Shadow Detection in High Resolution Remote Sensing Aerial Images using Relative Radiometric Correction Method & Polynomial Fitting

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Abstract— High resolution color remote sensing Aerial images and also undertaken to remove the shaded region in the both urban, rural areas and manmade buildings. The existing methods are Model-based method and shadow-feature-based methods, to detect the shaded region and then eliminate that region, but it have some drawbacks. Shadows may cause incorrect results during change detection. It is not suitable for high resolution images. The proposed Relative Radiometric Correction Method used for shadow detection. Shadow detection is used during image segmentation. Shadows are removed by using the homogeneous sections obtained by line pair matching. There are two approaches for shadow removal. One approach calculates the radiation parameter according to the homogeneous points of each object and then applies the relative radiation correction to each object. The other approach collects and analyzes all the homogeneous sections for polynomial fitting (PF) and retrieves all shadows directly with the obtained fitting parameters.

Key words: Relative Radiometric Correction; Polynomial Fitting; Shadow Detection

I. INTRODUCTION

Shadows can be engaged to sense buildings and approximate the elevation of the buildings. The major difficulty induced by shadows is either a lessening or overall loss of information in an image. The trouble of shadowing is principally considerable in high-resolution satellite imaging.

The surface below the shadows presents difficulties for image analysis, image toning, change detection and other applications. So this proposal mainly focus to get the aerial image of high resolution, and also undertaken to remove the shaded region in the urban area. Because of ambient light present in image, by comparing two pixels the ratio of them not same in red, green and blue color channels. The two pixels which are compared earlier will be different in hue, intensity and saturation. Thus, correcting intensity of the pixels which are covered with shadow does not confiscate the shadow, and we need to accurate the chromaticity values as well. Using density of the shadow, the area which is covered with shadow is segmented into sunshine, penumbra and umbra regions. For shadow detection there are some existing Techniques, Those techniques may classified into two Groups: model-based and shadow-feature-based. The first type uses prior knowledge such as camera altitude, scene, and moving targets to construct shadow models. This group of techniques frequently used in some specific scene conditions such as analysis of satellite imagery.

The second group of techniques recognizes shadow areas with knowledge such as gray scale, brightness, saturation, and texture. An improved algorithm presents that aggregate the two groups. First, according to the space coordinates of buildings the shadow areas are estimated, calculated from digital surface models and the altitude and azimuth of the sun. Then, to exactly recognize a shadow, the threshold value is obtained from the estimated grayscale value of the shadow areas. However, information such as scene and camera altitude is not usually readily available. Resolution of an image is the detail of that image holds. If image have more image detail than that is a high resolution image. Image resolution can be measured in different ways. Mainly, resolution measures how close lines can be to each other and still be visibly resolved.

Remote sensing is the process of gathering information about something without touching it. Visible, Near-Infrared; Thermal Infrared, and Radar sensors are applied to gathering information about ground targets and activities of national security significance.

Remote sensing is the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it. This is done by sensing and recording reflected or emitted energy and processing, analyzing, and applying that information. Satellite images are that they are photographs. In fact, they are quite different. Satellites use remote sensing to collect information digitally. People use computers to convert this information to images.

II. EXISTING METHOD

Many effective algorithms have been proposed for shadow detection. Existing shadow detection methods can be roughly categorized into two groups’ model-based methods and shadow-feature-based methods. The first group uses prior information such as scene, moving targets, and camera altitude to construct shadow models. This group of methods is often used in some specific scene conditions such as aerial image analysis and video monitoring. The second group of methods identifies shadow areas with information such as gray scale, brightness, saturation, and texture.

In this existing method, the shadow detection is undertaken by the Quick bird image which is obtained from the both rural and urban area. In this method some of the drawbacks like, there is no image calibration for the intensity and, the illumination adjustments. This technique is particularly suitable for our problem because many shadow regions may exist throughout the image, and each may have different radiometric profile.

A. *Disadvantage of Existing Method*

- Uncertainty information that may be of interest for probability estimation is lost.
- Second, the classification noise is added to the data leading to non-robust classifiers.

– Training datasets are always contains classification errors or uncertainties even when data is labeled by experts.

III. PROPOSED METHOD

An improved algorithm presents that aggregation of the two existing techniques. Every objects present in an image, which are going to be segmented marked by seeds. By comparing regions to the all unallocated neighboring pixels, the regions are grown by iteratively. The calculation of similarity is obtained by taking the difference among a pixel's value of intensity and the mean of the regions. The smallest value measured for a pixel by using this method is allocated to the respected region.

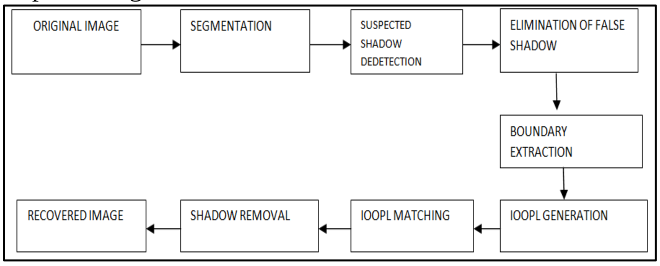

Fig. 4.1: Block Diagram of Object-Oriented Shadow Detection and Removal from Urban High-Resolution Remote Sensing Images

However, information such as scene and camera altitude is not usually readily available. Consequently, most shadow detection algorithms are based on shadow features. For example, the shadow region appears as a low grayscale value in the image, and the threshold is chosen between two peaks in the grayscale histogram of the image data to separate the shadow from the non-shadow region An illuminant invariance model has been used to detect shadows; this method can obtain a comparatively complete shadow out-line from a complex scene and derive the shadow-free image by using certain neutral interface reflecting assumptions .In a related study, images are converted into different invariant color spaces (HSV, HCV, YIQ, and YCbCr) to obtain shadows with Otsu's algorithm. This can effectively get rid of the false shadows created by vegetation in certain invariant spaces. Based on that work, a successive thresholding scheme was proposed to detect shadows To avoid the false shadows of dark objects such as vegetation and moist soil, the normalized difference vegetation index, the normalized saturation–value difference index, and the size and shape of the shadow area are considered. The method used by Makarau *et al.* accurately detected shadows with the blackbody radiation model. Recently, a hierarchical supervised classification scheme was used to detect shadows. The proposed method for shadow detection and removal is shown in Fig. 3.1.

IV. THE PRINCIPLES & PROCEDURES OF THE SHADOW DETECTION, & SHADOW REMOVAL METHOD

A. Principle of Shadow Detection

Shadows are created because the light source has been blocked by something. There are two types of shadows: the self-shadow and the cast shadow. A self-shadow is the shadow on a subject on the side that is not directly facing the light Source.

B. Procedure of Proposed Shadow Detection Method

1) Image Segmentation Considering Shadow Features

Images with higher resolution contain richer spatial information. The spectral differences of neighbouring pixels within an object increase gradually. Pixel-based methods may pay too much attention to the details of an object when processing high resolution images, making it difficult to obtain overall structural information about the object. In order to use spatial information to detect shadows, image segmentation is needed. We adopt convexity model (CM) constraints for segmentation. Traditional image segmentation methods are likely to result in insufficient segmentation, which makes it difficult to separate shadows from dark objects. The CM constraints can improve the situation to a certain degree. To make a further distinction between shadows and dark objects, color factor and shape factor have been added to the segmentation criteria. The parameters of each object have been recorded, including grayscale average, variance, area, and perimeter. The segmentation scale could be set empirically for better and less time-consuming results, or it could be adaptively estimated according to data such as resolution.

2) Detection of Suspected Shadow Areas

For shadow detection, a properly set threshold can separate shadow from non-shadow without too many pixels being misclassified. Researchers have used several different methods to find the threshold to accurately separate shadow and non-shadow areas. Bimodal histogram splitting provides a feasible way to find the threshold for shadow detection, and the mean of the two peaks is adopted as the threshold. In our work, we attain the threshold according to the histogram of the original image and then find the suspected shadow objects by comparing the threshold and grayscale average of each object obtained in segmentation. In addition, atmospheric molecules scatter the blue wavelength most among the visible rays (Rayleigh scattering). So for the same object, when in shadow and non-shadow, its grayscale difference at the red and green wavebands is more noticeable than at the blue waveband. Thus, we retrieve a suspected shadow with the threshold method at the red and green wavebands. Specifically, an object is determined to be a suspected shadow if its grayscale average is less than the thresholds in both red and green wavebands.

3) Elimination of False Shadows

Dark objects may be included in the suspected shadows, so more accurate shadow detection results are needed to eliminate these dark objects. Rayleigh scattering results in a smaller grayscale difference between a shadow area and a non-shadow area in the blue (B) waveband than in the red (R) and green (G) wavebands. Consequently, for the majority of shadows, the grayscale average at the blue waveband Gb is slightly larger than the grayscale average at the green waveband Gg. Also, the properties of green vegetation itself make Gg significantly larger than Gb, so false shadows from vegetation can be ruled out by comparing the Gb and Gg of all suspected shadows. Namely, for the object i, when $Gb + Ga < Gg$, i can be defined to be vegetation and be ruled out. Ga is the correction parameter determined by the image type.

After the elimination of false shadows from vegetation, spatial information of objects, i.e., geometrical characteristics and the spatial relationship between objects, is used to rule out other dark objects from the suspected shadows. Lakes, ponds, and rivers all have specific areas, shapes, and other geometrical characteristics. Most bodies of water can be ruled out due to the area and shape of the suspected shadows of the object that they produce. However, the aforementioned method still cannot separate shadows from some other dark objects. Spatial relationship features are used to rule out dark objects in the suspected shadows. Dark objects are substantive objects, while shadows are created by taller objects which block the light sources and may be linked together with the objects that result in the shadows. An obscured area (i.e., a shadow) forms a darker area in an image. The object blocking the light forms a lighter area in an image. At the same time, the sun has a definite altitude angle, and a shadow boundary reflects the boundary of a building and the position of a light source. Buildings, trees, and telegraph poles are the main objects creating shadows in urban remote sensing images. Their shadow boundaries usually have a certain direction. To retrieve shadows using spatial relationships, the linear boundaries of suspected shadows are first analyzed to predict the probable trend of a shadow, according to which the approximate position of a large object is predicted. To determine whether it is a shadow, the proximity of a dark object to a light object within this azimuth is measured. An average spectral difference can be used to decide whether there are light objects linked around a shadow.

4) Implementation of Shadow Removal

Shadows are removed by using the homogeneous sections obtained by line pair matching. There are two approaches for shadow removal. One approach calculates the radiation parameter according to the homogeneous points of each object and then applies the relative radiation correction to each object. The other approach collects and analyzes all the homogeneous sections for polynomial fitting (PF) and retrieves all shadows directly with the obtained fitting parameters.

a) Relative Radiometric Correction

In the same urban image, if objects in a shadow area and a non-shadow area belong roughly to the same category, and they are in different lighting conditions, relative radiation correction can be used for shadow removal. To avoid the influence of scattering light from the environment, each single object has been taken as a unit for which the shadow removal process is conducted for that object. This enhances reliability. Commonly used relative radiation correction generally assumes that a linear relationship exists between the grayscale value digital number (DN) of the image to be corrected and the DN of the reference image,

$$\text{DNref} = a \times \text{DNrect} + b.$$

DNref is the DN of the object in the reference image, DNrect is the DN of the object in the image to be corrected, and *a* and *b* are the gain and offset, respectively. By applying IOOPL matching to each shadow, homogeneous sections that represent objects of the same category in different lighting conditions are obtained. radiation value correction of the shadow can be realized through the obtained gain and offset values. Our experiments show that a straightforward and simple relative radiation correction, the mean variance method, for shadow removal can be applied as follows.

The concept of the mean variance method is that, after radiation correction, the homogeneous points on a line pair of the shadow have the same mean and variance at each waveband. The radiation correction coefficients of the mean and variance method are

$$a_k = S_{yk}/S_{xk};\ b_k - y_k - a_k.\ x_k$$

Where *xk* is the grayscale average of the inner homogeneous sections at the waveband *k*, *yk* is the grayscale average of the outer homogeneous sections at the waveband *k*, *Sxk* is the standard deviation of the inner homogeneous sections atthe corresponding waveband, and *Syk* is the standard deviation of the outer homogeneous sections at the corresponding waveband. We assume that the inner homogeneous sections reflect the overall radiation of the single shadow. After obtaining the correction coefficient, all points of the shadow are corrected according to

$$\text{DNnon shadow} = ak \times \text{DNshadow} + bk$$

Where *DN* non shadow stands for the pixel gray scale of the shadow after correction, *DN* shadow stands for the pixel gray scale of the shadow before correction, and *ak* and *bk* are the coefficients of the minimum and maximum method or mean variance method calculated with the homogeneous points of the object, respectively.

b) PF

As mentioned previously, in high-resolution remote sensing images, the inner and outer homologous points represent the grayscale level of the same type of object of both sides of the shadow boundary in shadow and under normal illumination. It has been found that shadows and the corresponding non shadows exhibit a linear relationship. However, in this study, according to goodness of fit, the relationship of the inner and outer homologous points is best described by the polynomial model (Fig. 5). Consequently, we adopt PF, and the grayscale value of the shadow area is directly obtained with the fitting parameters, as shown in

$$f(x) = ax^3 + bx^2 + cx + d.$$

After transforming the gray scale of the shadow area through f(x), the shadow removal result can be obtained. It is not appropriate to perform PF at greater than the third degree. One reason is to avoid the overly complex calculation; the otherreason is that higher fitting to degrees greater than three does not significantly improve accuracy. The next step assumes that the illumination model of the entire image is consistent. To ensure that enough statistical subjects are obtained, the grayscale values of all matching points on the inner and outer outline lines of all shadows in the entire image are determined. These provide the fitting parameters for shadow removal. This method has solved the problem of not being able to obtain the inner and outer outlines of the minor shadows and the lack of availability of enough IOOPL matching points.

V. RESULTS & DISCUSSIONS

Remote sensing color input image: Firstall we have taken the input as remote sensing color image shown in given figure 6.1.

Fig. 6.1: Original Image Color Input Image

A. Conversion of RGB Image into Gray Image

Because of computational problem we are converting the RGB image into gray image as shown Figure 7.2.

Fig. 6.2: Gray Scale Image

B. Image Segmentation

Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Fig. 6.3: Image after Segmentation

C. False Shadow Detection

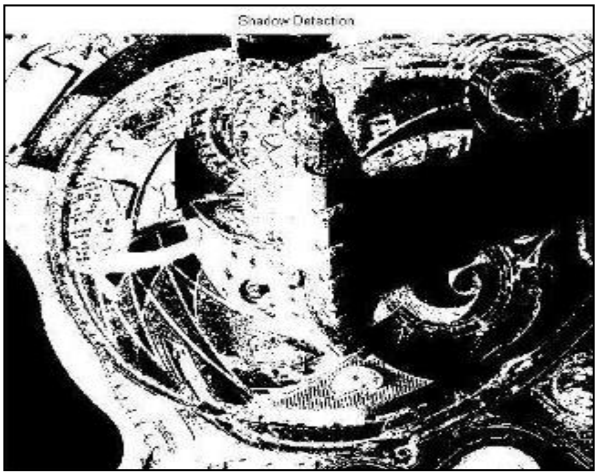

Fig. 6.4: Image after false Shadow Detection

D. False Shadow Elimination

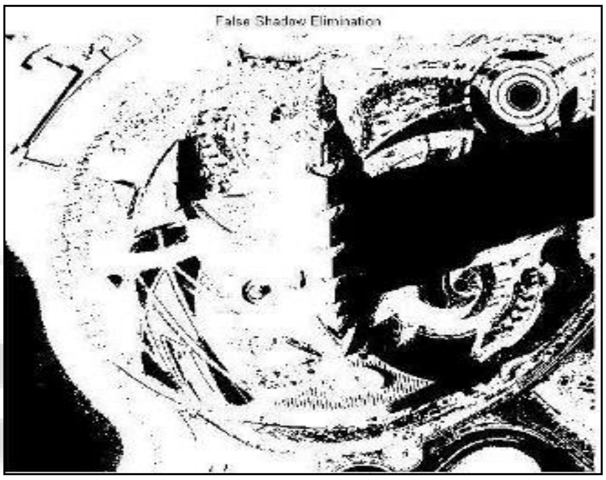

Fig. 6.5: Image after False Shadow Elimination

E. Boundary Extraction

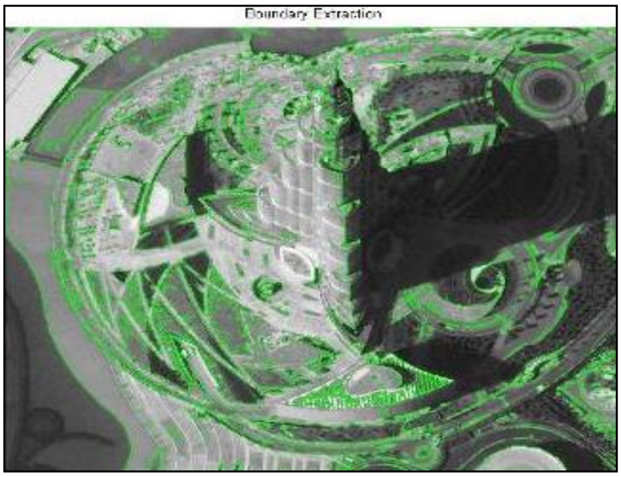

Fig. 6.6: Image After Boundary Extraction

F. Conversion of Image Into Three Wave Bands: Red Channel

Fig. 6.7: Red Channel

G. Green Channel

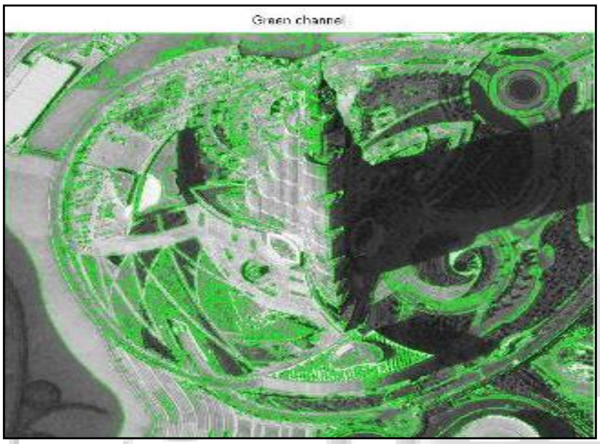

Fig. 6.8: Green Channel

H. Blue Channel

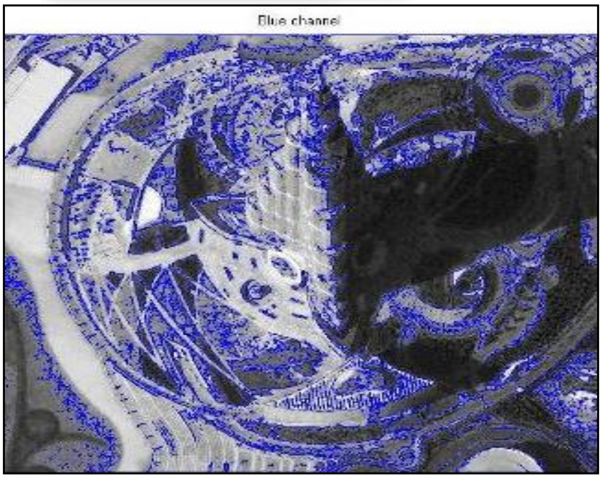

Fig. 6.9: Blue Channel

I. Output Image

Fig. 6.10: Recovered Image

VI. COMPARISONS BETWEEN SHADOW AREA AND SHADOW REMOVED AREA

Performed shadow detection and removal method to number of images with shadow and respected images shown below. In every image the shadowed input and removed shadow of output were marked, for those shadowed and non-shadowed areas mean and standard deviations were measured and tabulated. Input images all were Remote sensing images from IKONOS, Quick Bird, GeoEye, and Resource 3.

Fig. 6.11 (a): Original Image Alburj Dubai with Shadow, (b) Recovered Image with Non Shadow

Fig. 6.12 (a): Original Image by IKONOS image with Shadow, (b) Recovered Image with Non Shadow

Fig. 6.13 (a): Original Image of university image with Shadow, (b) Recovered Image with Non Shadow

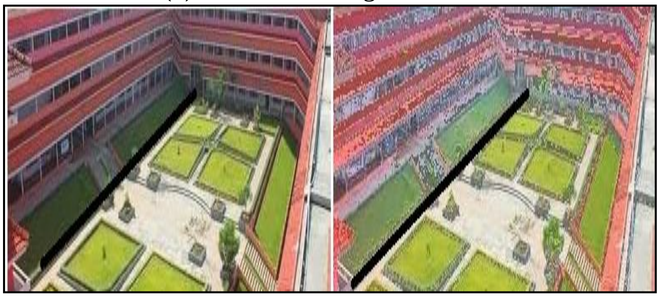

Fig. 6.14 (a): Original Image by GeoEye with Shadow, (b) Recovered Image with Non Shadow

Fig. 6.15 (a): Original Image by Quick bird image with Shadow, (b) Recovered Image with Non Shadow

A. *Sample Analysis*

Figure number	Type	Mean in dB	Standard Deviation
7.11(a)	Shadowed	47.47	45.56
7.11(b)	Non shadowed	87.13	40.55
7.12(a)	Shadowed	128.73	66.02
7.12(b)	Non shadowed	147.74	61.95
7.13(a)	Shadowed	201.57	75.76
7.13(b)	Non shadowed	205.32	69.86
7.14(a)	Shadowed	197.73	76.65
7.14(b)	Non shadowed	209.44	61.86
7.15(a)	Shadowed	183.01	91.66
7.15(b)	Non shadowed	201.61	69.35

Table 1: Sample Analysis

Table 6.1 shows the sample information, which verifies the effectiveness of our approach numerically. In Table 6.1, there is a tremendous difference between the non-shadow and shadow regions of the same scenes in spectral consistency according to the average value and standard deviation. After applying our approach, the average value and standard deviation of the shadow-removed region are close to that of the non-shadow region. Therefore, we could obtain the de-shaded data which meet the needs of both vision and spectral consistency through the presented approach.

B. *Advantages*

1) Threshold selection and false shadow removal can be conducted in simple but effective ways to ensure shadow detection accuracy.
2) Compared with pixel-level detection, the object-oriented shadow detection can make full use of the spatial information of an image and can effectively rule out speckles and false shadows in the detection result.
3) The shadow removal method based on IOOPL matching can effectively restore the information in a shadow area. The homogeneous sections obtained by IOOPL matching can show the radiation gray scale of the same object in a shadow area and a non-shadow area. The parameters calculated by using the radiation difference between inner and outer homogeneous sections can retrieve a shadow very effectively.
4) The two shadow removal strategies (RRN and PF) are both suitable for high-resolution urban remote sensing images. Moreover, there are advantages to each strategy: RRN can restore the texture details well while PF has a more stable background radiance.

VII. Conclusion

This methodology has illustrates a group of procedures that execute shadow investigation on high resolution aerial imagery. Each develops the association between man-made structures and cast shadows to execute structure shape calculation. First image segmentation considered for shadowed image. After the segmentation spectral features of suspected shadows are examined.

False shadows eliminated by utilizing previous results i.e. suspected shadow detection. Results obtained from this method compared with traditional segmentation methods.

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