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Optical remote sensing image enhancement with weak structure preservation via spatially adaptive gamma correction

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ABSTRACT

Image structure information is a watershed that distinguishes the content of an image, so it is very important for image enhancement techniques to correct uneven intensity of low-contrast optical remote sensing images with both strong and weak structures preservation. In this paper, a novel enhancement scheme, called spatially adaptive gamma correction (SAGC), is proposed to improve the visualization of optical remote sensing images with structures especially weak structure preservation. The SAGC method includes the following four parts: Firstly, the base image with strong structures and the detail image with weak structures are obtained by the employment of the relative total variation (RTV) method. Secondly, the base image is enhanced by a proposed adaptive gamma correction method. Thirdly, an enhancement factor is proposed to correct the detail image with weak structures. Finally, the high-contrast optical remote sensing image is obtained by the enhanced base image with the combination of the corrected detail image. Both quantitative and qualitative results on real low-contrast optical remote sensing images demonstrate that the proposed image enhancement scheme outperforms the state-of-the-arts in terms of brightness improvement, contrast enhancement, and detail preservation.

1. Introduction

High visual remote sensing images are very important for automatic detection and analysis of their components by intelligent systems (for example, for land-use surveys and monitoring, estimation of the growth and productivity of crops, watershed analysis, monitoring of flood, forest fire, and fish activity) [1,2], and other applications, such as pure materials restoration and their abundance fractions estimation [3] and image classification [4]. However, owning to the impact of undesirable environmental conditions (such as clouds and uneven illumination), these images are low-resolution and even dark, the contents in which are so hard to be distinguished that makes it inevitable to reduce the visual quality as well as restrain the accuracy of image interpretation and analysis [5]. Therefore, it is essential but difficult for image information processing methods to improve low-quality optical remote sensing images with structure preservation.

In recent years, image enhancement has been widely used in atmospheric sciences, astrophotography, medical image processing, satellite image analysis, texture synthesis, remote sensing, digital photography, surveillance, and video processing applications [6]. Many state-of-the-art methods had been proposed to improve the image quality, these methods can be mainly grouped into four categories: histogram equalization (HE)-based methods [7,8], gamma correction (GC)-based methods [9,10], transform-based methods [11–16] and Retinex-based methods [17–19]. The HE-based enhancement methods are the most popular enhancement techniques because of their easy and fast implementation. Although they have a considerable progress, they usually produce over-exposed results as well as inappropriate pixel values in some areas of non-uniform illumination. Some GC-based methods (especially adaptive Gamma correction (AGC) methods [9,10]) try to improve the brightness and enhance contrast but suffer from the loss of details of dark areas. Transform-based methods decompose an input image into different subbands and enhance the contrast by modifying specific components [20], singular value equalization is firstly used to adjust the image brightness in Ref. [11], which is further improved by combining with discrete wavelet transform called discrete wavelet transform and singular value decomposition (DWT-SVD) in Ref. [15] to achieve better contrast enhancement results. However, contrast and details are not obviously emphasized since these algorithms primarily maintain the illumination consistency [16].

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The Retinex theory was first proposed by Land [21] to simulate the human visual system for the brightness and color perception. Land viewed that each scene was produced by the illumination and reflectance (IR). However, it is an ill-posed problem for simultaneously estimating both the IR from a single image [22,23]. Many Retinex-based image enhancement methods had been proposed to remove the illumination, such as single-scale Retinex (SSR) [24], multi-scale Retinex (MSR) [25,26] and multi-scale Retinex with color restoration (MSRCR) [27]. These three typical methods used Gaussian convolution to estimate and remove the illumination. Although they performed well on the lighting improvement, color preservation and scene restoration, they are apt to halo artifacts near the high contrast between brightness and darkness and even yielded over-exposed results [28]. Then the variational framework of Retinex for simultaneously estimating illumination and reflectance was first introduced by Kimmel et al. [29], which used regularization schemes of the illumination to construct image enhancement model. Following this work, many Retinex-based variational methods have been proposed to enhance image with illumination and reflectance estimation and reduce the computational cost [17–19]. However, these methods usually produce an over-smoothed results and suffer from the loss of finer details, which makes the enhanced images undesirable.

In order to improve the image quality with brightness enhancement, contrast enhancement and detail preservation, this paper has proposed a spatially adaptive gamma correction (SAGC) method for uneven intensity correction of optical remote sensing images. Our contributions are as follows:

- A novel enhancement strategy is proposed to correct the uneven intensity of low-contrast optical remote sensing images.
- An adaptive correction parameter (ACP) γ is firstly constructed by the weighting distribution with globally cumulative histogram for the weighting probability density function. The ACP is simply implemented and can suppress "over-exposure".
- A correction factor is proposed to enhance weak structures of the detail image.

The above contributions lead to a better performance of the proposed methods compared to the state-of-the-arts. The remainder of this paper is arranged as follows: Section 2 introduces the proposed SAGC image enhancement method, including the low-contrast image divided by the relative total variation method introduced in Ref. [30], base image enhancement with adaptive gamma correction and weak structures enhancement with a novel spatial parameter. Section 3 gives the qualitative and quantitative experimental results and discussions. Finally, Section 4 concludes our work.

2. Image enhancement via spatially adaptive gamma correction (SAGC)

In the real world, the intensity of acquired optical remote sensing images is so uneven (for example, the image is in under-exposure (shown in Fig. 1(a)) or over-exposure (shown in Fig. 1(b)) or both the two cases occur in an image (shown in Fig. 1(d))) that most structures are submerged in the image and it is hard to distinguish the content of these images. Although the current enhancement approaches can yield well results with strong structures, they are usually not adaptive and smooth fine weak structures which may be the just information for researchers to analyze the local incidents such as the growth and productivity of crops and fish activity. Therefore, the enhancement techniques should improve the image visualization as well as preserve as many structures especially weak structures as possible. The relative total variation method proposed by Xu et al. [30] is a "cartoon" method that can produce "cartoon" results with strong textures. By the employment of this method, we can easily divide the low-contrast image into two sub-images: the base image and the detail image. Then we adaptively process the two sub-images, for example, the base image is enhanced by a proposed adaptive gamma correction method with its local spatial information, the detail image is corrected by a enhancement factor which is formed by the standard deviation between the enhanced base image and the low-contrast image. Finally, the results of respectively processing the two sub-images are combined to obtain a high-contrast image. The main procedure is shown in Fig. 2, and the results of using our method on *Mars* in each procedure of Fig. 2 are shown in Fig. 3.

2.1. The low-contrast image divided by the relative total variation method

The relative total variation model for "cartoon" results with main structures extraction can be represented as

$$\underset{I_{base}}{\operatorname{argmin}} \left\{ \frac{1}{2\lambda}(S-I_{base})^2 + R(I_{base}) \right\}, \tag{1}$$

where S is the observed low-contrast image, I_{base} is the resulting structure image, λ is a weight parameter. The data term $(S-I_{base})^2$ is to make the extracted structures similar to those in the observed image. $R(I_{base})$ is a regularization to help preserve prominent structures in I_{base}. In Ref. [30], $R(I_{base})$ is the ratio of windowed total variation D and windowed inherent variation L in the x and y directions, respectively, which can be written as

$$R = \frac{D_x}{L_x + \varepsilon} + \frac{D_y}{L_y + \varepsilon}, \tag{2}$$

where ε is a small positive number to avoid division by zero, D_x and D_y are the windowed total variations while L_x and L_y are the windowed inherent variations in the x and y directions, respectively. The readers can find the detail representation of the windowed total variations D_x and D_y as well as the windowed inherent variations L_x and L_y in Ref. [30], so they are not listed in this article.

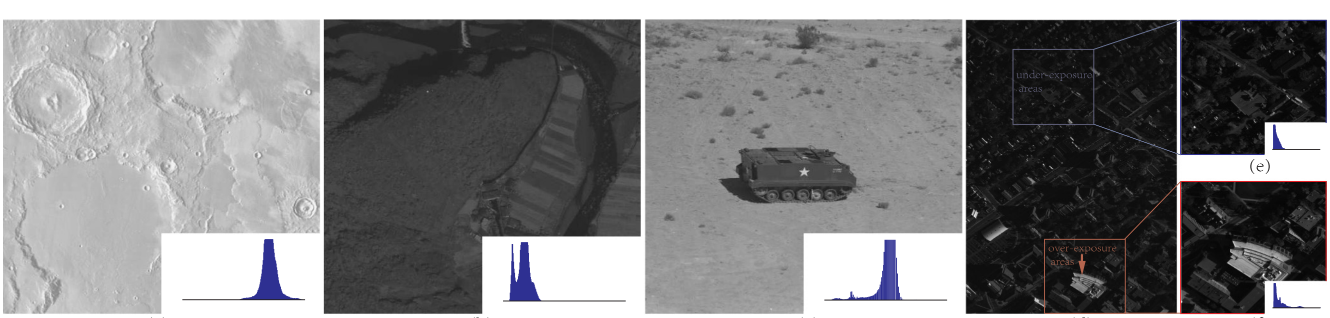

Fig. 1. Real optical remote sensing images degraded by uneven intensity. (a) The over-exposure Mars image. (b) The under-exposure River image. (c) The low-vision *Tank* image. (d) The uneven-lightness *City* image. (e)–(f) The sub-city images 1 and 2 of image shown in (d), respectively.