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SHADOW DETECTION AND REMOVAL FROM URBAN HIGH-RESOLUTION REMOTE SENSING IMAGES USING K-MEANS ALGORITHM

DEV KIRAN.B
PG Student
Department of ECE
Rajas Engineering College
Vadakkangulam.
Tamil Nadu. India
devkiran51@gmail.com

T.LEENA
ASSISTANT PROFESSOR
Department of EEE
Rajas Engineering College
Vadakkangulam.
Tamil Nadu. India
Mobile : +919442364207
leenaswamy@rediffmail.com

Abstract—In accordance with the characteristics of urban high resolution color remote sensing images, we put forward an object oriented shadow detection and removal method. In this method, shadow features are taken into consideration during image segmentation, and then, according to the statistical features of the images, suspected shadows are extracted. Furthermore, some dark objects which could be mistaken for shadows are ruled out according to object properties and spatial relationship between 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. 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.

Keywords— Shadow, IOOPL, Kmeans clustering, Shadow detection, Shadow removal, Reconstruction

I. INTRODUCTION

A shadow is caused by the interaction of light with objects. Shadows leads to the failure of images. Shadows are classified as-self shadows and cast shadows. A self-shadow is the shadow on a subject on the side that is not directly facing the light source. A 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 shadows are of two types- umbra and penumbra. Due to multiple lighting, these regions are created. The umbra is created because the direct light has been completely blocked while the penumbra is created by something partially blocking the direct light. There are several methods for shadow detection based on intensity, pixel values, Region growing, Dual-pass Otsu, and Gradient based, Pixel Intensity based, Support Vector Machine Method etc. All the methods have advantages and disadvantages. Using all these algorithms shadow can be detected and removed and using some methods image can be reconstructed. But here presenting two different methods for shadow detection, removal and reconstruction using IOOPL and KMEANS clustering and results are compared. The remaining paper is as follows section ii related works section iii system overview section iv experimental results section v conclusion.

II. RELATED WORKS

Shadow regions and non-shadow regions are separated by using segmentation process [2] [3] and using SVM approach [4] Hong-GyooSohn et.al [5] Proposed scheme includes data co-registration, detection of shadowed regions, segmentation of shadowed regions, correction of shadow effects, and potential application to asphalt road extraction. Supriya A. Hadke et.al [6] consider a VHR image I of dimensions m × n, composed of N bands and characterized by the presence of shadow areas. The resulting image will allow performing first a binary classification in order to distinguish between shadow and non-shadow regions. Using hsv color model [7] presents an efficient and simple approach for shadow detection and removal in complex urban color remote sensing images for solving problems caused by shadows.. P.Srinivasulu et.al [8] ex-tracting shadows from a single outdoor image is presented. Based on image formation theory relationship between shadow and its nonshadow background is derived based on image formation theory. Yan li et.al [9] presents methodology to automatically detect and remove the shadows in high-resolution urban aerial images for urban GIS applications. The system includes cast shadow computation, image shadow tracing a detection, and shadow removal. The method based on a region growing process [10] presents a simple and effective procedure to segment shadow regions on high-resolution colour satellite images on a specific *A Comparison of Shadow Detection Removal and Reconstruction Methods (IJSTE/ Volume 1 / Issue 10 / 062)* All rights reserved by *www.ijste.org* 309

band (namely, the c3 component of the c1c2c3 colour space). A novel processing chain for shadow detection and reconstruction in VHR images [11] main aim of this chain process is not only detect shadow region form image but also remove shadow region and reconstruct shadow less image. Using an (ICA) algorithm, gray scale histogram, RGB channels, HIS space transformation and multi-threshold retinex [12] to achieve the shadow detection and compensation method. Tapas Kanungo et.al[13] present a simple and efficient implementation of Lloyd's K-MEANS clustering algorithm, which call the filtering algorithm. This algorithm is easy to implement, requiring a kd-tree as the only major data structure. Qiang He1et.al[14] shadow removal method based on intrinsic image decomposition on a single color image using the Fisher Linear Discriminant (FLD).

III. PROPOSED SYSTEM

This paper compares the result of two methods for shadow detection, removal and reconstruction The first method is using IOOPL (Inner outer outline profile line) and another using K-MEANS clustering. In both methods the removal is done by same approach but the shadow detection is done by different approach.

A. IOOPL (Inner Outer Outline Profile Line)

In this method, shadow features are taken into consideration during image segmentation and then, according to the statistical features of the images, suspected shadows are extracted. Furthermore, some dark objects which could be mistaken for shadows are ruled out according to object properties and spatial relationship between 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 perfor med according to the homogeneous sections attained through IOOPL similarity matching.

Here the first step is the segmentation where watershed algorithm is used. The watershed transform is used to search for regions of high intensity gradients (watersheds) that divide neighbouring local minima (basins Watershed Segmentation). The key behind watershed transform for segmentation is to change the image into another image whose catchment basins are the objects which we want to identify. After segmentation thresholding is done to differentiate shadow and nonshadow region on basis of threshold value. Thresholding is done by Otsu's method. Otsu's method selects the threshold by minimizing the within-class variance of the two groups of pixels separated by the thresholding operator. It assumes a bimodal distribution of gray-level values. In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances. After finding its threshold, it is converted into binary maps. Now the shadow is detected and perfect boundary is identified. After identifying the boundary of shadow portions, a looping is applied (IOOPL) ie. Inner Outer Outline Profile Lines. The inner and outer outlines are obtained by contacting the shadow boundary inward and expanding it outward, respectively. The radiation features of the same type of object on both sides are obtained using inner and outer profile lines . Comparing the inner and outer loop, the colour is refilled and shadow is removed and the output is shadowless image.

B. K-MEANS Clustering

There are many methods to create mask. Here mask is created by using an adaptation method. One of the drawbacks of this mask is that it cannot identify the accurate edges and shadow areas. So an improved method for shadow detection is used called kmeans clustering. Clustering is the process of partitioning a group of data points into a small number of clusters. Here cluster number is decided on the basis of data points and clustering is done. In K-MEANS clustering the main parameter for classifying data points into cluster is distance measurement. Each point is included in the cluster on the basis of minimum distance. After clustering the cluster which is showing the shadow portion and the mask is compared and perfect shadow area is identified. After *A Comparison of Shadow Detection Removal and Reconstruction Methods (IJSTE/ Volume 1 / Issue 10 / 062)* All rights reserved by *www.ijste.org* 310 that for each and every point in the mask image and in the original image, the pixel values are identified and the difference in the intensity or pixel variation is found. Using this difference value the colour in the shadow portion is refilled. Shadow areas are viewed as unwanted information which affects the quality of an image. When the light source is illuminated on any object the shadow is observed on the other side of the object. The detection and compensation of shadow is important hotspot and difficulty of remote sensing image processing. There are different methods for detection and removal of shadows from images.

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The literature reports mainly two approaches to detect shadows, namely, model-based and shadow-property-based approaches. The former needs prior information about the scenario and the sensor. However, since, usually, such knowledge is not available most of the detection algorithms are based on shadow properties, such as the fact that shadow areas have lower brightness, higher saturation, and greater hue values.

Model-based methods the 3D geometry and illumination of the scene are assumed to be known. This includes the sensor/camera localization, the light source direction, and the geometry of observed objects, from which a priori knowledge of shadow areas is derived. For example, we can consider polygonal regions to approximate the shadows of buildings or urban elements in some simple urban scenes. However, in complex scenes with a great diversity of geometric structures, as it is usually the case of Quick Bird images, these models are too restrictive to provide a good approximation. In addition, in most applications the geometry of scene and/or the light sources are unknown. mountainous areas (topographic shadow), cloud shadows and composite shadows. Paper reviews the dominant shadow correction methods for both steps.

Here for the segmentation watershed algorithm is used. The aim of the watershed transform is to search for regions of high intensity gradients (watersheds) that divide neighbored local minima (basins Watershed Segmentation)gets its name from the manner in which the algorithm segment regions into Catchmentbasins.

The key behind using the watershed transform for segmentation is this: Change your image into another image whose catchment basins are the objects you want to identify. Use the Gradient Magnitude as the

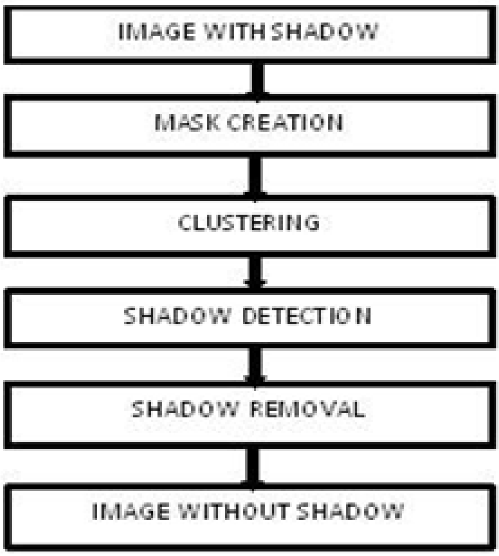

Fig. 2: Block Diagram of K-MEANS method

Fig. 3: Grey scale image

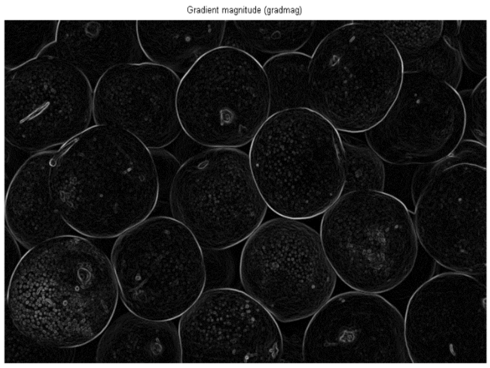

Fig 4: Gradient image

Step 2: Mark the foreground objects.

According to the above parameters, areas that would be in sunlight are highlighted and areas that would be in shadow are shaded. It is important to note that the relief algorithm identifies shadowed areas, i.e., those that are not in direct sun. However, this algorithm does not calculate the shadow that is cast by topographic features onto the surrounding surface. Apart from these methods, there are other less commonly used algorithms for detecting shadow regions, for example, the automatic cloud/shadow detection method, the Self-Adaptive Feature method the detection of shadow based on pulse coupled neural networks, object-based shadow extraction, and visual interpretation. In summary, thresholding is the most common approach for detecting shadow regions. This method is useful in many shadow detection applications, since it is simple, quick and available in most commercial and non-commercial remote sensing software

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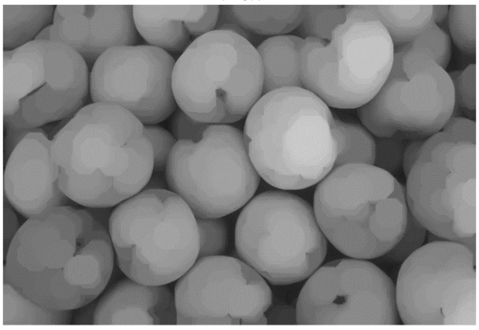

Fig. 5: Image with foreground objects

Fig. 6: Image of opening by reconstruction

Mathematical morphology is one of the data processing methods that is extremely useful for image processing and has many applications, such as, boundary extraction ,noise elimination, shape description, texture analysis, and so on. The mathematical base of morphological processing is dilation and erosion which are described by set analysis and can be expressed in logical AND, OR notation .The objective of this project is to write a program capable of performing binary dilation and erosion with an arbitrary structuring element of size 3 x 3 that can be extracted the boundary or edge of an image. To simulate these two operations, image processing toolbox functions of MATLAB programming language is used.

Step 3: computing the opening-by-reconstruction of the image

Also, the test for the possibility of ground feature extraction is implemented Detection of shadowed regions serves to calculate shadow length using height data from lidar data, the sun elevation angle, and the azimuth of the sun. Before detecting shadowed regions, the accurate height value of a building must be acquired for precise shadow effect correction. The building height could be acquired directly using lidar data. The lidar data within the building polygon had two homogeneous values. One value represented the height of the bulk of the building, while the other value represented the building height except its bulk.

Step 4: Following the opening with a closing can remove the dark spots and stem marks.

In the next stage, the detected shadowed regions are segmented according to land surface type using the attribute date of the digital maps. Finally, the shadow effects were corrected for each of the segmented shadowed regions. However, the building polygon was shown as one polygon in the digital map. To solve this problem, a polygon representing the bulk of the building was added. The boundary between the bulk and other part was delineated. In other words, one polygon was created by grouping peak points above 1.0 m in comparison with the average of the lidar data within the polygon. To detect shadowed regions, in addition to building height, solar positions are required at the time of image acquisition. To calculate the solar positions (the sun elevation angle and the azimuth), the accurate time, date, latitude, and longitude of the study area are needed. Here three basic assumptions are there to accomplish shadow treatment in aerial images were considered. These were:

- Complete information loss of region hindered by shadow does not occur.
- The influence of cast shadow caused by each object is uniform.
- The DN value of similar surface cover characteristic is uniform.

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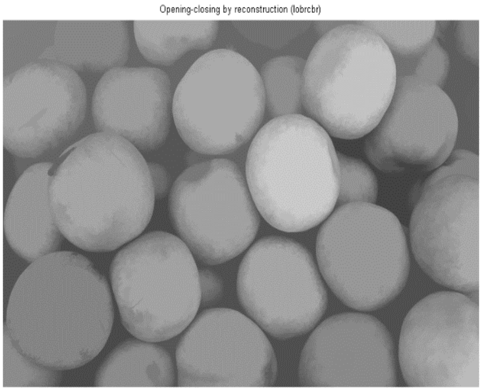

Fig 7: Image opening with a closing which removes the dark spots and stem marks

After the morphological filtering one need to do the border creation for shadow portion and non-shadow portion. Such classification allows the localization of the available couples of shadow and non-shadow related to the same object and, thus, to define the spectral relationship between them as a means to perform the reconstruction of the shadow areas.

Step 5: Calculate the regional maxima to obtain good foreground markers.

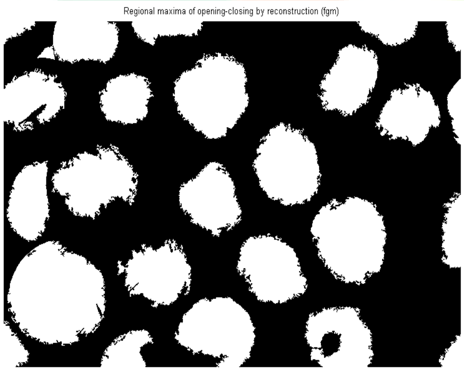

Fig 8: Image marking the bacground

Step 6: Superimpose the foreground marker image on the original image, Notice that the foreground markers in some objects go right up to the objects' edge In particular, the reconstruction is based on a linear regression method to compensate shadow regions where the intensities of the shaded pixels are adjusted according to the statistical characteristics of the corresponding non-shadow regions. Finally, the border between the reconstructed shadow and the non-shadow areas undergoes a linear interpolation operation to yield a smooth transition between them.

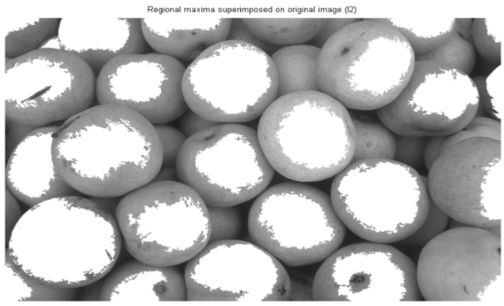

Fig 9: Superimpose image of foreground maker image on original image

Step 7: cleaning the edges of the marker blobs and then shrinking them a bit.

Using hsv color model presents an efficient and simple approach for shadow detection and removal in complex urban color remote sensing images for solving problems caused by shadows. In the proposed method shadows are detected using normalized difference index and subsequent thresholding based on Otsu’s method. Once the shadows are detected they are classified and a non -shadow area around each shadow termed as buffer area is estimated using morphological operators. The mean and variance of these buffer areas are used to compensate the shadow regions. Once shadows are detected they are removed using the mean and variance values of the buffer area which is the non -shadow area around each shadow.

Step 10: Visualize the Result, one of the techniques is to superimpose the foreground markers, background markers, and segmented object boundaries 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

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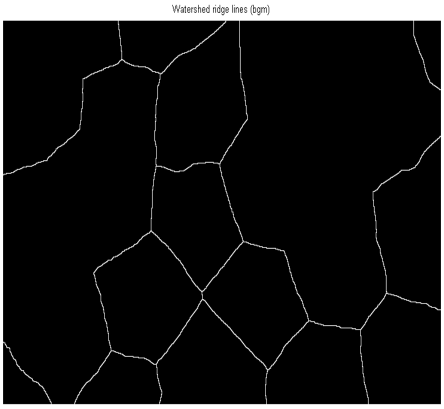

Fig 10:Watershed Transform

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. Shadows are removed by using the homogeneous sections obtained by line pair matching. There are two approaches for shadow removal. One approach calculates the radiation parameter according to the homogeneous points of each object and then applies the relative radiation correction to each object. The other approach collects and analyzes all the homogeneous sections for polynomial fitting (PF) and retrieves all shadows directly with the obtained fitting parameters. Using a DSM ray tracing proposes method of shadow removal to decide the visibility of a shadow in the projected image. Shadow restoration commonly is accomplished by histogram approaches, or homomorphologic filtering. These methods adjust the intensity of each pixel in the image, instead of locally processing the shadow area.

THRESHOLDING

Thresholding is done by otsu's method.It is to classify the segmented regions in two classes based on the threshold value .threshold value is calculated using an algorithm called ostus algorithm. A measure of region homogeneity is variance (i.e., regions with high homogeneity will have low variance).The method is setting the threshold value by finding the mean and variance of the given segmented image .The detailed description of ostusalgorith is described belowOtsu's method selects the threshold by minimizing the within-class variance of the two groups of pixels separated by the thresholding operator.

It assumes a bimodal distribution of gray-level values In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances

The steps in this method are:

- Compute histogram and probabilities of each intensity level
- Set up initial and
- Step through all possible thresholds maximum intensity
    - Update probability and mean
    - Compute the threshold (variance)
- Desired threshold corresponds to the maximum
- You can compute two maxima (and two corresponding thresholds) is the greater max and is the greater or equal maximum
- Desired threshold = threshold1 +threshold2/2

IV. EXPERIMENTAL RESULTS

The experiment is conducted by using different images. The experiment shows that using both methods the shadows can be detected and removed, but the output is more accurate using clustering method. Using IOOPL technique sometimes there occurs some colour variations in nonshadow region which reduces the quality of image and also, the data in the shadow area are not perfectly reconstructed. So Compared to IOOPL method, clustering using K-MEANS method is better. The result for two images using these techniques is given below.

IMAGE 1: A.

1. IOOPL

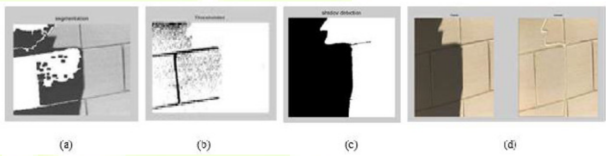

Fig. 3: Experimental result for Ioopl of image 1 (a) Segmented image (b) Thresholded image (c) Shadow detected image (d) Original and removed image

2. K-MEANS

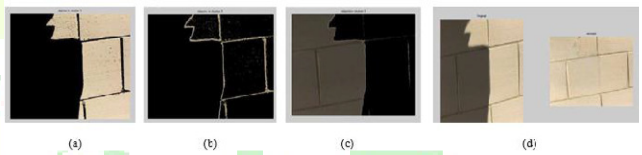

Fig. 4: Experimental result of Kmeans clustering of Image 1(a) Object in cluster 1 (b) Object in cluster 2 (c) Object in cluster 3 (d) original and removed image *A Comparison of Shadow Detection Removal and Reconstruction Methods (IJSTE/ Volume 1 / Issue 10 / 062)* All rights reserved by *www.ijste.org* 311

B. IMAGE 2

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1. IOOPL

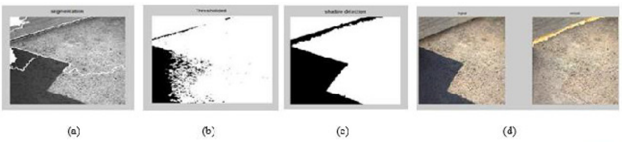

Fig. 5: Experimental result for Ioopl of image 2 (a) Segmented image (b) Thresholded image (c) Shadow detected image (d) Original and removed image

2.K-MEANS

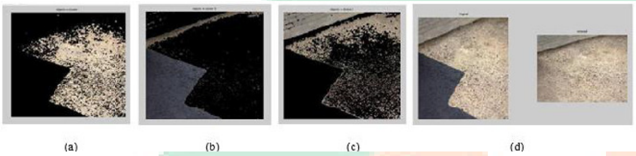

Fig. 6: Experimental result of Kmeans clustering of Image 2(a) Object in cluster 1 (b) Object in cluster 2 (c) Object in cluster 3 (d) original and removed image

Means and variances

Consider that we have an image with L gray levels and its normalized histogram (i.e., for each gray-level value i, P(i) is the normalized frequency of i). Assuming that we have set the threshold at T, the -normalized-fraction of pixels that will be classified as background and object will be:

The formulas to find the mean and variance which we have implemented in the Matlab according to the statistical are as follows

(The project is implemented using High-level language for technical computingImage Processing tool box.)

$$q_b(T)=\sum_{i=1}^{T}P(i)$$

$$q_O(T)=\sum_{i=T+1}^{L}P(i)(q_b(T)+q_o(T)=1)$$

The mean gray-level value of the background and the object pixels will be:

$$\mu_b(T)=\frac{\sum_{i=1}^{T}iP(i)}{\sum_{i=1}^{T}P(i)}=\frac{1}{q_b(T)}\sum_{i=1}^{T}iP(i)$$

$$\mu_o(T)=\frac{\sum_{i=T+1}^{L}iP(i)}{\sum_{i=T+1}^{L}P(i)}=\frac{1}{q_O(T)}\sum_{i=T+1}^{L}iP(i)$$

The mean gray-level value over the whole image (grand mean) is:

$$\mu=\frac{\sum_{i=1}^{L}iP(i)}{\sum_{i=1}^{L}P(i)}=\sum_{i=1}^{L}iP(i)$$

The variance of the background and the object pixels will be

$$\sigma_b^2(T)=\frac{\sum_{i=1}^{T}(i-\mu_b)^2P(i)}{\sum_{i=1}^{T}P(i)}=\frac{1}{q_b(T)}\sum_{i=1}^{T}(i-\mu_b)^2P(i)$$

$$\sigma_o^2(T)=\frac{\sum_{i=T+1}^{L}(i-\mu_o)^2P(i)}{\sum_{i=T+1}^{L}P(i)}=\frac{1}{q_O(T)}\sum_{i=T+1}^{L}(i-\mu_o)^2P(i)$$

The variance of whole image

$$\sigma^2=\sum_{i=1}^{L}(i-\mu)^2P(i)$$

V. CONCLUSION

In this paper we have put forward a systematic comparison of two different methods for shadow detection, removal and reconstruction of images. It is evident from the experimental results that kmeans provide better and accurate shadow detection by precisely detecting the edges of shadow. Also by using pixel comparison precise reconstruction of image becomes possible. Thus this method proves better than IOOPL.

(3.1)

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