COLOR COMPENSATION FOR CLOUD SHADOWS

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KEYWORDS: Remote Sensing Images, Shadow Detection, Histogram Matching

Abstract: Cloud covers are generally present in optical satellite images, thereby limiting the usage of optical images and increasing the difficulty of image analysis. In this paper, a cloud shadow compensation approach aiming at easing difficulties suffered from cloud covers is introduced. In the proposed approach, information of shadow pixels is compensated by a statistic adjustment method and a global optimization process. Experimental analyses on the satellite images acquired by the Landsat-7 Enhanced Thematic Mapper Plus (ETM+) sensor were conducted. The results including quantitative and qualitative analyses on simulated data show that our method can successfully compensate for the intensities of shadow pixels.

INTRODUCTION

The recent development of surveying and image processing techniques has increased interest in the application of satellite images. A satellite image has four resolutions, namely, *spatial*, *spectral*, *temporal*, and *radiometric resolution*. By combining all these resolutions, satellite images can provide a macroscopic view of land surface for researchers to observe the variations in land circumstances through computers.

General shadow compensation comprises two main procedures, namely, *cloud and shadow detection* and *pixel intensity compensation*. In the cloud and shadow detection, methods can be classified into two groups, namely, *model-based* and *property-based*. Model-based techniques are implemented using models, and require prior knowledge of the three-dimensional (3D) geometry of the scene, detected objects, and the information on illumination. This kind of technique is usually designed for aerial and dynamic video images where prior knowledge already exists. Rau et al. (2002) proposed an efficient method for shadow detection utilizing prior knowledge, such as 3D building models, multi-view aerial images, digital terrain models, and the orientation of sunlight to detect shaded regions in urban areas. However, this method requires the information of 3D building model. This makes this approach infeasible when satellite images are available. Choi et al. (2006) simplified the 3D model into two-dimensional model for efficient computation. Similarly, such method requires prior knowledge, which is not always available or is insufficient when the input information is obtained from only one image.

The property-based technique utilizes the characteristics of colors according to different components of a color space to recognize shaded regions, such as the red (R), green (G), and blue (B) components in the RGB color space; and the H, S, and V components in the HSV color space (Smith,1978). The method proposed by Jiang and Ward (1994) extracts shadows by analyzing the intensity and geometry of the shadows in gray scale images. Using only black and white information may yield some misclassification. Thus, other information, such as direction of light and geometrical properties, should be considered (Chung et al., 2009). Cucchiara et al. (2001) proposed an approach based on the HSV color model with Statistical and Knowledge-Based Object Tracker for traffic surveillance purposes. However, this approach requires background information. Otsu (1979) proposes the use of histogram analysis to determine an optimal threshold value, which was also applied in the method proposed by Tsai (2006). Tsai (2006) conducted a comparative study on shadow compensation in five different invariant color models for fast detection in color aerial images. They first create a ratio map for shadow detection. This shadow map preserves the information on the shape of shaded regions in complex urban color aerial images. Chung et al. (2009) proposeed a threshold scheme (STS) that improves Tsai's method using a modified ratio map. This modified ratio map can enlarge the difference between shaded and non-shaded areas.

Areas sheltered by clouds cannot be well compensated by simply adjusting brightness or contrast of color. It is because the details of these pixels are sheltered by clouds. For pixels inside shadows, the compensation method entails returning these pixels to their original condition to be as natural as possible. Boardman (1993) proposed an approach which is based on linear un-mixing of atmospherically correct data using spectral information in AVIRIS. This method cannot un-mix a single pixel or a homogeneous scene as it assumes a wide range of fractional abundances. Adler–Golden et al. (2002) proposed a rather simple matched filter-based de-shadowing algorithm for spectral reflectance images that uses an iterative application of the matched filter. With the help of such information as multi-view aerial images, digital terrain models, and the orientation of sunlight, Rau et al. (2002) not only detects shaded regions, but also efficiently compensates such areas. In the work of McKenna et al. (2000), they offered a normalized RGB method to recover the shaded areas. In the work of Soh et al. (2006), they proposed an invariant color-based procedure in color images to preserve both of chromaticity and brightness in color images by analyzing the foreground information. The first step is to extract the foreground from the image and then transform both foreground and background into a color space. All pixels in the image are divided into three classes, namely, bright pixel, color pixel, and non-color pixel, through a predefined threshold. Subsequently, the color and non-color pixels are classified as color blob and non-color blob. The ratio image is then calculated using these blobs and the threshold is applied to compensate the shadow using the method by Choi et al. (2004). In the work of Choi et al. (2004), they proposed a method to compute the ratio between the number of shadow pixels and the blob size. This method requires a lot of thresholds to formulate a decision. Shor et al. (2008) proposed a novel pyramid-based restoration process that avoids the loss of texture contrast in compensated areas with an affine shadow recovery model at multiple scales. Initially, users manually indicate the seed of the region growing in the shadow until the growing areas become similar to the shadow area. Invariant distance and threshold are then utilized to identify pixels in the same surface with the seed for compensation. Recently, Lin et al. (2010) proposes a seamless cloud removing algorithm for multi-temporal satellite images by applying the Poisson equation. With the help of a gradient image, the Poisson equation can seamlessly clone one image with another to generate a natural result in visualization.

METHODOLOGY

The proposed method consists of two main steps: *cloud shadow detection* and *color compensation*. In the step of cloud and shadow detection, cloud and shadow pixels are extracted from images. The pixel colors are first transformed into HSV color space, and the morphology is then used to connect those neighboring pixels together to form the cloud-shadow patch for the subsequent compensation. In the step of color compensation, the difference is calculated between the cloud-shadow patch and its buffer pixels with statistical analysis. The Poisson equation is then proceeded to perform color compensation.

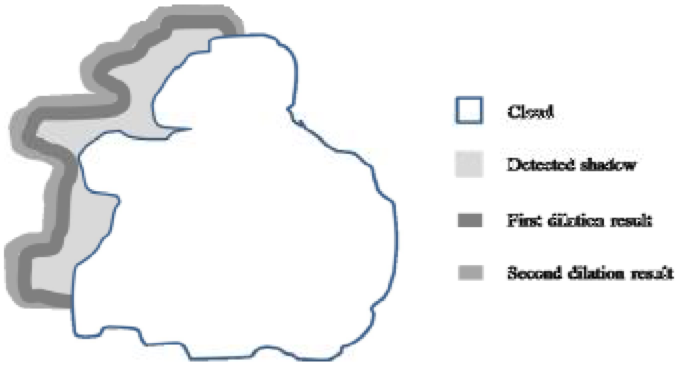

Figure 1: Illustration of dilation results.

Cloud Shadow Detection

Based on the properties of cloud shadow in images, the cloud shadows are detected by utilizing the ratio image. The ratio image, denoted as *RI*, is defined as:

$$RI = (H+1)/I + 1\,, \tag{1}$$

where H and I represent the hue and intensity components of the HSV color model. This ratio image can enhance the slight changes due to low illumination in the cloud-shaded areas. Next, the ratio image is normalized to the range [0, 255] to further enhance the difference between the shaded and non-shaded areas and determine the threshold. This threshold scheme may roughly detect the shadow region, and the detected shadow regions are general a little smaller than the real shadows. Thus, the dilation operator, which is the morphology operations, is performed two or three times to enlarge the detected shadows. One of the shadow properties is that the intensity of shadow becomes higher from the center to the shadow edge. This property indicates that the method should follow the variation of intensity to detect the different densities of the shadow. To achieve this goal, every circle of the dilation result is recorded for the next compensation process. As shown in Figure. 1, the area inside the blue frame is the detected cloud area, the lightest gray area presents the detected shadow, the darker gray circle is the first dilation result, and the gray circle presents the second dilation result.

Color Compensation

To preserve the details in shadows, we propose a method that modifies the standard deviations of pixel intensities in the gradient field. The Poisson equation, which is an optimal boundary solving algorithm, plays an important role in this procedure. Figure 2 illustrates the Poisson equation, where **O** stands for the original image, Ω is the target area (cloud-shaded area) to be compensated, and $\partial\,\Omega$ is the boundary of compensated area. In our case, f^* refers to the intensities of the non-shaded area, whereas the intensities within Ω are expressed as f. **V** presents the gradient value of the enhanced shaded area after the application of our compensation method. Our main idea in this step is to use the standard deviation of the ratio value of the non-shaded and shaded areas to adjust the gradient value **V** on shadow region and make the target region more natural in terms of visualization performance. This adjustment is executed by multiplying a ratio value, which is the standard deviation of the shadow buffer dividing the shaded area. Moreover, every circle in shaded area is applied. This method has the advantage of maintaining the details of texture. This method aims to smoothly blend the shaded and non-shaded pixels. Thus, a boundary constraint in the Poisson equation is set as follows:

$$\min_f \iint_\Omega \left|\nabla f - \mathbf{V}\right|^2, \quad \text{with } f\,|_{\partial\Omega} = f^*\,|_{\partial\Omega} \tag{2}$$

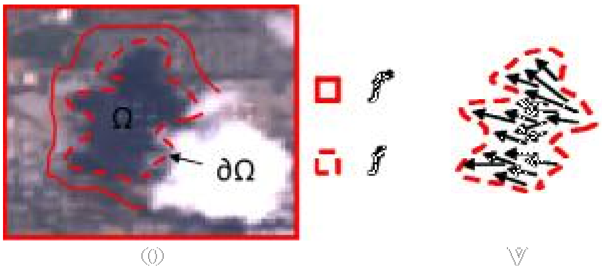

Figure 2: Illustration of color compensation.

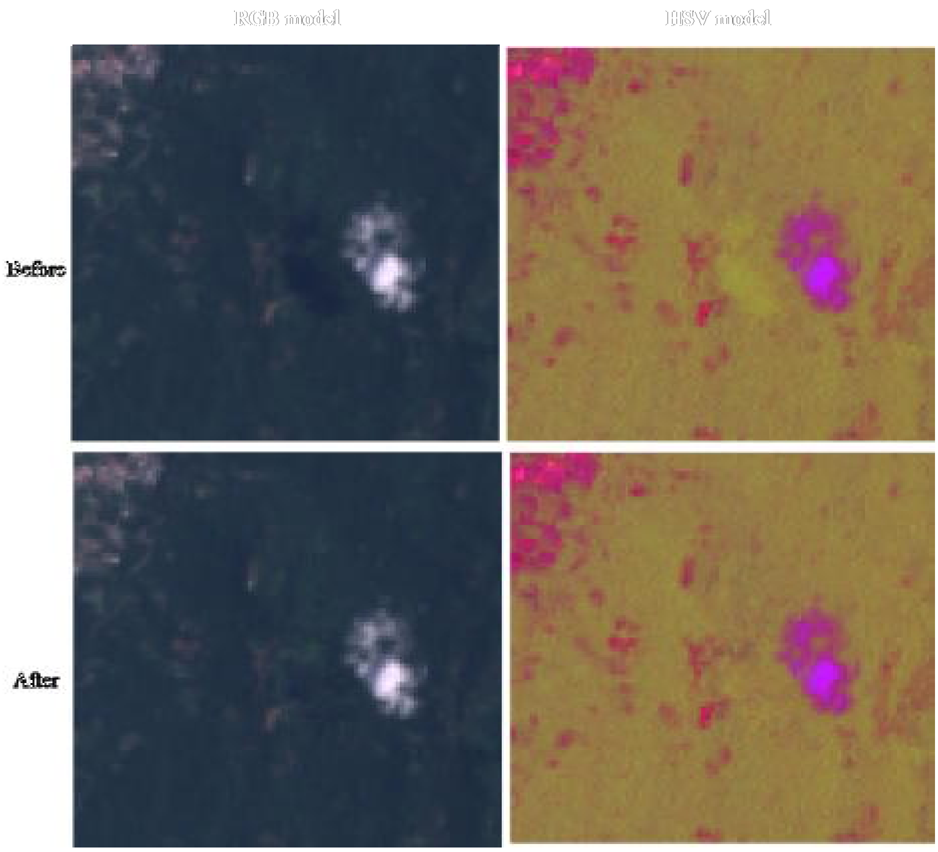

Figure 3: The test image (2001/06/17) before and after apply the proposed method in RGB and HSV color space.

RXPERIMENTAL RESULTS

In the experiment, the test images were downloaded from the USGS website. For simplicity, band-1 (0.45 to 0.52 *u*m), band-2 (0.52 to 0.60 *u*m), and band-3 (0.63 to 0.69 *u*m) of images acquired by Landsat-7 ETM+ sensor are used in the experiments. The results of color compensation is shown in Figure 3. The images in both HSV and RGB color models after applying the proposed method appears to be quite similar with the non-shaded area. This experiment shows the feasibility of the proposed method.

CONCLUSIONS

In this paper, a method to compensate color of pixels within cloud shadow areas is proposed. The proposed method contains the steps of shadow detection and compensation to produce a shadow-free satellite image. We viewed the color compensation as an optimization problem, and this optimization problem is formulated as Poisson equation without any parameter.

REFERENCES

Adler-Golden, S. M., Matthew, M.W., Anderson, G. P., Felde, G.W., and Gardner, J. A. An algorithm for de-shadowing spectral imagery, Proceedings of the 11th JPL Airborne Earth Science Workshop. pp. 3–4, 2002.

Boardman, J. W. Automating spectral unmixing of AVIRIS data using convex geometry concept, Summaries of the Fourth Annual Airborne Geoscience Workshop, pp. 11-14, 1993.

Choi, S. I., Kim, C. H., and Choi, C. H. Shadow compensation in 2D images for face recognition, The Journal of the Pattern Recognition, Vol.40, pp. 2118-2125, 2006.

Chung, K. L., Lin, Y. R., and Huang, Y. H. Efficient shadow detection of color aerial images based on successive thresholding scheme, IEEE Transactions on Geoscience and Remote Sensing, Vol. 47, No. 2, pp.671-682, 2009.

Cucchiara, R., Grana, C., Piccardi, M., Prati, A., and Sirotti, S. Improving shadow suppression in moving object detection with HSV color information, IEEE Intelligent Transportation Systems Conference Proceedings, pp. 334-339, 2001.

Jiang, C. X., and Ward, M. O. Shadow segmentation and classification in a constrained environment, CVGIP: Image Understanding, Vol.59, Issue.2, pp. 213-225, 1994.

Lin, C.-H., Tsai, P.-h., Lai, K.-H., and Chen, J.-Y.: Cloud Removal from Multitemporal Satellite Images Using Information Cloning, accepted to IEEE Transactions on Geoscience and Remote Sensing 2012.

McKenna, S. J., Jabri. S., Duric, Z., Wechsler, H., and Rosenfeld, A. Tracking groups of people, Computer Vision and Image Understanding, Vol. 80, No. 1, pp,42-56, 2000.

Otsu, N. A threshold selection method from gray-level histograms, IEEE Transaction on System, Man, and Cybernetics, Vol. 9, No. 1, pp. 62-66, 1979.

Rau, J. Y., Chen, N. Y., and Chen, L. C. True orthophoto generation of built-up areas using multi-view images, Photogrammetric Engineering and Remote Sensing, Vol. 68, pp. 581-588, 2002.

Shor, Y., and Lischinski, D. The shadow meets the mask: pyramid-based shadow removal, Computer Graphics Forum, Vol. 27, pp. 577-586, 2008.

Smith, A. R. Color gamut transform pairs, SIGRAPH, Vol. 3(ACM), Atalanta, GA, pp. 12–19, 1978.

Soh, Y. S., Lee, H. J., and Wang, Y. K. Invariant color model-based shadow removal in traffic image and a new metric for evaluating the performance of shadow removal methods, PRICAI: Trends in Artificial Intelligence, Vol. 4099, pp. 544-552, 2006.

Tsai, v. J. D. A comparative study on shadow compensation of color aerial images in invariant color models, IEEE Transactions on Geoscience and Remote Sensing, Vol. 44(6), pp. 1661-1671, 2006.