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Detection and Removal of Shadow Using Very High Resolution Remote Sensing Images

Sarita A. Ingale, Dr.Karbhari V. Kale

M.Tech Student, Department of Computer Science& IT, Dr. Babasaheb Ambedkar Marathada University,

Aurangabad, Maharashtra, India

Professor, Department of Computer Science& IT, Dr. Babasaheb Ambedkar Marathada University,

Aurangabad, Maharashtra, India

ABSTRACT- The shadows are mainly observed because of tall buildings, towers etc. in urban areas. Shadows in very high resolution (VHR) Remote Sensing images represent serious problems for their full development. To reduce the shadow effects in very high resolution (VHR) Remote Sensing images for their further applications, detection and removal of shadow is necessary which is developed. In this project we have addressed the issue of shadow detection and removal in VHR Remote Sensing images. The detection and classification tasks are implemented by means of support vector machine approach and for noise removal filtering is used. Shadow removal is done using linear regression method. In this method, the shadow blocks of the image are replaced by adjusting the intensities of the shaded points to the statistical characteristic of the non-shadow regions. Then fuse the original image and shadow removal image. Wavelet transform is used for image fusion. Inverse wavelet transform is used for getting original image back from decomposed image.

KEYWORDS: Shadow Detection; Shadow removal; Very High Resolutions (VHR) Remote Sensing Images.

I. INTRODUCTION

Very high resolution (VHR) Remote Sensing images create a new era in satellite image processing and remote sensing field. We can easily identify full detail of each object from VHR Remote Sensing image such as vehicles, roads, different shape of buildings, trees, seas etc. as well as shadow of buildings. Shadow is created, when any object lies in the way of light emerging source. The difference between shadows vs. non-shadow is shadows are having different color tones than non-shadow part of the image. An Undesired information of an image is known as shadow [1].Shadow represent an important problem for both sellers as well as users of remote sensing images as they may cause high risk to present false color tones or to lose objects [2]. Shadow can be lead to destroy shape of an object, or to merge objects. The classification mapping and interpretation is affected by the presence of shadow [3]. Therefore shadow detection and removal is necessary in VHR Remote Sensing images [4]. Shadow detection makes use of model based approach. However, this is one of the easiest approach due to it needs information before scenario and sensor information before processing the data. For such kind of problems shadow property based approach is also there as Shadow property based approach is more suitable. Shadow property based approach uses hue, saturation, intensity properties of shadow [5].

Shadow Reconstruction is to restore surface under shadow. Considering that a surface texture does not modify when shadowed, only neighboring non-shadowed segments are usually used to reconstruct shadowed ones. In different papers different algorithms are used for shadow Reconstruction like gamma correction, histogram. In the proposed work shadow detection is doneby using supervised classification scheme. Then shadow removal is implemented using linear regression method. For Shadow Detection and removal Very high resolution Remote Sensing images are required and depending on that images Shadow and Non-Shadow part can be identified which is implemented by using MATLAB.



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II. RELATED WORK

T. Kim presented a technique which might be extension of Tsai method. Experimental result shows that the accuracy is more. For shadow removal they used avalanche histogram equalization [1]. A solution to the problem of automatic detection and removal of shadow features proposed by P.M. Dare [3].

Binary classification for shadow and no shadow region of image analyzed by K. Kouchi and F. Yamazaki. To get clear borders, they first applied canny edge detection algorithm and then applied image imposing process. For reconstruction process, they calculated mean and standard deviation for shadow and no shadow pixels of image and applied mean difference, and for improving results normalization process with the help of standard deviation [4].

The several invariant color spaces to analyze shadows were introduced by E. Salvador, A.Cavallaro, and T. Ebrahimi. The advantage of invariant color features found as a low complexity of the classification stage as well as the method gave better performance in detecting and classifying shadows [6].

Tsai used the several invariant color spaces that decouple luminance and chromaticity, including HSI, HSV, HCV, YIQ, and YC C model, which gives dramatically improved visualization of features within recovered shadow regions [7]. Chung was found more accurately the successive thresholding scheme (STS) to detect shadows. STS-based algorithm has been implemented for identifying shadows of color aerial images under the observation of shadow maps.[10].D. Cai, M. Li, Z. Bao, Z. Chen, W.Wei, and H. Zhang presented an effective approach for shadow segmentation and compensation in colour satellite images. The approach uses (NSIDI) normalized saturation-intensity difference index in (HSI) Hue- Saturation-intensity colour space to detect the presence shadows [11] [12] [13]. P. Sarabandi, F. Yamazaki, M. Matsuoka, and A. Kiremidjian presented an efficient and simple approach for detection and removal of shadow based on Hue-saturation-value (HSV) color model. In the proposed method shadows are detected using (NDVI) normalized difference index and subsequent thresholding andbuffer area is calculated using morphological operators. The mean as well as variance of these buffer areas are used to compensate the shadow regions [14].

III.PROPOSED METHOD

The proposed method consist of two different phases; Training phase and testing phase.

A. *GENRAL*: In shadow detection and removal first part is training phase. In this manually select shadow and nonshadow block of original image and extract the features of that blocks in terms of R, G and B values. Then second part is testing phase, In this divide the original image and extract the features of that original image in terms of R, G and B values. Apply first binary classification to distinguish between shadow and non-shadow classes. To remove noise in the corresponding classes median filter is used. Then multi class classification is used to distinguish between the nonshadow classes and corresponding shadow classes. To remove isolated labels post processing is used. Then Shadow removal process is used to remove shadows in the image.

B. *TRAINING PHASE*:Fig1. Shows training phase is divided into two steps namely preprocessing followed by feature extraction.

1) **Preprocessing:** In training phase, first part is preprocessing. In region of interest creation manually select shadow and non-shadow blocks.

2) Feature extraction: Features of shadow and non-shadow blocks are extracted in terms of R, G and B values respectively. Then calculate the mean of R, G and B values. These features are stored in database.





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Fig1. Training Phase

C. *TESTING PHASE:* Fig. 2 Shows testing phase of the binary classificationBlock. In testing phase first divide the original image into 8*8 blocks. Then extract the features of that blocks in terms of mean of R, G and B values. Then apply these features of original image, training data and number of classes at input of SVM. For shadow pixel 1 will be selected and for non-shadow pixel 0 will be selected.



Fig2. Testing Phase

D. BINARY CLASSIFICATION: This classification procedure is used to implement in a supervised way by means of a support vector machine (SVM). For binary classification at the SVM, 3 inputs are given which is feature extracted of original image, training data and classes. The output of SVM shows either 0 or 1. For shadow 1, and for non-shadow 0 will be selected.

E. NOISE REMOVAL: The binary image may be contains noise in the image. Basically this noise is due to the small objects such as cars, trees etc. in the image. The problem in removing noise from binary image is due to image data and the noise share the same small set of values (either 0 or 1). Which gives the problems in the detection and removal of shadow areas. To minimize this problem right choice of filter is necessary. We are using Median filter to remove salt and pepper noise from VHR Remote Sensing image. It is possible for removing isolated shadow pixels in non-shadow area and isolated non shadow pixels in shadow area. The removal of noise in the binary image is performed by taking the place of window center by the median of center neighborhood. The main problem is related to distortion in the corners and thin lines present in the image.

F. MULTICLASS CLASSIFICATION: The previously obtained result which is obtained from noise removal process is applied to further level of classification separately to the shadow and non-shadow areas. The aim is to distinguish between the non-shadow classes on the one side and the corresponding shadow classes on the other side. TheResult, which is important to define relationship between the shadow and non-shadow regions of the same object and thus to perform removal of shadow areas. In multi class classification two multi class SVMs are trained for the classes of shadow and non-shadow respectively. If the sum of array elements of binary image is greater than 1, then at the SVM,



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3 inputs are given which is feature extracted of original image, train Tr1, and 4 different number of classes of shadow. If sum of array elements of binary image is less than 1, then at the SVM 3 inputs are given which is features extracted of original image, train Tr2, and 4 different number of classes for non-shadow areas. In the multiclass classification we are using 4 different no classes and different colors for shadow and correspondingly for non-shadow classes.

G. POST PROCESSING: To improve the classification result before exploiting it for the removal of shadow areas, post processing is applied on it. In this removing isolated shadow labels in non-shadow areas and isolated non shadow labels in shadow areas.

H. SHADOW REMOVAL: Shadow removal is important and last steps in our methodology. From the above result we observed that the relation between shadow class and corresponding non shadow class on the other side is of the linear type. We are using linear regression method for shadow removal. In this method replace the shadow blocks of image by corresponding non shadow blocks. Then fuse the original image and shadow removal image. Haar wavelet transform is used for image fusion. Inverse wavelet transform is used for getting the original image from decomposed image.Steps for removal of shadow in image we have adopted are as follows:

1) Load the pixels of non-shadow blocks images in training phase.

2) Divide the original image and multiclass shadow region into 8*8 blocks.

3) Calculate the mean of multiclass shadow block by replacing the shadow blocks by corresponding nonShadowblocks.

4) Calculate the different values means for boosting the colors of new shadow free image using gammaCorrection method.

5) After boosting the colors for improving the result image fusion is used.

6) Second level haar Wavelet transform is used for the image fusion.

7) Inverse wavelet transform is used for getting the original image from decomposed image.

IV. PSEUDO CODE

Step 1: Train SVM by Selecting the shadow and non-shadow blocks manually.

Step 2: Upload the original image.

Step 3: Apply Support Vector machine on the uploaded Original image for binary classification.

Step 4: If noise is present in binary image, then remove that noise using filtering.

Step 5: Apply Multiclass classification

If (sum of array elements of binary image >1)

Then at SVM, three inputs are given i.e. Feature extracted from original image, train data Tr1 And number of shadow classes.

Else

This three inputs are given to SVM i.e. Feature extracted from original image, train data Tr2 And number of non-shadow classes

End

Step 6: To improve the classification result, apply post processing.

Step 7: And then finally do shadow removal process as mentioned above.

Step 8: End.

V. EXPERIMENTAL RESULTS

The experimental computer environment is described as follow: in 64 bits windows 7 operating system. Before starting the shadow removal process, for eachDataset we prepared a ground truth by photo interpretation so as to generate classification map conveying the shadow and non-shadow classes. The dominant non shadow classes we define for Boumerdes image are the following:

1. Vegetation: - green;

2. Asphalt:-red;

3. Bare soil:-sky blue;

4. Side walk:-blue;



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After completing the ground truth, we defined the corresponding shadow counterparts for each image. As described in the previous section, the first task of the proposed methodology is to divide the image, extract R, G and B features, and then, a binary SVM based on the Gaussian kernel was trained to recognize the group of shadow classes from the group of non-shadow classes. Next, the SVM was applied on the whole image to get first binary image [see Fig. 4 (b)]. A visual inspection of the binary image suggest that, while for Boumerdes and the Jeddah images appear less noise as compare to the Atlanta image (very small shadow areas). Such noise is not due to the binary classifier but mainly to the presence of numerous cars, each characterized by its proper shadow. To reduce their presence in binary image, median filtering is applied. The outcome of this operation for the boumerdes image is shown in Fig. 4(c), which show a clear improvement in the binary images.

Concerning the multiclass classification, two multiclass SVMs with Gaussian kernel are trained on the basis of the available ground truth, one for discriminating between the shadow classes and the other between the non-shadow classes. The resulting classification map for non-shadow class is shown in Fig. 4(d) and for shadow classis shown in Fig. 4(e). Before moving to the shadow removal step, as described in the previous methodological section post processing is applied on multi class images in which removing isolated shadow labels in non-shadow areas and isolated non shadow labels in shadow areas. The resulting post processed multiclass non shadow result is shown in Fig. 4(f) and multiclass shadow result is shown in Figs. 4(g).

Finally, for each image and each type of shadow area which is successfully passed through linear regression is applied in which shadow areas which is successfully removed by replacing the shadow blocks by corresponding non shadow blocks. Then for boosting the colors gamma correction method is used. After boosting the colors for improving the result image fusion is used. Second level Haar Wavelet transform is used for the image fusion. Inverse wavelet transform is used for getting the original image from decomposed image. The final shadow removal for the Boumerdes images [see Fig. 4(h)]. In greater detail, focusing first on the Boumerdes image [see Figs. 4.1(h)], one can notice that some areas, mostly small, still remain dark (shaded) since they have not been reconstructed very well. From accuracy estimation table i.e. Table1, we observed that after reconstruction of shadow we get better results.





(b) Binary Image



(f) Post processed non shadow classification





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(c) Filter image

(g) Post processed shadow classification



(d)Multi class non shadow classification.

(h) Final output image.

Figure 4.1: Removal of shadow results for Boumerdes image. (a) Original image. (b) Binary Image. (c) Filter image. (d)Multi class non shadow classification. (e) Multi class shadow classification (f) Post processed non shadow classification (g) Post processed shadow classification (h) Final output image.

Accuracy Estimation Using PSNR and MSE:

PSNR: PSNR is nothing but peak signal to noise ratio between two images. It is used for Quality Measurement for original and noisy (compressed) image. If higher the PSNR, better the quality of an image.

Formula:PSNR= 10 log10 ([R. ^2]/MSE)

MSE (Mean Square Error): It is used to measure image compression quality, which represents squared error between original and noisy (compressed) image. If lower the MSE, lower the error in the image.

Formula:[I1 (m,n)-I2 (m,n)).^2]/ M*N (Where, M represents row and n represents Column.)

Table1: Accuracy Estimation

Estimation	PSNR Estimation	PSNR	MSE Estimation	MSE Estimation After
By PSNR and	Before	Estimation After	Before	Reconstruction
MSE	Reconstruction	Reconstruction	Reconstruction	
1)Boumerdes	62.08	63.75	62.47	63.81
Image				
2)Atlanta	60.04	60.99	59.33	60.28
Image				
3) Jeddah	64.73	64.96	64.23	64.84
Image				



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VI. CONCLUSION AND FUTURE WORK

This paper deal with the important and challenging problem of detection and reconstruction of shadow in VHR Remote Sensing image. In this project we examined first the basics of the shadow, how shadow occurs, then different types of shadows are also mentioned which can appear in the images. Detection and Removal of Shadow Regions may be useful for the geosciences department. Detecting of shadows in an image and reconstructing the shadow area gives the original information to some extent. As the performance of proposed method is analyzed by calculating PSNR and MSE values, in future work, we will try to get 100% reconstructed image. Also by using different methods of reconstruction of shadow, we will try to get better original information.

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BIOGRAPHY

Sarita A. Ingaleis a PG Student in the Computer Science and IT Department, Department of Computer Science & IT, Dr. BabasahebAmbedkarMarathwada University. She received Master of Technology (M.Tech) degree in 2016 from BAMU, Aurangabad, MS, India. Her research interests are Remote Sensing, GIS etc.