RETINEX-BASED PERCEPTUAL CONTRAST ENHANCEMENT IN IMAGES USING LUMINANCE ADAPTATION

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ABSTRACT

In this paper, we propose retinex-based perceptual contrast enhancement in images using luminance adaptation. We use the retinex theory to decompose an image into illumination and reflectance layers, and adopt luminance adaptation to handle the illumination layer which causes detail loss. First, we obtain the illumination layer using adaptive Gaussian filtering to remove halo artifacts. Then, we adaptively remove illumination of the illumination layer in the multi-scale retinex (MSR) process based on luminance adaptation to preserve details. Finally, we perform contrast enhancement on the MSR result. Experimental results demonstrate that the proposed method successfully enhances contrast in images while keeping textures in highlight regions.

***Index Terms*—** Contrast enhancement, human visual perception, halo artifact, image enhancement, luminance adaptation, multi-scale retinex

1. INTRODUCTION

Image enhancement has been a basic field of image processing [1], which highlights regions of interest and weakens unnecessary information. It has been popularly used in practical applications such as display enhancement, video surveillance, and medical diagnosis. Commonly used methods for image enhancement are histogram equalization (HE) [2], contrast enhancement, and image sharpening. However, they focus on detail enhancement and often produce unnatural-looking results. Thus, retinex theory has been introduced in image enhancement to remove the influence of light and restore the true face, and many retinex-based algorithms have been proposed so far. In 1963, the retinex theory was firstly proposed by Land [3] based on the human visual system (HVS), and the word "retinex" is synthesized from retina and cortex. The basic assumption of Retinex theory is the original image S is the product of illumination L and reflectance R as follows:

$$S(x,y) = R(x,y)L(x,y) \tag{1}$$

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Retinex theory decomposes an image into L and R by smoothing functions. The original image eliminates the influence of uneven illumination, and represents intrinsic features of the image. During the four decades, many retinex algorithms have been proposed: Single scale retinex (SSR)[4], multi-scale retinex (MSR) [5], MSR with color restoration (MSRCR) [6]. In RGB color space, MSR R_{MSR} is obtained as follows:

$$R_{MSR_i}(x,y) = \sum_{n=1}^{N} w_n \cdot \{\lg[S_i(x,y)] - \lg[F_n(x,y) * S_i(x,y)]\} \tag{2}$$

where S is the original input image; N is the number of scales; i represents color channels; w_n are weighting factors; and F_n are smoothing functions expressed as:

$$F_n(x,y) = K_n \exp\lfloor -(x^2+y^2)/\sigma_n^2 \rfloor \tag{3}$$

where σ_n is the scale for F_n; and the normalization parameter K_n is selected to be $\int\int F(x,y)\,dx\,dy = 1$. Smaller σ_n provides more dynamic range compression, while bigger σ_n is good for color constancy. According to the retinex theory that removes illumination from the original image and produces the object reflectance which represents intrinsic features in real-world scenes. However, it excessively increases noise in dark regions. Thus, we use a control factor based on luminance adaptation to adaptively remove illumination artifacts. First, we obtain the illumination layer using adaptive Gaussian filtering. Then, we adaptively remove illumination in the illumination layer in MSR process based on luminance adaptation to preserve image details. Finally, we perform contrast enhancement on the MSR result. Fig. 1 illustrates the whole framework of the proposed method.

2. PROPOSED METHOD

Adaptive gamma correction with weighting distribution (AGCWD)[7] is global image enhancement, which is formed on the form of transform-based gamma correction (TGC) as follows:

$$T(l) = l_{max}(l/l_{max})^{\gamma} \tag{4}$$

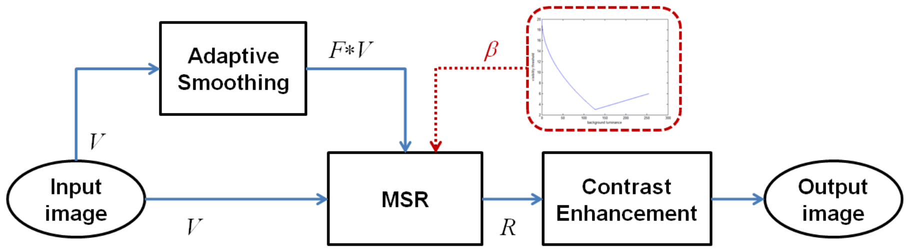

Fig. 1. Whole framework of the proposed method. MSR: Multi-scale retinex. V: Input image. F: Smoothing operator. β: Control factor. R: MSR result.

Fig. 2. Left: Original image. Right: Its enhanced result by AGCWD.

where l_{max} is the maximum intensity of the original image. Thus, the input image intensity l is transformed as $T(l)$ by (4), and γ is based on the probability density function (PDF) of the intensity histogram. The proposed adaptive gamma correction (AGC) is formulated as follows:

$$T(l) = l_{max}(l/l_{max})^{\gamma} = l_{max}(l/l_{max})^{1-cdf(l)} \tag{5}$$

The cumulative distribution function (CDF) is based on PDF, and a weighting distribution (WD) function is applied to update the statistical histogram as follows:

$$PDF_w(l) = PDF_{max}(\frac{PDF(l) - PDF_{min}}{PDF_{max} - PDF_{min}})^{\alpha} \tag{6}$$

where α is the adjusted parameter. However, AGCWD doesn't consider the local information, and thus makes the results unnatural-looking in some areas. As shown in Fig. 2, AGCWD achieves good detail enhancement in dark regions, but causes over-enhancement in the sky region. Therefore, we adopt the retinex theory to remove the over-enhancement effects while preserving details in images. According to the retinex theory, the object reflectance map is produced to keep intrinsic features in real-world scenes. However, the contrast in dark regions is over-enhanced by contrast enhancement, which would excessively increase noise in dark regions. We add a weakening factor to adjust the degree of illumination removal. We perform the proposed method in V channel of the color space HSV without considering color adjustment. We obtain R using MSR as follows:

$$R(x,y) = \sum_{n=1}^{N} w_n \cdot \{\lg[V(x,y)] - \beta \cdot \lg[F_n(x,y) * V(x,y)]\} \tag{7}$$

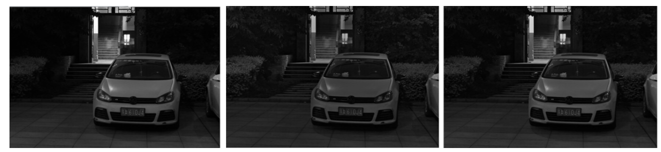

Fig. 3. Left: Original image. Middle: $\beta = 0.8$. Right: $\beta = 0.4$.

where R is the intensity after weakening illumination; V is the channel V of color space HSV, and β is the control factor. As shown in Fig. 3, the smaller β is, the more similar to the original image the result is. Also, the greater β is, the more obvious the details are. Thus, we set β adaptively according to local image content. In dark regions, β is small, thus making the MSR result similar to the original image. In bright regions, β is bigger, and the illumination would be weakened. In the early 1980s, Barten [8] discovered the relationship between the actual luminance and the brightness by human eye perception through experiments. Jayant [9] proposed a JND model based on the relationship. If the difference between two luminance values in an image is less the critical JND, the two luminance are merged into one luminance because human eyes cannot perceive their difference. According to the previous work[10][11], the relationship between the visibility threshold and the background luminance, i.e. luminance adaptation, is obtained by:

$$T_l(x,y) = \begin{cases} 17(1 - \sqrt{\frac{\overline{I(x,y)}}{127}}) + 3 & if \quad \overline{I(x,y)} \leq 127 \\ \frac{3}{128}(\overline{I(x,y)} - 127) + 3 & otherwise \end{cases} \tag{8}$$

where T_l is the visibility threshold; and I is the background luminance of input image.

As shown in Fig. 4, human eyes are more sensitive to bright regions than black regions. Thus, we use a liner mapping function to represent the human eye sensitivity to background luminance as follows:

$$\beta(x,y) = k \cdot (-\frac{1}{17}T_l(x,y) + \frac{20}{17}) \tag{9}$$

where k is to control the maximum value, and $T_l(x,y) = \sum_{n=1}^{N}(F_n(x,y) * V(x,y))$ is the background luminance. M-

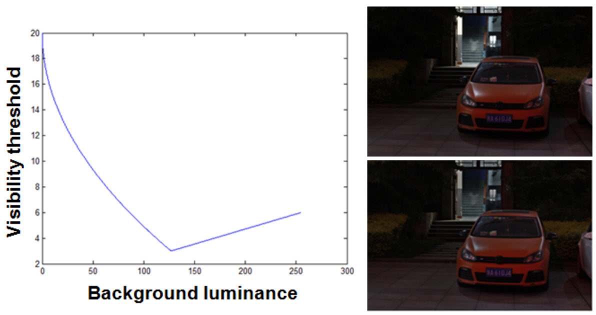

Fig. 4. Left: Relationship between visibility threshold and background luminance (luminance adatation). Top-right: Original image *DSCN*. Bottom-right: Illumination removed image I_{wea}.

Fig. 5. Top: Input image. Bottom-left: Mask without adaptive smoothing. Bottom-right: Mask with adaptive smoothing.

SR performs the convolution between Gaussian smoothing function and the original image to get the illumination layer. However, it causes halo artifacts along strong edges. In [12], adaptive filtering was used to prevent halo artifacts by adapting the shape of filter to the high-contrast edges in the image. It used a Canny edge detector to detect high-contrast edges. Then, the factor σ of Gaussian smoothing function is defined as follows:

$$\sigma = \begin{cases} \sigma_0 & \textit{no high contrast edge was crossed} \\ \sigma_1 & \textit{a high contrast edge was crossed} \end{cases} \tag{10}$$

That is, if the absolute difference of two pixels is more than the threshold value, we use σ_1; otherwise, we use σ_0.
The proposed method is briefly described in Algorithm 1.

Algorithm 1 Retinex-based perceptual contrast enhancement

Input: Input image S, scale σ_n.
$V \leftarrow RGBtoHSV(S)$.
Illumination layer $L \leftarrow$ adaptive Gaussian filtering with σ_n on V.
for each pixel **do**
  Visibility threshold $T_l \leftarrow L$ by (8).
  Weakening factor $\beta \leftarrow T_l$ by (9).
end for
for each pixel p **do**
  Calculate R for all pixels $\leftarrow \beta$ of target pixel by (7).
  R_{max} and $R_{min} \leftarrow \exp(R)$.
  $I_{wea} = \frac{R_p - R_{min}}{R_{max} - R_{min}} + R_{min}$ of p.
end for
$I_{out} \leftarrow AGCWD(I_{wea})$.
Output: Enhanced image I_{out}.

Fig. 6. Experimental results in *Villa*. Left: Input image. Middle: AGCWD. Right: Proposed method.

3. EXPERIMENTAL RESULTS

To verify the superiority of the proposed method, we perform experiments on nine test images: *Car*, *Campus*, *Carnival*, and *Seaside* (Dark images); *Church*, *DSCN*, *Alley*, *City*, and *Villa* (Shadow images). Their size is 720×480∼2048×1366). We perform our experiments on a PC with Core Duo 2.33 GHz CPU and 4G RAM using Matlab R2015b and Windows 7 operating system. We compare the performance of the proposed method with that of AGCWD[7], i.e. the-state-of-the art method. We set N to 3 in (2) and α to 1 in (6). In (9), we set k to 0.5, and thus β ranges from 0 to 0.5. In (10), we set σ_1 to at least $0.5\sigma_0$ for avoiding halo artifacts [12]. Figs. 6∼10 show the experimental results by the proposed method in comparison with AGCWD. As shown in the figures, AGCWD reproduces dark regions well with clear details, but excessively enhances bright regions while smoothing image details. AGCWD use the same gamma correction on pixels with the same intensity considering the proportion of each pixel. The proposed method weakens the illumination adaptively according the human eye sensitivity to background luminance. The proposed method has a similar to or better visual effect than AGCWD. In the sky regions in Figs. 6∼8, the proposed method achieves a better performance on local contrast enhancement compared with AGCWD by successfully preserving details. Figs. 9 and 10 show their zoomed results in *Car* and *Campus*. As shown in the figures, AGCWD produces over-enhancement and loss of textures in the results. Compared with AGCWD, details and edges in the bottom right images in Figs. 9 and 10 are enhanced well because we adjust the degree of the illumination removal from the original image based on luminance adaptation. We perform quantitative measurements on the results in terms of discrete entropy

Fig. 7. Experiment results in *DSCN*. Left: Input image. Middle: AGCWD. Right: Proposed method.

Fig. 8. Experiment results in *Alley*. Left: Input image. Middle: AGCWD. Right: Proposed method.

(DE) [13], feature similarity (FSIM) [14], and local-tuned-global (LTG) [15] as follows: (1) DE estimates image details according probability histogram distribution, which measures the degree of randomness, which is the average amount of information. The enhanced image with high contrast or uniform histogram distribution causes a high entropy value; (2) FSIM measures the overall feature similarity between the enhanced and reference images; (3) LTG introduces the human visual perception to image quality assessment by measuring the visual saliency from local distortions and global quality degradation.

Table 1 provides the objective evaluation results in terms of DE, FSIM, and LTG. In *Church*, *DSCN*, and *Villa*, the proposed method achieves a significant performance improvement over AGCWD in term of DE. DE is a statistical measure for randomness, and a higher value indicates containing more details. That is, the proposed method is very effective in producing image details by contrast enhancement. In terms of FSIM and LTG, the proposed method is similar to AGCWD. In strong light regions, the proposed method results are more

Table I Performance comparison between AGCWD[7] and proposed method (PRO) in terms of DE, FSIM, and LTG

Metric	DE		FSIM		LTG	
Image	[7]	PRO	[7]	PRO	[7]	PRO
Church	7.3411	7.7241	0.8793	0.8983	0.9915	0.9918
Car	7.3596	7.4799	0.7609	0.7568	0.9811	0.9776
City	7.3328	7.7161	0.9780	0.9800	0.9986	0.9970
Campus	7.3596	7.3900	0.7256	0.7219	0.9734	0.9699
DSCN	7.2818	7.6306	0.8998	0.8927	0.9916	0.9900
Seaside	7.2770	7.3404	0.8866	0.8825	0.9908	0.9905
Alley	7.5380	7.6272	0.8694	0.8563	0.9897	0.9882
Carnival	6.8583	7.0313	0.8212	0.8165	0.9833	0.9824
Villa	7.2983	7.4992	0.7934	0.8420	0.9847	0.9862
Average	7.2940	7.4932	0.8460	0.8496	0.9886	0.9857

Fig. 9. Experiment results in *Car*. Top left: Input image. Top middle: AGCWD. Top right: Proposed method. Bottom: Their zoomed images in the red boxes.

Fig. 10. Experiment results in *Campus*. Top left: Input image. Top middle: AGCWD. Top right: Proposed method. Bottom: Their zoomed images in the red boxes.

similar to their original images than AGCWD. Our method successfully enhances contrast in dark regions while preserving textures in bright regions. Consequently, it can be safely concluded that the proposed method successfully enhances contrast in images while keeping details and produces visually pleasing results.

4. CONCLUSIONS

In this paper, we have proposed retinex-based perceptual contrast enhancement based on luminance adaptation. Strong illumination often causes the loss of details and textures in images. Thus, we have employed luminance adaptation to handle the illumination problem in contrast enhancement. We have obtained the illumination layer using adaptive Gaussian filtering to remove halo artifacts. We have adaptively removed illumination of the illumination layer in MSR process based on luminance adaptation to preserve image details. Experimental results demonstrate that the proposed method successfully enhances contrast in images while successfully keeping textures in highlight regions.

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