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An Efficient Method for Shadow Detection and Removal in Satellite Images by Segmentation

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Abstract: Shadow features are taken into consideration during image segmentation, and then, according to the statistical features of the images, suspected shadows are extracted. Furthermore, some dark objects which could be mistaken for shadows are ruled out according to object properties and spatial relationship between objects. For shadow removal, inner–outer outline profile line (IOOPL) matching is used. First, the IOOPLs are obtained with respect to the boundary lines of shadows. Shadow removal is then performed according to the homogeneous sections attained through IOOPL similarity matching.

Keywords: Image Segmentation, IOOPL, Shadow Detection, Shadow Removal.

I. INTRODUCTION

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

The presence of shadows has been responsible for reducing the reliability of many computer vision algorithms, including segmentation, object detection, scene analysis, stereo, tracking, etc. Therefore, shadow detection and removal is an important pre-processing for improving performance of such vision tasks. The availability of high spatial- resolution satellites such as IKONOS, Quick-Bird, Geo-Eye, and Resource 3 for the observation of Earth and the rapid development of some aerial platforms such as airships and unmanned aerial vehicles, there has been an increasing need to analyze high-resolution images for different applications. In urban areas, surface features are quite complex, with a great variety of objects and shadows formed by elevated objects such as high buildings, bridges, and trees. Although shadows themselves can be regarded as a type of useful information in 3-D reconstruction, building position recognition, and height estimation, they can also interfere with the processing and application of high-resolution remote sensing images. For example, shadows may cause incorrect results during change detection. Consequently, the detection and removal of shadows play an important role in applications of urban high-resolution remote sensing images such as object classification, object recognition, change detection, and image fusion.

The obstruction of light by objects creates shadows in a scene. An object may cast a shadow on itself, called self-shadow. The shadow areas are less illuminated than the surrounding areas. In some cases the shadows provide useful information, such as the relative position of an object from the source. But they cause problems in computer vision applications like segmentation, object detection and object counting. Thus shadow detection and removal is a pre-processing task in many computer vision applications. Based on the intensity, the shadows are of two types − hard and soft shadows. The soft shadows retain the texture of the background surface, whereas the hard shadows are too dark and have little texture. Thus the detection of hard shadows is complicated as they may be mistaken as dark objects rather than shadows.

According to the work presented by Paul M., shows that high-resolution satellite imagery (HRSI) offers great possibilities for urban mapping. Unfortunately, shadows cast by buildings in high-density urban environments obscure much of the information in the image leading to potentially corrupted classification results or blunders in interpretation. Although significant research has been carried out on the subject of shadowing in remote sensing, very few studies have focused on the particular problems associated with high-resolution satellite imaging of urban areas. This paper reviews past and current research and proposes a solution to the problem of automatic detection and removal of shadow features. Tests show that although detection and removal of shadow features can lead to improved image quality, results can be image-dependent [01].

The work carried out by Weiqi Zhou., shows that a significant proportion of high spatial resolution imagery in urban areas can be affected by shadows. Considerable research has been conducted to investigate shadow detection and removal in remotely sensed imagery. Few studies, however, have evaluated how applications of these shadow detection and restoration methods can help eliminate the shadow problem in land cover classification of high spatial resolution images in urban settings. This paper presents a comparison study of three methods for land cover classification of shaded areas from high spatial resolution imagery in an urban environment. Method 1

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combines spectral information in shaded areas with spatial information for shadow classification. Method 2 applies a shadow restoration technique, the linear-correlation correction method to create a "shadow-free" image before the Classification. Method 3 uses multisource data fusion to aid in classification of shadows. The results indicated that Method 3 achieved the best accuracy, with overall accuracy of 88%. It provides a significantly better means for shadow classification than the other two methods. The overall accuracy for Method 1 was 81.5%, slightly but not significantly higher than the 80.5% from Method 2. All of the three methods applied an object-based classification procedure, which was critical as it provides an effective way to address the problems of radiometric difference and spatial misregistration associated with Multisource data fusion (Method 3), and to incorporate thematic spatial information [02].

The author J. J. Yoon., explained that a novel shadow removal technique that produces a shadow-free scene. There have been few studies concerning shadow removal, and the existing approaches cannot perfectly restore the original background patterns after removing shadows. With an acceptable number of differently illuminated images, the proposed algorithm simulates an artificial infinite illuminant plane over the field of view. By employing the offset reduction technique, the constancy of the brightness is also reliably guaranteed. Finally, a shadowless image without loss of textural details is obtained without any region extraction phase. Experimental results show that the method could successfully remove all of the visible shadows. The benefits of the proposed algorithm compared to the conventional shadow detection algorithms are the lower computational costs and the improved reliability [03].

The author Shwetali Wakchaure., conclude that the application potential of remotely sensed optical imagery is boosted through the increase in spatial resolution, and new analysis, interpretation, classification, and change detection methods are developed. Together with all the advantages, shadows are more present in such images, particularly in urban areas. This may lead to errors during data processing. The task of automatic shadow detection is still a current research topic. Since image acquisition is influenced by many factors such as sensor type, sun elevation and acquisition time, geographical coordinates of the scene, conditions and contents of the atmosphere, etc., the acquired imagery has highly varying intensity and spectral characteristics. The variance of these characteristics often leads to errors, using standard shadow detection methods. Moreover, for some scenes, these methods are inapplicable. In this paper, we present an alternative robust method for shadow detection. The method is based on the physical properties of a blackbody radiator. Instead of static methods, this method adaptively calculates the parameters for a particular scene and allows one to work with many different sensors and images obtained with different illumination conditions [04].

According to the work proposed by G. AMBROSIO et.al., explained that a new transformation which enables us to detect boundaries of cast shadows in high resolution satellite images is introduced. The transformation is based on color invariant indices. Different radiometric restoration techniques such as Gamma Correction, Linear-Correlation Correction and Histogram Matching are introduced in order to restore the brightness of detected shadow area [05].

II. PROPOSED SYSTEM

We propose a new technique: an efficient method for shadow detection and removal in satellite images. First, the shadow features are evaluated through image segmentation, and suspected shadows are detected with the threshold method. Second, object properties such as spectral features and geometric features are combined with a spatial relationship in which the false shadows are ruled out (i.e., water region). This will allow only the real shadows to be detected in subsequent steps. Shadow removal employs a series of steps. We extract the inner and outer outline lines of the boundary of shadows. The grayscale values of the corresponding points on the inner and outer outline lines are indicated by the inner–outer outline profile lines (IOOPLs). Homogeneous sections are obtained through IOOPL sectional matching. Finally, using the homogeneous sections, the relative radiation calibration parameters between the shadow and non-shadow regions are obtained, and shadow removal is performed. The block diagram of proposed system is show in Fig. 1.

A. Original Image

The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors. Grayscale images are distinct from one-bit bi-tonal black-and-white images, which in the context of computer imaging are images with only the two colors, black, and white (also called bilevel or binary images). Grayscale images have many shades of gray in between. Grayscale images are also called monochromatic, denoting the presence of only one (mono) color (chrome). Grayscale images are often the result of measuring the intensity of light at each pixel in a single band of the electromagnetic spectrum (e.g. infrared, visible light, ultraviolet, etc.), and in such cases they are monochromatic proper when only a given frequency is captured. But also they can be synthesized from a full color image; see the section about converting to grayscale.

B. 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

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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.

C. Binarization

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. We chose the grayscale value with the minimum frequency in the neighborhood of the mean of the two peaks as the threshold, as shown in

$$G_q = \frac{1}{2}(G_m + (G_s)$$

$$\text{h(T)} = \min \{\text{h}(G_q - €), \text{h}(G_q + €)\}$$

In the equations, *Gm* is the average grayscale value of an image; *Gs* stands for the left peak of the shadow in the histogram; *T* is the threshold; ε represents the neighborhood of *T*, where $T \in [Gq - \varepsilon, Gq + \varepsilon]$; and $h(I)$ is the frequency of *I*, where $I = 0, 1, \ldots, 255$.

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.

D. Elimination of False Shadow

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.

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. 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.

E. Boundary Extraction

There is a large probability that both shadow and non shadow areas in close range on both sides of the shadow boundary belong to the same type of object. The inner and outer outlines can be obtained by contacting the shadow boundary inward and expanding it outward, respectively. Then, the inner and outer outline profile lines are generated along the inner and outer outline lines to determine the radiation features of the same type of object on both sides. As shown in Fig. 2, *R* is the vector line of the shadow boundary obtained from shadow detection, *R*1 is the outer outline in the non shadow area after expanding *R* outward, and *R*2 is the inner outline in the shadow area after contracting *R* inward The objects on both sides of the shadow boundary linked with a building forming a shadow are usually not homogeneous, and the corresponding inner and outer outline profile line sections are not reliable. In addition, the abnormal sections on the inner and outer outlines that cannot represent homogeneous objects need to be ruled out. Consequently, similarity matching needs to be applied to the IOOPL section by section to rule out the two kinds of non-homogeneous sections mentioned previously. The parameters for shadow removal are obtained by analyzing the grayscale distribution characteristics of the inner and outer homogeneous IOOPL sections.

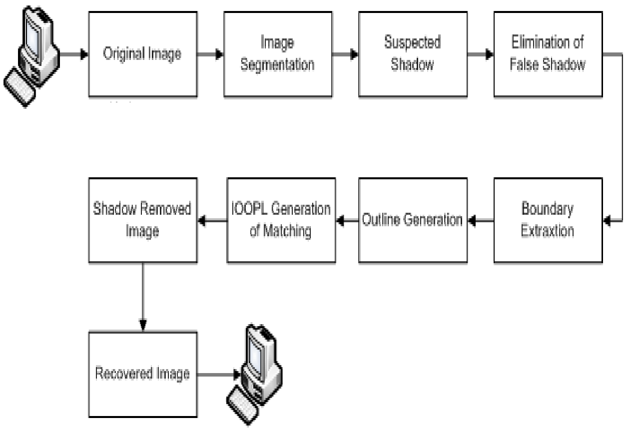

Fig. 1: Block Diagram for Proposed System.

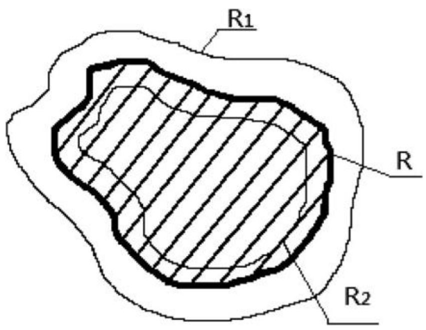

Fig. 2: Boundary extraction of the shadow in description.

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F. Shadow Removal

To recover the shadow areas in an image, we use a shadow removal method based on IOOPL matching. 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.

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 lightig 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

$$DN_{ref} = a\times DN_{ref} + b$$

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

$$a_k = \frac{S_{Yk}}{S_{Xk}};\ b_k \text{-}\overline{Yk}\text{-}a_k\ .\ \overline{Xk}$$

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 at the 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

$$DN_{nonshadow} = a_k \times DN_{shadow} + b_k$$

Input is boundary image and Output is shadow removed image.

III. EXPECTED RESULTS

In this paper a method for shadow detection and removal using inner–outer outline profile line (IOOPL) matching.

First, the IOOPLs are obtained with respect to the boundary lines of shadows. Shadow removal is then performed according to the homogeneous sections attained through IOOPL similarity matching.

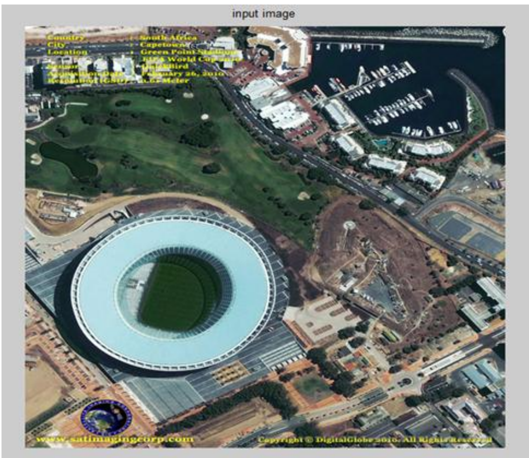

Fig. 3: Input Satellite Image

The Fig. 3 shows that the input satellite color image. In input image we need to find the shadow detection and also removal of shadow.

Fig. 4: Shadow Detected Image

The Fig. 4 shows that the shadow detected part from the selected input image.

The Fig. 5 shows that the suspected shadow suspected and false shadow detection from the segmented image.

Fig. 5: Suspected Shadow Detected and False Shadow Detection

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The Fig. 6 shows that the inner–outer outline profile line **(**IOOPL) graph generation. The blue color indicates that the inner section and gray color indicates that the inner section of the segmented grayscale image with IOOPL at input waveband and at Gaussian smoothed band.

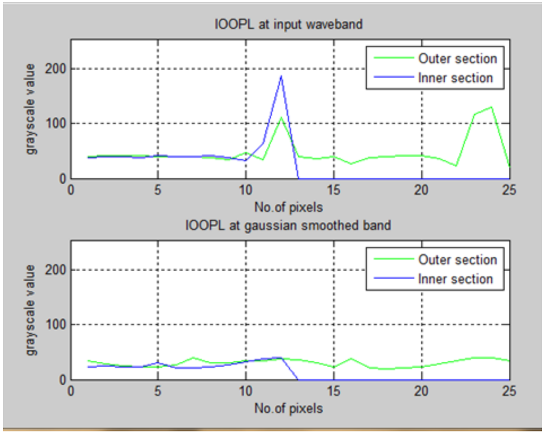

Fig. 6: IOOPL Graph Generation

The Fig. 7 shows that the shadow removed image from inner–outer outline profile line (IOOPL) generation and matching. An efficient method for shadow detection & removal from satellite image.

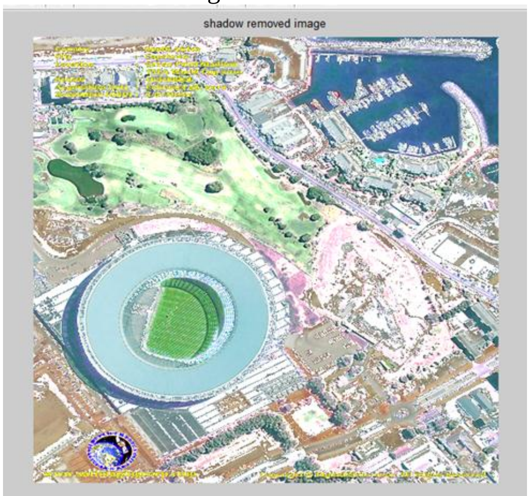

Fig. 7: Shadow Removed Image

The Table 1 shows that the result analysis from shadow removed image from inner–outer outline profile line (IOOPL). For different cases like non shadow, shadow and shadow removed what will be the average values and standard deviation.

TABLE 1 :RESULTS

	Area_Size (P)	Average_Values	Standard_Deviation
Non_Shadow	249360	108.0331	61.8850
Shadow	12784	55.5954	29.4251
Shadow_Removed	12710	184.6021	92.7286

IV. CONCLUSION

A systematic and effective method for shadow detection and removal in a single urban high-resolution remote sensing image is successful. In order to get a shadow detection result, image segmentation considering shadows is applied first. Then, suspected shadows are selected through spectral features and spatial information of objects, and false shadows are ruled out. The subsequent shadow detection experiments compared traditional image segmentation and the segmentation considering shadows, as well as results from traditional pixel-level threshold detection and object-oriented detection. Meanwhile, they also show the effects of different steps with the proposed method. For shadow removal, after the homogeneous sections have been obtained by IOOPL matching, we put forward two strategies: relative radiation correction for the objects one at a time and removal of all shadows directly after PF is applied to all the homogeneous sections and correction parameters are obtained. Both strategies were implemented in high-resolution images.

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BIOGRAPHIES

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