International Journal of Engineering & Technology, 7 (4) (2018) 3209-3212

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i4.19767
Research paper

A modified shadow segmentation technique for satellite images

D. Usha Nandini [1] *, Dr. Ezil Sam Leni [1]

[1] *Research Scholar, Sathyabama University, Chennai*
[2] *Professor, SRR Engineering College, Chennai*
**Corresponding author E-mail:* ushanandhiniduraisamy@gmail.com, *lenisatish@gmail.com*

Abstract

Satellite images provide plenty of information about the the earth and it's environment. However, presence of shadows hinders the image analysis process. This paper introduces a new technique for shadow identification which involves color models and an optimization algorithm. The RGB color image is transformed to C1C2C3 and HSI color images since they contain more shadow information than the RGB image. Subsequently these images are fed individually to the ant colony optimization algorithm which identifies shadows based on its properties. The resulting ouputs of the color models are combined using the Boolean operator which retrieves the binary image containing shadows.

Keywords: *Shadow; Shadow Detection; Color Model; Ant Colony Optimization.*

1. Introduction

Shadow detection and removal has become an essential prerequisite in various image processing applications particularly for high resolution and very high resolution satellite images. The shadows in images furnish the knowledge about the scene such as the position of the sun when the image was taken and also the details about the geometry of the object that cast the shadow. This knowledge can be used in a variety of applications such as 3D scene reconstruction, building height estimation, etc. On the contrary, the prevalence of shadows in the images reduces the radiometric information and also the hides the true shape, size and edge information of the underlying
object thus misguiding the image analysis process. Several techniques have been used for shadow detection. The various techniques used for shadow detection are mainly based on the radiometric information, spectral information or the geometrical and contextual information contained in the image under consideration. Most of the techniques work well for a specific application but fail on other applications. Moreover, they work well on simple scenes but their accuracy deteriorates as the complexity of the scene increases.
Formation of shadows in images occurs when an object obstructs the light emerging from a source of illumination. In a scene there are two types of lighting i.e., direct light and diffuse lighting. Direct light comes from the source of illumination whereas the scattering of light causes diffuse light by the atmosphere. Shadows are classified into two types: cast shadow and self-shadow. When an object casts its shadow on its underlying object it is called cast shadow. The second type of shadow namely self shadow is formed when a part of an object is illuminated only by diffuse light, i.e. it is not illuminated by direct sunlight.

(A)

(B)

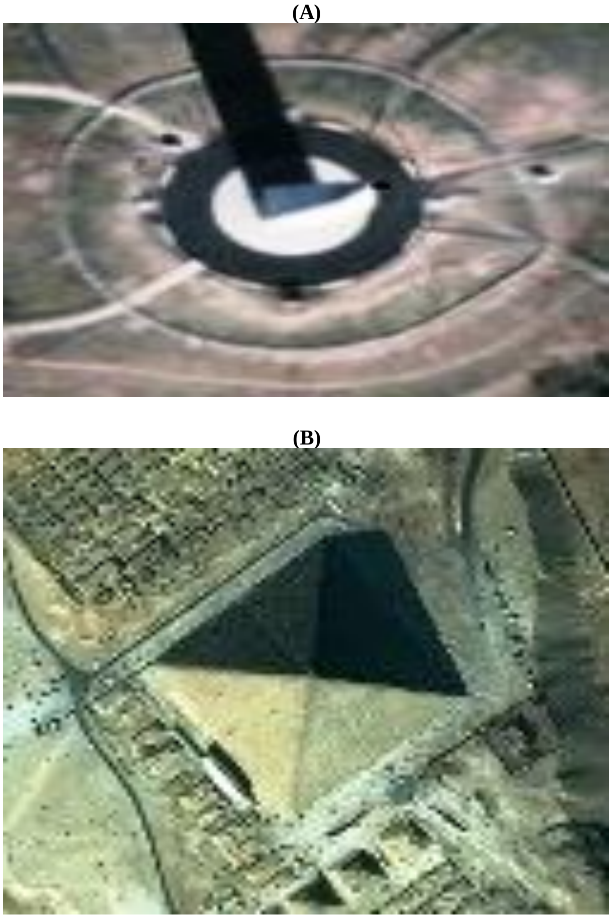


Fig. 1: Shadows in Satellite Images.

The figure 1 shows Quickbird images containing cast and self shadows. Cast shadow can further be classified into two categories namely the penumbra and the umbra regions. The penumbra region receives diffuse light and a fraction of the direct light whereas the umbra region is illuminated only by diffuse light. In indoor images the difference between umbra and penumbra is evident whereas in satellite images the discrimination between penumbra and umbra of cast shadows is difficult.

2. Literature survey

Several techniques for shadow detection are built on the properties of shadows have been proposed [11]. Some of the properties are:

- The shadow region has reduced intensity when compared to the neighbouring non-shadow regions.
- The chrominance of the shadow region is hardly changed while the luminance is reduced.
- The texture is preserved even in the presence of shadows. The texture of both the shadow and non shadow parts of the object remains the same.

Rosin et al. [1] proposed a region growing algorithm for shadow detection based on the properties of shadows. But the results are not accurate for the penumbra part of the shadow region. In [2], Zhang detected shadows for both indoor and outdoor scenes based on a ratio map which is obtained from the intensities of the pixels in the neighbourhood. Y.L.Tian [3] used a Gaussian Mixture Model combined with intensity and texture information to detect shadows in video sequences. Polidoro et al. [4] in his work detected shadows considering the properties of low luminance and highly saturated blue wavelength of shadow regions. J.D.Tsai [5] converted the RGB color image into invariant color models such as HSI, HSV, YIQ, etc and thresholded the difference between hue and intensity under the assumption that shadow regions have lower intensity than the non shadow regions. This technique failed on regions which contained dark objects such as water bodies and roads. K.L.Chung [6] further improved on Tsai's methodology by doing a connected component analysis and thresholding at various levels. Most of the techniques work well for a specific application but fail on other applications. Moreover, they work well on simple scenes but their accuracy deteriorates as the complexity of the scene increases.

3. Proposed method

An RGB color image can be converted to different color spaces such as HSV, HSI, HSL, YCbCr, YIQ, YUV, $C_1C_2C_3$, LAB, etc. The different color spaces are suited for different image processing applications. For example Tsai [5] used invariant color spaces such as HSV, HSI, YC_bC_r, etc. for shadow detection. In this paper, $C_1C_2C_3$ and HSI color models are used for shadow detection.

$C_1C_2C_3$ color model

The $C_1C_2C_3$ color model was first proposed in the year 1999 by Gevers and Smeulders, following which many researchers have used this model in various applications in image processing. Among the three channels, C3 channel has more shadow information. RGB color space can be converted to $C_1C_2C_3$ color model using the formula given below.

$$c1 = \arctan\left(\frac{R}{\max(G,B)}\right) \tag{1}$$

$$c2 = \arctan\left(\frac{G}{\max(R,B)}\right) \tag{2}$$

$$c3 = \arctan\left(\frac{B}{\max(R,G)}\right) \tag{3}$$

Here c1, c2 and c3 are the three chrominance components. Salvador in 2004 [7] first used this model for moving cast shadow detection. He first proposed that the c3 channel contains more shadow information than the other two channels. But his method has many limitations. This technique produces false positives i.e., the non shadow pixels are falsely identified as shadow pixels when the intensity of a pixel is too high or too low or when the saturation of the pixel is low [8]. Thus the shadow detection is low.

The RGB color image is first smoothed using a median filter in order to remove the noise from the image. A neighbourhood of size 3x3 has been considered over which the median has been computed. This pre-processing step is essential to improve the accuracy of the results.

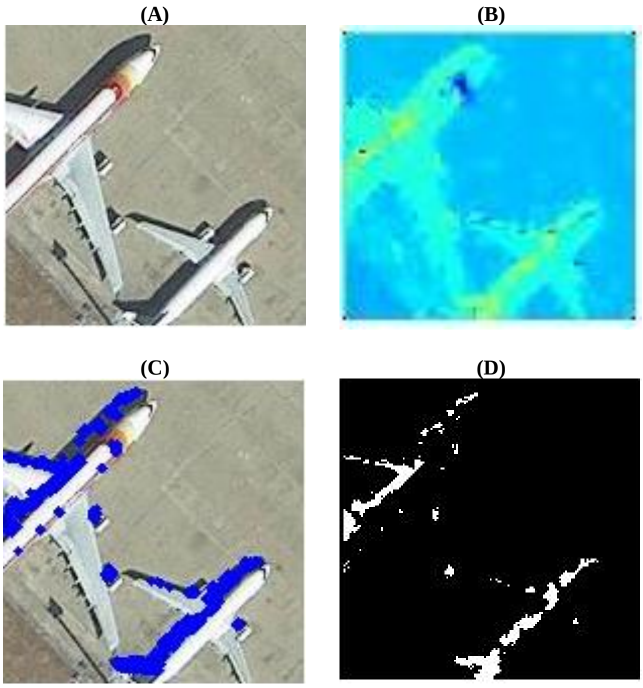


Fig. 2: A) Original Image B) C3 Channel C) Shadow Detection Results D) Binary Output.

From the above figure, it is clear that the output image using the $C_1C_2C_3$ color model has many false positives and false negatives thus reducing the accuracy of the algorithm. To overcome the drawbacks of the $C_1C_2C_3$ color model, the HSI color model is also considered.

HSI color Model

The RGB color space is transformed to the HSI color space using the formula given below [5].

$$\begin{bmatrix} I \\ V_1 \\ V_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{-\sqrt{6}}{6} & \frac{-\sqrt{6}}{6} & \frac{\sqrt{6}}{3} \\ \frac{1}{\sqrt{6}} & \frac{-2}{\sqrt{6}} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4}$$

$$S = \sqrt{V_1^2 + V_2^2} \tag{5}$$

$$H = \tan^{-1}\left(\frac{V_2}{V_1}\right) \tag{6}$$

Where $V_1 \neq 0$ otherwise H becomes invalid as $\frac{V_2}{V_1}$ becomes ∞

The C1C2C3 and the HSI images are fed as input to the Ant Colony Optimization (ACO) algorithm.

Ant Colony Optimization

ACO is an optimization technique which is based on the rummaging nature of ants where the ants deposit a substance called pheromone on their way to search for food [9]. Initially, the ants move in a random fashion in search of food. When they come across a pheromone trail they tend to follow it, and they deposit their own pheromone along their path thus making the path more attractive for other ants to follow. When a new ant arrives it is likely to follow the same path.

The pheromone matrix and the heuristic matrix are assumed to have the same size of the image (MxN). The pheromone matrix is initialized with an initial pheromone value. K ants are selected randomly and allowed to move in the image. The ants travel in an eight connected neighbourhood. The probability that ant would traverse a node depends on the pheromone value at that node and also the properties of shadow at that node. Here node denotes a pixel in the image. The possibility that an ant would travel from a node (i,j) to another node say (i,j+i) is given by the following equation.

$$p^{n}_{(i,j)\rightarrow(i,j+1)} = \frac{\tau^{\alpha}_{(i,j+1)}\,\eta^{\beta}_{(i,j+1)}}{\sum_{(i,j+1)\in\Omega_{i,j}} \tau^{\alpha}_{(i,j+1)}\,\eta^{\beta}_{(i,j+1)}} \quad (7)$$

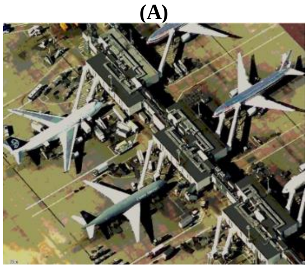
In the above equation, Ω represents the [8] connected neighbourhood of the possible motion of the ants in the nth iteration. Usually, 4 connected or 8 connected neighbourhoods are considered, here an 8 connected neighbourhood has been taken. $\tau_{i,j+1}$ represents the pheromone content at the node (i,j+1) and Ƞ stands for the heuristic data at the node (i,j+1). α and β are used to regulate the impact of the variables Ƞ and τ in the equation 7. When α is large, the ants are likely to follow the path that contains a higher trail of pheromone. When β value is large the pixel properties given by have a greater control over the path an ant is likely to follow. The properties of the shadow considered in this algorithm are intensity, hue and saturation. After each ant completes a tour, the pheromone matrix is updated. When all the ants have finished a tour a global update is made to the pheromone matrix depending on the best tour among all the ants [12]. This process is repeated for n number of iterations. After n iterations, the final pheromone matrix is thresholded using the threshold value obtained through Otsu's method [10]. The binary images containing shadow regions obtained using the C1C2C3 image and HSI image are finally unified together using the AND operator to retrieve the binary shadow image.

(A)

(B)

Fig. 3: A) Original Image B) Binary Image after Shadow Detection.

(A)



(B)

Fig. 4: A) Original Image and B) Binary Image after Shadow Detection.

4. Results and discussion

Precision and Recall parameters have been used for analysis of the shadow detection results. User's accuracy, Producer's accuracy and the Overall accuracy are evaluated for the output images [5] using the following metrics given in the table.
The performance evaluation of the image in Figure 3 are given below in Table 1.

Table 1: Performance Evaluation of the Image in Figure 3.A

Producers Accuracy		Users Accuracy		Overall Accuracy
η_S (%)	η_N(%)	P_S (%)	P_N (%)	τ (%)
86.5	96.6	92	89.9	92.3

The performance measurements of the image in Figure 4 are given below in Table 2.

Table 2: Performance Evaluation of the Image in Figure 4.A.

Producers Accuracy		Users Accuracy		Overall Accuracy
η_S (%)	η_N(%)	P_S (%)	P_N (%)	τ (%)
85.5	94.7	91	89.6	91.3

Tables 1 & 2 show the accuracy of the proposed shadow detection technique for the input images in Figure 3 and 4. The results show that the proposed technique has a remarkable improvement in the accuracy compared to the previous techniques.

5. Conclusions

This paper presents an alternative approach to detecting shadows in satellite images. The invariant color models such as $C_1C_2C_3$ color model and HSI color model have been exploited for shadow detection. The two images are given as input to ACO algorithm to produce the respective shadow images which are then unified using the and operator to get the final output. Results show an improvement in the accuracy of shadow detection as compared to previous techniques. The algorithm performs quite well even for dark regions.

References

[1] P. L. Rosin and T. Ellis, "Image Difference Threshold Strategies and Shadow Detection," in sixth British Machine Vision Conference, Birmingham, page 347-356, 1996.

[2] W. Zhang, X.Z. Fang, and X. Yang, "Moving Cast Shadows Detection Based on Ratio Edge," IEEE International Conference on Pattern Recognition, page 763-766, November 2006.

[3] Y. L. Tian, M. Lu, and A. Hampapur, "Robust and Efficient Foreground Analysis for Real-time Video Surveillance," IEEE Computer Vision and Pattern Recognition, 005, pp. I: 1182-1187.

[4] A.A.Polidorio, F.C.Flores, N.N.Imai, A.M.Tomaselli and C.Franco, "Automatic Shadow Segmentation in Aerial Images", Proc. Brazilian Symposium on Computer Graphics and Image Processing, 2003, pp. 270-277.

[5] V V.J.D.Tsai, "A Comparative Study on Shadow Compensation of Color Aerial Images in Invariant Color Models", IEEE Transactions on Geoscience and Remote Sensing, vol. 44, no. 6, pp. 1661-1671, June 2006. https://doi.org/10.1109/TGRS.2006.869980.

[6] K.L.Chung, Y.R.Lin, Y.H.Huang, "Efficient Shadow Detection of Color Aerial Images Based Successive Thresholding Scheme",

IEEE Transactions on Geoscience and Remote Sensing, pp. 671-682, 2009. https://doi.org/10.1109/TGRS.2008.2004629.
[7] Salvador E, Cavallaro A and Ebrahimi T, 2004, “Cast Shadow Segmentation using Invariant Color Features”, Computer Vision and Image Understanding, 95, pp. 238-259. https://doi.org/10.1016/j.cviu.2004.03.008.
[8] V.Arevalo, J.Gonzalez and G.Ambrosio, “Shadow Detection in Color High-resolution Satellite Images”, International Journal of Remote Sensing, Vol.29, No.7, April 2008, 1945-1963. https://doi.org/10.1080/01431160701395302.
[9] M.Dorigo, V.Maniezzo, A.Colorni “Ant System: Optimization by a Colony of Cooperating Agents”, Man and Cybernetics, vol.26, pp. 29-41, 1996. https://doi.org/10.1109/3477.484436.
[10] N.Otsu, “A Threshold Selection Method from Gray Level Histograms”, IEEE Transactions on System, Man and Cybernetics, 1979.
[11] D.Usha Nandini, Dr.Ezil Sam Leni, “A Survey of the Existing Shadow Detection Techniques”, International Conference on Control, Instrumentation, Communication and Computational Technologies, pp.175-177, 2014.
[12] D.Usha Nandini, Dr.Ezil Sam Leni, “Shadow Identification using Ant Colony Optimization”, Journal of Theoretical and Applied Information Technology, vol. 78,no.2, pp.195-200, 2015.
[13] M.Dorigo, L.M.Gambardella, “Ant Colony System: A Cooperative Learning Approach to the Travelling Salesman Problem”, IEEE Transactions on Evolutionary Computation, vol. 1, pp. 53-66, 1997. https://doi.org/10.1109/4235.585892.