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Low light image enhancement with dual-tree complex wavelet transform ☆,☆☆

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ABSTRACT

In low light condition, low dynamic range of the captured image distorts the contrast and results in high noise levels. In this paper, we propose an effective contrast enhancement method based on dual-tree complex wavelet transform (DT-CWT) which operates on a wide range of imagery without noise amplification. In terms of enhancement, we employ a logarithmic function for global brightness enhancement based on the nonlinear response of human vision to luminance. Moreover, we enhance the local contrast by contrast limited adaptive histogram equalization (CLAHE) in low-pass subbands to make image structure clearer. In terms of noise reduction, based on the direction selective property of DT-CWT, we perform content-based total variation (TV) diffusion which controls the smoothing degree according to noise and edges in high-pass subbands. Experimental results demonstrate that the proposed method achieves a good performance in low light image enhancment and outperforms state-of-the-art ones in terms of contrast enhancement and noise reduction.

1. Introduction

Contrast enhancement plays an important role in image processing, computer vision, and pattern recognition. Low contrast in images is caused by many reasons such as the user's operational error, poor quality of the imaging device, and low light condition. For instance, the image captured in a dark environment often contains large regions of too dark pixels whose visibility is remarkably reduced [1]. That is, ambient light is an indispensable factor for the quality of images captured by imaging devices. Above all, images captured in the dark condition often have low and concentrated gray scale, thus making images have a narrow dynamic range and low contrast [2]. It is required to improve contrast of images captured under low light condition. In general, contrast enhancement aims to make the image have a perceptually more pleasing or visually more informative vision effect [3].

Up to now, researchers have proposed a lot of contrast enhancement methods to improve the contrast of the low light images. Histogram equalization (HE) remapped input pixel values according to the probability distribution of the input image to make the enhanced image have a uniform distribution in its histogram and fully utilize the dynamic range [4,5]. However, since HE had not preserved the mean brightness effectively, over-enhancement was the main problem which caused visible distortions such as contouring or noise/artifacts [6–8]. To overcome the drawback of HE, researchers have proposed many outstanding methods in recent years, and the representative ones were the histogram modification framework (HMF) [9] and optimized contrast-tone mapping (OCTM) [10]. HMF constructed a generalized histogram modification framework, and formulated contrast enhancement as an optimization problem that minimized the special penalty terms to adjust the degree of enhancement [9]. OCTM formulated contrast enhancement as one of optimal allocation of an output dynamic range by maximizing contrast gains while minimizing tone distortions, which was solved by linear programming [10]. Both HMF and OCTM overcame excessive enhancement and produced visual-pleasing results by selecting the proper constraints. However, they ignored the special characteristics of images captured under poor ambient illumination conditions. In practice, low light images were different from natural scenes captured under ordinary conditions. In general, they had low signal-to-

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noise ratio (SNR), and thus caused noise and color distortions [11]. For this reason, some enhancement and denoising algorithms have been proposed in recent years. Malm et al. proposed a low light image enhancement algorithm based on adaptive spatiotemporal smoothing and contrast limited histogram equalization (CLHE) to reduce noise and expand the dynamic range of low light images [12]. However, this method required high computational costs and sufferers from motion blurs. Chen et al. [13] proposed an intra-and-inter-constraint based algorithm for video enhancement. This method analyzed features from different region-of-interests (ROIs) and created a global tone mapping curve for the entire image. Although this method could achieve relatively good intra-frame quality in a video, it involved the detection of ROIs, feature extraction, and some other complex operations. However, its computational costs were very high. Rao et al. [14,15] proposed image-based fusion video enhancement algorithm for night-time videos. This method fused video frames from high-quality day-time and night-time backgrounds with low-quality night-time videos. However, the moving objects in day-time videos were hard to be completely cleaned and the enhanced frames became unnatural. Moreover, the moving objects inevitably caused ghost artifacts. Yin et al. [16] 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. Huang et al. provided an automatic transformation technique to improve the brightness of dimmed images via the gamma correction and probability distribution of luminance pixels [17]. Although most gray-level transformation methods are performed in the spatial domain, some researchers have utilized wavelets for this purpose in recent years. The advantage of using these transformation methods is their ability to analyze and modify image features based on their spatial-frequency content at different resolutions. Artur et al. [18] 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. However, the effect of noise reduction in this method was not obvious. Recently, Glenn et al. [19] proposed a highly efficient denoising method which combined the shearlets with total variation (TV) diffusion. They reduced noise based on shearlet representation by constraining the residual coefficients from a projected adaptive total variation scheme. This method performed the diffusion adaptive to the local structure considering a type of content. Although they have improved visual quality of low-light images to some extent, it is a challengeable task to achieve both noise reduction and color reproduction from low light images.

In this paper, we propose a simple but effective low light image enhancement method based on DT-CWT [20]. In the DT-CWT framework, we perform contrast enhancement in the low-pass subbands by CLAHE [21]. Moreover, we apply TV diffusion to high-pass subbands for noise reduction. During the TV diffusion process, we adjust the diffusion degree in noisy areas of the image based on content information. Experimental results show that the proposed method achieves performance improvement in noise reduction, local contrast enhancement, and global brightness enhancement. Compared with existing methods, our main contributions are as follows:

(1) We achieve both contrast enhancement and noise reduction in the DT-CWT framework. We perform contrast enhancement in the low-pass subbands using CLAHE, while we apply TV diffusion to the high-pass subbands for noise reduction. During the TV diffusion process, we adjust the diffusion strength in noisy areas of the image based on content information. (2) We successfully preserve edges and details using the direction selective property of DT-CWT. The direction selective property is beneficial to the TV diffusion. Thus, details are successfully preserved while suppressing noise.

Experimental results demonstrate that the proposed method is very effective in enhancing low-light images and outperforms state-of-the-art ones in both contrast enhancement and noise reduction.

The remainder of this paper is organized as follows. Section 2 provides the proposed method in detail, while Section 3 presents the experimental results and their corresponding analysis. Conclusions are drawn in Section 4.

2. Proposed method

Fig. 1 illustrates the flowchart of the proposed method for low light image enhancement. As shown in the figure, we first convert the input image into the YUV color space to get the Y component. Then, we perform bilateral filtering to decompose the input Y channel into base and detail layers and enhance the detail layer to recall the lost details. We conduct a logarithmic mapping for global brightness enhancement by remapping a narrow intensity range in the input image to a wider range. Next, we remove noise in high frequency wavelet coefficients using edge directionality, and enhance local contrast in the low frequency ones using CLAHE via DT-CWT. Finally, we perform color correction to get the final result. The detailed descriptions are provided as follows:

2.1. Color space conversion

First, we convert the RGB color space in the input image to the YUV color space to get the Y channel for contrast enhancement and noise reduction. Since the chrominance channel provides relatively little information in low-light condition compared with the luminance channel, we use the Y channel. We obtain the Y channel as follows:

$$Y = 0.299 * R + 0.587 * G + 0.114 * B \tag{1}$$

where R, G, and B are three channels in the RGB color space.

2.2. Illumination compensation

Images captured under poor illumination condition often suffer from a low dynamic range, thus resulting in losing much detail information in low light images. Illumination compensation is to solve this problem. To enhance the detail information, we utilize bilateral filtering to decompose the Y channel into base and detail layers. After smoothing by bilateral filtering, we get the base layer Y_b that preserves region boundaries and other structures in the Y channel. By subtracting Y_b from the Y channel, we obtain the detail layer Y_d which contains detail information in images. Thus, we obtain the enhanced detail layer Y'_d from Y_b and Y_d as follows [16]:

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

where the range of Y is $[0, 1]$.

Moreover, the Y channel of images captured in low-light condition is often characterized by a very low dynamic range, and not matched with the dynamic range of the sensing and/or display devices. Thus, it is necessary to adjust the illumination by a mapping function to promote the global brightness. Because the logarithmic function is strongly correlated to the nonlinear response of the human eye to the luminance, the adjusted Y_p is obtained as follows:

$$Y_p = \frac{\log(Y' + 1)}{\log(Y'_{\max} + 1)} \cdot \frac{\log 10}{\log\left(5 + \left(\left(\frac{Y'}{Y'_{\max}}\right)^{\frac{\log b}{\log 0.5}}\right) \cdot 5\right)} \cdot Y'_{\max} \tag{3}$$