RESEARCH ARTICLE OPEN ACCESS

Detection and Reconstruction of Images from Satellite Images: GIS

Mr. Vinod Shinde*, Ms. Pallavi Bafna**
*(Department of Electronics, North Maharashtra University, Jalgaon)
*(Department of Electronics, North Maharashtra University, Jalgaon)

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.

I. INTRODUCTION

Recently, very high resolution (VHR) satellite images opened a new era in the remote sensing field. Because of the increase of spatial resolution, new analysis, classification, and change detection techniques are required[1]. Indeed, VHR images exhibit resolutions which give detailed features from small objects, like little building structure, trees, vehicles, and roofs. In the high spatial resolution have some drawbacks like the unsought presence of shadows, particularly in urban areas where there are larger changes in surface elevation (due to the presence of buildings, bridges, towers, etc.) and consequently longer shadows. Although it is feasible to exploit shadow characteristics to recognize building position, estimate their height and other useful parameters. Usually, shadows are viewed as undesired information that strongly affects images. Shadows may cause a high risk to present false colour tones, to distort the shape of objects, to merge, or to lose objects [5]. They represent an important problem for both users and sellers of remote sensing images. Shadows can impact negatively in the exploitation of VHR images, influencing detailed mapping, leading to erroneous classification or interpretation (e.g., biophysical parameters such as vegetation, water, or soil indexes), due to the partial or total loss of information in the image. To attenuate these drawbacks and to increase image exploitability, two steps are necessary.

1. Shadow detection
2. Shadow compensation (reconstruction).

Most of the detection algorithms are based on shadow properties, such as the fact that shadow areas have lower brightness, higher saturation, and greater hue values. In order to compensate/reconstruct shadow areas, there exist essentially three different methods: 1) gamma correction; 2) histogram matching; and 3) linear correlation [5].

To remove shadows, contextual texture analysis performed between a segment of shadow and its neighbours. Knowing the kind of surface under the shadow, a local gamma transformation is then used to restore the shadow area. After the detection of shadows, 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 [4]. 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 [4].

The whole processing chain includes also two important capabilities:

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

II. PROBLEM DEFINITION

In the urban areas, the presence of shadows may completely destroy the information contained in those images. Information missing in shadow areas directly influences common processing and analysis operations, such as the generation of classification maps. By conciedering these problems, we tried to find solution for this problem using LibSVM Algorithm.

1. Identification of the Shadow and non shadow area
2. Saperate shadow and non shadow area of the image
3. Reconstruction of the Shadow area.

III. 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 restorethe original background patterns after removing the shadows.

B) Assumptions of Shadow: Here are our basic assumptions are as follows

1) The illumination image is spatially smooth.
2) There is no change in the texture inside the shadow region.
3) In the shadow regions, the illumination image is close to being constant. Pixels inside shadow regions have different colours because of the reflectance image, not the illumination one

C) 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.

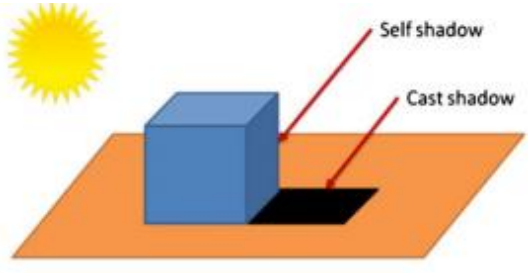


Fig. 1. Illustration of cast and self shadows.[7]

Various Methodologies Of Shadow Detection

Shadow detection is applied to locate the shadow regions and distinguish shadows from foreground objects. In order to systematically develop and evaluate various shadow detectors, it is useful to identify the following three important quality measures: (a) Good detection (low error probability to detect correct shadow points should occur). (b) Good discrimination (the probability to identify wrong points as shadow should be low, i.e. low false alarms rate). (c) Good localization (the points marked as shadows should be as near as possible to the real position of the shadow point). There are two general approaches based on shadow properties to detect shadow.

<u>Model Based Techniques</u>

In this, the 3D geometry and illumination of the scene are assumed to be known. This includes the sensor/camera localization, the light source direction, and the geometry of observed objects, from which a priori knowledge of shadow areas is derived. For example, consider polygonal regions to approximate the shadows of buildings or urban elements in some simple urban scenes. However, in complex scenes with a great diversity of geometric structures, as it is usually the case of quick bird images, such models are too restrictive to provide a good approximation. In addition, in most applications the geometry of scene and/or the light sources are unknown.

<u>Image Based Techniques</u>

This makes use of certain image shadow properties such as colour (or intensity), shadow structure (umbra and penumbra hypothesis), boundaries, etc., without any assumption about the scene structure. Nevertheless, if any of that information is available, it can be used to improve the detection process performance. Some common ways of exploiting image shadow characteristics are:

- The value of shadow pixels must be low in all the RGB bands. Shadows are, in general, darker than their surrounding, thus it is delimited by noticeable borders (shadow boundaries).
- Shadows do not change the surface texture. Surface markings tend to continue across a shadow boundary under general viewing conditions.
- In some colour components (or combination of them) no change is observed whether the region is shadowed or not, that is, this is invariant to shadows.

<u>Colour/ Spectrum Based Techniques</u>

The colour /spectrum model attempts to describe the colour change of shaded pixel and find the colour feature that is illumination invariant. some investigated the Saturation-Value (HSV) colour property of cast shadows, and it is found that shadows change the hue component slightly and decrease the saturation component significantly. The shadow pixels cluster in a small region that has distinct distribution compared with foreground pixels. The shadows are then discriminated from foreground objects by using empirical thresholds on HSV colour space It was proposed a normalized RGB colour space, C1C2C3, to segment the shadows in still images and video sequences. Some considered the pixel's intensity change equally in RGB colour components and a diagonal model is proposed to describe the colour distortion of shadow in RGB space.

Texture Based Techniques

The principle behind the textural model is that the texture of foreground objects is different from that of the background, while the texture of shaded area remains the same as that of the background. The several techniques have been developed to detect moving cast shadows in a normal indoor environment. The technique proposed which include the generation of initial change detection masks and canny edge maps.

Geometry Based Techniques

Geometric model makes use of the camera location, the ground surface, and the object geometry, etc., to detect the moving cast shadows. The Hsieh [18], Gaussian shadow model was proposed to detect the shadows of pedestrian. The model is parameterized with several features including the orientation, mean intensity, and centre position of a shadow region with the orientation and centroid position being estimated from the properties of object moments.

User interaction methods

A common way to sidestep the difficulty of shadow detection is to assist the detection algorithm with user supplied information. Leaving aside algorithms that require users to input the entire shadow mask, a number of the most recent and best performing methods incorporate user input to either "seed" or correct the detection process. In Wu et al. users are asked to submit a quad-map containing shadow, non-shadow, and penumbra regions of similar textures. Simplifications of these user requirements are focused towards reducing the time spent selecting shadow and non-shadow regions. Wu and Tang employ user-supplied context that indicates candidate shadow regions, Arbel and Hel-Or's method allows a shadow mask to be calculated using only a few key points, and Shor and Lischinski proposed reducing external information to one user-supplied key point per shadow region. Instead of "growing" a shadow region based on a few key points, Drew and Reza calculate invariant images based on a few selected patches in the image. While these detection algorithms are arguably the most accurate ones for still images and can deliver impressive subsequent shadow removal, their requirements are strongly dependent on the complexity of the image. Indeed, an image that contains a single shadow cast on similarly textured background is simple enough to be processed accurately. On the on the other hand, if the scene has a lot of strong material changes in the shadow as well as simultaneous shadow/material changes, e.g., occlusion shadows, it can then become difficult for a user to assess how many key points/patches to input. Moreover, even minimal user interaction prevent the detection algorithm to be adapted to a fully automatic work flow, such as in-camera image processing.

Image-based automatic algorithms

Automatic shadow detection on a single or a couple of images has been addressed in a variety of approaches. Gradient-based methods, where edges are classified as either shadow or material transitions depending on their direction and magnitudes, have been proposed. illumination, showed that grey scale illumination-invariant images could be obtained by projecting an image's log chromaticitis in an appropriate direction comparing the edge content of the original image with the edges of the invariant one effectively yields shadow edges. An approach using similar assumptions than and a tri chromatic attenuation model has been proposed. Despite their relatively simple assumptions, these methods often work well and still are state-of-the-art regarding automatic shadow detection from a single image. None of them, however, account for simultaneous material/illumination changes, which can limit their usefulness in more complex scenes. To minimise the ambiguities induced by simultaneous material and illumination changes, some research has focused towards multi-image (generally two) methods. For instance, flash/no-flash image pairs can be combined to either estimate the illuminant or to remove shadows. The chromagenic illuminant estimation postulated that capturing two images of a given scene, using a broadband coloured filter to capture the second image, and comparing them adequately would produce accurate illumination maps. In the right context, these multi-image algorithms perform remarkably well since being pixel-based methods they can detect soft shadows as well as occlusion shadows. However, that context is oftentimes limited. Flash cannot illuminate all outdoor shadows, and the chromagenic approach requires image segmentation, an accurate training step, and has a non-negligible complexity due to the fact that every pair of trained illuminants has to be tested. On the other hand, the chromagenic approach is not limited to shadows but can incorporate a number of multi-illuminant scenes. In previous work, we proposed that near-infrared information could be used to identify Planckian illuminants among a training set, and showed that approximate, smooth, illumination maps could easily be computed.

IV. PROPOSED METHOD

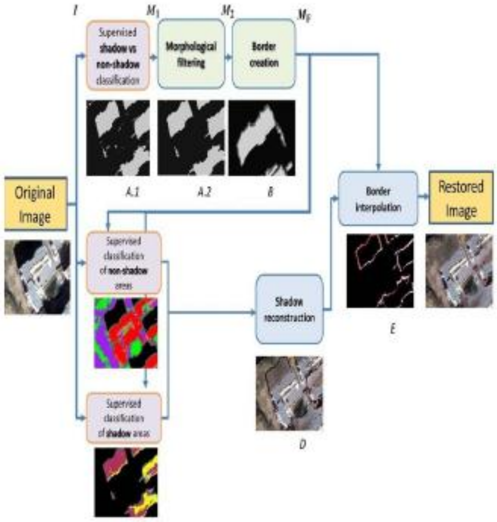


Figure 3. Flowchart of the proposed method for VHR images

V. DESIGN STEPS

A. Mask Construction

The shadow versus non-shadow mask is created in two steps, namely, binary classification followed by a post-processing.

1) Binary Classification: The binary classification procedure [see M1 in Fig. 1] is implemented in as supervised way by means of a support vector machine (SVM), which proved its effectiveness in the literature of remote sensing data classification[6] [7].

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 transforms 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 (most of the coefficients are near 0) while enforcing texture areas(wavelet coefficients are of high value on the presence of singularities). For an original image *I* composed of *B* spectral bands, the resulting feature space thus consists of $B \times (1 + 4)$ dimensions.

2) 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[8]. The choice of morphological filters to deal with this problem is motivated by their effectiveness and better shape preservation capabilites 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 are and also isolated non shadow pixels in a shadow area.

B. 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.

$$B[x,y] = \delta\left(c\_imgB2[x,y]\right) - \varepsilon\left(c\_imgB2[x,y]\right).$$

……..(4)

The final mask image becomes

$$c\_imgB_{NEW}[x,y] = \begin{cases} B[x,y], & \text{if } B[x,y]=1 \\ c\_imgB2[x,y], & \text{if } B[x,y]=0. \end{cases}$$

……….(5)

C. 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 then on shadow class (*Y*) and the corresponding shadow classes (*X*) is of the linear type[10]. We have empirically observed that shadow classes and the corresponding non shadow classes reasonably exhibit linear relationship .Regarding the statistical model of the classes, three estimation ways may be envisioned:

Histogram estimation by box counting, Kernel density estimation,& parametric estimation. In our case, we will adopt the last method by assuming that the classes follow a Gaussian distribution. Al though can be expected that such a hypothesis does not ways hold, it is however useful to get a simple and fast solution to the reconstruction problem. Indeed ,denoting the shadow class as $X \sim N(\mu_S, \sigma_S^2)$ and the corresponding non shadow class as, $Y \sim N(\mu_{\bar{S}}, \sigma_{\bar{S}}^2)$ the reconstruction of the shadow class will be reduced to a simple random variable transformation

$$X \sim N(\mu_S, \sigma_S^2) \rightarrow X' \sim N(\mu_{\bar{S}}, \sigma_{\bar{S}}^2).$$

where μ and Σ stand for the mean and covariance matrix, respectively. Since the two distributions area assumed linear y correlated, *x* and *y* may be linked by

$$y = Kx + c$$
$$\begin{cases} \mu_{\bar{S}} = K\mu_S + c \\ \Sigma_{\bar{S}} = K\Sigma_S K^T \end{cases}$$
……..………(7)

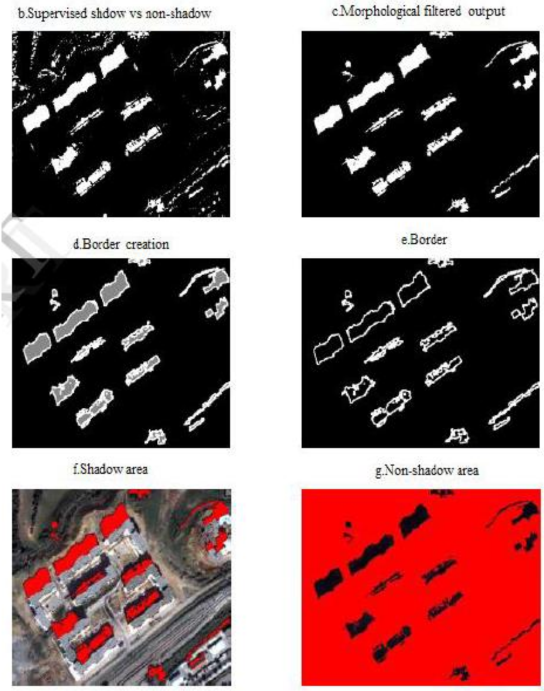
where *K* is a transformation matrix, *KT* is intranspose, and *c* a bias vector. To estimate *K* and *c*, the Cholesky factorization is applied

$$\begin{cases} c = \mu_{\bar{S}} - K\mu_S \\ K = U_{\bar{S}} V_S^{-1} \end{cases}$$
… **……...…..(8)**

where and 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.

VI. Expected Results: VHR Image Simulation Results:

a.Original Image



h.Partially Reconstructed Image

VII. Conclusion

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 S V M approach.

Drawbacks and Limitations

The proposed method for detecting and removing of shadows described in method may fail in some conditions such as presence of darker regions(not shadows) in the image will be detected as shadows and will be removed in the process .Secondly, in the proposed method for detecting and removing shadows in Very High Resolution(VHR)images described shadow reconstruction part ,shadows are not completely removed instead they are partially removed. This is due to lack of obtaining original database of high resolution images. As the proposed algorithm works only for very high resolution images ,it is impossible to get the desired output.

References

[1] J.M. Wang, Y.C. Chung, C.L. Chang, S.W. Chen, "Shadow Detection and Removal for Traffic Images", Proc. IEEE International Conference on Net working, Sensing and Control, vol. 1, pp. 649 –654, 2004.

[2] T. Chen, W. Yin, X.S. Zhou, D. Comaniciu, and T.S. Huang, "Illumination Normalization for Face Recognition and Uneven Background Correction Using Total Variation Based Image Models", Proc. CVPR, vol. 2, pp. 532-539, 2005.

[3] Y. Adini, Y. Moses, and S. Ulman, "Face recognition: The problem of compensating for changes in illumination direction", IEEE Trans. Pattern Anal. Machine In tell. 19(7):721–732, 1997.

[4] T. Kaset kasem and P. K. Varshney, "An optimum land cover mapping algorithm in the presence of shadow," IEEE J. Select. Topics Signal Process.,vol. 5, no. 3, pp. 592–605, Jun. 2011

[5] D. Comaniciu and P. Meer. Mean shift: A robust approach toward feature space analysis. PAMI,24(5):603–619, 2002.

[6] N. Ghoggali and F. Melgani, "Genetic SVMapproach to semisupervised multitemporalclassification," IEEE Geosci. Remote Sens. Lett., vol.5, no. 2, pp. 212–216, Apr. 2008.

[7] T. Habib, J. Inglada, G. Mercier, and J. Chanussot, "Support vector reduction in SVMalgorithm for abrupt change detection in remotesensing," IEEE Geosci. Remote Sens. Lett., vol. 6, no.3, pp. 606–610, Jul. 2009.

[8] P. Soille, Morphological Image Analysis. NewYork: Springer-Verlag, 1999.

[9] V. Tsai, "A comparative study on shadowcompensation of color aerial images in invariantcolor models," IEEE Trans. Geosci. Remote Sens.,vol. 44, no. 6, pp. 1661–1671, Jun. 2006.

[10] Giorgos Mountrakis, Jungho Im, Caesar Ogole "Support vector machines in remote sensing: A review" in ISPRS Journal of Photogrammetry and Remote Sensing.

[11] E. Salvador, A. Cavallaro, and T. Ebrahimi "Shadow identification and classification using invariant color models" in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2001, vol. 3,pp. 1545–1548.

[12] Victor J. D. Tsai "A Comparative Study on Shadow Compensation of Color Aerial Images in Invariant Color Models" in IEEE Trans. Geosci. Remote Sens., vol. 44, no. 6, Jun. 2006.

[13] Ken 'chi Kouchi and Fumio Yamazaki "*Characteristics of Tsunami-Affected Areas in Moderate-Resolution Satellite Images*" in IEEE Trans. Geosci. Remote Sens., vol. 45, no. 6, Jun.2007.