

An Improved Approach in Shadow Detection and Reconstruction INVHSR Images

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Abstract

Background/Objectives: The objective of this study is detection and reconstruction of shadows from Very High Spatial Resolution Images (VHSR images). **Methods/Statistical Analysis:** This paper, presents an effective unsupervised method of segmentation for detecting shadows using modified Self Organizing Maps (SOM and MRF). This term MRF is adapted with SOM to segment the shadows without giving more trained sample data set and linear regression method is applied in shadow regions for compensating the shadows by non shadow regions (Reconstruction process). **Findings:** Experimental result of proposed method gives a significant result on VHSR images and assess the various quality metrics to obtain the better performance, quality and accuracy than the other conventional methods. **Application/Improvement:** The Modified SOM network eliminates the fake shadows, avoids over segmentation reduces the execution time for segmenting the shadows and improves accuracy as appx 92%. It is mainly used for various remote sensing applications such as change identification, object recognition, scene restoration, color tuning etc.

Keywords: Linear Regression Method, MRF, Reconstruction, Self-organizing Maps, Shadow Detection, VHSR images

1. Introduction

Satellite images have increased various demanding research areas for remote sensing field, such as object matching, classification, detection and removal, change detection and object mapping¹ etc. When light source is illuminated on any object the shadow is observed on the other side of the object. Inevitably, tall standing objects (e.g Buildings) among these small features cast long shadows in most of the captured satellite images. On the one hand, these shadows may be utilized as a critical cue for detecting the existence of the objects in the overhead images which is affected image information partially or totally. Hence reliable detection of shadow is very essential to remove it effectively. Model and property based methods are two important categories of Shadow detec-

tion methods²⁻⁴. Generally, two steps are involved in this procedure: 1) shadow detection and 2) shadow reconstruction (compensation). However, detection of shadows in satellite images is a challenging problem, in addition to missing the color information, many objects and scene contents tend to be dark/almost dark and distinguishing them from the shadows regions adds to further difficulty. Shadow compensation is to restore the surface under shadows. Allowing for that a surface texture does not considerably change when shadowed. Nearby non shadowed regions are usually used to compensate shadowed ones. The shadow detection and removal has been done in few approaches but the image restored by existing approaches fails to perfectly restore original background patterns once shadows removed. Gradient based background subtraction method⁵ focused on shadow detection for

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moving human cast shadow and is removed without affecting self-shadow. Yuewang, Shugenwang proposed a method⁶ with partial differential equations which are used to detect shadow in urban color aerial images. Lorenzi et al.⁷ introduced an approach using processing chain mechanism to detect the shadows and also classified to allow their customized compensation. State-of-the-art support vector machine approach is used to identify the detection and classification tasks of shadow with a quality check mechanism in order to reduce subsequent misreconstruction problems. Gamma correction method⁸, Linear correlation method⁹, Posteriori probabilities method¹⁰, these approaches are operated using spectral information (band by band) in RGB color, which builds the composite color not natural. Liu et al and Adeline et.al developed algorithms^{11,12} using multibands for shadow detection in aerial images and to enhance the classification. Huihui Song et al.¹³ developed a hybrid approach of Morphological Filtering and Example-Based learning for effective shadow detection in VHSR (Very High Spatial Resolution) images. In this study, we propose an alternative shadow detection and reconstruction algorithm based on modified Self organizing maps with MRF and linear regression method respectively. During the shadow detection procedure, the unsupervised self-organizing maps segments the shadow and non-shadow region of satellite images. During the shadow reconstruction procedure, we model the relationship between non-shadow and the corresponding shadow pixels with the compensation technique of neighboring non-shadow pixels by employing linear regression method.

2. The Methodology Used

The proposed methodology consists of three steps.

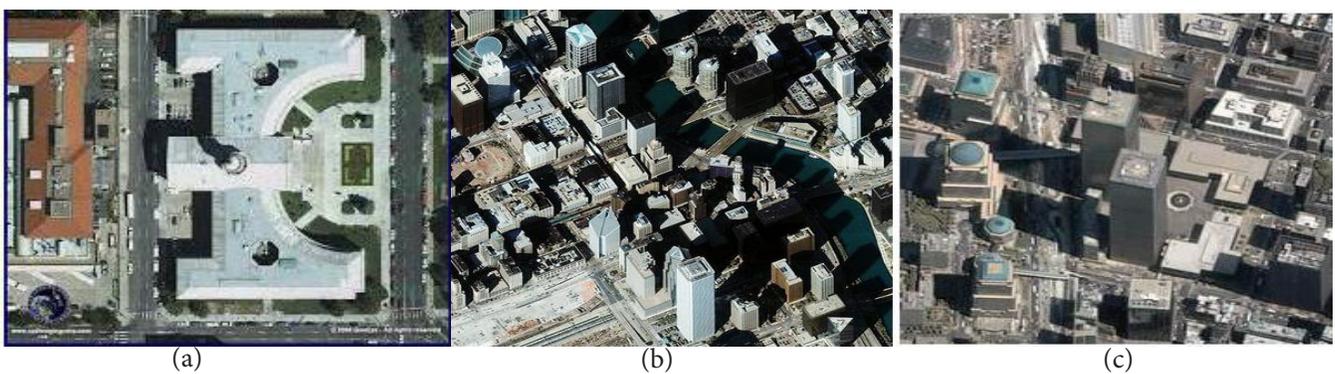


Figure 1. (a), (b) and (c) Remote sensing Input images.

First, shadow regions are obtained by SOM algorithm. Second, Shadow classification is obtained by Modified self-organizing map with MRF method. Finally, Shadow Reconstruction is based on linear regression method. The overall system sketch is shown in Figure 3.

2.1 Pre Processing

In this, proposed method initially high resolution input RGB image size is examined by the user whether it is less than double range then it needs to resize and convert into gray. In order to perform the SOM algorithm, all the shadows of grey image must be detected. Modified SOM method is examined to verify the shadows and non-shadow regions. Figure 1 shows image 1(a) and image 1(b) from IKONOS images and Image 1(c) from GEOEYE-I image having a number of buildings casting shadows and segmentation results are shown in Figure 4. Analyzing the shadow levels of input images shown in Figure 2.

2.2 System Sketch

Steps:

1. An RGB image with shadows is given as input.
2. This input image is resized and converted to grey image.
3. The gray image is denoised.
4. Shadow segmentation (SOM): Shadow regions are identified by applying segmentation on the gray image.
5. Shadow removal (SOM+MRF): Separating shadow regions from non-shadow regions
6. Shadow reconstruction: Reconstructing the shadow region by applying linear regression method
7. Shadow less image: Finally, reconstructed shadow less images is resulted.

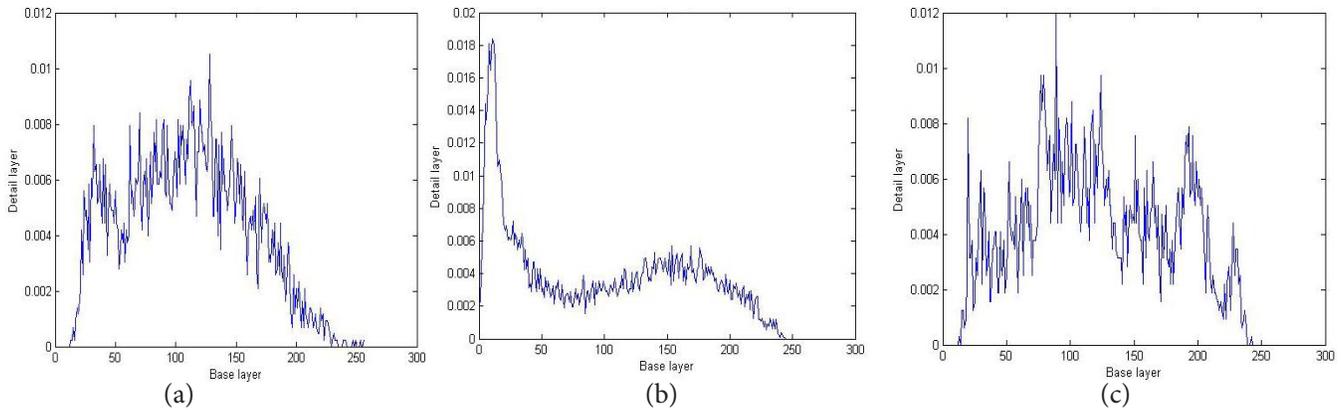


Figure 2. Shadow analyzer of Input images.

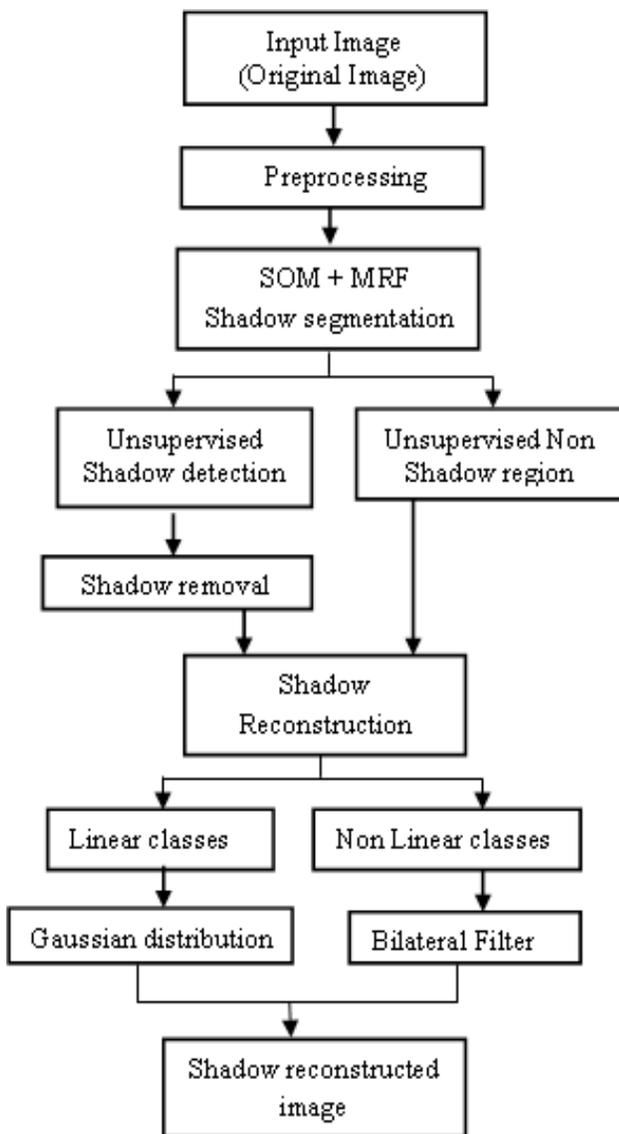


Figure 3. System Sketch.

2.3 Shadow Detection: SOM Segmentation

Self-organizing Feature maps (SOM) is an unsupervised learning Neural Network method which is introduced by Kohonen (2001). This method improves the performance of the segmentation than other clustering algorithms¹⁶ and an important self organizing property is its ability to process noisy data. Instead of using rule set, it makes the classification by a competitive learning approach that learns from input pattern. It converts high dimensional input pattern into one or two dimensional arrays of neuron units and preserves neighbouring input nodes (Neurons). Each node of the map is defined by a weight vector W_{ij} whose elements are adjusted during training. This map retains topological relationship between input neurons and its neighboring neuron. The competitive learning process consists of two steps: ordering (weight modification) and tuning (fine settings) which is selected a winning neuron according to some criteria which is used to minimize a Euclidean distance between input vector and weight vector.

The basic SOM model includes an input layer and an output layer. Each input neurons is mapped through weights to every output nodes. The weights are adjustable for each iteration. Let $IP = [a_0, a_1, a_2, \dots, a_{n-1}]^k$ be the set of n number of input nodes in R^n and which includes each a_i dimensions. Let $OP = [b_0, b_1, b_2, \dots, b_{n-1}]^T$ be the set of n number of output nodes which has two dimensions space vector and W denotes the set of weights $W_j = [w_{0j}, w_{1j}, \dots, w_{(n-1)j}]^T$ and represent as reference vectors. The weight vector w_{ij} represents the weight from input node i to output node j iteration h .

The weights are updated by the winning entity and finding the best matching unit is determined by the

minimum of Euclidian distance to the input and neighborhood is nearer to the accessible input node. The Best matching unit is found by whose distance d_{ij} is in least value. A Euclidean distance is measured by d_{ij} , as follows:

$$d_{ij} = \min_j \|a_i(t) - w_{ij}(t)\|^2 \tag{1}$$

Let $\beta_{ij}(t)$ be a learning rate, $\beta_{ij}(t)$ which is used to adjust the weight vector of winning neuron and to calculate its neighbours. The weight updating rule is defined as:

$$w_{ij}(t_1 + 1) = w_{ij}(t_1) + \beta_{ij}(t_1)[a_i - w_{ij}(t_1)] \tag{2}$$

Where at the time t_1 with n neurons gaining the sequence ($0 < \beta_{ij} < 1$) and the neighbourhood node of winning neuron is ($1 < R^i < n$). While doing sliding neighbourhood operation, the output values may be computed by assuming that the input image is surrounded by additional rows and columns of zeroes. Here SOM segments all shadows in the gray image by competitive learning process. But the implementation of SOM method, original shadows and other dark regions also consider as shadows Figure 4.

2.4 Shadow Removal: Modified SOM with MRF

Markov Random Field (MRF) is a set of random variables which has a Markov property. It is applied for image segmentation, restoration and other image processing applications. We can append more spatial/spectral constraints into SOM training algorithm for enhanced

segmentation results. SOM training algorithm can update the connection weights by adding MRF properties to remove fake shadows. For each pixel, pixel intensity and its label is assigned as s_i and $s_i, s_i = c_i$ respectively. Each pixel fit into its region c_i .

Let $S = \{s_i\}$ denotes the image segmentation not including the i^{th} pixel intensity s_i . A region process which generates the spatial connectivity which is represented by a MRF (Markov Random Field) as follows:

$$P(s_i | S - \{s_i\}) = P(s_i | s_j, j \in N_i) \tag{3}$$

Here N_i specifies the neighbourhood of the pixel i . Gibbs density produces the density of s which formulates the equation as given below:

$$P(s_i | s_j, j \in N_i) = \frac{1}{Z} \exp \left\{ - \sum_{C_i} V_c(s_i) \right\} \tag{4}$$

Here the number possible cliques that contain i^{th} pixel, clique potentials denoted as C_i and $V_c(s_i)$ respectively. The partition constant Z is normalized to produce partition function as

$$Z = \sum_{s \in S} m^{-\sum_{c \in C} V_c(s)}$$

The Clique potentials using 2-point are characterized as:

$$V_c(s) = \begin{cases} -\xi(s_i - \mu_{s_i}) & \text{if } s_i = s_j \text{ and } j, i \in C \\ 0 & \text{if } s_i \neq s_j \text{ and } j, i \in C \end{cases} \tag{5}$$

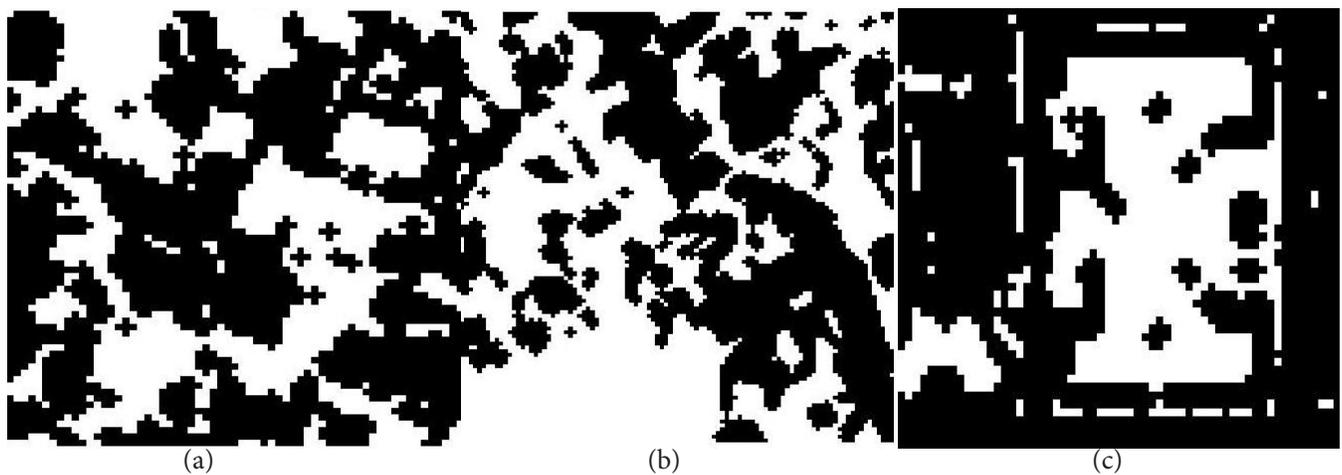


Figure 4. (a), (b) and (c) Shadow regions and other dark regions using SOM method.

Here, $0 < \xi < 1$ and mean intensity μ_{s_i} is computed for the region s_i in addition to derive the MRF energy function as

$$U(s_i) = \sum_{c_i} V_c(s_i) \quad (6)$$

The function, $U(g_i)$ is a sum of clique potentials $V_c(g_i)$ over all possible cliques C . By taking Equation (6) and the adapted SOM Algorithm with MRF rule is:

$$w_{ij}(t_1 + 1) = w_{ij}(t_1) + \beta_{ij}(t_1)[a_i - w_{ij}(t_1)] + U(s_i) \quad (7)$$

Where $U(s_i)$ updated the weight connection and to classify the regions based on spatial clustering of pixels with MRF rule. It improves the segmentation results without adding more training data sample set and provides prior spatial information regarding the pixel intensity, various active contours, direction and angle of the regions to be segmented. Each spatial constraint evaluates for the natural contiguity of pixels belonging to the same type of image region. If a pixel is a specific type, the neighbour pixels would have a high possibility of being the same type. It is identified that intensity of original shadow regions are higher than normal dark regions. When the intensity differs, mean and variance of the pixel values also varied from original and fake shadow region. Hence, modified SOM algorithm can remove original shadows without having fake shadows Figure 5.

2.5 Reconstruction Work

Shadow regions and non shadow regions are separated by using segmentation process. The shadow reconstruction process is required when this shadow removal procedure is losing the desired data. The reconstruction is based on linear regression method to compensate shadow regions by adjusting the intensities of the shaded pixels according to the statistical characteristics of the corresponding non shadow regions. Then, the border between the reconstructed shadow and the non shadow areas undergoes a linear interpolation operation to yield a smooth transition between them. In the following sections, a detailed description of all these steps is provided. Shadow Reconstruction images are shown in results and discussions (Section III).

2.5.1 Linear Regression Method (Gaussian Distribution): Linear Classes

We take that the linear type which has underlying relationship between the non shadow class (A) and the corresponding shadow classes (B). We have examined that shadow classes and the corresponding non shadow classes sensibly exhibit a linear relationship and three estimation statistical model of the classes are available. In this research, we implement the parametric estimation method by assuming that the classes track a Gaussian distribution. This is easily derived, traced and easy-to-implemented reconstruction method tend to this assumption $A \sim N(\alpha, \Sigma)$ and $B \sim N(\alpha, \Sigma)$, where α and Σ stand for the mean and covariance matrix, respectively.

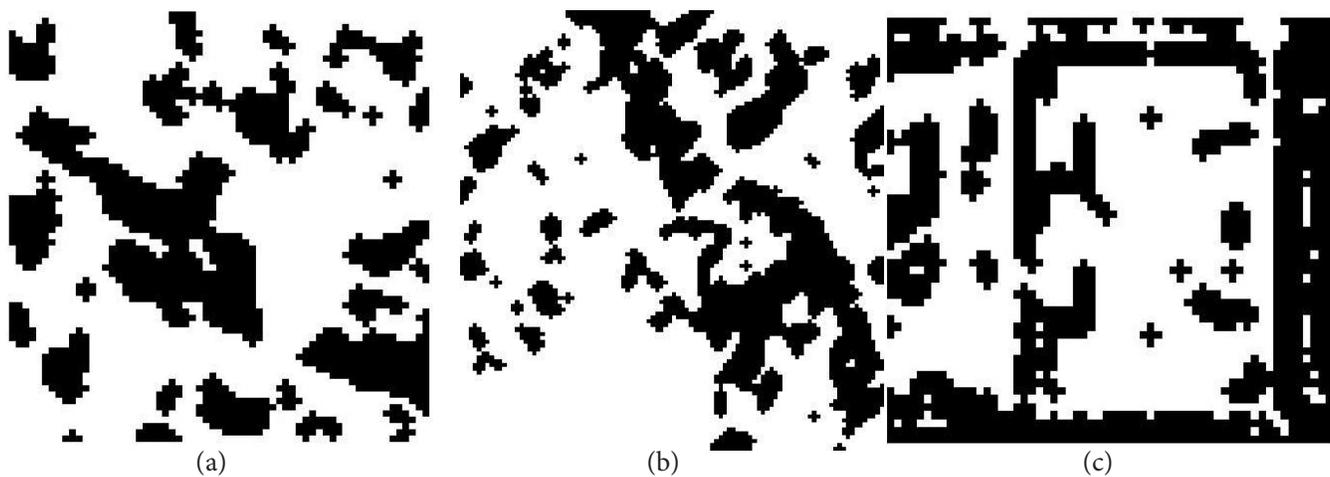


Figure 5. Original shadow regions detected using modified SOM method.

Since the two distributions are assumed linearly correlated, a and b may be linked by $b = Ta + c$.

$$\alpha_s = T \alpha_{ns} + c \text{ and } \alpha_{ns} = T \alpha_s + T^t \tag{8}$$

Here T and T^t is a transformation matrix and its transpose respectively. Cholesky factorization is applied to estimate T and c values.

2.5.2 Bilateral Filter: Non-linear Classes

When the neighboring image values are in nonlinear combination, by applying Bilateral filtering method preserving edges and smoothes images. It is straight forward and non-iterative method used to merge the gray or color based on geometric familiarity and photometric resemblance. It chooses the best neighbor values in all domain and range. The bilateral filter is applied texture-illuminance decoupling filter tend to decouple large and small-scale features thereby discounting the effect of illumination on uniformly textured areas. This method assumes that all large scale variations on such surfaces

come from changes in illumination and does not handle detailed shadows of small objects correctly. Furthermore, the user is required to specify the texture feature size.

3. Experimental Results and Discussions

The proposed method has been examined with variety of high resolution satellite images obtained under dissimilar illumination conditions in urban areas. The images are taken 256 X 256 pixel size of a typical urban scene which has major shadow regions. The shadow detection method may be confused by low intensity regions (concrete), saturated white areas and dark non-shadow regions which have similar gray values (water regions). Reconstruction work shows the original structure of buildings Figure 6, Figure 7 and Figure 8.

The proposed algorithm evaluates the accuracy of shadow detection using quantitative metrics^{14,15}. The

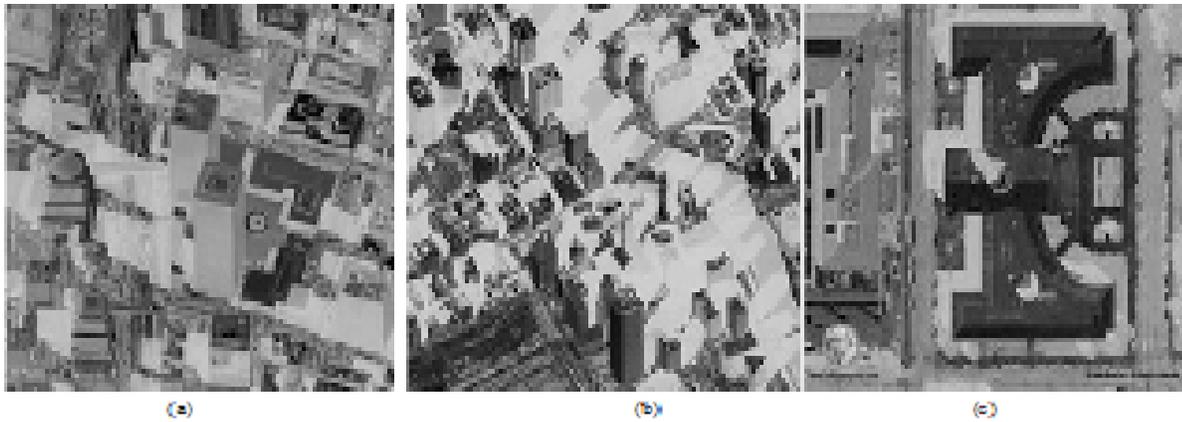


Figure 6. (a), (b) and (c) Shadowless grey images.



Figure 7. (a), (b) and (c) Reconstructed images with color map.

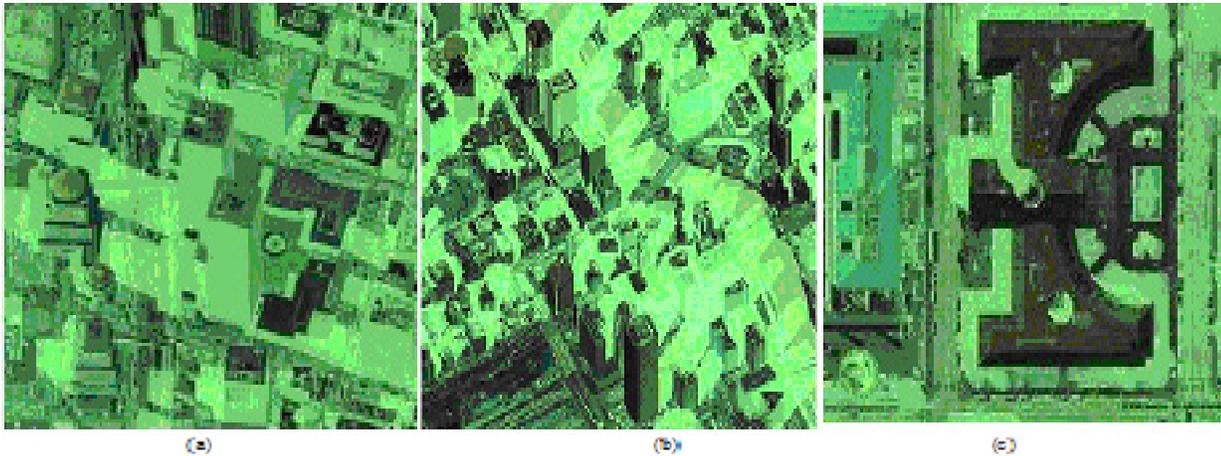


Figure 8. (a), (b) and (c) Final reconstructed images.

following metrics are implemented as follows. The first metric type measures the correctness of the algorithm and indicate how well the true shadow and non-shadow pixels are correctly classified is called as True detection rate (producer’s accuracy), which. The second metric type is the user accuracies that measure the exactness of the algorithm and indicate the probabilities of correctly detected and classified pixels (shadow and non-shadow). The third metric type measures the correct quality percentage (overall accuracy).

$$BF = \frac{FP}{TP} \text{ and } MF = \frac{FN}{TP} \tag{9}$$

$$PAs = \frac{TP}{TP + FN} \times 100 \quad \text{and} \quad PAnS = \frac{TN}{TN + FP} \times 100 \tag{10}$$

$$UAs = \frac{TP}{TP + FP} \times 100 \quad \text{and} \quad UAnS = \frac{TN}{TN + FN} \times 100 \tag{11}$$

$$QP = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \tag{12}$$

Where TP+TN is the no of correctly detected and identified true shadow and non shadow pixels and TP+TN+FP+FN is the total no of pixels in the input

Table 1. Quality assessment with different metrics

Images \ Quality metrics	Image 1(a)		Image1(b)		Image 1(c)	
	Shadow region	Non shadow region	Shadow region	Non shadow region	Shadow region	Non shadow region
Branching factor	0.05	0.12	0.09	0.25	0.11	0.30
Miss Factor	0.05	0.05	0.06	0.06	0.06	0.05
Detection Percentage % (Producers Accuracy)	95.5	95.5	93.33	93.33	91.2	91.2
User accuracy	91.5	88.07	88.98	78.85	93.89	90.94
Quality Percentage %	91.23	85.33	89.00	83.00	97.62	85.51

image. Improved Shadow detection is evaluated by the Quality percentage shown in Table 1 is better than existing methods¹⁷.

4. Conclusion

In this study an improved method for shadow detection, removal and reconstruction is proposed. This technique, segments the shadows of buildings by using the gray level satellite image without using color information. Since both the qualitative (approx 90%) and quantitative (92%) experimental results are effectively evaluated and it is seen that shadows are detected correctly in addition to the areas under the shadow are illuminated. This method is not limited to remote sensing images and can be easily applied for other imagery from different sources even those with composite outdoor scenes and it can be utilized as automated method for building detection from remote sensing images which is a difficult task. Further study can be implemented for the shadow compensation to get shadow invariant image of the same region.

5. References

1. Junli W, Shugen W. A method of image shadow detection based RGB colour space. *Information Technology*. 2002; 26(12):7–9.
2. Li Y, Gong P, Saagawa T. Integrated shadow removal based on photogrammetry and image analysis. *International Journal of remote sensing*. 2005; 26(18):3911–29.
3. Tsai VJD. A comparative study on shadow compensation of color aerial images in invariant color models. *IEEE Transactions on Geoscience and remote sensing*. 2006 Jun; 44(6):1661–71.
4. Salvador E, Cavallaro A, Ebrahimi T. Cast shadow segmentation using invariant color features. *Computer vision and invariant color features*. *Computer vision and Image Understanding*. 2004 Jun; 95(2):238–59.
5. Shohib M, Dragon R, Ostermann J. Shadow detecting for moving humans using gradient based background subtraction. *IEEE International Conference on Acoustics, Speech and signal processing (ICASSP)*; 2009 Apr; Taipei; p. 773–6.
6. Wang Y, Wang S. Shadow detection for urban color aerial images based on the partial differential equations. *The international archives of the photogrammetry, remote sensing and spatial information sciences*. 2008; XXXVI (Part B2).
7. Lorenzi L, Melgani F, Mercier G. A complete processing chain for shadow detection and reconstruction in VHR images. *IEEE Geoscience and Remote Sensing*. 2002 Sep; 50(9):3440–52.
8. Massalabi A, He D-C, Benie GB, Beadury E. Detecting information under and from shadow in panchromatic Ikonos image of the city of sherbrooke. *Proceedings of IGARSS*. 2004 Sep; 3:2000–4.
9. Sarabandi P, Yamazaki F, Matsuoka M, Kiremidjian A. Shadow detection and reaiometric restoration in in satellite high resolution images. *2004 Proceedings of IGARSS*. 2004 Sep; 6:3744–47.
10. Suzuki A, Shio A, Arai H, Ohtsuka S. Dynamic shadow compensation of aerial images based on color and spatial analysis. *Proceedings of 15th International Conference on pattern Recognition*. 2000; 1:317–20.
11. Liu J, Fang T, Li D. Shadow detection in remotely sensed images based on self-adaptive feature selection. *IEEE Transactions Geosci remote sensing*. 2011 Jun; 49(6):2049–59.
12. Adeline KRM, Chen M, Briottet X, Pang SK, Paparoditis N. Shadow detection in very high spatial resolution aerial images: a comparative study. *ISPRS Journal of Photogrammetry Remote Sensing*. 2013 Jun; 80:21–38.
13. Song H, Huang B, Zhang K. Shadow detection and reconstruction in high-resolution satellite images via morphological filtering and example-based Learning. *IEEE Transactions Geoscience and Remote Sensing*. 2013 Jun; 52(5):2545–54.
14. Al-Najdawi A, Bez HE, Singhai J, Edirisighe EA. A Survey of cast shadow detection algorithms. *Pattern Recognit Lett*. 2012 Apr; 33(6):752–64.
15. Sanin A, Sanderson C, Lovell BC. Shadow detection: a survey and comparative evaluation of recent methods. *Pattern recognition*. 2012 Apr; 45(4):1684–95.
16. Arumugadevi S, Seenivasagam V. Comparison of clustering methods for segmenting color images. *Indian Journal of Science and Technology*. 2015 Apr; 8(7):670–7.
17. Arevalo V, Gonzalez J, Ambrosio G. Shadow detection in colour high resolution satellite images. *International Journal of Remote sensing*. 2008 Apr; 29(7):1945–63.