ISSN: 2321-7782 (Online)
Volume 3, Issue 5, May 2015
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

Shadow Detection and Reconstruction in Satellite Images

Afzal F[1]
Signal Processing
College of Engineering Cherthala
Alappuzha, Kerala, India

Abdul Kareem[2]
Signal Processing
College of Engineering Cherthala
Alappuzha, Kerala, India

Abstract: The presence of shadows in very high resolution (VHR) images can represent a serious obstacle for their full exploitation. This work will face this problem as a whole through the proposal of complete processing steps, which deals with various advanced image processing and pattern recognition tools. In high spatial resolution satellite images, shadows are usually cast by long objects such as buildings and towers in urban region. Shadows may cause loss of feature information, false colour tone and shape distortion of objects, which seriously affect the quality of images. This work shows an effective and robust approach for shadow segmentation and compensation in colour satellite images with high spatial resolution. The approach uses normalized saturation-intensity difference index (NSIDI) in Hue- Saturation-intensity (HSI) colour space to detect the presence shadows and exploits linear correlation to recover the information under shadows.

Keywords: shadow detection, shadow reconstruction, very high resolution (VHR) images, normalized saturation-intensity difference index (NSIDI).

I. INTRODUCTION

A shadow which is known to be caused by the interaction of light with objects claims a fraction of the image surface. Shadows in images hold importance for a variety of reasons. On one hand, shadows may lead to the failure of image analysis processes and also cause deterioration in the quality of information which in turn leads to problems in implementation of algorithms say for scene understanding, object recognition and many other applications. But, on the other hand, they aid information as useful in building detection, path finding etc. Since, shadows sometimes create unwanted effects on images, shadow reconstruction is considered important, and detection of shadows is the first step towards the goal. Also, in cases where they act as an aid, shadow detection in images plays a important role. It is used for land monitoring, remote sensing, change detection, image segmentation, face recognition etc. Shadows usually claim most of the space behind opaque objects when light falls on them. Cross section of a shadow is seen as a projection- an overturned one, of the object which blocks light. It is two dimensional. Hence, when light is blocked, an image is produced known as shadow. Shadows can be classified as- self shadows and cast shadows. A self-shadow is one which falls on a part or portion of object whereas cast shadows do not fall on object but are projected on surrounding surfaces. Cast shadows are of two type umbra and penumbra. These regions are created due to multiple lighting. And the difference between the two lies in the contrast they have to the background. Self-shadow generally do not have hard boundaries and hence are referred to as vague, the reason being gradual intensity change. Cast shadows whereas have clearly defined boundaries.

In urban remote sensing images, shadows are usually cast by elevated objects such as various cultural features (buildings, bridges, towers, etc.) when they are illuminated by the Sun at the time of exposures. Shadow in remote sensing image is conflict information in computer image processing application. But, it can reduce the successful rate of edge extraction, object recognition, image matching, change detection and other processing for the corresponding ground objects in the shadow. On the other hand, it can produce a great deal of useful information about shape, relative position, surface character and other characters of the object generating shadow. It is a necessary step to remove shadow and restore the scenes in the shadow area before performing object recognition and image matching tasks for the shadow area. Thus, shadow detection and reconstruction has become very important in image processing. Shadow detection and removal has lot of application in change detection from remote sensing images done to assess damage due to natural disasters like earthquake tsunamis landslides etc. since shadows obstruct the correct extraction of buildings and shadows lead to false detections.

Also shadow is a basic feature in high resolution remote sensed images. Shadows have played an important role in remote sensing for almost as long as the science has been in existence. From the earliest days of aerial photography, the effects of shadowing have been utilized to highlight ground features in applications such as archaeology and aerial reconnaissance. However, shadows are considered a nuisance obscuring important object space detail. Unlike airborne imaging where shadows can be minimized by flying at certain times during the day, low Earth orbit satellite based sensors are limited to acquiring images at fixed times of the day. If the solar elevation is low at the time, then the presence of shadows will be unavoidable. The poor visibility of features in shadows directly influences operations such as object recognition change detection and scene matching. Therefore, the research on shadow is of great significance. The processing of shadow includes the detection of and compensation for shadows.

There are two approaches to detect shadows, namely, model- based and shadow- property-based approaches. The former needs prior information about the scenario and the sensor. 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. There are methods which attempt to detect shadows using a space color transformation and an automatic threshold estimator. Other algorithms rely on the idea of adding features capable to better discriminate shadow areas e.g., normalized difference vegetation index, Normalized Saturation-Value Difference Index (NSVDI), and maximally stable external regions.

There exist essentially three different methods for reconstruction of shadow areas: 1) gamma correction; 2) histogram matching; and 3) linear correlation. If the surface texture is assumed to be not radically changing when it is shaded, a contextual texture analysis can be performed between a segment of shadow and its neighbors to remove shadows. Knowing the kind of surface under the shadow, a local gamma transformation is then used to restore the shadow area. In some other schemes, it is assumed that the restoration of shadows almost depends on the spectral signature of the spectral bands. Accordingly, first, the bands are threshold in an independent way, determining the optimal threshold values by visual inspection. Then, a linear regression in each spectral band is carried out to correct the shadow effects.

Here i implement an alternative method to solve both problems of detection and reconstruction of shadow areas through the proposal of a complete processing chain, which relies on various advanced image processing and pattern recognition tools. The approach uses normalized saturation- intensity difference index (NSIDI) in Hue- Saturation- intensity (HSI) color space to detect shadows and exploits histogram matching to recover the information under shadows. Experimental results by applying the proposed approach in the IKONOS color images of urban area demonstrate the effectiveness and feasibility of the proposed approach.

II. PROBLEM FORMULATION

Disadvantages in the existing methods are dark object under sunlight is detected as shadow and light object in sunlight shadow is detected as non-shadow, dark objects like water cannot be distinguished from shadow, some methods valid only for single objects In VHR optical images, particularly in 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. Normally, shadows appear when objects occlude the direct light from the illumination source, usually the sun. However, shadows are not all the same; they can be divided into two different classes: cast and self- shadows. Cast shadow is caused by the projection of the light source in the direction of the object. Self-shadow is still a shadow but represents the part of the object that is not illuminated directly by the light source. It can come from the diffuse light present in the scene, and it may have a nonlinear behavior.

For simplicity, this work does not distinguish between self an*d* cast shadows. It assumes *that* most of the shadows in a given image belong to the cast type, producing homogeneous dark areas with a loss of information that we desire to recover. Main Disadvantages in the existing methods are: Objects under the shadows are not detected properly, Poor reconstruction error handling, Shadow Borders are not handled properly and Black objects are detected as shadow.

In this method, based on the particular properties of shadows, project presents an effective and robust approach for shadow segmentation and compensation in color satellite images with high spatial resolution. The approach uses the normalized saturation-intensity difference index in HSI color space to detect shadows and exploits histogram matching method to recover the information under shadows.

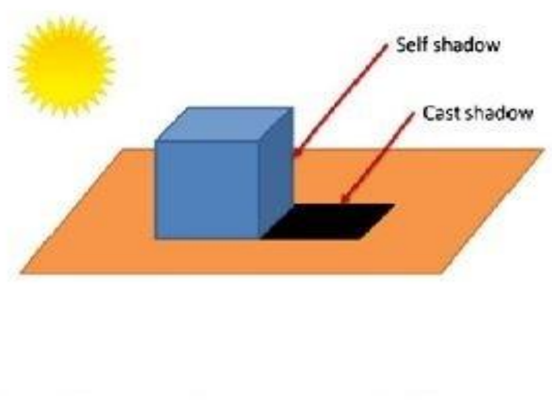


Fig: Illustration of cast and self shadows

The project proceeds as follows. First section presents the approach for shadow segmentation and compensation based on particular properties of shadows in HSI color space. In the next section, some experimental results in the SATELLITE images are presented. Final section gives some conclusions and future directions.

III. Proposed Method

Figure shows the block diagram of the proposed approach. It performs shadow segmentation and compensation as follows. First, original RGB-based color images are converted into the HSV color space. Second, based on particular properties of shadows in HSV color space, the normalized saturation-value difference index is constructed to identify shadows. Third, in segmented shadow regions, linear correlation method is used to adjust the shadow area by adjusting shadow area with the mean value of surrounding non shadow area. The result images are converted back to RGB color space for the shadow reconstruction.

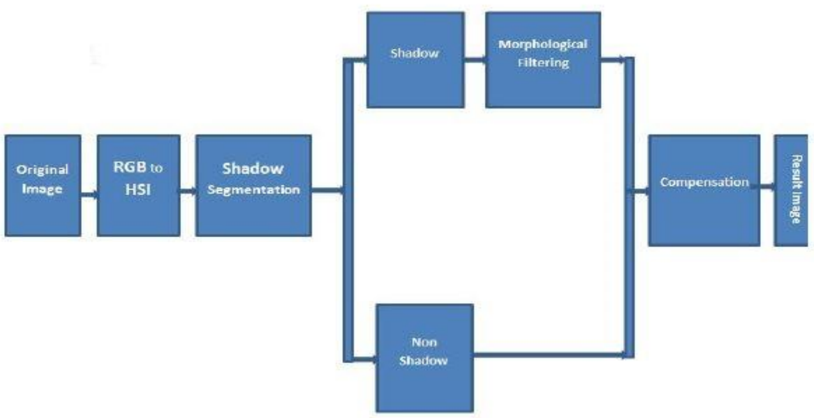


Fig:Method Flowchart

1. SHADOW CHARACTERISTICS

Shadow occurs when objects totally or partially occlude the direct light projected from a source of illumination. Although problems such as false color and shape distortions, shadow provide important geometric and semantic information such as the shape and position of objects, as well as about the characteristics of surfaces and light sources. In order to segment shadow, many color characteristics of shadow in RGB and HIS color space have been suggested. Situations, but has been found to be very sensitive to image noise. One benefit of this type of flow is the fact that no global constraints are placed on the image.

Hue defines pure colour in terms of green, red or magenta, Hue also defines mixtures of two pure colours like red-yellow (orange), or yellow-green (limitations to this statement will be addressed later). Hue is usually one property of three when used to determine a certain colour. Saturation is a colour term commonly used by (digital / analog) imaging experts, Saturation is usually one property of three when used to determine a certain colour and measured as percentage value .Saturation defines a range from pure colour (100 %) to grey (0 %) at a constant lightness level. A pure colour is fully saturated. The intensity is related to the strength of the light beam. Intensity is very tricky to specify because the apparent brightness and the actual brightness can differ significantly. Loosely speaking, intensity is related to the total power in the light beam as measured by some objective instrument (such as a photographic light meter), but the perceived brightness of a light (or lightness of a surface) is strongly influenced by lots of other factors and cannot always be specified objectively.

1.1 RGB to HSI conversion

RGB colour and HSI colour can be easily transformed to each other. Assume that are hue, saturation and value component respectively, and are red, green and blue component respectively. Given a RGB image which is normalized, the hue, saturation, and value component are calculated by the equations as follows:

First, we convert RGB color space image to HSI space beginning with normalizing RGB values:

$$r = \frac{R}{R+G+B}, g = \frac{G}{R+G+B}, b = \frac{B}{R+G+B}$$

Each normalized H, S and I components are then obtained by,

$$h = cos^{-1} \frac{.5[(r-g)+(r-b)]}{[(r-g)^2+(r-g)(g-b)]^{\frac{1}{2}}}, h\varepsilon[0,\Pi]\text{for}$$

$$h = 2\Pi - cos^{-1} \frac{.5[(r-g)+(r-b)]}{[(r-g)^2+(r-g)(g-b)]^{\frac{1}{2}}}, h\varepsilon[\Pi,2\Pi]$$

$$s = 1 - 3min(r,g,b)\,,\, s\varepsilon[0,1]$$

$$i = (R+G+B)/3\,,\, i\varepsilon[0,1]$$

For convenience, h, s and i values are converted in the ranges of [0,360],[0,100],[0,255], respectively by, $H = h \times 180 \div \Pi$; $S = s \times 100$;$I = i \times 255$.

It has been observed that shadow areas are dark and saturated strongly with the blue and violet wave-length. In HSI color space, shadows hold some different spectral properties as follows (see Figure).

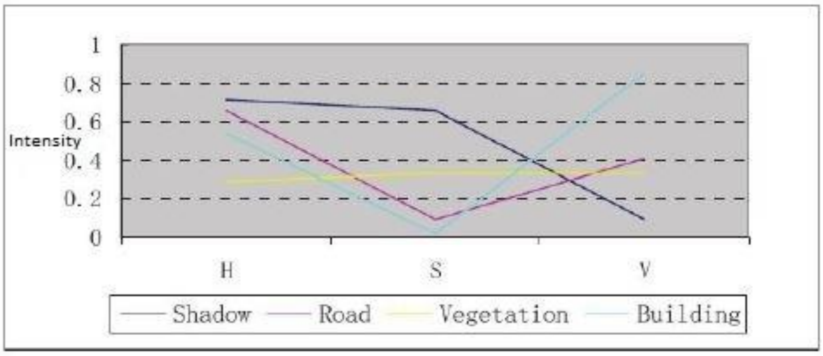


Fig: Spectrums in HSI color space.

1. Low intensity because the direct light from the Sun is occluded by elevated objects; 2.High saturation with short blue-violet wavelength due to atmospheric Rayleigh scattering effect; 3. High hue values because shadow areas are dark.

2. *SHADOW SEGMENTATION*

Compared with other type of objects such as roads, vegetation and buildings, shadow areas have the maximum value of saturation component and the minimum value of value component in HSI color space. Based on this particular property of shadows, a normalized saturation- intensity difference index (NSIDI) is constructed to identify shadows. For each image pixel .NSIDI is calculated by the following formula.

$$NSIDI = \frac{saturation - intensity}{saturation + intensity}$$

In which, a component of saturation and intensity are normalized and NSIDI€ [1, 1].

For shadow pixels, NSIDI gets a positive value which is more than zero; for road and building pixels, NSIDI gets a negative value which is less than zero; while for vegetation pixels, the value of NSIDI approximates zero. In order to detect shadow areas, a positive threshold T can be found to segment the NSIDI images. Image pixels which have a higher NSIDI than the threshold are accepted as shadow pixel; otherwise not.

Pixel = shadow when NSIDI $\geq$ T

Pixel = non-shadow when NSIDI $\leq$ T

Now for more accurate shadow detection we take into account the intensity component of the image also. Since for shadow area the intensity will be low and for non-shadow area intensity will be high. Here also, in order to detect shadow areas, a positive threshold T can be found to segment the Intensity images. Image pixels which have a lower intensity than the thresholds are accepted as shadow pixel. otherwise non-shadow area.

Pixel = shadow when Intensity $\leq$ T

Pixel = non-shadow when Intensity $\geq$ T

After computing this value we make a comparison between the two images for better classification of shadow areas. Actually an AND operation is performed for this comparison, the area where both the images having shadow region is taken as the actual shadow. And the other parts are classified as non-shadow region.

As the last step to deal with noise, which may result in the obtained binary mask, two mathematical morphological operators are applied, namely, opening and closing by reconstruction. 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 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.

Analysis of local regions leads to the construction of a family of local energies at each point along The curve. In order to optimize these local energies, each point is considered separately, and moves to Minimize (or maximize) the energy computed in its own local region. To compute these local energies, Local neighborhoods are split into local interior and local exterior by the evolving curve. The energy Optimization is then done by fitting a model to each local region.

3. SHADOW COMPENSATION

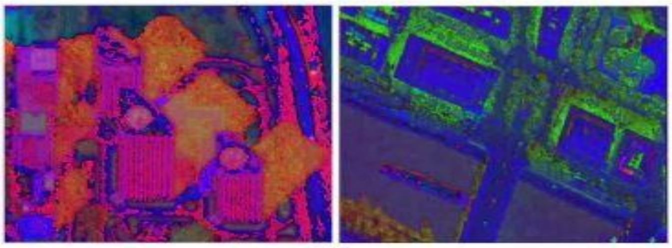
Shadow compensation is to restore the surface under shadows. Considering that a surface texture does not significantly change when shadowed, neighboring non- shadowed segments are usually used to compensate shadowed ones. Histogram matching is one the classical methods that used in order to bring brightness distribution of two given images as close as possible to each other. Image reconstruction is one of the most important steps in our methodology; here we assume that the underlying relationship between the non-shadow class (Y) and the corresponding shadow classes (X) is of the linear type. We have empirically observed that shadow classes and the corresponding non-shadow classes reasonably exhibit a linear relationship.

Here in this method the shadow reconstruction is done by replacing the shadow area with the mean values of the surrounding non shadow regions.

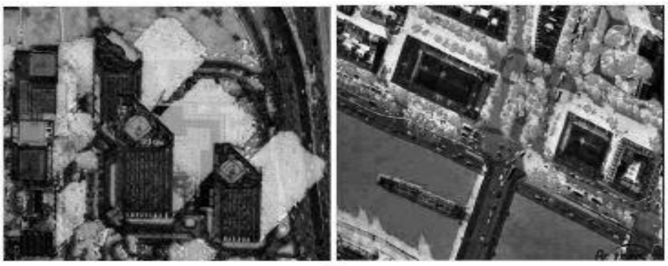
IV. EXPERIMENTAL RESULTS

The approach of shadow segmentation and compensation has been applied in some SATELLITE images of urban area. Here are some results in Figure to demonstrate the effectiveness and feasibility of the approach. The original image shown in figure (a) is segmented by the presented shadow, and the segmented shadow areas are shown in figure (d).The figure (c) shows the output image after the morphological operations. Figure (b) is the result of the color transformation from RGB to HSV color space, and the result of morphological filtering is shown in Figure (e).

(a)

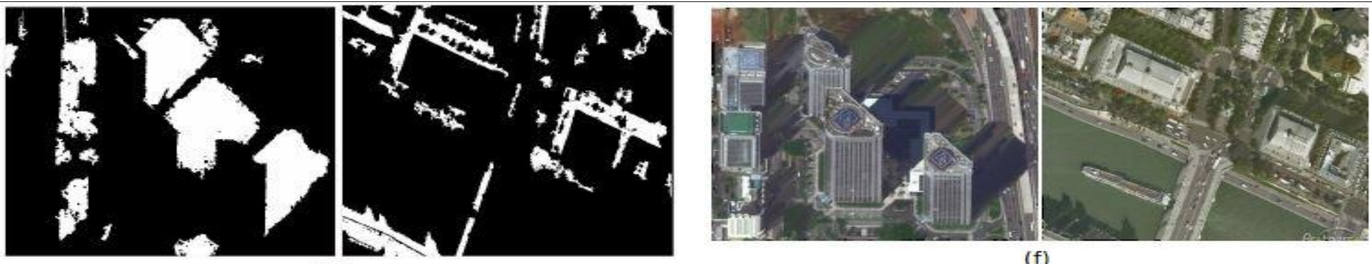


(b)



(c)

(d)



(e) (f)

Fig: Reconstruction results for Satellite image. (a) Original image, (b) RGB to HIS conversion, (c) NSIDI image, (d) shadow mask, (e) Morphological filtering, (f) Reconstructed image

V. CONCLUSION

In high resolution satellite images, shadow segmentation and compensation is important for image analysis an interpretation applications. An approach based on normalized saturation-intensity index is presented to segment shadows for color images, and is proved to be effective. However, due to the similarity of spectrum, some dark objects like water still cannot be distinguished from shadows. Thus, method using other knowledge like shape and spatial relationship is the future direction of research. Histogram matching is used to compensate information under shadows. Due to the loss of information, complete information compensation for shadow area in a single image.

First, the problem of the structural element (SE for morphological operation) shape and size could be faced by means of an automatic adaptation procedure according to the sensor resolution. Second, since the reconstruction of shadow regions strongly depends on the accuracy of the classification maps, the height derived from a digital elevation model could be considered as an additional input feature to better discriminate between the thematic classes. Finally, a third future direction could be to face the reconstruction problem with more sophisticated statistical models. Although they would increase the computational complexity, they would lead to a better fitting of the shadow and non-shadow classes, thus resulting in a potentially better reconstruction quality.

References

1. L. Lorenzi, F. Melgani, and G. Mercier, A complete processing chain for shadow detection and reconstruction in VHR images, IEEE Trans.Geosci. Remote Sens., vol. 50, no. 9, pp. 3440-3452, Sep. 2012,

2. H. Ma, Q. Qin, and X. Shen, Shadow segmentation and compensation in high resolution satellite images, in Proc. IEEE IGARSS, Jul. 2008, vol. 2, pp. 1036-1039.

3. E. Salvador, A. Cavallaro, and T. Ebrahimi, Shadow identication and classication using invariant color models, in Proc. IEEE Int. Conf. Acoust., Speech, Signal Process., 2001, vol. 3, pp.1545-1548.

4. K. L. Chung, Y. R. Lin, and Y. H. Huang, Efcient shadow detection of color aerial images based on successive thresholding scheme, IEEE Trans. Geosci. Remote Sens., vol. 47, no. 2, pp. 671-682, Feb. 2009.

5. S. Wang and Y. Wang, Shadow detection and compensation in high resolution satellite images based on retinex, in Proc. 5th Int. Conf. Image Graph., 2009, pp. 209-212.

6. T. Nakajima, G. Tao, and Y. Yasuoka, Simulated recovery of information in shadow areas on IKONOS image by combining ALS data, in Proc. GIS Develop., 2002, pp. 17.

7. J. Su, X. Lin, and D. Liu, An automatic shadow detection and compen- sation method for remote sensed color images, in Proc. 8th Int. Conf. Signal Process., Nov. 2006, vol. 2, pp. 14.

8. P. Sarabandi, F. Yamazaki, M. Matsuoka, and A. Kiremidjian, Shadow detection and radiometric restoration in satellite high resolution images, in Proc. IEEE IGARSS, Sep. 2004, vol. 6, pp3744-3747.

9. Luca Lorenzi, Farid Melgani .Assessing the Reconstructability of Shadow Areas in VHR Images IEEE Trans on Geoscience and Remote sensing VOL. 51, NO. 5, MAY 2013

10. Arevalo V, Gonzlez J, Ambrosio G, ”Detecting Shadow QuickBird satellite images,” ISPRS 2006 Commission VII Mid-term Symposium ’Remote Sensing: From Pixels to Processes’. Enschede, the Netherlands, 8-11 May, pp. 330,335

11. E. Salvador, A. Cavallaro, and T. Ebrahimi, Cast shadow segmentation using invariant color features, Comput. Vis. Image Understand., vol. 95, no. 2, pp. 238259, Aug. 2004. roc. Computer Vision and Image Understanding 95(2004) 238-259 .

12. Huihui Song; Bo Huang; Kaihua Zhang, ”Shadow Detection and Reconstruction in High-Resolution Satellite Images via Morphological Filtering and Example-Based Learning,” IEEE Transactions on Geoscience and Remote Sensing, , vol.52, no.5, pp.2545,2554, May 2014

13. Ariel Amato, Ivan Huerta, Mikhail G. Mozerov, F. Xavier Roca and Jordi Gonz‘alez: ”Moving Cast shadow Detection Methods for Video surveillance Application,” pp. 125 (2013)

14. F. Yamazaki, W. Liu, and M. Takasaki, Characteristic of shadow and removal of its effects for remote sensing imagery, in Proc. IEEE IGARSS, 2009, vol. 4, pp. IV-426IV-429

15. YD. Shen, Image registration by local histogram matching, Pattern Recognit. J., vol. 40, no. 4,pp. 1161-1172, Apr. 2007

16. H. A. David and H. N. Nagaraja, Order statistics, in Wiley Series in Probabilities and Statistic, 3rd. Hoboken, NJ: Wiley, 2003.

17. J. Holland, Adaptation in Natural and Articial Systems. Ann Arbor, MI: Univ. Michigan Press,1975.

18. J. M. Scanlan, D. M. Chabries, R. W. Christiansen, A Shadow Detection and Removal Algorithm for 2D Images, International Conference on Acoustics, Speech, and Signal Processing (ICASSP), 1990

19. R. Irvin, D. Mckeown, Methods for exploiting the relationship between buildings and their shadows in aerial imagery, IEEE Trans. Syst., Man, Cybernet. 19 (1989) 1564-1575

20. Y. Sonoda, T. Ogata, Separation of moving objects and their shadows, and application to tracking of loci in the monitoring images, in: Proc. IEEE Int. Conf. on Signal Processing, 1998, pp. 1216-1264

21. Kuo-Liang Chung, Yi-Ru Lin, and Yong-Huai Huang,Efficient Shadow Detection of Color Aerial Images Based on Successive Thresholding Scheme IEEE Trans on Geoscience and Remote sensing ,feb. 2009

22. Luus, F.P.S.; van den Bergh, F.; Maharaj, B.T.J., ”Adaptive Threshold-Based Shadow Masking for Across-Date Settlement Classification of Panchromatic QuickBird Images,” Geoscience and Remote Sensing Letters, IEEE , vol.11, no.6, pp.1153,1157, June 2014

23. Leone, A. Distante, C.; Buccolieri, F., ”A texture-based approach for shadow detection,” IEEE Conference on Advanced Video and Signal Based Surveillance, 2005. AVSS 2005., vol., no., pp.371,376, 15-16 Sept. 2005

24. Sun, B. and S. Li, 2010. Moving cast shadow detection of vehicle using combined color models.Proceedings of the Chinese Conference on Pattern Recognition, Oct. 21-23, IEEE Xplore Press,Chongqing

25. Xin Liu; Bin Dai; Hangen He, ”Real-Time On-Road Vehicle Detection Combining Specific Shadow Segmentation and SVM Classification,” Second International Conference on Digital Manufacturing and Automation (ICDMA),IEEE,2011, vol., no.,pp.885,888, 5-7 Aug.2011

26. Ruiqi Guo; Qieyun Dai; Hoiem, D., ”Single-image shadow detection and removal using paired regions,” IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2011, vol., no., pp.2033,2040, 20-25 June 2011

27. T. Kim, T. Javzandulam, T. Y. Lee, Semiautomatic Reconstruction of Building Height and Footprints from Single Satellite Images, IEEE International Geoscience and Remote Sensing Symposium (IGARSS), 2007

28. N. Otsu, A Threshold Selection Method from Gray Level Histograms, IEEE Transactions on Systems, Man, and Cybernetics, Vol. Smc-9, No. 1, 1979

29. J. Tian, J. Sun, Y. Tang, Tricolor Attenuation Model for Shadow Detection, IEEE Transactions on Image Processing, Vol. 18, Issue 10, 2009

30. C. Lu, M. S. Drew, Shadow Segmentation and Shadow-Free Chromaticity via Markov Random Fields, CIC13: Color Imaging Conference, Scottsdale, 2005

31. A. Prati, I. Miki, R. Cucchiara, M. M. Trivedi, Comparative Evaluation of Moving Shadow Detection Algorithms, IEEE CVPR workshop on Empirical Evaluation Methods in Computer Vision, 2001

32. R. Bolter, Reconstruction of Man-Made Objects from High Resolution SAR Images, IEEE Aerospace Conference, 2000

33. James J. Simpson, James R. Stitt, A Procedure for the Detection and Removal of Cloud Shadow from AVHRR Data over Land, IEEE Transactions On Geoscience And Remote Sensing, 1998

34. T. P. Wu, C. K. Tang, A Bayesian Approach for Shadow Extraction from a Single Image, IEEE International Conference on Computer Vision (ICCV), 2005

35. C. Jiang, M. O. Ward, Shadow Identification, IEEE Conference on Computer Vision and Pattern Recognition (ICCVPR), 1992

36. J. Huang, W. Xie, L. Tang, Detection of and compensation for shadows in colored urban aerial images, 5th World Congress on Intelligent Control and Automation, 2004

37. A. M. Polidorio, F. C. Flores, N. N. Imai, A. M. G. Tommaselli, C. Franco, Automatic Shadow Segmentation in Aerial Color Images XVI Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI), 2003