BUILDING EXTRACTION FROM HIGH RESOLUTION SATELLITE IMAGES USING HOUGH TRANSFORM

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ABSTRACT:

An approach was developed for the automatic extraction of the rectangular and circular shaped buildings from high resolution satellite imagery using Hough transform. First, the candidate building patches are detected from the imagery using the binary Support Vector Machines (SVM) classification technique. In addition to original image bands, the bands NDVI (Normalized Difference Vegetation Index), and nDSM (normalized Digital Surface Model) are also used in the classification. After detecting the building patches, their edges are detected using the Canny edge detection algorithm. The edge image is then converted into vector form using the Hough transform, which is a widely used technique for extracting the lines or curves of the objects. The vector lines and curves that represent the building edges are grouped based on perceptual groupings, and the building boundaries are constructed. The proposed approach was implemented using a program written in MATLAB® v. 7.1 programming environment. The experimental tests were carried out in the residential and industrial urban blocks selected in the Batikent district of Ankara, the capital city of Turkey using the pan-sharpened and panchromatic IKONOS images. The results obtained indicate that the proposed building extraction procedure based on SVM and Hough transform can be effectively used to extract the boundaries of the rectangular and circular shaped buildings. For the industrial buildings, we obtained quite satisfactory results with the average Building Detection Percentage (BDP) and the Quality Percentage (QP) values of 93.45% and 79.51%, respectively. For the residential rectangular buildings, the average BDP and QP values were computed to be 95.34% and 79.05%, respectively. For the residential circular buildings, the average BDP and QP values were found to be 78.74% and 66.81%, respectively.

1. INTRODUCTION

Automatic building extraction is being increasingly used for urban planning and management. Therefore, it has been the focus of intensive research for the last decade. Traditionally, the building boundaries are delineated through manual digitization from digital images in stereo view using the photogrammetric stereo plotters. However, this process is a tiresome and time-consuming task and requires qualified people and expensive equipments. For this reason, building extraction using the automatic techniques has a great potential and importance.

In the previous studies conducted by Mayer (1999), Sowmya and Trinder (2000), Baltsavias (2004), and Brenner (2005) the automatic and semi-automatic building extraction approaches were extensively reviewed. The high resolution satellite images have become valuable data sources for urban objects extraction and GIS database updating. The high resolution space imagery from new generation sensors made remote sensing technology more attractive, providing new opportunities for potentially more detailed mapping and more accurate area estimation of land cover than that of medium and low resolution images. Because they are cheaper and easier to access the high resolution satellite images can be preferred instead of the aerial photographs. Sunar Erbek et al. (2005) stated that high resolution satellite images can be used to produce land-use maps of the current status of the urban areas that can be used as the base for the municipal GIS and can be used for updating existing topographic maps.

Most of the past studies conducted to extract buildings from high resolution satellite images have used the spectral values of the images via classification approaches. Lee et al. (2003) proposed a classification-based approach to extract building boundaries from the IKONOS multispectral and panchromatic images. Initially the multispectral image was classified using the ECHO region-based classifier technique. Then, the classified images were vectorized to define the working windows. After that, the panchromatic image was classified using an unsupervised classification technique to separate buildings from the background. Finally, the building boundaries were delineated using a building squaring approach, which is based on the Hough transform. A methodology that uses fuzzy pixel-based and object-based approach for classification of the pan-sharpened IKONOS images was presented by Shackelford and Davis (2003). First a fuzzy pixel-based classifier was performed. Then, the image was segmented and the features were derived from this segmented image. After that, to improve the classification results, a fuzzy object-based classification was carried out using the segmented image. Benediktsson et al (2003) investigated the classification and feature extraction from panchromatic satellite images using the morphological and neural network classification approaches. Similarly, Jin and Davis (2005) presented a method based on differential morphological profile concept to extract buildings from high resolution panchromatic images.

Sohn and Dowman (2001) developed an approach to extract building boundaries from IKONOS panchromatic images. Initially, the line segments were extracted. Then, a local Fourier

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analysis was used to do an analysis of the dominant orientation angle in a building cluster and the line segments were regularized using this information. Finally, the building boundaries were extracted based on a binary-space partitioning. Ünsalan and Boyer (2005) presented a novel system for automatic map generation from IKONOS multispectral images. First, the analyses of multispectral image were performed to detect cultural activity. Then, the images were segmented using the K-means clustering algorithm and a binary image that contains the possible street network and houses was obtained. Next, the segmented images were decomposed using a balloon algorithm based on the binary mathematical morphology. Finally, to extract street networks and houses, these decompositions were represented with a weighted graph.

The man-made objects generally have straight and/or circular edges that cause straight and circular forms in an image. Although, in the present case, the predominant building shape is rectangular in the selected study area, there are also buildings with different shapes, such as circular, ring, C, and S shapes. In this study, we present an approach for extracting the rectangular and circular buildings from high resolution satellite imagery. We use Hough transform to delineate the rectangular and circular shaped building boundaries. The proposed approach contains two main steps that are building detection and building delineation. In the building detection step, the Support Vector Machines (SVM) classification is used to detect the building patches from the high resolution satellite images by including the additional bands. In the building delineation step, the detected building patches are delineated using the sequential edge detection, Hough transform, and the perceptual grouping algorithms.

2. THE STUDY AREA AND DATA SETS

The study area is located in the Batikent district of Ankara, the capital city of Turkey (Figure 1). Batikent is situated in north-west of Ankara. The Batikent Project, which was implemented in the area, is the biggest mass housing project through cooperatives in Turkey (Batikent, Kent-Koop, 2007). The project covers 10 km^2 and planned for 50000 housing units and 250000 people. The project was started in 1979 by Kent-Koop, the Union of Batikent Housing Construction Cooperatives. Therefore, Batikent has become a planned and regularly developed settlement, which includes buildings with different shapes and usage, such as the residential and industrial facilities.

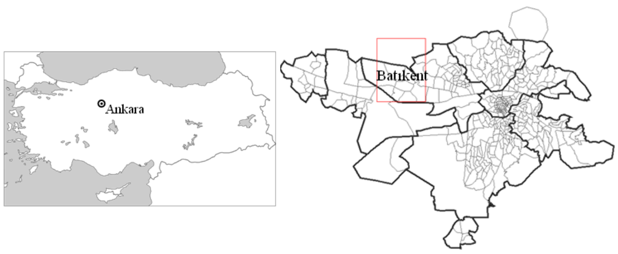

Figure 1. The study area located in the Batikent district of Ankara, Turkey.

In the study area, different types of buildings exist according to their usage, dwelling type, and storey. The residential buildings are usually rectangular/square and the mutual lines are usually parallel to each other, while the adjacent lines are perpendicular to each other. In addition to rectangular and right angle shaped buildings, the area also contains buildings with different shapes, such as circular, ring, C, and S shapes. The roofs of most of the buildings are in brick color although several buildings exist with the gray and white color roofs. In terms of the height, the residential buildings can be grouped as the low-rise, middle-rise, and high-rise. Also contained in the area are the industrial zones. The industrial buildings are usually rectangular in shape and their roofs are in gray, white, and blue colors. Almost all of the industrial buildings are two or three storey buildings and compared to residential buildings their sizes are larger.

3. THE METHODOLOGY

The flowchart of the proposed building extraction procedure is illustrated in Figure 2. The approach includes two main stages: detecting the building patches and delineating the building boundaries. The building patches are detected from high resolution satellite imagery through Support Vector Machines (SVM) classification. Once the building patches are detected, in other words the areas of interests are known, those patches belonging to non-building objects are excluded. To obtain the building boundaries, the detected building patches in raster form are converted into vector form. To do that, initially the edges are detected using an edge detection algorithm. The resulting edge image is a binary image that shows the edges of the building patches. These edges are then converted into vector form using a Hough transform, which is a widely used method for extracting the lines and/or curves forming the objects. After detecting the lines and/or curves in vector form, they are grouped perceptually to obtain the building boundaries.

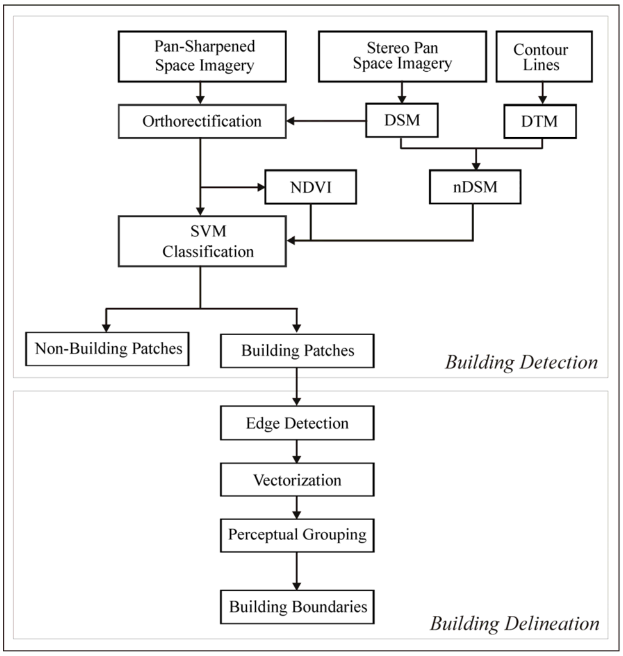

Figure 2. The flowchart of the building extraction procedure.

3.1 Detecting the Building Patches

To detect the building patches, first, a Digital Terrain Model (DTM) is generated from existing vector data. Then, a Digital Surface Model (DSM) is generated from the high resolution stereo panchromatic image pairs. After generating the DTM and DSM, a normalized Digital Surface Model (nDSM) is calculated by subtracting DTM from DSM and then 3D objects are separated by applying a 3m threshold to nDSM. Next, an orthoimage is generated from the high resolution satellite images using the DSM. The orthorectification of the image is necessary to accurately overlay the image with the reference building database. Next, a Normalized Difference Vegetation Index (NDVI) is calculated. To detect the candidate building patches, the orthorectified high resolution image with the additional bands nDSM and NDVI is classified using the SVM classifier.

In this study, the SVM classification was performed using ENVI 4.3 image processing software. The Radial Basis Function (RBF), which can handle linearly non-separable problems and works well in most cases, was selected as the kernel method (ENVI Manual, 2006). The γ was determined as the inverse of the number of bands in the input image and 1000 was taken as the value of C. The building class was the class of interest, while the other classes including vegetation, road, bare land, shadow, and pavement composed the non-building class. After performing the binary SVM classification, those areas classified as building represent the candidate building patches. However, due to misclassification, the candidate building patches may contain artefacts. Therefore, these artefacts are removed using the *opening* and *closing* morphological operations.

In the building delineation stage it is important to deal with each patch individually as those patches that are close to each other may not be able to delineated. For this reason, the patches were delineated sequentially one after the other. To do that each candidate building patch was labeled using a label matrix operation. The pixels belonging to separate building patches were assigned unique integers starting from 1 to the number of candidate building patches, and the background pixels were assigned the value of 0.

3.2 Delineating the Rectangular Buildings

Usually, the shapes of the buildings are rectangle, the mutual lines are parallel and the adjacent lines are perpendicular to each other. To delineate the boundaries of the rectangular buildings, the edges were detected using the Canny Edge Detection algorithm. Then, the detected edges were vectorized using the Hough transform, which detects the analytically defined shapes, such as lines, circles or ellipses in the image. This is a strong method and can be successfully used for the extraction of the overlapping or semi-occluded objects from noisy images (Ecabert and Thiran, 2004).

In Hough transform, a point (x_i, y_i) and all the lines that pass from it are considered. Infinitely many lines pass through (x_i, y_i), all of which satisfy the slope-intercept equation:

$$y_i = ax_i + b \qquad \text{(Eq. 1)}$$

where, a is the slope of the line and b is the y intercept. For all lines that pass through a point (x_i, y_i), there is a unique value of b for a:

$$b = -x_i a + y_i \qquad \text{(Eq. 2)}$$

The difficulty in slope-intercept approach is that the slope of the line moves towards to infinity when the line is about vertical and the slope is 0 when the line is horizontal. To handle this problem, in the Hough transform normal representation of a line can be used (Equation 3).

$$r = x \cos\theta + y \sin\theta \qquad \text{(Eq. 3)}$$

where, r represents the length and θ is an angle from the origin of a normal to the line.

The computational attractiveness of the Hough transform arises from sub-dividing the $r\theta$ parameter space into so-called accumulator cells (Gonzales et al., 2004). The transform is implemented by quantizing the Hough parameter space into accumulator cells. In the beginning, the accumulator cells are set to zero. As the algorithm runs, each (x_i, y_i) is transformed into a discretized (r, θ) curve and the accumulator cells that lie along this curve are incremented. Resulting peaks in the accumulator array represent strong evidence that a corresponding straight line exists in the image.

In the present case, after detecting the Hough lines, they are grouped to generate the building boundaries. First, the centroid is found for each building patch. Then, the collinear Hough lines are merged together, if the distance between the collinear line segments are shorter than the determined threshold values considering the minimum distance between the buildings (Figure 3 (a)). Next, the dominant line is found (Figure 3 (c)). We take the longest Hough line as the dominant line based on the assumption that the dominant line represents the true edge of the building. After detecting the longest line, the second longest line, which is perpendicular (90° ± 10°) to the dominant line, is selected from the remaining line segments (Figure 3 (d)). And, the boundaries of the building are delineated based on these two lines. Next, the intersection point of these two lines is calculated and these lines are extended or shortened to end with this point (Figure 3 (e)). After that, the distance between the intersection point and the centroid of the building patch is calculated and a new point with an equal distance from the centroid of the building patch in the opposite direction is generated (Figure 3 (f)). Next, two new lines one parallel to the longest line and the other parallel to the longest perpendicular line are drawn passing through the new point (Figure 3 (g)). Finally, these four lines are combined to generate the building boundary (Figure 3 (h)).

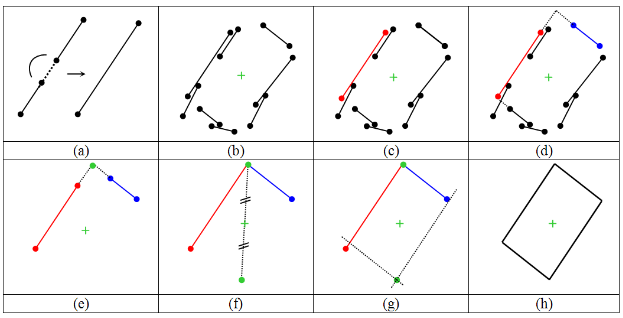

Figure 3. The stages of the perceptual grouping.

3.3 Delineating the Circular Buildings

The original Hough transform was designed to detect lines and curves (Hough, 1962). However, it can be extended to detect analytic shapes. The aim of Circular Hough transform is to extract circular objects from digital images. It is similar to the Hough transform for lines, but uses the parametric form for a circle. Each edge point (x, y) generates a circle in a 3D parameter space with radius *r* and the circle can be expressed with equation 4.

$$(x - a)^2 + (y - b)^2 = r^2 \qquad \text{(Eq. 4)}$$

The parametric representation of the circle is given in equations 5 and 6.

$$x = a + r\cos(\theta) \qquad \text{(Eq. 5)}$$

$$y = b + r\sin(\theta) \qquad \text{(Eq. 6)}$$

To find the circles using Circular Hough transform, for each edge point, a circle is drawn in the parameter space with the desired radius. The accumulator array is incremented for the coordinates that belong to the perimeter of the drawn circle. This process is performed for all edges. At the end of this process the highest numbers in the accumulator space corresponds to the centers of the circles in the image space.

The parameters used in the Circular Hough transform include *seg_no*, *r_range*, and *tol_val*. The parameter *seg_no* indicates the number of segments (points on the detected circle) that determines the number of sides the polygon will have. The more the number of segments the smoother the circle. In the present study the segment number was taken to be 32. The parameter *r_range* is for determining the possible radius ranges (minimum and maximum values) of the circular buildings and determined by the user. The parameter *tol_val* is the tolerance value for concentric circles. The “ring”, “C”, and “S” shape buildings contain concentric circles/semi-circles. Therefore, for the buildings with these shapes, a tolerance value is determined to detect multiple circles that have the same center point.

For delineating the “circle” and “ring” shape buildings, applying the edge detection and Circular Hough transform algorithms sequentially is enough. The delineation of the “circle” and “ring” shape buildings consists of the following steps: (a) Smoothing the building patch images, (b) Edge detection, and (c) Circular Hough Transform.

Due to the complexities of the “C” and “S” shape buildings their delineations require that the results of the Circular Hough transform should be refined. The steps followed to delineate the “C” Shape Buildings are as follows: (a) Smoothing the building patch images, (b) Edge Detection, (c) Circular Hough transform, (d) Semi-circle generation by evaluating the pixels under the circle points, (e) Finding the start/end points of concentric semi circles, and (f) Grouping the points and delineating the building boundaries. The first three steps are same as the steps followed for the delineation of the “circle” and “ring” shaped buildings. To delineate the “C” shape buildings, the circles are converted to semi-circles by evaluating the building patch pixels that correspond to the circle points. If the pixel under the circle point is not a building pixel then, the point is deleted. Otherwise, the point is preserved. Next, the start and end points of the semi-circles are determined by calculating the distances between the sequential points. Those points, between which the distance is the maximum, are determined to be the start and end points of the semi-circle. The points corresponding to semi circles are grouped sequentially starting from the start point and finishing at the end point of the outside circle. Then, the similar grouping process is also carried out from the end point to starting point of the inside circle to form the “C” shape building.

The steps to delineate the “S” Shape Buildings are as follows: (a) Smoothing the building patch image, (b) Edge Detection, (c) Circular Hough transform, (d) Semi-circle generation by evaluating the pixels under the circle points, (e) Finding the start and end points of the semi-concentric circles, (f) Finding the nearest points of the outside and inside semi-circles that have different centroids, and (g) Grouping the points and delineating the building boundaries. The first five steps of delineating the “S” shape buildings are same as for the “C” shape buildings. After applying the Circular Hough transform, the semi-circles are generated and the start and end points (S1, S2, E1, E2) of the semi-circles are found as explained for the “C” shape building delineation process. Then, the points of the inside semi-circle 1 and outside semi-circle 2, which are closest to each other, are detected. Similarly, the points of the inside semi-circle 2 and outside semi-circle 1, which are closest to each other, are also detected. Next, for each semi-circle, starting from the above detected closest points, those points falling inside the building patch are deleted in the clockwise direction. Finally, the semi-circle points are grouped sequentially to form the “S” shape building.

4. THE RESULTS

The developed algorithm was tested in the residential and industrial urban areas that contain different shapes and dwelling types. In figure 4, the extracted building boundaries are illustrated for urban blocks that contain (a) the industrial rectangular buildings, (b) the residential rectangular buildings, and (c) the residential circular buildings.

Based on the visual evaluation of the results we can state that almost all buildings were delineated successfully. In the study area there were a total of 394 buildings. Of these buildings, 387 were successfully delineated with the accuracy rate of 98.22% (Table 1). In selected urban blocks, seven buildings were not able to be extracted. This is because, some of the buildings are quite small or the buildings, which are close to each other but not adjoined, were delineated erroneously as a joint building.

	Count	%
Delineated Buildings / Reference Buildings	387 / 394	98.22 / 100

Table 1. Error matrix of the extracted building boundaries

To assess the results of the extracted buildings, the areas were classified into one of the four categories that are; True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) by comparing the extracted building boundaries with the reference building boundaries (Shufelt and McKeown, 1993). Then, the *Branching Factor*, *Miss Factor*, *Building Detection Percentage*, and *Quality Percentage* were calculated for each urban block.

Branching Factor (BF): FP / TP
Miss Factor (MF): FN / TP
*Building Detection Percentage (BDP): 100 * TP / (TP + FN)*
*Quality Percentage (QP): 100 * TP / (TP + FP + FN)*

These measurements give us an idea about the accuracy of the extracted building areas. The BF indicates the rate of incorrectly labelled building areas. The MF describes the rate of building areas missed. The BDP gives the percentage of building areas correctly extracted by the automatic process and the QP is the overall measure of performance and describes how likely a building area produced by the automatic extraction is true.

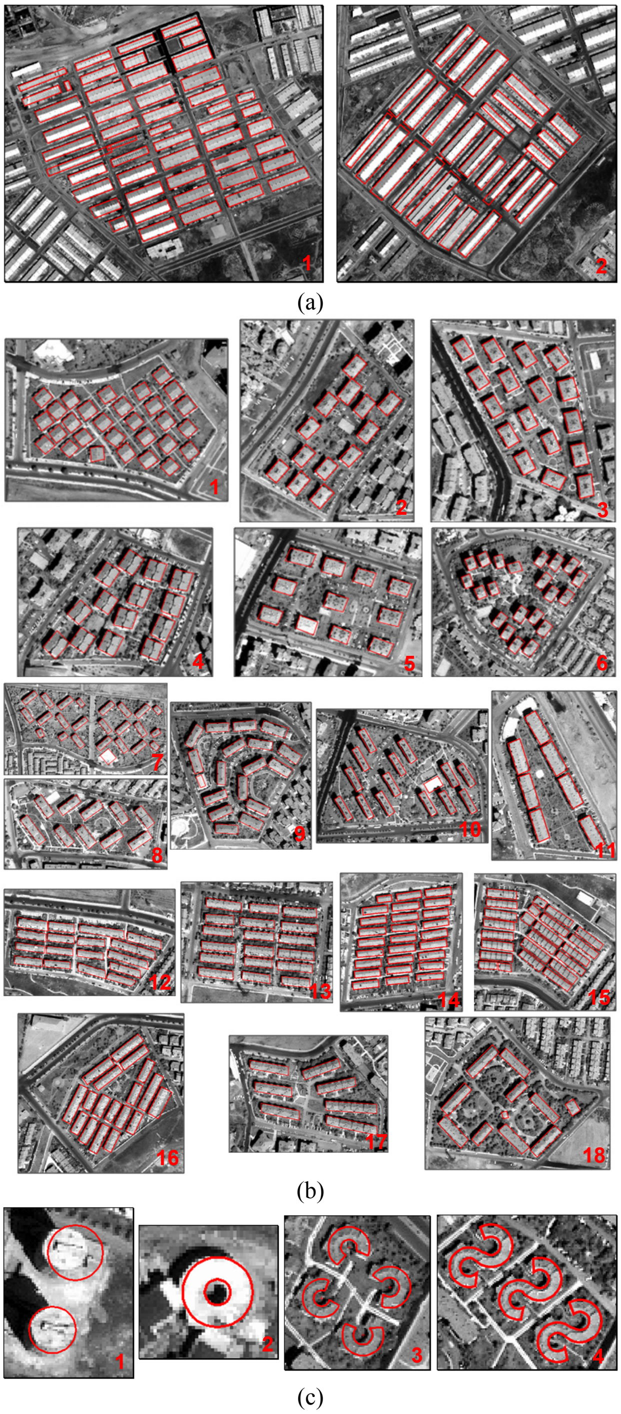

Figure 4. The delineated building boundaries for urban blocks that contain (a) industrial rectangular buildings, (b) residential rectangular buildings, and (c) residential circular buildings

The quality assessments for the urban blocks that contain industrial rectangular, residential rectangular, and residential circular buildings are given in table 2. For all urban blocks, the BDP values were computed to be in the range of 68.56 - 98.26 and the QP values were found to be in the range of 60.50 - 85.48. On the other hand, the BF values were computed to be in the range of 0.55 - 0.05 and the MF values were found to be in the range of 1.47 - 0.02.

Building Type	Urban Block No	BF	MF	BDP	QP
Industrial	1	0.14	0.06	94.17	82.88
Rectangular	2	0.29	0.09	91.83	72.67
Average		**0.19**	**0.07**	**93.45**	**79.51**
	1	0.20	0.08	92.44	77.97
	2	0.24	0.04	96.38	78.44
	3	0.13	0.07	93.11	83.32
	4	0.29	0.03	97.22	75.70
	5	0.18	0.04	95.73	81.67
	6	0.40	0.03	96.79	69.70
	7	0.14	0.06	94.57	83.61
	8	0.29	0.05	95.50	74.57
	9	0.16	0.05	95.28	82.48
Residential	10	0.15	0.03	97.36	85.11
Rectangular	11	0.24	0.02	97.90	79.48
	12	0.29	0.02	98.26	76.43
	13	0.29	0.04	96.46	75.16
	14	0.15	0.13	88.39	77.75
	15	0.21	0.04	96.28	80.05
	16	0.28	0.04	96.50	75.99
	17	0.17	0.03	97.09	83.23
	18	0.20	0.04	95.73	80.16
Average		**0.22**	**0.05**	**95.34**	**79.05**
	1	0.55	0.11	90.37	60.50
Residential	2	0.05	0.12	89.14	85.48
Circular	3	0.19	1.47	68.50	61.00
	4	0.15	0.35	73.88	66.52
Average		**0.23**	**0.27**	**78.74**	**66.81**

Table 2. The quality assessment results of the building extraction

The results show that the proposed approach is quite successful for extracting the buildings from high resolution satellite images with the average BDP and QP values of 93.45% and 79.51%, respectively for the industrial rectangular buildings, 95.34% and 79.05%, respectively for the residential rectangular buildings, and 78.74% and 66.81%, respectively for the residential circular buildings.

5. THE CONCLUSIONS

High resolution satellite images have become quite valuable data sources for geographic information extraction. In the present study, an approach was developed for the automatic extraction of the rectangular and circular shaped buildings from high resolution satellite imagery using Hough transform. The results obtained indicate that high resolution satellite imagery has great potentials in building extraction.

In the present case, the delineation of the building boundaries was carried out from a panchromatic building patch image, which is generated by masking the classified building areas. Therefore, the success of the developed building extraction approach is dependent on the success of the detection of the building patches. If the building patches are not detected accurately due to the characteristics of the land use classes, the buildings may not be delineated correctly. By confining the search area over the candidate building patches, the building delineation process becomes easier as the unnecessary edges are not included in the process and therefore, the processing operations are carried out over the building areas only.

The results obtained in this study indicate that the developed building extraction procedure can be effectively used to delineate the boundaries of the rectangular and circular shaped buildings. The results prove that if the mutual lines of the buildings are parallel and the angles between the adjacent lines are perpendicular, or if the buildings are circular or curved shape, the Hough transform can said to be an efficient technique.

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