1. Introduction

Nowadays, automatic extraction of man-made objects such as buildings and roads in urban areas has become a topic of growing interest for photogrammetric and computer vision community. Researches in this domain started from late 1980s and used quite different types of source images ranging from single intensity images, color images, laser range images to stereo and multiple images (Peng et al., 2005). Some useful applications are automation information extraction from images and updating geographic information system (GIS) databases. The establishment of the database for urban areas is frequently done by the analysis of aerial imagery since photogrammetric data is three-dimensional, accurate, largely complete and up-to-date. Because manual interpretation is very time consuming, a lot of efforts have been spent to speed up this process by automatic or semi-automatic procedures. A wide range of techniques and algorithms have been proposed for automatically constructing 2D or 3D building models from satellite and aerial imagery.

In this field Dash et al. in 2004 used height variation in the context of object periphery data to develop a method based on standard deviation to distinguish between trees and buildings (Dash et al., 2004). Sohn et al. employed Lidar (Light Detection and Ranging) data in 2007 to generate height data for features in an urban region (Sohn and Dowman, 2007). They carried out the following steps for building extraction: first, they identified all features that were a certain height above ground level. Next, using the NDVI index and other information, they distinguished the buildings from other features. Finally, they detected the sharp edges of buildings and matched polygons to the close edges, in order to robustly identify building boundaries (Sohn and Dowman, 2007). In 1999, Halla and co-workers extracted building locations from images using classification algorithms and height data (Halla and Brenner, 1999). Zimmermann et al. in 2000 produced a Digital Surface Model (DSM) data from stereo images. They then used the model to detect building roofs by applying slope and aspect operators (Zimmermann, 2000). Finally, in another study, height data and morphological operators were utilized to extract buildings (Zhao and Trinder, 2000).

As reported by Hongjiana and Shiqiang (2006), another approach involves extracting the data and connecting edge pixels. This allows for the derivation of building heights from sparse laser samples and can be used to reconstruct 3D information for each building. Miliareis and Kokkas (2007) proposed a new method for extracting a class of buildings using digital elevation models.
(DEMs) generated by Lidar data on the basis of geomorphometric segmentation principles. Lafarge et al. (2008) presented an automatic building extraction method that involved digital elevation models based on an object approach. Using this method, a rough approximation of all relevant building footprints was first calculated from marked point processes. The resulting rectangular footprints were then normalized by improving the connections between neighboring rectangles and detecting any roof height discontinuities (Lafarge et al., 2008). Samadzadegan et al. (2005) proposed a novel approach for object recognition, based on neuro-fuzzy modeling, in which height data were integrated with textural and spectral information by means of a fuzzy reasoning process.

One method frequently used in building extraction is the snake model, and approach that was originally introduced by Kass et al. (1988). In 2004, Peng introduced a variation on the snake model by incorporating a new energy function to extract building boundaries from aerial images (Peng et al., 2004). Another study used a semi-automatic algorithm to extract buildings from Quickbird images (Mayunga et al., 2005). Under that algorithm, a point is first selected within the boundary of each building. Thereafter, the curves of the model are reproduced and accurate building boundaries are detected using an iterative procedure (Mayunga et al., 2005). Guo and Yasuoka (2002) estimated building boundaries from Lidar data, and then applied the snake model to determine their exact positions. Also, Cao and Yang (2007) extract man-made features from aerial images by using Fractal error metric and multi-stage active contour. Finally, Karantzalos and Paragios (2009) have applied prior shape knowledge of buildings in active contours to detect buildings with special shapes from aerial images.

Due to the fact that the most important characteristics of buildings in urban areas are their height discrepancies in relation to other features, a large number of above investigations have focused on integrating height data with aerial or satellite images to automatically extract buildings. Also, other researches have been done in this field (Rottensteiner et al., 2005; Schenk and Cspatho, 2002; Weidner and Forstner, 1995; Baillard and Maitre, 1999; Vestri, 2006). Those types of algorithms require high computational efforts and need significant technological resources in the production and analysis of the data. But it should be noted that DEM information can be used to increase their performance for isolated building detection.

In this work, a new model, based on level set formulation, is introduced to detect buildings in aerial images using active contour models. In our model, all building boundaries are detected by introducing certain points in the buildings’ vicinity. Similarly to the classical snake model, we avoid the need for initial curves. Moreover, our proposed model detects most relevant building boundaries and it does not need height data and additional information to distinguish between buildings and other features.

This paper is organized into five sections. The new active contour model for building boundary detection is elucidated in Section 2. Experimental results are listed in Section 3, and an accuracy assessment of the model is provided in Section 4. Finally, Section 5 concludes.

2. Development of a new active contour model to automatically extract buildings

This study utilizes an active contour model for automatic building boundary detection and extraction. The active contour, or snakes model, was first introduced by Kass et al. in 1987 (Kass et al., 1998). This model involves dynamic curves or surfaces that move within an image domain to capture desired image features. The curve’s motion is driven by a combination of internal and external forces, which achieve a minimal energy state when the curve/surface reaches the targeted image boundaries. Active contour models have been used in handling a variety of image problems, including image segmentation, shape recovery, and visual tracking (Li et al., 2005).

Active contour models can be classified into two categories: parametric snakes and geometrical snakes. Parametric snakes are represented explicitly as parameterized contours, and the snake evolution is only performed on the predetermined spline control points. Parametric active contours have two main drawbacks: (1) the initial contour must, in general, be close to the true boundary; otherwise it would likely converge to the wrong points (Hou and Han, 2005) and (2) these models can never change topologies during evolution. This means that when there is more than one object to capture in an image, multiple snakes must be manually and separately initialized within the neighborhood of each object (Li et al., 2005; Yan and Kassim, 2006).

Geometrical snakes, on the other hand, are represented implicitly as the zero-level sets of higher dimensional surfaces, and the updating is performed on the surface function within the entire image domain (Li et al., 2005). Geometrical active contours consist of two major types of edge based and region-based active contours. Edge based methods primarily use gradient information to locate object boundaries in the images. Caselles et al. (1995) and Malladi et al. (1995) presented the original geometric active contours independently. In addition, other researches have contributed in order to improve this model (Caselles et al., 1997; Yezzi et al., 1997; Siddiqi et al., 1998; Vasilierskiy and Siddiqi, 2002; Pi et al., 2007; Yung et al., 2009a,b).

Conversely, region-based geometrical active contours rely on the homogeneity of spatially localized features such as gray level intensity, texture, and other pixel statistics. The active contour model based on the Mumford–Shah function for image segmentation was first proposed by Chan and Vese in 2001 (Chan and Vese, 2001). The most important advantage of the active contour model is the implicit handling of topological changes and its ability to extract objects without noticeable edges from images. Another advantage of this model is its low sensitivity to noise (Chan and Vese, 2001). Several other studies in this field have worked with this approach (Chan et al., 2000; Lie et al., 2006; Brox and Weickert, 2004; Chen et al., 2006).

The above-mentioned advantages of the region-based geometrical active contour model motivated our decision to use it in this study.

In the Chan and Vese active contour model, the image is partitioned into regions that exhibit maximum homogeneity and similarity. The object boundaries are extracted from the images based on the following contour energy function (Chan and Vese, 2001):

\[ E_1(C) + E_2(C) = \int_{\text{inside}(C)} |u - c_{in}|^2 dx dy + \int_{\text{outside}(C)} |u - c_{out}|^2 dx dy \]

(1)

Here, \( C \) stands for the curve of the active contour, \( u \) represents the pixel value of the image, and \( c_{in} \) and \( c_{out} \) illustrate the average of pixel values inside and outside of \( C \), respectively (Chan and Vese, 2001).

In Eq. (1), the term \( \int_{\text{inside}(C)} |u - c_{in}|^2 dx dy \) represents sum of the differences between pixels’ gray values inside the contour and their corresponding mean value. Similarly, the term \( \int_{\text{outside}(C)} |u - c_{out}|^2 dx dy \) represents sum of the differences between pixels’ gray values outside the contour and their corresponding mean value. Then the contour shape changes in order to find the minimum value for sum of the above-mentioned terms. In this way, the contour would fit to the edges of objects.
If the curve \( C \) is the inside of an object, then \( E_1(C) \approx 0 \) and \( E_2(C) > 0 \). Conversely, if the curve \( C \) is the outside of the target object, then \( E_1(C) > 0 \) and \( E_2(C) \approx 0 \). Finally, if some part of the curve \( C \) is inside and some part of the same curve is outside of the target object, then \( E_1(C) > 0 \) and \( E_2(C) > 0 \) (Chan and Vese, 2001). Minimizing the function in Eq. (1), the curve \( C \) is fitted to the boundary of the target object \( (C_0) \) and the relation is obtained as:

\[
\inf_{C} \{ E_1(C) + E_2(C) \} \approx 0 \approx \{ E_1(C_0) + E_2(C_0) \}
\]  

(2)

To obtain a regularizing version of the function, Chan and Vese included two terms like length of \( C \) and area inside \( C \) in Eq. (1):

\[
E(C) = \mu \cdot \text{length}(C) + v \cdot \text{area}(\text{inside}(C))
\]

\[
+ \lambda_1 \int_{\text{inside}(C)} |u - c_1|^2 \, dxdy + \lambda_2 \int_{\text{outside}(C)} |u - c_2|^2 \, dxdy
\]  

(3)

Here, \( \mu \geq 0 \), and \( \lambda_1, \lambda_2 \geq 0 \) are constant parameters (Chan and Vese, 2001).

The above-mentioned active contour model detects all regions that exhibit a given similarity and homogeneity. Therefore, by changing the parameters in Eq. (3), different regions with various degrees of similarity and homogeneity can be detected from the image. The Chan and Vese model detects and extracts the boundaries as training data. Then the system can make a difference introducing of some pixel values of points inside buildings which is given to the system by knowledge about the buildings is given to the system by training samples from target objects (e.g. \( m \) pixels) and background image (e.g. \( n \) pixels) chosen by the user to train the contour. For each training data, the function \( (E_5, E_6) \) is calculated and the minimum value among them is chosen to be considered as final value for term \( (E_5) \). The same manner is performed to obtain the term \( (E_6) \) value. In this way, the trained contour position evolves to edges of the objects which are radiometrically similar to one of the training data.

So, if our test scenario involves different types of building roofs and complex image \( (B) \) backgrounds, then Eq. (3) becomes:

\[
E_{\text{total}} = \mu \cdot E_1 + v \cdot E_2 + \lambda_1 \cdot E_3 + \lambda_2 \cdot E_4 + \alpha \cdot E_5 + \beta \cdot E_6
\]  

(6)

In this function \( E_1, E_2, E_3 \) and \( E_4 \) have already been defined in Eq. (5) and \( E_5 \) and \( E_6 \) are obtained from the following equations:

\[
E_5 = \min \{ A_i \}_{i=1}^n, \quad A_i = \int_{\text{inside}(C)} |u - d_i|^2 \, dxdy, \quad i = 1, 2, \ldots n
\]

\[
E_6 = \min \{ B_j \}_{j=1}^m, \quad B_j = \int_{\text{outside}(C)} |u - e_j|^2 \, dxdy, \quad j = 1, 2, \ldots m
\]  

(7)

where \( d_i \) is the gray values of the \( i \)th building classes, \( e_j \) is the gray values of the \( j \)th background classes, \( n \) and \( m \) are number of building and background classes, respectively.

Also, we note that the model uses only grayscale or single band images as input data, and cannot utilize multiband information to detect features such as buildings. Therefore, the above model energy function should be extended for multicolored buildings and multiband images. The extended new \( E_5, E_4, E_3 \) and \( E_6 \) are defined in RGB color space by summation of the corresponding function values in each band as follows:

\[
E_3 = \sum_{b=1}^{3} \left( \int_{\text{inside}(C)} |u_b - c_{3b}|^2 \, dxdy \right)
\]

\[
E_4 = \sum_{b=1}^{3} \left( \int_{\text{outside}(C)} |u_b - c_{2b}|^2 \, dxdy \right)
\]

\[
E_5 = \min \{ A_i \}_{i=1}^n, \quad A_i = \sum_{b=1}^{3} \left( \int_{\text{inside}(C)} |u_b - d_{3b}|^2 \, dxdy \right), \quad i = 1, 2, \ldots n
\]

\[
E_6 = \min \{ B_j \}_{j=1}^m, \quad B_j = \sum_{b=1}^{3} \left( \int_{\text{outside}(C)} |u_b - e_{3b}|^2 \, dxdy \right), \quad j = 1, 2, \ldots m
\]  

(8)

where \( b \) is the number of RGB bands. To minimize the above energy function, we use the level set method.

### 2.1. The level set formulation of the model

The level set method is used to calculate energy functional of the model over the entire image domain \( \Omega \). In the level set method
(Osher and Sethian, 1988), curve C is represented by the zero-level set of a Lipschitz function \( \phi: \mathbb{R}^2 \rightarrow \mathbb{R} \), such that (Chan and Vese, 2001):
\[
\begin{cases}
C = \{ x \in \mathbb{R}^2; \ \phi(x,y) = 0 \} \\
\text{inside} \quad \mathcal{C}_0 = \{ x \in \mathbb{R}^2; \ \phi(x,y) < 0 \} \\
\text{outside} \quad \mathcal{C}_0 = \{ x \in \mathbb{R}^2; \ \phi(x,y) > 0 \}
\end{cases}
\]
(9)

To define the functional energy based on the level set method, Chan and Vese introduced two additional functions (Chan and Vese, 2001) (Heaviside function \( H \) and the one-dimensional Dirac measure \( \delta \)):
\[
H(\phi) = \begin{cases}
1, & \phi \geq 0 \\
0, & \phi < 0
\end{cases}
\]
\( \delta(\phi) = \frac{d}{d\phi} H(\phi) \)

Based on level set method and using Eqs. (9) and (10), the definition of each element of Eq. (6) becomes:
\[
\begin{align*}
\text{length}\{\phi = 0\} & = \int \nabla H(\phi) \cdot dx = \int \delta(\phi) \nabla |\phi| dx dy \\
\text{area}\{\phi \geq 0\} & = \int \Omega H(\phi) dx dy \\
E_1 & = \int \Omega \delta(\phi) \nabla |\phi| dx dy \\
E_2 & = \int \Omega H(\phi) dx dy \\
E_3 & = \int \Omega |u - c_{\text{in}}|^2 H(\phi) dx dy \\
E_4 & = \int \Omega |u - c_{\text{out}}|^2 (1 - H(\phi)) dx dy
\end{align*}
\]
(11)

where \( c_{\text{in}} \) and \( c_{\text{out}} \) are obtained from the following equations:
\[
\begin{align*}
c_{\text{in}}(\phi) & = \int \Omega u \cdot H(\phi) dx dy \\
c_{\text{out}}(\phi) & = \int \Omega u \cdot (1 - H(\phi)) dx dy \\
& \quad \int \Omega (1 - H(\phi)) dx dy
\end{align*}
\]
(12)

More details can be found in (Chan and Vese, 2001). Also, based on new formulation \( E_5 \) and \( E_6 \) in Eq. (6) are obtained from the following equations:
\[
\begin{align*}
E_5 & = \text{Min}\{ \left\{ A_i \right\}_{i=1}^{n}, \quad A_i = \int \Omega |u - d_i|^2 H(\phi) dx dy, \quad i = 1,2,\ldots n \\
E_6 & = \text{Min}\{ \left\{ B_j \right\}_{j=1}^{m}, \quad B_j = \int \Omega |u - e_j|^2 (1 - H(\phi)) dx dy, \quad j = 1,2,\ldots m
\end{align*}
\]
(13)

where \( \Omega \) is the entire image domain in the above equations.

2.2. Minimizing the energy functional of the model

Now consider the minimization of the functional \( E_{\text{total}} \). It can be solved by the following evolution equation (Evans, 1998):
\[
\frac{\partial \phi}{\partial t} = - \frac{\delta E_{\text{total}}}{\delta \phi}
\]
(14)

Here \( t \) represents the time. Therefore, the function \( \phi \) that minimizes this functional satisfies the Euler–Lagrange equation. The steepest descent process for minimization of the functional \( E_{\text{total}} \) is the following equation:
\[
\frac{\partial \phi}{\partial t} = - \frac{\delta E_{\text{total}}}{\delta \phi} = \delta(\phi)[\mu \cdot F_1 - v - \lambda_1 \cdot F_2 + \lambda_2 \cdot F_3 - \alpha \cdot F_4 + \beta \cdot F_5] = 0
\]
(15)

Here, \( F_1, F_2, F_3 \) and \( F_4 \) are obtained from the following equations:
\[
\begin{align*}
F_1 & = \text{div} \left( \frac{\nabla \phi}{|\nabla \phi|} \right) \\
F_2 & = (u - c_{\text{in}})^2 \\
F_3 & = (u - c_{\text{out}})^2 \\
F_4 & = \text{Min}\{ \left\{ M_i \right\}_{i=1}^{n}, \quad M_i = |u - d_i|^2, \quad i = 1,2,\ldots n \\
F_5 & = \text{Min}\{ \left\{ N_j \right\}_{j=1}^{m}, \quad N_j = |u - e_j|^2, \quad j = 1,2,\ldots m
\end{align*}
\]
(16)

To solve the above set of equations, \( H(\phi) \) and \( \delta(\phi) \) should be normalized because the building boundaries in the images have not been smoothed. Chan and Vese (2001) proposed the following formulas:
\[
H_{\text{c}}(\phi) = \frac{1}{2} \frac{1}{\pi} \arctan \left( \frac{\phi}{\varepsilon} \right)
\]
\( \delta_{\text{c}}(\phi) = \frac{1}{2} \frac{1}{\varepsilon^2 + \phi^2} \)
(17)

In the above equations \( \varepsilon \) is a very small number greater than zero. When \( \varepsilon \to 0 \) both \( H(\phi) \) and \( \delta(\phi) \) converge to \( H(\phi) \) and \( \delta(\phi) \) respectively. More details can be found in (Chan and Vese, 2001).

2.3. The numerical approximation of the model

To discretize the equation in \( \phi \), we use a finite differences implicit scheme (Chan and Vese, 2001). Therefore, the discretization and linearization of the curve evolution function are written as:
\[
\begin{align*}
\frac{\phi_{i,j}^{n+1} - \phi_{i,j}^{n}}{\Delta t} & = \delta_{c_{i,j}} \left[ \frac{\mu}{h^2} \nabla^2 \left( \frac{\Delta \phi_{i,j}^{n+1}}{h^2} + \frac{\Delta \phi_{i,j}^{n+1} - \Delta \phi_{i,j}^{n}}{(2h^2)} \right) \right] \\
& \quad + \frac{\mu}{h^2} \nabla^2 \left( \frac{\Delta \phi_{i,j}^{n+1}}{h^2} + \frac{\Delta \phi_{i,j}^{n+1} - \Delta \phi_{i,j}^{n}}{(2h^2)} \right) \\
& \quad - v - \lambda_1 (u_{i,j} - c_{\text{in}}(\phi^n))^2 + \lambda_2 (u_{i,j} - c_{\text{out}}(\phi^n))^2 \\
& \quad - \alpha \text{Min}_{k=1}^{n} \left[ (u_{i,j} - d_k(\phi^n))^2 \right] + \beta \text{Min}_{k=1}^{m} \left[ (u_{i,j} - e_k(\phi^n))^2 \right]
\end{align*}
\]
(18)

where \( \Delta t \) and \( h \) are time iteration step and space iteration step respectively and the forward differences of \( \phi_{i,j}^{n+1} \) are calculated based on:
\[
\begin{align*}
\Delta_x \phi_{i,j} & = \phi_{i+1,j} - \phi_{i,j} \\
\Delta_x \phi_{i,j} & = \phi_{i,j+1} - \phi_{i,j} \\
\Delta_y \phi_{i,j} & = \phi_{i,j+1} - \phi_{i,j} \\
\Delta_y \phi_{i,j} & = \phi_{i,j+1} - \phi_{i,j}
\end{align*}
\]
(19)

More details about discretization of Eq. (16) can be found in (Chan and Vese, 2001). For the level set formulation, the new proposed building extraction model incorporates five major stages. In the first stage, geometric and radiometric corrections are applied to the input image. The next step, depending on the number of buildings and background classes, introduces appropriate pixel values for points inside and outside building boundaries as training data. Then, the proposed active contour model is activated, and building boundaries are extracted. Subsequently, the extracted building boundaries are then generalized to smooth out jagged lines by using perpendicular angles and straight lines (Dutter et al., 2007). Finally, the accuracy of the detected buildings is evaluated. Fig. 1 illustrates the process.
3. Experimental results

The proposed model was implemented and tested on an aerial image from Lavasan (central Iran). Fig. 2 shows the original images from the test regions. The spatial resolution of the image is 0.5 and it was acquired on August 2005.

The model was initialized by introducing sample data of two points from buildings (for two classes of buildings) and two points from the background (for two classes of image background) in the image. The initial curves were generated automatically as a series of regular circles all over the image (Fig. 3).

Based on our experimental results, we conclude that if there are more than 36 initial curves (6 \times 6 circles), then the curve number will only impact the model’s speed of execution. By increasing the initial curve number, the model’s output does not vary. However, having too few initial curves can impact the model’s accuracy, leading to some buildings going undetected.

In the next stage, the constant parameters of the model are set and the active contour model suggests initial positions for the curves. After ten iterations, the curves had been linked with the building boundaries. The optimum values of the model parameters were determined experimentally using a trial and error approach. It should be mentioned that once the parameters are determined for an image, then the parameters have a slight change for other test images. For instance, if parameter alpha is found to be 1 for an image, then there would be a small variation for alpha parameter for other images such as \( \alpha = 1.15 \). Thus the parameters do not change extensively and it can be easily adopted for other images. Table 1 represents the optimum values of the constant parameters.

Table 1

<table>
<thead>
<tr>
<th>Constant parameters</th>
<th>Optimum number</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \mu )</td>
<td>1</td>
</tr>
<tr>
<td>( \nu )</td>
<td>1</td>
</tr>
<tr>
<td>( \lambda_1 )</td>
<td>1.5</td>
</tr>
<tr>
<td>( \lambda_2 )</td>
<td>2</td>
</tr>
<tr>
<td>( \alpha )</td>
<td>4</td>
</tr>
<tr>
<td>( \beta )</td>
<td>0.8</td>
</tr>
</tbody>
</table>

In the next stage, the constant parameters of the model are set and the active contour model suggests initial positions for the curves. After ten iterations, the curves had been linked with the building boundaries. The optimum values of the model parameters were determined experimentally using a trial and error approach. It should be mentioned that once the parameters are determined for an image, then the parameters have a slight change for other test images. For instance, if parameter alpha is found to be 1 for an image, then there would be a small variation for alpha parameter for other images such as \( \alpha = 1.15 \). Thus the parameters do not change extensively and it can be easily adopted for other images. Table 1 represents the optimum values of the constant parameters.

After ten iterations, the contours remained static and the process could be terminated. Fig. 4 demonstrates curve positions from 10th iterations.

The extracted building boundaries had many vertices and were highly irregular—entirely unsuitable for importing into Geographic Information Systems. Therefore, in the final stage, we generalized all of our primary building boundaries to eliminate the redundant points. Our chosen generalization method mirrors that recommended by Dutter et al. in 2007 (Osher and Sethian, 1988). The output of this step was a series of regular building polygons with semi-perpendicular angles and straight lines (Fig. 5). An accuracy assessment of the presented model is presented in the next section.
4. Accuracy assessment of the model

Many parameters affect the accuracy of the proposed model and can impact its outputs. The most important effective parameters are listed below:

- Number of initial curves
- Number of building and background classes
- Values of constant parameters
- Iteration number

(I) Number of initial curves: Based on our experimental results, we conclude that if there are more than 16 initial curves (circles) for the image ($4 \times 4$ circles), then the curve number will only impact the model’s speed of execution. By increasing the initial curve number, the model’s output does not vary. However, having too few initial curves can impact the model’s accuracy, leading to some buildings going undetected.

(II) Number of building and background classes: The principle factor in achieving the best model result is the number of building and background classes selected. Using fewer building classes than the actual number of building classes will result in some buildings not being extracted or being detected incorrectly. Also, if there are more than 8 classes of buildings in the image, then the proposed model cannot detect all buildings precisely and probably some buildings are not detected.

(III) Value of the constant parameters: The model incorporates parameters that determine the effect of each term consistent with the energy function in the model. These can be assigned experimentally for each image.

(IV) Iteration number: This parameter controls the curve evolution process and terminates the model after a certain iteration number. In our model, all of the curve positions would change for up to ten iterations with image, after which the contours would become essentially immobile.

To evaluate the accuracy of our model, we calculated McKeon’s shape accuracy metric (McKeown et al., 2000), completeness and correctness factors of the extracted building boundaries.

- **Shape accuracy**: To calculate the shape accuracy, all true building areas were compared to the model values (McKeown et al., 2000):

\[
\text{shape accuracy} = \left(1 - \frac{|A_1 - A_2|}{A}\right) \times 100
\]

\[
(20)
\]

\[
\text{Table 2}
\]

Shape accuracy as obtained from the model given image of the tested region.

<table>
<thead>
<tr>
<th>Shape accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum shape accuracy</td>
</tr>
<tr>
<td>Minimum shape accuracy</td>
</tr>
<tr>
<td>Mean shape accuracy</td>
</tr>
</tbody>
</table>

\[
\text{Table 3}
\]

The completeness factor for the proposed model.

<table>
<thead>
<tr>
<th>Completeness factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>All buildings</td>
</tr>
<tr>
<td>Extracted buildings</td>
</tr>
<tr>
<td>Completeness factor</td>
</tr>
</tbody>
</table>

In this equation, $A_1$ is the true building area and $A_2$ is the area of its corresponding detected value. It should be mentioned that in this research the true position of buildings are generated manually in ArcGIS software. Table 2 demonstrates the results of applying our model to the tested images.

- **Completeness**: The completeness of the presented model is obtained from the ratio of extracted buildings to the total number of existing buildings in the image domain. Table 3 illustrates the completeness factor for our model.

Because of radiometric similarity between some buildings and image background, these buildings are not extracted. Also, size of some buildings in the image is very small, so this type of buildings is not detected. In the above-mentioned equations by changing $\mu$ and $v$ with respect to other parameters, the operator can adjust the minimum size of buildings that are detected. In Fig. 6 some of the buildings that have not been extracted are presented by using green ellipses.

- **Correctness**: This factor demonstrates the accuracy of the model in terms of boundary extraction performance. The factor is the ratio of accurately extracted buildings to the total. Table 4 shows the correctness factor for our model.

Some buildings in the image are not extracted correctly because the radiometric characteristic of this building is similar to image background. Fig. 7 shows some of inaccurately extracted buildings.

\[
\text{Table 4}
\]

The correctness factor of our model.

<table>
<thead>
<tr>
<th>Correctness factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extracted buildings</td>
</tr>
<tr>
<td>Accurate Extracted buildings</td>
</tr>
<tr>
<td>Correctness factor</td>
</tr>
</tbody>
</table>
References

Milaire, G., Kokkas, N., 2007. Segmentation & object based classification for the extraction of the building class from LiDAR DEMs. Computers & Geosciences 33, 1076–1087.

