Automatic Building Extraction Using a Fuzzy Active Contour Model

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Abstract
Automatic building extraction is currently an important research topic in the field of photogrammetry. An active contour model is a well-received approach in this field. This paper proposes an improved active contour model that focuses on building extraction from aerial images and lidar data. The main research concern in this paper is the development of energy functions to the optimum use of expert human knowledge in the overall process. Based on this approach, a new fuzzy inference system for evaluating energy functions was developed by modeling the human perception of various effective parameters in the energy functions. Compared to the existing active contour models, the new algorithm is capable of directing the initial contour to building feature boundaries more quickly and robustly. Accuracy assessment showed that the proposed model is capable of achieving a shape accuracy of 98 percent and a total accuracy of 97 percent in complex urban areas.

Introduction
Urban feature extraction is currently one of the most difficult and complicated processes that machine vision and photogrammetry experts are addressing. Information concerning urban features is necessary for various applications such as urban planning and development, GIS (Geographic Information System) database updates, and urban model generation. In conventional methods, feature extraction from digital images is conducted manually, slow, and expensive process requiring professional operators. The development of automatic approaches have been considered for the past decade.

Buildings are considered a vital group of urban features by researchers in this area. The extraction of building features from digital images is more complicated, because buildings have different shapes, roof composite materials, and radiometric characteristics.

Numerous methods and algorithms for the 2D and 3D reconstruction of building models using various sources of information are reported in the literature. In Dash (2004), the height variation of objects was used to develop an approach to separate buildings and vegetation based on the standard deviation of elevation. Hongjian (2005) extracted and joined the edge pixels and then computed the building elevation by using laser scanner data to reconstruct the 3D building model. The fusion of IKONOS satellite imagery and aerial laser scanner data was used by Sohn (2007) to extract buildings automatically. An automatic method for building extraction from the digital elevation model was also proposed by Lafarge et al. (2008). Tanathong et al. (2009) presented a robust rectangular building detection process that can discover small-size buildings in residential areas and large-size buildings in industrial areas. Huang and Zhang (2011) proposed a new morphological building index for automatic building extraction. By using this index, the relationship between the implicit characteristics of the building and the properties of morphological operators has been determined. Huang et al. (2011) also investigated information fusion approaches with high-resolution aerial images and elevation data from lidar (Light Detection and Ranging) for urban environment mapping. You and Lin (2011) proposed a novel approach for building extraction from lidar data. In their paper, a tensor field has been used to represent the geometric features of lidar points. Meng et al. (2012) presented an object-oriented method to detect residential buildings for a land use map. In their method, a multidirectional ground filter was first applied to generate a bare ground surface from lidar data. Then, using a morphology-based algorithm, the buildings were detected. Huang and Zhang (2012) proposed a method for building extraction from high-resolution imagery that aims to alleviate both commission and omission errors for the original MB (morphological shadow index) algorithm. In this paper, the improvement includes three aspects: (a) a MSI (morphological shadow index) is proposed to detect shadows that are used as a spatial constraint of buildings, (b) a dual-threshold filtering is proposed to integrate the information of MSI and MSI, and (c) the proposed framework is implemented in an object-based environment where a geometrical index and a vegetation index are then used to remove noise from narrow roads and bright vegetation.

The active contour model proposed by Kass (1988) was a successful method that was widely used in image processing tasks such as image segmentation, image monitoring, and 3D object reconstruction. An active contour model is an energy minimization method that directs the contour to features such as image edges and lines. To illustrate the capabilities of this model in object extraction, the model was also used in building extraction by the researchers in this area. Ruther (2002) proposed a method for semi-automatic building extraction from aerial images in dense irregular areas. This method used an appropriate strategy to extract the initial boundaries of buildings. An improved active contour model was proposed by Peng (2005) for building extraction from single-band high-resolution imagery. This model represented an improvement over existing models in the initial seed point selection process as well as the external energy function. In Mayunga (2005), a semi-automatic algorithm was presented for building...
extraction in structured and non-structured urban areas from single-band high-resolution imagery. Karantzalos and Paragios (2009) applied prior shape knowledge of buildings in active contours to detect buildings with special shapes from aerial images. In Kabolizade et al. (2010), an improved snake model was proposed that focused on building extraction from color aerial images and lidar data. Their proposed snake model included a new height similarity energy factor and regional similarity energy as well as gradient vector flow (GVF). A new model of active contours that optimized automatic building extraction was presented in Ahmadi et al. (2010). Their active contour model was trained using gray levels of building roof pixels.

Active contour models are divided into two categories from the modeling point of view: non-parametric, or geometric, models and parametric models. Active contour models can also be divided into edge-based and region-based depending on the energy function determination used. In edge-based models, the contour is determined based on the image gradient information. Region-based models are defined based on the homogeneity of some of the properties of each area. The fusion of edge-based and region-based models can improve the results in images with weak gradient information or where the gradient information is insufficient for determining the contour properly because of the presence of noise or other problems influencing the record of gray levels (Chan et al., 2000; Brox and Weickert, 2004; Chen et al., 2006). To improve the efficiency of the model in automatic building extraction, the fusion of edge-based and region-based terms in the design of the energy function is used in this research.

A problem of most existing active contour models in the building extraction area is ignorance of the usefulness of human information and knowledge in the computation of the energy function. In existing models, the user controls the effect of the energy function parameters by using weighting coefficients. These coefficients are usually determined by an expert using a trial-and-error process. This process causes the model to be dependent on the user and reduces the ability of the user to control the influence of various parameters in the energy function.

A tool that can be used to enter expert human knowledge into the contour improvement process is a fuzzy logic system. When the energy function is computed by using the fuzzy inference system, control over different parts of the energy function can be increased.

Another benefit of the use of expert knowledge is that expert knowledge facilitates the fusion of various information sources in the design of the external energy function. The definition of rules based on the expert’s knowledge of the responses of building objects obtained from different information sources can help to achieve the appropriate fusion of these information sources and improve the building extraction process. This paper focuses on a design of a fuzzy inference system to incorporate human knowledge into active contour models in order to extract buildings from both the image data and the lidar height data.

Methodology

In this research, an improved active contour approach is used for building extraction from high-resolution images. Lidar height data provide useful information for separating buildings from other urban features in the scene, and in this research, both optical images and lidar data are used for better direction of contours. A fuzzy inference system has been used to calculate the external energy function and optimize the performance of the model.

Figure 1 shows the flowchart of the method used in this research. This method can extract the buildings from the scene in three steps:

1. Initial contour detection: In this step, the goal is to divide the entire scene into buildings and background. The initial contours of buildings are generated by using two thresholds for the elevation and roughness of the DSM of the scene.
2. Designing energy function: In this stage, the energy function is computed by use of expert knowledge rules in form of a fuzzy inference system and the fusion of extracted edge-based and region-based information from lidar data and images.
3. Building extraction: In the last step, minimum amounts of the energy function in the image are searched as the main candidates of the building region by using dynamic programming, and the final building boundaries are extracted.

The above steps are described in detail in the following subsections.

Initial Contour Detection

Initial contours are automatically extracted from scene elevation data provided by an aerial laser scanner. In the first step of the proposed method, the DSM is produced by using the first return of the aerial laser scanner pulses. To generate a rough DEM (Digital Elevation Model) of the scene, a Sohn filter (Sohn and Dowman, 2002) is used to separate on-terrain and off-terrain points in two steps. By subtraction of DEM from DSM, the NDSM (normalized Digital Surface Model) of the scene is generated. This model includes objects that are higher than the terrain. These objects include trees, vegetation, automobiles, buildings, and any other elevated features. A height threshold can be used to eliminate those objects having a lower elevation than buildings. Assuming that the minimum elevation of buildings in the scene is approximately 3 meters, most of the non-building objects including cars and low vegetation, such as bushes, would be eliminated from the normalized DSM by setting the height threshold to 3 meters. The remaining objects would normally be buildings and some trees. To separate buildings from trees, the surface roughness of the NDSM can be used. Because the variety in elevations of trees is much more than that of buildings, the entropy of

Figure 1. The main steps of the proposed building extraction method.
elevation can be applied to discriminate buildings from trees (Equation 1):

$$ \text{Local entropy} = -\sum_{i,j} p_i[i,j] \times \ln(p_i[i,j]) $$

where $p_i[i,j]$ represents the gray level co-occurrence matrix arrays, and $\ln(p_i[i,j])$ is the logarithm of this array (Ashour et al., 2007). If multispectral data are available for the scene, the use of vegetation indices, such as NDVI, is more appropriate to eliminate the vegetation. After the roughness index is applied to the lidar data, vegetation areas are detected and eliminated from the NDSM of the scene. After this stage, the remaining objects on the NDSM represent the building areas of the scene with a high level of confidence.

Designing the Fuzzy Active Contour Model

An active contour model directs the initial boundary to an optimum location, mainly the true boundary of image objects, using minimization of an energy function. The proper definition of this function greatly affects the final outcome of object extraction. The energy function used in this model is composed of two parts including the internal and external energies (Equation 2):

$$ E = \int_0^1 (E_{\text{int}}(v(s)) + E_{\text{ext}}(v(s))) ds $$

where $E_{\text{int}}$ and $E_{\text{ext}}$ are the internal and external energies estimated for the current position of the contour $v(s) = \{x(s), y(s)\}$; $s$ is the independent parameter of the position of the contour, and $x$ and $y$ are the image coordinates (Kass, 1988). The purpose of the algorithm is to find a location that minimizes the energy function.

The internal energy is a function of the geometric characteristics of the contour including its continuity and smoothness (Equation 3). Minimizing this term adjusts the geometric characteristics of the contour in the search process.

$$ E_{\text{int}}(v(s)) = \frac{1}{2} (\alpha(v'v''|s + \beta|v|v|) $$

In Equation 3, $v'(s)$ and $v''(s)$ are the first and second order derivatives of the contour (Kass, 1988). The first part of the above equation controls the continuity of the contour as well as the distance between its points, while the second part controls the smoothness of the contour. The parameters $\alpha(s)$ and $\beta(s)$ are the constant weights of each part, and their value depends on the desired object.

The external energy is the force exerted on the contour that guides it to converge with the true boundary of the desired image object. The proper definition of the external energy function has a significant effect on the final outcome of object boundary extraction. The external energy function parameters define how the image data are used in the process of contour direction.

In edge-based active contour models, the external energy function is designed based on gradient information, so such a model directs the contour to locations with high image gradient positions. Sudden and strong changes in the gray levels, due mainly to noise as well as the edges of non-building objects or objects on building roofs, are high-gradient locations of the image which deviate from the contour conduction process. More serious problems are observed in images with weak gradient information or complex texture as well as noise.

Both edge-based and region-based information are used in this research to achieve optimized and better performance. The design of the region-based energy function is based on the homogeneity of certain surface characteristics. The noise sensitivity of these models is reduced so that the use of these functions can improve the model performance (Kabolizade et al., 2010).

However, assigning the proper values to the weighting coefficients of the external energy functions is the most problematic stage in the previous active contour models. The weights in the energy function adjust the amount of contribution of each parameter to the final object extraction results. Traditionally, weighting values are determined by users on a trial and error basis and have a significant role in the final extraction results.

The external energy in an ideal case not only applies a variety of information sources (edge-based, region-based, height information, etc.) but also allows the influence of each source to be properly adjusted according to well-defined weight parameters. Expert knowledge concerning the conceptual importance of each feature in the separation of the building from other objects must be considered, and expert knowledge should be the basis that determines its influence in the energy function.

Because the use of intelligent systems such as fuzzy systems provides the tools for introducing expert knowledge to computational algorithms, this computational intelligence method is used in this research.

Because a fuzzy inference system is the most appropriate intelligent system for introducing expert knowledge to the computational algorithms, a fuzzy inference system is used in this research to provide the external energy function. The use of fuzzy systems for the computation of the external energy function makes it possible to adjust the influence of each parameter according to the expert knowledge of the user during the design process.

A classic fuzzy inference system consists of a rule base, membership functions, and an inference engine. The rule base includes rules derived from expert knowledge, which are expressed mostly as if-then conditional sentences. A fuzzy conditional expression can be written as follows (Fuller, 1995):

$$ \text{If } x \text{ is } A, \text{ then } y \text{ is } B $$

In this expression, $A$ and $B$ are linguistic variables defined on the whole possible interval for $x$ and $y$. The rule base is the most important part of a fuzzy inference system. The definition of appropriate and comprehensive rules is very effective in the performance of the system. In this research, the rules are defined and used based on the conceptual model of buildings with respect to different information sources.

The second part of a fuzzy inference system is the membership functions. In the crisp case, the membership of a member in a set could be zero (non-member) or one (full membership) while in fuzzy logic this membership is defined in the $[0, 1]$ interval. The fuzzy set $A$ defined on $X$ can be shown as follows (Fuller, 1995):

$$ A = \{x, \mu_A(x) | x \in X\} $$

where, $\mu_A(x)$ is the membership value of $x$ to the set $A$. Membership functions are used to determine the degree of membership of a member in a fuzzy set, and these functions are defined in various forms with respect to the type of the problem. For the problem in this research, Gaussian membership functions are used to fuzzify the linguistic variables. A Gaussian function, as shown in Equation 6, can be modeled with three parameters ($a$, $b$, and $c$) (Fuller, 1995). Different forms of the function can be designed by changing the values of these parameters.

$$ \mu_A = \exp\left(-\left[\frac{(x-c)}{\sigma}\right]^2\right) $$

where $a$, $b$, and $c$ are linguistic variables defined on the whole possible interval for $x$. The membership value of $x$ to the set $A$ is given by $\mu_A(x)$. The membership values of $x$ to the set $A$ are calculated using the Gaussian membership function.

The inference engine is another important part of a fuzzy inference system and defines how the system makes decisions based on the expert knowledge stored in the rule base. The Mamdani inference system was used in this research (Sivarao, 2008).
To design the external energy function of the active contour model, four image properties as well as a property extracted from height information are used. Image properties include edge intensity, edge length, gray level difference between the two sides of the edge, and the amount of curvature of the edge pixels. The extracted height of objects from NDSM is also used as the height property.

The fuzzification of each property, which makes the definition of expert rules and their entrance to the fuzzy inference system possible, as previously discussed. The energy function design on the fuzzified properties in the fuzzy inference system based on expert rules is then presented. Finally, the minimization of this energy function is discussed.

**Fuzzification of Input Features**

In this paper, high-resolution optical images and the elevation data obtained by lidar are used as the input data sources. Input features, applied to define the energy function, are extracted from these two data sources. From the optical image data source, image edge intensities are extracted to be used as an input feature. For this reason, the Sobel edge extraction operator is used where the lowest possible threshold is set so that it has the maximum sensitivity and the minimum loss of the weak edges. In the following paragraphs, the extracted properties from the optical image and then the height feature from elevation data are presented as well as their fuzzification process.

**Edge Intensity**

The edge information is one of the most important pieces of information used in active contour models for object recognition. Common binary edge detection operators divide the image into edge and background classes based on a threshold defined by the user. All pixels with gradient values more than the predetermined threshold are considered to be edge pixels while the remaining pixels are labeled as background. The binary edge detection approach clearly leads to the loss of edge information due to the nature of the thresholding. The binary edge detection approach is accordingly motivated to use edge intensity as a fuzzy parameter. In this way, all the image pixels contribute to the energy function proportionally to their edge intensities, which prohibits the information loss caused by thresholding.

To design the membership functions for the edge intensity feature, three linguistic variables are used, namely: “strong,” “medium,” and “weak” edges. The three Gaussian membership functions shown in Figure 2 are $\mu_A^1$ for weak edges, $\mu_A^2$ for medium edges and $\mu_A^3$ for strong edges.

**Edge Length**

Edge detection operators are primarily searching for abrupt gray level changes, and many undesired noises are usually detected. Additionally, the edge detection operators are prone to have many image edges which do not represent the building boundaries, which are usually related to small image objects.

Structural edges that represent building boundaries are mainly long edges. In some research (e.g., Kabolizade et al., 2010), a length threshold was used to eliminate undesired edges. However, determination of this threshold so that it would not eliminate the structural edges of buildings is a problematic issue usually resolved with a trial-and-error approach of an experienced operator.

The aim is to determine the role of each edge in the energy function of the active contour model proportional to its length by defining suitable linguistic variables.

Three linguistic variables, including “long,” “medium,” and “short” edges, are used again. The Gaussian membership functions $\mu_B^1$ for short edges, $\mu_B^2$ for medium edges, and $\mu_B^3$ for long edges are defined to compute the membership of each edge for these linguistic variables (see Figure 2). The edge lengths are normalized in the [0, 1] interval, and the membership function parameters are computed in such a way that most of the building edges have maximum membership in the long edges set.

**Gray Level Difference across Edge**

Using region-based terms in an external energy function can reduce the sensitivity of active contour models to noise and background object edges. A fuzzy region-based term is therefore used. The definition of this region-based term is based on the gray level difference of the two sides of the building edges.

The gray level difference across the edges of objects located on the roofs is usually low, while this value increases for the structural edges of the buildings. The application of this term is intended to discriminate the true edges of the building boundaries from the edges of the objects located on the roofs, which are the most deflecting features in the search process of the active contour model.

As the first step, the edge orientation is determined for each edge pixel. The edge direction information or the location of the previous and next edge pixels can be used to determine the edge orientation. Then, the absolute differences of gray levels across the estimated orientation of the edge pixels are determined to be the region-based term in the external energy function. This term can be expected to improve the active contour search process by avoiding non-building edges.

The design of the membership functions for this feature is also carried out in favor of the maximum achievable separation between building and non-building pixels. Similarly, the linguistic variables for this feature include “high,” “medium,” and “low”, and the parameters of the Gaussian membership functions are similar to the functions that are used for the edge intensity feature (Figure 3).

**Edge Curvature**

Considering the behavior of building and non-building edges, building edges exhibit less curvature than other image edges. Therefore, curvature can be regarded as another feature to enhance the ability of the model to isolate building edge pixels from non-building pixels. For this reason, edge curvatures

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**Figure 2.** Membership functions of the edge intensity linguistic variables.

**Figure 3.** Membership functions of the edge curvature linguistic variables.
are fuzzified and introduced to the fuzzy inference system as other parameters of the external energy function. Two linguistic variables, namely “low curvature” and “high curvature,” are used for this feature. To compute the membership of each edge pixel in these linguistic variables, the Gaussian membership functions $\mu_{C1}$ for edges with low curvature and $\mu_{C2}$ for edges with high curvature are used (see Figure 3).

**Elevation**

Elevation is considered an important feature to separate elevated objects, such as buildings, from the background. This feature is therefore another parameter applied in the fuzzy inference system.

To fuzzify the elevation feature, two linguistic variables, including “low elevation” and “high elevation,” are used. To compute the membership of each edge pixel in these linguistic variables, Gaussian membership functions, namely $\mu_{E1}$ for “low elevated” and $\mu_{E2}$ for “high elevated” pixels, are defined. Considering the height range of buildings in the study area that are between 3 to 5 meters, the parameters of the membership function are determined (see Figure 4).

**Design of the External Energy Function based on Fuzzy Inference System**

The external energy function defines how image information is used in the direction of the contour. This function determines the force exerted in the contour and guides the force to converge with the proper edges of the desired object. Appropriate definition of this part of the energy function therefore has a significant impact on the final extraction results of the active contour model.

In this research, the computation of the energy function is accomplished in the form of a fuzzy inference system. The definition of the fuzzy rules in the system is performed based on expert knowledge of the building object. These rules are introduced to the system as if-then conditional sentences, and the fuzzy rules are fixed for every edge pixel.

The antecedents of these rules are generated based on the input features introduced (i.e., edge intensity, edge length, curvature, etc.) while the consequence is devoted to the linguistic variables of the external energy function.

In this research, the linguistic variables of the energy function are composed of “very high,” “high,” “medium,” “low,” and “very low” (see Figure 5). To speed up the process of the algorithm, the amount of the energy function is computed only for edge pixels.

Table 1 shows some of the defined rules, which are based on the building model in different data sources and introduced by an expert.

When suitable expert rules are defined, the estimated values of the five input properties for each edge pixel are introduced. The membership functions needed in the antecedent parts of rules are then estimated. Finally, the membership function of the consequence, which is the same as the external energy function, is obtained based on the Mamdani inference model. By using a defuzzification function, the quantitative value of the membership function is calculated similar to the quantitative value assigned to the external energy function.

**Minimizing the External Energy Function**

An active contour model conducts the initial contour to the proper edges of the building by minimizing the energy function. In this research, a dynamic programming method is used to minimize the external energy function.

Dynamic programming is a solution strategy for optimizing problems that involve sequential or multistage decision-making. The theory of dynamic programming was explained by Bellman and Dreyfus (1962), Nemhauser (1966), Ballard and Brown (1992), Cooper and Steinberg (1970), and Amini et al. (1990). Through dynamic programming, building contour optimization is solved as a discrete multistage process. For this reason, initial building contours are introduced as the inputs into the dynamic programming optimization process from which final building contours are extracted.
obtained from the edge image resulting from the implementation of the Sobel operator on the test optical image.

Figure 8 is a gray level representation of fuzzy values for the input features. The input features also involve the height obtained from lidar data. (Figure 6b)

According to the input fuzzy parameters and based on the rule base provided, the external energy was estimated iteratively and applied as input to the dynamic programming. The minimized energy function directed the initial contours of Figure 7 to the building boundaries. Figure 9 shows the extracted buildings by using the fuzzy active contour method.

Ground truth data collected manually from some parts of the image are used for the evaluation of the system. To this end, extracted buildings should be compared with those extracted manually. In the method presented by McKeown et al. (2000), a building-to-building comparison was performed to evaluate the effectiveness of the proposed method. In their method, the shape accuracy of each extracted building was evaluated based on the overlap with its corresponding buildings in the ground truth data (Equation 7).

\[
\text{Shape accuracy} = \left(1 - \frac{A - B}{A}\right) \quad (7)
\]

where, \(A\) is the area of a building in the ground truth, and \(B\) is the area of its corresponding building extracted by the method. This factor determines the accuracy of the shape of buildings and their area completeness. The results of this investigation are presented in Table 2. These measures are calculated to compare the efficiency of the proposed model to previous models. They were also computed for the active contour model proposed by Kabolizade et al. (2010), which used a similar, non-fuzzy energy function.

However, the shape accuracy assessment in Table 2 does not consider the commission and omission errors of the system output (McKeown et al., 2000). For a better assessment of the algorithm, some statistical assessment parameters computed from the confusion matrix are also determined. The confusion matrix is useful for visualizing image classification results and for statistically measuring the results (Congalton, 2005). A measure of overall accuracy can be calculated by dividing the sum of all the entries in the major diagonal of the matrix by the total number of sample units in the matrix (Story and Congalton, 1986). The confusion matrix also provides omission and commission errors. Omission errors (Producer Accuracy) can be calculated by dividing the total number of correctly classified sample units in a category by the total number of sample units in that category from the

**Implementation and Evaluation of the Developed Method**

In this research, an RGB aerial image with a size of 1,872 × 1,757 pixels, taken from an urban region with 15 centimeter ground pixel size, is used as the optical data (Figure 6a), and the lidar data (Figure 6b) from the same region is used as well.

The region selected includes buildings with relatively complex structures and various textures as well as a complex background that makes it a proper example of object variety for the evaluation of the proposed model.

In multisource data analysis, georeferencing is a crucial stage achieved using co-registration (e.g., optical and laser scanner data sources) or separate geo-referencing of each data source. Considering that the image was acquired by a camera on the same platform as the lidar sensor, an accurate co-registration was achieved.

Figure 7 shows the initial building contours of the scene that are obtained according to the process previously described.

To provide the input data required for the estimation of the external energy function, all the input features (i.e., edge intensity, edge length, gray level difference between the two sides of the edge, and the curvature of the edge) were first obtained from the edge image resulting from the implementation of the Sobel operator on the test optical image.

TABLE 1. SOME RULES USED TO COMPUTE THE EXTERNAL ENERGY FUNCTION AS A FUZZY INFERENCE SYSTEM

<table>
<thead>
<tr>
<th>Rule Number</th>
<th>Rule Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>If the “height is highly elevated” and the “curvature is low” and the “RBT” is high and the “edge intensity is strong” and the “edge length is long”, then the “external energy is very high”.</td>
</tr>
<tr>
<td>2</td>
<td>If the “height is highly elevated and the “curvature is low” and the “RBT” is medium and the “edge intensity is strong” and the “edge length is medium”, then the “external energy is medium”.</td>
</tr>
<tr>
<td>3</td>
<td>If the “height is at low elevation”, then the “external energy is very low”.</td>
</tr>
<tr>
<td>4</td>
<td>If the “height is highly elevated” and the “RBT” is low, then the external energy is low”.</td>
</tr>
</tbody>
</table>

1 Region Based Term (Gray Level Difference Across Edge)

(1) If the “height is highly elevated” and the “curvature is low” and the “RBT” is high and the “edge intensity is strong” and the “edge length is long”, then the “external energy is very high”.

(3) If the “height is at low elevation”, then the “external energy is very low”.

(2) If the “height is highly elevated and the “curvature is low” and the “RBT” is medium and the “edge intensity is strong” and the “edge length is medium”, then the “external energy is medium”.

(4) If the “height is highly elevated” and the “RBT” is low, then the external energy is low”.

Figure 6. Study area: (a) high-resolution aerial image, and (b) lidar height data.

Figure 7. Initial contours extracted from the test image.
Producer Accuracy and 4.9 percent in User Accuracy proves the higher performance level of the proposed model.

Existing algorithms have difficulties with building extraction in such areas, and there is a need for new solutions. Figure 9 shows that the final extracted contours are sufficiently close to the true boundaries of the buildings. We conclude that the use of expert knowledge combined with an active contour model not only reduces the practical problems in traditional active contour models but also increases the automation level and extraction accuracy of the buildings.
Conclusions
In this research, an object extraction method based on the active contour model and a fuzzy inference system was developed. The proposed approach consists of three important steps: (a) initial contour detection, (b) design of energy function, and (c) building extraction. In the initial contour detection, the NDSM roughness parameter is used as an efficient parameter to discriminate buildings from trees. In the second step, a fuzzy inference system is applied for the first time as the external energy function in the active contour model. The enhanced energy function is composed of five parts that each plays a different role in the extraction of buildings with various features. In the extraction step, a dynamic programming algorithm is used efficiently to minimize the energy function and direct the initial contour to the true building boundaries. Computing the external energy function by using a fuzzy inference system makes the model more applicable, particularly for noisy images.

Effects of buildings with different shapes and complex backgrounds on the performance of the proposed model are investigated by applying the method to a complex data set. Despite the problems mentioned, the method has efficiently extracted the buildings with a shape accuracy of 97 percent, an overall accuracy of 98 percent and a K factor of 89 percent.

The implementation and accuracy assessment of the results obtained proves the efficiency of the proposed method in both shape accuracy and overall accuracy for extracted building boundaries. Additionally, the comparison with traditional active contours shows the superiority of fuzzy active contour models that emphasize expert knowledge in contour updating.

The use of other properties such as texture, roughness, shape information, etc., is suggested to enhance the model in future work.

References