An Improved Snake Model for Automatic Extraction of Buildings from Urban Aerial Images and LiDAR Data Using Genetic Algorithm

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ABSTRACT:

Automatic extraction of objects from images has been a topic of research for decades. The main aim of these researches is to implement a numerical algorithm in order to extract the planar objects such as buildings from high resolution images and altitudinal data. Active contours or snakes have been extensively utilized for handling image segmentation and classification problems. Parametric active contour (snake) is defined as an energy minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines or edges. The snake deforms itself from its initial position into conformity with the nearest dominant feature by minimizing the snake energy. The snake energy consists of two main forces, namely: internal and external forces. The coefficients of internal and external energy in snake models have important effects on extraction accuracy. These coefficients together control the weights of the internal and external energy. The coefficients also control the snake's tension, rigidity, and attraction, respectively. In traditional methods, these weight coefficients are adjusted according to the user's emphasis. This paper proposes an algorithm for optimization of these parameters using genetic algorithm. Here, we attempt to present the effectiveness of Genetic Algorithms based on active contour, with fitness evaluation by snake model. Compared with traditional methods, this algorithm can converge to the true coefficients more quicker and more stable, especially in complex urban environments. Experimental results from used dataset have 96% of overall accuracy and 89.6% of k-Factor.

1. Introduction

Nowadays, automatic extraction of man-made objects such as buildings and roads in urban areas has from high resolution images become a topic of growing interest for photogrammetry, computer vision and remote sensing. Research in this area started in the late 1980s and used different types of source images ranging from single intensity images, color images and laser range images to stereo and multiple images (Peng 2005). Some useful applications are the automation of information extraction from images and updating geographic information system (GIS) databases. The establishment of databases for urban areas is frequently done by the analysis of aerial imagery.

Because manual interpretation of images is very time consuming, efforts have been made to speed up this process by automatic or semi-automatic procedures. Development in photogrammetry and remote sensing and accessibility of high resolution images provide numerous sources of spatial data causing difficulty for manually object extraction. Many researchers have had contribution in development of automatic object extraction from images. 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, Hongjian and Shiqiang (2006), after extraction and connection of edge pixels, extracted the height of buildings from a sparse laser sample and reconstructed the 3D information for each building. Sohn and Dowman (2007) extracted building tracks automatically in a combination of the IKONOS imagery with pan-sharpened multispectral bands and the low-sampled airborne laser scanning data. Lafarge (2010) presented an automatic building extraction method from digital elevation models based on an object oriented approach. One of the methods frequently used in building extraction is the snake model. Snakes, or active contour models, were originally introduced by Kass et al. (1988). This model, which uses global information of the image contour to obtain a closed or open curve, does not require any prior knowledge about the image. Therefore, it is widely used in many image processing areas, such as image segmentation, image tracking and 3-D reconstruction (Lam 1994). The snake model is an energyminimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges (Shih 2004). Since the introduction of the original snake model, many studies that extend and improve the snake method have been proposed. Ruther (2002) presented a novel approach for semi-automatic building extraction in informal settlement areas from aerial photographs. In the proposed approach he uses a strategy of delineating buildings by optimizing their approximate building contour position. Approximate building contours are derived automatically by locating elevation blobs in digital surface models. Building extraction is then applied by means of the snake algorithm and the dynamic programming optimization technique. Peng (2005) proposed an improved snake model focusing on building detection from high resolution graylevel aerial images.

First step in using snake model is determining the initial contour. Initialization can be done manually or automatically depending on the application. The performance of parametric snakes is in general sensitive to the initial position of the contour curve. Initial contour of snake model delineating approximate limits of building are provided by digital surface model (DSM). In order to define regions of interest using this method, building detection is performed by searching for local maxima in a DSM. This is based on the knowledge that buildings are objects of limited size rising from the terrain surface. Within these regions, feature extraction is performed using DSM data in combination with height data. The DSM used to detect buildings can be produced by stereo matching or from airborne laser scanning rangefinder data, although the results of stereo matching are not very good in urban areas. The airborne scanning laser rangefinder can acquire high density of laser points to generate the DSM of a city (Mass, 1999).

The performance of active contour model is extremely affected by the value of weight coefficients of energy function. In traditional methods these values determined using user emphasis. In this paper we use genetic algorithm to calculate optimum value of these parameters. The GA theory was first proposed by Holland (1975). Thereafter, GA was applied in many optimization problems. They are inspired by the mechanics of natural genetics and natural selection where stronger individuals are likely to survive in competing environment. The unknown parameters will be coded as a finite -length string in the binary form and are regarded as the genes of a chromosome. A string, therefore, represents the potential solution of the optimization problem. By generating a set of strings, the GA algorithm applies three operators, reproduction (selection), crossover and mutation, to evolve better generations.

In section two, the building extraction method, including the selection of initial points, optimizing problem and the snake model, are described. In section three, the experimental results resulting from implementation of the new model are presented. In section four, numerical evaluation and limitations of the method are discussed, and finally, we draw conclusions in section five.

2. Building Extraction Method

The main steps followed in the proposed methodology are given in Fig. 1. Our approach consists of three steps: first, the raw point cloud has to be classified into terrain points and off-terrain points. Then, the off-terrain points (the potential buildings) have to be aggregated to form connected building blobs. Those blobs that exceed a certain size and have certain characteristics (e.g. more height and low roughness) are supposed to be building candidates. In a second step, the coefficients of internal and external energy function using GA were calculated. Finally, based on snake model, minimizing the energy function and optimizing the approximate building are carried out and buildings are extracted.



Fig.1. the main stages of the proposed building extraction method

2.1 Selection of initial points

The overall aim of the detection process is to partition an image into regions where buildings can be constructed. This primary segmentation is carried out to reduce the dimensionality of the search space and consequently reduce the computational time required in subsequent processes. Moreover, one difficulty in the traditional snake model is to initiate the model close to the object contour. Otherwise, the model may converge to a false result. For the selection of an initial point a DSM, generated by LiDAR data, is used. A digital elevation model (DEM) is the elevation model of the landscape that does not include above ground objects, and a digital surface model (DSM) includes the objects with their heights above the ground as well as the topography (Fig. 2a). The basic idea of using a DSM in a building extraction method is that the man-made objects with different heights over the terrain can be detected by applying a threshold to DSM. The difficulty in this process is the separation of the buildings from the trees, as both features have heights above the ground. However, their separation can be achieved using a roughness index. Based on this index to specify trees, it is supposed that roughness in trees is more than buildings (Fig. 2.b). With thresholding, the higher values of roughness have been removed as trees and vegetations.

Then, a threshold value of 3 m was applied to NDSM for separating the above ground features from the terrain surface. For determining the threshold value of 3 m it is assumed that the heights of the buildings were higher than 3 m (Fig. 2c).

To analyze the height value along the boundary of the segmented object, the edges in the image should be extracted in order to obtain the edges of buildings. For this purpose, after removing trees from DSM data, edges are detected from the DSM by a canny edge detection operator. There are two types of pixels in the resulting image: edge pixels and non-edge pixels. Most of edge pixels are edges of buildings, and some are not, like the edges of walls that don't belong to buildings and noisy pixels in the segmented image, so the breaklines of buildings from the segmented image should be extracted. The geometric feature of

lines is that there is a connected path among pixels; therefore, pixel connectivity is used to extract line segments. Length threshold segmentation is used to remove short edges and noises by determining the length of the connected path. If the path is longer than the threshold, the line segment extracted. The edges, extracted by these operators, are not continuous. First, the edges belonging to one building are connected, and the next stage is grouping the edges. In this stage the lines are formed by linking the edges. The edges with distances lower than two pixels are connected. Grouping is performed by linking the edges of the lines extracted as initial points. The extracted breaklines of buildings are shown in Fig. 2d, and as it can be seen most edges of buildings are correctly extracted.



Fig.2. a) DSM generated by LiDAR data. b) Roughness image. c) In this figure, DSM objects with height less than 3 m and trees were removed. d) Edges in LiDAR data and results of detected regions of interest.

2.2 Active Contour Model

The original snake model (Kass et al., 1988) is represented by a vector v(s) = (x(s), y(s)) having arc length s, as parameter. The energy function is defined as

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

Where E_{int} is the internal energy, through which geometric constraints such as continuity and smoothness are imposed on the shape of the contour, which is given by:

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

where v'(s) and v''(s) refer to the first and second order derivatives of v(s), respectively. The first order derivative reflects the continuity of the curve, constraining the curve moving towards shortest in length; second order derivative reflects the lubricity of the curve, controlling the contour to be smooth. $\alpha(s)$ and $\beta(s)$ are the position dependent weights for v'(s) and v''(s), respectively. Under the force of the internal energy alone, a closed contour is supposed to be stabilized to a circle with minimal radius. E_{ext} is the external constraint force acting on the contour, which can be either radiometric or geometric, that attracts the contour to features of interest in the image. In this paper, improved snake model proposed by Kabolizade et al. (2009) are used. This model has the advantage of integrating edge-based and region-based snakes that are applicable on high resolution aerial images. The proposed model performance was considered acceptable with a significant reduction of the need for human support (eq. 3).

$$E_{ext} = \gamma \times E_{GVF} + \mu \times E_{RVE} + \varepsilon \times E_{AVE}$$
(3)

Where RVE is regional variance energy, AVE is altitudinal variance energy and γ , μ and ε are coefficients that control the influence of each energy function. These coefficients can be optimized using GA.

2.2 Optimizing Coefficients of Energy Function

After 2D building detection, genetic algorithm is used to optimizing the coefficients of internal and external energy. The internal force is for continuity and smoothness of the snake. The external force pushes the snake toward salient image features. As mentioned before, the coefficients of internal and external energy in snake models have important effects on extraction accuracy. These coefficients together control the weights of the internal and external energy. The coefficients also control the snake's tension, rigidity, and attraction, respectively. In traditional methods, these weight coefficients are adjusted according to the user's emphasis. The optimization problem formulated in this paper has a cost functions and continuous variables. Thus, continuous GA will be appropriate for such problems with parameters that have continuous and floating values. The genetic algorithm is an appropriate method for this kind of problem, as validated in the literature. Genetic Algorithms (GAs) are a randomized search and optimization method, guided by the principles of evolution and natural genetics. A major advantage of GA lies in its ability to locate true optimal solutions in least number of runs and simultaneously searches from a wide sampling of the cost surface.

2.2.1 Formulation of the optimization problem

The introduced variables are part of the formulated optimization problem, which consists of some variables and cost functions as presented below.

Variables

The variables considered in this study can be categorized into two groups: internal and external energy coefficients, which were defined in previous section. These variables together define snake performance.

Cost functions

In order to design cost function, we use ground truth data that are buildings extracted manually from a part of the image. Cost function is calculated by separation between manually and automatic building extraction using deferent coefficients which are extracted from chromosomes.

2.2.2 Genetic algorithm

The GA implemented in this study has the following features:

- The GA begins by defining an array of variable values to be optimized. In this step 30 chromosomes are defined by different parameters.
- In mutation step the probabilities assigned to the chromosomes in the mating pool are inversely proportional to their cost. A chromosome with the lowest cost has the greatest probability of mating, while the chromosome with the highest cost has the lowest probability of mating. In this research, weighted crossover with crossover value probability between

[0.6-1] and mutation value probability between [0.01-0.06] is used.

 The value of cost function and comparison with termination condition is cheked.

3. Experimental Results

The method was applied to a subsection of a color aerial image of the suburban and urban areas of Taft in Iran (Fig. 3). The complexity of each optimization problem is a function of the number of buildings and complexity of urban area. Therefore, for any given image, the population size and maximum number of generations are set using experimentally determined heuristics. The first step in implementing genetic algorithm is generation of first population. In this step, determining population size and chromosome length is done (Goldberg, 1989). Each solution of the problem can be considered as a population member and must be represented properly. As mentioned before this problem has continuous variables. Thus continuous GA will be appropriate for such problems with parameters that have continuous and floating values. According to equations 2, 3 the energy function has five sub-functions and for these sub-functions we define five weight coefficients. Thus length of each chromosome is 5 (Fig. 4).



Fig.3. original image used in this paper

2.54	1.39	0.67	1.08	0.01	

Fig.4. A sample of used chromosome

Members of the first generation are selected randomly. In this research, the weight coefficients can be changed between 0 and 3. In order to compute the cost function of each chromosome, coefficients are extracted from chromosomes and active contour model using these coefficients extracted sample buildings. Sample buildings are some of buildings that previously extracted manually. Cost function is calculated by separation between manually and automatic building extraction using these coefficients.

$$cost = \frac{FP + FN}{N} \tag{4}$$

Where FP is the number of pixels that belongs to background but erroneously classified as building, FN is the number of pixels that belongs to the building but classified as background and N is the number of ground truth pixels.

The population size in GA is an important parameter and has great effect on the results. In this paper, this parameter has been selected empirically. Chromosome which has lowest cost has the greatest probability of mating, while the chromosome with the highest cost has the lowest probability of mating. According to the probability of mating the parents have been selected and offsprings of next generation are made using weighted mating.

offspring $1 = \alpha \times parent 1 + \beta \times parrent 2$

offspring $1 = \gamma \times parent \ 1 + \delta \times parrent \ 2$

Where α , β , γ and δ are random numbers. Using weighted mating causes that all the search space is evaluated and increases the probability of converging to true optimum.

In genetic algorithm, when %95 of the chromosomes is the same, algorithm is stopped.

After the convergence of GA algorithm, the weight coefficients where extract from the best chromosome. The buildings in the image were extracted using snake model and calculated coefficients. Results have been shown in fig. 5.

For assessment of the accuracy of the active contour model with these coefficients, a binary image was produced manually, assigning 1 to buildings and 0 to background. Confusion matrix parameters have been calculated for this algorithm. The best coefficients of the best chromosome are used for final building extraction. Obtained results show that, buildings extracted from dense and complex suburban area have good performance (table 1).



Fig. 5. Final result of active contour model

	Over. Acc.	K fac.	P A	U A	No	М
Improved Snake Model	0.992	0.962	0.980	0.953	0.155	0.06

Table 1: numerical results of the active contour model

4. Conclusions

In this research, we improved the boundary extraction method based on a GVF snake model. This method has the advantage of integrating edge-based and region-based snakes that are applicable on high resolution aerial images. The proposed model performance was considered acceptable with a significant reduction of the need for human support. Compared with the published snake models, this algorithm takes advantage of three aspects. (1) The initiation criteria present a more reliable measure to select proper initial seeds and sharply reduce the influence caused by spurs. (2) The external energy function consisting of building edges and surface consistency makes the snake model more stable to converge to the true building contours. (3) With benefit from genetic algorithm, snake model has fewer needs to operator and the speed increase. Experimental results show that this model can even work robustly with images taken from urban areas with buildings of complex structure. In contrast with the good results obtained for single building-blocks.

6. References

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