Automatic Building Extraction with Multi-sensor Data Using Rule-based Classification

Melis Uzar

Department of Geomatic Engineering, Yildiz Technical University, Faculty of Civil Engineering
Yildiz Technical University, Davutpasa Campus 34210 Esenler/Istanbul, Turkey
Corresponding author, e-mail address: auzar@yildiz.edu.tr

Abstract
This paper presents a new approach for automatic building extraction using a rule-based classification method with a multi-sensor system that includes light detection and ranging (LiDAR), a digital camera, and a GPS/IMU positioned on the same platform. The LiDAR data (elevation and intensity) and ortho-image are used to develop a rule set defined by parameter analyses during the segmentation and fuzzy classification processes to improve the building extraction results. The proposed approach was tested using the data derived from a multi-sensor system in Sivas, Turkey. Moreover, analyses of completeness (8.7%) and correctness (87.64%) were performed by automatic comparison of the extracted buildings and reference data.

Keywords: LiDAR, intensity, building extraction, segmentation, rule-based classification, fuzzy logic.

Introduction
The monitoring of urban construction activities and identification of current situations have become important topics of research in photogrammetry and remote sensing. Remote sensing is a science that offers the opportunity for urban and regional data management with the development of new approaches in data acquisition, processing, integration, and evaluation. New technologies, i.e., the multi-sensor system composed of light detection and ranging (LiDAR) equipment, a digital camera, a Global Positioning System (GPS) and an Inertial Measurement Unit (IMU) positioned on the same platform, have broad application potential in automatic building extraction. Automatic building extraction is an active research area in computer vision that encompasses remote sensing data use in updating digital maps and geographic information system (GIS) databases.

Although automatic building extraction has great importance in city planning and for natural disaster and crisis management, it remains a complex problem for scientists. The main problem encountered in building extraction approaches is confusion of the building class with other object classes, such as shadows, vegetation, and the ground. The detection
of a non-building as a building and mixture of trees and shadows are examples of other misclassification problems. These misclassification problems, which are attributable to a single dataset and method, have a negative effect on the accuracy of the classification process. For this reason, different approaches and methods have been proposed to solve the problems caused by the complexity of classification process. The datasets obtained from different sensor systems create the opportunity for development of methods to extract objects [Baltsavias, 1999; Tarsha-Kurdi, 2007; Matikainen, 2009; Rottensteiner et al., 2012]. Several authors [Haala and Brenner, 1999; Sohn and Dowman, 2007; Lee et al., 2008; Demir et al., 2009; Awrangjeb et al., 2010; Beger, 2011; Nex and Rinaudo, 2011; Moussa and El-Sheimy, 2012] prefer the use of a fusion of data sets (i.e., aerial photography, multi-band images, and LiDAR) rather than the use of only a single data set. Regarding the data source, due to the limitations of using single-source data, the integration of multi-sensor data is desired because this method preserves the many advantages of the involved datasets [Gruen, 2008; Kwak et al., 2012].

In the late 1980s, studies on multi-datasets gained popularity with the use of different images, colors, intensities, and stereo- and multi-images [Peng, 2005]. Haala and Brenner [1999] used multi-spectral information provided by a color-infrared aerial image with geometric information from a Digital Surface Model (DSM) laser scanner in an integrated classification method for the extraction of buildings, trees, and grass-covered areas. The method of the normalized DSM (nDSM), the heights of which directly reflect the heights of objects relative to the terrain, has been used in many building detection approaches [Rottensteiner et al., 2005, 2007; Aref, 2008; Khoshelham et al., 2010; Grigillo and Kanjir, 2012]. The generation of the DSM from LiDAR is also used for the classification of vegetation, ground, and buildings with simultaneous classification of the similar reflectances of trees and grass-covered areas. However, in certain cases, a simple method is not sufficient because the success rate of building extraction depends on the resolution of the laser scanner data, which is still lower than the resolution of aerial imagery. In such cases, intensity data obtained from modern LiDAR technology are used to classify objects at the same altitude for the purpose of improving the classification results [Baltsavias, 1999; Schenk and Csatho, 2002; Habib, 2008].

In parallel with the development of multi-sensor system technology, scientists began to improve different methods using the fusion of multi-datasets to address the classification problems related to shadows, occlusions, and poor contrast [Rottensteiner, 2012]. Rottensteiner et al. [2005] developed a method based on the Dempster Shafer theory to detect buildings from LiDAR data and multi-spectral images. Additional details on the Dempster Shafer theory can be found in the papers by Rottensteiner et al. [2004] and Khoshelham et al. [2010].

The method of object-oriented image analysis with rule-based classification was developed to bridge the gap between the increasing amount of detailed geo-spatial data and complex feature recognition problems [Blaschke, 2010]. This method is preferred over the traditional classification techniques for automatic building extraction [Rottensteiner and Briese, 2002]. Classification problems can be solved using a set of rules and instances evolved from the expert systems domain for a given occurrence. Each instance results in a decision, and the associated rule set is composed of a series of logical steps that are built on an existing set of variables to explain the occurrence [Navulur, 2007]. Feature-level data fusion is
performed to combine the advantages of having several datasets and to maximize accuracy and completeness [Beger, 2011]. Rule-based classification can remarkably improve the classification accuracy via fuzzy logic. The fuzzy logic method can be viewed as a special case of classification used to solve the issues of building extraction. One of the most powerful soft classifiers is the fuzzy classification system [Benz et al., 2004]. The main aim of fuzzy-based classification is to categorize an image and to correct the feature classes using membership values. Rottensteiner et al. [2005] used fuzzy logic classification in the detection of building candidates as segments rather than on a per-pixel basis.

The proposed approach presented in this paper uses data from a multi-sensor system composed of LiDAR, a digital camera, and a GPS/IMU positioned on the same platform. The multi-sensor system exhibits high potential in automatic building extraction in terms of the data supplied and the automation opportunities. Baltsavias [1999], Rottensteiner et al. [2005], and Lafarge et al. [2008] have discussed multi-sensor system data as a solution to misclassification problems. The aim of this study was to create a new approach for automatic building extraction using rule-based classification. This approach was developed to solve these problems using multi-sensor system data with fuzzy classification. The rule sets were developed based on the determination of the differences between buildings and other classes, followed by improvement of the classification using these differences. Different segmentation (multi-resolution and contrast splitting) techniques were applied to the data sets using shape, scale, slope, and homogeneity criteria to separate buildings from the shadow, ground, and vegetation classes. Additionally, this situation allows the user to apply different strategies for the analyses. Within the scope of this work, building extraction was performed via detection of object boundaries. In overlapping threshold positions, fuzzy logic classification was used to provide a gradient of membership at the class boundaries. The final buildings were subsequently detected with the improvement of morphological operations.

The remainder of this paper is organized as follows. The properties of the study area and the dataset obtained by the multi-sensor system are presented in the next section, followed by a discussion of the methodology. The results of the experiment are reported together with an accuracy assessment of the building extraction results, and the conclusions are stated in the last section.

**Study Area and Dataset**

The dataset was obtained from the “NABUCCO Gas Pipeline Project”. The dataset was collected for corridor mapping for a pipeline that will link the eastern border of Turkey to Baumgarten in Austria via Bulgaria, Romania, and Hungary. The study area consists of a suburban neighborhood located in the city of Sivas, Turkey (Fig.1). This test area was selected as the study area because the dataset was obtained from the multi-sensor system (LiDAR, digital camera, and GPS/IMU). The components of the integrated system on the Pilatus HB-FKL plane included a Leica ALS60 LiDAR, a GLM 60 (GPS/ CUS6-“uIRS” IMU) and DiMAC, and a Dalsa Area Bayer RGB charge-coupled device (CCD) digital camera. The GPS/IMU technology is integrated into the LiDAR for the datasets pre-processing. The GPS provides the coordinates of the LiDAR and the IMU provides the direction of the pulse. The 3D point cloud data were used as the dataset in the system, which was obtained with the LiDAR laser scanner at 0.2 m resolution.
The point cloud data were filtered to remove noise and unnecessary data, and smoothing operations were performed during the pre-processing stage. After the point cloud data were processed in the processing phase, a DSM was derived from the LiDAR data, which included both vegetation and buildings. This DSM raster generation was interpolated from the ALS point cloud data with a grid width of 20 cm using ERDAS Imagine 8.7 Leica Photogrammetry Suite. Details of the information from the multi-sensor system and collected data are listed in Table 1.

**Table 1 - Multi-sensor system and data specifications.**

| Sensor          | System                                  | Date of data collection | Specification                                      |
|-----------------|-----------------------------------------|-------------------------|----------------------------------------------------|
| LiDAR           | Leica ALS60 LiDAR                       | 1 November 2010         | Point cloud (3 points/m²) and intensity data       |
| GPS/IMU         | GLM 60 (GPS/CUS6-“uIRS“ IMU)            | 1 November 2010         | Position and attitude information (IMU:200 Hz, GPS:1 Hz) |
| Digital Camera  | DiMAC, Dalsa Area Bayer RGB Charge Coupled Device (CCD) | 1 November 2010         | RGB image (0.2 m GSD)                              |

The intensity image was obtained from the intensity values, which were measured and recorded by LiDAR. This image was generated using the intensity data by forming pyramids with the image matrix that contains the image intensity data taken from an ASCII file in the raw LiDAR data. The intensity image is an important multi-sensor dataset that provides better differentiation of gray-scale-coded objects. Another advantage of the integrated system involved the images (RGB) obtained by the digital camera. The ortho-image and
intensity image were generated with the data from the integrated system for successful building extraction. A slope image was generated with the slope analyses of the DSM in addition to images of shadow and vegetation produced from the ortho-image. The multi-sensor system dataset was included in the processes of the segmentation and classification stages. The dataset from the multi-sensor system is shown in Figure 2.

![Figure 2 - Ortho-image (a); intensity image (b) and DSM (c) of the study area.](image)

As shown in Figure 2, the study area used to test the proposed approach for automatic building extraction consists of a complex collection of buildings. The different heights, roof colors, roof materials (such as metal, brick, and concrete), sloped topographies, and adobe walls of the building together with the shadows and trees make the extraction of buildings quite difficult.

**Methodology**

In this study, object-oriented image analysis with a rule-based classification method was performed using a new approach for automatic building extraction. With this approach, a set of rules was developed using a multi-sensor system based on data obtained from an ortho-image and LiDAR data. The advantages of the dataset and the method of fuzzy logic classification were leveraged in this work. The building class represents the target class of this study, but in addition to the building class, the shadow, ground, building candidate, vegetation, and building border classes were also extracted automatically. Additionally, the proposed method applied defined rules that were organized to improve the building class and to obtain higher classification accuracy.

The proposed building extraction strategy was based on an object-oriented image analysis method that consists of two major stages of segmentation and classification. The first process of this method is segmentation, which divides the image into regions or objects with common properties [Navulur, 2007]. This process plays an important role in meaningful analysis and correct representation of the objects in the image prior to classification. In the segmentation process, the detection of the object boundaries was improved using different weight values. In this phase, the spectral and positional properties of the object were taken into consideration, and they were divided into groups based on their pixel values. These values
were computed using properties such as color, morphology, texture, and shape to represent the objects with segments. Multi-resolution and contrast-split segmentation methods were applied to create correct object segments. The multi-resolution segmentation method uses a heterogeneity criterion that includes scale, color, shape, smoothness, and compactness parameters [Benz et al., 2004; Beger et al., 2011]. The contrast-split segmentation method uses the edge ratio of bright and dark pixel values to detect the object contours [Trimble Definiens, 2010]. After the determination of the object segments in the segmentation stage, fuzzy logic classification was applied to classify the target classes. In the classification phase, analyses were performed using statistical data such as area, shape, and intensity from the produced multi-sensor dataset. We chose the rule-based classification with multi-sensor data to develop the rule set for solving the misclassification problems. The segmentation and classification processing stages are repeated with a loop in each rule to generate the object classes and are organized to improve the building class for successful extraction in Definiens eCognition Developer 8.64.

**Automatic Extraction of Buildings using the Rule-Based Classification Method**

In the object-oriented image analysis with rule-based classification conducted in this study, after the image was segmented, the segments were classified by creating a rule set according to suitable segment attributes (i.e., spatial, spectral, geometrical, texture) using the rule set classifications [Grigillo and Kanjir, 2012]. Before the objects can be separated into different types by classification, the object attributes must be analyzed [Baatz et al., 2008]. In the analysis stage, object attributes, such as spectral characteristics, scale parameters, shape, completeness, brightness, contrast difference, and statistical parameters, were determined until they formed the target object class. If two different objects have the same attributes and the analysis is not sufficient to distinguish between them, misclassification has occurred. Therefore, fuzzy logic was combined with rule-based classification. The fuzzy logic method is an important decision-making tool in remote-sensing applications that offers the ability to define uncertainties with a mathematical expression. In fuzzy classification, objects can be defined as fuzzy memberships to separate the two classes with high accuracy. Unlike classical sets, fuzzy sets are defined by membership functions that express the degree of membership related to the considered event [Aksoy and Ercanoglu, 2012]. An object or a segment can be determined to be a member of a target class with the membership functions of fuzzy sets using the fuzzy classifier.

Figure 3 shows a diagram of the proposed building extraction strategy. The input information consists of a DSM, an intensity image, and an ortho-image of the study area generated with the dataset obtained from the LiDAR, GPS/IMU, and digital camera located on the same platform. The proposed method for automatic building extraction consists of subsequent steps with defined rules. The initial step is the generation of a shadow class from the ortho-imagery, which is necessary to avoid the complexities of the building and shadow classes. A multi-resolution segmentation process was performed to analyze the scale, shape, and compactness parameters of the ortho-image. Prior to the fuzzy classification, the shadow image was generated from the analyses of the shadow threshold values. This image was used to classify the shadows and was computed with the band operations given in Eq. 1. Finally, the shadow class was generated as a result of the processing shown in Rule 1.

\[
\text{The shadow image} = \frac{\text{Blue} - \text{Green}}{\text{Blue} + \text{Green}} \quad [1]
\]
In the second step, the ground class was created with the LiDAR data (height information) and is defined as Rule 2. The generated DSM from the LiDAR point cloud data was used to separate the ground and non-ground classes using slope analysis. In the next step, the nDSM, which represents the subtraction of the DTM from the DSM, was used for generation of the initial building class with Rule 3, as shown in Figure 3. To determine the object boundaries, the slope image was produced using the slope differences in the objects. The slope was used to distinguish the buildings from the objects. In general, the slope image was obtained from the Zevenbergen and Thorne [Zevenbergen and Thorne, 1987] analysis method based on the slope differences of the objects. This method computes the slope value for each pixel in the DSM. After the generation of the slope image from the LiDAR data, a building candidate class was created with Rule 4. In this rule, contrast split segmentation with fuzzy rule classification was used to define the overlapping threshold to provide a gradient of membership at the class boundaries.

The goal of this paper is to investigate the fusion of the LiDAR data and the ortho-image data with rule-based classification for automatic building extraction. As mentioned previously, the proposed method improves the building class with rules that employ thresholding operations and fuzzy logic classifiers in situations where overlapping thresholds can be defined. After the generation of building candidate class, the ortho-image was used to distinguish vegetation from buildings in Rule 5. The objects and building candidate classes were included in this process to assign the objects to the correct class. Prior to the classification of vegetation, different band combinations of ortho-images were analyzed with the vegetation
index to form an additional image. Contrast-split segmentation was performed with the green-band threshold values for vegetation extraction. The classification was performed with the defined fuzzy rules, and the results were improved with morphological operations to accurately represent the vegetation class. Morphological operations, which yield good localization via calculation of the smallest distance between the detected and real edges, were used in the proposed method. After the morphological operations were performed, the building boundaries were ready for capture with a rule-based algorithm. Finally, the building border class was acquired as a result of multi-resolution segmentation and the fuzzy classification with the determined building threshold. Because the building borders were previously created, the final building class was produced with the region-growing algorithm and the morphological operations in Rule 6. Prior to the extraction of buildings, the threshold values of the rectangular fit, area, and intensity image parameters were also used to optimize the mixed classes. All of these processes were performed to obtain a high accuracy for the building class.

Results

In this section, the execution of the proposed strategy is described and the results obtained using the developed rules are discussed. According to Rule 1, multi-resolution segmentation was performed using the ortho-image to generate the shadow class as a first step in the hierarchical classification scheme for automatic building extraction (Fig. 4). The scale, shape, and compactness parameters were set as 25, 0.6, and 0.5, respectively, for the multi-resolution segmentation. In the classification steps, the threshold values were determined from the shadow image, which was obtained from the band operation of the ortho-image (Eq. 1). The shadow class was generated using the fuzzy rules defined with the membership type of “Larger than”, and the shadow index (si) threshold values were determined as 0.11 ≤ si ≤ 0.28 (Fig. 4).

Figure 4 - Processing steps of shadow class in Rule-1: ortho-image (a); multi-resolution segmentation (b); shadow image (c) and classification of shadow (d).
The ground class was extracted using classification with the threshold value from the quantile statistical analysis, which was calculated using the height in the DSM that is less than the quantile ground threshold (DSM ≤ 1593.53 m) determined from Rule 2. During the process associated with Rule 3, the initial building class was created to distinguish the elevated objects (trees and buildings) from the ground using the generated nDSM. The generation of the nDSM is described in additional detail in the previous section.

The next step in the classification workflow rules out misclassification by detecting the different properties of the building candidate class versus the initial building class. For this purpose, after the generation of the initial building class, we defined Rule 4 using the slope image to create a building candidate class. The slope image was used to distinguish the buildings from other objects with the processes of contrast-split segmentation and fuzzy rule classification. The thresholds were defined as a slope value less than or equal to 185 and greater than or equal to 120 for segmentation and less than or equal to 31 and greater than or equal to 75 for fuzzy classification. The processing steps of Rule 4 are shown in Figure 5.

Misclassification occurs between the buildings and trees in the building candidate class, as shown in Figure 6a. To eliminate the trees, the ortho-image was used to generate the vegetation class in the Rule 5 step. Resolution of the limits of the LiDAR data with the ortho-image is the goal of the proposed method by leveraging the advantages of the multi-sensor data. To this end, the determined threshold values were applied and were defined as less than or equal to 57 and greater than or equal to 146 for fuzzy classification (Fig. 7a). The vegetation class was processed using a morphological closing operation (image dilation followed by erosion) to improve the vegetation class and to correctly capture the objects that represent vegetation (Fig. 6b).

![Figure 5 - Slope image (a); contrast split segmentation (b) and fuzzy classification of building candidate class (c).](image)

The building border class was created using the result from the multi-resolution segmentation and fuzzy classification (Fig. 6c). This class was represented with interior and external segments characterized by multi-resolution segmentation parameters, and values of scale = 25, shape = 0.4, and compactness = 0.6 were used. Next, the arithmetic average (mean) of
the ortho-image was defined with a threshold value less than or equal to 780 and greater than or equal to 450 for use in fuzzy classification. The fuzzy classification of the membership function for the building border class is shown in Figure 7b.

![Figure 6](image1.png)  
![Figure 7a](image2.png)  
![Figure 7b](image3.png)  

**Figure 6** - Processing steps of initial building improvement: building candidate class (a); vegetation class (b) and building border class (c).

![Figure 7](image4.png)  
![Figure 8](image5.png)  

**Figure 7** - Fuzzy logic classifications of membership function samples for automatic building extraction: vegetation class (a) and building border class (b).

**Figure 8** - The image of the final building class with the proposed method.
As a result of the classification and to eliminate non-building objects classified as buildings, an intensity image threshold value less than 55 was adopted. All classes other than the building class were merged to achieve the goal of this study. The processing step of building class improvement was implemented in Rule 6 with several special indices and methods, such as area determination, rectangular fitting, morphological operations, and a region-growing algorithm (coating), to correctly create the final building class. Finally, automatic building extraction was performed using the defined rules with the proposed approach as shown in Figure 8.

![Figure 9](image1.png)

**Figure 9** - The elimination of non-building objects appearance as building in ortho-image: (a) is the original image part in ortho-image; (b) is the detection of a non-building as a building and (c) is the result of the proposed approach.

Several instances are given to evaluate the proposed approach. Figure 9 indicates the elimination of non-building objects appearance as building in ortho-image. It also shows the original image part in ortho-image (Fig. 9a), the detection of a non-building as a building (Fig. 9b) and the result of the proposed approach (Fig. 9c). The misclassification problems of automatic building extraction are described in Introduction section. The example of misclassification problem in extracting building is shown in Figure 10 with the original image part in ortho-image (Fig. 10a), the detection of a non-building as a building (Fig. 10b) and the result of the proposed approach (Fig. 10c).

![Figure 10](image2.png)

**Figure 10** - Misclassification problem in extracting building: (a) is the original image part in ortho-image; (b) is the detection of a non-building as a building and (c) is the result of the proposed approach.
Figure 11 shows the elimination of non-building objects detect as building in DSM data with the original image part in ortho-image (Fig. 11a), the original image part in DSM (Fig. 11b), the detection of a non-building as a building (Fig. 11c) and the result of the proposed approach (Fig. 11d). Moreover, the extraction of missing buildings is shown in Figure 12 with the original image part in ortho-image (Fig. 12a), the detection of missing building (Fig. 12b) and the result of the proposed approach (Fig. 12c). Finally, the example of processing step of building class improvement are shown in Figure 13 with initial building class (Fig. 13a), detecting building border (Fig. 13b) and the result of the proposed approach (Fig. 13c).

**Figure 11** - The elimination of non-building objects detect as building in DSM data (a) is the original image part in ortho-image; (b) is the original image part in DSM; (c) is the detection of a non-building as a building and (d) is the result of the proposed approach.

**Figure 12** - The extraction of missing buildings: (a) is the original image part in ortho-image; (b) is the detection of missing buildings and (c) is the result of the proposed approach.

**Accuracy Assessment**

In the process of determining the accuracy of automatic building extraction, we compared the data obtained from the proposed automatic building extraction approach with the reference data. The reference data were created by digitizing the building polygons in the digital ortho-photo. Prior to the evaluation process, the two datasets were prepared to ensure the completeness and correctness of the results [Rottensteiner et al., 2005]. A detailed description of the evaluation techniques is provided in Rutzinger et al. [2009].
Figure 13 - Processing step of building class improvement (a) Initial building class, (b) detecting building border, (c) is the result of the proposed approach.

The completeness is the percentage of entities in the reference data that were detected, and the correctness indicates how well the detected entities match the reference data and is closely linked to the false alarm rate [Grigillo and Kanjir, 2012]. The main approach in this accuracy analysis method involves performance of the completeness and correctness analyses (Eq. 2 and Eq. 3). According to this technique, TP is the number of pixels classified as a building, FN is the number of building pixels in the reference data that are not classified as a building in the automatic extracted image, and FP is the number of building pixels in the automatic extracted image that are not classified as a building in the reference data [Rutzinger et al., 2009].

\[
\text{Completeness} = \frac{TP}{TP + FN} \quad [2] \\
\text{Correctness} = \frac{TP}{TP + FP} \quad [3]
\]

An accuracy assessment method for correctness and completeness was applied for the building class results of the rule-based classification. In this method, we compare the automatically extracted buildings with those of the reference data manually digitized from digital ortho-photos with 0.20-m resolution using the automated ISODATA (Iterative Self-Organizing Data Analysis Techniques) algorithm. The building class was constructed in the form of vector data that contains area information and height information from the building boundaries and DSM. In this study, Figure 4 represents the image of reference buildings and Figure 5 represents the image of extracted buildings with the proposed method. For evaluation of the automatic building extraction, the completeness and correctness were evaluated as 8.7 and 87.64%, respectively. The accuracy assessment of buildings which have been compared the areas with the reference data and extracted data from the multi-sensor system dataset are shown in Table 2. After the evaluation of the accuracy assessment three missed buildings, which were numbered as 8, 10 and 19 were analyzed. The missed buildings were mostly small residential buildings consisting of many small faces and having areas about 50 - 63 m². However, 9% of the buildings were mistakenly removed, and 3% of the buildings were incorrectly included into the final output in terms of the total area of extracted buildings. The results of each building accuracy assessment were shown in Table 2.
Conclusions
This paper proposed a new automatic building extraction method that uses a developed rule set that demonstrates the advantages of fusing LIDAR data and ortho-images obtained from a multi-sensor system composed of LiDAR, a digital camera, and a GPS/IMU. To overcome misclassification problems, the rules are defined using digital image processing techniques, multi-resolution and contrast-split segmentations, and the fuzzy classification method. The model parameters were determined with the analyses from the segmentation and classification steps to find the optimum strategy for extraction of buildings. The rules were applied to classify shadows, ground vegetation, and buildings. In addition, the classes of initial buildings, building candidates, and building borders were used to extract the final buildings with the goal of improving the accuracy of the building class.
Table 2 - Accuracy assessment of buildings.

| Building No | Reference Building Area (m²) | Result Building Area (m²) | Accuracy (%) |
|-------------|------------------------------|---------------------------|--------------|
| 1           | 84.88                        | 102.26                    | 79.52        |
| 2           | 112.59                       | 94.23                     | 83.69        |
| 3           | 134.65                       | 132.84                    | 98.66        |
| 4           | 219.28                       | 224.79                    | 97.49        |
| 5           | 106.75                       | 124.09                    | 83.76        |
| 6           | 100.35                       | 124.36                    | 76.07        |
| 7           | 119.37                       | 120.29                    | 99.23        |
| 8           | 62.95                        | 0.00                      | 0.00         |
| 9           | 229.91                       | 238.18                    | 96.40        |
| 10          | 53.26                        | 0.00                      | 0.00         |
| 11          | 182.61                       | 197.40                    | 91.90        |
| 12          | 182.20                       | 186.02                    | 97.90        |
| 13          | 90.50                        | 86.16                     | 95.20        |
| 14          | 82.80                        | 106.78                    | 71.04        |
| 15          | 255.28                       | 250.81                    | 98.25        |
| 16          | 126.19                       | 137.37                    | 91.14        |
| 17          | 104.83                       | 103.66                    | 98.88        |
| 18          | 234.01                       | 242.40                    | 96.41        |
| 19          | 60.27                        | 0.00                      | 0.00         |
| 20          | 97.88                        | 98.07                     | 99.81        |
| 21          | 106.15                       | 185.23                    | 25.50        |
| 22          | 146.79                       | 140.60                    | 95.78        |
| 23          | 50.74                        | 88.98                     | 24.64        |
| 24          | 214.20                       | 122.00                    | 56.96        |
| 25          | 356.35                       | 369.91                    | 96.19        |
| 26          | 206.81                       | 217.71                    | 94.73        |
| 27          | 141.93                       | 136.83                    | 96.41        |
| 28          | 156.51                       | 146.23                    | 93.43        |
| 29          | 137.01                       | 138.24                    | 99.10        |
| 30          | 148.62                       | 139.27                    | 93.71        |
| 31          | 568.91                       | 572.10                    | 99.44        |
| 32          | 113.09                       | 100.77                    | 89.11        |
| 33          | 138.12                       | 152.62                    | 89.50        |
| 34          | 130.07                       | 135.31                    | 95.97        |
| 35          | 166.11                       | 161.49                    | 97.22        |

The DSM and the images of slope, shadow, and intensity were generated using the dataset
from a multi-sensor system and the developed rule set to avoid confusion of the building class with other classes. Additional methods, such as morphological operations and region growing, were used in the processing steps for improvement of the building class. As a result of the developed rules, the classification confusion problems were resolved, and the building data were obtained automatically. Accuracy analysis was performed on the automatically extracted building class with completeness and correctness values of 81.71 and 87.64%, respectively.

The proposed automatic building extraction method is a helpful and effective tool that could be used in important earth science subjects, such as environmental assessment, control of natural disasters, and crisis management, as well as for the tracking and prevention of unorganized urbanization. This method will become an indispensable support for geographical information systems in the future due to its high accuracy, reliability, speed, and automation.

Acknowledgements
The author thanks the SEBAT Project Inc. for providing the dataset.

References
Aksoy B., Ercanoglu M. (2012) - Landslide identification and classification by object-based image analysis and fuzzy logic: An example from the Azdavay region (Kastamonu, Turkey). Computers & Geosciences, 38: 87-98. doi: http://dx.doi.org/10.1016/j.cageo.2011.05.010.
Arefi H., Engels J., Hahn M., Mayer H. (2008) - Levels of detail in 3D building reconstruction from LiDAR data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B3b, Beijing.
Awrangjeb M., Ravanbakhsh M., Fraser C. (2010) - Automatic detection of residential buildings using LIDAR data and multispectral imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 65: 457-467. doi: http://dx.doi.org/10.1109/DICTA.2010.17.
Baatz M., Hoffmann C., Willhauck G. (2008) - Progressing from object-based to object-oriented image analysis. In: Blaschke, T., Lang, S., Hay, G.J., (Eds), Object-Based Image Analysis. Springer, Berlin, pp. 29-42. doi: http://dx.doi.org/10.1007/978-3-540-77058-9_2.
Baltsavias E.P., (1999). A comparison between photogrammetry and laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing, 54: 83-94. doi: http://dx.doi.org/10.1016/S0924-2716(99)00014-3.
Beger R., Gedrange C., Hecht R., Neubert M. (2011) - Data fusion of extremely high resolution aerial imagery and LiDAR data for automated railroad centre line reconstruction. ISPRS Journal of Photogrammetry and Remote Sensing, 66: 40-51. doi: http://dx.doi.org/10.1016/j.isprsjprs.2011.09.012.
Benz U., Hofmann P., Willhauck G., Lingenfelder I., Heynen M. (2004) - Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry & Remote Sensing, 58: 239-258. doi: http://dx.doi.org/10.1016/j.isprsjprs.2003.10.002.
Blaschke T. (2010) - Object Based Image Analysis for Remote Sensing. ISPRS Journal of Photogrammetry & Remote Sensing, 65: 2-16. doi: http://dx.doi.org/10.1016/
Demir N., Poli D., Baltavias E. (2009) - Detection of buildings at airport sites using images & Lidar data and a combination of various methods. IAPRS, Paris, France, pp. 71-77.

Grigillo D., Kanjir U. (2012) - Urban object extraction from digital surface model and digital aerial images. Proceedings of XXII ISPRS Congress, Melbourne, Australia.

Gruen A. (2008) - Reality-based generation of virtual environments for digital earth.

Haala N., Brenner C. (1999) - Extraction of buildings and trees in urban environments. ISPRS Journal of Photogrammetry and Remote Sensing, 54: 130-137. doi: http://dx.doi.org/10.1016/S0924-276(99)00010-6.

Habib A. (2008) - Integration of LiDAR and Photogrammetric Data: Triangulation and Ortho Rectification. Topographic Laser Ranging and Scanning Principles and processing. Taylor & Francis Group, pp. 371-400.

Khoshelham K., Nardinocchi C., Frontoni E., Mancini A., Zingaretti P. (2010) - Performance evaluation of automated approaches to building detection in multi-source aerial data. ISPRS Journal of Photogrammetry and Remote Sensing, 65: 123-133. doi: http://dx.doi.org/10.1016/j.isprsjprs.2009.09.005.

Kwak E., Al-Durgham M., Habib A. (2012) - Automatic 3D building model generation from lidar and image data using sequential minimum bounding rectangle. Proceedings of XXII ISPRS Congress, Melbourne, Australia.

Lafarge F., Descombes X., Zerubia J., Pierrot-Deseilligny M. (2008) - Automatic building extraction from DEMs using an object approach and application to the 3D city modeling. ISPRS Journal of Photogrammetry & Remote Sensing, 63: 365-381. doi: http://dx.doi.org/10.1016/j.isprsjprs.2007.09.003.

Lee D., Lee K., Lee S. (2008) - Fusion of lidar and imagery for reliable building extraction. Photogrammetric Engineering and Remote Sensing, 74: 215-225. doi: http://dx.doi.org/10.14358/PERS.74.2.215.

Matikainen L., Hyyppä J., Ahokas E., Markelin L., Kaartinen H. (2009) - An improved approach for automatic detection of changes in buildings. Proceedings of the ISPRS Workshop ‘Laserscanning 09’, Paris, France. In: Remote Sensing and Spatial Information Sciences, Vol. XXXVIII, Part 3/W8, pp. 61-67.

Moussa A., El-Shimy N. (2012) - A new object based method for automated extraction of urban objects from airborne sensors data. Proceedings of: XXII ISPRS Congress, Melbourne, Australia.

Navulur K. (2007) - Multispectral image analysis using the object-oriented paradigm. CRC Press, Taylor & Francis Group, Boca Raton, 205 pp.

Nex F., Rinaudo F. (2011) - LiDAR or Photogrammetry? Italian Journal of Remote Sensing, 43: 107-121. doi: http://dx.doi.org/10.5721/IJRS20114328.

Peng J., Zhang D., Liu Y. (2005) - An improved snake model for building detection from urban aerial images. Pattern Recognition Letters, 26: 587-595. doi: http://dx.doi.org/10.1016/j.patrec.2004.09.033.

Rottensteiner F., Briese C. (2002) - A new method for building extraction in urban areas from high-resolution. LIDAR data. ISPRS XXXIV 3A, pp. 295-301.

Rottensteiner F. (2012) - Advanced methods for automated object extraction from lidar in urban areas. IEEE International Geoscience and Remote Sensing Symposium, Munich,
German, ISBN 978-1-4673-1160-1.
Rottensteiner F., Trinder J., Clode S., Kubik K. (2004) - *Fusing airborne laser scanner data and aerial imagery for the automatic extraction of buildings in densely built-up areas*. The International Society for Photogrammetry and Remote Sensing’s Twentieth Annual Congress, Istanbul, Turkey, pp. 512-517.
Rottensteiner F., Trinder J., Clode S., Kubik K. (2005) - *Using the Dempster-Shafer method for the fusion of LiDAR data and multispectral images for building detection*. Information Fusion, 6: 283-300. doi: http://dx.doi.org/10.1016/j.inffus.2004.06.004.
Rottensteiner F., Trinder J., Clode S., Kubik K. (2007) - *Building detection by fusion of airborne laser scanner data and multispectral images: performance evaluation and sensitivity analysis*. ISPRS Journal of Photogrammetry and Remote Sensing, 3: 135-149. doi: http://dx.doi.org/10.1016/j.isprsjprs.2007.03.001.
Rutzinger M., Rottensteiner F., Pfeifer N. (2009) - *A comparison of evaluation techniques for building extraction from airborne laser scanning*. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2: 11-20. doi: http://dx.doi.org/10.1109/JSTARS.2009.2012488.
Schenk T., Csatho B. (2002) - *Fusion of LiDAR data and aerial imagery for a more complete surface description*. ISPRS XXXIV 3A, pp. 310-317.
Sohn G., Dowman I. (2007) - *Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction*. ISPRS Journal of Photogrammetry and Remote Sensing, 62: 43-63. doi: http://dx.doi.org/10.1016/j.isprsjprs.2007.01.001.
Tarsha-Kurdi F., Landes T., Grussenmeyer P. (2007) - *Hough transform and extended Ransac algorithms for automatic detection of 3D building roof planes from lidar data*. Proceedings of: ISPRS XXXVI, Workshop on Laser Scanning 2007 and SilviLaser 2007, Espoo, Finland, pp. 407-412.
Trimble Definiens A.G. (Ed.) (2010) - *E-Cognition 8.64 Reference Book*. Trimble, Munich.
Zevenbergen L.W., Thorne C. (1987) - *Quantitative analysis of land surface topography*. Earth Surface Processes and Landforms, 12: 47-56. doi: http://dx.doi.org/10.1002/esp.3290120107.

© 2014 by the authors; licensee Italian Society of Remote Sensing (AIT). This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).