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Variational framework for low-light image enhancement using optimal transmission map and combined ℓ_1 and ℓ_2-minimization

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ABSTRACT

This paper presents a novel variational framework for low-light image enhancement. The proposed enhancement algorithm simultaneously performs brightness enhancement and noise reduction using a variational optimization. An edge-preserved noise reduction is performed by minimizing the total variation constraint term in the energy function. In addition, the proposed method estimates the optimal transmission map to restore the low-light image by minimizing the ℓ_2-norm smoothness and data-fidelity terms. To minimize the proposed energy functional, the proposed method splits the ℓ_1-derivative term under the split Bregman iteration framework. The performance of the proposed method is evaluated using both simulated and natural low-light images. Experimental results show that the proposed enhancement method can significantly improve the quality of the low-light images without noise amplification.

1. Introduction

The low-light image restoration methods play an important role in various image processing application fields to detect and recognize objects as a pre-processing step [1]. However, in a low-light condition an acquired image is degraded by a narrow dynamic range due to the low-sensitivity of an imaging sensor. In addition, the automatic gain control (AGC) function in the image signal processing (ISP) chain amplifies the noise, and it results in a low signal-to-noise (SNR) ratio. For this reasons, it is very difficult to restore a high-quality image with a high SNR because of the low-light noise amplification. To solve this problem, the combined low-light image enhancement and noise removal method is required to prevent the noise amplification, color distortion, and brightness saturation in the restored images.

Many low-light image restoration methods have been proposed in the literature over the past few years. These methods can be categorized into three groups: (i) histogram-based, (ii) Retinex-based, and (iii) transmission map-based methods. Histogram-based methods use the cumulative distribution function (CDF) of an input histogram as an intensity transform function to enhance the global or local contrast. These methods modify the CDF to redistribute a concentrated histogram of the input image to a specified region [2–8]. However, these methods often produce an over-enhanced result in the bright region and it results in both noise amplification and color distortion.

The original Retinex theory was first introduced by Land et al. to explain the color perception property of the human visual system, which is more influenced by the surrounding surfaces than the color of the target surface [9,10]. In addition, they proposed the ratio-threshold-reset Retinex method to estimate the 'lightness' of an image in the different wavelengths by computing the paths between the target and neighboring pixels [11]. Recently, Provenzi et al. proposed the random spray Retinex (RSR) algorithm, which analyzes the paths to the target pixel using the neighbor pixels in the specified spray region. Banić et al. proposed an improved version of the RSR algorithm to reduce the amplified noise in the enhancement process [12].

Horn's Retinex method estimated the reflectance component using the Laplacian operator to the logarithmically transformed input image [11]. In the variational framework, the differential operator is used to estimate the smoothness prior on the illumination and reflectance components, respectively. Kimmel et al. presented a variational Retinex

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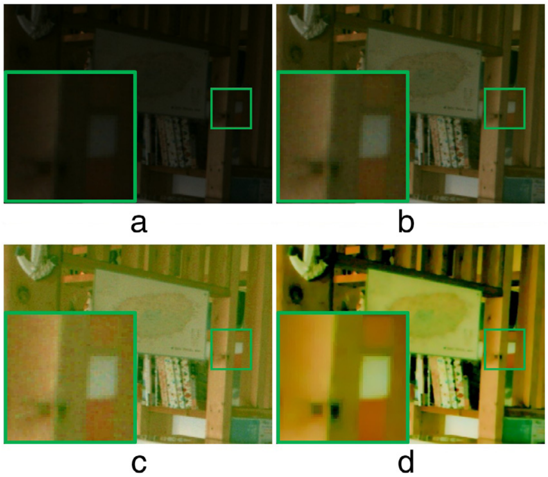

Fig. 1. Results of low-light image enhancement. Top Left: real low-light image. Top Right: Ma's method [14]. Bottom Left: Jiang's method [19]. Bottom Right: the proposed method.

method using ℓ_2-minimization to estimate the illumination and reflectance components [13]. Ma et al. estimated the illumination component using ℓ_1-minimization [14]. Although the ℓ_1-based Retinex method can produce an edge-preserved restoration result without halo effects, it cannot avoid the over-enhancement in the gamma correction step.

Jobson et al. estimated the illumination component using a Gaussian low-pass filter and the logarithmic transformation, and enhanced only the reflectance component by separating the estimated illumination component [15]. However, the single-scale Retinex (SSR) method generates halo effects near edges according to the variance of Gaussian low-pass filter. To solve this problem, the multi-scale Retinex method produced a better restored result using the weighted sum of multiple SSR results. To further reduce the color distortion, multi-scale Retinex color restoration (MSRCR) method was proposed using the color constancy [16,17]. However, the Retinex-based methods can neither estimate the accurate illumination component because of the insufficient amount of the incoming light nor overcome the undesired artifacts such as noise amplification and color distortion.

Recently, transmission map-based restoration methods have been proposed [18,19]. These methods use *a priori* statistical property of natural images, which is called the dark channel prior (DCP). The DCP assumption says that at least one of R, G, and B pixel values is close to zero in a non-hazy region. Jiang et al. was estimated the DCP from the pixel-wise inversion of low-light image, which looks similar to a hazy image and restored the low-light image using the transmission map. The transmission map-based methods produce better restored result, but it cannot completely avoid the noise amplification and color distortion.

Most existing low-light image restoration methods cannot reduce the noise amplification in the restoration process as shown in Fig. 1. Furthermore, additional post processing steps including noise removal and color correction cannot produce the optimally restored results. To solve this problem, this paper presents a variational low-light image restoration algorithm to perform both brightness enhancement and noise reduction, simultaneously. The proposed method estimates the optimized transmission map using the pixel-wise inversion of a low-light image by minimizing the ℓ_2-norm of smoothness constraint. In addition, in order to effectively reduce the noise amplification, the proposed method performs ℓ_1-norm minimization using the split Bregman iteration method [20]. Therefore, the proposed method produces significantly improved result without undesired artifacts.

The paper is organized as follows. Section 2 briefly describes the theoretical background of haze removal and total variation. Section 3 presents the proposed low-light image restoration algorithm using the variational optimization. Experimental results are shown in Section 4, and Section 5 concludes the paper.

2. Theoretical background

This section presents a brief review of the dark channel prior-based haze removal and total variation (TV)-based denoising methods for a theoretical background of the proposed low-light image enhancement algorithm.

2.1. Dark channel prior-based haze removal

A hazy image commonly consists of the scene radiance component that is reflected from the objects and the airlight component scattered by the atmosphere [21]. The degradation model of the hazy image is defined as

$$g_H^c = f^c e^{-k\mathbf{d}} + \alpha\left(1 - e^{-k\mathbf{d}}\right), \tag{2.1}$$

where g_H^c, and f^c represent the observed hazy image and scene radiance, respectively, $c \in \{R, G, B\}$. k represents the scattering coefficient of the atmospheric light, $\mathbf{d}$ the disparity map between the objects and camera. $e^{-k\mathbf{d}}$ is the transmission map indicating the degree of the haze according to the disparity map, and α the global atmospheric light.

To compute the scene radiance f^c, the hazy removal method estimates the global atmospheric light and transmission map. In order to indicate the amount of haze in each pixel, the dark channel prior (DCP) is used as *a priori* knowledge of the haze-free image [22]. The DCP is defined as

$$g_D = \min_{c\in(r,g,b)}\left(\min_{y\in\omega(x)}\left(\frac{g_H^c(y)}{\alpha}\right)\right), \tag{2.2}$$

where g_D represents the DCP.

The transmission map $e^{-k\mathbf{d}}$ is computed as

$$e^{-k\mathbf{d}} = 1 - \beta g_D, \tag{2.3}$$

where β represents a weighting parameter of the DCP.

Finally, the haze removed image can be computed as

$$\hat{f}^c = \frac{g_H^c - \alpha}{e^{-k\mathbf{d}}} + \alpha. \tag{2.4}$$

2.2. Total variation based noise reduction

The degradation model of a noisy image is defined as

$$g = f + \eta, \tag{2.5}$$

where g and f represent the noisy and ideal noise-free images, respectively. η is an additive Gaussian noise with the variance σ and zero mean.

In order to remove the noise without blurring edges, Rudin et al. proposed the total variation (TV)-based optimization algorithm [23]. The energy function of the TV method is expressed as

$$\underset{f}{\operatorname{argmin}} \|g - f\|_2^2 + \lambda \|\nabla f\|_1, \tag{2.6}$$

where $\|g - f\|_2^2$ represents a data-fidelity term, $\|\nabla f\|_1$ the regularization or TV term as a smoothness constraint, and λ the regularization parameter that controls the relationship between the data-fidelity and regularization terms.

The ℓ_2-minimization method such as Tikhonov regularization cannot avoid the blurring artifact near the edges since it globally minimizes the gradient of the image [24]. However, the total variation method can perform edge-preserving noise reduction using the anisotropic property of the TV constraint term. In addition, the energy function (2.6) of non-differentiable and convex formula can be solved using various variational-based optimization methods [20,25,26].