READABILITY ENHANCEMENT OF LOW LIGHT IMAGES BASED ON DUAL-TREE COMPLEX WAVELET TRANSFORM

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ABSTRACT

Since images captured under low light conditions have low dynamic range and are seriously degraded by noise, it is a challengeable task to achieve both contrast enhancement and noise reduction from low light images. In this paper, we propose a readability enhancement method of low light images based on dual-tree complex wavelet transform (DTCWT). We perform contrast enhancement and noise reduction for low light images based on wavelet coefficients. First, we conduct illumination compensation to contain fine details and fully utilize dynamic range. Then, we decompose the image into high-pass and low-pass sub-bands by DTCWT, and perform contrast limited adaptive histogram equalization (CLAHE) and a nonlinear transform in low-pass and high-pass sub-bands, respectively, to achieve both contrast enhancement and noise reduction. Finally, we perform color correction to deal with the color distortion problem caused by contrast enhancement. Experimental results demonstrate that the proposed method outperforms state-of-the-art ones in contrast enhancement, noise reduction, and color reproduction in terms of both subjective and objective evaluations.

***Index Terms*—**Contrast enhancement, color correction, dual-tree complex wavelet transform, noise reduction, wavelet coefficient.

1. INTRODUCTION

Ambient light is an indispensable factor for the quality of images captured by imaging devices. In general, images captured in the dark condition have a narrow dynamic range and low contrast [1]. It is required to improve contrast of images captured under low light condition to make the image have a perceptually more pleasing or visually more informative vision effect [2]. Up to now, researchers have proposed a lot of contrast enhancement methods to improve the contrast of the images [3][4]. However, they didn't consider the characteristics of low-light images with low signal-to-noise ratio (SNR) and noise, which are different from natural scenes captured under ordinary conditions [5]. Thus, traditional contrast enhancement methods had a limit in achieving noise reduction and color reproduction while enhancing contrast. For this reason, some enhancement and de-noising methods have been proposed in recent years. Yin et al. presented a novel framework for low light image enhancement and noise reduction by performing brightness/contrast stretching and noise reduction in the HSI and YCbCr color spaces [6]. Huang et al. provided a automatic transformation technique to improve the brightness of dimmed images using gamma correction and probability distribution of luminance pixels [7]. Artur et al. proposed an automatic contrast enhancement method for low-light images based on local statistics of wavelet coefficients. They used a nonlinear enhancement function based on the local distribution of the wavelet coefficients modeled as a Cauchy distribution to stretch brightness/ contrast and utilized a shrinkage function to prevent noise amplification [8]. Although they have improved visual quality of low-light images to some extent, it is hard to achieve both noise reduction and color reproduction from low light images.

In this paper, we propose readability enhancement of low light images to achieve both noise reduction and color reproduction while enhancing contrast based on dual-tree complex wavelet transform (DT-CWT). We first convert the original RGB image into the YUV color space. Then, we perform illumination compensation on the Y-component to make the output contain more details and fully utilize the dynamic range. After DT-CWT, we perform contrast enhancement and noise reduction to improve the readability of images captured under low-light conditions based on the characteristics of wavelet coefficients in the wavelet domain, and then conduct the inverse DT-CWT to change the image to the spatial domain. Finally, we perform color correction to overcome the color distortions caused by the contrast enhancement process. The flow chart of the proposed method is illustrated in Fig. 1. Compared with existing methods, our main contributions are as follows:

1) We achieve both contrast enhancement and noise reduction using DTCWT. Since noise mainly appears in high-pass sub-bands, we perform noise reduction in high-pass sub-bands after DTCWT.

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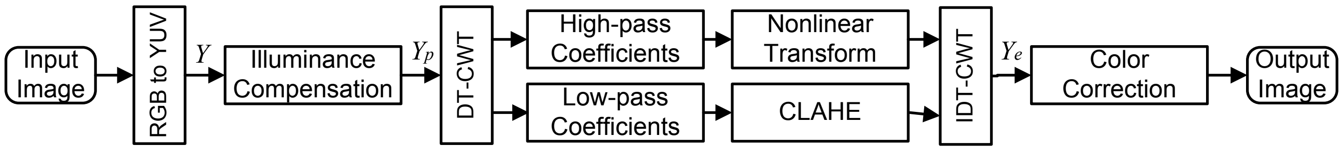


Fig. 1. Flow chart of the proposed low light image enhancement.

DTCWT is useful for de-noising due to its advantage of approximate shift invariance, good selectivity, perfect reconstruction, and low-redundancy.

2) We enhance the readability of low-light images using a wavelet coefficient-based nonlinear transform in high-pass sub-bands and CLAHE [15] in low-pass ones.

The remainder of this paper is organized as follows. Section II provides the proposed method in detail, while Section III presents the experiment results and their corresponding analysis. Conclusions are drawn in Section IV.

2. PROPOSED METHOD

A. Color Space Conversion

We convert the original RGB image into the YUV color space, and get the Y component as follows:

$$Y = 0.299 * R + 0.587 * G + 0.114 * B \qquad (1)$$

Since the YUV color space is good for image de-noising and contrast enhancement [9], we adopt it.

B. Illumination Compensation

Images captured under poor illumination conditions often suffer from a low dynamic range, thus resulting in low contrast and losing much detail information. To enhance contrast and improve details in low light images, we utilize bilateral filtering to decompose the Y channel into base and detail components. The response of the bilateral filter to the brightness image is the base layer image Y_b, and the difference between Y and Y_b is the detail layer image Y_d. Thus, the enhanced detail layer Y'_d is formulated as follows [6]:

$$Y_d^{'} = (1 + Y_d)\log(Y+1) - \log(\log(Y_b + 1) + 1) \qquad (2)$$

where the range of Y is [0,1]. Combining Y'_d and Y_b, we get the processed brightness image Y' including more detail information. However, the dynamic range of Y' is still narrow, which does not use the dynamic range of display devices. To use the dynamic range fully, we use normalization based on a stretching function as follows:

$$Y_p = \frac{Y' - Y'_{\min}}{Y'_{\max} - Y'_{\min}} \times 255 \qquad (3)$$

where $Y'_{\max}$ and $Y'_{\min}$ are the maximum and minimum value of Y', respectively.

C. Dual-Tree Complex Wavelet Transform

The wavelet theory has a superior performance in noise reduction due to multi-resolution properties [10][11].

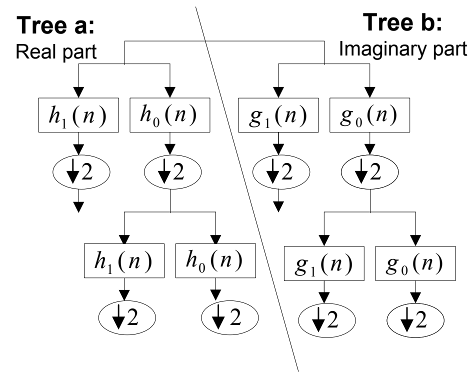
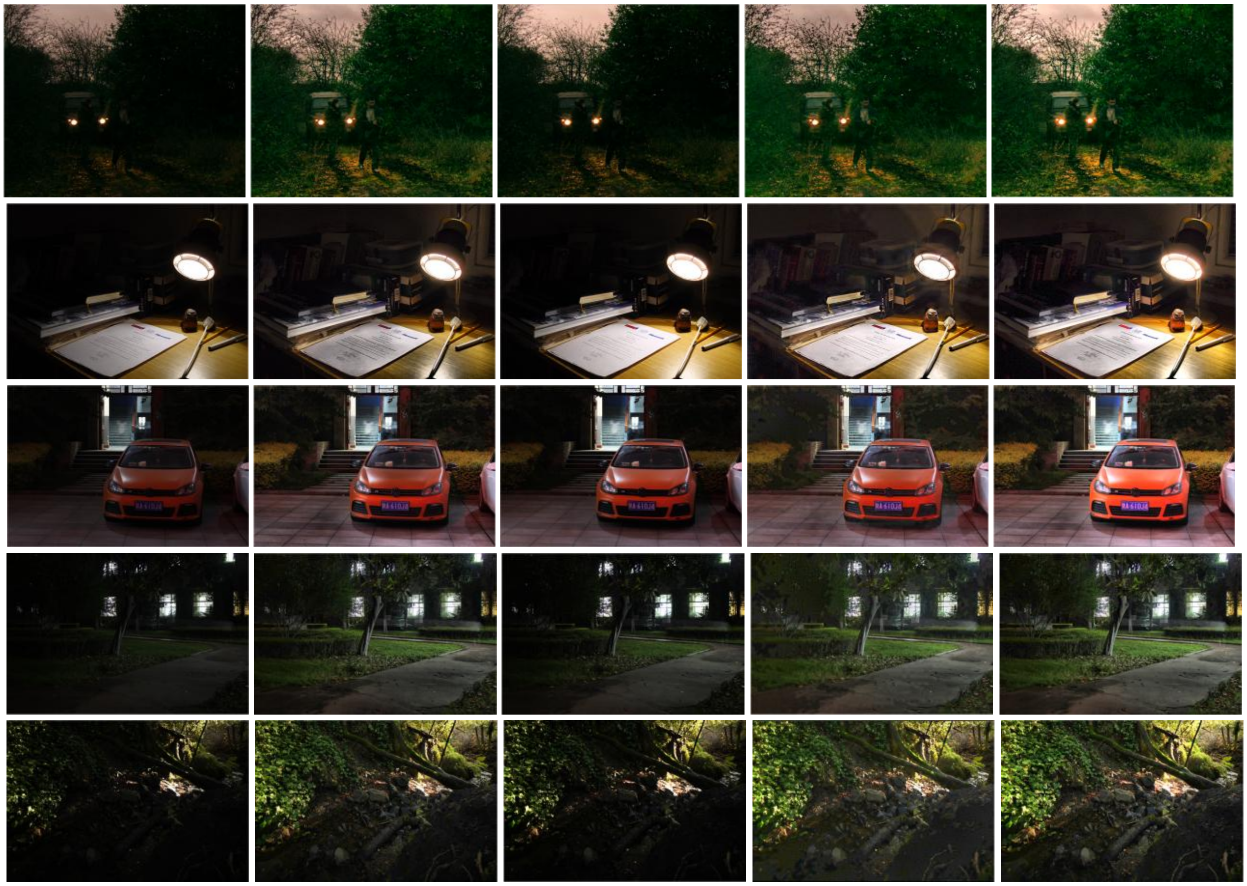


Fig. 2 1D Dual-tree complex wavelet transform (DTCWT).

Thus, we adopt DTCWT [12] for low light images to improve contrast enhancement. DTCWT uses two wavelet trees: 1) **Tree a**: Generating the real part of the complex wavelet coefficients real tree; 2) **Tree b**: Producing the imaginary part of the complex wavelet coefficients imaginary tree. Fig. 2 gives the illustration of the one dimensional DTCWT [13]. However, because images are two-dimensional signals, it required to extend one dimensional (1D) DTCWT to two dimensional (2D) transform by performing the separable filtering on rows and columns of the image. Thus, 2D-DTCWT decomposes the image into two low-pass sub-images and six high-pass sub-bands referring to ±15°, ±45°, and ±75°, respectively, which reduces blur artifacts in the decomposition process.

D. Contrast Enhancement and Noise Reduction

The wavelet domain with low entropy and multi-resolution characteristics is able to achieve noise reduction by dealing with the wavelet coefficients [11]. Thus, we perform contrast enhancement and de-noising for low light images in the wavelet domain using DTCWT. DTCWT decomposes the image into low-pass and high-pass sub-bands. Since noise mainly appears in high-pass coefficients, we perform different contrast enhancements in low-pass and high-pass sub-bands. Contrast enhancement is mainly achieved in the low-pass sub-bands. We use CLAHE [15] for contrast enhancement in the low-pass sub-bands. CLAHE constrains the local contrast gain by restricting the maximum number of pixels at a grayscale level to improve the contrast of low-pass sub-bands while preventing over-enhancement in images.



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

Fig. 3. Contrast enhancement results of different methods. (a) Original image. (b) CLAHE. (c) AGC. (d) ACE. (e) Proposed method. From the first row to the last row: *Land*, *Lamp*, *Car*, *Tree*, and *Ditch*.

The high-pass coefficients are divided into three categories of sharp edge, weak edge, and noise [22]. In the case of sharp edge, the coefficient values are high in all sub-bands. In the case of weak edge, the coefficient values are high in some sub-bands, but low in other sub-bands, i.e. weak edge has directionality. However, in the case of noise, there is little directionality, and thus its coefficient values are low in all sub-bands. Thus, we classify the wavelet coefficients into three categories as follows [22]:

$$\begin{cases} mean(w_{i,j}) \geq k\sigma; & \text{sharp edge} \\ mean(w_{i,j}) < k\sigma, \max \geq k\sigma; & \text{weak edge} \\ mean(w_{i.j}) < k\sigma, \max < k\sigma; & \text{noise} \end{cases} \quad (4)$$

where $mean(w_{i,j})$ is the local mean of the wavelet coefficient $w_{i,j}$ in each sub-band; max is the maximum value in the sub-band; k and σ are the adjustable parameter and standard deviation, respectively. We obtain σ from the observed data by computing median absolute deviation (MAD) of the high frequency coefficients at the each decomposition level of wavelet decomposition [14]. To enhance the contrast while reducing noise, we use a nonlinear enhancement function based on characteristics of noise and signal in the wavelet domain as follows [22]:

$$w'_{i,j} = \begin{cases} w_{i,j}, & \text{sharp edge} \\ w_{i,j} \cdot \max((\frac{k\sigma}{|w_{i,j}|})^{p}, 1), & \text{weak edge} \\ w_{i,j} \cdot 0, & \text{noise} \end{cases} \quad (5)$$

where p is a parameter varying with the range of [0,1]. This is because sharp edges are less affected by noise, but weak edges are easily affected by noise. Thus, we enhance weak edges in images by adjusting their weights in (5). Moreover, we set the coefficients of noise to zero for noise reduction. We apply $w'_{i,j}$ to high-pass sub-bands. The readability of low-light images is significantly enhanced by noise reduction and contrast enhancement in high-pass and low-pass sub-bands.

E. Color Correction

After noise reduction and contrast enhancement in the wavelet domain, we perform inverse DTCWT to reconstruct the luminance image as output. Denote the luminance image by Y_e. We obtain the output color image by the ratio of the three color components as follows [16]:

$$\begin{bmatrix} R' \\ G' \\ B' \end{bmatrix} = \begin{bmatrix} Y_e/Y & 0 & 0 \\ 0 & Y_e/Y & 0 \\ 0 & 0 & Y_e/Y \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (6)$$

where [R',G',B'] and [R,G,B] represent the color channels of the output and input color images, respectively.

3. EXPERIMENTAL RESULTS

To verify the superiority of the proposed method, we perform experiments on a PC with Intel Core i5 3.20GHz CPU and 4.00 GB RAM using MATLAB. We use five images for tests: *Land*, *Lamp*, *Ditch*, *Car*, and *Tree*, which are taken by the Eden project multi-sensor data set [17], HDR shop dataset [18], and captured by a digital camera of Canon EOS 60D. In (4), we set k to 5. We compare the performance of the proposed method with 3 conventional contrast enhancement ones of CLAHE [15], AGC [7], ACE [8]. Experimental results are shown in Fig. 3. As shown in the Fig. 3(b), CLAHE improves visual quality of low-light images to some extent. However, it often produces noise in results as well as its brightness enhancement is not satisfactory to find the detail information (see Fig. 3(b)). AGC often generates too dark regions in the results, which is not effective in producing detail information (see Fig. 3(c)). ACE successfully performs contrast enhancement and noise reduction by DTCWT. It generates a more visually pleasing result than previous ones, but is not effective in image de-noising (Fig. 3(d)). Fig. 3(e) shows the experimental results by the proposed method. As shown in Fig. 3(e), the proposed method outperforms the others in noise reduction while effectively enhancing contrast. Moreover, the whole brightness and color of the enhanced images are more natural-looking as shown in Fig. 3(e). That is, the readability of the enhanced low-light images is greatly improved as well as the visual effect is better than the other methods.

For more quantitative measurements, we provide performance evaluation results on them in TABLE I in terms of discrete entropy (DE) [19], absolute mean brightness error (AMBE) [20], and colorfulness metric (CM) [21]. In the table, bold numbers represent the best performance in each metric.

▪ DE computes the amount of information in an image and higher DE indicates that the image contains more details as follows:

$$H(p) = -\sum_{i=0}^{L-1} p(i)\log_2^{p(i)} \quad (8)$$

where p is the probability density function.

▪ AMBE is the absolute difference between input and output means as follows:

$$\text{AMBE}(X, Y)=|X_M - Y_M| \quad (9)$$

where X_M and Y_M are means of the illumination channel for input and output images, respectively.

TABLE I
OBJECTIVE EVALUATION RESULTS OF TEST IMAGES IN TERMS OF DE, AMBE, AND COLORFULNESS

Metric	Method	*Land*	*Lamp*	*Car*	*Tree*	*Ditch*
DE	CLAHE	6.7786	6.9316	7.2810	6.5869	6.4795
	AGC	5.505	6.0006	6.1584	5.2431	5.0279
	ACE	6.9085	**7.1739**	7.3744	6.6440	6.6833
	Pro.	**6.9111**	7.0921	**7.3836**	**6.8758**	**6.8784**
AMBE	CLAHE	25.1544	16.7818	34.6658	24.6526	25.4825
	AGC	13.4028	17.065	19.6726	11.3596	9.503
	ACE	25.2706	45.2766	30.5207	17.5708	16.1791
	Pro	**35.5396**	**33.663**	**48.8996**	**37.8616**	**39.3632**
CM	CLAHE	15.2903	11.9324	15.8767	6.6857	12.1426
	AGC	9.5358	13.3111	12.5439	4.1794	8.4600
	ACE	19.2529	16.8588	19.4393	9.0404	15.5055
	Pro.	**20.8678**	**21.6104**	**31.7544**	**12.8627**	**18.6837**

Bold numbers represent the best performance in each image.

▪ CM measures the perceived color of an image, and is computed based on the mean and standard deviations of two parameters α=R-G and β=0.5·(R+G)-B [36] as follows:

$$M = \sqrt{\sigma_\alpha^2 + \sigma_\beta^2} + 0.3\sqrt{\mu_\alpha^2 + \mu_\beta^2} \quad (10)$$

where σ_α and σ_β are standard deviations; and μ_α and μ_β are the means of α and β, respectively.

As listed in TABLE I, the value of DE in the proposed method is better than the existing methods. That is, the proposed method preserves more detail information in the enhanced images. Moreover, the AMBE value indicates the proposed method remarkably improves the brightness of the image. The colorfulness value means the proposed method performs better in decreasing color distortions. Consequently, we can safely conclude that the proposed method outperforms other ones in terms of information preservation, brightness enhancement, and color fidelity.

4. CONCLUSIONS

We have proposed readability enhancement of low light images using DTCWT. Low light images have low dynamic range, much noise, and poor colors. Considering the properties of low light images, we have employed DTCWT to decompose the input image into low-pass and high-pass sub-bands. Then, we have utilized CLAHE in the low-pass sub-bands to improve the contrast of the image while avoiding over-enhancement. Moreover, we have adjusted the coefficients in the high-pass sub-bands based on a nonlinear enhancement function to reduce noise while improving the readability of the image. Experimental results verify that the proposed method successfully produces informative, natural looking, and visually pleasing images while remarkably enhancing the readability of low light images.

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