# Naturalness Preserved Enhancement Algorithm for Non-Uniform Illumination Images

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***Abstract*— Image enhancement plays an important role in image processing and analysis. Among various enhancement algorithms, Retinex-based algorithms can efficiently enhance details and have been widely adopted. Since Retinex-based algorithms regard illumination removal as a default preference and fail to limit the range of reflectance, the naturalness of non-uniform illumination images cannot be effectively preserved. However, naturalness is essential for image enhancement to achieve pleasing perceptual quality. In order to preserve naturalness while enhancing details, we propose an enhancement algorithm for non-uniform illumination images. In general, this paper makes the following three major contributions. First, a lightness-order-error measure is proposed to access naturalness preservation objectively. Second, a bright-pass filter is proposed to decompose an image into reflectance and illumination, which, respectively, determine the details and the naturalness of the image. Third, we propose a bi-log transformation, which is utilized to map the illumination to make a balance between details and naturalness. Experimental results demonstrate that the proposed algorithm can not only enhance the details but also preserve the naturalness for non-uniform illumination images.**

***Index Terms*— Bi-log transformation, bright-pass filter, image enhancement, lightness-order-error measure, naturalness.**

## I. Introduction

The PRINCIPLE objective of image enhancement is to process an image so that the result is more suitable than the original image for specific applications [1]–[4]. Up to now, image enhancement has been applied to varied areas of science and engineering, such as atmospheric sciences, astrophotography, biomedicine, computer vision, etc. [1]–[4]. Many image enhancement algorithms, such as the Retinex-based algorithms [5]–[15], the unsharp masking algorithms [16], [17], the histogram equalization (HE) algorithms [18]–[25], etc., have been proposed. Part of the algorithms focus on detail enhancement, but usually result in unnatural looks, such as light source confusion and artifacts. Hence, some others attempt to reduce over-enhancement at the cost of details.

Manuscript received October 12, 2012; revised February 20, 2013, April 4, 2013, and April 19, 2013; accepted April 19, 2013. Date of publication May 2, 2013; date of current version August 9, 2013. This work was supported in part by the National Science Fund for Distinguished Young Scholars under Grant 61125206 and the 973 Program under Project 2010CB327900. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Sina Farsiu.

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Digital Object Identifier 10.1109/TIP.2013.2261309

Retinex theory assumes that the sensations of color have a strong correlation with reflectance, and the amount of visible light reaching observers depends on the product of reflectance and illumination [10], [26]. Most Retinex-based algorithms extract the reflectance as the enhanced result by removing the illumination, and therefore they can enhance the details obviously [5]–[7]. But it is impossible to exactly remove the illumination for the scenes of unsmooth depth. Some center/surround algorithms take the local convolution of the lightness instead of the illumination without considering the limit of the reflectance [5]–[7]. In fact, the reflectance should be within [0], [1], which means the surface cannot reflect more light than that it receives. Moreover, it is unreasonable to simply remove the illumination which is essential to represent the ambience [13].

The algorithms based on the unsharp masking usually decompose an image into high-frequency terms and low-frequency terms, and process these two parts respectively [16], [17]. It is useful to restrain over-enhancement for these algorithms taking into account the low frequency information. However, these algorithms simply integrate the processed high- and low-frequency information together by addition, which often fails to achieve good tradeoff between details and the naturalness. As a result, these algorithms need a rescaling process which should be performed carefully for each image to achieve the best result.

HE technique is simple but widely-used for image enhancement. Since conventional HE algorithms may result in over-enhancement, many algorithms with restrictions, such as brightness preservation [18], [19] and contrast limitation [20], have been proposed. Brightness preservation is useful in the applications that need to preserve the intensity. However, for non-uniform illumination images, brightness preservation is disadvantageous to detail enhancement in the areas of inappropriate intensity, such as the dark areas. Contrast limited algorithms restrain over-enhancement by redistributing the histogram in such a way that its height does not go beyond the clip limit. But, it is not easy to fix the clip limit for the images of seriously non-uniform illumination, in which the histograms of different areas are quite different.

In order to preserve the naturalness as well as enhance details, Chen *et al.* proposes the concept of naturalness preservation for image enhancement as follows. The ambience of the image should not be changed greatly after enhancement, no light source should be introduced to the scene, no halo effect should be added and no blocking effect should be amplified due to over-enhancement [11]. As no artifact is

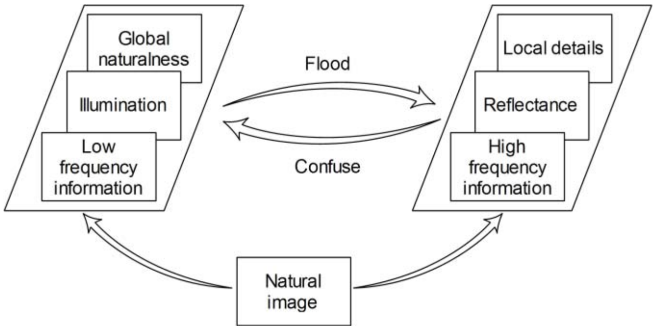


Fig. 1. The relationship between naturalness and details.

the basic requirement for information fidelity, we refine the concept as: the global ambience of the image should not be changed seriously and the direction of the light source should not be altered obviously. Recently, some natural enhancement algorithms based on Retinex theory [11]–[13] are proposed to enhance details with the naturalness preserved. However, these algorithms are not suitable for non-uniform illumination images.

Therefore, we propose a naturalness preserved enhancement algorithm for non-uniform illumination images in this paper. In general, we discuss three major issues, namely, the naturalness preservation, the intensity decomposition, and the illumination effect. Firstly, the lightness-order-error (LOE) measure for the naturalness preservation is proposed to assess enhanced images. Secondly, we decompose the image through the proposed bright-pass filter, which insures the reflectance is restricted in the range [0], [1]. Thirdly, the bi-log transformation is proposed to process the illumination, so that the illumination will not flood details due to spatial variation while the lightness order is preserved. Experimental results demonstrate that the proposed algorithm can achieve appropriate results on non-uniform illumination images.

The remainder of this paper is organized as follows. The next section presents the observation on detail enhancement and naturalness preservation. Section III gives the definition of the LOE measure. The technique details of the proposed enhancement algorithm, including the bright-pass filter and the bi-log transformation, are described in Section IV. We present the experimental results conducted against some state-of-the-art algorithms in Section V. Finally, the paper is concluded in Section VI.

## II. Observation

In this section, we present the observation on detail enhancement and naturalness preservation, which is finally summarized as two constraints for image enhancement.

As shown in Fig. 1, an image can be decomposed into different feature spaces. For example, the wavelet-based algorithms [27], [28], the curvelet-based algorithms [29], etc., regard an image as the compound of different frequency terms [30], and the Retinex-based algorithms usually decompose an image into illumination and reflectance [5]–[15]. Generally, the low-frequency information and illumination represent the global naturalness, and the high-frequency information and reflectance represent the local details.

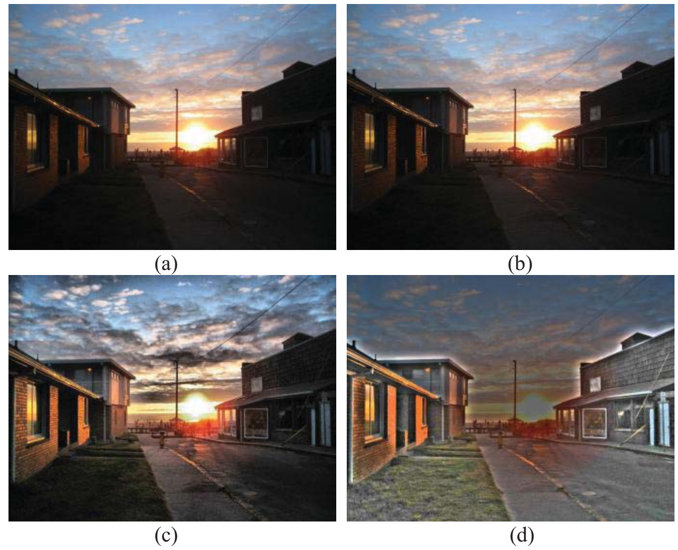


Fig. 2. (a) Original image. (b) Image processed by GUM with contrast_factor = 0.0005 and maximum_gain = 3. (c) Image processed by GUM with contrast_factor = 0.005 and maximum_gain = 3. (d) Image processed by SSR.

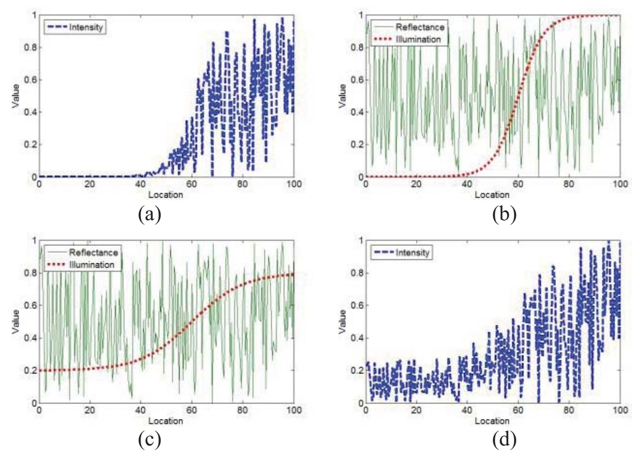


Fig. 3. 1D signal illustration. (a) Original intensity. (b) Reflectance and illumination decomposed from (a). (c) Reflectance and compressed illumination of (b). (d) Product of the reflectance and illumination in (c).

Since the resolution of an image is limited, it is essential for an enhancement algorithm to make an appropriate balance between different information. In general, the extreme low-frequency information may flood details, and the extreme high-frequency information may result in unnaturalness. Fig. 2 shows a group of images processed by Generalized Unsharp Masking (GUM) [17] and Single Scale Retinex (SSR) [5]. From Fig. 2(b), we can see that the details in the dark area are still invisible. That is because the low frequency information is too extraordinary. On the contrary, the sky areas of Fig. 2(c) look unnatural. SSR simply removes the illumination without considering the range of reflectance, so that it results in light source confusion and over-enhancement as shown in Fig. 2(d).

Intuitively, we further illustrate the effect of the illumination through 1D signal as Fig. 3 shows. The dash line in Fig. 3(a)

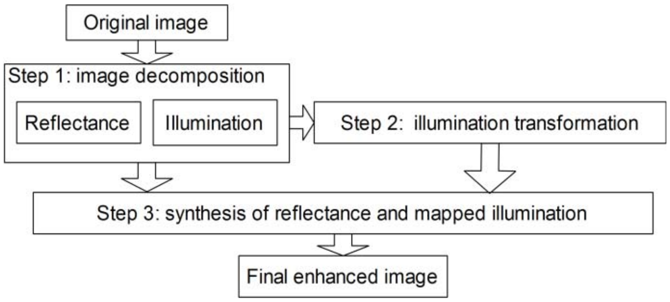


Fig. 4. Flowchart of the proposed enhancement algorithm.

(a) (b) (c)

Fig. 5. Example for image decomposition. (a) Original image. (b) Illumination image. (c) Reflectance image.

indicates the original intensity, which is the product of the illumination and the reflectance in Fig. 3(b). We can see that the original intensity vary slightly in some local areas so that it is hard to observe the details. Some algorithms take the reflectance as the enhanced result of the intensity. Although the reflectance has obvious local contrast, it cannot represent the global trend of the original intensity. Instead, we take a compressed version of the illumination into consideration and obtain the enhanced result as shown in Fig. 3(d). We can see that the local variation of Fig. 3(d) is obvious while its global trend is in accordance with the original intensity.

Therefore, in order to enhance details with naturalness preserved, the proposed algorithm aims to improve the local variation of the image and to preserve the global trend of the intensity at the same time. Therefore, from the physics point of view, we propose two constraints. The first one is the detail constraint, that the reflectance should be limited to a proper range [0], [1] by considering the property of reflectance [31]. The second one is the naturalness constraint, that the relative order of illumination in different local areas should not be changed drastically. As a result, the rest of this paper focuses on (a) reflectance extraction regarding to its range property, and (b) illumination compression without changing the relative order seriously.

## III. Performance Measure of Naturalness Preservation

Since image quality assessment is related to Human Visual System, there is no universal measure that satisfies subjective validity for image enhancement [32], [33]. Most algorithms are used to measure the important characteristics of images (e.g. contrast is used to evaluate the improvement of details and entropy is used to measure the gray level distribution) [33], [34]. According to the analysis in the above section, the relative lightness order is important for the naturalness preservation [13], we propose the LOE measure to objectively assess the naturalness preservation.

Since the relative order of lightness represents the light source directions and the lightness variation, the naturalness of an enhanced image is related to the relative order of lightness in different local areas. Therefore, we define the quantitative LOE measure based on the lightness order error between the original image $I$ and its enhanced version $I_e$. The lightness $L(x, y)$ of an image is given as the maximum of its three color channels:

$$L(x, y) = \max_{c \in \{r,g,b\}} I^c(x, y). \tag{1}$$

For each pixel $(x, y)$, the relative order difference of the lightness between the original image $I$ and its enhanced version $I_e$ is defined as follows:

$$RD(x, y) = \sum_{i=1}^{m} \sum_{j=1}^{n} (U(L(x, y), L(i, j)) \oplus U(L_e(x, y), L_e(i, j))) \tag{2}$$

$$U(x, y) = \begin{cases} 1, & for\ x \geq y \\ 0, & else \end{cases} \tag{3}$$

where $m$ and $n$ are the height and the width, $U(x, y)$ is the unit step function, $\oplus$ is the exclusive-or operator.

The LOE measure is defined as:

$$LOE = \frac{1}{m * n} \sum_{i=1}^{m} \sum_{j=1}^{n} RD(i, j). \tag{4}$$

From the definition of LOE, we can see that the smaller the LOE value is, the better the lightness order is preserved.

In order to reduce the computational complexity, we take the down-sampled versions $DL$ and $DL_e$ of size $dm \times dn$ instead of $L$ and $L_e$. The ratio $r$ between the size of the down-sampled image and that of the original images is set as $r = 50/\min(m, n)$. As a result, the size $dm \times dn$ of the down-sampled image is $\lfloor m \cdot r \rfloor \times \lfloor n \cdot r \rfloor$.

## IV. The Proposed Algorithm

In this section, we present the technique details of the proposed enhancement algorithm which includes three parts, as shown in Fig. 4. Firstly, the original image is decomposed into reflectance and illumination through the bright-pass filter. Secondly, the illumination is processed by using the bi-log transformation. Finally, the enhanced image is obtained by synthesizing the reflectance and the mapped illumination.

### A. Definition of the Bright-Pass Filter

Although many algorithms are available for illumination estimation [5]–[15], they do not take the range of reflectance into consideration (e.g. 50% of the reflectance obtained by SSR is more than 1) and usually result in over-enhancement. Therefore, we propose the bright-pass filter which is able to restrict the reflectance to [0], [1]. The basic idea of the bright-pass filter is that, for an adjacent pixel of value $a$ affecting a

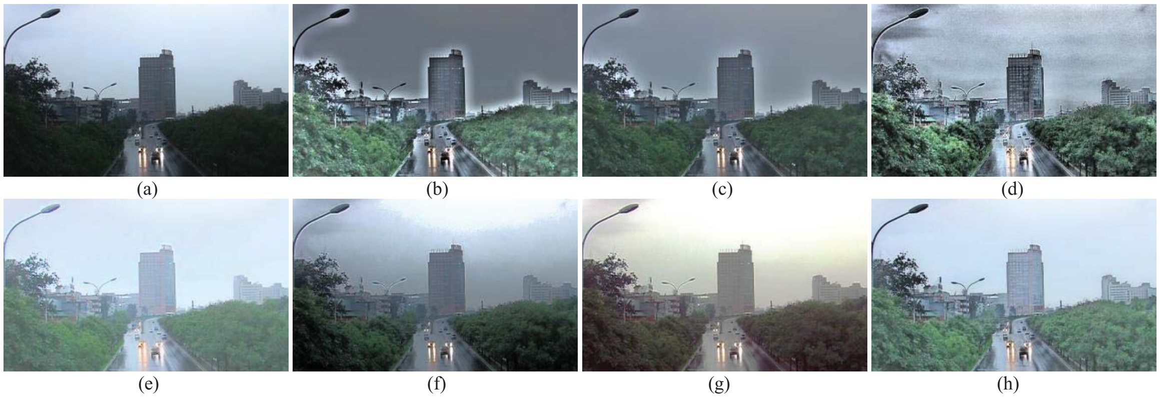

Fig. 6. Results for image *Road*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

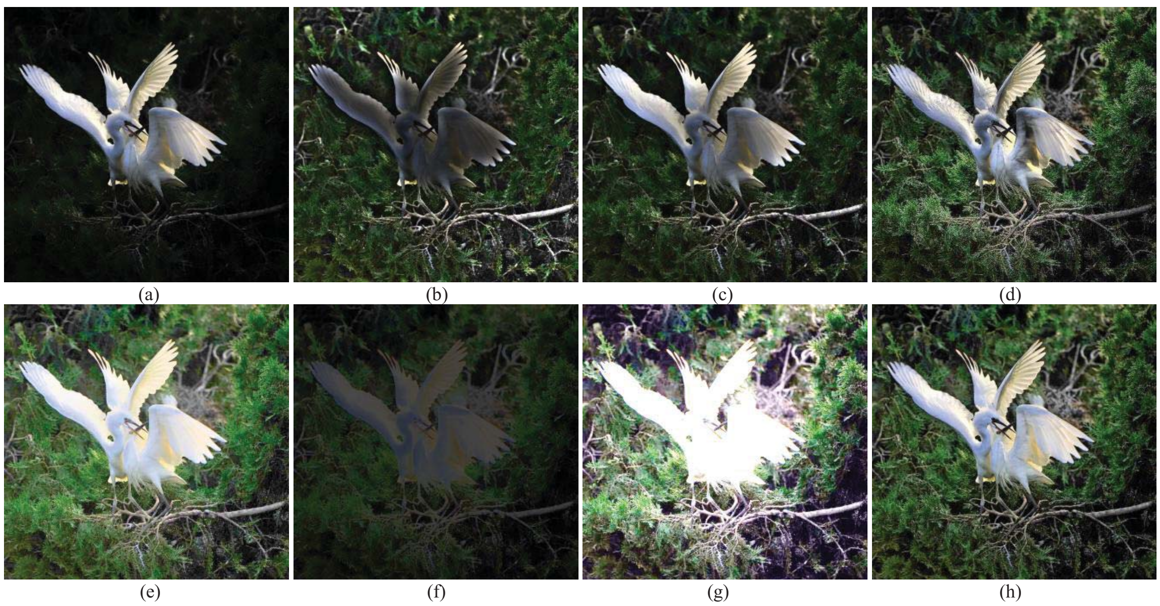

Fig. 7. Results for image *Birds*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

central pixel of value $b$, the effect is positively related to the frequency for pixels of value $a$ and pixels of value $b$ being neighbors all over the image.

Generally, the neighbors can be defined flexibly for different applications. As the frequency is a statistic and its normalized version is used as the weight of adjacent pixels in the bright-pass filter, we assume there is no obvious difference between the filtering results by using slightly different neighbors. Correspondingly, experiments demonstrate that the filtering results obtained using four-connectivity and other neighbors, such as eight-connectivity, are similar. For simplicity, we set the neighbors of a pixel $G(x, y)$ as a five-pixel square in four-connectivity:

$$NB(x, y) = \{G(x, y-1), G(x, y+1), G(x-1, y), G(x+1, y), G(x, y)\}. \tag{5}$$

For the pixel of value $k$ at $(x, y)$, $NN_{k,l}(x, y)$ indicates the number of its neighbors of value $l$. The frequency $Q^{'}(k, l)$ for pixels of values $k$ and $l$ to be neighbors all over the image is expressed as follows:

$$Q^{'}(k, l) = \sum_{x=1}^{m} \sum_{y=1}^{n} NN_{k,l}(x, y) \tag{6}$$

where $m$ and $n$ are the height and the width of the image.

Since the frequency $Q^{'}(k, l)$ of digital signal is prone to suffer from noise and varies roughly, we utilize its local mean $Q(k, l)$ instead:

$$Q(k, l) = \left( \sum_{i=l-win}^{i=l+win} Q^{'}(k, i) \right) \Big/ (2 \cdot win + 1) \tag{7}$$

where $win$ is the window size. In order to remove the noise as well as preserve the local trend of the frequency, $win$ should not be too small or too large. In addition, some images occupy narrower gray-level range than the others, so that the window size should be set with the range of the gray levels. The window size is empirically set as follows.

$$win = \lfloor (\max(G(x, y)) - \min(G(x, y)))/32 \rfloor. \tag{8}$$

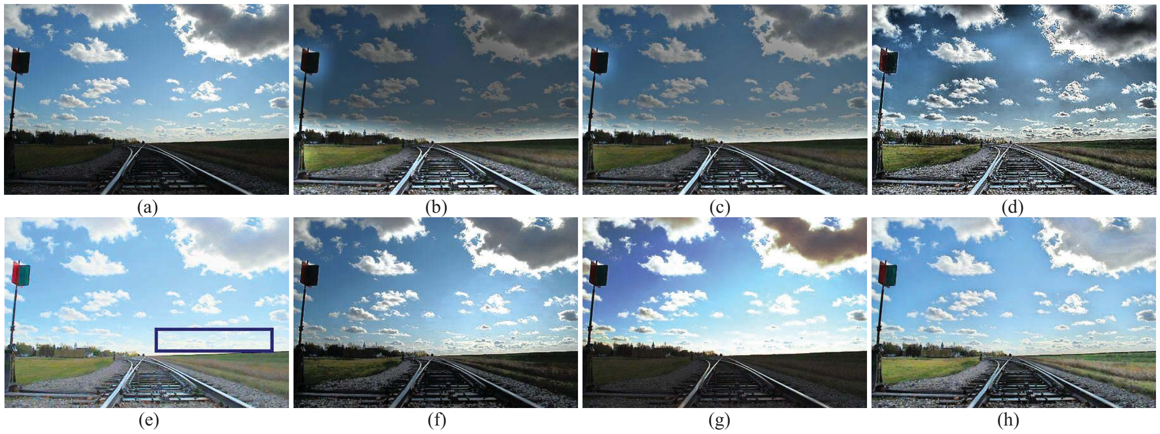


Fig. 8. Results for image *Rail*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

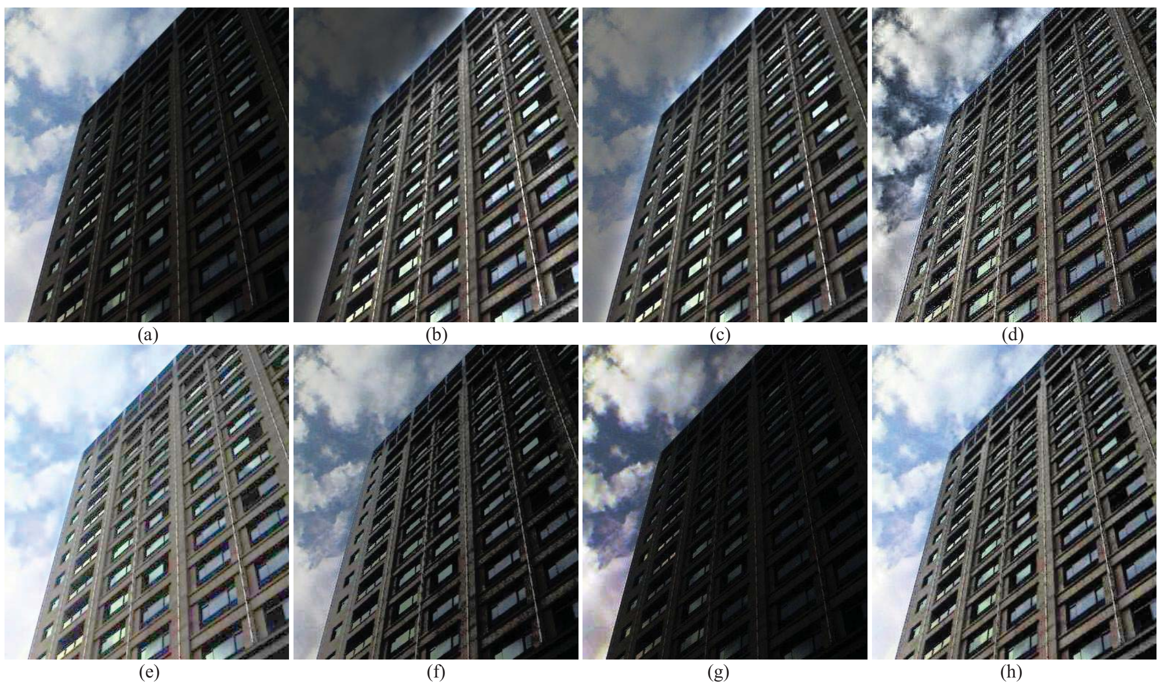


Fig. 9. Results for image *Skyscraper*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

The bright-pass filter, $BPF[\cdot]$, is a weighted average of adjacent pixels with the weight positively related to the frequency $Q(k,l)$ as follows:

$$BPF[G(x,y)] = \frac{1}{W(x,y)} \sum_{(i,j)\in\Omega} (Q(G(x,y), G(i,j)) \cdot U(G(i,j), G(x,y)) \cdot G(i,j)) \quad (9)$$

where $\Omega$ denotes the local patch centered at coordinate $(x, y)$, the size of the local patch is set to $15 \times 15$ in this paper, the unit step function $U(x, y)$ ensures that only brighter neighbors are taken into consideration, the normalization factor $W(x, y)$ ensures the sum of pixel weight to be 1.

$$W(x,y) = \sum_{(i,j)\in\Omega} (Q(G(x,y), G(i,j)) \cdot U(G(i,j), G(x,y))). \quad (10)$$

### B. Image Decomposition Using the Bright-Pass Filter

According to the Retinex theory, the reflex lightness is the product of reflectance and illumination as shown in (11) [26].

$$I^c(x,y) = R^c(x,y) \cdot F(x,y) \quad (11)$$

where $I^c(x, y)$ is the lightness of the color channel $c$, $R^c(x, y)$ is the corresponding reflectance, and $F(x, y)$ is the illumination, which indicates the light cast on the surface of the scene.

Most of the center/surround Retinex algorithms evaluate illumination using the Gaussian filter or the bilateral filter [5]–[7], which usually causes the illumination to be darker than the reflex lightness. That unreasonably means the reflectance is more than 1 and the surface reflects more light than it receives.

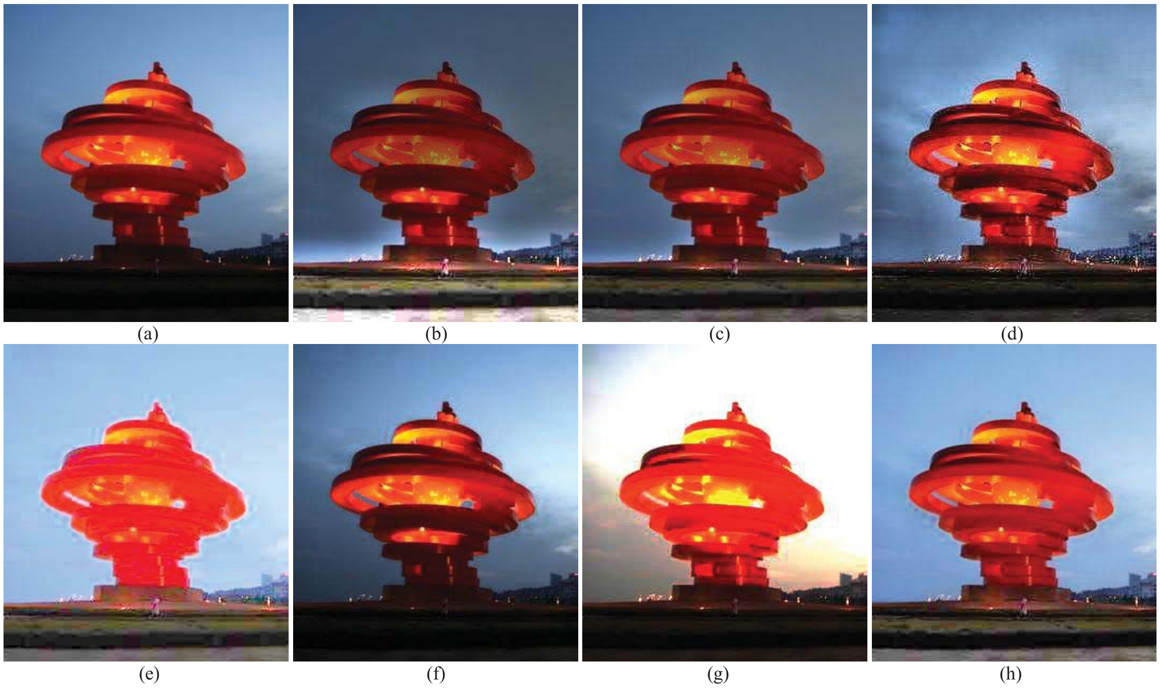


Fig. 10. Results for image *Sculpture*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

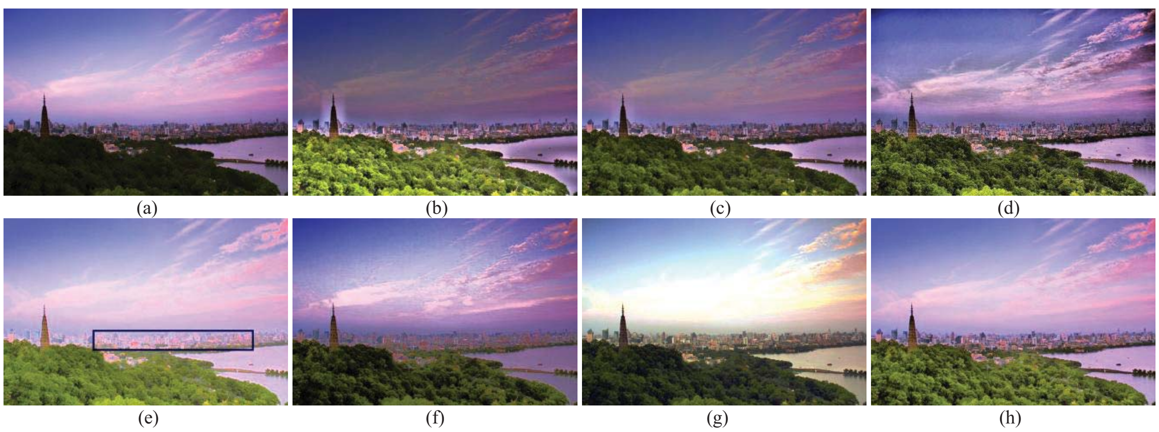


Fig. 11. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

We evaluate the illumination using the bright-pass filter, based on the assumption that the illumination is the local maxima for each pixel. For simplicity, we assume that the three color channels have the same illumination.

Unlike traditional filters, we only take the neighbors that are brighter than the central pixel into account. Compared with darker areas, it is obvious that brighter areas are closer to illumination. We take the intensity $L(x, y)$ obtained using (1) as the coarse evaluation of the illumination and we refine it through the bright-pass filter:

$$L_r(x, y) = \frac{1}{W(x, y)} \sum_{(i,j)\in\Omega} (Q(L(x, y), L(i, j)) \cdot U(L(i, j), L(x, y)) \cdot L(i, j)). \quad (12)$$

Then, the reflectance $R(x, y)$ can be obtained by removing the illumination:

$$R^c(x, y) = I^c(x, y)/L_r(x, y). \quad (13)$$

Fig. 5 shows an example of image decomposition through the bright-pass filter. We can see that the reflectance image presents the details and the illumination image presents the ambience of incident light, which is in accordance with our previous analysis.

### C. Illumination Mapping Using the Bi-Log Transformation

As the mapped illumination will be synthesized with the reflectance to get the final enhanced image, it should not suppress the details so that it should be bright enough, and meanwhile the lightness order should be preserved. Inspired

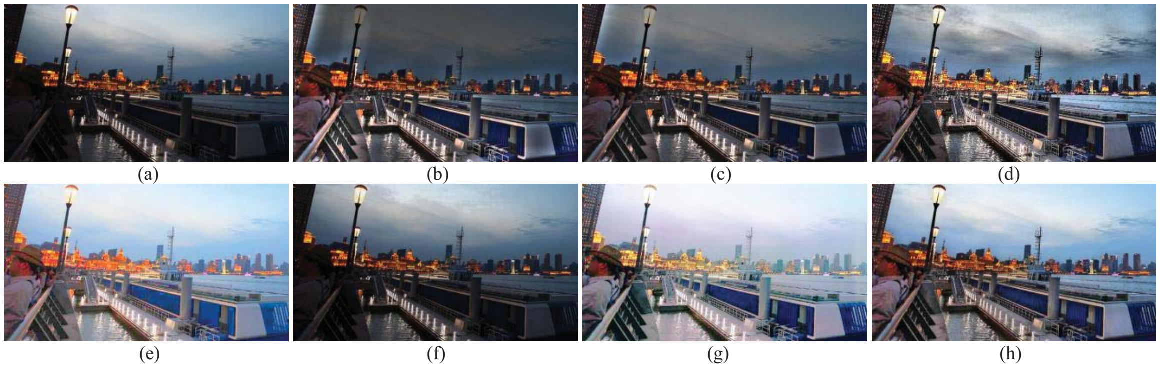


Fig. 12. Results for image *Harbor*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.


Fig. 13. Results for image *Parking Area*. (a) Original image. (b) Enhanced image of SSR. (c) Enhanced image of MSR. (d) Enhanced image of GUM. (e) Enhanced image of NECI. (f) Enhanced image of BPDHE. (g) Enhanced image of RACE. (h) Enhanced image of the proposed algorithm.

by that histogram specification is able to preserve the lightness order, we map the illumination through histogram specification and our task focuses on finding an appropriate shape for the specified histogram. According to our experimental results, the log shape, given by (14), performs well for most images.

$$L_{\lg}(x, y) = \log(L_r(x, y) + \varepsilon) \tag{14}$$

where $\varepsilon$ is a small positive constant and is empirically set as 1.

However, the intensity of the images processed by histogram specification appears similar. In fact, the mapped illumination should look slightly different based on different intensity of input images. As log-shape histogram specification can render the mapped illumination bright enough, we represent the difference by slightly increasing the pixels of low gray levels, according to the gray-level distribution of the input illumination. Experimental results demonstrate that it performs well with the weight of the histogram set as the log of the illumination. Therefore, we utilize the weighted histogram, $mp(n)$, instead.

$$mp(k) = \frac{\sum_{i=0}^{m}\sum_{j=0}^{n} L_{\lg}(i, j) \cdot \delta(L_r(i, j), k)}{\sum_{i=0}^{m}\sum_{j=0}^{n} L_{\lg}(i, j)} \tag{15}$$

$$\delta(x, y) = \begin{cases} 1, & \mathit{for}\ x = y \\ 0, & \mathit{else} \end{cases} \tag{16}$$

where $\delta$ is the impulsive function. The modified histogram not only takes the numbers of pixels into consideration, but also considers the values of the gray levels.

According to the definition of the Cumulative Density Functions (CDF) [23], [24], the CDF of the weighted histogram is:

$$cL(v) = \sum_{k=0}^{v} mp(k) = \frac{\sum_{i=0}^{m}\sum_{j=0}^{n} L_{\lg}(i, j) \cdot U(v, L_r(i, j))}{\sum_{i=0}^{m}\sum_{j=0}^{n} L_{\lg}(i, j)}. \tag{17}$$

Similarly, the CDF of the specified histogram, $s(z)$, is defined as follows:

$$cf(z) = \sum_{i=0}^{z} s(i) \Big/ \sum_{i=0}^{255} s(i) \tag{18}$$

$$s(z) = \log(z + \varepsilon), \quad z \in N[0, 255] \tag{19}$$

where $z$ is a non-negative integer within [0, 255], $\varepsilon$ is a small positive constant.

According to the definition of histogram specification [23], [24], the purpose of BLT is to seek values of $z$ that satisfies

$$cf(z_v) = cL(v), \quad \text{for } v = 0, 1, 2, \ldots, L - 1. \tag{20}$$

The values of $z_v$ is given by

$$z_v = cf^{-1}[cL(v)], \quad \text{for } v = 0, 1, 2, \ldots, L - 1. \tag{21}$$

The mapped illumination can be obtained through the BLT transformation.

$$L_m(x, y) = cf^{-1}[cL(L_r(x, y))], \quad \text{for } v = 0, 1, 2, \ldots, L - 1. \tag{22}$$

TABLE I
QUANTITATIVE MEASUREMENT RESULTS OF DISCRETE ENTROPY

| Images \ Methods | Orig. | SSR | MSR | GUM | BPDHE | NECI | RACE | Prop. |
|---|---|---|---|---|---|---|---|---|
| Road | 6.97 | 6.46 | 6.57 | 6.80 | 7.13 | 4.73 | 7.24 | 7.41 |
| Birds | 5.66 | 6.69 | 6.71 | 7.02 | 5.68 | 7.49 | 5.64 | 7.19 |
| Rail | 7.38 | 6.76 | 7.12 | 7.31 | 7.40 | 6.03 | 6.76 | 7.85 |
| Skyscraper | 6.84 | 7.26 | 7.52 | 7.81 | 7.02 | 7.13 | 6.40 | 7.61 |
| Sculpture | 7.18 | 6.61 | 6.82 | 7.58 | 6.92 | 5.38 | 5.53 | 7.07 |
| Nightfall | 6.96 | 6.32 | 6.43 | 6.73 | 7.17 | 4.95 | 6.67 | 7.67 |
| Harbor | 7.56 | 6.70 | 7.02 | 7.82 | 7.50 | 7.49 | 7.47 | 7.74 |
| Parking Area | 7.46 | 6.56 | 7.22 | 7.91 | 7.34 | 6.05 | 5.86 | 7.49 |
| **Average** | **7.00** | **6.67** | **6.93** | **7.37** | **7.02** | **6.16** | **6.45** | **7.50** |

TABLE II
QUANTITATIVE MEASUREMENT RESULTS OF VISIBILITY LEVEL DESCRIPTOR

| Images \ Methods | Orig. | SSR | MSR | GUM | BPDHE | NECI | RACE | Prop. |
|---|---|---|---|---|---|---|---|---|
| Road | 1 | 3.54 | 1.82 | 4.37 | 2.24 | 1.49 | 1.92 | 2.85 |
| Birds | 1 | 3.66 | 2.99 | 5.42 | 2.16 | 5.22 | 8.16 | 4.92 |
| Rail | 1 | 1.32 | 1.33 | 3.52 | 1.70 | 1.74 | 1.20 | 1.84 |
| Skyscraper | 1 | 3.20 | 2.70 | 4.27 | 1.76 | 3.41 | 0.60 | 3.88 |
| Sculpture | 1 | 2.48 | 2.03 | 2.84 | 1.20 | 2.70 | 1.69 | 2.48 |
| Nightfall | 1 | 2.95 | 1.94 | 3.99 | 1.95 | 1.99 | 1.70 | 2.73 |
| Harbor | 1 | 2.17 | 1.90 | 3.80 | 1.15 | 2.19 | 2.95 | 2.57 |
| Parking Area | 1 | 2.98 | 2.54 | 3.44 | 1.26 | 2.80 | 3.45 | 2.86 |
| **Average** | **1** | **2.79** | **2.16** | **3.96** | **1.68** | **2.69** | **2.71** | **3.02** |

### D. Synthesis of Reflectance and Mapped Illumination

As mentioned above, the drastic variation of illumination is disadvantageous to the display of details, but illumination is essential for naturalness preservation. In order to enhance details and preserve naturalness, the mapped illumination is taken into consideration.

We synthesize $R(x, y)$ and $L_m(x, y)$ together to get the final enhanced image:

$$EI^c(x, y) = R^c(x, y) \times L_m(x, y). \tag{23}$$

Since the relative order of lightness in different local areas of the mapped illumination is the same as that of the original illumination, it is easy to verify that the relative order for the pixels, whose reflectance is 1, does not change. In addition, according to the definition of the hue in different color space, such as HSI and HSV, the hue value of a pixel is dependent on the ratio of its three color values (R, G, and B). Since the ratio of the three color values has no change before and after enhancement, the proposed algorithm is able to preserve the hue values of the image.

## V. EXPERIMENTS AND DISCUSSION

The proposed algorithm has been tested on our dataset of more than 150 images, compared with two conventional algorithms, SSR [5] and Multi Scale Retinex (MSR) [6], and four recently proposed algorithms, GUM [17], Natural Enhancement of Color Image (NECI) [12], Brightness Preserving Dynamic Histogram Equalization (BPDHE) [19], and RACE [15]. The dataset consists of: 46 images captured using the Cannon digital camera, and 110 images downloaded from the websites of some organizations/companies, such as NASA and Google. All the images of the dataset have low contrast in local areas but serious illumination variation in global space. We are glad to share the dataset and the codes in executable form, which are available in our Sina Blog http://blog.sina.com.cn/u/2694868761.

The major parameters of the compared algorithms are set as follows. SSR: the spatial extent of the Gaussian function is 80. MSR: the spatial extents of the three Gaussian functions are respectively 20, 80, and 200. GUM: the adaptive gain is utilized with the maximum gain set as 5 and the contrast enhancement factor is 0.005. NECI: the texture coefficient is set as 5. RACE: the number of spray pixels is 20 and the number of averaged spray contributions is 400. For an in-depth description of the parameters, we refer the reader to the literatures [5], [6], [12], [15], [17], [19].

Due to the space limitation, this section presents eight representatives, including a rainy image, a clear image, two cloudy images, two nightfall images, and two nighttime images. We first test the algorithms from the subjective aspect, and then perform objective assessment, using the discrete entropy [34], the visibility-level descriptor [35], and the proposed LOE measure.The processed results of the selected images are shown in Figs. 6–13.

### A. Subjective Assessment

Since SSR and MSR simply take reflectance as the final results, the light source directions of their enhanced images are confused, as Figs. 6(b)–13(b) and 6(c)–13(c) show. Meanwhile, some constant areas, such as the skies areas in Figs. 8(b) and 8(c), are rather dark. In addition, we can see that SSR introduces obvious halo effects into nighttime images and MSR restrains halo effects to some extent at the cost of details, as Fig. 6(b) and (c) shows. In comparison with SSR and MSR, our algorithm can avoid artifacts and preserve the light source directions.

TABLE III
QUANTITATIVE MEASUREMENT RESULTS OF LOE

| Images \ Methods | Orig. | SSR | MSR | GUM | BPDHE | NECI | RACE | Prop. |
|---|---|---|---|---|---|---|---|---|
| Road | 0 | 50.34 | 19.76 | 9.50 | 0.03 | 9.98 | 3.27 | 3.25 |
| Birds | 0 | 5.25 | 2.46 | 2.77 | 0.15 | 1.01 | 1.48 | 1.17 |
| Rail | 0 | 50.85 | 35.50 | 36.83 | 3.09 | 25.21 | 12.23 | 9.41 |
| Skyscraper | 0 | 39.41 | 25.74 | 18.71 | 0.25 | 6.95 | 5.45 | 6.12 |
| Sculpture | 0 | 66.89 | 27.81 | 45.36 | 2.89 | 39.66 | 29.97 | 7.10 |
| Nightfall | 0 | 38.47 | 21.16 | 32.75 | 0.88 | 6.52 | 6.52 | 4.43 |
| Harbor | 0 | 47.96 | 27.34 | 30.92 | 0.04 | 11.85 | 4.12 | 6.13 |
| Parking Area | 0 | 68.21 | 35.78 | 40.91 | 0.10 | 29.08 | 23.04 | 8.48 |
| **Average** | **0** | **45.92** | **24.44** | **27.22** | **0.93** | **16.28** | **10.76** | **5.76** |

GUM considers both low- and high-frequency information, but it is not an easy task for GUM to balance well. We can see from Figs. 6(d)–13(d) that GUM highlights details obviously, but most enhanced images look unnatural due to over-enhancement. BPDHE is a global histogram equalization algorithm, which is effective to preserve the lightness order of the input image. However, as BPDHE preserves the intensity of the input image, it is disadvantageous to highlight the details in areas of low intensity, as Figs. 6(f)–13(f) show. Comparatively, our algorithm achieves a good tradeoff between the detail enhancement and the naturalness preservation.

NECI preserves the naturalness well, but it often results in detail loss in some local areas, such as the area marked by rectangles in Figs. 8(e) and 11(e). RACE is useful in the scenes, where it is necessary to correct the color shift. As Figs. 6(g), 12(g) and 13(g) demonstrate, RACE corrects the global color to meet the GW and WP priors. However, the enhanced images lose their original ambience, which is important to represent the scene. And meanwhile the details of some images enhanced by RACE, such as Fig. 9(g), are still hard to be observed. From the enhanced images, we can see that our algorithm preserves the ambience as well as enhances the details.

### B. Objective Assessment

As subjective assessment depends on human visual system, it is hard to find an objective measure that is in accordance with the subjective assessment. Objective assessment is often used to explain some important characteristics of the image [32], [35]. We assess the detail enhancement through the discrete entropy [34] and the visibility level descriptor [35]. Meanwhile we assess the naturalness preservation through the proposed LOE measure.

Table I demonstrates the discrete entropy of the eight groups of images. As defined in [34], discrete entropy is a statistical measure of randomness, and higher entropy value usually indicates more details. From Table I, we can see that the entropy values of our algorithm are similar to that of GUM, and outperform that of the other five algorithms. NECI has the lowest entropy values among the seven algorithms, in accordance with its performance on detail enhancement.

Table II demonstrates the quantitative measure of the visibility level descriptor, which expresses the quality of contrast improvement of the enhanced images [35]. In general, higher visibility level corresponds to more obvious details. From Table II, we can see that GUM gets the highest visibility level and our algorithm gets the second. However, the high visibility level of GUM is partly due to serious over-enhancement in some local areas, such as the sky areas in Figs. 6(d) and 12(d).

Table III demonstrates the quantitative measure of LOE, which is utilized to quantitatively evaluate the naturalness preservation. Our algorithm can preserve the lightness order, outperforming SSR, MSR, GUM, NECI, and RACE. However, BPDHE gets the lowest LOE value. Note that BPDHE is a global histogram equalization technique and it cannot enhance the local details effectively sometimes, as shown in Figs. 7(f) and 8(f), where some dark areas are not enhanced adequately.

In summary, compared with the current enhancement algorithms, the proposed algorithm can not only enhance the details, but also maintains the naturalness for the non-uniform illumination images. The proposed algorithm can achieve good quality from both subjective aspect and objective aspect. Although our algorithm cannot perform well as some other algorithms (e.g. RACE) do, in the application for color correction, our algorithm is promising to correct the color shift by calculating the illumination respectively for the three color channels.

## VI. CONCLUSION

This paper proposes an algorithm of naturalness preserved enhancement for non-uniform illumination images, which not only enhances the details of the image but also preserves the naturalness. A LOE measure, which performs well in accordance with objective assessment on naturalness preservation, is proposed as well. Experimental results demonstrate that the images enhanced by the proposed algorithm are visually pleasing, artifact free, and natural looking. However, since our enhancement algorithm does not take into consideration the relation of illumination in different scenes, it may introduce slight flickering for video applications in case that the scenes vary apparently. This will be our future works.

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