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Single Backlit Image Enhancement

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ABSTRACT Backlit images are from an excessive reflection of light being opposite to a capturing device. The existing image enhancement methods cannot be directly applied to the backlit images because they are not designed to enhance both broad light and dark regions simultaneously. Moreover, the techniques have several limitations about over-saturation or losing contrast. This paper presents a single backlit image enhancement method based on the novel full-piecewise non-linear automatic stretching, without input parameter provided by a user, e.g., gamma and so on. The computer simulation results confirm that the proposed approach can (i) undoubtedly reveal hidden details in the dark region; (ii) preserve features and color of common and light (over-brightness) regions, and (iii) increase a local contrast of dark areas. The proposed approach tested on Li's backlit image database and several backlit images from commercial devices. The simulation results demonstrate the efficiency of the proposed approach and its advantages over the cutting-edge backlit image enhancement methods in perceptual quality.

INDEX TERMS Backlit images, color correction, contrast enhancement, image segmentation.

I. INTRODUCTION

Backlighting generally encounters ill-illumination conditions that cause degradation of image quality. The backlight images have a complex structure that makes them different from other types of images, including low-light once (images captured in low-light conditions, such as, thermal imaging and near-infrared illuminations are the three most commonly used night vision technologies [31], [35]), which have wide dynamic ranges of light regions.

Also, unlike classical low light images, the backlit photos: (i) contain concurrently both, well-exposed, very dark, and very bright areas (over-exposed); and (ii) display detail lost or washed-out color areas [29]–[32]. The goal of backlit image enhancement is to remove or reduce the backlit degradation and to recover ''backlit scenes sectors'' while still preserving image details and colors [5], [32]. As a result, the conventional, including low-light, image enhancement (for instance, histogram equalization algorithms or Retinex-based algorithms), cannot accomplish the proper enhanced effects of backlit images. For example, they are over-saturated images, losing contrast.

Recently, supervised image enhancement methods [22], [31] require a lot of imaging data to train the supervised algorithms. The primary limitation of these methods is, they need a substantial image database, and they are also time-consuming. Reference [32]–[34] proposed the supervised algorithms for low-light illuminance imaging conditions. The algorithms are computationally expensive. Furthermore, these algorithms have several other limitations; for exemplar, the *Wei et al* enhancement follows increasing both details and noise in the dark regions simultaneously [32]; the Shi *et al.* method generates a halo effect [33], or, the Wang *et al*. process cannot distinguish the black colored objects and foreground in extreme backlit conditions [34]. For many applications, such as smartphones, cameras, and displays, there is the need to develop a new unsupervised, image-driven image enhancement approach tailored specially to the backlit images.

Researchers have investigated this problem for recent years and have proposed quite a few tools [1]–[6]. Despite those efforts, the existing methods also have some significant

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TABLE 1. The advantages and disadvantages of state-of-the-art stretching methods.

Stretching Method	Advantages	Disadvantages	Applications
Linear	• Intensities are uniformly distributed. • It can be applied to rescale in other domains [19]. • It expands the range of intensity levels [15-16].	• Intensities cannot be distributed in the case that the imaging signal has a full range distribution.	• The correction of the wrong setting of a lens aperture during the image acquisition phase [15]. • Low contrast imaging signals. • High Dynamic Range (HDR) rendering [16].
Piecewise Linear [24-25, 30]	• It can partially increase contrast and slightly preserve local brightness [15]. • Transform intensities to the middle of the brightness range. [24]. • Under-exposed, adequately exposed and over-exposed regions are enhanced in dynamic ranges [25]. • Details cleared for medical applications [30].	• The brightness is mainly controlled by adjusting the threshold [15, 18]. • Contrast is not enhanced in some regions [24-25]. • *Local stretching:* colors destroyed [30]. • *Global stretching:* [30]. • 1) luminance on middle luminance re-organized and • 2) the rest of them are compressed.	• The customization of texture enhancements [18]. • Leukemia detection [25, 30]. • Low contrast in grayscale images [24].
Non-Linear	• Intensities can be re-distributed if the imaging signal has a full range distribution [20].	• The intensity of some pixels may be overlaid with other intensities. It depends on the scale of non-linear parameters [17].	• Micro-calcifications in breast tissue [17].
Piecewise Non-Linear [17,20,26]	• The brightness and contrast are mainly controlled by adjusting the threshold and the scale of non-linear parameters [17]. • Reduce mixed noises with different distributions without losing many details [26].	• The scale of non-linear parameters. Plays an essential role in increasing artifacts [20]. • The highly noisy image might come out from under-exposed regions [26]. • Commonly exposed regions might be over-brightness [26].	• The details improvement in a dark component for low light images [20]. • Backlit image applications [26].

TABLE 2. Existing cutting-edge backlit restoration methods.

Name year	Method	Limitation	Advantages
Brian *et al* (2004) [32]	Retinex in MATLAB™	• Introduces artifacts in image decomposition. • Some cases induce blurriness and noise error in color images.	• Enhances images under varying illuminance conditions.
Petro *et al* (2014) [31]	Multiscale Retinex	• The color restoration step leads to the wrong colors.	• If the original image is slightly dark, it can be enhanced.
Xiaojie Guo *et al* (2017) [34]	LIME: Low-light image enhancement via illumination map estimation	• It generates over-enhancement in bright regions. • It works well to increase details and visualization, but it loses contrast.	• The algorithm takes an inexpensively computational complexity.
Li *et al* (2018) [23]	Learning-Based Restoration of Backlit Images	• Long-time processing in segmentation. • The quality of output heavily relies on the accuracy of segmentation. • The complicated kernel grids confuse the classifier.	• Identifies the backlit regions. • Enhances degraded image details by fusing two optimal mapping functions: one designed for backlit and another for the remainder.
Vonikakis *et al* (2018) [33]	Calculating Retinal Contrast from Scene Content: A Program (Research-based commercial software package: Orasis^{HD})	• Under-exposed regions are slightly enhanced.	• It enhances dark and bright image regions. • Reveals information that is not visible. • Not affect the right parts of an image.

limitations, including the problems of unnatural colors, over-saturation, and brightness exposure. Although these methods significantly increased the details, the contrast and brightness are slightly over-enhanced; and finally, they require multiple images with different exposure information to enhance a backlit image.

To address this problem, we present an unsupervised single backlit perception-preserving (the enhanced images look real, comprises content, and color) image enhancement method. The main contributions of this article are: (i) a no-reference color quality assessment for backlit image enhancement, (ii) new method of decomposing an image into under-exposed, over-exposed, and common regions; (iii) an extended stretching method of controlling over-enhancement, sharpness, and colorfulness quality backlit image; and (iv) a local weighted logarithmic histogram equalization method. Also, the presented method outperforms the existing methods both qualitatively and quantitatively. It has low complexity, making it suitable for real-time applications such as the angular viewing range of backlit image displays or video surveillance applications. The rest of this paper is organized as follows: Section 2 presents the background of contrast stretching methods and backlit image enhancement. Section 3 introduces the proposed technique to enhance backlit images. Computer simulation results are presented in Section 4. Finally, Section 5 offers the conclusion and ideas that can be done for further research.

II. BACKGROUND

In this section, we presented an introduction to the analysis of the related existing contrast stretching and backlit image enhancement works. We first introduce linear and nonlinear contrast stretching methods, and then the present works on backlit image enhancement.

A. LINEAR AND NON-LINEAR CONTRAST STRETCHING METHODS

The concept behind contrast stretching is to expand a dynamic range of the image [12]. The stretching techniques can apply to several image processing applications, such as (i) enhancing the hazy, lowlight, night-vision, thermal, underwater, and backlit images; (ii) the adjustment of imaging sensors resolution; and (iii) the improving display screen brightness [15]. The advantages and disadvantages of state-of-the-art stretching methods presented in Table 1. A lack of dynamic range results of lack of illumination, or even wrong configuration of a lens aperture (see Table 1).

B. BACKLIT IMAGE ENHANCEMENT

Cutting-edge backlit image restoration methods [28]–[30] operate on under-exposed and common regions indiscriminately, avoiding the fact that there are several kinds of region property. Li *et al.* [22] proposed a region-based backlit image restoration and enhancement by categorizing the background and foreground histograms. The accuracy of the segmentation directly affects the image quality (see Table 2).

III. PROPOSED METHOD

We introduce the backlit image enhancement framework by non-linear stretching luminance in piecewise regions. The key steps of the proposed framework (see Fig. 1) are: (i) the calculation of backlit and common region thresholds; (ii) the design of stretching functions with optimal parameters; (iii) the calculation of a logarithmic weighted bi-histogram equalization function; and (iv) the image fusion using a minimal weighting fusion metric.

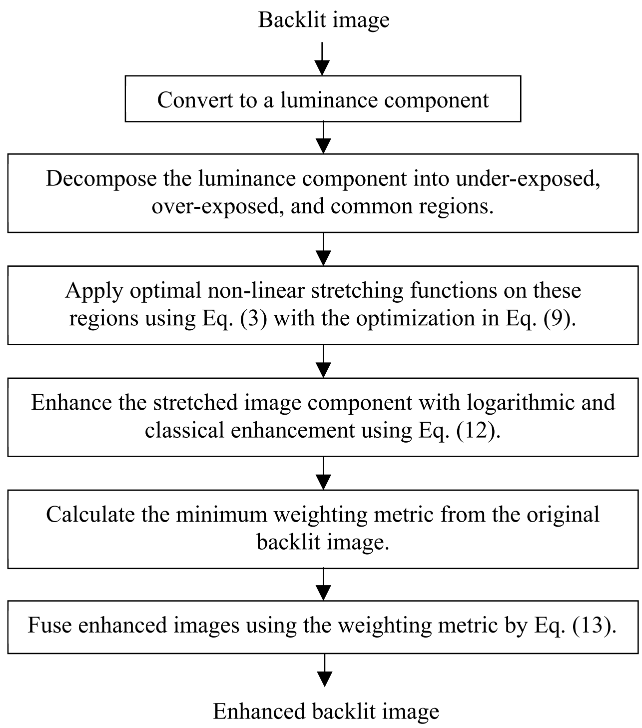


FIGURE 1. **The proposed backlit image enhancement algorithm.**

A. THRESHOLD CALCULATION

Backlit images caused by light irregularities can be divided into three components: a dark component, a gray component, and a bright component. Let I_t be the intensity component of an original backlit image, which consists of intensity level t starting from 0 to $L-1$, whereas L is the total intensity level. The pixel density of backlit images mostly locates on a dark component, *e.g.,* $L < 100$ for an 8-bit component. The calculations of existing thresholds cannot appropriately categorize the pixel density for images having the special illuminance conditions of light reflection. For calculating the threshold for the intensity component of a backlit image, the first threshold is to divide the whole intensity into dark and bright components, which represent the foreground and the background, respectively. The first threshold is calculated by the relative local bright average of any intensities giving the highest correlation of a dark component and a bright component.

$$T = arg \max_t \left(-\bar{\mu}_t^{\mathrm{d}} log \left(\frac{\bar{\mu}_t^{\mathrm{d}}}{\bar{\mu}_t^{\mathrm{b}}} \right) \right) \tag{1}$$

where

$$\bar{\mu}_t^{\mathrm{d}} = \frac{\mu_t^{\mathrm{d}} - min \left\{ {\mathrm{d} \atop t} \right\}}{max \left\{ {\mathrm{d} \atop t} \right\} - min \left\{ {\mathrm{d} \atop t} \right\}} \quad \text{and } \bar{\mu}_t^{\mathrm{b}} = \frac{\mu_t^{\mathrm{b}} - min \left\{ {\mathrm{b} \atop t} \right\}}{max \left\{ {\mathrm{b} \atop t} \right\} - min \left\{ {\mathrm{b} \atop t} \right\}} \tag{2}$$

$\bar{\mu}_t^{\mathrm{d}}$ and $\bar{\mu}_t^{\mathrm{b}}$ represent the normalized local average brightness of a dark component and a bright component, respectively.

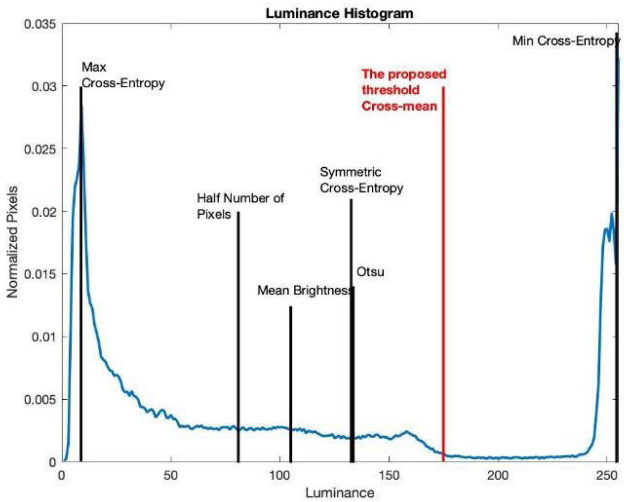


FIGURE 2. **Threshold comparison of a backlit image.**

The proposed threshold tends to a light gray luminance level. It divides the under-exposed regions into a new grayscale distribution for more than half of the permitted range (see Fig. 2). Therefore, the details within those regions will be re-organized in a wider range.

B. DESIGN OF STRETCHING FUNCTIONS WITH OPTIMAL PARAMETERS

A stretching contrast method is the most straightforward contrast and brightness enhancement. However, state of the art stretching routines have some limitations see Table 1).

To enhance the backlit images, we (1) decompose it under-exposed, "general/gray" and exposed regions using a backlit driven threshold, (2) apply the new contrast stretching on both components dark and the bright components, and (3) perform a specialized new parametric image enhancement (so-called, a local weighted logarithmic histogram equalization method) on the gray component. The new dynamic intensities are calculated by the equations below.

$$S_{i,j} = \begin{cases} f^{\mathrm{d}}\left(I_{i,j}\right), & 0 < I_{i,j} \leq x_t \\ I_{i,j}, & x_t < I_{i,j} \leq x_{\mathrm{O}} \\ f^{\mathrm{b}}\left(I_{i,j}\right), & x_{\mathrm{O}} < I_{i,j} \leq x_{L-1} \end{cases} \tag{3}$$

$$f^{\mathrm{d}}\left(I_{i,j}\right) = \left(S^{\mathrm{d}}_{\max} - S^{\mathrm{d}}_{\min}\right)\left(\frac{I_{i,j} - I^{\mathrm{d}}_{\min}}{I^{\mathrm{d}}_{\max} - I^{\mathrm{d}}_{\min}}\right)^{\gamma_\alpha} + I^{\mathrm{d}}_{\min} \tag{4}$$

$$f^{\mathrm{b}}\left(I_{i,j}\right) = \left(S^{\mathrm{b}}_{\max} - S^{\mathrm{b}}_{\min}\right)\left(\frac{I_{i,j} - I^{\mathrm{b}}_{\min}}{I^{\mathrm{b}}_{\max} - I^{\mathrm{b}}_{\min}}\right)^{\gamma_\beta} + I^{\mathrm{b}}_{\min} \tag{5}$$

where $I_{i,j}$ is a backlit luminance at any i^{th} and j^{th} pixel placement. $I^{\mathrm{d}}_{\min}, I^{\mathrm{b}}_{\min}, I^{\mathrm{d}}_{\max}$ and $I^{\mathrm{b}}_{\max}$ are the minimum and maximum luminance of under-exposed regions and exposed regions. $S^{\mathrm{d}}_{\min}, S^{\mathrm{d}}_{\max}, S^{\mathrm{b}}_{\min}$ and $S^{\mathrm{b}}_{\max}$ are the new minimum and maximum intensities of under-exposed regions and exposed regions, respectively. γ_α and γ_β are a contrast correction $\left(0 < \gamma_\alpha < \gamma_\beta < 1.0\right)$.

To find the best parameter of a contrast correction, we use two conditions: (i) highest contrast, by evaluating block-based EME concepts - the relationship between the spread and the sum of the two luminance values calculated in a local block [12], and (ii) least luminance error, by using logarithmic brightness error entropy.

- The calculation of the CEME contrast,

$$\begin{aligned} &CEME_{\gamma_\alpha,\gamma_\beta} \\ &= \frac{1}{MN}\sum\nolimits_{i=1}^{M}\sum\nolimits_{j=1}^{N}\Big[\psi\left(EME_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} \\ &\quad + (1-\psi)\left(MEME_{i,j}\right)_{\gamma_\alpha,\gamma_\beta}\Big]; \quad 0 \leq \psi \leq 1 \end{aligned} \tag{6}$$

$$\begin{aligned} &\left(EME_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} \\ &= -20L_{i,j}\frac{\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} - \left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta}}{\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} + \left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} + c} \end{aligned} \tag{7}$$

$$\begin{aligned} &\left(MEME_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} \\ &= 20L_{i,j}\left(\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} - \left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta}\right) \end{aligned} \tag{8}$$

$$\begin{aligned} &\left(L_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} \\ &= log\left(\frac{\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} - \left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} + c}{\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} + \left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta} + c}\right) \end{aligned} \tag{9}$$

- The calculation of brightness error

$$LBE_{\gamma_\alpha,\gamma_\beta} = 10\left(\frac{\mathbb{E}_I - \mathbb{E}_R}{\mathbb{E}_I + \mathbb{E}_R}\right)^{\lambda} log^{\lambda}\left(\mathbb{E}_I - \mathbb{E}_R + c\right) \tag{10}$$

- The optimization function

$$\left[\gamma_\alpha, \gamma_\beta\right] = \underset{\gamma_\alpha,\gamma_\beta \in [0,1]}{argmin}\left(CEME_{\gamma_\alpha,\gamma_\beta} - LBE_{\gamma_\alpha,\gamma_\beta}\right) \tag{11}$$

where $\left(\left[I_{max}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta}$ and $\left(\left[I_{min}\right]^{m,n}_{i,j}\right)_{\gamma_\alpha,\gamma_\beta}$ are based local maximum and minimum luminance of local $m\times n$-block; c is a small number to avoid the error of logarithmic calculation. E_I and E_R are the mean luminance of a captured image and a stretched image. λ is a power factor.

C. LOGARITHMIC HISTOGRAM EQUALIZATION

It is well-known that Histogram Equalization (HE) can increase image contrast by calculating the new brightness levels of a mapping function. There is much research that relies on histogram-based contrast enhancement [7], [8], [10], [13], [14], that focuses on the definition of different thresholds or even the calculation of weighting functions in global and local regions, spatial and transformed domains, or different color domains. However, those methods cannot be effective for backlit images, directly.

In this sub-section, we bring the properties of the logarithmic function to calculate the luminance level of the mapping function. Let T_t be the essential mapping function of

Bi-Histogram Equalization (BHE) using a cross-mean threshold method. t is the luminance level in a permitted range. Consequently, the calculation of the logarithmic weighted luminance function can be written as:

$$F_t = \rho T_t + (1 - \rho) \log (T_t); \quad 0 \leq \rho \leq 1 \tag{12}$$

where ρ is a weighting parameter.

D. MINIMAL WEIGHTING FUSION

In general, the existing region-based backlit enhancement method is the accuracy of the region classification [21], [22]. Those image segmentation methods take time to process depending on the size of an image. The minimal weighing fusion metric is designed for reducing the complexity of region segmentation and processing time. Let's define $[\sigma_{min}]_{i,j,k}$; $k = 1, 2, 3$ as a normalized minimal luminance metric by taking the lowest intensity in an original backlit image. The fused image can be calculated as:

$$[\mathbf{Y}_{EN}]_{i,j,k} = [\sigma_{min}]_{i,j,k} [\mathbf{Y}_{LBHE}]_{i,j,k} + [1 - \sigma_{min}]_{i,j,k} [\mathbf{Y}_{LHE}]_{i,j,k} \tag{13}$$

The combination of image features using the lowest luminance of the original image will fuse two features into the same image. The proposed logarithmic image ($\mathbf{Y}_{LBHE}$) has uniform brightness in both backlit regions and common regions while the local enhanced image ($\mathbf{Y}_{LHE}$) improve the details on backlit areas and the contrast of the whole image. When considering the backlit regions – the weights (σ_{min}) are close to zero, and the backlit areas are transformed underexposed parts to uniform brightness regions with substantial contrast enhancement. On the other hand, the common regions are preserved brightness with slight contrast enhancement.

IV. EXPERIMENTAL RESULTS

The experiments are conducted on Li's dataset and backlit images taken by different devices are from [22]. In Eq. 3, we set $x_t = T$ and x_O is the Otsu's threshold.

A. PERFORMANCE OF STRETCHING ALGORITHMS

First, we demonstrate the performance of the proposed stretching algorithm in the color restoration of dark regions. Figure 3 shows a comparison of restored backlit images that are produced by the intended optimal stretching function with several existing stretching algorithms. It prevails that the new contrast stretching-based backlit image restoration method, by spatially adaptive luminance stretching functions, achieve to organize intensities in uniform lighting conditions with all parts of the image properly exposed, leading to superior image quality. Other stretching methods fail to achieve the same visualization level in the background and foreground regions.

The colorfulness (CF) [25], [26] image assessments (see Table 3), which are the property of chrominance information human sense, show excellent performance in evaluating the proposed backlit stretched images. The illustrative example in Fig. 3(e) shows three significant achievements. The proposed stretching algorithm with optimizations can: (i) bring the considerable details in dark regions (foreground); (ii) preserve the details in the bright areas (background), and their colors; and (iii) avoid over-enhancement.

CF-1 = 21.1561, CF-2 = 0.0772 | CF-1 = 49.6618, CF-2 = 0.1654
(a)
CF-1 = 17.8839, CF-2 = 0.0665 | CF-1 = 53.7448, CF-2 = 0.1569
(b)
CF-1 = 21.1561, CF-2 = 0.0772 | CF-1 = 49.6618, CF-2 = 0.1654
(c)
CF-1 = 20.4200, CF-2 = 0.0839 | CF-1 = 45.0529, CF-2 = 0.1276
(d)
CF-1 = 31.7019, CF-2 = 0.1201 | CF-1 = 64.5046, CF-2 = 0.1768
(e)

FIGURE 3. Restored Backlit Image. (a) Original image; (b) Yelmanov's model [23]; (c) Leow's model [24]; (d) Xin's model [20]; (e) the proposed optimal stretched image.

B. BEST COLOR MODELS FOR OUR BACKLIT ENHANCEMENT

Second, we simulate the proposed backlit enhancement framework on different color domains. In this experiment,

(a)
(b)
(c)
(d)
(e)
(f)

FIGURE 4. The proposed backlit enhanced images in various color domains. (a) Original image; (b) RGB; (c) CIELAB 1976; (d) NTSC; (e) YCbCr; and (f) HSV.

we evaluate the best suitable color domain for the proposed method and the final restoration resulting images in comparison with various color models, as shown in Fig. 4.

For our simulation in the various color domains, we tested our method on a luminance component. However, the RGB domain intimately relates to color and luminance components. For testing on the RGB domain, we combined three individual components into a single component by concatenating components, and its histogram automatically reflects the luminance of an image.

TABLE 3. The performance of stretching methods.

Method	CF-1 [25]	CF-2 [26]
Yelmanov's model [23]	28.5836	0.0936
Leow's model [24]	28.3331	0.0942
Xin's model [20]	26.0733	0.0951
Proposed	**37.7490**	**0.1200**

TABLE 4. The performance of the proposed method in different color domains.

Domain	CF-1 [25]	CF-2 [26]
RGB	28.0782	0.1054
CIELAB 1976	25.8228	0.0906
NTSC	27.9255	0.0934
YCbCr	27.9645	0.0938
HSV	**37.7490**	**0.1200**

We compare the performance of the proposed backlit enhancement framework through various color domains. As shown in Fig. 4, the proposed images on the HSV domain tend to be the most colorful. Meanwhile, the enhancement of the RGB domain destroys colors. This causes the relationship between colors and a luminance component. However, the proposed method produces content in dark regions. The enhancement on YCbCr domain loses brightness while on CIELAB1976 and NTSC domains achieve to preserve colors, but their resulting images lack contrast.

Since subjective assessment depends on the human visual system (HVS), it is challenging to estimate an objective evaluation that relates to a personal assessment. We evaluate the performance of various color model domains and choose the best suitable color model (HSV domain) for backlit image enhancement applications (see Figure Table 4).

C. QUALITY ASSESSMENT FOR BACKLIT IMAGE ENHANCEMENT

Third, we introduce the no reference color quality measure for backlit image enhancement (CQBIE). We take the attribute combination from [29]. CQBIE consists of two components: a) feature components are calculated by several color methods to combine chrominance information with colorfulness, sharpness, and contrast; and (b) color artifact components (over-enhancement, color saturation) are taken by the error of hue and saturation components.

$$CQBIE = Feature - Artifact \tag{14}$$

$$Feature = (\alpha \cdot CF) + (\beta \cdot CEME) + (\gamma \cdot EMES) \tag{15}$$

$$EMES = 2\chi_k \cdot \sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{3} log\left(\frac{[G_{max}]_{i,j,k}^{m,n}+c}{[G_{min}]_{i,j,k}^{m,n}+c}\right) \tag{16}$$

$$Artifact = \delta \cdot \Delta H + \varepsilon \cdot \Delta S \tag{17}$$

$$\Delta H = \frac{1}{3NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{3} \Delta H_{i,j,k} \tag{18}$$

$$\Delta S = \frac{1}{3NM}\sum_{i=1}^{N}\sum_{j=1}^{M}\sum_{k=1}^{3} \Delta D_{i,j,k} \tag{19}$$

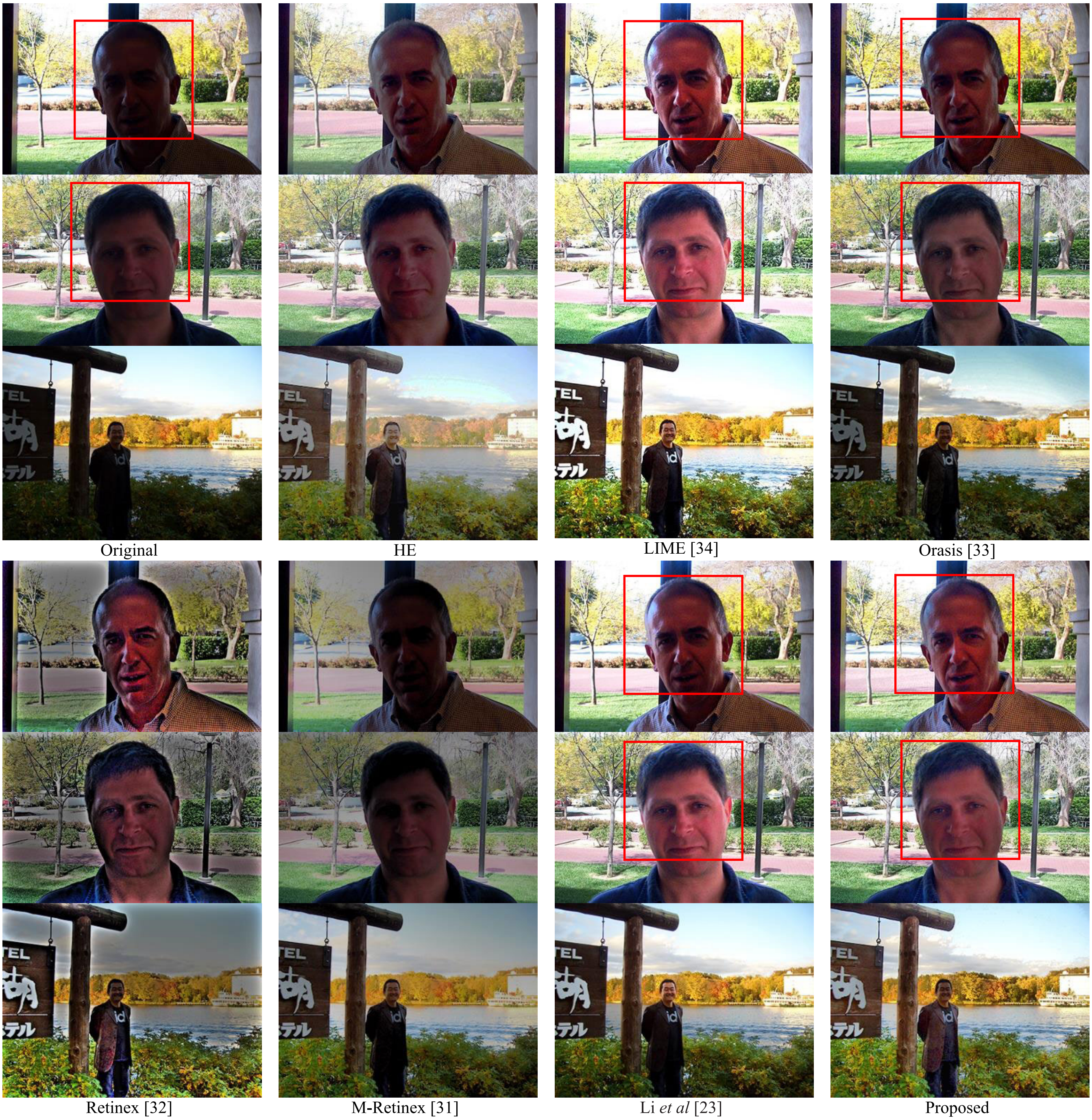


FIGURE 5. Backlit images enhanced by existing contrast enhancement methods and the proposed method. The introduced existing methods include: Histogram Equalization (HE), Low Light Image Enhancement [31], Orasis Commercial Software Package [30], Retinex [29], Multiscale Retinex (M-Retinex) [28] and Li's algorithm [22].

$$\Delta D_{i,j,k} = \left|E_{i,j,k} - I_{i,j,k}\right| \tag{20}$$

where α, β, γ, δ and ε are a constant. CF denotes a colorfulness. *CEME* represents a contrast. $[G_{min}]_{i,j}^{m,n}$ and $[G_{max}]_{i,j}^{m,n}$ are a local minimum gradient metric and a local maximum gradient metric. $\chi_k = 0.299, 0.587$ and 0.114 [4], k is the the order of a color component, $k = 1, 2, 3$. $E_{i,j,k}$ and $I_{i,j,k}$ represent an enhanced image and an original image on the HSV domain, respectively. N and M are the sizes of an image.

D. THE PROPOSED BACKLIT IMAGE ENHANCEMENT RESULTS

Finally, we present the no-reference quality assessment metric for the backlight image. Computer simulations show that

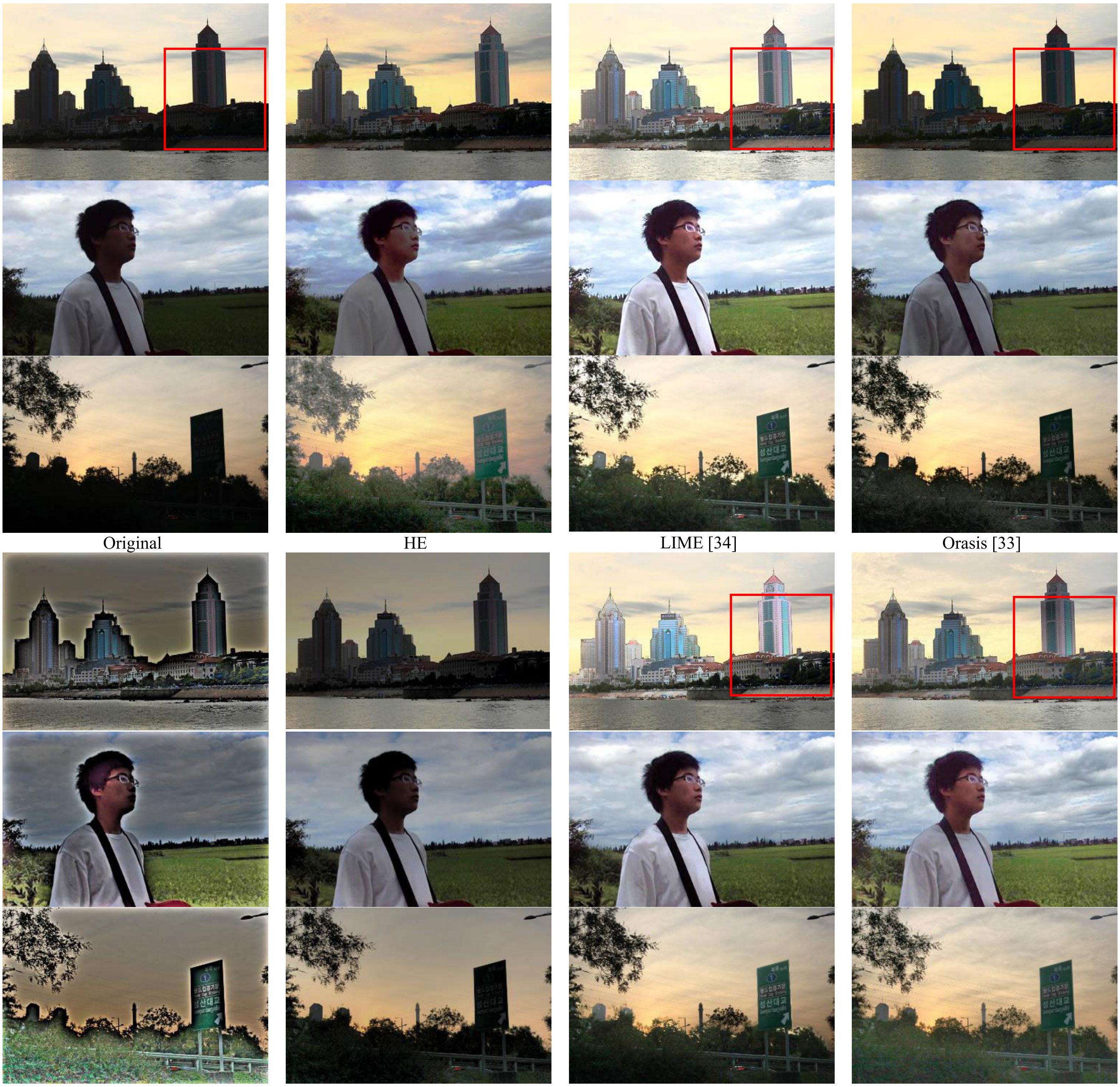
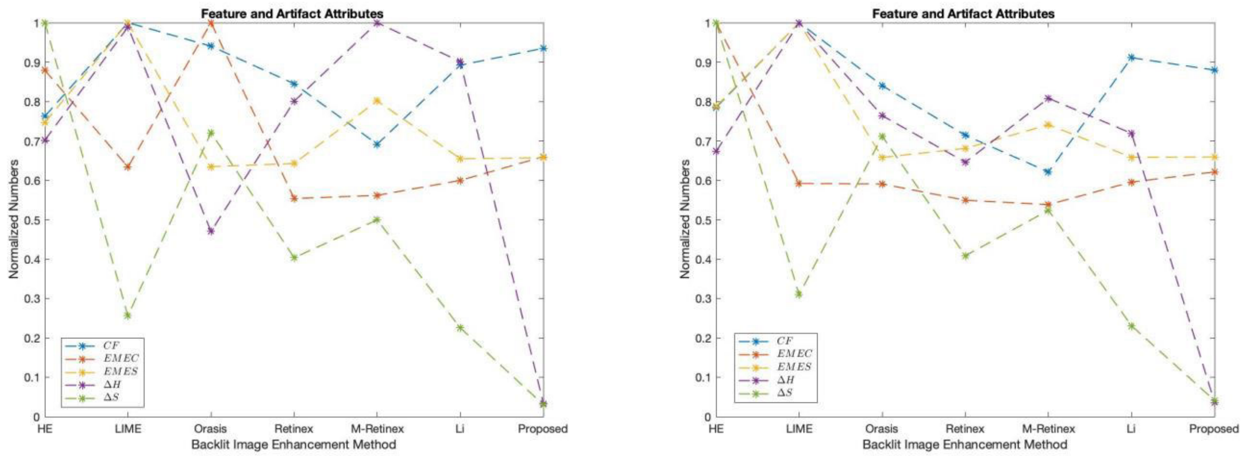


FIGURE 5. ***(Continued.)***

TABLE 5. The performance of the proposed method with feature and artefact assessments of Fig. 5.

Image Name	HE	LIME [34]	Orasis [33]	Retinex [32]	Multiscale Retinex [31]	Li *et al* [23]	Proposed
01 – Bald man	23.6230	33.3535	35.6657	21.5759	20.8468	27.8572	39.5815
02 – Hairy man	22.5871	23.2212	11.6895	17.2315	14.3385	21.8461	30.4685
03 – Fat Man	0.1518	71.8817	47.7118	67.8218	62.9924	57.2320	84.4149
04 – Building	13.8346	15.7374	3.3275	13.9851	18.2326	19.9417	22.9683
05 – Boy	16.4780	18.5323	12.6359	10.8711	10.7390	21.1897	21.7007
06 – Highway	13.5375	22.3489	10.4388	20.0995	23.5196	25.9065	25.3104



Bald Man

Hairy Man

FIGURE 6. Feature and artifact attributes of existing contrast enhancement methods and the proposed method of Fig. 5.

TABLE 6. The normalized performance of the proposed method with feature andartifact assessments.

Method	CF	EMEC	EMES	ΔH	ΔS	CQBIE
HE	0.9108	**1.0000**	**1.0000**	1.0000	1.0000	0.4037
LIME [34]	**1.0000**	0.8497	0.7374	0.9049	0.1624	0.8283
Orasis [33]	0.9234	0.9876	0.6041	0.7002	0.6109	0.5436
Retinex [32]	0.8603	0.7855	0.6266	0.7895	0.2332	0.6784
Multiscale Retinex [31]	0.7010	0.7605	0.7847	0.8982	0.2900	0.6745
Li *et al* [23]	0.9256	0.8167	0.6286	0.6551	0.1567	0.7786
Proposed	0.9500	0.8861	0.6369	**0.0517**	**0.0265**	**1.0000**

the state of art no-reference metrics is not working correctly for backlight image [4], [7], [36]–[40]. We define CQBIE parameters as $\alpha = 4, \beta = 5, \gamma = 10, \delta = 1$, and $\varepsilon = 3$. The average results over the set of testing images reported in Table 5 and Table 6. They show that the proposed method achieves the highest quality in backlit (Under-exposed) regions and common regions.

Common regions typically do not suffer from a low contrast issue, and it is less critical to increasing the contrast of these regions. Classical enhancement (HE, Retinex, and M-Retinex) methods produce under-exposed, over-enhanced, and saturated details (see Fig. 5). Orasis [30], LIME [31] and Li *et al.* [22] methods reduce the color artifacts (see Fig. 5 and Fig. 6), but some regions of the visually extracted images (see Fig. 6) reflect a slight color saturation and an under-exposed luminance in the local areas.

To prove the image quality by visualization, the powerful ill-luminance image enhancement methods, such as Orasis [30], LIME [31] and Li *et al.* [22], have some limitations.

- LIME: it achieves to increase details on under-exposed regions, but it generates over-exposure and over-brightness on background (see region no. 2, and 7). Some details of over-exposed regions are washed out. Occasionally, it cannot bring more details when storing brightness of other regions (see region no. 12).
- Orasis: it focuses on under-exposed regions to enhanced details while preserving over-exposed regions, but the quality of enhanced regions is not good enough (see region no. 3, 8, and 13).
- Li's method: it achieves to preserving background details and attempts to increase more details on under-exposed regions, but it is unable to remove shadows (see region no. 4, 9, and 11).
- The proposed method: it reveals the details of under-exposed regions and preserves the details of over-exposed regions (see region no. 5, 10, and 15).

In the CQBIE measure, Fig. 5 and Table 6 reflect the fact of image quality metric corresponding to the human visual system (HVS) that such methods are prone to over-enhancement, under-explosion and color saturation artifacts. The proposed method achieves superior perceptual image quality by boosting the features in under-exposed regions and enhancing contrast without presenting undesirable artifacts.

V. CONCLUSION

This article presents a novel, automated, simple combine stretching-based backlit image enhancement and optimal tone mapping functions technique for the restoration of backlit images. The presented method is a single image unsupervised image enhancement method that does not

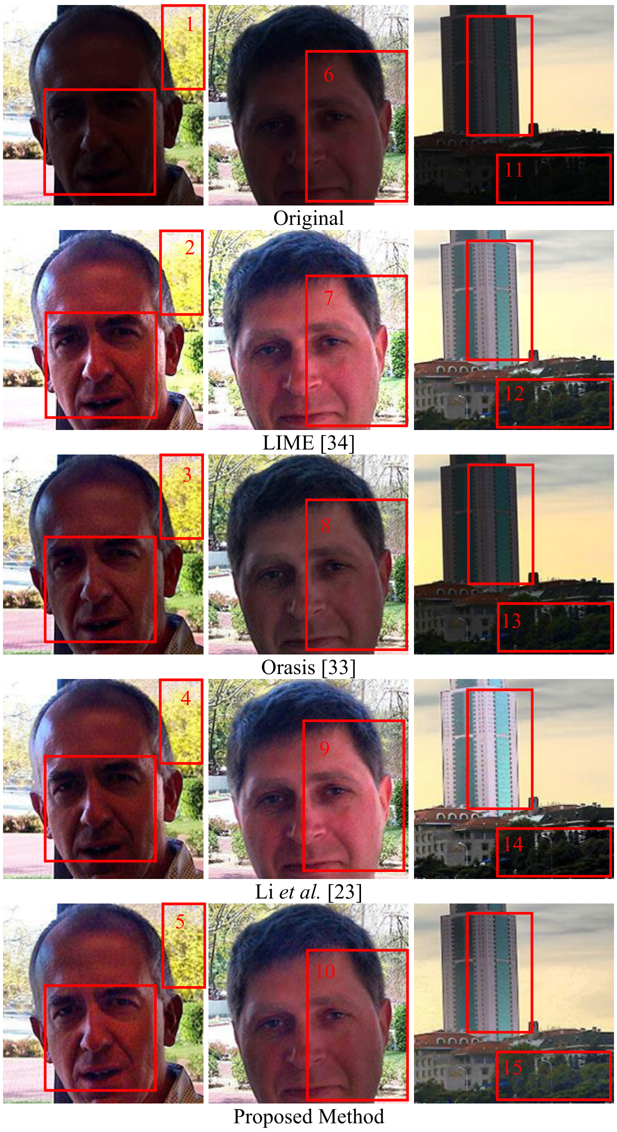


FIGURE 7. **Cropped Resulting in Backlit images of Fig. 5. The artifact comparison between existing novel methods and the proposed method.**

FIGURE 8. **Examples of Backlit images captured by a commercial.**

require specialized hardware or knowledge about the backlit image scene structure. The new procedure identifies the best non-linear parameters for managing the overall image luminance by detecting the highest contrast while maintaining the least logarithmic luminance error. Our extensive quantitative evaluation shows that the proposed enhanced images characterized by better exposedness of the dark regions, improved global contrast, edges sharpness, and less color and lightness distortion compared to several state-of-the-art methods, such as HE, Retinex, Multiscale Retinex, LIME, Li's method, and Orasis. Besides, the proposed method is valuable for real-time applications; for instance, surgery cameras, surveillance, and other commercial uses (The illustrative example is available on the appendix section).

APPENDIX

See Figure. 8.

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