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Performance Evaluation of Quality Enhancement Methods of Remote Sensing Images by Object Oriented Shadow Detection and Removal

Leethu Lakshmi A L[1], Jasmine George[2]

PG Student, Department of ECE, College of Engineering, Kallooppara, Thiruvalla, India [1]

Assistant Professor, Department of ECE, College of Engineering, Kallooppara, Thiruvalla, India[2]

Abstract: Shadow will occur by sunlight or any light sources. In the area of machine vision, shadows occur 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 method, shadow features are taken into consideration during image segmentation, after that an SVM based classifier is used for the accuracy and then, according to the statistical features of the images, suspected shadows are extracted. Dark objects may be included in the suspected shadows, so more accurate shadow detection results are needed to eliminate these dark objects. For shadow removal, inner–outer outline profile line (IOOPL) matching is used. First, the IOOPLs are obtained with respect to the boundary lines of shadows. Shadow removal is then performed according to the homogeneous sections attained through IOOPL similarity 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. Also another approach based on YCbCr colour space is used for the shadow detection process and the performance evaluation of the both methods is carried out. The new methods can accurately detect shadows from urban high-resolution remote sensing images and can effectively restore shadows.

Keywords: 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, mean, standard deviation.

I. INTRODUCTION

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.

High resolution satellite imagery (HRSI) offers great possibilities for urban mapping. In urban areas, 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/or 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

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object-based classification approaches is very dependent on the quality of the image segmentation.

II. LITERATURE SURVEY

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 Color 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.

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.

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A. SHADOW DETECTION

I. YCbCr Colour space based method

Fig.1 shows the block diagram of the proposed Shadow detection and removal system using YCbCr colour space. A simple framework using the luminance, chroma: blue, chroma: red (YCbCr) color space to detect shadows from images.

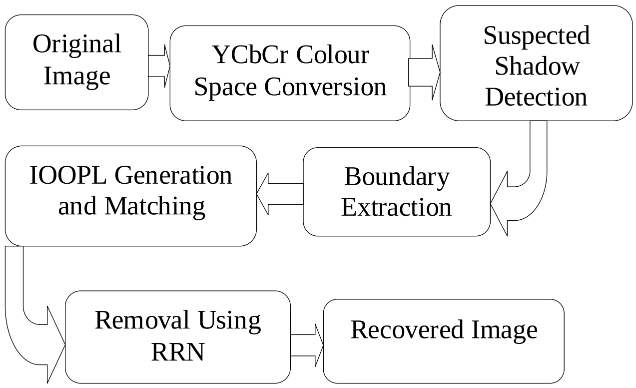

Fig 1 Block diagram of the proposed Shadow detection and removal system using YCbCr colour space

Initially, an approach based on statistics of intensity in the YCbCr colour space[13] is proposed for detecting shadows. Shadow removal employs a series of steps. We extract the inner and outer outline lines of the boundary of shadows. The gray scale 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.

YCbCr Colour Model used for digital video, and was defined in the ITU-R BT.601 standards of ITU (International Telecommunication Union) which is the widely used European TV signal and represents the encoding form of non RGB signal .The Individual components of YCbCr colour model are; luminance Y component and chroma components where Cb and Cr components stand for difference of the blue and red.

The YCbCr image can converted to/from RGB image. There're several standards defined for the conversion at different context. The conversion below is based on the conversion used in JPEG image compression

$$Y = 0.299R + 0.587G + 0.114B \quad (1)$$

$$Cb = 128 – 0.168736R – 0.331264G + 0.5B \quad (2)$$

$$Cr = 128 + 0.5R – 0.418688G – 0.081312B \quad (3)$$

An approach [13] based on statistics of intensity is used for shadow detection. Initially the RGB image is converted to an equivalent YCbCr image. In the YCbCr colour space, the Y represents luminance information while Cb and Cr represent the colour information. Next, focusing on the Y channel, its histogram is computed. Histogram dissension gives us a higher contrast image in the Y channel. After that, the mean of the image in the Y channel is computed. Then sliding-window iteration through the image is performed. The sliding window size is 3×3 matrices. In order to decide which pixels belong to the shadow, two approaches are followed. First, shadow pixels that have intensity less than one standard deviation of the whole image are classified. This step cannot identify the shadow regions properly; some shadow pixels are identified as non-shadow pixels. So next, the non-shadow point's mean and standard deviations for the sliding window are computed. Now, the pixels that have intensity less than the one standard deviation of the windows are considered shadow pixels.

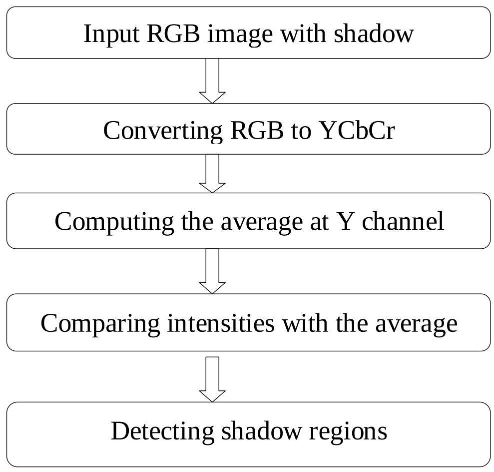

Fig 2 Flowchart of YCbCr method for shadow detection

IV. SVM CLASSIFIER BASED APPROACH

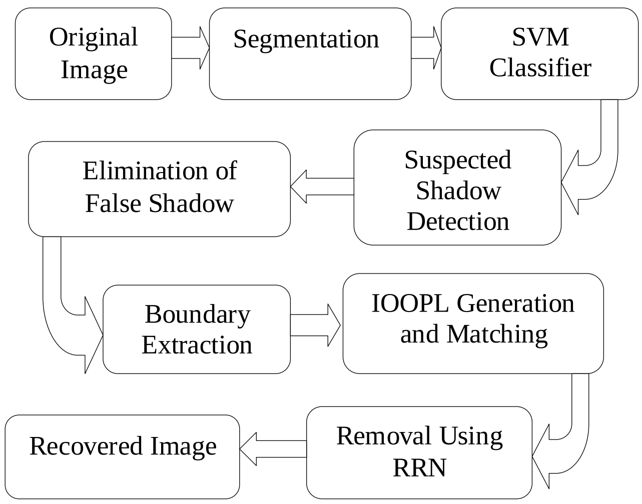

Fig 3. Block diagram of the proposed Shadow detection and removal system using SVM classifier

1. Image Segmentation

Images with higher resolution contain richer spatial information. The spectral differences of neighboring 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

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object. In order to use spatial information to detect shadows, image segmentation is needed. 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 color, gray values, or texture: discontinuity and similarity. First category is to partition an image based on abrupt changes in intensity, such as edges in an image.

2. 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.

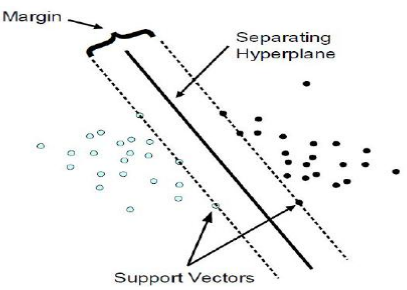

Fig 4. SVM classification with a hyper plane that maximizes the separating margin between the two classes. Support vectors are elements of the training set that lie on the boundary hyper planes of the two classes.

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

$$f(X) = W^T X + b \qquad (4)$$

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:

$$J(W) = \frac{1}{2} W^T W = \frac{1}{2} \|W\|^2 \qquad (5)$$

Subject to the separability constraints

$$W^T X_i + b \geq +1 \quad ,for\ y_i = +1 \qquad (6)$$

or

$$W^T X_i + b \leq -1 \quad ,for\ y_i = -1 \ \text{i=1, 2....,l} \qquad (7)$$

Equivalently, these constraints can be written more compactly as

$$y_i(W^T X_i + b) \geq 1 \qquad (8)$$

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 (8) as follows:

$$y_i(W^T X_i + b) \geq 1 - \varepsilon_i \quad \varepsilon_i > 0 \ \text{i=1,2,….l} \qquad (9)$$

Accordingly, the cost function can be modified as follows:

$$J(W, \varepsilon) = \frac{1}{2} \|W\|^2 + C \sum_{i=1}^{l} \varepsilon_i \qquad (10)$$

Where 'C'is a user-specified,positive,regularization parameter. In (10), the variable ε is a vector containing all the slack variables ε_i, i=1,2,….l

The modified cost function in (10) 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.

3. Detection of Suspected Shadow Areas

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 [3] splitting provides the most robust method of threshold level selection for this particular study since the image has only two features of interest: shadow and non-shadow. It was found by experiment that taking the mean of the two peaks gave consistently accurate threshold levels from separating the shadow from the non-shadow regions. We chose the grayscale value with the minimum frequency in the neighborhood of the mean of the two peaks as the threshold, as shown in

$$G_{q=} \frac{1}{2}(G_m + G_s) \qquad (11)$$

$$h(T) = Min\{h(G_q - \varepsilon), h(G_q + \varepsilon)\} \qquad (12)$$

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G_m 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 neighborhood of T, where $T\epsilon[G_q-\varepsilon, G_q+\varepsilon]$

4. Elimination of False Shadows

Dark objects [1] 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. G_gAlso, 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

B. 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.

To remove the shadow areas from the image in this use IOOPL section matching. 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 analyse 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.

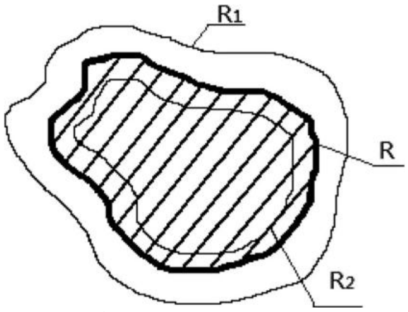

Fig 5.Diagram of shadow boundary, inner, and outer outline lines.

In addition, the abnormal sections on the inner and outer outlines that cannot represent homogeneous object 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.

I. 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 need to smooth the image. As a result IOOPL matching homogenous and non homogenous section are obtained in the figure the green line shows the homogenous line and red line indicate non homogenous line the non homogenous line which is the result of low correlation is to be eliminated. The homogenous section also reflect the illumination property i.e. if the correlation coefficient is very big, then it means that the features like shade and light fluctuation of the IOOPL line pair at this section are consistent or stable. For effective matching the non homogenous section can be further segmented and detecting the inner and outer line gets other homogenous section.

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. The sections that have failed the matching are indicated in red. 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 [1] is calculated by

$$\text{similarity}(A,B)=\frac{\sum_{i=1}^{n}(C_i^A-C^{\bar{A}})(C_i^B-C^{\bar{B}})}{\sqrt{\sum_{i=1}^{n}(C_i^A-C^{\bar{A}})^2 \cdot \sum_{i=1}^{n}(C_i^B-C^{\bar{B}})^2}} \tag{13}$$

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V. RELATIVE RADIOMETRIC CORRECTION

In the same urban image, 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 is a pre-processing technique to reconstruct physically calibrated values by correcting the spectral distortions caused by sensors, sun angle, topography and the atmosphere, Radiometric correction is classified into two types; absolute and relative correction.

Absolute correction**:** Correct radiance or reflectance should be measured or converted by using the sensor calibration data, the sun angle and view angle, atmospheric models and ground truth data. The incident energy input to sensors should be analysed correctively by radiometric correction. However it cannot be applied in most applications, therefore the relative correction is applied because the atmospheric model is so complicated and the exact measurement of atmospheric condition is difficult.

Relative Correction**:** Relative correction is to normalize multi-temporal data taken on different dates to a selected reference data at specific time. The following techniques will be typical.

- Adjustment of average and standard deviation values.
- Conversion to normalized index.

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. This enhances reliability. Commonly used relative radiation correction generally assumes that a linear relationship exists between the grayscale value digital number (DN) of the image to be corrected and the DN of the reference image.

$$DN_{ref} = a \times DN_{rect} + b \quad (14)$$

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

$$a_k = \frac{S_{yk}}{S_{xk}} \quad ; \quad b_k - \overline{y_k} - a_k.\overline{x_k} \quad (15)$$

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

$$DN_{nonshadow} = a_k \times DN_{shadow} + b_k \quad (16)$$

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.

VI. 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. 5,6(a)–(e)]. The fig 5[(a)-(d)] shows the result of the shadow detection process carried out using the YCbCr colour space methods and the shadow removal based on IOOPL and relative radiative correction method. It can be seen from the segmentation result [Fig.6 (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 colour 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. The results, shown in Fig. 6(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 5(c),6(d) shows the generated IOOPL lines for the shadow removal process. And 5(d) and 6(e) shows the shadow removed reconstructed image after a series of processes in both YCbCr colour space approach and SVM Classifier based approach.

The performance of the method can be evaluated by the area in pixels of shadow region and non shadow region and shadow removed region. There is a tremendous difference between the non shadow and shadow regions of the same scenes and it is clear from the results that the area of the showed area and the shadow removed area are equal which represents efficient reconstruction.

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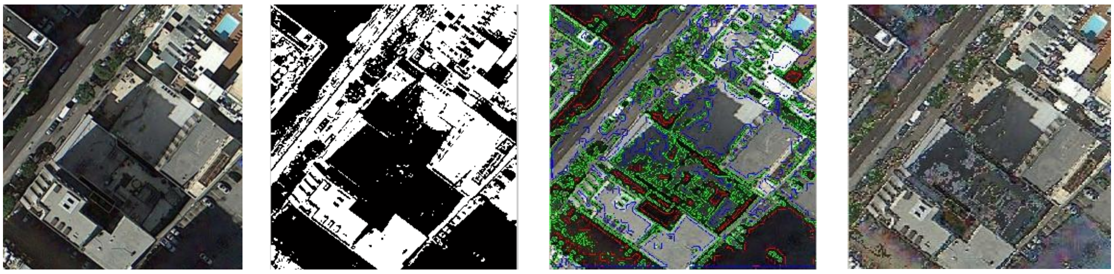

Fig.5.Examples of shadow detection and removal using YCbCr colour space method (a) QuickBird image (b) shadow detected region (d) IOOPL generated (e) Reconstructed image

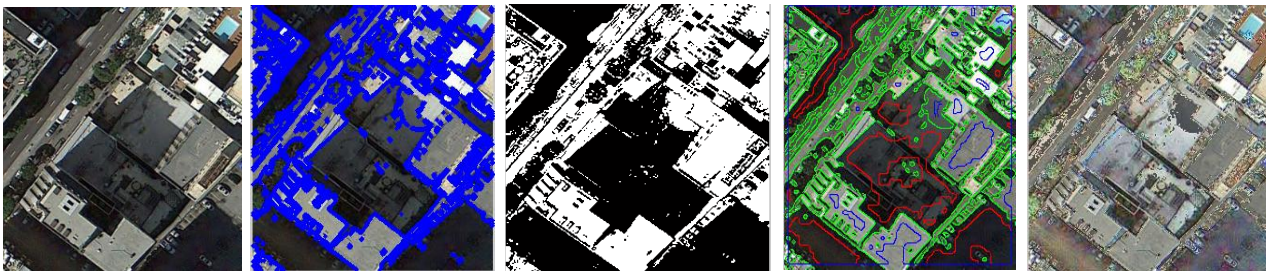

Fig.6.Examples of shadow detection and removal using SVM classifier (a) QuickBird image (b) Segmentation result of (a). (c) Threshold shadow detection result after segmentation. (d)IOOPL generated (e) Reconstructed image

Table 1 Analytic result of YCbCr Colour space approach

Area (YCbCr colour space approach)	Area Size (pixel)	Mean	Standard Deviation
Non-Shadow	28270	92.0283	55.0685
Shadow	37266	31.1682	18.3447
Shadow Removed	37266	100.3208	50.8017

After applying our approach, the 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. The better results are obtained using the SVM classifier based approach since there is only a little variation between the mean and standard deviation of the non shadow region and shadow removed region in this approach rather than YCbCr colour space approach.

Table 2.Analytic result of SVM classifier approach

Area (SVM classifier approach)	Area Size (pixel)	Mean	Standard Deviation
Non-Shadow	28270	130.3338	53.6823
Shadow	37266	49.0499	24.8669
Shadow Removed	37266	131.6708	52.5380

VII. CONCLUSION

Shadow is the biggest problem in remote sensing images; shadows are created during day times because the light 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, in the first method YCbCr colour space approach is used for the detection and in the second method 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 source has been block by some objects. Shadow includes are selected through spectral features and spatial information of objects, and false shadows are ruled out. For shadow removal, 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.

In addition to the visual acceptance while comparing the both methods for the detection of shadows using the mean and standard deviation method, the SVM classifier based approach yields better result The shadow may be detected more efficaciously and accurately. The approach is simple, effective, and may obtain more satisfactory results.

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BIOGRAPHIES

Leethu Lakshmi A L is currently pursuing M-TECH in electronics with specialisation in signal processing, College of Engineering, Kallooppppara. 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 master's 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