A REVIEW ON SHADOW DETECTION AND REMOVAL FOR OCCLUDED OBJECT INFORMATION RECOVERY IN URBAN HIGH RESOLUTION SATELLITE IMAGES

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Abstract : ***The presence of shadows in high-resolution satellite image can occlude some of the objects in the image. This problem mainly caused in urban areas. Shadows are usually cast by long objects such as buildings and towers in urban areas. The existence of shadows may cause loss of feature information, false color tone and shape distortion of objects, which seriously affect the quality of images. In order to restore the obscured object information shadow detection and shadow removal is an essential pre-processing step. To find the best shadow detection and removal methods a large number of researches have been going. Many algorithms and methods had been developed so far. This paper is aimed at the study of different shadow detection and removal algorithms for urban high resolution satellite images.***

IndexTerms - Shadow Detection, Shadow Removal, VHR images

I. INTRODUCTION

In recent years satellite images are one of the most powerful and important tools used by the meteorologist. They are essentially the eyes in the sky. These images reassure forecasters to the behaviour of the atmosphere as they give a clear, concise, and accurate representation of how events are unfolding. It would be extremely difficult to forecasting the weather and conducting research without satellites. Satellite images provide data that can be interpreted "first-hand". Satellites images give a good representation of what is happening at every point in the world, especially over oceans where large gaps in data occur. The high resolution remote sensing data opened new time in remote sensing field, various remote sensing satellites like IKONOS, QUICKBIRD, BIRD, RESOURCE3 and so on are risen for the perception of earth ,and their flying advancement. Consequently there is an increase in need to process these remote detecting pictures. But these high determination pictures has few downsides like presence of shadows, which strongly affect the interpretation of satellite images. Also 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. The shadows causes the partial or total loss radiance information, particularly that of occluded objects by the large shadow. In that case, the objects in the shadow regions are difficult to be extracted for further applications. Shadow detection and shadow removal is an essential preprocessing step in urban high resolution satellite images for restoring the obscured objects. Many effective algorithms of shadow removal have been proposed for natural images or remote sensing multispectral images.

Shadows are formed when a fraction of direct light from a source of illumination is blocked, as shown in “Fig. 1” the phenomenon frequently occurs in dense urban areas. It is very important to solve the shadow problem for urban object applications in very high resolution satellite images. Shadows can be categorized into two classes: self-shadows and cast shadows. Self-shadow occurs on the portion of the object which is not illuminated by the direct light; whereas cast shadow is projected by the object in the direction of sunlight. Cast shadows can be further categorized into the umbra and penumbra. In the umbra, the direct light is fully obscured, whereas for the penumbra, only a fraction of direct light is blocked. The penumbra is often located at the transition between umbra and sunlit regions in the scene and as a result it may be ambiguous on the image. Fortunately, it generally only occupies a small percentage of cast shadow.

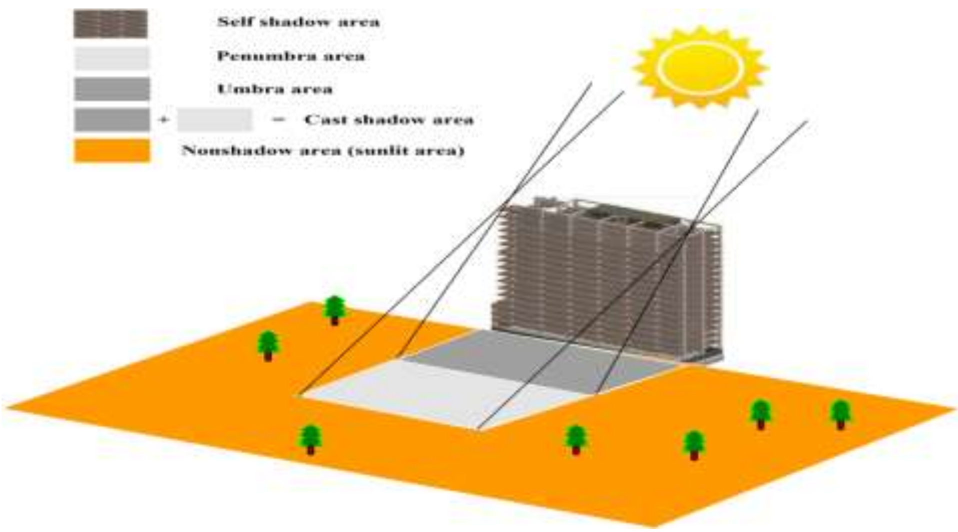

Figure 1. Formation of the shadow

II. SHADOW DETECTION AND REMOVAL METHODS

Many effective algorithms have been proposed for shadow detection as well as shadow removal. Here we are discussing a few methods related to shadow detection and shadow removal.

2.1 Shadow Detection

High-resolution satellite-based imaging sensors (Eg: Quickbird, Ikonos) provide one band of panchromatic data and four bands of multispectral data. The choice of which bands to use for shadow detection (panchromatic, multispectral, or a combination of both) depends on the type of detection algorithm. spatial detection will require higher spatial resolution, whereas spectral detection (Eg: classification) will require greater spectral resolution. Three techniques are presented below for separating shadow pixels from non-shadow pixels such as classification, segmentation, thresholding, and geometric modelling. Each of these procedures is described in more detail below.

2.1.1 Thresholding

Thresholding is the simplest method of binarizing an image by setting all pixels whose values are greater than some threshold level to “high”, and the remaining pixels to “low”. One of the main problem associated with thresholding is, selecting the most suitable threshold level to separate desired features from undesired features. Since the shadows in high resolution satellite images occupy the lower end of the histogram, thresholding is a potentially ideal method of shadow detection. Thresholding should be straightforward method to separate shadow from non-shadow if we choose a correct threshold level, without too many pixels being misclassified. Thresholding as a method of shadow detection has been used by many previous researchers. Nagao et al. [1] used bimodal histogram splitting as a method of shadow detection in high-resolution aerial photographs. Bimodal histogram splitting provides a feasible way to find the threshold for shadow detection. In this method a threshold value is obtained according to the histogram of original image and then find the suspected shadow objects by comparing the threshold and gray scale average of each object obtained in the segmentation. Shettigara and Sumerling [2] thresholded SPOT images to extract shadows of buildings and trees, but due to the low resolution of the data, there was no distinct peak in the histogram denoting shadow pixels.

2.1.2 Classification

Image classification is most commonly used with multispectral data, rather than panchromatic data, to extract image features. However, the lower resolution of the Ikonos multispectral data (4 m compared to 1 m for the panchromatic data) the spatial precision of shadow boundaries detected by classification of the multispectral image would be poorer than shadow boundaries extracted from the panchromatic image. Classification was tested with both multispectral data and single band panchromatic imagery. Both images were classified using an unsupervised classification algorithm in order to give two final classes: shadow and non-shadow. The tests showed that results for both the panchromatic data and the panchromatic data were almost identical.

2.1.3 Region Growing Segmentation

Segmentation is simply the process in which an image is split into a contiguous spatial array of discrete regions (Gonzalez and Woods [3]). Unlike with classification, in region growing segmentation pixels are assigned to regions based on their spatial and spectral distance from those regions to which they could be assigned. The main problem with region growing segmentation is that the result is dependent on the starting points (seed points) from which regions are grown. Since shadows generally represent the lowest pixel values in the image in shadow detection, this problem is much less issue, and thus the points with the lowest grey values in the image can be used as seed points from which regions can be grown. However, at first the criteria by which pixels are assigned to a segment must be defined. The common approach is to use the spectral distance between the pixel in question and the mean grey value of the neighbouring region: pixels which are radiometrically too distant from the region will not be added. Another problem associated with this method is, what distance should be used to ensure maximum likelihood of agglomerating all the shadow pixels with fewest non-shadow pixels added. The solution to choosing the optimum parameter for pixel agglomeration comes once again from an examination of the histogram of the shadowed image.

2.1.4 Three Dimensional Modelling

Each of the above described shadow detection methods uses the radiometric properties of the image to detect shadows. An alternative technique is to use knowledge of the imaging geometry and solar illumination at the time of image acquisition. This method has been used by Rau et al. [4] in urban areas, and Giles [5](2001) in mountainous areas. It focus on knowledge of the three-dimensional structure casting the shadows, which in an urban context would be a 3D city model and the corresponding underlying terrain model. Assuming a sufficiently accurate city model is available, simple geometry that can be used to determine in ground coordinates, which points will be in shade and which will be directly illuminated. This information can then be re-projected back into the image to separate shadow pixels from non-shadow pixels. The problem of this method is the acquisition or creation of a suitably accurate city model. If a model cannot be acquired from a source such as a topographic database, then either significant manual processing is required to create one from high resolution imagery or automatic processing must be used. However, the difficulties of automatically creating accurate 3D city models from aerial or satellite imagery are well documented (Gülch, 2000; Fraser et al.,) [6]. Due to the limited availability of stereo data and the high cost of precision data high-resolution satellite imagery poses more difficulties.

2.2 Shadow Removal

After the shadow detection we have to restore the obscured object information. Some methods for restoring the object information are described below.

2.2.1 Masking

The most straightforward method for removing shadows from imagery after they have been detected is to simply mask them out, i.e., set all shadow pixels to black. The result is an image with no shadows, but even less information than the original image. For manual interpretation, this approach to shadow removal is not favoured, since in many cases the shadows are actually useful for recognizing buildings. In automatic image interpretation, for example classification, the removal of a complete class will reduce the likelihood of pixels being misclassified as this class. However, if the shadow class is well-defined, misclassification may well be unlikely to occur, and hence, pre-classification masking is unnecessary.

2.2.2 Multi Source Data Fusion

Multisource data fusion is another technique for shadow removal. This method has already been applied to removal of cloud shadows in low resolution satellite imagery (Wang et al.) [7], but its application to high resolution images of urban environments poses a much more significant challenge. The procedure works by replacing shadow pixels in one image with non-shadow pixels of the same region on the ground from another image acquired at a different time. Although useful in low and moderate resolution imaging, there are a number of clear problems with applying this technique to high-resolution satellite imagery. First, since the limitations on image acquisition time will lead to the same regions on the ground being in shadow, it is unlikely that non-shadowed data can be extracted from another high-resolution satellite image. Second, assuming non-shadowed data is available (from another source, such as aerial photography), the question must then be asked: if aerial photography is available to fuse with the satellite imagery, why is the satellite imagery required at all? Third, assuming there is good reason to fuse aerial photography and high-resolution satellite imagery for shadow removal, the problem of radiometric differences between the two sensors must be addressed: high-resolution satellite imagery has four bands (near infrared, red, green, blue) while aerial photography is either greyscale, color or color infrared. Thus, there is no guarantee that patching in data from aerial photography to eliminate shadows in high resolution imagery is going to aid image interpretation, such as classification. Finally, there is the problem of image registration: the images must be accurately registered to each other to ensure the correct pixels are being used in the fusion procedure. In a region where there is little topographic variation, this is not a problem. However, in a high density urban environment accurate image registration poses significant problems. The only real solution is to perform rigorous photogrammetric processing on all the data sets to be registered, a procedure which would necessarily require a high-resolution 3D city model. As a result of these issues, it would not be a useful exercise to evaluate multisource data fusion as an option for shadow suppression in high-resolution imagery in urban environments.

2.2.3. Radiometric Enhancement

Radiometric enhancement as a method of reducing the severity of shadows in high-resolution imagery has been proposed by Shu and Freeman [8] and Rau et al.[4]. The technique described, based on histogram matching, is similar to image balancing in orthomosaic generation: the histograms of neighbouring regions are adjusted to match each other in order to minimize the radiometric differences across the boundary of the regions. Shu and Freeman [8] proposed three methods to carry out this task: an algebraic greyscale transformation, histogram equalization, and a mean and variance transformation; they found the third method to be most successful. Since the radiometry of an image can vary spatially quite considerably, histogram matching is best carried out on a local rather than global level. It is beneficial to match the histogram of the shadow with the histogram of the region immediately surrounding the shadow. However, unless individual buildings and their corresponding shadows are spatially isolated from each other, matching on a region by region basis can be very difficult to achieve in practice. In such cases there is no other option but to use the statistics for the entire shadow region.

III. CONCLUSION

In conclusion, among the various methods that were studied, there is no 'the best Algorithm/method for shadow detection and removal'. The choice of the best algorithm/method is depend on data-set characteristics which being processed. For any application, a particular classifier which performs very well it may also give poor performance in a different setting. As well the cost plays import role while selecting the algorithm.

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