SHADOW REMOVAL BASED ON CLUSTERING CORRECTION OF ILLUMINATION FIELD FOR URBAN AERIAL REMOTE SENSING IMAGES

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ABSTRACT

The presence of shadows in urban aerial images can degrade the quality of the images and cause problems in image interpretation. In this paper, a novel shadow removal method based on the clustering correction of illumination field is proposed. We construct a spatially adaptive weighted total variation model to achieve the optimized illumination field. The land surface types are considered to correct the distribution of the illumination field based on the clustering moment matching method. Then the shadows are recovered in the illumination field with the texture well preserved and the shadow boundary smoothed. Experiments and comparisons are presented to verify the effectiveness of the proposed method.

***Index Terms*—** Shadow removal, spatially adaptive weight, illumination field, clustering moment matching, urban aerial images.

1. INTRODUCTION

Shadow is a natural phenomenon, existing in most aerial remote sensing images. In urban areas, the shadow effect is more obvious because the surface features are quite complex, with a great variety of objects such as high buildings, trees and so on, which cast shadows on the ground [1]. On the one hand, shadows can provide useful information for 3-D scene reconstruction, such as building detection and building height estimation, with the shape and position of its casting objects [2]. On the other hand, shadows cause the information reduction of the casting region, which makes the image interpretation difficult [3]. Therefore, it is essential to remove the shadow effect before the interpretation of remote sensing images. It involves two basic stages: shadow detection and shadow removal, and we focus on the shadow removal in this paper.

A variety of shadow removal methods have been proposed in the past decades. Linear-correlation correction is the most popular method, which has been widely used by many researchers [4-7]. This method is based on a linear relationship between shadow classes and the corresponding nonshadow classes [7], however it is difficult to match the shadow regions and nonshadow regions correctly because of the information reduction in shadow regions. Li et al. [8] introduced an adaptive nonlocal (NL) regularized shadow removal method for aerial remote sensing images by regularizing the shadow scale and the updated shadow-free image, but the NL Laplacian prior may cause texture detail blurring. The shadow reconstruction algorithms based on the example learning have been proposed in recent years, which could successfully remove the shadow [3, 9], but the shadow samples need be collected from the images manually by visual judgment before the example-based training, which increased the workload.

In this paper, we propose a novel shadow removal algorithm based on clustering correction of illumination field, which combines the advantages of linear correlation correction and the regularized method without manual participation, and solves the problems above effectively. Especially, we focus on the shadows cast on the ground, while self-shadows located on buildings have been excluded.

2. METHODOLOGY

The proposed shadow removal method mainly composes of three parts. The spatially adaptive weighted total variation model is firstly constructed to separate the illumination field from the reflectance field in a given image. In consideration of land cover variation in the shadow regions, the image is clustered combining the clustering results of the nonshadow regions in the original image and the shadow regions in the reflectance field. At last, the shadow information is corrected in the illumination field using the clustering moment matching method. Fig. 1 shows the overview of the proposed shadow removal method.

An image I is composed of the production of the reflectance field R and the illumination field L [10], which can be expressed as following:

$$I(x,y) = R(x,y) \cdot L(x,y) \tag{1}$$

where (x,y) denotes the pixel position, and $\cdot$ denotes pixel-wise multiplication. In order to simplify the computation, the formulation is converted into log domain, as shown:

$$i(x,y) = r(x,y) + l(x,y) \tag{2}$$

where i, r, l are the logarithms of I, R and L, respectively.

2.1. Spatially Adaptive Weighted Total Variation Model

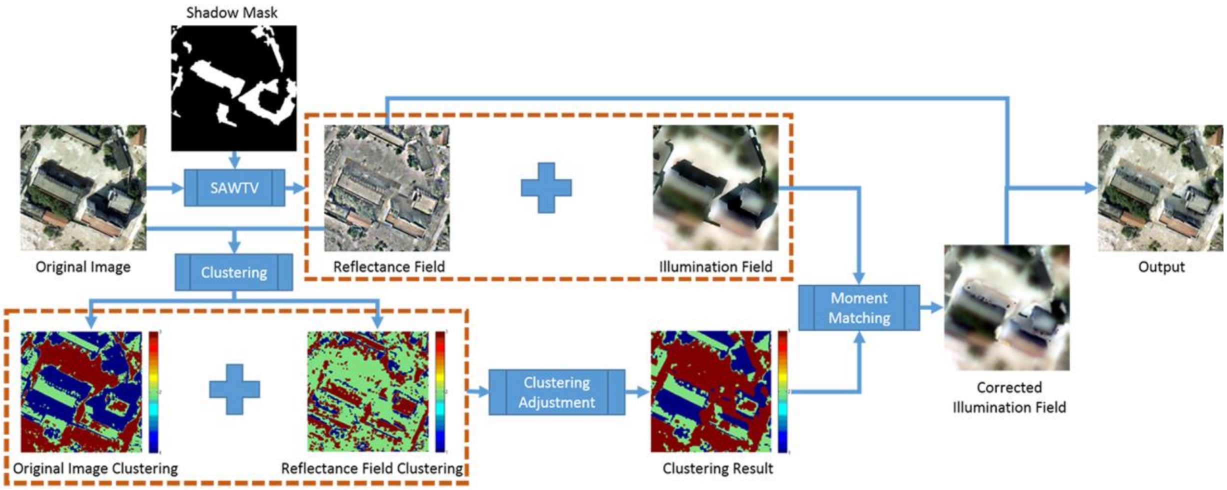


Fig. 1 Flowchart of the proposed method

In the shadow image, we assume that the illumination field is spatial piecewise smooth, and the reflectance field is related to the physical characteristics of the object, which could not be affected by the noise and shadow boundary.

Based on the above assumptions, the Spatially Adaptive Weighted Total Variation Model (SAWTV) is constructed as:

$$\hat{l} = \underset{l}{\operatorname{argmin}} \sum_{\Omega} \|l-i\|_2^2 + \alpha \|\nabla(l-i)\|_2^2 + \beta Wg \|\nabla l\|_{TV} \quad (3)$$

where Ω is the image domain, the first fidelity term $\|l-i\|_2^2$ forces the proximity between l and i, the second term $\|\nabla(l-i)\|_2^2$ forces the reflectance field spatial smoothness, the third term $\|\nabla l\|_{TV}$ forces the illumination field piecewise smoothness in entire nonshadow regions and umbra regions, preserving the penumbra regions. α and β are positive parameters, which control the contribution of each item in the model.

In order to better preserve the shadow boundary in the illumination field, we construct a spatially adaptive regularization weight parameter Wg depending on the shadow boundary information, which is defined as:

$$Wg_i = \frac{1}{\delta_i + \varepsilon} \quad (4)$$

where δ_i is the gradient value of shadow boundary pixel i, ε is a small number which is used to avoid the denominator being zero. In the nonshadow and umbra areas, the value of δ_i is close to 0, then Wg is very large, so the TV regularization is strong to make the illumination field smooth. In the shadow boundary regions, δ_i is large, then Wg is small, which means that the strength of the TV regularization is weak, so the shadow boundary regions will be well preserved.

The split Bregman iteration [11] is employed to solve the model optimization problem. Then the illumination field containing shadow boundary and piecewise smoothing land cover is achieved, and the reflectance field is computed based on Equation (2). The shadows are obvious in illumination field while the reflectance field is shadowless and noiseless. So the illumination field should be corrected considering of the land surface.

2.2. Correction of the Illumination Field based on Clustering Moment Matching

The shadows cast on the ground are usually compound and the illumination information varies according to the different land surfaces. Therefore, the image should be clustered and the shadow information is corrected based on clustering moment matching method in the illumination field.

2.2.1 Land Surface Clustering

The reflectance field is less affected by the shadows, so the clustering result of it can be used for shadow correction, but the illumination field takes some information from the reflectance field, which may reduce the accuracy of the clustering. The feature information of nonshadow regions in original image is accurate, so the clustering result of original image could be used for adjusting the clustering. The aim of the clustering adjustment is that the clustering result of nonshadow regions is from original image, while the clustering result of the shadow regions is from the reflectance field. In this procedure, it contains two steps:

Step 1: The original image and reflectance field are clustered using k-means method individually, then the preliminary clustering results are obtained.

Step 2: The classes of the original image in nonshadow region are regarded as the adjustment standard. For each class of the reflectance field, the statistics analysis is performed on the classes of original image in the nonshadow regions, then the class of reflectance field will be adjusted to the maximum ratio class of the original image.

After these two steps, the adjusted land surface clustering result is achieved.

2.2.2 Clustering Moment Matching

There should be a linear relationship between the shadow classes and the corresponding nonshadow classes [7], so the improved clustering result could be used for moment matching [12] in the illumination field. We compensate the shadow information using the nonshadow information of the same class. The moment matching is conducted for each class in the illumination field which can be expressed as following:

$$I_{adjusted} = \frac{\sigma_{ns}}{\sigma_s}(I_{initial} - \mu_s) + \mu_{ns} \tag{5}$$

where $I_{initial}$ is gray value of shadow region, $I_{adjusted}$ is the grey value of the corrected result. μ_s and μ_{ns} are the mean values of the shadow regions and nonshadow regions. σ_s and σ_{ns} are the standard deviation of shadow regions and nonshadow regions.

After the clustering correction process above, the illumination of shadow regions has been corrected. Based on Equation (2), adding the corrected illumination field to the reflectance field and then transforming the result to spatial domain through applying exponential operation, the shadow-free image can be finally obtained.

3. EXPERIMENTAL RESULTS

In this section, the proposed shadow removal method is performed on two urban aerial images from Wuhan city to verify the effectiveness of the proposed method, as shown in Fig. 2. We compare the results with three other shadow removal methods which are linear correlation correction method(LCC) [5, 13], Xiao's method[14] and Li's method [8]. In order to make the comparison reliable, all shadow removal methods use the same shadow mask detected by image matting method [15, 16].

In Fig. 2(a), the main shadow land cover of the first image is cement. All of these four methods can remove the shadows to a certain extent in Fig. 3(a)-(d). In order to compare these four methods better, a part of the result is enlarged, as show in Fig. 3(e)-(h). In Fig. 3(h), it can be seen that the proposed method can not only preserve the texture information well, such as red-brown paint ground and vegetation, but also recover the illumination around the shadow boundaries, while some texture information is missing and the shadow boundaries are obvious in the results of LCC method, Xiao's method and Li's method in Fig. 2(e)-(g).

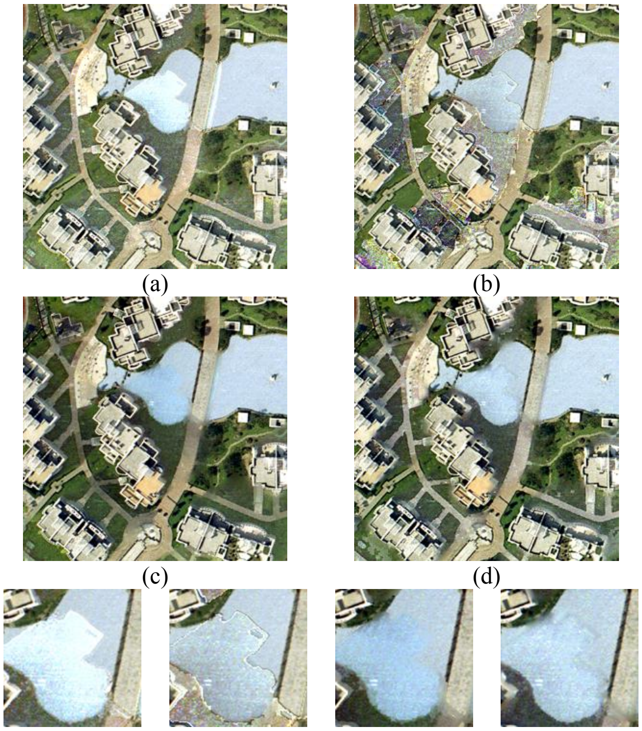
In Fig. 2(b), the second image with complex textures is chosen, and the shadow regions cover four types of land surfaces, i.e., cement, road, lawn and lake. LCC method does not work well in Fig. 4(a). The color of the restored shadow region is distorted and the shadow boundaries are still obvious after the process of LCC method. Xiao's method segments the image into subregions, and the mismatching between the shadow subregions and the nonshadow subregions leads to a poor result in Fig. 4(b). In Fig. 4(c), Li's method can remove the shadows well, but there existing chromaticity difference between the shadow and nonshadow regions of the lake, as shown in Fig. 4(g). Compared with the three methods above, the reconstructed shadow regions from the proposed method are more visually nature and consistent with their surroundings in Fig. 4(d) and (h).

(a) (b)

Fig. 2 Urban aerial images of Wuhan city, China. (a) First image. (b) Second image.

(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 3 Shadow removal results of first image. (a) Result of LCC method. (b) Result of Xiao's method. (c) Result of Li's method. (d) Result of the proposed method. (e)-(h) Four enlarged clipped regions from (a)-(d), correspondingly.



(a) (b) (c) (d) (e) (f) (g) (h)

Fig. 4 Shadow removal results of second image. (a) Result of LCC method. (b) Result of Xiao's method. (c) Result of Li's method. (d) Result of the proposed method. (e)-(h) Four enlarged clipped regions from (a)-(d), correspondingly.

4. CONCLUSIONS

In this paper, we have presented a novel shadow removal method for urban aerial images. The spatially adaptive weighted total variation model can effectively separate the illumination component from the original image. The advantage of removing shadows in the illumination field is that it could effectively recover the shadow regions and preserve nonshadow information. The experimental results show that the corrected shadow regions by the proposed method are more consistent with their surroundings, comparing to linear correlation correction method, Xiao's method and Li's method. In the future research, we would like to improve the clustering accuracy and use adjacent blocks of the same class to correct shadows better.

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