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Object based Segmentation using KFCM Technique for Shadow Detection and Removal from Satellite Image

B.Pavithra, P.Rasukkannu.,Msc.,M.Phil

Student, Dept. of Computer Science, Sakthi College of Arts and Science for Women, Oddanchatram, TamilNadu, India

Assistant Professor, Dept. of Computer Science, Sakthi College of Arts and Science for Women, Oddanchatram, TamilNadu, India

ABSTRACT: Remote sensing image segmentation is the basis of image pattern recognition. It is significant for the application and analysis of remote sensing images. Clustering analysis as a non-supervised learning method is widely used in the segmentation of remote sensing images. It has made good results in the segmentation of low-resolution and moderate-resolution remote sensing images. As the improvement of image resolution, however, they have problems in the segmentation of high-resolution remote sensing images. In this paper we propose a KFCM based high-resolution remote sensing image segmentation algorithm. 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. Experiments show that the new method can accurately detect shadows from urban high-resolution remote sensing images and can effectively restore shadows with a rate of over 85% .The segmentation experiments show that the result of this algorithm is better than the existing methods and is close to the results of artificial extraction.

I. INTRODUCTION

1.1 INTRODUCTION TO REMOTE SENSING

Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object and thus in contrast to in situ observation. In modern usage, the term generally refers to the use of aerial sensor technologies to detect and classify objects on Earth (both on the surface, and in the atmosphere and oceans) by means of propagated signals (e.g. electromagnetic radiation). It may be split into active remote sensing (when a signal is first emitted from aircraft or satellites) or passive (e.g. sunlight) when information is merely recorded. Passive sensors gather natural radiation that is emitted or reflected by the object or surrounding areas. Reflected sunlight is the most common source of radiation measured by passive sensors. Examples of passive remote sensors include film photography, infrared, charge-coupled devices, and radiometers. Active collection, on the other hand, emits energy in order to scan objects and areas whereupon a sensor then detects and measures the radiation that is reflected or backscattered from the target. RADAR and LiDAR are examples of active remote sensing where the time delay between emission and return is measured, establishing the location, speed and direction of an object.

Illustration of Remote Sensing

Remote sensing makes it possible to collect data on dangerous or inaccessible areas. Remote sensing applications include monitoring deforestation in areas such as the Amazon Basin, glacial features in Arctic and Antarctic regions, and depth sounding of coastal and ocean depths. Military collection during the Cold War made use of stand-off collection of data about dangerous border areas. Remote sensing also replaces costly and slow data collection on the ground, ensuring in the process that areas or objects are not disturbed.

Orbital platforms collect and transmit data from different parts of the electromagnetic spectrum, which in conjunction with larger scale aerial or ground-based sensing and analysis, provides researchers with enough information to monitor trends such as El Niño and other natural long and short term phenomena. Other uses include different areas of the earth sciences such as natural resource management, agricultural fields such as land usage and conservation, and national security and overhead, ground-based and stand-off collection on border areas.

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Data acquisition techniques

The basis for multispectral collection and analysis is that of examined areas or objects that reflect or emit radiation that stand out from surrounding areas. For a summary of major remote sensing satellite systems see the overview table.

Applications of remote sensing data

Conventional radar is mostly associated with aerial traffic control, early warning, and certain large scale meteorological data. Doppler radar is used by local law enforcements' monitoring of speed limits and in enhanced meteorological collection such as wind speed and direction within weather systems in addition to precipitation location and intensity. Other types of active collection include plasmas in the ionosphere. Interferon metric synthetic aperture radar is used to produce precise digital elevation models of large scale terrain (See RADARSAT, TerraSAR-X, and Magellan).

II. LITERATURE SURVEY

2.1 Topographic correction (also called terrain correction)

In rugged mountains, as a result of terrain, the effective illumination of pixels varies considerably. In a remote sensing image, the pixel on the shady slope receives weak illumination and has a low radiance value, in contrast, the pixel on the sunny slope receives strong illumination and has a high radiance value. For the same object, the pixel radiance value on the shady slope will be different from that on the sunny slope. Additionally, different objects may have similar radiance values. These ambiguities seriously affected remote sensing image information extraction accuracy in mountainous areas. It became the main obstacle to further application of remote sensing images. The purpose of topographic correction is to eliminate this effect, recovering the true reflectivity or radiance of objects in horizontal conditions. It is the premise of quantitative remote sensing application.

2.2 Atmospheric correction

Elimination of atmospheric haze by rescaling each frequency band so that its minimum value (usually realised in water bodies) corresponds to a pixel value of 0. The digitizing of data also makes it possible to manipulate the data by changing gray-scale values.

Interpretation is the critical process of making sense of the data. The first application was that of aerial photographic collection which used the following process; spatial measurement through the use of a light table in both conventional single or stereographic coverage, added skills such as the use of photogrammetry, the use of photomosaics, repeat coverage, Making use of objects' known dimensions in order to detect modifications. Image Analysis is the recently developed automated computer-aided application which is in increasing use.

Object-Based Image Analysis (OBIA) is a sub-discipline of GIScience devoted to partitioning remote sensing (RS) imagery into meaningful image-objects, and assessing their characteristics through spatial, spectral and temporal scale.

Old data from remote sensing is often valuable because it may provide the only long-term data for a large extent of geography. At the same time, the data is often complex to interpret, and bulky to store. Modern systems tend to store the data digitally, often with lossless compression. The difficulty with this approach is that the data is fragile, the format may be archaic, and the data may be easy to falsify. One of the best systems for archiving data series is as computer-generated machine-readable ultrafiche, usually in typefonts such as OCR-B, or as digitized half-tone images. Ultrafiches survive well in standard libraries, with lifetimes of several centuries. They can be created, copied, filed and retrieved by automated systems. They are about as compact as archival magnetic media, and yet can be read by human beings with minimal, standardized equipment.

III. SYSTEM DESCRIPTION

3.1 EXISTING SYSTEM

Due to the shortcomings of pixel-level shadow detection, in this study, we propose a new technique: an object-oriented shadow detection and removal method. 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 nonshadow regions are obtained, and shadow removal is performed.

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3.2 PROPOSED SYSTEM

Images with higher resolution contain richer spatial information. The spectral differences of neighboring pixels within an object increase gradually. Pixel-based methods may pay too much attention to the details of an object when processing highresolution 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. A segmentation-based shadow detector is proposed that utilises a Kernel Fuzzy C-Means Clustering algorithm with parameters that are robust against dynamic range variances seen in multitemporal imagery. 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 nonshadow area. The parameters calculated by using the radiation difference between inner and outer homogeneous sections can retrieve a shadow very effectively.

IV. SYSTEM IMPLEMENTATION

4.1 Image segmentation using KFCM

Images with higher resolution contain richer spatial information. The spectral differences of neighboring pixels within an object increase gradually. Pixel-based methods may pay too much attention to the details of an object when processing highresolution 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. Traditional image segmentation methods are likely to result in insufficient segmentation, which makes it difficult to separate shadows from dark objects. The KFCM 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. The algorithm is obtained by modifying the main function in the primitive fuzzy c-means algorithm using a kernel. Experimental results show that the proposed algorithm is more prone to noise than the conventional fuzzy image segmentation algorithms. KFCM confines the prototypes in the kernel space that are actually mapped from the original data space. The different types of image pixels with different information are combined in the kernel space are combined using different kernel functions Here $1 - k(x_j, o_i)$ can be considered as a direct measure for measuring the distance between the kernel space .

4.2 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. A cast shadow is the shadow of a subject falling on the surface of another subject because the former subject has blocked the light source. A cast shadow consists of two parts: the umbra and the penumbra. The umbra is created because the direct light has been completely blocked, while the penumbra is created by something partly blocking the direct light. In this paper, we mainly focus on the shadows in the cast shadow area of the remote sensing images. For shadow detection, a properly set threshold can separate shadow from nonshadow without too many pixels being misclassified. Researchers have used several different methods to find the threshold to accurately separate shadow and nonshadow 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.

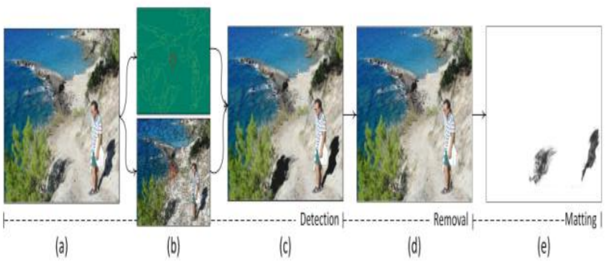

Fig. 1: From left to right: Original image (a). Our framework first detects shadows (c) using the learned features along the boundaries (top image in (b)) and the regions (bottom image in (b)). It then extracts the shadow matte (e) and removes it to produce a shadow free image (d).

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4.3 **Inner and outer outlines generation**

To recover the shadow areas in an image, we use a shadow removal method based on IOOPL matching. There is a large probability that both shadow and nonshadow 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. *R* is the vector line of the shadow boundary obtained from shadow detection, *R*1 is the outer outline in the nonshadow area after expanding *R* outward, and *R*2 is the inner outline in the shadow area after contracting *R* inward.

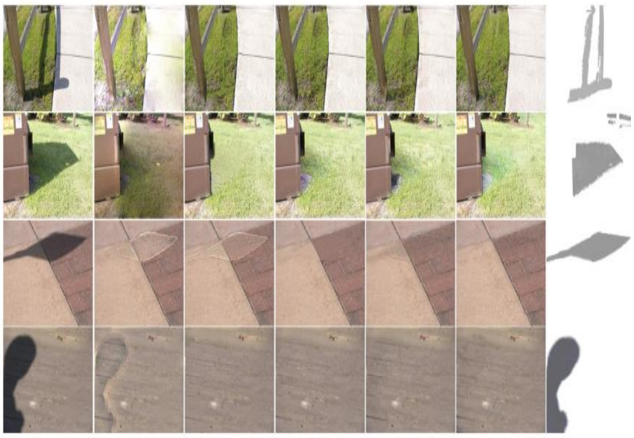

Fig: Comparison with Automatic/Semi-Automatic Methods: Recovered shadow-less images are compared with the state-ofthe-art shadow removal methods which are either automatic [13, 23] or require minimal user input [21, 35]. We compare our work with:

The Gaussian smoothing template parameters were $\sigma = 2$ and $n = 11$. To rule out the nonhomogeneous sections, the IOOPL is divided into average sections with the same standard, and then, the similarity of each line pair is calculated section by section. If the correlation coefficient is large, it means that the shade and light fluctuation features of the IOOPL line pair at this section are consistent. If consistent, then this line pair belongs to the same type of object, with different illuminations, and thus is considered to be matching. If the correlation coefficient is small, then some abnormal parts representing some different types of objects exist in this section; therefore, these parts should be ruled out. The sections that have failed the matching are indicated in red. If more accurate matching is needed, the two sections adjacent to the section with the smallest correlation coefficient can be segmented for matching again.

4.4 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. *1) Relative Radiometric Correction:* In the same urban image, if objects in a shadow area and a nonshadow 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.

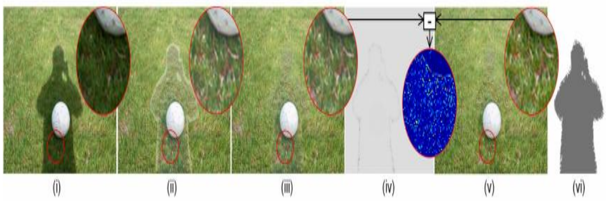

Fig. 8: Shadow Removal Steps: (from *left* to *right*) (i) An original image with shadow. (ii) An initial estimate of the shadow-less image using a multi-level color transfer strategy. (iii) Improved estimate along the boundaries using in-painting. (iv, v and vi) The Bayesian formulation is optimized to solve for α (iv) and β matte (vi) and the final shadow-less image (v).

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This enhances reliability. *2) 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 by Lorenzi *et al.* that shadows and the corresponding nonshadows exhibit a linear relationship. 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 other reason 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. CONCLUSION AND FUTURE WORK

5.1 CONCLUSION

In this paper, accuracy assessment is an integral part in an image classification procedure. In case of noise, the input image undergoes pre-processing before the segmentation process. The output of the segmentation is the best image out of the three images obtained y KFCM. We have put forward a systematic and effective method for shadow detection and removal in a single urban high-resolution remote sensing image. 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, and their performances were compared in experiments.

5.2 FUTURE WORK

Future research will focus on swarm based feature selection with segmentation to improve the shadow removal process.

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