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SHADOW DETECTION AND RECONSTRUCTION OF IMAGES FROM SATELLITE IMAGES: GIS

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ABSTRACT

The increase in spatial resolution has enabled analysis and detection of images obtained through satellite. To increase the accuracy in image processing, an unwanted shadow needs to be processed effectively. A quality check mechanism governs the false reconstruction problems. In the proposed paper we would like to suggest use of Lib SVM algorithm. The original image obtained from satellite is first supervised to identify shadow and non shadow regions. The shadow region is then filtered using morphological filter and a border is created around shadow. With the help of Lib SVM algorithm the shadow image can be removed using post classification methods and shadow free image can be obtained.

KEYWORDS: Morphological Operator, Pattern Recognition, Reconstruction of Images, Shadow, Spatial Resolution, Vector Machine Approach

INTRODUCTION

The remote sensing of an object has become possible because of very high resolution (VHR) satellite images. The increase of spatial resolution demands new analysis, classification, and change in detection techniques. The objects, like small building structures, trees, vehicles, and roofs can be revealed with the help of VHR images. In urban areas the presence of high rise structures such as buildings, towers causes large change in surface elevations and results in longer shadows. Though shadow characteristics are used in recognition of building position, height and other useful parameters it may cause a high risk to produce false color tones, to distort the shape, to merge, or to lose objects. Due to the partial or total loss of information in the image, shadows may impact adversely in the exploitation of VHR images as it influences detailed mapping that leads in flawed classification/interpretation. To soothe these drawbacks and to increase image credulous ability, two steps are necessary.

- Detection of Shadow
- Reconstruction of Shadow

The shadow detection algorithms are based on properties, such as lower brightness, higher saturation, and greater hue values. There exist essentially three different methods: 1) Gamma Correction 2) Histogram Matching 3) Linear Correlation, in order to compensate/reconstruct shadow areas.

Shadows can be removed by contextual texture analysis performed between a segment of shadow and its neighbors. Knowing the kind of surface under the shadow, a local gamma transformation is then used to restore the shadow area. Once the shadow detected, the HIS values in shadow regions are adjusted respectively according to the analogous values in the local surrounding of each shadow region by adopting the histogram matching method. The method consists of recovering spectral information in shadow areas in an IKONOS image by exploiting the height data from the airborne laser scanner. Such information is used to overlay and eliminate the real shadow.

The whole processing chain includes also two important capabilities:

- A rejection mechanism to limit as much as possible reconstruction errors
- Explicit handling of the shadow borders

PROBLEM DEFINITION

In the urban areas, the presence of shadows destroys the information contained in their images. This missing Information in shadow areas directly influences common processing and analysis operations, such as the generation of classification maps. By considering these problems, we tried to find solution for this problem using Lib SVM Algorithm.

- Identification of the Shadow and non shadow area
- Separate shadow and non shadow area of the image
- Reconstruction of the Shadow area

LITERATURE SURVEY

Shadow

A shadow is an area where direct light from a light source cannot reach due to obstruction by an object. There have been few studies concerning shadow removal, and the existing approaches cannot perfectly restore the original background patterns after removing the shadows.

Assumptions of Shadow

Here are our basic assumptions as follows

- The illumination image is spatially smooth.
- There is no change in the texture inside the shadow region.
- In the shadow regions, the illumination image is close to being constant. Pixels inside shadow regions have different colors because of the reflectance image, not the illumination one Self and Cast Shadow: Shadow detection and removal is an important task in image processing when dealing with the outdoor images. Shadow occurs when objects occlude light from light source. Shadows provide rich information about the object shapes as well as light orientations. Some time we cannot recognize the original image of a particular object. Shadow in image reduces the reliability of many computer vision algorithms. Shadow often degrades the visual quality of images. Shadow removal in an image is an important pre-processing step for computer vision algorithm and image enhancement.

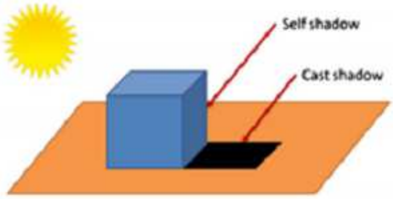

Figure 1: Illustration of Cast and Self Shadows

Shadow Detection Techniques

Table 1

Sr. No	Method	Key Idea	Advantages	Disadvantages
1	Region growing	Seed pixels have been selected and set as shadow group mean and standard deviation are calculated.	Orientation based technique	Region growing failed when the pixel intensity varied widely in the shadow region.
2	Dual pass Otsu method	Pixels value is separated into high and low level intensity. Threshold is set to distinguish between self and cast shadow. Cast shadow pixels are than replaced by background pixels.	It is computational inexpensiveness.	Performance is poorest.
3	Edge subtraction and Morphology	Canny edge detection is used to detect background edge and foreground edge. Resultant edge image is calculated by difference of both background and foreground edge centered of vehicle shadow region is found by formula.	Method is best when scenes containing light and dark vehicles	It is most computationally expensive
4.	Gradient based background subtraction	Fixed threshold is set for T vertical and T horizontal boundary of object is extracted using neighbored ratio. Foreground is extracted by using mixture of Gaussians.	Location is used to detect the shadow. Shadow detection is done correctly .Real time application take advantage of the algorithm.	
5.	Based on intensity Information	Standard deviation is calculated for ratio value. Conditions are set for a shadowed pixel.		Actually the pixel intensity value is susceptible to illumination changes.
6	Based on photo metric invariants information	Intensities in the neighbor pixels in the foreground region is equal to the ratio of neighbor pixels in the background image in the presence of shadow	Performance is better by using robust features. It takes little time. The average time consumption is good for real-time application.	
7	Partial Differential Equations.	Different filters are used to smooth the image. Gradient vector is used to detect shadow. Image information is used.	Shadow detection is successful and effective.	

PROPOSED METHOD

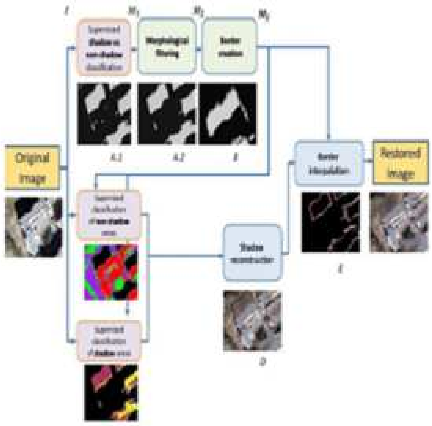

Figure 2: Flow Chart for Proposed Method

DESIGN STEPS

Mask Construction

The shadows versus non-shadow mask are created in two steps:

- Binary Classification
- Post-Processing

Binary Classification

This classification is implemented using support vector machine (SVM), which proved its effectiveness in the literature of remote sensing data classification. The feature space where the classification task is performed is defined by the original image bands and features extracted by means of the wavelet transform. In particular, a one-level stationary wavelet transform is applied on each spectral band, thus obtaining for each band four space-frequency features. The symlet Wavelet is adopted in order to maximize the sparseness of the transformation while enforcing texture areas. For an original image *I* composed of *B* spectral bands, the resulting feature space thus consists of $B \times (1 + 4)$ dimensions.

Post Processing

The binary image M1 may be characterized by a “salt and pepper” effect due to the presence of noise in the image. An opening by reconstruction, followed by a closing by reconstruction, is applied on M1 to attenuate this potential problem. The choice of morphological filters to deal with this problem is motivated by their effectiveness and better shape preservation capability as shown in the literature and by the possibility to adapt them according to the image filtering requirements as is the case in the border creation. Both morphological operators are needed in order to remove isolated shadow pixels in a non shadow area and also isolated non shadow pixels in a shadow area.

Border Creation

The transition in between shadow and non shadow areas can raise problems such as boundary ambiguity, color inconstancy, and illumination variation [9].

Indeed, the presence of the penumbra induces mixed pixels which are difficult to classify. The penumbra is a region where the light source is only partially obscured. For this reason, a border between the shadow and non shadow classes is defined in order to appropriately handle the border pixels. These lasts are not processed within the shadow reconstruction procedure as is, but separately. The border region is constructed by means of morphological operators. The mask c_imgB2 is dilated (δ) and eroded (ε).Then, the difference between these two images is computed to form the border image B:

$$B[x, y] = \delta\,(c\_imgB2[x, y]) - \varepsilon\,(c\_imgB2[x, y]) \tag{1}$$

The Final Mask Image becomes:

$$C\_imgB_{NEW[x,y]} = \begin{cases} B[x,y] & \text{if } B[x,y]=1 \\ c_{imgB2[x,y]} & \text{if } B[x,y]=0 \end{cases}. \tag{2}$$

Shadow Reconstruction

Image reconstruction is one of the most important steps in our methodology. For the sake of getting a simple but satisfactory reconstruction model, we assume that the underlying relationship between the non shadow class (*Y*) and the corresponding shadow classes (*X*) are of the linear type [10]. We have empirically observed that shadow classes and the corresponding non shadow classes reasonably exhibit a linear relationship. Regarding the statistical model of the classes, three estimation ways may be envisioned. Histogram estimation done by box counting, Kernel density estimation. We assume that the classes follow a Gaussian distribution. Although it can be expected that such a hypothesis does not always hold, it is however useful to get a simple and fast solution to the reconstruction problem. Indeed, denoting the shadow class as:

$$X \sim N(\mu_s, \sigma_s^2) \tag{3}$$

And the corresponding non shadow class as:

$$Y \sim N(\mu_s, \sigma_s^2) \tag{4}$$

The reconstruction of the shadow class will be reduced to a simple random variable transformation:

$$X \sim N(\mu_s, \sigma_s^2) \rightarrow X' \sim N(\mu_s, \sigma_s^2) \tag{5}$$

Where: μ and Σ stand for the mean and covariance matrix, respectively. Since the two distributions are assumed linearly correlated, *x* and *y* may be linked by

$$y = Kx + c \tag{6}$$

$$\mu_{\bar{s}} = K\mu_s + c \tag{7}$$

$$\Sigma_{\bar{s}} = K\Sigma_s K^T \tag{8}$$

Where *K* is a transformation matrix, *KT* is its transpose, and *c* a bias vector. To estimate *K* and *c*, the Cholesky factorization is applied

$$c = \mu_{\bar{s}} - K\mu_s \tag{9}$$

$$K = U_{\bar{S}} V_s^{-1} \tag{10}$$

Where: c and K are the lower and upper triangular Cholesky matrices related to the non shadow and shadow classes, respectively. Once *K* and *c* are estimated, equation applied to compensate the pixels of the shadow class. Note that this process needs to be carried out for each couple of shadow and non shadow classes.

EXPECTED RESULTS

Figure 3

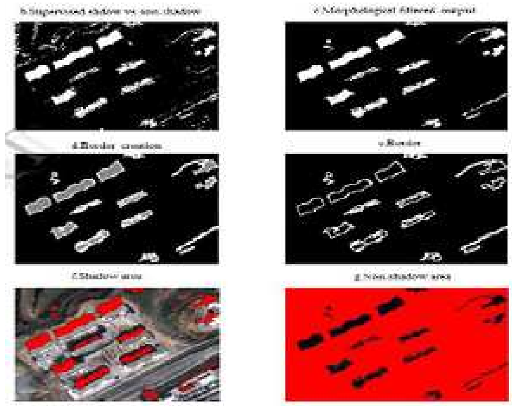

Figure 4

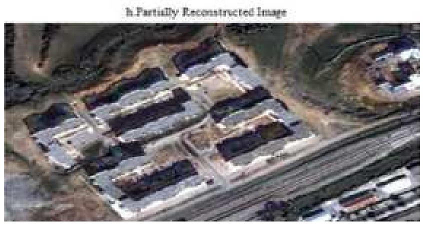

Figure 5: VHR Image Simulation Results

CONCLUSIONS

For VHR images, the proposed methodology is supervised. The shadow areas are not only detected but also classified so as to allow their customized compensation. The classification tasks are implemented by means of the state-of-the-art SVM approach.

Drawbacks and Limitations

The proposed method for detecting and removing of shadows described may not be up to expectations in some conditions such as presence of darker regions and thus may be detected as shadows thus will be removed. Secondly, in the proposed method shadows are removed partially, not completely.

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