Shadow Detection and Removal from QuickBird Images

Aparna P[1], Kavitha N Nair[2]

[1]M.Tech Scholar, [2]Lecturer, ECE Department

MGUCE, Thodupuzha, Kerala, India

Abstract - The urban high resolution color remote sensing images contain shadows. To obtain the exact picture of the image, the shadows are to be detected and removed. It is in this context, shadow detection and removal method for QuickBird images becomes relevant. The image captured by QuickBird satellite is termed as QuickBird image. In this method shadow features are taken into consideration during superpixel image segmentation, and suspected shadows are extracted according to the statistical features of the images. Some dark objects which could be mistaken for shadows are ruled out according to spatial relationship between objects and object properties. The true shadows which are detected are to be removed. For that the boundary of actual shadow is traced. Inner and outer outline lines of the detected shadow are then generated. For shadow removal, first the IOOPLs are obtained with respect to the boundary lines of shadows. Sections obtained through IOOPL similarity matching is analyzed whether they are homogeneous or not. There is presence of shadow if inner and outer boundaries are not homogeneous in IOOPL matching. Shadow removal is then performed by implementing combined shadow removal technique. These methods can accurately detect and remove shadows.

Keywords - Combined shadow removal, inner-outer outline profile line (IOOPL), QuickBird image, shadow detection, shadow removal, superpixel segmentation.

1. INTRODUCTION

The presence of shadow in an image is responsible for reducing the reliability and clarity of the image and so shadow detection and removal is important in order to improve the performance of the image. Many techniques have been proposed over the years, but still shadow detection and removal is a challenging problem. Hence reliable detection of shadow is very essential to remove it effectively. Most of the images captured by QuickBird satellite contain shadow. These shadows prevents from obtaining the original image so they have to be detected and removed. Images captured by satellites are required for urban planning, land studies, height estimation of man-made structures , traffic control and earth observation. Applications include intelligent highway systems, automotive surveillance, picture restoration and tracking applications. Problem of shadowing is normally significant in very high-resolution satellite imaging. Thus, shadow detection and removal is an important pre-processing for improving performance of such vision. To remove shadow, initially shadow should be detected once the image is segmented. For better segmentation results superpixel segmentation is adopted instead of watershed. The detected true shadow can be removed by combined shadow removal techniques instead of other techniques which uses digital number.

2. SYSTEM MODEL

Shadows are created because light source has been blocked by something [1]. There are two types of shadows: self shadow and cast shadow. Self shadow is the shadow on a subject on the side that is not directly facing the light source. Cast shadow is the shadow of a subject falling on the surface of another subject because the former subject has blocked the light source. Cast shadow has two parts: umbra and penumbra. Umbra is created because direct light has been blocked completely, while penumbra is created by something partly blocking direct light, as shown in Fig.1.

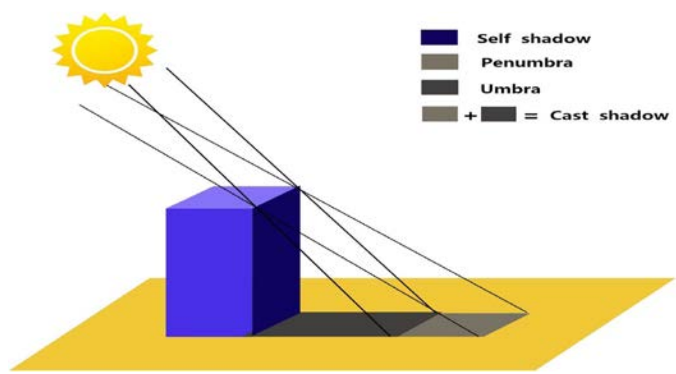

Fig. 1. Principle of shadow formation

In urban areas, surface features are quite complex, with a great variety of objects and shadows formed by elevated objects such as high buildings, bridges, and trees. Detection and removal of shadows play an important role in applications of urban high-resolution remote sensing images such as object classification, object recognition, change detection, and image fusion. In this method, shadows in cast shadow area of image are focused. The Quickbird image containing shadow is first segmented then suspected shadows are detected and then false shadows are ruled out. Instead of watershed segmentation, superpixel segmentation is adopted. Superpixel segmentation is used because it can even separate small size shadows into independent objects. These steps come under shadow detection. After detecting true shadow, shadow removal steps are to be performed. These steps start by extracting the shadow boundary and generating inner and outer profile lines. Later shadow removal is to be performed according to the homogeneous sections attained through IOOPL similarity matching. Then the combined shadow removal can be implemented.

3. PREVIOUS WORK

A thorough review has been conducted on shadow detection and removal for various images. Different techniques adopted for shadow detection and removal of images are summarized. The most relevant contributions in this field are also presented here.

Hongya Zhang et. al. [1] proposed object-oriented shadow detection and removal from urban high-resolution remote sensing images. Image containing shadows are segmented by watershed, suspected shadows are detected and false shadows are eliminated. Boundary of detected shadows is traced and IOOPL matching is performed and shadow removal is followed by employing two strategies such as RRN (Relative Radiometric Normalization) and PF (Polynomial Fitting). Finally the original image is recovered. Watershed segmentation is having certain limitations, it is difficult to separate even small size shadows into independent objects. Implementation of shadow removal is difficult to carry out using RRN and PF since it requires DN (digital number) which depends on the atmospheric factors when the photo is being captured.

G. Finlayson et. al. [2] developed a method to process a 3-band colour image to locate, and remove shadows. A 1-d illumination invariant shadow-free image is derived initially. Using this invariant image with the original image, shadow edges are located. By setting shadow edges to zero in an edge representation of the original image, and by subsequently re-integrating this edge representation by a method paralleling lightness recovery, full colour shadow free image is obtained. An artifact introduced into the images due to the fact that the determination of the shadow-edge is imperfect is the main limitation.

P.M. Dare [3] prepared a method for shadow analysis in high-resolution satellite imagery of urban areas. High-Resolution Satellite Imagery (HRSI) offers great possibilities for urban mapping. The principal problem caused by shadows is either a reduction or total loss of information in an image. Reduction of information could lead to the corruption of biophysical parameters derived from pixels values, such as vegetation indices. Total loss of information means that areas of the image cannot be interpreted, and value-added products, such as digital terrain models, cannot be created. The effects of shadowing can be reduced slightly by increasing the look angle of the sensor. Presence of artifacts and difficulty in selecting the most appropriate threshold level are the main issues.

R. B. Irvin and D. M. McKeown, Jr [4] introduced computational techniques for utilizing the relationship between shadows and man-made structures to aid in the automatic extraction of man-made structures from aerial imagery. Four methods are described. Key issues involve the accurate localization of the structure/shadow boundary and shadow edge, and attribution of shadow segments to structure hypotheses.

L. Lorenzi et. al. [5] presented a complete processing chain, which relies on various advanced image processing and pattern recognition tools. The presence of shadows in Very High Resolution (VHR) images can represent a serious obstacle for their full exploitation. The detection and classification tasks are implemented by means of the state-of-the-art Support Vector Machine (SVM) approach. The reconstruction is based on a linear regression method to compensate shadow regions by adjusting the intensities of the shaded pixels according to the statistical characteristics of the corresponding nonshadow regions. There is possibility for reconstruction problems.

The solution for the problems from previous research as mentioned above is to develop a new processing chain for shadow detection and removal from aerial images. The purpose of this study is to implement a shadow detection and removal technique which is simple without any complicated calculations especially for QuickBird images.

4. PROPOSED METHODOLOGY

In imaging science, image processing is any form of signal processing for which input is an image, such as a photograph or video frame; output may be either an image or a set of characteristics or parameters related to the image. The basic blocks for developing the system are given in Fig.2. The chain of process is carried out in a sequential manner to obtain shadow free image.

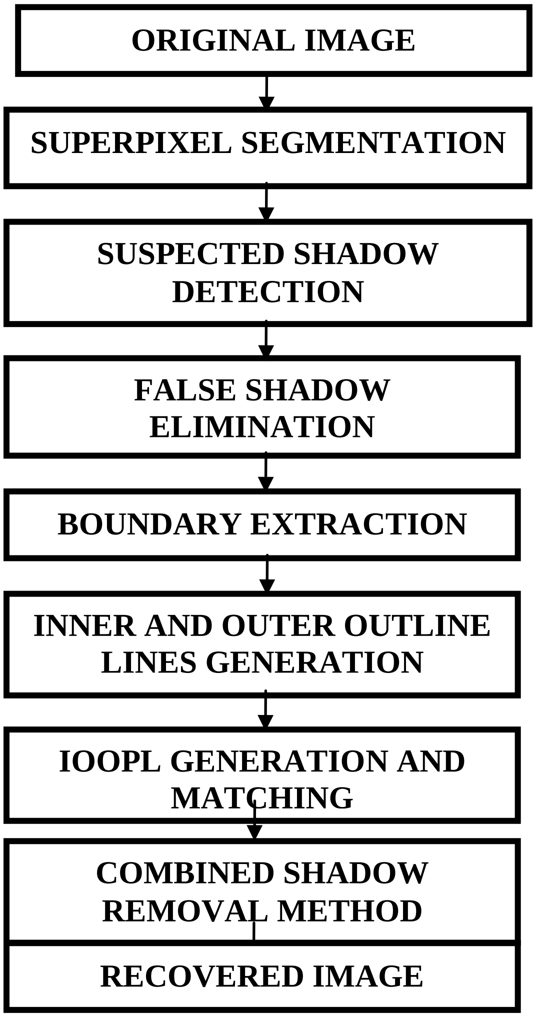

Fig. 2. Block diagram of shadow detection and removal from QuickBird image.

QuickBird image considered here is a high resolution color remote sensed image. Due to the presence of shadow in cast shadow area, a clear idea of image is not obtained [6]. To get exact view of the image and to make the image fit its purpose shadow detection and removal is necessary. Shadow detection plays an important role in remote sensing [3]. Shadow detection includes image segmentation, detection of suspected shadow and false shadow elimination. Shadow removal steps include boundary extraction, inner and outer outline lines generation, IOOPL matching and generation and employing combined shadow removal technique.

5. SIMULATION/EXPERIMENTAL RESULTS

To validate this method work, datum used is a QuickBird image of Las Vegas, USA. Total data set covers an area of buildings, green grass ,roads, vehicles and water body.

A. Original image

The shadow in the QuickBird image is analyzed through a chain of steps [5]. Fig. 3 shows remote sensed QuickBird image, which is said to be the original image. Existence of shadow is clearly seen. Edge detection is performed and morphological filtering is done to minimize effect of noise. Shadow in this image is first detected through segmentation.

Fig. 3. Original QuickBird image of Las Vegas, USA.

B. Superpixel segmentation

In order to use spatial information to detect shadows, image segmentation is needed [8]. Superpixel segmentation is adopted which provides better segmentation results. It segments small size shadows into independent objects.

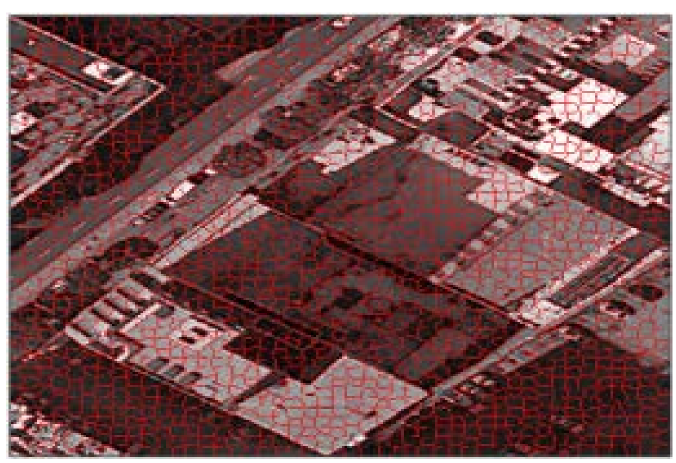

Fig. 4. Superpixel segmentation result of original image

Fig. 4 shows superpixel segmentation result. Traditional image segmentation methods are likely to result insufficient segmentation, which makes it difficult to separate shadows from dark objects. The segmentation scale could be set empirically for better and less time-consuming results.

C. Suspected shadow detection

After superpixel segmentation, suspected shadows are to be detected according to the statistical features of the images. A properly set threshold can separate shadow from nonshadow. The threshold according to the histogram of original image is attained. The suspected shadow objects are determined by comparing the threshold and grayscale average of each object obtained in segmentation [1].The grayscale value with minimum frequency in the neighbourhood of the mean of the two peaks as the threshold is chosen, as shown in

$$Gq=1/2(Gm+Gs) \quad (1)$$

$$h(T) = \mathrm{Min}\{h(Gq - \varepsilon), h(Gq + \varepsilon)\} \quad (2)$$

In the equations, Gm is the average grayscale value of an image; Gs stands for the left peak of the shadow in the histogram; T is the threshold; ε represents the neighbourhood of T, and $h(I)$ is the frequency of I, where $I = 0, 1, \ldots, 255$.

$$T \text{ is } [Gq - \varepsilon, Gq + \varepsilon] \quad (3)$$

Fig. 5 shows suspected shadow detection result. For the same object, when in shadow and nonshadow, its grayscale difference at the red and green wavebands is more noticeable than at the blue waveband since atmospheric molecules scatter the blue wavelength most among the visible rays (Rayleigh scattering). Thus, a suspected shadow with the threshold method at the red and green wavebands is retrieved. An object is determined to be a suspected shadow if its grayscale average is less than thresholds in both red and green wavebands.

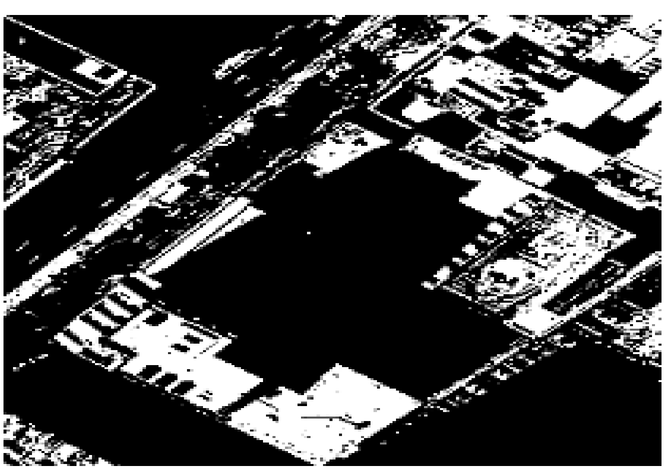

Fig. 5. Suspected shadow detection result after segmentation

D. False shadow elimination

Suspected shadows may contain false shadows such as vegetation and waterbodies which is to be eliminated. Dark objects may be included in the suspected shadows, so more accurate shadow detection results are needed to eliminate these dark objects. Rayleigh scattering results in a smaller grayscale difference between a shadow area and a nonshadow area in the blue (B) waveband than in the red (R) and green (G) wavebands. Consequently, for the majority of shadows, the grayscale average at the blue waveband Gb is slightly larger than the grayscale average at the green waveband Gg. Also, the properties of green vegetation itself make Gg significantly larger than Gb, so false shadows from vegetation can be ruled out by comparing the Gb and Gg of all suspected shadows. Namely, for the object i, when $Gb + Ga < Gg$, i can be defined to be vegetation and be ruled out. Ga is the correction parameter determined by the image type.

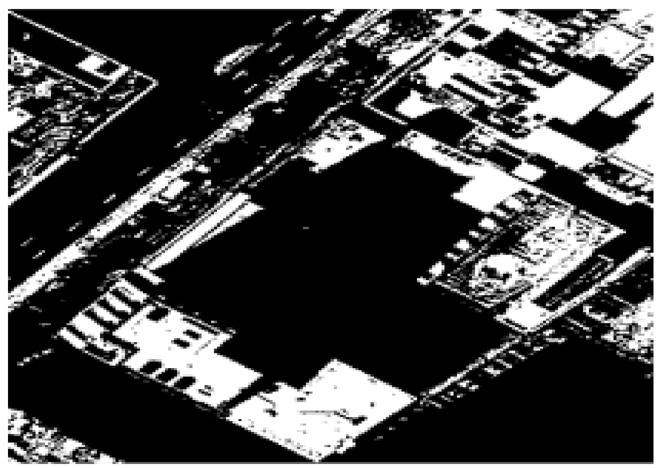

Fig. 6. False shadow eliminated image

Geometrical characteristics and spatial relationship between objects, is used to rule out other dark objects from the suspected shadows [7]. Lakes, ponds, and rivers all have specific areas, shapes, and other geometrical characteristics. Most bodies of water can be ruled out due to area and shape of the suspected shadows of the object that they produce. Fig. 6. shows false shadow eliminated image.

E. Boundary extraction

After detecting true shadow from QuickBird image, the main boundary of shadow is extracted. Boundary of the detected shadow is extracted and is termed as main boundary. Fig. 7 shows boundary extraction result. The green lines in the figure below represent the shadow boundary. Based on this boundary, inner and outer outlines are generated and its matching is carried out to find the non homogenous sections.

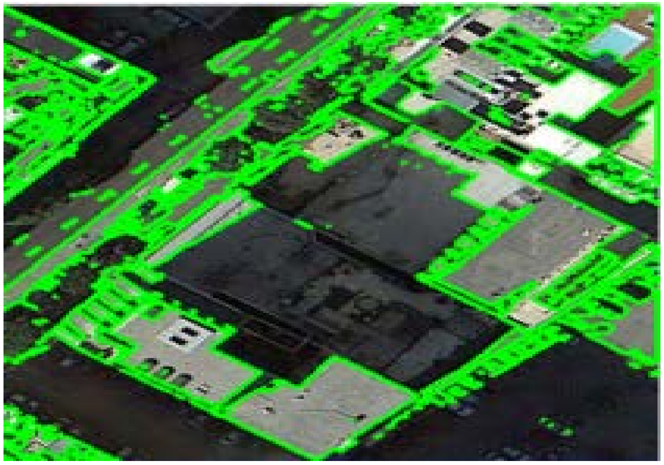

Fig. 7. Boundary extraction result

F. Inner and outer outline lines generation

The inner and outer outlines of the main boundary can be obtained by contracting the main shadow boundary inward and expanding it outward. As shown in Fig. 8, *R* is the vector line of shadow boundary obtained from shadow detection, *R*1 is the outer outline in the nonshadow area after expanding *R* outward, and *R*2 is the inner outline in the shadow area after contracting *R* inward. There is a one-to-one correspondence between nodes on *R*1 and *R*2. The grayscale value of the corresponding nodes along *R*1 and *R*2 at each waveband is collected to obtain the IOOPL. The Outer Profile Lines (OPLs) in the shadow area are marked as inner OPLs; OPLs in the nonshadow area are marked as outer OPLs.

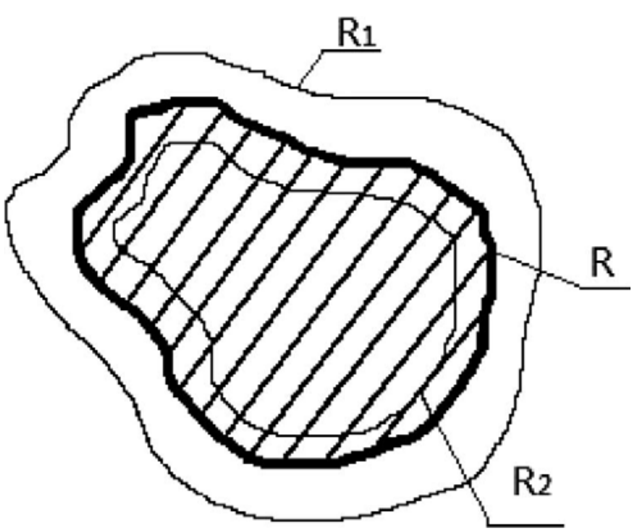

Fig. 8. Diagram of shadow boundary, inner, and outer outline lines.

The result of inner and outer outline lines generation is showed in Fig. 9. The inner outline line is obtained by contracting the boundary of detected shadow inward and it is represented by blue line. The outer outline line is obtained by expanding the boundary of detected shadow outward and it is represented by red line.

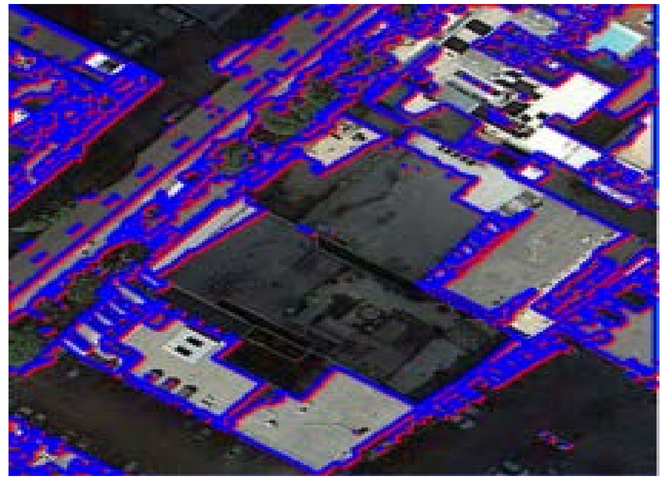

Fig. 9.Inner and outer outline lines of extracted boundary

G. IOOPL generation and matching

After generating inner and outer outline lines, IOOPL matching is done. The grayscale value of the corresponding inner and outer outlines at each waveband is collected to obtain the IOOPL. There is presence of shadow if inner and outer boundaries are not homogeneous in IOOPL matching. Fig. 10 shows IOOPL generation and matching result.

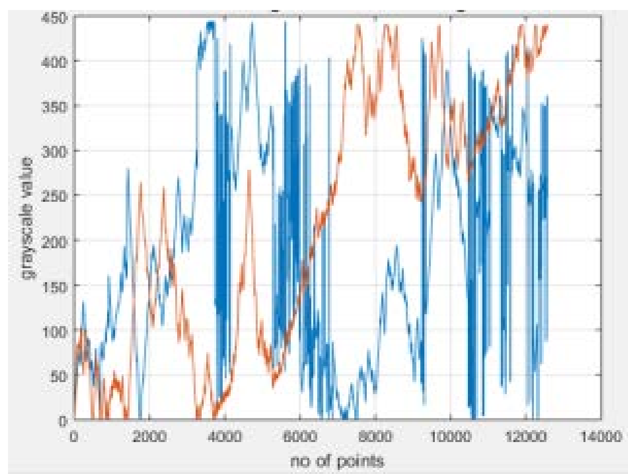

Fig. 10. IOOPL generation and matching

During the process, Gaussian smoothing is performed to simplify the view of IOOPL. Fig. 11 shows IOOPL generation and matching after Gaussian smoothing. After carrying out Gaussian smoothing, the mismatch regions in the inner and outer outlines can be clearly seen.

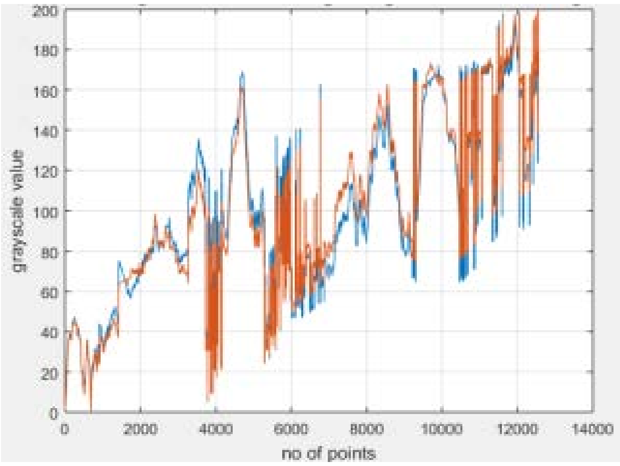

Fig. 11. IOOPL generation and matching after Gaussian smoothing

H. Combined shadow removal method for image recovery:

The dissimilar regions in the plot contain shadows which are to be removed by shadow removal method. Implementation of shadow removal is performed using Combined shadow removal method .This method doesn't require digital number. So it is easy to implement. This shadow removal method is the combination of the model based shadow removal and additive shadow removal method. Model Based Shadow Removal is a simple shadow model, where there are two types of light sources: direct and ambient light. Direct light comes directly from the source, while environment light is from reflections of surrounding surfaces [4]. Based on this model, our goal is to relight each pixel using this coefficient in order to obtain a shadow free image. Additive Shadow Removal is another simple shadow removal technique which is an additive correction of the color intensities in the shadow area. The average pixel intensities in the shadow and lit areas of the image are computed and added this difference to the pixels in the shadow areas.

Fig. 12. Recovered image after performing combined shadow removal technique

Combined Shadow Removal is another shadow removal method which is the combination of the previous two ones. The images are converted to the YCbCr color-space. The additive method is used for the correction on the Y channel, and the model-based method for the correction of the Cb and Cr channels. Thus combined shadow removal technique is implemented to remove shadow in QuickBird image.

Recovered image obtained after performing combined shadow removal technique is shown in Fig. 12. Thus recovered image which is free from shadow can be used in Remote sensing field as well in the surveillance system [2].

6. CONCLUSION

A systematic and efficient method for shadow detection and removal in QuickBird images is put forward. Shadow free QuickBird image is utilized for specific applications. It is expected that the shadow detection method used in the study will help to identify shadows accurately. The shadow detection and removal methods considered could achieve a recovered image without complicated calculation. The approach is simple, and effective. It is possible to segment the small size shadows into an independent object by superpixel segmentation. Even though shadow removal is a difficult task, detected shadows are removed using combined shadow removal technique. The recovered image posses only a small mean square error but high peak signal to noise ratio. It can be concluded that recovered image has less effect of noise. Thus it can be summarized that detection and elimination of the shadow from obtained QuickBird image is expected.

7. FUTURE SCOPES

Further improvements are needed in the image segmentation. Although image segmentation considering shadows can have better segmentation results, insufficient segmentation still exists. For example, parts of the shadow from low trees cannot be separated from the leaves. Because of the filming environment or some other reasons, obvious color cast can be seen in some parts of a shadow area. IOOPL matching could relieve this case to a certain extent but not completely resolve the problem and so this can be another future improvement

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AUTHOR'S PROFILE

Aparna P has received her Bachelor of Engineering degree in Applied Electronics & Instrumentation Engineering from Vedavyasa Engineering College, Malappuram, India in the year 2013. At present she is pursuing M.Tech. with the specialization of Applied Electronics in Mahatma Gandhi University College of Engineering, Thodupuzha, India. Her areas of interests include Power Plant Instrumentation and Biomedical Instrumentation.

Kavitha.N.Nair completed her M.Tech in Applied Electronics from Mahatma Gandhi University College of Engineering, Thodupuzha in 2012. At present she is working as lecturer in Electronics in Department of Electronics and Communication Engineering, Mahatma Gandhi University College of Engineering, Thodupuzha, India. Her areas of interests include Digital Signal Processng and Computer hardware. She has two journals and two conference papers in her credit.