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Framelet-based sparse regularization for uneven intensity correction of remote sensing images in a retinex variational framework

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ABSTRACT

Correcting uneven intensity distribution from a single image has long been a challenging problem with remote sensing image. In this paper, an analysis-based sparse prior is employed in the retinex variational framework for the uneven intensity correction of remote sensing images. This sparse regularization model is used to adjust uneven intensity by regularizing the sparsity of the reflectance component under framelet transform. Furthermore, the alternating minimization algorithm and split Bregman method are adopted to solve the framelet-based sparse regularization model. The experiments, with both simulated images and real-life images, show that the proposed model can effectively correct the uneven intensity distribution.

1. Introduction

Uneven intensity distribution exists in most remote sensing images. However, the remote sensing images are very important for the subsequent image processing, i.e., change detection, image classification, and other applications [15,16]; thus, it is extremely important to correct the uneven intensity.

In order to overcome the drawback of absolute radiometric correction, many relative radiometric correction algorithms have been developed to adjust the uneven intensity distribution. The homomorphic filter (HF) and histogram equalization (HE) are the popular approaches used to adjust the uneven illumination and redistribute the intensity distribution [5,19]. According to retinex theory [9], a number of retinex-based models are utilized to correct the uneven intensity [6,11,12,14]; besides, some retinex variational models have also been applied in this field [7,10,13]. Kimmel et al. [7] proposed a L2 regularized model for the illumination component to indirectly obtain the reflectance. Li et al. [10] provided a joint L2 and TV regularized model for the reflectance component. Michael et al. [13] used the L2 regularized term of the illumination and the TV regularized term of the reflectance. Although great advances have been made, there is still room for improvement.

It is well known that most images have a sparse approximation. Thus, in recent years, the sparsity-based prior has been a common choice for the regularization term [3], and has been widely used in the fields of denoising [4], deblurring [3], super-resolution [18], and so on. There are two typical sparse priors, namely, the synthesis-based and analysis-based sparse priors [3]. These priors are based on the fact that natural images usually be represented or approximated sparsely in some redundant transformed domain, such as wavelet, framelet, etc. In this paper, the analysis-based sparse prior regularization is adopted to correct the uneven intensity in the retinex variational framework. Since the reflectance component can be approximated sparsely, this sparse regularization model is used to adjust the uneven intensity by regularizing the sparsity of the reflectance component under tight frame system. For its efficiency and simplicity, the framelet tight frame system is selected to approximate the reflectance component. Moreover, the split Bregman algorithm is used to solve the proposed model, i.e., the framelet-based sparse regularization model in retinex variational framework.

The rest of this paper is organized as follows. In Section 2, we review the analysis-based sparse prior regularization and the framelet system. Section 3 presents the proposed framelet-based uneven intensity correction model and the split

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Bregman algorithm is used to solve it. The experiment results are presented in Section 4. Section 5 provides the conclusion.

2. The analysis-based sparse prior the framelet system

In this section, a brief review of the analysis-based sparse prior is given. First, we denote the observed image g as the lexicographically ordered column vector in $\mathbb{R}^n$, and $W \in \mathbb{R}^{m\times n}$ is an analysis operator. The data $g \in \mathbb{R}^n$ can be transformed to some coefficients $Wg \in \mathbb{R}^m$ by the analysis operator W. In general, W is a redundant transform operator, where $m > n$.

When the analysis-based prior is used for the regularization model, the goal is to look for the most sparse solution among the transform coefficient vectors (the coefficients Wg decomposed by the analysis operator W) [3]. In the different application fields, different analysis operators can be used to regularize the data. Thus, it is important to choose a suitable redundant transform, e.g., a tight frame system. In this paper, a piecewise linear B-spline tight frame is used, which is derived by using the piecewise linear B-spline function as the refinable function [3]. The framelet is as follows [2,3]:

$$h_0 = \frac{1}{4}[1, 2, 1]; \quad h_1 = \frac{\sqrt{2}}{4}[1, 0, -1]; \quad h_2 = \frac{1}{4}[-1, 2, -1] \tag{1}$$

In the numerical computation, the wavelet frame transform can be represented by the decomposition matrix W, which is constructed depending on the boundary condition. The complete generating procedure of the matrix is presented in [2,3]. With the decomposition matrix, the data g can be transformed to the frame coefficient vector

$$t = Wg \tag{2}$$

The reconstruction algorithm W^* is the inverse transform of W, as shown

$$g = W^* t \tag{3}$$

where $W^*W = I$. Generally speaking, $WW^* \neq I$ unless W is an orthonormal basis.

3. The proposed framelet-based sparse regularization model

3.1. The proposed model

The proposed model belongs to the retinex variational framework. According to retinex theory, image intensity is composed of two factors: illumination and reflectance. In the spatial domain, the product of these two components forms the image intensity, i.e.,

$$S(x) = L(x) \cdot R(x) \tag{4}$$

In order to facilitate computation, the product form (4) is converted to the logarithmic domain, i.e.,

$$s = l + r \tag{5}$$

where s, l, and r are equal to $\log(S)$, $\log(L)$, and $\log(R)$, respectively. $S(x)$, $L(x)$, and $R(x)$, respectively, represent the observed image intensity, the natural illumination and the object reflectance, which depends on the physical characteristics of the object materials [10]. x is the pixel location in the image. In (4), the reflectance component is normalized as $0 \leq R \leq 1$, owing to its natural characteristics [10,13]. Thus, we can get the constraints $r \leq 0$ and $l \geq s$. The relationship (4) between these three variables is still valid for each channel of the multiband image [10].

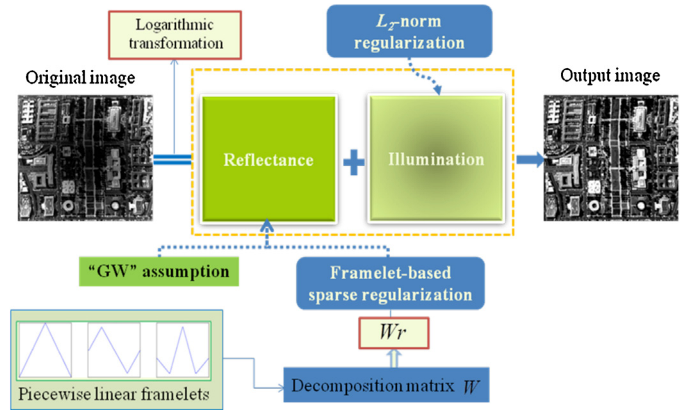

Fig. 1. The main procedure of the proposed method.

Our goal is to solve the reflectance component r from (5). In this paper, we propose a framelet-based sparse regularized variational model to correct the uneven intensity distribution. There are four terms in this variational model. The first term, the data fidelity term $||s - l - r||_2^2$, is used to preserve data consistency, where $||\cdot||_2$ denotes the L_2-norm. The use of the data fidelity term can ensure that the reflectance component does not deviate from the observed value. Secondly, according to the "gray world" (GW) assumption [1,10], the average color intensity in a scene is perceived as the middle gray intensity. Thus, in the logarithmic domain, this constraint term is translated as $[\exp(r) - 0.5]^2$.

It is well known that a regularized prior term is important for a variational model. Next, we introduce two regularized prior terms for illumination and reflectance, respectively. According to the characteristics of natural illumination, the illumination component l is spatially smooth. In the proposed model, the regularization term $||\nabla l||_2^2$ is used to preserve the continuity of the illumination component.

Finally, the most important task is to choose the regularization prior for the reflectance. Since the reflectance component r can be approximated sparsely, the sparse regularization term is used to adjust the uneven intensity by regularizing the sparsity of the reflectance component r under framelet system. When this sparse prior of the reflectance is used in the variational model, it can alleviate the distortion caused by the uneven illumination and can preserve the information of the intensity and structure. Thus, the analysis-based sparse regularization term is employed, as shown:

$$\text{sparse prior}: \ ||Wr||_1 \tag{6}$$

where W is the framelet transform introduced in the last section. Here, $||\cdot||_1$ denotes the L_1-norm. Summarizing the above analysis, the main procedure is shown in Fig. 1.

Finally, we give the framelet-based sparse regularized variational model in the retinex variational framework, as follows:

$$\min F(r, l) = \sum_{\Omega} \left\{ \left\| s - l - r \right\|_2^2 + \lambda_1 \left\| Wr \right\|_1 + \lambda_2 \left\| \nabla l \right\|_2^2 + \alpha [\exp(r) - 0.5]^2 \right\} \quad \text{s.t.} \quad r \leq 0, \ \ l \geq s \tag{7}$$

where the positive parameters λ_1, λ_2, and α are used to trade off each term in the proposed model.

3.2. Numerical algorithms

In this section, our aim is to look for the solution to the proposed model (7). Since two unknown variables r and l are involved in the proposed model, the alternating minimization algorithm is adopted [13]. The alternating minimization scheme (Algorithm 1)