfulness Enhancement Factor.

Images	Garden	Auditorium	Sunset	Face	Palace	Cloudy	Avg.
CLAHE	2.043	1.349	1.76	0.772	1.234	1.545	1.451
BPDFHE	1.269	1.210	0.786	0.922	1.097	0.846	1.022
LSLR	0.767	0.605	0.646	0.962	1.197	0.966	0.857
NPEA	3.021	1.810	3.603	1.064	1.344	2.257	**2.183**
NL-Retinex	1.023	0.929	0.967	0.943	0.895	1.324	1.014
LIME	2.189	1.668	1.680	1.238	2.272	1.895	1.824
RRM	1.155	1.378	1.232	1.846	2.438	1.621	1.612
SDD	2.629	1.472	1.994	1.640	2.665	1.723	**2.021**
Proposed	2.752	1.534	2.509	1.892	3.012	1.528	**2.205**

Table 3. Quantitative measurement results of LOE.

Images	Garden	Auditorium	Sunset	Face	Palace	Cloudy	Avg.
CLAHE	5.81	18.56	48.36	3.95	58.23	27.12	27.05
BPDFHE	6.78	14.65	55.28	5.28	35.45	34.18	25.27
LSLR	8.47	15.36	42.15	7.23	40.12	23.18	22.75
NPEA	2.01	24.65	60.25	20.4	38.45	58.45	34.03
NL-Retinex	11.04	30.12	58.36	17.04	28.42	25.69	28.44
LIME	1.17	11.26	18.63	2.5	10.56	18.49	10.43
RRM	1.24	5.64	12.56	1.2	18.37	8.25	**7.87**
SDD	3.78	5.89	11.35	2.57	2.59	6.32	**5.41**
Proposed	1.21	2.81	13.26	3.25	3.27	7.36	**5.19**

In summary, both qualitative analysis and quantitative analysis show the improved performance of the algorithm in both aspects. The enhanced images have better visual perception and color reproduction than conventional and recently proposed method.

4. CONCLUSION

In this paper, we propose a Retinex based enhancement algorithm for uneven illumination images using GF and NPIT function. In order to estimate the illumination component effectively GF is used. The proposed NPIT function, which is based on human vision perception, maps the pixels based on prominent luminance level and relative visibility. Global information obtained from the prominent luminance level and local information from relative visibility controls the modified gamma function to enhance the image by preserving its ambience. The algorithm improves the quality of images by enhancing the local details in a naturally looking and artifact free manner. The color balancing performed as post processing step improves the perceived colorfulness of the image. The ambience sustained color balanced image looks more visually appealing. Both subjective and objective evaluation reveals the effectiveness of the proposed algorithm for enhancing local detail of uneven illumination images by retaining its original ambience.

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