Fusion of IKONOS remote sensing filtered images using shadow information to improve the rate of building extraction in urban images

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***Abstract*— Deficiency of unsharp mask filter in elimination of some regions in IKONOS remote sensing urban image is one of serious difficulties in building extraction from such images. Sometimes, saturation of intensity levels in filtered image makes some regions of image disappear. As a compensation for this issue, in this paper a method for fusion of unsharp mask filtered image and histogram equalized image is presented. In the first step, fusion of filtered images is accomplished. Since shadows give some information about the location of buildings, fusion of filtered images with considering the shadow location can be a satisfactory cure for elimination of image components such as buildings. Afterward, Bayesian classifier is applied to the fused laplacian and edge images to extract the buildings. Experimental results justify application of the proposed method in building extraction for IKONOS remote sensing images.**

Keywords-remote sensing, image fusion, unsharp mask.

I. INTRODUCTION

In the recent decades, remote sensing imagery makes the monitoring of the earth surface and atmosphere possible. As the technology of the imagery sensors has improved, the remote sensing images with higher quality have become available. Sine extraction of useful information from remote sensing data is important; Scientists manage to propose efficient algorithms for automatic extraction of constructive information from the satellite images. In this way, classification of remote sensing images of urban areas may obtain valuable information for many GIS applications, such as traffic surveillance, map updating and planning, and emergency response and management. Thus, automated and semi automated methods for the classification of roads, buildings, and other land cover types in the urban areas attract many research interests.

Classification of man-made objects is realized using pixel-based or object-based methods. Pixel-based methods [1]-[2] include making n-dimensional vectors from the gray level data of each part of input image and comparing the vectors to a reference vector which is trained using a remote sensing image database. Whilst, in the object based approaches, pixels of input image are not considered individually for recognition and groups of pixels are processed to be recognized as objects. So neighborhood relationships and shape characteristics are significant for classification of such images.

As the resolution of images increases, the accuracy of pixel-based methods for classification of multispectral remote sensing imagery such as minimum distance from means and maximum likelihood [3],[4] decreases. Furthermore, spectral characteristics of some of different classes are indistinguishable. Meanwhile, Fuzzy based methods for classification can better confront the classification of satellite image components. In such methods attribution of fuzzy membership class to pixels [5], [6], [7], [8], [9] is accomplished. In [7] a fuzzy-based classifier has been proposed and its superiority over a simple ANN classifier has been shown. Fusions of fuzzy approaches have been utilized in [8] to improve accuracy. In [9], based on spectral similarity of many urban remote sensing data and spatial information an accurate classification map from input image has been provided. After that, a fuzzy classifier has been utilized for the classification of urban area. An object-based method for the classification of dense urban areas from pan-sharpened multispectral IKONOS remote sensing images is introduced [10] in which a cascade combination of a fuzzy pixel-based classifier and a fuzzy object-based have been exploited. The fuzzy pixel-based classifier extracts the spectral content of the scene while, fuzzy object-based classifier analyzes the spatial context information. Use of support vector machine (SVM) for classification of urban area in remote sensing images is presented in [11]. In which, the hierarchical relationships between each pixel in the image and the adaptive regions to which it is associated at different levels are considered to make the feature vectors. Then, this feature vectors have been fed to SVM classifiers.

In [12], segmentation techniques have been applied to remote sensing imagery for classification. The residuals of morphological opening and closing transforms have been utilized for segmentation in [12]. In [13], [14], [15] Bayesian discriminator is used for extraction of buildings. In [14] image laplacian is obtained. After that, it is fed to a special Bayesian classifier for classification of buildings. Finally, urban areas, roads and highways are extracted using size and some of the morphological operations such as opening and closing.

In this approach, a method for image fusion using shadow location is presented. Unsharp mask filter intensifies high frequency components of image by adding some dark and white edges to the image. As a result of adding dark edges, some of the image components disappear. Since the

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fused image is achieved by unsharp mask filter, its local contrast is improved. Afterward, Bayesian classifier is applied to image laplacian to extract buildings of image.

II. METHODOLOGY

A. Local and global enhancement of IKONOS remote sensing image

Fig. 1 depicts some parts of IKONOS remote sensing image from urban areas. It is clear that the building regions have low contrast in original image. Most of buildings classification approaches are inefficient to detect such buildings because the edges of these objects are not sharp enough for building extraction algorithms to segment. To deal with this problem two main method can be used including local and global enhancement of image. Fig .1 shows the filtered image using unsharp mask filter. Unsharp mask filter subtracts Gaussian blurred version of image from its original version. As a result, low frequency components of image are weakened and the local contrast of image is improved. For better understanding let I be the input image. The filtered image using unsharp mask is given by:

$$\widetilde{I} = I - a.G.T$$

$$G(i,j) = \sum_{h=-m/2}^{m/2} \sum_{k=-m/2}^{m/2} A(h,k) I(i-h, j-k)$$

$$A(h,k) = \frac{1}{2\pi\sigma^2} e^{-\frac{h^2+k^2}{2\sigma^2}}$$

Where G is blurred image using Gaussian blurring filter. Three parameters are used to control the unsharp mask filtering. α is a parameter that determines how much white and black edge is allowed to be added to the original image(as a result of unsharp mask filtering). σ, which is equal to one fifth of m, the size of the Gaussian mask, determines how much Gaussian blur is used to find high frequency components and edges present in the image for addition to the original image.

Furthermore, T is used as a factor to prevent addition of noise to image. It specifies the difference between original and blurred image pixels that is needed to apply unsharp mask filter on image pixels. Since the dark and white edges have been produced using blurred image, the contrast of image pixels increase locally as a result of unsharp masking. So, this filter makes buildings more visible in the remote sensing image. Effect of the unsharp mask filter and histogram equalization is presented in Fig .1

As previously discussed, unsharp mask filter intensify edges of image by darkening and lightening some parts of the original image. In some cases, adding or subtracting of image intensity, if exceeds the maximum value of image, makes some regions of image invisible. Fig .1 shows this

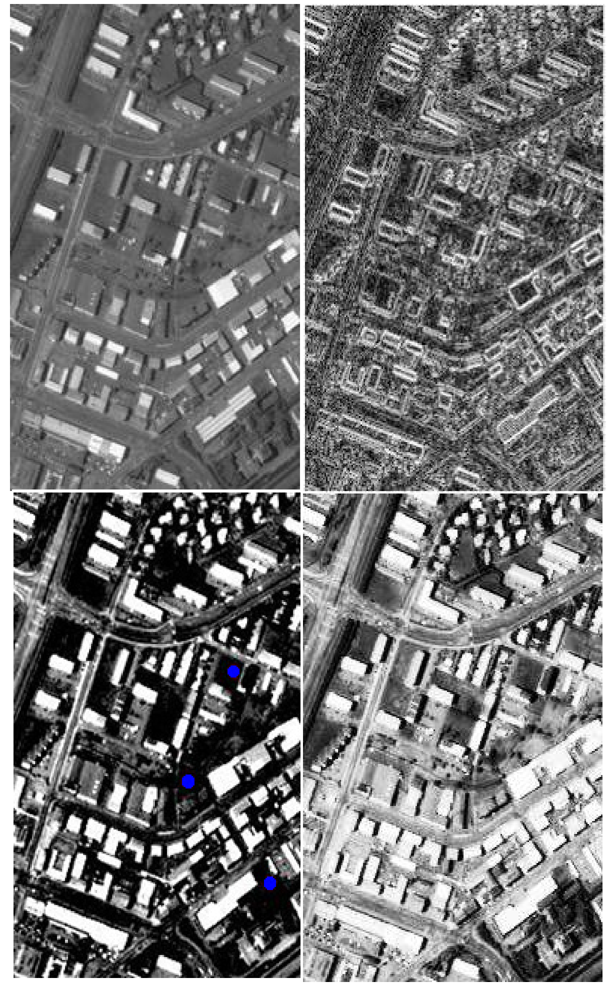

Figure 1. Original image (upper left), its laplacian (upper right), filtered image using unsharp mask (left) and histogram equalized image (right). Disappearance of some parts of image near to the blue circles as a result of unsharp masking.

effect. While in global image enhancement, this problem cannot occur.

Global enhancement of image can be accomplished using histogram equalization. This technique adjusts the contrast of image globally so that the levels of brightness in image are divided equally between image pixels. In Fig .1 the results of image contrast improvement is presented.

B. Building extraction using of modified Bayesian discrimination function

Laplacian is one of the most important criterions to evaluate the intensity variation of image. Image laplacian represents some information about intensity variations such as smoothness and roughness of image regions. Let $I(i,j)$ be the matrix which presents the intensity of input image in i, j position.

$$E_{m\times n} = \nabla^2 (I_{m\times n})$$
$$i = 1, \ldots, m \text{ and } j = 1, \ldots, n$$

$I_{m\times n}$ denotes original image with n columns and m rows and $E_{m\times n}$ denotes image laplacian. In two dimensional images, edges are considered as linear features in which the magnitude of the first derivative component along the gradient direction is maximum.

There are many methods for edge detection such as Sobel, Prewitt, Robert, Canny and etc. Generally Canny edge detector provides better results in comparison with another methods, because Canny edge detection is adjustable and provides thinned map of edges. In this approaches Canny edge detector is utilized to obtain high frequency map of IKONOS remote sensing image including building edges. To this aim, after obtaining image laplacian, it is normalized to 0 and 1 and following operations are accomplished:

$$\mathrm{E(i,j)} = \max\left(E(i,j), \mathrm{E}_{\mathrm{e}}\,(i,j)\right)$$
$$i = 1, \dots, m \text{ and } j = 1, \dots, n$$

Where E denote image laplacian and E_e denotes edge map. Morphological operations have been used for modification of structure of objects and spatial form of image components. Dilation and erosion are two fundamental morphological operations. With dilation, an object grows uniformly in spatial extent, whereas with erosion an object shrinks uniformly according to its structure element.

The image laplacian, depicted in Fig .1, indicates that the buildings have special edginess amounts. These quantities are relatively large in edges and very small in ceilings. While in another parts of image, laplacian quantity is different. In Fig .2 the probability density function of image according to its laplacian is presented. λ denotes laplacian intensity of image. For building extraction two classes are considered including W_1 and W_2. W_1, W_2 denote building class and non-building class.

Fig .2 shows the class-conditional probability density function (PDF) which shows the probability density of mentioned classes according to λ, laplacian intensity of corresponding image pixels. $P(W_1 \mid \lambda)$ represents the probability of W_1 which refers to building class. In the same way W_2 refers to open area, shadow and road classes. Each PDF has been provided from IKONOS remote sensing images from Iceland.

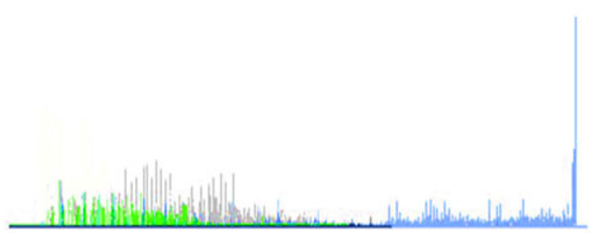

Figure 2. In PDF (Probability Density Function) chart, vertical axe is Laplacian intensity λ and horizontal axe is P(ω|λ). The green, gray and light blue colors represents buildings P(ω1|λ), streets P(ω2|λ) and open area P(ω3|λ) respectively.

$$\lambda \in \begin{cases} \omega_1 & P(\omega_1|\lambda) \rangle P(\omega_2|\lambda) \\ \omega_2 & otherwise \end{cases}$$

By considering $\lambda > 0.5$ and $\lambda < 0.15$ we have $P(W_1 \mid \lambda) > P(W_2 \mid \lambda)$. For $\lambda > 0.5$ in laplacian spectrum, building can be extracted so λ = 0.5 is considered as a boundary of two classes. Other part of buildings spectrums which have lower amounts of laplacian exist in ceiling regions. To detect ceiling regions a threshold is set to 0.15 to apply on image laplacian. Remaining part of laplacian spectrum ($\lambda < 0.15$) exists in open area and ceilings of building image. These two classes can be discriminated by considering size criterion since open areas are larger than buildings. Each part of image which has greater size than a predefined threshold, classified as a member of open area class, so open area region is deleted from building map. In the next step with a same method, houses are specified from large buildings.

Shadows and vegetations have lowest intensity in satellite images. To improve accuracy of classifier, before building detection, vegetations are deleted from original image according to their green layer (from RGB image), consequently only shadows have lowest intensity. Fig .4 shows the shadows yielded by considering a threshold level on original image.

C. Making fused image for building extraction

After applying the building extraction algorithm on locally and globally enhanced IKONOS remote sensing images it is observed that some problems occur. Fig .3 presents the result of the proposed method in section B which has been applied to the locally and globally enhanced images for building extraction.

As Fig .3 shows, in locally enhanced classified image, due to partial disappearing of filtered image components and undesirable effects of unsharp mask, some buildings are not detected. As a result of unsharp mask filtering, saturation of intensity level is occurred consequently some image regions disappear.

However, detected buildings in unsharpened mask images are suitably discerned. In contrast, in the globally enhanced classified image all of buildings are extracted but some other parts of image are erroneously classified as buildings.

This error is because of changes in frequency components of image which occurs as a result of histogram equalization. Consequently, building boundaries are not correctly visible. While in locally enhanced classified image the building are suitably discriminated from each others.

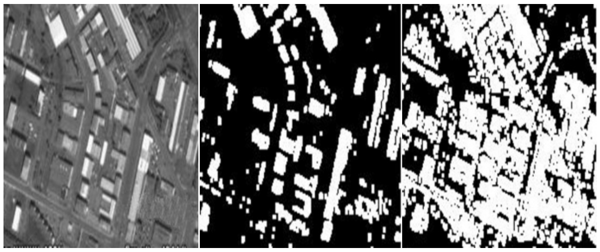

Figure 3. The original image (left), locally enhanced classified image (middle) and globally enhanced classified image (right).

To achieve a good extraction rate and solve the mentioned problems, image fusion is accomplished. To this end, following operations are used:

$$I_{e_{usm}} = (I_{usm} < th)$$

$$I_{sh} = (I < th)$$

$$I_{sh}^{*} = dillate(I_{sh})$$

$$I_{hq_L} = \nabla^2(I_{hq})$$

$$I_{sh_L}^{*} = (I_{sh}^{*} \,.\, I_{hq_L} \,.\, I_{e_{usm}})$$

Where I_{usm}, $I_{e_{usm}}$, I_{sh}, I and I_{hq} are filtered image using Unsharp mask, its deleted part, shadows, original image and histogram equalized image, respectively. After obtaining $I_{sh_L}^{*}$ image, it is labeled to investigate each region of the deleted part of I_{usm}. If in the eliminated part of I_{usm} image the amount of laplacian is higher than a threshold value, this part should be recovered from I_{hq} image.

Following algorithm is used to produce fused image:

1 begin initialize $l = 0,\ R = \{\ \}$
2 $J^{l} = labeling(I_{sh_L}^{*})$
3 do $l \leftarrow l + 1$
4 if max $(J^{l}) > thl$ then $R \leftarrow R \cup J^{l}$
5 until $l = n$
6 $I_{Fused} = (I_{usm} - I_{e_{usm}}) + R$
7 end

Where thl denotes minimum amount of building edges in image laplacian. Recovering of deleted parts of I_{usm} using histogram equalized image results in the fused image, the purpose of this section. Fused image (I_{Fused}) is an image in which the building boundaries are suitably distinguishable. Fig .5 shows the I_{Fused} image.

III. EXPERIMENTAL RESULTS

The block diagram of our approach is given in Fig .4. Gaussian mask is a 35-by-35 matrix. A 3-by-3 matrix as structure element (SE) of opening operator is utilized to remove the redundant particles of image in each step. Rectangular structure element for dilation of locally enhanced image is considered as a 5-by-5 matrix. The size of rectangular SE for dilation of shadows is 10-by-10. For unsharp mask filter, T and σ of the Gaussian filter are 5, 0.01 and 7, respectively. Gaussian mask is a 35-by-35 matrix. The results of some of our IKONOS remote sensing images from Iceland are shown in Fig .6.

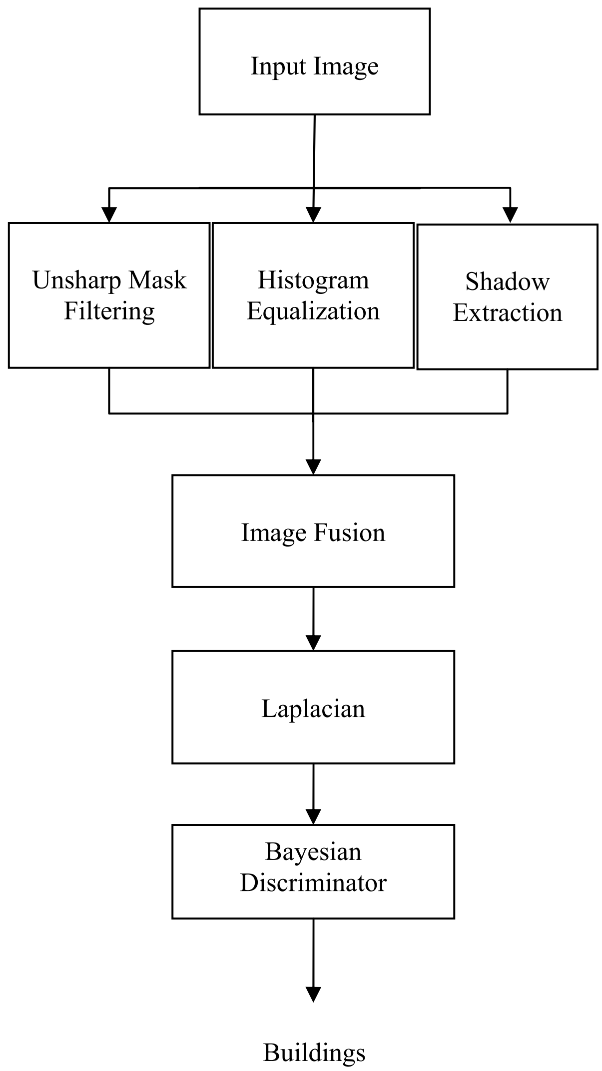

Figure 4. Flowchart of the proposed method

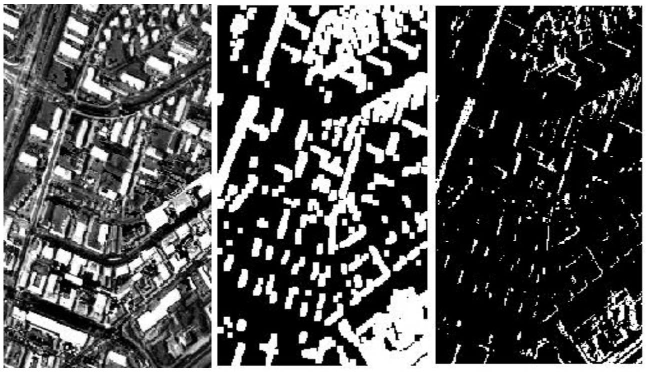

Figure 5. Shadow image (right), its dilated version (middle) fused image (left)

The minimum size applied to labeled image pixels to discriminate small buildings from large buildings is 250. To separate large building from open areas, 500 pixels are considered as maximum size of large building label. These quantities are considered if we suppose that the earth is observed from a distance of about 4000 feet.

Quantitative results obtained with the proposed method are shown in Table I. a comparison is also given with the extraction results using presented method in [7]. According to the images presented in Fig .6 detection accuracies including large buildings and Houses are 95.5% and 70.2%, respectively.

TABLE I. COMPARISON OF THE PROPOSED APPROACH WITH THE METHOD PRESENTED IN [7].

Detection Accuracy		
	[7]	*The proposed Method*
Large Buildings %	94.8	95.5
Houses %	67.4	70.2

IV. CONCLUSION

A fully automated algorithm for extraction of building from commercial very high resolution satellite imagery is presented. First, Vegetations were deleted from color image and grayscale image is obtained. Afterward, fused image is made using unsharp mask filtered and histogram equalized images. Thereafter, Buildings are extracted by Bayesian discrimination function. Three features including image intensity, laplacian intensity and morphological operations such as opening and closing, which represents the size of each object, are used to extract buildings from fused image. When the algorithm is applied to some of IKONOS remote sensing images from Iceland, it produced extraction of approximately all of the buildings which have enough contrast from their surrounding background as a result of enhancement steps.

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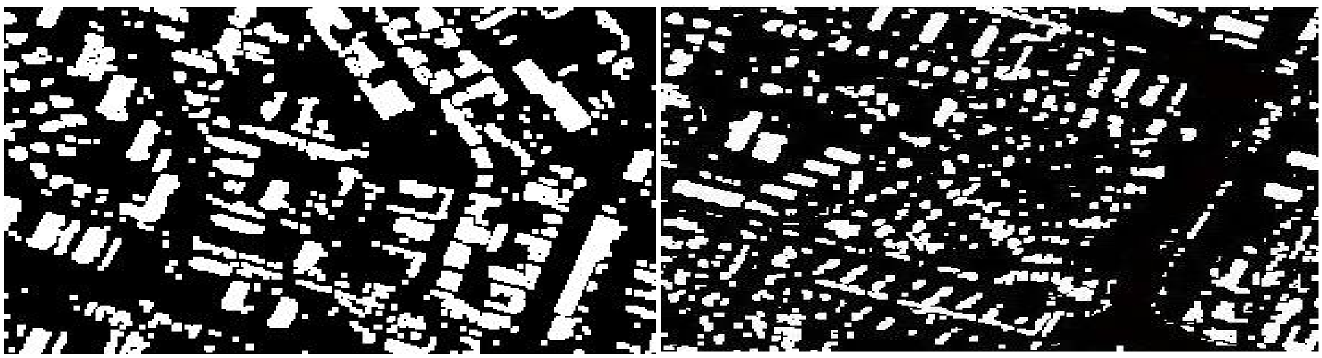
(a) (a)



(b) (b)

Figure 6. Original images (a) and the results of the proposed method (b)