Quality Enhancement of Remote Sensing Images by Object Oriented Shadow Detection and Removal using SVM and IOOPL

Leethu Lakshmi A L, Jasmine George

***Abstract*—Shadows will occur by sunlight or any light sources. It occurs frequently in a wide variety of scenes. In many cases, this is undesirable due to the fact that they often lead to the result of irretrievable processing failures. In this paper, we introduce a novel shadow detection and removal technique that produces a shadow-free scene. In this approach shadow features are taken into consideration during image segmentation and an SVM classifier based training scheme is used after the segmentation for accuracy and then, according to the statistical features of the images, suspected shadows are extracted. Dark objects misclassified as shadows are also removed. For shadow removal, inner–outer outline profile line (IOOPL) similarity matching is used. Finally, using the homogeneous sections obtained after the matching process, the relative radiation calibration parameters between the shadow and non-shadow regions are obtained, and shadow removal is performed. The proposed method can accurately detect shadows from urban high-resolution remote sensing images and can effectively restore shadows.**

***Index Terms*—Object-oriented, remote sensing images (RSI), change detection, support vector machine (SVM) classifier, inner–outer outline profile line (IOOPL), relative radiometric correction, shadow detection, shadow removal.**

I. INTRODUCTION

‘’Shadow is Light’s child. It is nothing without the Light and nothing if it falls into Darkness.”Shadows, created wherever an object obscures the light source, are an ever-present aspect of our visual experience. Shadows have played an important role in remote sensing for almost as long as the science has been in existence. Shadows can either aid or confound scene interpretation, depending on whether we model the shadows or ignore them. If we can detect shadows, we can better localize objects, infer object shape, and determine where objects contact the ground. Detected shadows also provide cues for illumination conditions and scene geometry and shadows themselves can be regarded as a type of useful information in 3-D restoration, change detection, building location recognition and height estimation they can also interfere with the processing and application of high-resolution remote sensing images. But, if we ignore shadows, spurious edges on the boundaries of shadows and confusion between albedo and shading can lead to mistakes in visual processing. For these reasons, shadow detection has long been considered a crucial component of scene interpretation. Yet despite its importance and long tradition, shadow detection remains an extremely challenging problem, particularly from a single image.

Leethu Lakshmi A L, Department of ECE, College of Engineering kallooppara,Thiruvalla,India,Phone:0479-2427241.

Jasmine George, Department of ECE, College of Engineering kallooppara,Thiruvalla,India,Phone:0469-2677890.

High-resolution satellite imagery (HRSI) offers great possibilities for urban mapping. In urban areas, the surface landscapes are quite difficult, with a great variety of objects and shadows formed by elevated objects such as high buildings, bridges, and trees. Shadows and shadings in images lead to undesirable problems on image analysis. That’s why much attention was paid to the area of shadow detection and removal over the past decades and covered many specific applications such as traffic surveillance, face recognition and image segmentation.

Shadow detection and removal can be accomplished using either pixel-based or object-based approaches. Pixel-based classification schemes seek to identify the class of each pixel in the imagery by comparing the -dimensional data vector for each pixel with the prototype vector for each class. The data vectors typically consist of a pixel’s gray level values from multispectral channels and textural and contextual measures that have been computed from those channels. Textural and contextual measures contain information about the spatial distribution of tonal variations within a band. Object-based approaches do not operate directly on individual pixels but on objects consisting of many pixels that have been grouped together in a meaningful way by image segmentation. In addition to spectral and textural information utilized in pixel-based classification methods, image objects also allow shape characteristics and neighbourhood relationships to be used for the object’s classification. However, the success of object-based classification approaches is very dependent on the quality of the image segmentation.

II. LITERATURE REVIEW

Considerable research has been conducted to investigate shadow detection and removal in remotely sensed imagery. Existing shadow detection methods can be classified into two. First one is model-based methods [3] which use prior information such as scene, moving targets, and camera altitude to construct shadow models and shadow-feature-based methods. The second one is the shadow feature based method [5] which identifies shadow areas with information such as gray scale, brightness, saturation, and texture. The second approach is more general and identifies shadows by exploiting their properties in geometry, brightness and colour.

A. Shadow Detection Methods

1. Shadow Identification and Classification Using Invariant Colour Models

The method [6] works under the following hypotheses on the scene and on the lighting conditions. A simple environment is assumed where shadows are cast on a flat, or nearly flat, non textured surface. Objects are uniformly colored. Only one light source illuminates the scene, and shadows and objects are within the image. The light source must be strong, thus shadows are well visible. This method exploits color information for shadow detection by using the invariance properties of some color transformations. These transformations (photometric color invariants) are functions which describe the color configuration of each image point discounting shadings shadows and highlights. They are invariant to a change in the imaging conditions, such as viewing direction, object's surface orientation and illumination conditions.

The first step toward identifying shadows involves the exploitation of the luminance properties of shadows. The luminance image, which is sensitive to shadows, and the color components of the invariant color model, are obtained through a color space conversion step and edge detection is performed on the luminance image, Then the obtained edge map is used, together with the luminance image, as the input for a scheme that extracts regions in the scene that are darker than their surroundings. Dark regions are candidate shadow regions. Edges on the photometric invariant color space are obtained to find object contours and discount shadow contours. Dark regions that are not contained in the object contours are classified as cast shadow regions, while dark regions that are inside the detected object contours are classified as self shadow regions.

But this process is valid when there is only one object in the image. In the case of a scene composed by multiple objects, it is possible to limit the analysis to each single object by applying a connected component labelling.

2. Successive Thresholding Scheme algorithm

The STS-based algorithm [8] is presented to detect shadows for color aerial images. Instead of using the ratio map obtained by Tsai's algorithm, here use the modified ratio map to distinguish the candidate shadow pixels from non shadow pixels. Then on the modified ratio map, the global thresholding process is first performed to obtain the coarse-shadow map, which separates the input image into candidate shadow pixels and non-shadow pixels. Based on the coarse-shadow map, the candidate shadow regions can be identified by using the connected component analysis, and then, we perform the local thresholding process to each region iteratively to detect true shadow pixels from candidate shadow pixels.

Furthermore, we present a fine-shadow determination process to distinguish true shadows from candidate shadows, and then, we enforce the remaining candidate shadows to be the non-shadows. In STS-based algorithm, only the candidate shadow pixels are required to perform the local process to identify true shadow pixels. For the candidate shadow pixels in the coarse-shadow map, we construct candidate shadow regions by applying the connected component analysis to these pixels. Next, for each candidate shadow region, the local thresholding process is applied to distinguish true shadow pixels from candidate shadow pixels. Here, based on Otsu's thresholding method, the separability factor SP is used to determine whether each candidate shadow region can be separated into the true shadow region and the candidate shadow region or not.

B. Existing Shadow Removal Techniques

1. Histogram Matching

In image processing, histogram matching [2] is the transformation of an image so that its histogram matches a specified histogram. 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. The method is used to recover the *DN* values of the shadow-covered pixels by matching the histogram of the shadow regions to the histogram of the non-shadow areas of the same class. This operation is sensitive to the window size in which the histograms are matched. The Quad-tree partitioning is applied in order to automatically select the appropriate window sizes.

2. *Radiometric Enhancement*

Radiometric enhancement [9] is a method of reducing the severity of shadows in high-resolution imagery .The technique is based on histogram matching, is similar to image balancing in orthomosaic generation. The histograms of neighbouring regions are adjusted to match each other in order to minimize the radiometric differences across the boundary of the regions.

3. *Companion Area and Intensity Mapping*

The intensities of the shadow pixels can be restored by mapping them to the bright pixels refer to the same objects, which is called companion area intensity mapping (CAIM) [10].The shadow removal module contains two stages. The first stage is deciding the companion area to the shadow area. The second stage is computing the statistics of the two regions and mapping shadow intensities to their companion intensities. It is difficult to decide the area containing exactly the same objects with those in a shadow area automatically. A companion area should satisfy the following criteria's such as it must not include any shadow pixels, should be neighbour to the relevant shadow area and It should be a rational area. According to these conditions, trace the companion area forward along the direction of shadow casting.

Intensity mapping is implemented to the shadow pixels based on the histogram analysis to the shadow area and the corresponding companion area. Both of the histograms of the two areas contain a head and a tail parts. They cover a certain ranges but contain fewer pixels. To acquire better performance of algorithm, limit these two parts in mapping by setting an upper cut-off and a lower cut-off to the histogram.

Those intensities within the head and tail are replaced by the upper cut-off and the lower cut-off respectively in mapping CAIM maps the upper and lower cut-off of the shadow area to the upper and lower cut-offs of the companion area respectively, and so for the means of the shadow and companion areas. Thus, the gamma parameter can be decided by the averages of the two areas. The intensities at the edges of the shadow area are higher than those in the inner, because the illuminating condition is a little different at the edge from in the inner. They generally belong to or close to the upper cut-off of the shadow area, and become very bright after restoring. This edge effect is reduced by smudging.

Currently there are many shadow detection and removal methods used in the high resolution remote sensing images, but those methods are based on pixel level techniques. Pixel-based methods may pay too much attention to the details of an object when processing high resolution images, making it difficult to obtain overall structural information about the object. Pixel level methods also results in non normal distribution of results, greater probability of errors, causes pseudo colours in image fusion techniques, incomplete information in change detection matrix, optimum threshold is need to find out for method. Due to the shortcomings of pixel-level shadow detection, we go for the object oriented shadow detection and removal technique which gives better results as compared to the earlier method.

III. PROPOSED METHOD

Shadow detection is the process of identifying the shaded pixels in remotely sensed imagery, whereas shadow removal is to restore the spectral information of the shaded areas to obtain a shadow-free image Shadow removal is often used interchangeably with the term shadow restoration, but shadow removal also refers to the process that simply removes the shaded pixels from the imagery.

Fig.1 shows the block diagram of the proposed Shadow detection and removal system. First, the shadow features are evaluated through image segmentation, an SVM classifier based training scheme is used after the segmentation for better segmentation results and suspected shadows are detected with the threshold method. Second, the false shadows are ruled out using Rayleigh scattering principle. This will allow only the real shadows to be detected in subsequent steps. Shadow removal employs a series of steps. We extract the inner and outer outline lines of the boundary of shadows. The grayscale values of the corresponding points on the inner and outer outline lines are indicated by the inner–outer outline profile lines (IOOPLs). Homogeneous sections are obtained through IOOPL sectional matching. Finally, using the homogeneous sections, the relative radiation calibration parameters between the shadow and non shadow regions are obtained, and shadow removal is performed.

A. *Image Segmentation*

Image segmentation refers to the decomposition of a scene into different components thus to facilitate the task at higher levels such as object detection and recognition. Segmentation algorithms are based on one of two basic properties of colour, gray values, or texture: discontinuity and similarity. Images with higher resolution contain richer spatial information. The spectral differences of neighbouring pixels within an object increase gradually. Pixel-based methods may pay too much attention to the details of an object when processing high resolution images, making it difficult to obtain overall structural information about the object. So that the object oriented approach is used in which the operations are carried out on a set of pixel grouped together in a meaningful way. In order to use spatial information to detect shadows, image segmentation is needed.

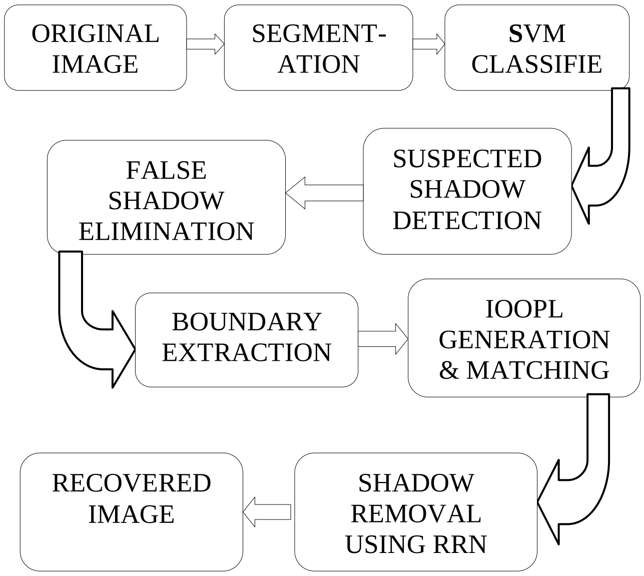


Fig.1. Block diagram of the proposed System

B. *SVM Classifier*

The SVM classification is employed after the segmentation to discriminate between non shadow regions and shadow regions. Support vector machines [11] (SVMs) are supervised learning algorithms that have been widely and successfully used for pattern recognition. The method is also known as a “maximal margin classifier” since it determines a hyper plane that separates the two classes with the largest margin between the vectors of the two classes. Most problems in real life are however linearly not separable. SVM can deal with such problems using a kernel that transforms the feature space into a higher (possibly infinite) dimension feature space. The linearly separable hyper plane in the higher dimensional space gives a nonlinear decision boundary in the original feature space. Here we use the linear case since we have only two set of regions shadowed region and non shadow region.SVM algorithm has a good validity of calculation, robustness and statistical stability.

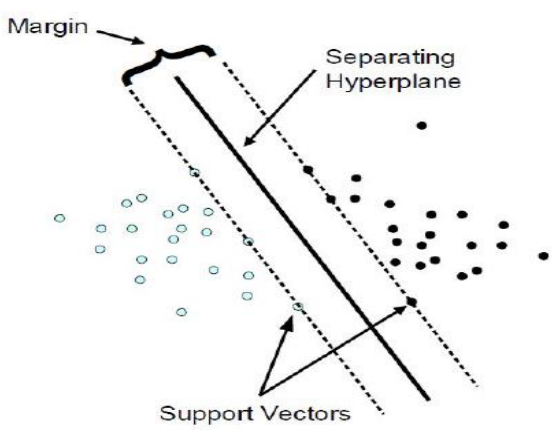


Fig.2.SVM classification with a hyper plane that maximizes the separating margin between the two classes. Support vectors are elements of the training set that lie on the boundary hyper planes of the two classes.

1. Linear SVM Classifier

Linear SVM classifiers are the simplest case in which the training patterns are linearly separable. That is, there exists a linear function of the form

$$f(X) = W^T X + b \quad (1)$$

Such that for each training example X_i ,the function yields $f(X) \geq 0$ for $y_i = +1$ and $f(X) < 0$ $for\ y_i = -1$. In other words, training examples from the two different classes are separated by the hyper plane $f(X) = W^T X + b = 0$

For a given training set, while there may exist many hyper planes that separate the two classes, the SVM classifier is based on the hyper plane that maximizes the separating margin between the two classes. . In other words, SVM finds the hyper plane that causes the largest separation between the decision function values for the "borderline" examples from the two classes. Mathematically, this hyper plane can be found by minimizing the following cost function:

$$J(W) = \frac{1}{2} W^T W = \frac{1}{2} \|W\|^2 \quad (2)$$

Subject to the separability constraints

$$W^T X_i + b \geq +1 \quad ,for\ \ y_i = +1$$

or

$$W^T X_i + b \leq -1 \quad ,for\ \ y_i = -1\ i=1, 2....,l \quad (3)$$

Equivalently, these constraints can be written more compactly as

$$y_i(\ W^T X_i + b) \geq 1 \quad (4)$$

This specific problem formulation may not be useful in practice because the training data may not be completely separable by a hyper plane. In this case, slack variables, denoted by ε_i , can be introduced to relax the separability constraints in (4) as follows:

$$y_i(\ W^T X_i + b) \geq 1 - \varepsilon_i \quad \varepsilon_i > 0\ i=1,2,....l \quad (5)$$

Accordingly, the cost function in (2) can be modified as follows:

$$J(W, \varepsilon) = \frac{1}{2} \|W\|^2 + C \sum_{i=1}^{l} \varepsilon_i \quad (6)$$

Where 'C'is a user-specified,positive,regularization parameter. In (6), the variable ε is a vector containing all the slack variables ε_i, $i=1,2,....l$

The modified cost function in (6) constitutes the so-called structural risk, which balances the empirical risk (i.e., the training errors reflected by the second term) with model complexity. The regularization parameter 'C' controls this trade-off. The purpose of using model complexity to constrain the optimization of empirical risk is to avoid over fitting, a situation in which the decision boundary too precisely corresponds to the training data, and thereby fails to perform well on data outside the training set.

C. Suspected Shadow Detection

Thresholding to be the ideal method of shadow detection in high resolution satellite images due to the spectral content of the images. However, the difficulty with thresholding lies in selecting the most appropriate threshold level. Bimodal histogram splitting[1] provides the most robust method of threshold level selection since the image has only two features of interest: shadow and non-shadow. It can be calculated by taking the mean of the two peaks and it gives a consistently accurate threshold level. We chose the gray scale value with the minimum frequency in the neighbourhood of the mean of the two peaks as the threshold, as shown in

$$G_{q=} \frac{1}{2}(G_m + G_s) \quad (7)$$

$$h(T) = Min\{h(G_q - \varepsilon), h(G_q + \varepsilon)\} \quad (8)$$

G_m is the average gray scale 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, where $T\epsilon[G_q - \varepsilon, G_q + \varepsilon]$.

D. False Shadow Elimination

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 gray scale difference between a shadow area and a non-shadow area in the blue (B) waveband than in the red (R) and green(G) wavebands. Spatial relationship features are used to rule out dark objects in the suspected shadows. Dark objects are substantive objects, while shadows are created by taller objects which block the light sources and may be linked together with the objects that result in the shadows. An obscured area (i.e., a shadow) forms a darker area in an image. The object blocking the light forms a lighter area in an image. At the same time, the sun has a definite altitude angle, and a shadow boundary reflects the boundary of a building and the position of a light source. For the majority of shadows, the grayscale average at the blue waveband G_b is slightly larger than the grayscale average at the green waveband [1]. G_g Also, the properties of green vegetation itself make G_g significantly larger than G_b so false shadows from vegetation can be ruled out by comparing the G_b and G_g of all suspected shadows. Namely, for the object i, when $G_b + G_a < G_g$, i can be defined to be vegetation and be ruled out. G_a is the correction parameter determined by the image type.

E. Shadow Removal

For the majority of remote sensing applications, it would be preferable that high-resolution satellite imagery could be acquired when lighting conditions were at their optimum and shadows minimized. Unfortunately this is not always possible, and thus, alternative techniques have to be developed to cope with the problems caused by shadows. The solution to the problem is a technique called IOOPL matching.

To remove the shadow areas from the image in we use IOOPL section matching. There is a large probability that both shadow and non-shadow areas in close range on both sides of the shadow boundary belong to the same type of object. The inner and outer outlines can be obtained by contacting the shadow boundary inward and expanding it outward, respectively. Then, the inner and outer outline profile lines are generated along the inner and outer outline lines to determine the radiation features of the same type of object on both sides

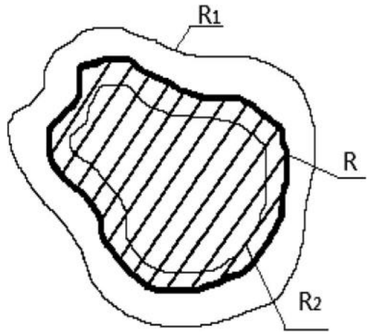


Fig.3.Diagram of shadow boundary, inner, and outer outline lines

For this first consider the shadow boundary and use vector representation to mark the inner and outer lines. when a shadow boundary is consider the area beyond the boundary may be part of the object and also the area inside the boundary belongs to shadow region so efficient shadow removal the area on the both sides of boundary need to analyze for that mark the shadow boundary by vector R and contract inwards to get inner line marked as R1 and dilate the boundary outwards for outer line R2 ,then to plot the inner and outer outline profile line and the gray scale value of both line is noted to determine the radiation features of the same type of object on both sides.

The objects on both sides of the shadow boundary linked with a building forming a shadow are usually not homogeneous, and the corresponding inner and outer outline profile line sections are not reliable. In addition, the abnormal sections on the inner and outer outlines that cannot represent homogeneous objects need to be ruled out. Consequently, similarity matching needs to be applied to the IOOPL section by section to rule out the two kinds of non homogeneous sections mentioned previously. The parameters for shadow removal are obtained by analysing the gray scale distribution characteristics of the inner and outer homogeneous IOOPL sections.

1. IOOPL Matching

In this process a section by section analysis of inner and outer line is done and there by homogenous sections are obtained which i.e. used for shadow removal for effective matching [1] need to smooth the image.

To rule out the non homogeneous sections, the IOOPL is divided into average sections with the same standard, and then, the similarity of each line pair is calculated section by section. If the correlation coefficient is large, it means that the shade and light fluctuation features of the IOOPL line pair at this section are consistent. If consistent, then this line pair belongs to the same type of object, with different illuminations, and thus is considered to be matching. If the correlation coefficient is small, then some abnormal parts representing some different types of objects exist in this section; therefore, these parts should be ruled out.. If more accurate matching is needed, the two sections adjacent to the section with the smallest correlation coefficient can be segmented for matching again. The similarity is calculated by

$$similarity(A,B) = \frac{\sum_{i=1}^{n}(C_i^A - C^{\bar{A}})(C_i^B - C^{\bar{B}})}{\sqrt{\sum_{i=1}^{n}(C_i^A - C^{\bar{A}})^2 . \sum_{I=1}^{n}(C_i^B - C^{\bar{B}})^2}} \quad (9)$$

2. Relative Radiometric Correction

In the urban images, if objects in a shadow area and a non shadow area belong roughly to the same category, and they are in different lighting conditions, relative radiation correction can be used for shadow removal. Radiometric correction is a pre-processing technique to reconstruct physically calibrated values.

To avoid the influence of scattering light from the environment, each single object has been taken as a unit for which the shadow removal process is conducted for that object which enhances reliability. Commonly used relative radiation correction generally assumes that a linear relationship exists between the gray scale value digital number (DN) of the image to be corrected and the DN of the reference image.

$$DN_{ref} = a \times DN_{rect} + b \quad (10)$$

DN_{ref} is the DN of the object in the reference image, DN_{rect} is the DN of the object in the image to be corrected, and a and b are the gain and offset, respectively. By applying IOOPL matching to each shadow, homogeneous sections that represent objects of the same category in different lighting conditions are obtained. According to the equation the gain and offset of the linear
function can be estimated by the DN of the homogeneous sections. DN_{rect} is the DN of the outer homogeneous sections, and DN_{rect} is the DN of inner homogeneous sections. Finally, the radiation value correction of the shadow can be realized through the obtained gain and offset values. Our experiments show that a straightforward and simple relative radiation correction, the mean variance method, for shadow removal can be applied as follows.

The concept of the mean variance method is that, after radiation correction, the homogeneous points on a line pair of the shadow have the same mean and variance at each waveband. The radiation correction coefficients of the mean and variance method are

$$a_k = \frac{S_{yk}}{S_{xk}} \quad ; \quad b_k - \overline{y_k} - a_k.\overline{x_k} \quad (11)$$

where x_k is the grayscale average of the inner homogeneous sections at the waveband k, y_k is the grayscale average of the outer homogeneous sections at the waveband k, S_{xk} is the standard deviation of the inner homogeneous sections at the corresponding waveband, and S_{yk} is the standard deviation of the outer homogeneous sections at the corresponding waveband.

We assume that the inner homogeneous sections reflect the overall radiation of the single shadow. After obtaining the correction coefficient, all points of the shadow are corrected according to

$$DN_{nonshadow} = \quad a_k \times DN_{shadow} + b_k \quad (12)$$

where $DN_{nonshadow}$ stands for the pixel gray scale of the shadow after correction, DN_{shadow} stands for the pixel scale of the shadow before correction, and a_k and b_k are the coefficients of the minimum and maximum method or mean variance method calculated with the homogeneous points of the object, respectively.

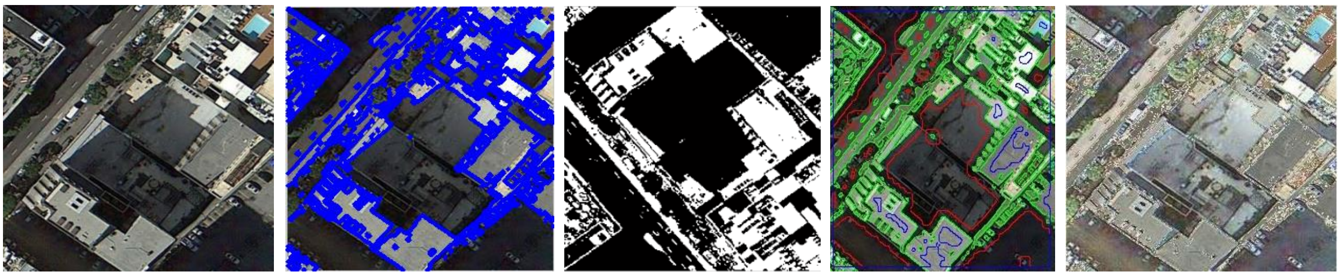
IV. EXPERIMENTAL ANALYSIS AND RESULTS

To validate that our method works, the following experiment was performed. The datum used in this experiment is a Quick-Bird image. Each step of this method is described herein, and the steps and corresponding results of each step are given [from Fig. 4,5(a)–(e)]. It can be seen from the segmentation result [Fig.4 (b)] that segmentation that considers shadow features can effectively segment shadows and dark objects such as vegetation and bodies of water into different subjects. Here the shadows and non shadow regions are segmented as different units. Blue color denotes the edges of each regions. This means that, in the following process, the problem of shadow and dark objects being segmented as a whole subject can be avoided. The results are obtained with the use of a SVM based training set after the segmentation; process and without an SVM classifier . The results, shown in Fig. 4(c), show the retrieval of a rough shadow with the threshold, which indicates that vegetation, rivers, dark moist soil, and true shadows can be detected. The Bimodal histogram splitting method thresholding is carried out and the false shadow ie the vegetation misclassified as shadow is eliminated using the Rayleigh scattering principle And the figure 4(d) shows the generated IOOPL lines for the shadow removal process. And 4(e) shows the shadow removed reconstructed image. After the segmentation, SVM classifier based training, thresholding, false shadow elimination the shadow is perfectly detected, and after IOOPL extraction, matching, relative radiometric correction the shadow removed and the image is reconstructed.

Furthermore, we choose the samples with same scene in the non shadow area, shadow area, and shadow removed area to analyse. Table I shows the sample information, which verifies the effectiveness of our approach numerically. In Table I, there is a tremendous difference between the non shadow and shadow regions of the same scenes in spectral consistency according to the no of pixels, mean and standard deviation. After applying our approach, the no of pixels, mean and standard deviation of the shadow-removed region are close to that of the non shadow region. Therefore, we could obtain the deshaded data which meet the needs of both vision and spectral consistency through the presented approach.

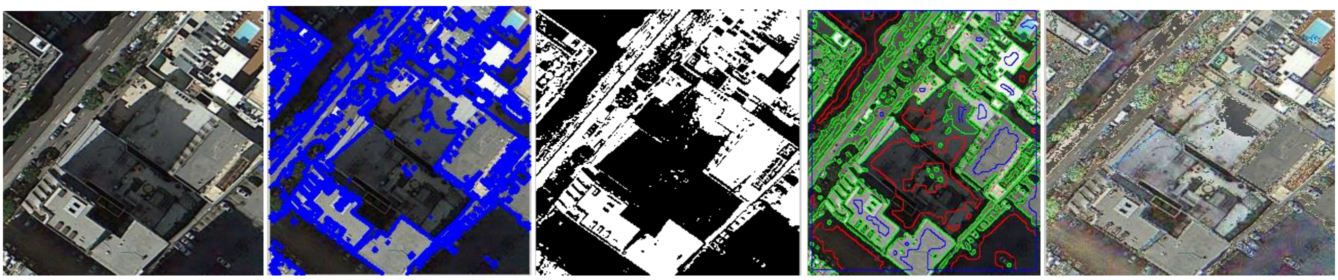
Table.1.Analytic result of the approach

Area	Area Size (pixel)	Mean	Standard Deviation
Non-Shadow	38890	130.3338	53.6823
Shadow	26646	49.0499	24.8669
Shadow Removed	26646	132.6708	52.5380



(a) (b) (c) (d) (e)

Fig.4.Examples of shadow detection and removal without using SVM classifier. (a) Quick Bird image. (b) Segmentation result of (a). (c) Threshold shadow detection result after segmentation. (d)IOOPL generated (e) Reconstructed image



(a) (b) (c) (d) (e)

Fig.4.Examples of shadow detection and removal using SVM classifier. (a) QuickBird image. (b) Segmentation result of (a). (c) Threshold shadow detection result after segmentation. (d)IOOPL generated (e) Reconstructed image

V. CONCLUSION

Shadow is the biggest problem in remote sensing images, shadows are created during day times because the light source has been block by some objects. Shadow includes some black objects, so it is very difficult job to separating shadows and black objects .The proposed method is a systematic and effective method for shadow detection and removal in a single urban high-resolution remote sensing image. Object-level technology is a comparatively advanced processing method, showing notable effects in remote-sensing image classification and information extraction. The proposed methodology can yield visually realistic shadow-free images with a promising preservation of the spectral and textural properties of the obscured objects .In order to get a shadow detection result, image segmentation considering shadows is applied first. Then an SVM classifier based training scheme is applied which yields better segmentation results. Since the success of object-based classification approaches is very dependent on the quality of the image segmentation, the use of SVM classifier based training scheme increases the effectiveness of the approach to high extent. Then, suspected shadows are selected through spectral features and spatial information of objects, and false shadows are ruled out. For shadow removal, after the homogeneous sections have been obtained by IOOPL matching ,and after that the relative radiometric correction is used for obtaining the shadow reconstructed image. RRN can restore the texture details well.

The shadow may be detected more efficaciously and accurately. The approach is simple, effective, and may obtain more satisfactory results.

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Leethu Lakshmi A L is currently pursuing M-TECH in electronics with specialisation in signal processing, College of Engineering,kalloopppara.She received her B-Tech(ECE) from the Musaliar College of Engineering and Technology,Pathanamthitta in 2014.Her areas of interest are Digital communication, Digital image processing and embedded design.

Jasmine George is currently an Assistant Professor with the Department of Electronics and Communication,College of Engineering,Kallooppara.She received her masters in Applied Electronics from the Sathyabhama University ,Chennai. She received her B-Tech from Saintgits College of Engineering,Kottayam.Her areas of interest are applied electronics,power electronics,digital image processing and instrumentation.

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