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# 3D Buildings Modeling In Urban Satellite Imagery Applying A Novel Fuzzy Based Method

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## ABSTRACT

A fuzzy based method for modeling of buildings and towers applying a single satellite image in the form of 3D is addressed. This technique is unlike the common method utilized one single satellite image for this modeling. Firstly vegetations will filter out based on green layer of image and amount of gradient and image intensity. Then, using the segmentation technique based on the method presented in [13] building will be modeled. In the next step, according to the fuzzy membership functions, obtained from structural context, the roof of each building is segmented from building walls. To make a 3d model of buildings, the side of building walls that present their height is manually selected by the human operator. Other buildings are modeled by the attained angle. To benchmark the algorithm, some images from Sydney, Australia have been used. The results indicate that the method could efficiently model the buildings which have at least two visible sides in the satellite image.
Keywords; remote sensing; building extraction; fuzzy logic theory; satellite imagery; Urban satellite Imagery.

## 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 multi-spectral 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 multi-spectral 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], [19], [22] 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

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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 [16], reconstruction of has considered for finding 3D buildings. The inputs of the method are on airborne scanning data and 2D buildings boundaries. The scheme includes two major parts: (1) the extraction of the building primitives, and (2) the shaping of the building roofs.

The improvement of digital elevation map (DEM) to convert DEM to make reconstructed roof superstructures from DEM images. The inputs of the system are building model and digital elevation map. Coarse detection, model refinement and model selection have used to make confidence output [17].

The improved ground resolution of up to date synthetic aperture radar (SAR) sensors suggests utilizing SAR data for the analysis of urban scenes [18]. In high resolution SAR data of built-up areas, especially bright lines are a distinctive building feature. They are often caused by double reflection between ground and building wall. In [15], base on contextual information obtained from shadows the detected buildings are verified.

The rest of this paper is organized as follow. In section 2, we present the fuzzy based approach for segmentation of building roofs. The result of experiments is presented in section 3, Followed by conclusions in section 4.

## II. GENERATION OF 3D BUILDINGS MODELS

### A. *Segmentation of Vegetation and Building Regions*

Classification of remote sensing images particularly from urban area is one of the considerable vicinity under discussion of scientific researches and papers. USM or MUSM methods have been used for extraction of buildings because they have been more efficient in case of classification of remotely sensed urban images compared with other same methods [13], [20]. Here, we utilizes building extraction method as a primary step before modeling the 3D shape of large buildings and tower. Before any action to segment buildings, detection and deletion of vegetations is necessary because it can make some mistake in other parts of this approach. Vegetation areas have more intensity in the green layer of color image and also it has more value in amount of gradient. It is considerable that the rate of intensity in vegetation areas is less than other part of image components in grayscale image.

$I_G$ denotes the gradient of intensity image. It calculates as follow: $I_G = gradient(I) = \left\|\frac{\partial I}{\partial x}\right\| + \left\|\frac{\partial I}{\partial y}\right\|$ (1)

$I_{Vegetations}$ denotes the vegetation regions in image. It will be classified by some qualifications as:

$$I_{Green} > \varepsilon \quad (2)$$

$$I_G > \eta \text{ and } |I| < o$$

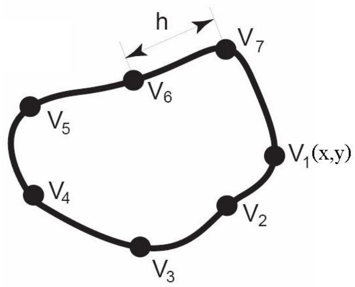


Figure 1. Contour surrounds the buildings region edge.

$\varepsilon, \eta, o$ are obtained experimentally from satellite images. The values of mentioned parameters declared in experimental results section. Consequently, according to the green layer of RGB satellite color image and amount of gradient, detecting and removing of vegetation is accomplished.

After classification of buildings using USM or MUSM methods, we concentrate to find whole of the building regions in the image. It means that for finding 3D shape of buildings, we need to extract roofs and walls of buildings. The Canny method has been utilized to extract the edges. These edges are used to separate each building to some regions with no connectivity. In the next step we aim at categorizing the regions into walls and roofs. $I_C$ denotes the results of canny edge detector filter.

$$I_C = \text{Canny}\{I\}$$

$$I_C \in C_C\,; \quad \begin{matrix} C_W \subset C_C \\ C_R \subset C_C \end{matrix}$$

$$I_W \in C_W\,, I_R \in C_R$$

$$\mathrm{I_W} = \text{Wall},\ \mathrm{I_R} = \text{Roof} \qquad (3)$$

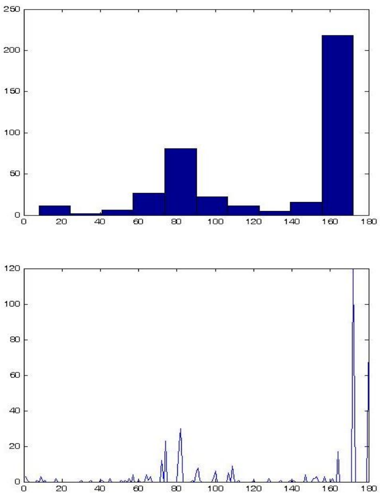


Figure 2. Histograms of H are presented. (up) before and (bottom) after applying the filter.
Two significant peaks have been considered as the major perpendicular angles.

$\varphi$ denotes the angle of walls in urban area satellite imageries. It can be obtained by the majority of walls edges or by following operator.

$\varphi = Major\ Walls\ Angel\ in\ towers\ or\ Large\ Buildings$

### *B. Roof Detection*

For more analysis, we investigate the contours of edges. By obtaining the contour of $\mathrm{I_C}$ we have a set presented below:

$$V = [v_1,\ \ldots, v_n]$$
$$v_i \in I = \{(x, y) | x, y = 1,2,..,M\} \qquad (4)$$

$v_i, M$ denotes the nodes of the edge contours and the size of contours in the images, respectively. $v_i$ include $x_i$, $y_i$ in Cartesian coordinate so we will have:

$$x_{1\times n} = [x_1,\ \ldots, x_n] \quad \text{and} \quad y_{1\times n} = [y_1,\ \ldots, y_n] \qquad (5)$$

If we would like to obtain angle of edge region in contours we should use the formula which is represented below. $P_1, P_2$ are two points in a edge contour. $\theta_{P_1 \vee P_2}$ represents the angle between mentioned points and it is obtained as follow:

$$\theta_{P_1 \vee P_2} = Arctg\left(\frac{y_1 - y_2}{x_1 - x_2}\right) \qquad (6)$$

We use a filter to make $y_1$-$y_2$, $x_1$-$x_2$ in the contours. This filter is used to reduce the rate of calculation and computational costs. On the other hand, it increases the correctness of roof coordinate angles.

$$F_{1\times 7} = [1\ 0\ 0\ 0\ 0\ 0\ -1]$$

$$x_{d\,1\times n} = x_{1\times n} * F_{1\times 7} = [x_1, \ \ldots, x_n] * [1\,0\,0\,0\,0\,0\,-1]$$
$$y_{d\,1\times n} = y_{1\times n} * F_{1\times 7} = [y_1, \ \ldots, y_n] * [1\,0\,0\,0\,0\,0\,-1] \quad (7)$$

$x_{d1\times n}, y_{d1\times n}$ represents the $x_{1\times n}$ and $y_{1\times n}$ in contours after applying $F_{1\times 7}$.

$$Ang(i) = Arctg(\frac{y_{d\,1\times n}(i)}{x_{d\,1\times n}(i)}) \quad i = 1,2,\ldots.,n \quad (8)$$

Where n is the size of contour. Then, 1D median filter with size of 1-by-5 is applied to $Ang(i)$ to reduce sudden variations in contour's angles. H represents the set which is obtained from output of median filter. The histogram of H is shown in figure 2. Two significant peaks, appeared in the histogram of angles, represent the major angle of edge in roof of tall buildings and its perpendicular direction. To detect these angels we use a filter which emphasizes the perpendicular angles. The filter is given as follow:

$$F_{1\times 180} = \left[ 1\,\overbrace{0\,0\,0\ldots.0\,0}\,1\,\overbrace{0\,0\,0\ldots.0\,0}\,1 \right]$$

$$HF = H_{1\times 360} * F_{1\times 180} \quad (9)$$

In Figure 2 the lower histogram is obtained by applying the mentioned filter to the upper histogram.

As it's depicted in figure 2, the buildings have two important angles. In general, these angles can be more than two. $\theta_1, \theta_2$ are the angles attained from following formula:

$$\theta_1 = \arg\max\,(HF)$$
$$\theta_1 = \theta_2 + \frac{\pi}{2} \quad (10)$$

$\theta_1, \theta_2$ are used for making discrimination between roofs, $I_R \in C_R$ and walls. As it's mentioned before, $\varphi$ shows the directions of buildings walls which used for evaluating altitude of buildings and the roofs following the $\theta_1, \theta_2$ directions. Moreover, we can follow the walls in the direction of $\varphi$ to attain roofs. So summarizing our actions to find roofs we have:

1. The amount being far from $\varphi$.
2. The degree of closeness to $\theta_1, \theta_2$.
3. Distance from beginning points and closing from ending points.

*C. Morphological Operations Utilized in This Approach*

In general, there is a large scale of using morphological operation (opening and closing) in different part of this method. The results, achieved from applying morphological operation in different part of this approach.

*1) Structure Element (SE)*

During our algorithm parts; morphological operation with octagonal-shape structure element are used several times. On the whole, we couldn't separate structure element block of diagram into algorithm because it is used in each part of our approach. The structure elements are used in various scales to find the buildings by different sizes. The primary size for structure element has been adjusted to extract buildings from urban area images. This size is attained by experimental testing.

*D. Fuzzification of The Input Variables and Rule evaluation*

The mathematics assigns a membership value of 1, to elements that are members of a set, and 0 to those which are not, thus defining "crisp sets." In the different "fuzzy set" theory handles the thought of partial membership to a set, by means of real-valued membership degrees ranging from 0 to 1. Fuzzy set theory was introduced in 1965 by Zadeh [21] as a mean to represent the uncertainty and ambiguity in complex systems. It is now extensively used to process imprecise or uncertain data [7], [8]. In particular, it is a suitable framework to handle the output of a given classifier for additional processing. The output is usually not in a binary form and comprises some vagueness. In this section, we initially recall general definitions and properties of fuzzy sets. Then, we assign the model used for the representation of the classifiers output.

The peaks, obtained from last sections, depict the major angles of roof contour, $\theta_1, \theta_2$. $\mu_\theta$ is defined as membership function to determine fuzzy amount related to $\theta_1, \theta_2$. Both of $\theta_1, \theta_2$ can represent a certain amount so we consider $\theta$ instead of $\theta_1, \theta_2$. It reduces the computational expenditure.

$$\mu_\theta(x,y) = e^{\frac{-1}{2}\frac{((x,y)-C_\theta)^2}{\sigma_\theta^{\ 2}}} \tag{11}$$

$C_\theta$ Shows the points by $\theta_1^{\circ}$ *or* $\theta_2^{\circ}$. $\sigma_\theta$ is a scalar value. $\mu_\theta$ shows a fuzzy value of membership function related to $\theta$ angle. It means the amount of $\mu_\theta$ indicates the consistency of roofs in fuzzy domain. $C_\varphi$ shows the points which have $\varphi^{\circ}$ direction. $\sigma_\varphi$ is a scalar value.

$$\mu_\varphi(x,y) = e^{\frac{-1}{2}\frac{((x,y)-C_\varphi)^2}{\sigma_\varphi^{\ 2}}} \tag{12}$$

$\mu_\beta(x,y)$ is defined as membership function about "How much distance is it between the current point and the beginning points in direction of the line which is elongated with angle of $\varphi^{\circ}$". This membership function is linear plane obtained by one point in plane and the angle of plane.

$$\mu_\beta(x,y) = ax + by + d \tag{13}$$

*E. Aggregation of The Rule Outputs and Defuzzification*

In the last section, we obtain some of the membership functions related to essential parameters as: $\varphi^{\circ}, \theta$, and the distance from beginning points in direction of the line which is prolonged in angle of $\varphi^{\circ}$. The decision rule must organize the reliable answer which is rightly combined by the state of other membership functions. In such case, all membership parameters are same in aspect of intervening in final accuracy. So Mamdani product can offer reliable decision. Now if we

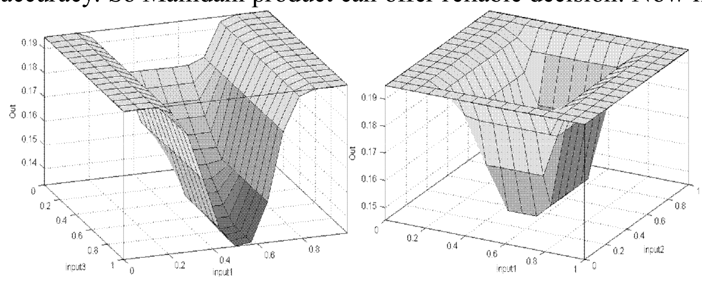

Figure 3: The output of fuzzy sets for three inputs is depicted.

use Mamdani product implication and algebraic product for the t-norm, then the membership functions of all rule consequents clipped and combined into a single fuzzy set. $\mu_{Decision}$ is the decision membership to determine the correct answer for specific values for $\mu_\varphi(x,y), \mu_\theta(x,y)$, and $\mu_\beta(x,y)$ which are previously obtained. $\mu_{Decision}$ represents the original membership function for the rule consequently adjusted by multiplying all its membership degrees by the truth value of the rule antecedent. This method generally loses less information in the final accuracy. The input for the defuzzification process is the aggregate output fuzzy set which is a single number.

The center of the gravity (COG) defuzzifier specifies the crisp value as the center of the area covered by the membership function. By using this technique some of the criteria will be considered as Plausible, Computational Simple, and Continuous.

## III. EXPERIMENTAL RESULTS

In this section, we demonstrate the result of the proposed method. The proposed approach is applied to two very high resolution IKONOS remote sensing images from Sydney, Australia. Three principal classes were considered in each case, namely:

1) Large buildings;

2) Houses (small buildings);

3) Shadows.

Each image consists of urban area components including buildings, roads and open areas. As it's presented in USM method, the first step is the feature extraction by morphological and Laplacian operators. The second step is classification using Bayesian discrimination function. The classification accuracies for the different pre-processing methods are compared to determine the global confidence in each pre-processing method. It is also compared with previous methods presented in [13], [16], and [17].

### *A. Results of the USM Based Method for Building Extraction Methods*

The first image which is used to test is 1024 × 716 pixels size. To test the general ability of the Bayesian classifier; some IKONOS remote sensing images are used to benchmark the approach. The Bayesian training PDF function is obtained from manually marked images, namely training map. In the training map amounts of Laplacian, size, and intensity of each class is considered to make the PDF function of each class. Appropriate levels of discriminated frequency, corresponding amounts of laplacian, according to high frequency components of buildings and other low frequency levels of buildings are obtained using the training map. It is considerable that, the small buildings have high-frequency components since they have a grained texture on their edges but we have focused on finding large buildings and towers. Furthermore, building roofs have smooth texture in satellite images.

The USM-based method outperformed the [13], [20] with regards to Bayesian discriminator accuracy. The value of discriminating parameters in mentioned method, the $\gamma_{SF}$ and $\lambda$ values, are 150, and 0.5, respectively. Particularly, the enhancement methods have introduced by improvement of Bayesian discriminator efficiency in buildings extraction.

This objective is reachable by adjusting frequency components of the IKONOS remote sensing images, by applying high-pass filters. It makes the buildings with similar levels of intensity as image background, discernable and improves local contrast of IKONOS remote sensing images. It minimizes the drawback of such methods such as unsharp mask which makes some of image regions disappear. For instance, image intensity reduction, occurred in some part of the image such as buildings due to extra addition of dark edges.

### *B. Consequences of Segmentation of Vegetation Regions*

The proposed method is introduced in the first part of the methodology. RGB satellite image in green layer of color and amount of gradient in the vegetations could extract vegetation regions. Vegetation areas have more saturation in color of green and more value in amount of gradient. It's worth noting that the rate of intensity in vegetation areas is less than other part of image components in grayscale image. It means that we used RGB satellite images in grayscale version for extraction of vegetation

Figure 4. The results of the 3D modeling step

regions. The values of $\varepsilon, \eta, o$, presented before, are the vegetation regions in the image, the gradient of the intensity, and the intensity itself, correspondingly. They are obtained experimentally from satellite images and their amounts are 0.4, 0.5 and 0.45, respectively. It is noticeable that the values of the images are normalized between 0 and 1.

### *C. Roof Detections Results*

In the previous section we describe some of last parts and their parameters. The results of buildings extraction using USM method and the imperative part of our approach for finding the roofs are obtained. Here the experimental results of roof detections are presented. For using Cartesian coordinate to find $Ang(i)$, $F_{1\times7}$ plays a very significant role. It helps to find $y_{d1\times n}$ and $x_{d1\times n}$ reliably. In the section of finding the angle of roof sides, $\theta_1, \theta_2$, especially to calculate of $HF$, the $F_{1\times180}$ filter intensify the local maximums. Sometimes, the local maximums couldn't be obviously determined in the histogram of edges angles.

### *D. Results of Fuzzification*

As it is presented before, there are several parameters, obtained from consideration of large buildings and towers in satellite images. On the other hand, there are some relations among obtained parameters which are helpful to determine objects and parameters in their own sites. Fuzzification could implement the rules and improve our decision in this approach. We presented the complete proposed fuzzy scheme. In a first step, each part is applied separately (but no decision is taken). Then the results, provided by the different algorithms, are aggregated. The last decision is made by selecting the class with the largest membership value. The fuzzy steps are organized as follows:

1) Separately build fuzzy sets for the classes in each source.
2) Compute the fuzziness degree of each fuzzy set.
3) Select the class corresponding to the highest resulting membership degree.

The flowchart of our process is given in Figure 5. The range of the fuzzy sets is rescaled before the decision step for combining data with the same range. The results of the experiment are illustrated in figure 4. According to the results, the method is efficient in modeling of the large buildings and towers.

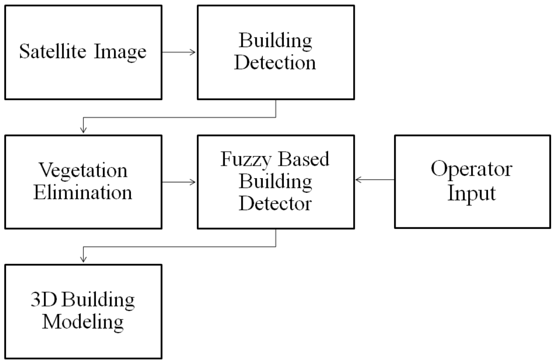


Figure 5. The block diagram of the proposed method

## IV. CONCLUSION

A semiautomatic algorithm for extraction of buildings from commercial very high resolution satellite imagery is presented. First, Vegetations were deleted in accordance to the color image, image texture and intensity level of the grayscale image. Afterward, the enhanced image is made using unsharp mask filter. 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 the buildings from the enhanced image. After detection of buildings, each of them is segmented into roof and wall regions. Segmentation is done using a fuzzy based method according to the angle of the edges in each region and the location of each region. Finally, with respect to the length of the building wall that represents the building elevation and the detected roof, 3D building modeling is accomplished. When the algorithm is applied to some of the IKONOS remote sensing images from Australia, 3D building modeling is promisingly accomplished.

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