Using Structural Features to Detect Buildings in Panchromatic Satellite Images

Beril Sırmaçek
German Aerospace Center (DLR)
Remote Sensing Technology Institute
Weßling, 82234, Germany
E-mail: Beril.Sirmacek@dlr.de

Cem Ünsalan
Computer Vision Research Laboratory
Yeditepe University
Istanbul, 34755, Turkey
E-mail: unsalan@yeditepe.edu.tr

***Abstract*—Detecting buildings from very high resolution aerial and satellite images is very important for mapping, urban planning, and land use analysis. Although it is possible to manually locate buildings from these very high resolution images; this operation may not be robust and fast. Therefore, automated systems to detect buildings from very high resolution aerial and satellite images are needed. Unfortunately, solution is not straightforward due to diverse characteristics and uncontrolled imaging conditions of the scenes. To overcome these difficulties, herein we propose a novel solution to detect buildings from very high resolution grayscale aerial and panchromatic Ikonos satellite images using structural features and probability theory. For this purpose, we extract structural features from given test image using a steerable filter set. Extracted structural features indicate geometrical properties of objects in the image. Using them, we estimate probability density function (pdf) which indicates locations of buildings to be detected. Our extensive tests on a large and diverse data set including images taken from different scenes and from different sensors indicate high robustness and practical usefulness of the algorithm.**

I. Introduction

Remotely sensed satellite and aerial images provide very valuable information. However, their covering areas and resolution make manual analysis very difficult and prone to errors. Furthermore, especially urban areas are dynamic environments. Hence, they should be monitored and analyzed periodically. Due to these problems, developing algorithms to detect particular objects in remotely sensed images is a very important research field. Especially, automatic detection of urban region boundaries can provide useful information to municipalities, mapping agencies, military, government agencies, or unmanned aerial vehicle developers. Unfortunately, automatic object detection algorithms cope with some difficulties on remotely sensed images. First, buildings generally have diverse characteristics with different texture, color, and shape. In addition to that, in their appearance on the image, the illumination, view angle, scaling, occlusion effects are uncontrolled. Therefore, classical object detection algorithms cannot provide an acceptable detection performance. Therefore, more advanced methods are required for robust detection of the objects in remotely sensed images.

In the last two decades, researchers mostly concentrated on developing automated building detection methods for detecting buildings from aerial and satellite images. There are nice review papers on building detection in aerial and satellite images [8], [16]. In the most recent work, Kim and Muller [6] used graph theory to detect buildings in aerial images. They extracted linear features in the given image and used them as vertices of a graph. Then, they extracted buildings by applying subgraph matching with their model building graph. Finally, they used intensity and shadow information to verify the building appearance. Different from us, they used color aerial images and linear features. Krishnamachari and Chellappa [7] introduced a Markov Random Field (MRF) based building detection method in aerial images. They benefit from straight line segments in the image and form their MRF based detection method on their interactions. Compared to ours, this system is more complex. Segl and Kaufmann [11] combined supervised shape classification with unsupervised image segmentation in an iterative way. Their method allows searching small objects (like buildings) in high-resolution satellite images. Molinier *et al.* [9] considered detecting boundaries of man-made structures in satellite images by training a SOM (Self Organizing Map). Gamba *et al.* [4] used boundary information to extract the map of an urban area. They fed the boundary and non-boundary data to two different classifiers. Then, they combined the results to detect urban area buildings on VHR imagery. In these studies, there is always a need for training set. Benediktsson *et al.* [2] used mathematical morphological operations to extract structural information to detect the urban area in satellite images. This method can be used to detect buildings in the image. Ünsalan and Boyer [16] studied on multispectral satellite images to detect buildings and street networks in residential regions. Their method uses vegetation indices, clustering, decomposing binary images, and graph theory. Although this method is promising, multispectral information is needed to detect buildings. Akçay and Aksoy [1] also proposed a novel method for unsupervised segmentation and object detection in high-resolution satellite images. This method also needs multispectral information. Idrissia *et al.* [5], extracted edges of man-made structures (buildings and roads) using Gabor filters together with the NDVI (Normalized Difference Vegetation Index) in SPOT5 images. Comparing edges of two image sequences taken from the same region, they also detected changes. Different from us, they benefit from multispectral information. In a recent study, we introduced a method to detect buildings in panchromatic Ikonos satellite images using scale invariant feature transform (SIFT) keypoints and graph theory formalism [12]. This method gives good detection results, however it has a high computation load. It also depends on template building images as a training set. In order to bring a fast and robust solution to building detection problem, in previous study we proposed a probabilistic framework using local features to detect buildings without using any training data. However, obtained performances on aerial and satellite images were very promising, unfortunately our local features and their descriptor vectors were sensitive to intensity values of buildings and their surroundings. To overcome this difficulty, herein we propose a novel building detection method which depends on extracting structural features from image. These structural features indicate geometrical properties of objects in given image independent from the intensity of the building and its surrounding. To extract these structural features, we use a steerable filter set. Then, extracted features help us to construct a probability density function (pdf) which indicates locations of the buildings to be detected. We test our algorithm on very high resolution panchromatic Ikonos satellite images and grayscale aerial images including buildings with diverse characteristics. Next, we introduce our structural feature extraction method.

II. Extracting Structural Features Using Steerable Filters

Edges and curvilinear structures are crucial features to detect buildings in remotely sensed images. For example, buildings generally have edges or curves around one center. In order to extract object edges, herein we benefit from steerable filters. Before using steerable filters, we apply bilateral filtering to eliminate noise terms in the taken image $I(x,y)$ [15]. In our previous study, we explain usage of bilateral filter on remotely sensed images in detail [12]. After obtaining smoothed image $I_b(x,y)$, we apply steerable filters in different orientations.

Steerable filters provide directional edge-like structure detection since they behave as band-pass filters in particular orientations. Differently from Gabor filters, steerable filters can be synthesized easily as a linear combination of a set of basis filters. In this study, we use steerable filter as shown by Freeman and Adelson [3].

For a symmetric Gaussian function $G(x,y) = exp(-(x^2 + y^2))$, it is possible to define basis filters Gp_0 and $Gp_{\frac{\pi}{2}}$ as

$$Gp_0 = \frac{\partial}{\partial x} G(x,y) = -2x \exp(-(x^2+y^2)) \qquad (1)$$

$$Gp_{\frac{\pi}{2}} = \frac{\partial}{\partial y} G(x,y) = -2y \exp(-(x^2+y^2)) \qquad (2)$$

We can find a derivative in an arbitrary direction θ using the following rotation

$$Gp_\theta = cos(\theta) Gp_0 + sin(\theta) Gp_{\frac{\pi}{2}} \qquad (3)$$

After obtaining steerable filter function in θ direction, we convolve the smoothed image $I_b(x,y)$ with filter Gp_θ ($J_\theta(x,y) = I_b(x,y) * Gp_\theta$), to detect structural features in the θ direction. In $J_\theta(x,y)$, we expect to obtain high responses on structures which are perpendicular to the filtering direction. Therefore, we obtain our features by thresholding $J_\theta(x,y)$. To obtain an adaptive method, we pick the threshold value as the 20% of maximum magnitude in $J_\theta(x,y)$. We picked this value after extensive testing. After thresholding $J_\theta(x,y)$, we obtain a binary image $B_\theta(x,y)$ with pixel locations having value of one for representing structural feature pixels. In order to talk about a structural feature, we apply connected components analysis to $B_\theta(x,y)$ and obtain each local feature separately. By definition, two pixels are assumed as connected pixels (in a binary image) if there is a path (of pixels with a value of one) connecting them [14]. We assume each connected pixel group as one structural feature. We expect this novel local feature to behave more robust than local features that we have used in our previous studies [13], [12], since it also gives structural information about objects. We extract structural features in all θ directions. Since we do not have a prior knowledge about the building alignments, these different directions are necessary. In this study, we pick our steerable filtering directions as $\theta \in [0, \pi/12, ..., 23\pi/12]$ interval. Therefore, we have a total of 12 filtering directions.

After this structural feature extraction operation, we may have either a straight line segments or an L shaped curves in $B_\theta(x,y)$ $\theta \in [0, \pi/12, ..., 23\pi/12]$ martices. In fact, the L shaped curves are more valuable in representing building appearance, since they can give a coarse idea about approximate location of the building center. Therefore, straight features and L shaped curved features should have different effects to the result. In order to do this analysis, we first classify our local features into two groups as straight line segments and curves.

To detect curved features, Orrite *et al.* [10] developed a nice approach. They extended end points of curves, if extended end points of two curves intersect each other then they grouped these two curves as a close shape. In our problem, we have many buildings in a scene, hence applying this test to all edge couples may require too much computation time. Therefore, in this study we developed a novel and fast approach to detect curved features. For feature classification, we apply the following test. First, we obtain the skeleton of the local feature [14]. Then, we detect the endpoints of this skeleton. Endpoints are chosen as two pixels which have only one neighbor pixel and which have highest Euclidean distance between each other. Assume that, we obtain two endpoints as (x_1, y_1) and (x_2, y_2). We demonstrate curved feature detection process in Fig. 1. We calculate (x_m, y_m) as the midpoint of the skeleton, and (x_o, y_o) as the midpoint of the virtual line (dashed line) which connects endpoints. We obtain the Euclidean distance between (x_m, y_m) and (x_o, y_o). If the local feature is a straight line then (x_m, y_m) and (x_o, y_o) overlaps. Therefore, the distance between them equals to zero. On the other hand, if the local feature is a curve, then this distance is greater than zero. This way, we can classify our structural features as either a straight line or a L shaped curve. Next, we use detected structural features for building detection based on probability theory.

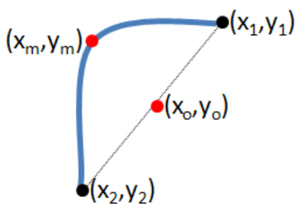


Fig. 1. Representation of a structural feature.

III. Building Detection

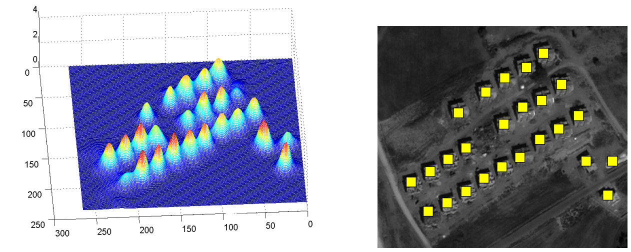
After extracting and classifying structural features, we merge the information coming from them using a probabilistic approach. In our previous work, we introduced a density estimation based method for building detection [13]. There, we assumed coordinates of extracted local features as observations of probability density function (pdf)to be estimated. Here, we follow a similar approach and form the pdf again using extracted structural features as follows,

$$p_b(x,y) = \frac{1}{R}\sum_{i=1}^{K_i}\frac{1}{\sqrt{2\pi\sigma_o}}\exp\left(-\frac{(x-x_o)^2+(y-y_o)^2}{2\sigma_o}\right) \tag{4}$$

Here (x_o, y_o) coordinates are the possible building centers obtained for each structural feature coming from each filtering direction. For L shaped curve structural features, (x_o, y_o) coordinate position is calculated as in the demonstration given in Fig. 1. For straight structural features, (x_o, y_o) coordinate is assumed to be the position which is $l/2$ pixels away from (x_m, y_m) in the filtering direction, where l is equal to the total length of the feature. We assume that, curved structural features have higher certainty to estimate building location. Therefore, we selected σ_o as equal to 1 for curved structural features (in order to make higher effect on probability density function generation), and as equal to $0,5$ for straight structural features. We provide obtained kernel density estimation result $(p_b(x,y))$ in Fig. 2 at the left hand side.

In our estimated pdf $p_b(x,y)$, we hypothesize that the modes of pdf are possible building centers. Therefore, we detect building locations by the modes of $p_b(x,y)$. In order to prevent false detections, we assume that for a location to be a building center, it should have at least a minimum probability. We pick the mode location having the highest probability as a building location, $(x_b, y_b) = \arg\max_{(x,y)} p_b(x,y)$. Then, we pick the remaining mode locations having probabilities at least $0.4 \times p_b(x_b, y_b)$ as building locations. As a result, we detect building locations automatically as in Fig. 2. As can be seen in this figure, we detected all buildings in the given scene.

In Fig. 3 we provide a sample building detection result of our algorithm on a large Ikonos image. However there are some false alarms especially on roads, overall building detection performance of proposed method is satisfactory.



(a) (b)

Fig. 2. (a) p_b function (possible building centers) for the $Adana_8$ test image, (b) Detected buildings.

IV. Experiments

We test our probabilistic urban region detection methods on panchromatic Ikonos and grayscale aerial images of Istanbul and Adana cities of Turkey. In these images, the size and shape of buildings, their proximity, environment, and contrast of the building rooftops with respect to background all differ. These test images are specifically selected to represent wide and diverse building and region characteristics. We tabulate performance of the algorithm on each test image in Table I. As can be seen in this table, using steerable filter features we detected 820 of the 911 buildings. We have 124 false alarm. As a result, we obtained TP and FA as 90.0% and 13.6% respectively. Comparing our local feature detection based previous studies [13], [12], we can conclude that the proposed structural feature detection based system increased detection performance and decreased false positives dramatically.

We also test our steerable filtering based building detection algorithm on aerial images. In Table II, we also tabulate detection results for each aerial image in our data set. As can be seen in this table, we detected 422 of the 652 buildings. We have 101 false alarm. TP and FA ratios are 64.7% and 15.5% respectively. By checking low ratio of false alarms we can conclude that, our steerable filtering based features are robust to small details of the image. Unfortunately, our detection percentage is decreased comparing with the results of satellite images. In our study region, road edges are very close to building roof edges (they are generally detected as a single edge). Therefore, road edges caused false building edge curvature calculations.

V. Conclusion

Herein, we proposed a novel approach to detect buildings from remotely sensed images automatically, without using any prior information or training data. For this purpose, we proposed usage of structural features which are obtained by using a set of steerable filters. Extracted structural features are classified as straight or curved feature, and they are used to generate a probability density function (pdf) which indicates possible building centers to be detected. In pdf generation, curved features made higher effect since they hold higher

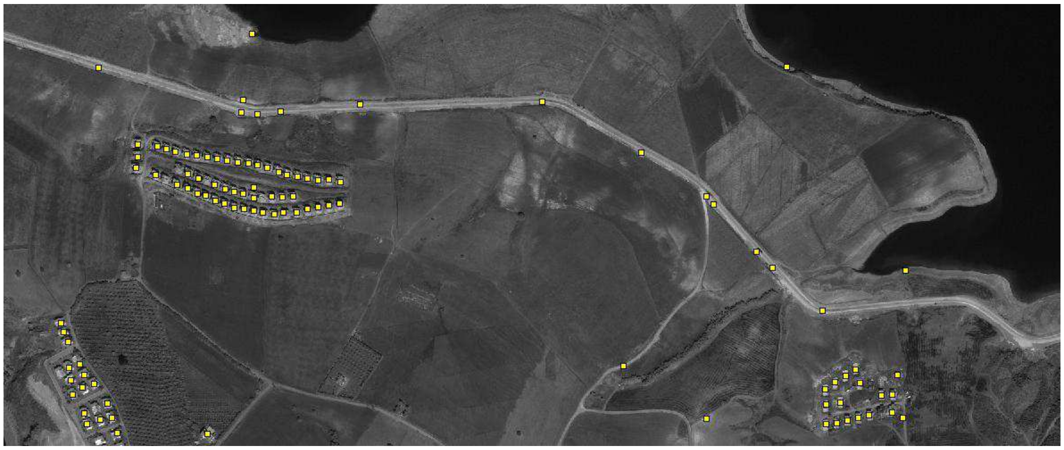


Fig. 3. Building detection results using steerable filters on a sample large Ikonos test image.

TABLE I
BUILDING DETECTION PERFORMANCES IN IKONOS SATELLITE IMAGES USING STEERABLE FILTERING.

Image Name	**Buildings**	**TP**	**FA**	**TP** (%)	**FA** (%)
$Adana_1$	18	17	3	94.4	16.7
$Adana_2$	9	9	1	100.0	11.1
$Adana_3$	31	30	0	96.8	0.0
$Adana_4$	21	21	1	100.0	0.0
$Adana_5$	54	53	3	98.1	5.6
$Adana_6$	47	43	3	91.5	6.4
$Adana_7$	28	27	5	96.4	17.9
$Adana_8$	24	23	1	95.8	4.2
$Adana_9$	24	15	0	62.5	0.0
$Adana_{10}$	14	13	6	92.9	42.9
$Adana_{11}$	21	13	2	61.9	9.5
$Adana_{12}$	32	25	4	78.1	12.5
$Adana_{13}$	67	64	1	95.5	1.5
$Adana_{14}$	33	27	5	81.8	15.2
$Adana_{15}$	28	25	2	89.3	7.1
$Adana_{16}$	23	17	0	73.9	0.0
$Adana_{17}$	24	24	15	100.0	62.5
$Adana_{18}$	70	50	6	71.4	8.6
$Adana_{19}$	24	24	4	100.0	16.7
$Adana_{20}$	20	18	0	90.0	0.0
$Adana_{21}$	18	18	10	100.0	55.6
$Adana_{22}$	27	27	4	100.0	14.8
$Adana_{23}$	48	45	7	93.8	14.6
$Ankara_1$	18	18	4	100.0	22.2
$Ankara_2$	44	37	2	84.1	4.5
$Ankara_3$	14	14	3	100.0	21.4
$Ankara_4$	23	23	30	100.0	130.4
$Ankara_5$	61	60	0	98.4	0.0
$Istanbul_1$	8	8	2	100.0	25.0
$Istanbul_2$	13	7	0	53.8	0.0
$Istanbul_3$	14	14	0	100.0	0.0
$Istanbul_4$	11	11	1	100.0	9.1
Total	**911**	**820**	**124**	**90.0**	**13.6**

TABLE II
BUILDING DETECTION PERFORMANCE USING STEERABLE FILTERING ON AERIAL IMAGES.

Image Name	**Buildings**	**TP**	**FA**	**TP** (%)	**FA** (%)
$Aerial_1$	17	12	0	70.6	0.0
$Aerial_2$	27	21	14	77.8	51.9
$Aerial_3$	6	6	1	100.0	16.7
$Aerial_4$	9	8	4	88.9	44.4
$Aerial_5$	11	10	5	90.9	45.5
$Aerial_6$	16	16	1	100.0	6.3
$Aerial_7$	9	6	3	66.7	33.3
$Aerial_8$	11	11	1	100.0	9.1
$Aerial_9$	42	20	6	47.6	14.3
$Aerial_{10}$	50	23	5	46.0	10.0
$Aerial_{11}$	47	23	12	48.3	25.5
$Aerial_{12}$	57	31	3	54.4	5.3
$Aerial_{13}$	30	28	17	93.3	56.7
$Aerial_{14}$	19	19	2	100.0	10.5
$Aerial_{15}$	57	30	2	52.6	3.5
$Aerial_{16}$	56	28	1	50.0	1.8
$Aerial_{17}$	44	20	8	45.5	18.2
$Aerial_{18}$	65	52	8	80.0	12.3
$Aerial_{19}$	11	10	1	90.9	9.1
$Aerial_{20}$	16	12	3	75.0	18.7
$Aerial_{21}$	52	36	4	69.2	7.7
Total	**652**	**422**	**101**	**64.7**	**15.5**

certainty to represent building centers. Modes of obtained pdf helped us to detect building centers. Our extensive tests which are done using diverse panchromatic Ikonos satellite images and grayscale aerial images of different cities indicate practical usefulness, high reliability, and robustness of the proposed algorithm.

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