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Shadow Removal of Individual Tree Crowns in a High Resolution Satellite Imagery

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ABSTRACT

Satellite image processing involves many techniques for enhancement/segmentation of raw (Raster) images acquired from cameras or sensors placed on satellites, space probes and aircrafts. These pictures have numerous applications in regular day to day life. Remote sensing is a process of creating thematic maps as spatial sharing of exacting information and is used to discover and isolate the coherent parts of the surface objects (trees/buildings) and the water bodies.

Shadow detection and removal is an main preprocessing for improving act of such (segmentation, thing recognition, view study, tracking, etc) vision tasks. Shadow removal of individual tree top in a coniferous vegetation test zone involves complex procedures. For extracting vegetation zone from a satellite, a pair of spectral indices called Normalized Difference Vegetation Index(NDVI) and Saturation Index(SI) are available. The difficulty of shadows occurring in satellite images need to be addressed while segmenting the tree crowns. In the object slanting shadow detection and deletion or removal method, shadow features are taken into deliberation during image segmentation, and then, according to the statistical features of the images, assumed shadows are extracted. In addition to, some dim objects which could be incorrect for shadows are lined out according to object properties and spatial bond between objects. The retrieved image can be obtained by considering the cross projection advance or approach for shadow free image.

KEYWORDS: *Raster, surface objects, shadow removal, NDVI,SI*

I. Introduction

Today's forest management inventories are still obtained by mapping forest stands and their content via the interpretation of medium scale aerial photographs, backed by field assessments and plot measurements (Leckie and Gillis, 1995). These are both expensive and time-consuming endeavours, and the resulting stand level inventory is not always very accurate (e.g., Quebec Government, 2004). Although designed and used for long term planning and, with stratification, used in calculating wood volume and estimating allowable cut, these inventories are rarely sufficient for operational (i.e., short-term) planning. An individual tree inventory would be extremely useful in that regard. However, this could not be completely realistic yet. Our current and more modest objectives are to examine if an individual tree based approach can be used to gather detailed information at the stand level, replacing the photo interpretation phase in the manufacture of forest management inventories.

II. Imagery, Study Site and Field Data

The proposed algorithm is applied on the Madrid image located in Spain with a resolution of 0.3m. The test image is taken from the original image with a small area of 736x736 pixels.

III. Techniques and Methods

The automatic delineation of tree crowns by the valley following technique (Gougeon, 1995b) relies on the occurrence of shaded material between those crowns. It generally leads to good crown delineation in high to medium density coniferous forests at spatial resolutions of 30-60 cm/pixel. It is also skilled of separating deciduous tree crowns but, with a lower success rate, as their rounder shapes make the presence of significant shade between them less common. Several steps are necessary in the delineation and arrangement of individual trees. These include: preprocessing which is typically needed to eliminate large non-forested areas and, if possible, non-treed surfaces within forested areas; selection or creation of an illumination image for tree delineation or detection; smoothing and possibly resampling the illumination image, and selecting tree isolation algorithm settings. It is anticipated that modifications to preprocessing procedures and algorithm settings will be needed due to the specific nature of IKONOS imagery (e.g., 1 m resolution of the panchromatic imagery and lack of multispectral data with corresponding resolution). Various preprocessing procedures and algorithm settings were explored. This section outlines the general procedures found appropriate with other high resolution imagery for our individual tree crown marking out and classification processes and for the local maxima tree detection technique, and discusses modifications found necessary for the IKONOS imagery.

IV. Pre-Processing

The valley following technique relies on some pre-processing to eliminate (mask-out) non-forested areas from contention. Simple thresholds or multispectral rules such as “detect pixels having a near-infrared radiance smaller than its mean visible band radiance”, can sometimes be used to create effective non- vegetation masks. Here, only the road and the snow, in the summer and winter images respectively, were eliminated this way. With the winter panchromatic image, a grey level threshold of 550 succeeded in removing most of the snow-covered areas from further analysis, including most of the snow-covered road. With the summer image, the road and its shoulders were masked by manually delineating them on the image.

Also, because of its basic premise (i.e., shade between trees), some pre-processing is usually desirable in the more open, lower density forested areas, where non-shaded background material is often visible between tree crowns. A pixel-based classification or a texture analysis is occasionally helpful. However, this can have important side-effects. For example in this study, the very open stand of large Norway spruce trees could not be adequately analyzed on the summer imagery because crown-like reflectance from grassy areas between the trees could not be reliably removed. As part of preprocessing, the input illumination image (here, the panchromatic band) is usually smoothed using a 3x3 mean filtering kernel, as the valley following process is facilitated by smooth spectral topography. The rule-based isolation process, which is run after the valley following process, finishes the delineation of crowns on an object-by-object basis. Various combinations of filtering and spatial resampling were tested regarding both ITC crown delineation and the Tree Tops crown detection. It was found that a doubling of the spatial resolution (to 0.5 m/pixel) by cubic convolution followed by a 3x3 mean filtering was most effective. The algorithms function better when there are not too few pixels per crown. This resampling appears to preserve or even enhance the image intensity topography that characterizes the shadow between trees and peaks of the trees, and provides a reasonable number of pixels per crown.

V. Individual Tree Crown Classification

Using a multispectral dataset, an ITC-based supervised classification typically proceeds as follows:

a) Representative samples of crowns, picked individually or within training areas, are used to generate signatures for every class,

b) a maximum possibility classification process is run to discover the species of every tree in the image, and,

c) the ITC classification is evaluated with single species test areas (or individually identified test trees) from which a confusion matrix is generated; alternately, the classification can be tested on a stand- composition-basis via field samples (e.g.,plots, transects).

VI. Proposed Method for Satellite Images

6.1 Shadow Detection Algorithm:

There are number of algorithms for the detection shadow. presented shadow detection methods can be generally categorized into two groups [6]: model-based methods and feature-based methods. In the first group, it is based preceding information such as scene, moving targets, and camera height to make shadow models [7], [8]. These methods are regularly used in some specific scene situations such as aerial image analysis and video monitoring. The second method identifies shadow areas with information of grayscale, brightness, saturation, and quality. By combining the two methods we can construct improved algorithm [4]. At first, the shadow area estimation is done according to the space coordinates of trees or objects intended from digital surface models, the altitude and azimuth of the sun. Then, to precisely identify shadow, the threshold value is set which is calculated from the predictable grayscale value of the shadow areas. Generally most shadow algorithms for detection are based on shadow features. For example, the shadow area is appears like low grayscale value in the image, and for the threshold value is chosen between two peaks in the grayscale histogram of the image data to separate the shadow from the non shadow region [3], [9]. According to many theories, images are transformed into different invariant color spaces like HSV, HCV, YIQ to gain shadows with Otsu's algorithm [11]. This helps to avoid the false shadow shaped by undergrowth in assured invariant places. According to that work, for the shadow detection a consecutive thresholding method was proposed. To eliminate the artificial shadows of dark things such as moist soil, the normalized difference vegetation index, the normalized saturation–value difference index and the size and shape of the shadow area are considered. Recently, to detect shadows, a hierarchical supervised classification scheme was used.

For the recognition by Tsai algorithm of color airborne image, the input image can be first altered into hue, saturation and intensity (HSI) or other like luma, blue difference chroma, red difference chroma (YCbCr) or in hue, chrome and value(HCV) color model [5-6]. Under transformed or altered invariant color model, ratio map is construct by calculation of ratio of hue over the intensity and then the global thresholding is used to recognize the shadow. Tsai algorithm detection performance is more precise for HSI model by comparing with preceding work. In our new method, at first we change RGB color aerial image in to the gray image and then applied the global thresholding plan using otsu's method to create a shadow map used for the classification of input color image into the shadow pixels and non-shadow pixels. By applying both the methods on same image, we observe that the accuracy of the latest technique is more than the previously available Tsai method.

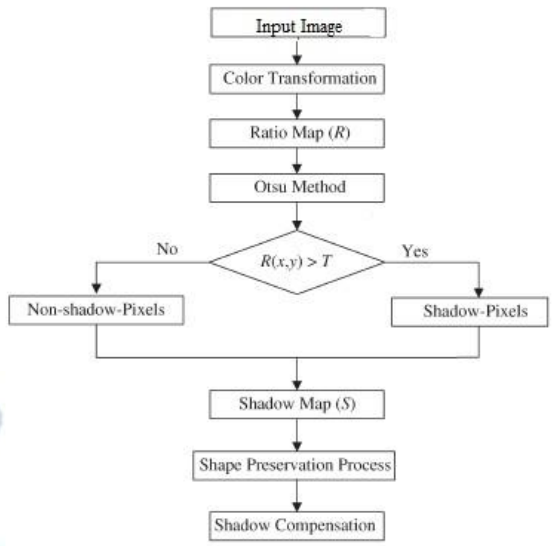


Fig 1: Proposed Algorithm

The flow chart of the Tsai method is shown in fig.1. In this algorithm, color alteration is applied on the input RGB color image into invariant color model like HIS, HCV, YIQ, or YCbCr . to transform the RGB color image into his color model following formula is used:

$$\begin{bmatrix} I \\ V1 \\ V2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{\sqrt{6}}{6} & -\frac{\sqrt{6}}{6} & -\frac{\sqrt{6}}{6} \\ \frac{1}{6} & -\frac{2}{6} & 0 \end{bmatrix} \quad (1)$$

$$H = \begin{cases} \tan^{-1}\left(\frac{V_2}{V_1}\right), \; if \; V1 \neq 1 \\ H \quad is \; undefined \end{cases} \quad (2)$$

After this we calculated the ratio map R by using formula no. (2), which is used to decide whether pixel is shadow pixel or non-shadow pixel by comparing with threshold 'T'.

$$R(x,y) = \frac{H_e(x,y)+1}{I_e(x,y)+1} \quad (3)$$

Where R(x, y), H_e(x, y) and I_e(x, y) are pixel position at(x, y) of R, image H_e and image I_e respectively. In Tsai method the range of R(x, y) is [0-255].

For the calculation of threshold 'T', Otsu method is used. After calculation of T and comparing it with ratio map R, we take decision about shadow pixel like if the R is less than threshold then it is non shadow pixel and if it is greater than threshold then that pixel is shadow pixel.

$$S(x,y)=\begin{cases}1, R(x,y)>T \\ 0, \quad \text{otherwise}\end{cases} \qquad (4)$$

6.2 Shadow Removal Algorithm:

We present a method for shadow removal from un-sourced imagery based on the observation that the projection angle which yields the minimum entropy produces a grey-scale image which is invariant of illumination conditions; hence, shadow-free. Shadow edges can then be located by intersecting the edges in the shadow-free image and the original image. By thresholding the edge information, and reintegrating the gradient, we arrive at the shadow-free 3-band color image. Results of our experiments suggest that this method is appropriate for natural images when camera information is not available, with some constraints on image compression levels.

Shadow removal is a well addressed problem in computer vision due to the negative effect shadows pose on object tracking, segmentation, recognition and etc. A shadow is caused by a change in illumination intensity and color [1]. Human vision is robust to changes in illumination; hence, it is possible for humans to recognize colors in the presence of different lighting conditions (such as shadows). Mimicking this process for images is known as the color constancy problem [2]. In this work, we try to remove shadows from images by producing an illumination invariant grey scale image. In previous approaches, the angle for an invariant direction was found by camera calibration. However, to make our approach adaptable to any camera without calibration, we build on the observation that the correct projection angle is the one that minimizes the entropy [3]. Projecting in to the correct angle produces a 1-D grey scale image (as shown in Figure 1). After acquiring the grey scale image, we recover the shadow-free L-1 chromaticity image by adding back the light of the brightest pixels. As the final step, we find the shadow mask from the edge maps of the original image andv the invariant image, which is reintegrated to produce the 3-band shadow less color image.

Algorithm

Input: RGB Image with shadow.

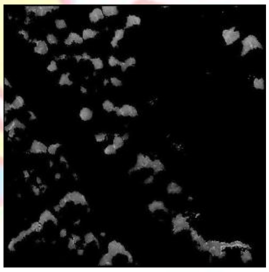
1. Adjust the intensity of satellite image.
2. Extract R, G, B using median filter.
3. Calculate shadow ratio for masking the shadow.
4. Apply threshold to extract the shadow mask.
5. Apply fusion technique on both original image and filtered image.

Output: Shadow free image.

VII. Results and Discussion

(A) Input Image

(B) Shadows detected from input image



C) Shadows removed from B image

(C) Recovered shadow free image

Fig 2: Proposed Algorithm for shadow detection and removal from satellite images

In the above, Fig.2(A) shows a remote sensing satellite image of an urban area with trees it contains shadows cast by the elevated objects, i.e., trees. Fig.2(B) shows the shadows detected, the shadows are shown in red color. The buffer area around each shadow is shown in Fig.2(C).It can be seen that the shadows are removed quite efficiently as shown in Fig.2(D).

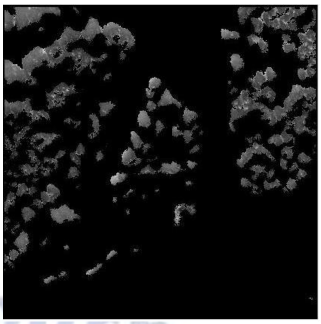
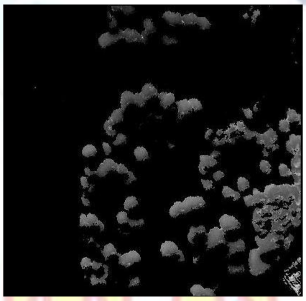
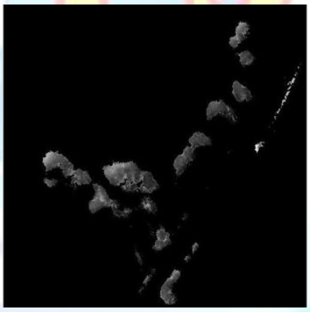
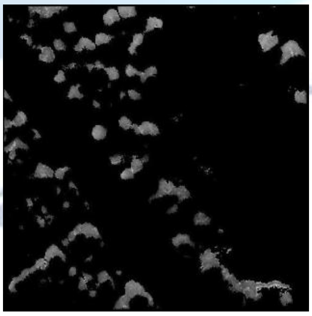
Test samples/input image (A)	Detected shadow image(B)	Shadow obtained from (B)	Shadow removed (C)
1. 			
2. 			
3. 			
4. 			

Table 1: The different test samples of satellite images

A special case for detection are small trees which are either young or severely pruned each year, resulting in a crown which is smaller than the resolution cell size of VHR infrared satellite imagery. Examples of these trees are shown in the above Table 1, where crown diameter is less than 3 meters for the shown trees. Due to sun illumination and reflectance of vegetation in the infrared, a local radiometric peak is found near the center of tree crowns.

VIII. Conclusion

For shadow detection, in urban high resolution remote sensing image we have put forward efficient method. To detect shadows and then uses Otsu's thresholding method for this purpose. After the shadows are detected, they are removed by using the illumination invariant value of the buffer area around each shadow .The buffer area is estimated with the morphological operators. The results are quite efficient and it is seen that shadows are detected properly. The shadow free image is also quite efficient and the areas under the shadow are illuminated.

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