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A Novel Approach for Shadows detection and Shadows Removal from High-Resolution Satellite Image

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Abstract: In recent years, researchers are giving much consideration towards the shadow detection and removal techniques due to the increasing need of restoring a high quality image in minimum rates. A remote sensing image's shadow appears mainly due to obstruction by an object. The shadow affects the clarity of the images partially or totally. But very few studies only have focused on how the applications of these shadow detection and removal method can help to detect and eliminate the shadow problem from high resolution images. By considering this, three important contributions are presented in this paper. The first contribution is a watershed algorithm. The second contribution is a bimodal histogram splitting method. The third contribution is mean difference. Accordingly, watershed algorithm, bimodal histogram splitting and mean difference are developed are shadows accurately detected, then shadows eliminated and the high quality images can be restored with a minimum rate. Four different images are used for the experiments and the result shows that the proposed algorithm attained the highest accuracy.

Key words: Segmentation · Gray scale Conversion · Shadow and Statistical features · Pipelining · Spatial relationship

INTRODUCTION

City high resolution satellite images may contain the shadows which can affect the clarity of the images. Many researchers have been conducted to examine the shadow detection and removal method from city high resolution remote sensing images. The high spatial resolution satellites which are all observing the earth day by day. When capturing the images through satellites a variety of objects and shadows are formed by elevated objects such as tall buildings, bridges, telephone poles, trees in urban environments. Shadows are present in most high resolution images. Size, shape and direction are the important properties when reconstructing the shadow less images.

The combination of pixel and object based classification approach shows the multispectral data over the urban areas. The pixel based classifications utilize the spatial and spectral information to distinguish between spectrally similar roads and buildings from urban land cover areas. The object based classifications is used to identify the dark objects from urban areas. This could be identified the buildings, surfaces and roads in dark areas with great accuracy [1]. The method invariant color models identify and classify the shadows in shadow images. In this method first shadow areas are extracted, then identified the dark areas, according to the shadow properties. Next classification is done in separating the shadows of the dark objects [2]. Many current researches have focused on correcting the shadows effectively. The investigation of object based shadow detection and correction first detects the shadows using classification method that employs brightness values and their relationships with neighboring areas. Next shadow areas are corrected according to the linear functionality.

A comparison study the urban land cover classification compares three methods. Method1: The shadow classification the spectral information is combined with spatial resolution information. Method2: The linear correlation to reconstruct the shadow less images. Method 3: Combination of above methods [3]. Many successful algorithms are proposed for shadow

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detection and removal [4, 5] such as model based and shadow features based methods. The first method focuses the moving targets, scenes, camera heights. This method is frequently used in some exact condition such as airborne image analysis and video monitoring. The second method identifies the shadow areas by using the grayscale value, brightness, saturation, composure and textures [6]. During the shadow detection first shadow areas are estimated according to the space coordinates and then accurately detect the shadow areas by using thresholds methods.

Generally shadow regions are appearing in low grayscale values, from that select the two peak values using threshold method.This could separate the shadow areas from non-shadowed areas [5, 7]. When the shadow detection the dark objects are taken as shadows such as block color vehicles, wet soil, water, lands and plants [8, 9].

[8] images are converted into different color invariant spaces such as HSV, HCV, YIQ and YCbCr with Otsu's algorithm. To remove false shadows of dark objects such as plants and wet soil, the normalization methods and size, shape factors are considered [7, 10] presented shadow detection used the combined application of a bimodal histogram splitting method and image matting technique.shadow removal used to a spatial adaptive nonlocal sparse shadow removal method.It gives effectiveness. Different image quality improvement methods are proposed for shadow removal such as histogram matching) [5, 8] gamma correction, linear correlation correction, color invariance model [11] relative radiometric correlation, polynomial fitting. By calculating the difference between the shadow and non-shadow areas the paired region based single image shadow detection and removal methods are used.

The organization of the paper is as follows: The literature review of the related works is presented in Section 2. Section 3 defines the methodology. The results of this paper are given in Section 4 and conclusion is given in Section 5.

Literature Review: In city aerial images contain shadows which may cause the clarity of the satellite images. Generally shadows are formed when light source has been blocked by something. During the shadow formation there are two types of shadow are formed. One is the self-shadow another one casts shadows. A self-shadow is raised when the sunlight not directly facing the shadow on the subject. In cast shadow the shadow of the subject is falling on the surface of another subject because the main object has been blocked from sunlight.

A cast shadow consists of two parts: the umbra and the penumbra. The umbra is created since the direct light has been totally blocked, while the penumbra is formed by something partly blocking the direct light. In these studies, we mainly focus on the shadows in the cast shadow areas of the remote sensing images [4, 5, 9]. Unfortunately, shadows cast by buildings in high-density urban environments obscure much of the information in the image leading to potentially corrupted classification results or blunders in interpretation Although significant research has been carried out on the subject of shadowing in remote sensing, very few studies have focused on the particular problems associated with high-resolution satellite imaging of urban areas. Automatic shadow detection and enhancement of shadow features can lead to improve image quality. Very difficult to detect errors in the Shadow boundaries. [5]. This paper explains an automatic property-based approach for detecting and compensating of the shadow regions with shape information preserved in difficult urban color aerial images for solving problems caused by cast shadows in digital image mapping The technique is applied in several invariant color spaces that decouple luminance and chromaticity.The automatic property-based approach effectively eliminating the information about the scene and the source of illumination. To recover the images from high resolution images is very difficult [11]. In this paper, we proposed the problem of shadow detection and removal from single images of natural scenes. Classification results are used to build a graph of segments and graph-cut is used to solve the labeling of shadow and non-shadow regions. Detection results are later refined by image matting and the shadow free image is recovered by relighting each pixel based on our lighting model. We evaluate our method on the shadow detection dataset. In addition, we created a new dataset with shadow-free ground truth images, which provides a quantitative basis for evaluating shadow removal. During the shadow detection result lightening conditions for each pixel in the image are reflected in better. The region is growing field when the pixel intensity varied widely in the shadow region. [12] This paper proposes a comparative study of 3 methods for the classification land cover of shaded areas from high spatial resolution imagery in an urban environment. Method 1 (classification of shaded areas using spatial information) combines spectral information in shaded areas with spatial information for shadow classification. Method 2 applies a shadow restoration technique, the linear-correlation correction method to create a "shadow-free" image before the classification. Third method uses multisource data

Table 1: Compare various shadow detection and removal algorithms

S.No	Method	Key Point	Merits	Demerits
1	Region Growing	Calculated Mean and Standard Deviation	The technique is Orientation	If the pixel intensity varied widely in the shadow region, Region growing is failed.
2	Edge subtraction and Morphology	Canny edge detection is detected and calculated by difference of both background and foreground	If scenes consisting light and dark vehicles, it will give best results	Expensive
3	Pixel Intensity based approach	Conditions are set for a shadow pixel. Standard deviation is computed for ratio value.	The probability density function for pixel intensity is expected directly from the data without any other assumptions.	The pixel intensity value is susceptible to illumination changes.
4	Illumination Assessment Method	Occurrence of shadow on objects is confirmed by the illumination assessment method.	Less processing time	Only foreground figure is measured to study the presence of shadow. It cannot apply for all kinds of applications
5	Partial Differential Equations	Smooth the image is used by different filter. The Shadow is detected by Gradient vector	Achieved Effective shadow detection	It cannot apply for all kinds of applications

fusion to aid in classification of shadows. Simple and easy to implement and provide better accuracy for shadow classification. Shadows of small objects are sometimes missing. [3] This paper proposes a simple method to detect and remove shadows from a single RGB image. A shadow detection method is selected on the basis of the mean value of RGB image in A and B planes of the LAB equivalent of the image and shadow removal method is based on the identification of the amount of light impinging on a surface. The lightness of shadowed regions in an image is increased and then the color of that part of the surface is corrected so that it matches the lit part of the surface. Increasing the lightness of shadowed regions in an image. It is a very simple method for shadow detection and removal. So the detection of hard shadow is very difficult [13]. During the segmentation process the segmentation of the small size shadows from the independent object is very difficult because which will cause error. Image segmentation considering shadows can have better segmentation results, insufficient segmentation still exists. The shadow detection method proposed in this paper can stably and accurately identify shadows. It has improved the quality of the image. It is easy to detect the boundary. So, view image accurately. Image segmentation is still difficult [14, 15] Compared various shadow detection and removal methods critically.

Methodology: The proposed system has to be divides into three parts, 1) Image Pre-processing 2) Shadow Detection 3) Shadow Removal. An image pre-processing first step is image segmentation. First segment the input image into significant region with the help of the watershed algorithm then convert this image into gray scale images using gray scale features such as brightness and luminosity. The second step is finding the suspected shadow areas using bimodal histogram splitting then eliminates those false shadows from that image. Bimodal histogram splitting is the feasible way to find out the false shadows. After that extract the shadow boundary, this can be identified the shadow regions. In the last step shadows are removed according to the shadow removal methods. First compute the mean and standard deviation of shadows and non-shadow areas. Next find the difference between shadow and non-shadow regions. Finally get the shadow free images.

The different components of the proposed architecture are discussed below:

Image Preprocessing

Segmentation: Segmentation is the process of splitting the entire images into smaller groups. The purpose of the image segmentation is to separate the images into significant region with respect to the particular applications such as thresholds, region-based method, edge detection method, graph partitioning method, model based method etc., Segmentation subdivides the input images into selective its region/area/object based. This subdivision carries depends on the problem (images) being solved. That is segmentation must stop when the object/ region of interest in an application have been detected.

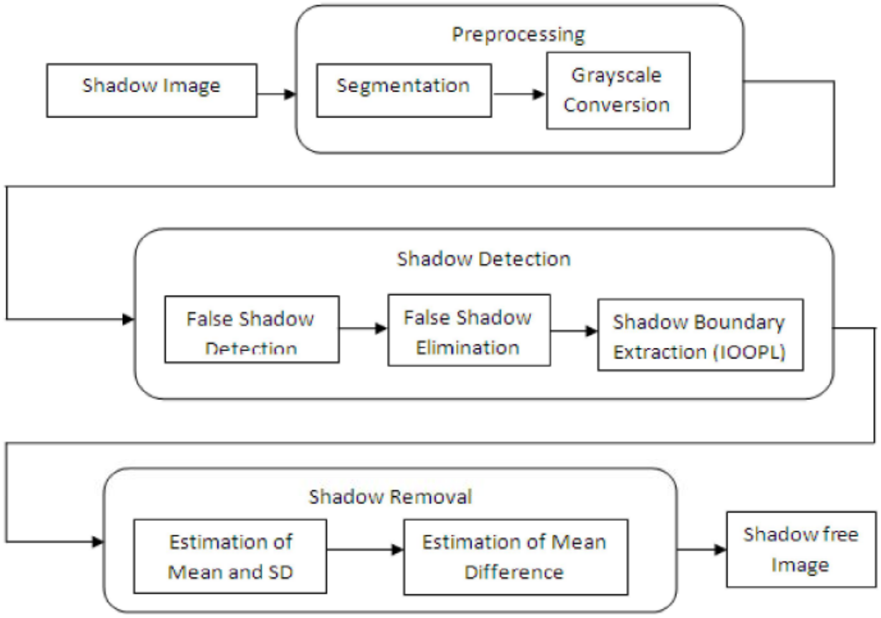


Fig. 1: Architecture diagram of segmentation followed by Shadow detection and Removal from high resolution images using pipelining

The high resolution remote sensing images contain high spatial information. The spectral differences of neighboring pixels within an objects increase gradually. In order to use spatial information to detect shadows, need image segmentation. So we adopt the watershed segmentation. This comes under the edge based image segmentation. The watershed segmentation will effectively segment the shadows and dark objects. The dark objects such as vegetation and water bodies. The traditional image segmentation methods are insufficient segmentation which makes difficult to separate the shadows from dark objects. To find the difference between the shadows and dark objects, we have been added the color and shape factor in segmentation criteria.

Grayscale Conversion: Grayscale conversion is implemented by grayscale algorithm which converts the color images into black and white images. Several grayscale algorithms are followed by converting the grayscale image such as brightness, luminosity and average.

- General steps for converting the color images into grayscale image.
- Get RGB (Red, Green and Blue) color values of each pixel.
- Fancy mathematical calculation to turn RGB color values into single grayscale values.

Next replace original RGB values with new grayscale values.

In grayscale conversion first calculate the length (l) and width (w) of the whole image. Get pixel values into integer format at (x, y) where x denotes the distance from the horizontal axis, y denotes the distance from the vertical axis.

Luminosity is the better grayscale conversion method compare with other grayscale features (brightness and average).

Shadow Detection

False Shadow Detection: Capturing the images through satellite contains shadows which may cause the image quality. The water, land like pools, lakes and smaller size trees, bridges, black color vehicles are shown as shadowed image. Many researchers have been conducted to investigate the suspected shadow detection. To separate the shaded area from non-shaded area using brightness; the threshold value was determined by a bimodal histogram splitting method. This method is able to provide the feasible way to find out the shadowed area. In our work we reach the threshold according to the histogram of original images and find the suspected shadowed areas by comparing the threshold and a grayscale average of an each and every object.

False Shadow Elimination: Dark object may be considered as suspected shadow objects, so need more accurate suspected shadow results to eliminate these dark objects. The Rayleigh scattering results will provide a feasible way to eliminate the dark objects. RGB wave bands are the smaller grayscale difference of Rayleigh is scattering. According to that the grayscale average of blue waveband (GSb) is slightly larger than green waveband (GSg), also the properties of green vegetation are larger than blue wave bands (Gsb). Finally, false shadows are ruled out according to the spatial and the spectral connection between the object by comparing the GSb+GSa > GSg. Here GS is grayscale average; GSa is correlation parameters that determine the image types. Generally shadows are created when light source has been blocked. Building, trees and telephone poles are the main objects for creating shadows in urban areas. Their shadow boundaries have the certain direction. To retrieve shadows first analyze the boundaries of suspected shadow using the spatial relationship to then predict the approximation position of the shadow objects. The spectral relationship difference can be used to decide the light objects from shadowed objects. When the spectral difference between an object and its linked light object is larger than a specific threshold, this object is considered to be linked with the light object and determined to be a shadow.

Boundary Extraction: Boundary extraction is one of the data processing methods that are very constructive applicable for shadow boundary extraction. This process conducted after the false shadow detection and elimination. There are two approaches for boundary extraction that are dilation and erosion. Dilation is an operation that grows or thickens object in binary images and erosion shrinks or thins in binary images.

$$\alpha(X) = X - (X \Theta Y) \quad (1)$$

where $\alpha(X)$ is denotes the boundary set of X, Y is a suitable structuring element, '-' is difference operation on sets. Let X be an image matrix and Y be a structuring element. First step convert the image into binary image. Then perform the erode operation $(X \Theta Y)$. Next, subtract the binary image from the eroded image. Structuring element is a rectangular array of pixels that containing the values 0's and 1's. To recover the shadow areas in an image, we use a shadow removal method based on IOOPL matching.

```
Algorithm: IOOPL Algorithm
Input    : Image
Output   : Optimal Split
Start
         Get Image
         Apply Gaussian smoothing of the image
         Split objects in the image into smaller subsections
         Similarity matching will be done for each object, employed by image
End
```

Fig. 2: Description of IOOPL algorithm

Shadow Removal

Estimation of Mean and SD: In this section first estimate the mean values of shadow and non-shadow. For mean calculation first workout length and width of the image. Let us assume the image (i) = (x, y) where x represents the distance from the horizontal axis, by the distance from the vertical axis.

Each pixel of the image contains integer values. Change this integer value in hexadecimal format.

By doing this conversion we can get the RGB color pixel values again. Initially set the total of RGB colors are Rr, Gg, Bb. Then add the hexadecimal values into the equation (2) in one by one. The same procedure follows in equation (3) and (4) respectively.

$$Rr = Rr + R \quad (2)$$

$$Gg = Gg + G \quad (3)$$

$$Bb = Bb + B \quad (4)$$

Next work out the mean (μ) values of RGB by equation (5), (6) and (7).

$$\mu R = Rr / (l*w) \quad (5)$$

$$\mu G = Gg / (l*w) \quad (6)$$

$$\mu B = Bb / (l*w) \quad (7)$$

Now apply the same procedure for calculating the mean values of non-shadow images. After calculating the mean (μ) of shadow and non-shadow SD (Standard Deviation) for shadow and non-shadow regions are calculated.

Estimation of Mean Difference: After the estimation of the mean and standard deviation of shadow and non-shadow region next calculate the mean difference of the shadows and non-shadows region.

When applying this mean difference on RGB of non -shadow part of an image by using normalization we finally get shadow free images.

RESULTS

The experimentation is done with a system with i3 processor and main memory 2GB RAMS with windows 7 operating system. The implementation of the proposed algorithm is done using MATLAB with the version of MATLAB 7.14(R2012 a). The performance is evaluated with four different images which are widely used in shadow detection and removal experiments.

Evaluation metrics are important to estimate the performance of shadow detection and removals in terms of both shadow is accurately detected, then removal and recover high quality images. Here the complete analysis is done with two different evaluation metrics such as the Mean and Variance. Table 2 is a sample analysis for shadow and non-shadow areas. Table 3 shows the accuracy measurement of shadow detection and removal.

To evaluate the performance of shadow removal, above examples are used. As shown in Figure 3 initially we accept shadow contain image as input. After that segmentation of images, we detect the shadows from non-shadow areas.

False shadow area detection by using the histogram splitting method. Next need to eliminate the false shadows from the result of previous images. False shadows such as bridges, lamp post, small trees etc. After that remove the original shadows from the high quality images and Inner and Outer outline generation from the satellite images. Finally, calculate the mean and standard deviation also means difference; we get the shadow free images. The Producers and customer accuracy defined by

Table 2: Sample Analysis

Name	Size	Mean	Variance
Shadow1	6029	58.98	56.63
Shadow2	3998	85.49	74.17
Shadow 3	8059	78.84	75.70

Table 3: Comparison of Shadow Detection and Removal result of images

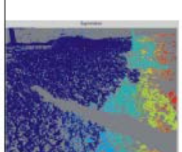
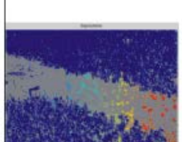
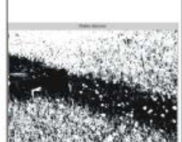
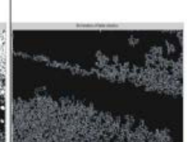
S.NO	Shadow Image	Segmentation	Shadow detection	Elimination of false shadow	Inner and Outer outline generation	Shadow Removal Result
1						
2						
3						

Table 4: Accuracy Measurements of Shadow Detection

Method	Producer's Accuracy	Customer's Accuracy	Overall Accuracy
Proposed	85.72	46.53	73.72

$$\alpha s = \frac{TP}{TP + FN} \times 100$$

The parameter αs and βs indicate the ratio of the number correctly detected shadow pixels over that of total true shadow pixels.

$$\beta s = \frac{TP}{TP + FP} \times 100$$

$$\eta S = \frac{TP + TN}{TP + FN + TN + FP} \times 100$$

ηS Used to calculate the accuracy percentage of the algorithm. TP+FN and TN+FP are shadow and non-shadow ground data.

CONCLUSION

A watershed algorithm, bimodal histogram splitting and the mean difference in image coding is presented in this paper. The proposed algorithms presented a new shadow accurately detected and removed. A watershed algorithm is used to convert images into gray scale images using gray scale features such as brightness and luminosity. Bimodal histogram splitting is the feasible way to find out the false shadows. The Mean difference is used to get non -shadow part of an image by using normalization. These three contributions are solved to improve the performance of the shadow detection and removal. The performance of the proposed algorithm is evaluated using four images with accuracy like Producers accuracy, customer's accuracy and overall accuracy. For the four images experimented the proposed algorithm reached the highest accuracy.

The shadow detection process to detect the shadow and extract the shadow boundary; to calculate the mean and variance of the shadow and non-shadow regions we get the high resolution shadow free images. Further improvements are needed for effective results.

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