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A Statistical Model for Shadow Removal of Man-Made Objects and Change Detection in Satellite Images

Kesini Krishnan V, Smitha P. S

***Abstract**: In this paper shadow detection and removal done as the pre processing steps for change detection beacause the presence of shadow causes mistakes in change map. For shadow detection there is a convexity analysis which are multiphase object segmentation and thresholding for suspected and false shadow removal also considering the object properties such as shape ,area ,perimeter ,average gray scale value and standard devitaion for more perfection. Shadow removal is employed by the method IOOPL (Inner Outer Outline Profile Lines) matching and relative radiometric correction. For IOOPL generation, first forms the object boundaries,then form two additional boundaries by expanding and contracting object boundaries. Build a graph,grayscale versus no of points. When doing a similarity test in IOOPL graphs secton by section, matching coefficient become high, that region treated as homogeneos and data reconstructed compared to non shadow area. Removal is done by relative radio metric correction. In Change analysis find the binary descriptors of each pixel in the two images and find hamming distance as similarity measure between binary descriptors of each pixel at the same location in two images. After there is a ranking system in change analysis and which is done by Lloyd-Max Quantization. Here in this paper we employed M=2, M=3 quantization levels In shadow treatment validation is done by comparing the gray scale average and standard deviation of non shadow area,shadow area and shadow removed area. The results are shown that it is very efficient compared to existing methods. . Shadow detection and removal is 93% accurate compared to existing methods. Average running time of change detection is better compared to previous works. Also most of the previous works are dealing with two levl quantization. Here more than 2 levels can be done with in seconds.*

Index Terms: multiphase segmentation, histogram, thresholding, Inner Outer Outline Profile Lines (IOOPL), shadow detection, shadow removal, change detection, binary descriptor, hamming distance, Lloyd Max quantization

I. INTRODUCTION

In applications such as residential development planning, damage evaluation, and military target detection experts want to detect changes which happened. Change detection is the process by which can identify, describe and quantify differences between images of the same scene at different times or under different conditions. Since the images are taken at different times have different illumination conditions andalso may have presence of shadows. A shadow is a region where light from a light source is obstructed by an opaque object. In urban areas bridges, elevated buildings like man-made objects are the main causes of shadows.

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Kesini Krishnan V, M.Tech Student, SCT College of Engineering, Pappanamcode, Trivandrum, Kerala, India.
Smitha P. S, Asst. Prof., SCT College of Engineering, Pappanamcode, Trivandrum, Kerala, India.

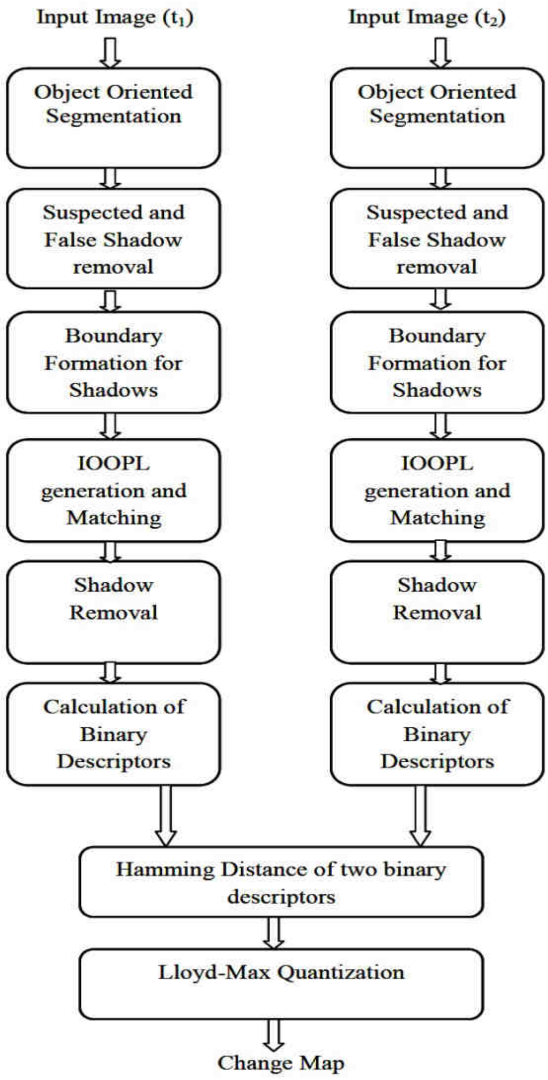

Fig. 1. Block diagram of entire work.

But in the case of height estimation, building position recognition etc., shadow information is valuable. Shadow detection is also a challenge for object detection, image fusion, change detection, object classification etc. Presence of shadow leads to imperfect change map. So for improving the result, do shadow detection and removal as preprocessing steps. Here the paper has three main parts, shadow detection, shadow removal and change detection as shown Fig.1

II. PREVIOUS WORKS

There are many algorithms are existing for shadow detection, removal and also for change detection. Shadow detection can be done by considering the shadow features

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such as gray scale, brightness, saturation, and texture. There is also another method, model based approaches. This group uses prior information such as scene, moving targets, and camera altitude to construct shadow models. But information such as scene and camera altitude is not usually readily available. For this reason shadow feature based approaches are highly preferable. The first step of shadow detection is the segmentation. Watershed segmentation [1], graph-cut methods [2], Image thresholding [3] etc., are the region based methods. Image thresholding is a method that thresholds an image intensity using histograms. The thresholding approaches are not very effective in separating the object from one another or even from the background. On the other hand, the methods that use watershed algorithm are popular, However, a major drawback of the watershed algorithm is the over segmentation error due to the presence of multiple markers resulting from a poor or inadequate initialization. To solve these problems, here we use SVMLS (statistical and variation multiphase level set) [4], in segmentation field. First define a maximum likelihood objective function for each point in a transformed domain, and then an energy functional is defined by integrating the maximum likelihood function over the entire image domain. Advantage of this method is that the smoothness of the computed bias field is ensured by the normalized convolution without extra cost. Also many methods for shadow detections are proposed. An illumination invariant [5] shadow free image used along with original image to locate shadow edges. By setting these shadow edges to zero in an edge representation of the original image, and set out to recover an RGB color image from which the shadows are removed focus on the derivative images of both the original image and the illumination invariant image. The Shades of Gray (SoG) algorithm [6] based on the color constancy theory is chosen to remove shadows (especially building shadows). The optimum parameters in SoG algorithm for aerial image shadow removal are obtained from the quantitative analysis. In [7], ShadowFlash produces a shadow free image by removing shadows in an actively illuminated environment by simulating a light source with infinite dimensions. A shadow less image without loss of textural details is obtained without any region extraction phase. Paired region approach [8] predicts relative illumination conditions between segmented regions from their appearances and performs pairwise classification. Here estimate a soft mask of shadow coefficients, which indicate the darkness of the shadow, and to recover a shadow-free image that depicts the scene under uniform illumination. Detection of shadows is made through a hierarchical supervised classification process [9]. The reconstruction of shadow areas is based on the hypothesis that both shadow and nonshadow classes follow a Gaussian distribution and a rejection mechanism to limit as much as possible reconstruction errors. Normalized saturation-value difference index (NSVDI)[10] in Hue- Saturation-Value (HSV) color space to detect shadows and exploits histogram matching to recover the information under shadows. A new successive thresholding scheme (STS) [11] to detect shadows for color aerial images. Ratio map, which is obtained by applying the exponential function to the ratio map, is presented to stretch the gap between the ratio values of shadow and nonshadow pixels. In this paper multiphase segmentation and thresholding used for shadow detection. Also suspected shadow detection and false shadow detections are performed. Shadow removal done by IOOPL (Inner Outer Outline Profile Lines) matching. Shadows are removed by using the homogeneous sections obtained by line pair matching. Then applies the relative radiation correction to each object. There is also a threshold scheme for adjusting brightness of the result image. A lot of works are proposed for change detection. Traditionally change detection is done by using MRF [12] model assumes that subimages applied to extracting features are homogeneous, but that is not always true and causes low accuracy. Change detection done by taking difference image [13] for unsupervised change detection in terms of the Bayes decision theory. In [14] the non-overlapping blocks of the difference image are used to extract eigenvectors by applying PCA. Also taking minimum Euclidean distance between its feature vector and mean feature vector of the clusters for finding change pixels. Triplet Markov field model [15] used for change map creation. But these types of techniques have only two level ranking no-change and change. But in this paper there are improvements in terms of average running time and ranking. Change map can be quantized into many levels, also has high speed for execution of map using Lloyd-Max quantization. Similarity measurements are in terms of hamming distance. There build a binary descriptor representing the gradients in the neighborhood around that pixel.

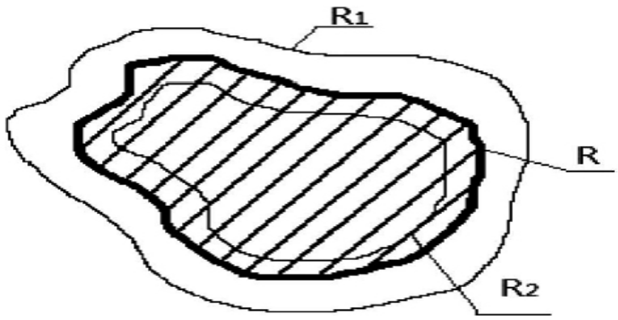

Fig. 3. Inner and outer boundary lines of shadow

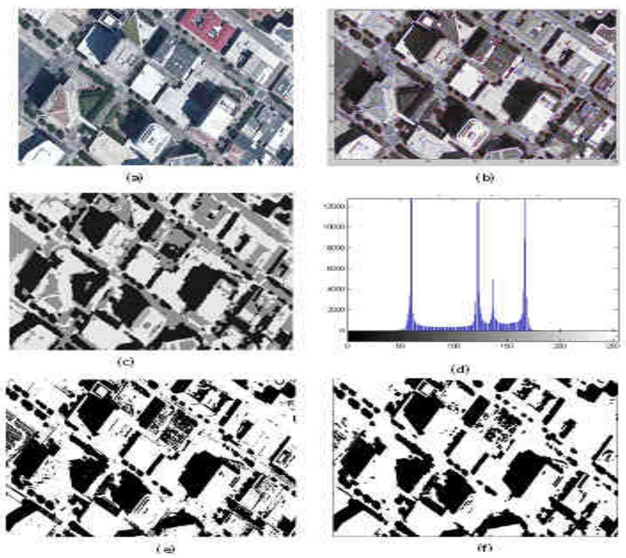

Fig. 2. Shadow detection. (a) input image, (b) segmentation process (c) segmented image (d) histogram of segmented image (e) shadow detection after thresholding (f) suspected and false shadow removal

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III. SHADOW DETECTION AND REMOVAL

Shadows are mainly divided into two types, self-shadow and cast shadow. A self-shadow is the shadow on a subject on the side that is not directlyA 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. A point source of light casts only a simple shadow, called an "umbra". For a non-point or "extended" source of light, the shadow is divided into the umbra, penumbra and antumbra. The wider the light source, the more blurred the shadow becomes. If two penumbras overlap, the shadows appear to attract and merge. Shadow detection method consists of segmentation, elimination of false shadow and suspected shadows shown in Fig. 2.

A. *Object Oriented Segmentation*

Pixel based methods are only deals about pixel details, and do not work on structural information. Each pixel is segmented based on gray-level values, no contextual information, only histogram. Due to that reason dark image pixels are treated as shadows. In this paper there is a convexity based segmentation using SVMLS (statistical and variational multiphase level set) [4] is opted which is briefly reviewed hereinafter. First find a maximum likelihood function for each point which decreases the distribution overlap between different objects up to some extent. Then an energy functional is defined by integrating the maximum likelihood function over the entire image domain.

Image is modeled as

$$I(x) = b(x)J(x) + n(x), x \in \Omega \qquad (1)$$

where $I(x)$: $\Omega \rightarrow R$ is the measured image; $b(x)$: $\Omega \rightarrow R$ is the bias field which is spatially variant; $J(x)$: $\Omega \rightarrow R$ is the true signal which is assumed to be piecewise constant. Noise $n(x)$ is assumed to be Gaussian distributed with zero mean and variance σ^2.

$$ci = \frac{\int (Kp * b) I Mi(\Phi 4) dy}{\int (Kp * b2) Mi(\Phi 4) dy}$$

$$b = \frac{\sum_{i=1}^{4} Kp * (IMi(\Phi 4)) \cdot \frac{ci}{\sigma i2}}{\sum_{i=1}^{4} Kp * Mi(\Phi 4) \cdot \frac{ci}{\sigma i2}} \qquad (2)$$

$$\sigma i = \sqrt{\frac{\iint Kp(y,x)(I(y) - b(x)Ci)^2 \, Mi(\Phi 4(y)) dydx}{\iint Kp(y,x) \, Mi(\Phi 4(y)) dydx}}$$

Corresponding gradient descent as follows

$$\frac{\partial \varphi_1}{\partial t} = -[(d1 - d2 - d3 + d4)H(\varphi_2) + d2 - d4]\delta(\varphi_1)$$
$$\frac{\partial \varphi_2}{\partial t} = -[(d1 - d2 - d3 + d4)H(\varphi_1) + d3 - d4]\delta(\varphi_2) \qquad (3)$$

The main steps of the algorithm can be summarized as

i. Initialize $\Phi_1$and $\Phi_2$to be signed distance function (SDF) s or constants withdifferent signs inside and outside contour, respectively.
ii. Keep Φ_1 and Φ_2 fixed, optimize and update the variables c, b, and σ by Eq. (2) respectively.
iii. Keep c, b, and σ fixed, evolve Φ_1 and Φ_2 according to Eq. (3), respectively
iv. Check whether the convergence has been reached. If not, return to B.

For improving the result, some factors such as color and shape and also some parameters like perimeter, area, gray scale average can be added.

B. *Suspected And False Shadow Removal*

When doing pixel based segmentation dark pixels are treated as shadows. So here chose grayscale value with the minimum frequency in the neighbourhood of the mean of the two peaks as the threshold using histogram.Let G_s is the left peak (indicate shadow) in the histogram and G_m is the gray scale average.Then

$$G_q = \frac{1}{2}(G_m + G_s) \qquad (4)$$

T is the threshold; ε represents the neighbourhood of *T*, where $T \in [G_q - \varepsilon, G_q + \varepsilon]$; and *h(I)* is the frequency of *I*, where $I = 0, 1, \ldots, 255$.

$$h(T) = Min\{h(G_q - \varepsilon), h(G_q + \varepsilon)\} \qquad (5)$$

When the left peak is not obvious, G_s can be replaced by half of the grayscale average. Thus, we retrieve a suspected shadow with the threshold method at the red and green wavebands because it is more noticeable than blue waveband. For shadows gray scale value of blue G_b is greater than G_g. For green vegetation $G_g > G_b$. So for an object i , $G_b + G_a < G_g$, i can be verified and ruled out, G_a is the correction parameter depends on image type. For accuracy we did some additional things such as colour space inversion. RGB space can be converted in to lab (l-lightness,a,b - two different colourchannels) space. Because lab compactable for any operations. Then find the mean and standard values of each colour component and doing a threshold operation. If sum of the means of a and b less than 256, do a condition as l ≤ (mean (l) – standard deviation (l)/3) as shadow pixels and others as non-shadow pixels. Then did some morphological operations closing and cleaning. These techniques are done before segmentation steps. After segmentation image is divided in to 4 sub images, such as white region, light gray region, dark gray region and black region. Then do the suspected shadow removal steps for each region.

C. *Boundary Formation for Shadows*

Shadow removal is done by IOOPL matching. So for generating IOOPL first we found the shadow boundaries, and did the contraction and expansion of boundaries. As a result we got two boundaries below and above the shadow boundary. In Fig.3 R is the object boundary and R1 is the inner boundary by contracting and R2 is the outer boundary by expanding.

D. *IOOPL Generation and Matching*

After getting the boundaries check the correlation between R1 and R2 by the equation (6)

$$Diff = \frac{1}{n}\sum_{i=1}^{1} |\overline{C_R} - \overline{C_{Ri}}|, \overline{C_R} < \overline{C_{Ri}} \qquad (6)$$

In (6) $\overline{C_R}$is the grayscale average of the object R, and $\overline{C_{Ri}}$is the grayscale average of the object R_i. If Diff value is high then there is a large probability that these locations are to be same type. Then inner OPL change the values according to the OPL. If there is a high matching that regions treated as

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homogeneous. If correlation coefficient is small, then treated as non-homogeneous and should be ruled out. IOOPL is the graph where number of points on the X- axis and gray scale value on the Y-axis. This graph have two data, one is for outer profile lines and another for inner profile lines. Then we did the matching by divide the graph into sections. Then do the similarity as mentioned above. For simplify IOOPL matching we employed a smoothing by Gaussian filter with $\sigma = 2$ and $n = 11$. After the first matching contact the inner profile line R1 and got new inner line, and check similarity with this new profile line and R1. We did the same similarity procedure, repeat the procedure till there is no inner boundary.

E. Shadow Removal by Relative Radiometric Correction (RRN)

Radiometric is a pre-processing technique to reconstruct physically calibrated values by correcting the distortions. Homogenous sections after matching have different lighting conditions. So here we use relative radiometric correction. Here the correction is done by least square method where linear function of$y = ax + b$ is determined, where y is reference data and x is data to be normalized. Let $DN_{nonshadow}$ stands for the pixel gray scale of theshadow after correction, DN_{shadow} stands for the pixel grayscale 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. Then radiometric correction expression as equation (7)

$$DN_{nonshadow} = a_{k*} DN_{shadow} + b_k \qquad (7)$$

For change detection we use two images. Then shadow detection and shadow removal are performed in these images. Then we did the change map creation as follows

IV. CHANGE DETECTION

Majority of change detection methods are done by taking the difference image. We started our work by taking binary descriptors of each pixel of two images. Then do the similarity by taking hamming distances between each image. Then apply the Lloyd-Max quantization for change map also for ranking.

A. Calculation of Binary Descriptors

We calculated binary descriptors for each pixel, and form a 3*3 matrix for each pixel (9 entries, center is the selected pixel). For one pixel, did the binary test of test pixel P with respect to neighbour pixel O, given by equation (8)

$$T_t(O,P) = \begin{cases} 1, & \text{if } I^{(t)}(O) < I^{(t)}(P) \\ 0, & \text{other wise} \end{cases} \qquad (8)$$

Where $T_t(O,P)$is the binary test and here $I^{(t)}(O)$ and $I^{(t)}(P)$ are the pixel intensities at points $\boldsymbol{O} = (Ox, Oy)^Tand\boldsymbol{P} = (Px, Py)^T$, respectively, at time *t*.

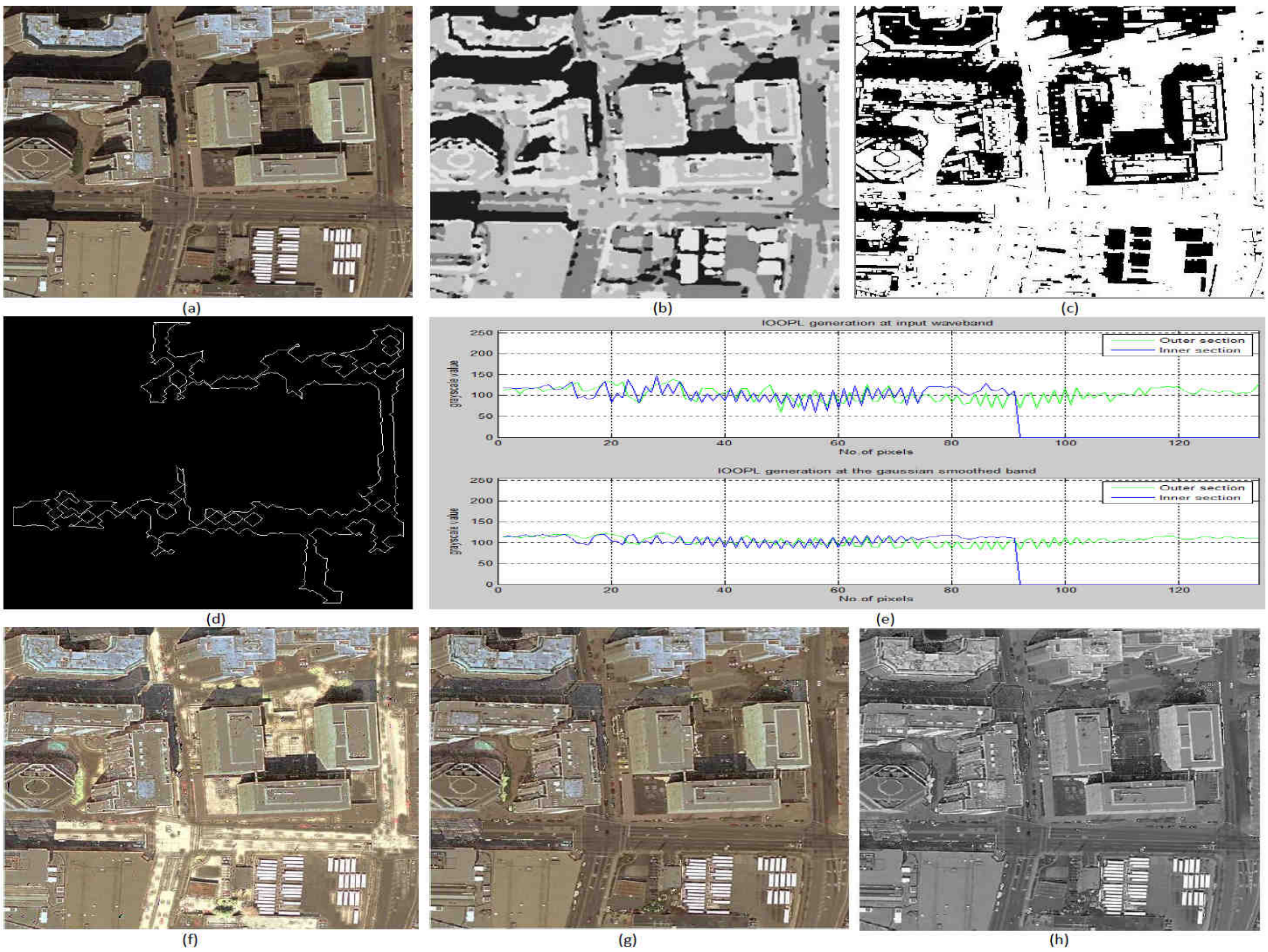

Fig. 3. Example of shadow detection and removal (Washington, http://www.mapmart.com/Samples.aspx) , (a) input image, (b)image after segmentation,(c) suspected and false shadow removed image (d) boundary formation (e) IOOPL generation (f) shadow removed image (g) shadow removed image after intensity adjustment (h) gray scale of shadow removed image

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B. *Hamming Distance Of Two Binary Descriptors*

High satellite images pixels are seems to be noise, for improving stability we did a filtering as pre-processing step. In areas where there is no change, the elements of both descriptors at the same point are likely to repeat more often if the images are smoothed before performing the binary tests. The Hamming Distance is a number used to denote the difference between two binary strings (number of bits which differ between two binary strings). Here we took pixels in the same position in two images and calculated the hamming distance of their binary descriptors. If B_1 and B_2 are the binary descriptors, then hamming distance is,

$$H(B_1, B_2) = \sum_{I=1}^{n} B_1(i) \oplus B_2(i) \qquad (9)$$

The operator ⊕ is modulo 2 addition or X-OR operation. Hamming distance measures the number of times test.

C. *Lloyd-Max Quantization*

Change map is created using the Lloyd-Max quantization, which also gives the ranking map. Brief explanation of quantization is given below, For a signal x with given PDF find a quantizer with M representative levels such that

$$d = MSE = E\left[\left(X - \hat{X}\right)^2\right] \text{ should be minimum} \qquad (10)$$

M-1 decision thresholds exactlyhalf way between representativelevels.

$$t_q = \frac{1}{2}\left(\hat{x}_{q-1} + \hat{x}_q\right), \; q = 1,2, \dots M-1 \qquad (11)$$

M representative levels in the centroid of the PDF between two successive decision thresholds.

$$\hat{x}_q = \frac{\int_{t_q}^{t_{q+1}} x.f_X(x)\,dx}{\int_{t_q}^{t_{q+1}} f_X(x)\,dx}, \; q = 0,1,2, \dots M-1 \qquad (12)$$

In the case of unknown probability distribution equation (12) become

$$\hat{x}_q = \frac{1}{\left\|T_q\right\|} \sum_{x \in T_q} x \qquad (13)$$

Where $Tq = \{\, x \mid t_q \le x \le t_{q+1} \,\}$ and ||.|| denotes the no of elements in the set. Here in this paper we implemented results for M=2, M=3, and M=4. Also we can implement more than 4 levels of changes.

V. EXPERIMENTS

Images for shadow detection, removal and change detections are easily available in Satellite Imaging Corporation (http://www.satimagingcorp.com/gallery/). This site contains images of different satellites, QuickBird, Worldview, IKONOS, GeoEye, etc.

A. *Shadow Detection*

Our shadow detection steps are shown in Fig 2. ((a)-(f)) . Fig 2.(b) is the image under segmentation, which contains red and blue colored contours. That contours are used for determining shadows and non-shadows. From Fig2. (c),it can be see that shadow features are effectively segmented. Histogram of segmented image has clear peaks, means that perfectly segmented the features. Fig2. (e) suspected shadows and false shadows are removed

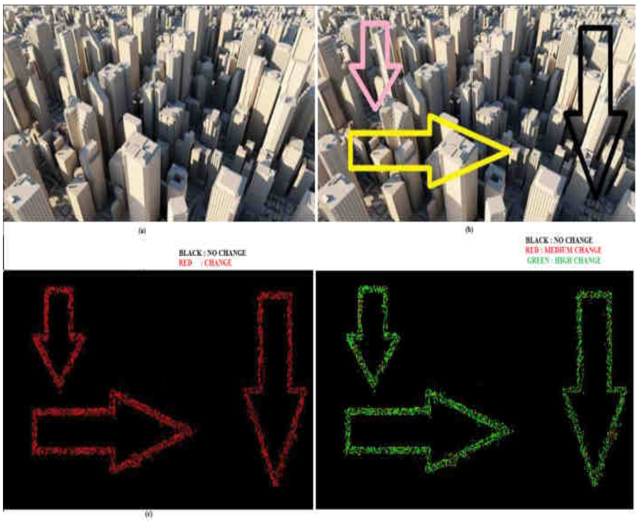

Fig 4. Change detection (a) input image (b) synthetic image (c) change map with 2 level ranking (d) change map with 3 level ranking

REGIONS	AREA SIZE (PIXEL)	AVERAGE VALUE	STANDARD DEVIATION
NON-SHADOW	197253	154.6215	46.8627
SHADOW	198637	90.9201	34.9131
SHADOW-REMOVED	198637	147.3226	47.9143

Table 1: numerical validation of shadow removal

B. *Shadow Removal*

As the shadow removal example, for this paper we adopt image of Washington DC shown in Fig.3 from,http://www.mapmart.com/Samples.aspx. After the shadow detection steps (fig.3 (a-c)) we did boundary extraction steps. When we got the boundaries, made inner and outer profile lines by contracting and expanding respectively. In each pair of contracting and expanding we generated IOOPL graphs and did the matching. Then after take radiometric correction. After that we got shadow removed image. There employed a thresholding mechanism for image intensity adjustment between segmented image and shadow removed image. Then for understanding the output accuracy took the grayscale values of resultant image as shown in Fig 3.(h). Numerical validation is done after the removal as shown in Table (1), which verifies the effectiveness of method. For comparing regions we selected two parameters average pixel value and standard deviation. From the table there is a remarkable difference of values between shadow and nonshadow region. And also there is a negligible difference between non shadow area and shadow removed area.

C. *Change Map Creation*

For change map creation we took one image and made another image by added three arrows on the first image. The second image, we called synthetic image is compared with original image. First found the binary descriptors two image. After that calculated the hamming distance of each binary descriptors of two image at same location. We did many quantization levels in the change map.

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Here in fig 4.(c) M=2, and in Fig 4.(d), M=3, shown different levels with different colors. Time-consuming part ofthe change detection, filtering for smoothing. Using a simple box filter, which is less timeconsuming, serves our purposes well and canbe regarded as agood compromise if compared to Gaussian-like low-pass filters.

D. Average Running Time

Running time taken for change map creation is very less, about 2.2 seconds. But compared to change detection shadow detection is time consuming.Because of IOOPL generation and matching takes most of the time required for shadow detection. But compared to existing methods, accuracy is better for this work.

VI. CONCLUSION

Satellite images of urban areas contain the large amount of shadows. When doing change detection on these areas (images at different time), change map become corrupted. So shadow detection and removal did as the preprocessing step. For shadow detection, segmentation is the first step, after that suspected and false shadows are eliminated. IOOPL matching follows boundary extraction, and IOOPL generation. Shadow removal by RRN can restore the texture details. While doing false shadow removal, some green vegetation cannot be restored. So as the future improvement better segmentation can be used. Change map creation uses binary descriptors of each pixel, which are the neighborhood details of that pixel. Similarity measurement is done by hamming distance calculating between binary descriptors of two images, at same pixel location. Arrange Hamming distances using Lloyd-Max quantization into different levels. Also time consuming for this ranking is very efficient compared to existing one. Also the method is local (i.e., it takes into account the changes that occur in the area around each pixel).

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Kesini Krishnan V: - is currently doing the M.Tech. degree in Signal Processing with the Department. of Electronics and Communication Engineering, SCT College of Engineering, Pappanamcode, Thiruvananthapuram, Kerala. She received the B. Tech degree from the CUSAT university, Thiruvananthapuram, in 2011 in Electronics and Communication Engineering. Her research interests include image processing, pattern recognition and signal and speech processing.

Smitha P.S:- is the Assistant Professor, Dept. of Electronics and Communication Engineering., SCT College of Engineering , Trivandrum, Kerala. She received the M.Tech degree in Communication Engineering from National Institute of Technology, Karnataka, India in 2011 and she is the Second Rank holder in M.Tech. She received B.Tech degree in Electronics and Communication Engineering from University of Kerala, India in 2002.

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