An Adaptive Active Contour Model for Building Extraction from Aerial Images

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***Abstract*—Building extraction from aerial images is one of the recent topics of remote sensing used in many applications such as urban planning, disaster management, military planning, and Geographic Information Systems (GIS).**
One of the commonly used approaches in building extraction is Active Contour Model (ACM), also called snake model, for its ability to extract contours of structured and unstructured shapes of objects. However, using traditional ACM model in building extraction faces the problem of narrowly concave contour regions. In this research, we propose to solve the deep concavities problem with the use of a concavity index which adaptively determines the rigidity coefficient of the snake points located in the deeply narrow segments of the contour.
Our adaptive model was tested on different sets of buildings extracted from aerial images. Results were evaluated using two evaluation approaches. One in terms of accuracy, precision and recall, and the other in terms of the Error Distance Ratio (ER_d) which is the average ratio of distance between each snake point and the true edge map point (by pixels). Result were compared with the GVF snake model in terms of both accuracy and execution time.

Keywords—Building extraction, ACM Model, Snake Model, GVF Model.

I. Introduction

Building extraction from aerial images is an important problem of remote sensing field and it became a research topic for its important value in many applications such as urban planning, disaster management, military planning, geographic information systems (GIS) and other applications. Building extraction is the process of defining the correct contour of buildings using extracted features with decreasing human support. Figure 1 shows an extracted buildings example from an aerial image.

Many approaches have been proposed for building extraction from aerial images, these approaches can be generally categorized to automatic and semi-automatic approaches, both use different image characteristics to extract building objects.

Many challenges hinder object extraction from aerial images such as image quality, resolution, noise, and lighting conditions [1]. Moreover, buildings are usually close to each other, and many other objects are close proximity such as trees, vehicles, parking areas, power lines, shadows, and buildings have differentiated structures. These challenges make it difficult to perform a full automatic and accurate building extraction process and it became a research area and researchers have improved different approaches to overcome these challenges.

One of the mostly used approaches rely on the Active Contour Model or (ACM). The ACM (also called snake) was defined by Kass et al. [2] as an energy minimizing, deformable spline influenced by constraints and image forces that pull it towards object contours. The ACM is used for object tracking, shape recognition, segmentation, edge detection, and stereo matching.

More details about the ACM are given in Section 3. In the rest of this section we present some of the related work that used ACM for building extraction from aerial images.

Salman Ahmady et al. [3], proposed a full automatic building extraction approach using an improved ACM model called Chan-Vese model. In Chan-Vese model, image is segmented to regions that the value of all pixels within each region have maximum similarity. In their method snakes are initialized with a point inside a building introduced to model as a training data.

Antonio and Aluir in their paper [5], proposed to use Dynamic Programming (DP) as an optimization algorithm to

Figure 1: Building extraction from aerial image

reduce the number of required operations to find set of optimal variables for the energy function. The initial snake curve done by human operator, then optimization process done based upon sampling edge points, then select the best set of edge points describe a building roof contour that results a minimum energy value. These steps are sequentially repeated until the goal function is minimized, that is, no more vertices are added to the current building roof contour. Their results showed that depending on edges as an external force, cues extraction of false objects or inaccurate roof contours, and snakes are unable to converge correctly to weak edges. Also they didn't solve the snakes convergence in concavity contours.

Lau Theng [6] proposed to improve automatic building detection by circular casting active contour model. Firstly, he intends to detect a corner point of building using Haris corner detector, then a circular ACM cast is initiated from any of the first found corner points as a control point. Finally, it start checking pixels within the cast's boundary, and the iteration stops when active contour locks a building outline. Theng's proposed model solved the problem of determining the number of the radial lines wanted to detect the complex shapes of building contours accurately, but internal strong edges also will stop the snake convergence to boundaries.

In Kabolizade et al paper [7], Digital Surface Model (DSM) is used for automatic detection of man-made objects, where different heights over the terrain can be detected automatically by applying a threshold. After that, they applied Genetic Algorithm (GA) to define array of variable values in 30 Chromosome. Then in mutation step, the chromosome with lowest cost will have high probability of mating. Finally, parents are selected according mating and offsprings of next generation are made. After convergence of GA algorithm, the weight coefficients of snake are extracted from the best chromosome. Then buildings are extracted using GVF snake model and calculated coefficients. In Kabolizade paper, using GVF still have some shortcomings in operating with concavity contours as we will compare our improvements with GVF.

Other researchers [8] used Balloon ACM model to identify approximated building regions without human intervention depending on edge lines as an external force. Their approach done in five steps, firstly they applied Burns line edge detector to detect edges that used later as an external force for snake movement. After that, close edges to balloons are selected, then buildings hypothesizes are initiated with proposed rules for some predicted building shapes such as: F and U shapes, and to prevent other shapes such as Z and H shapes. Finally, hypothesis verification step is done by finding hypothesis value, which is sum of pixels needed to connect line components of building hypothesis. Their approach failed in some cases where external force (line segments) is not enough to pull balloons or stop growing of balloons to contours, also internal force was - in some cases - not enough to extract complicated shapes (such as concave regions).

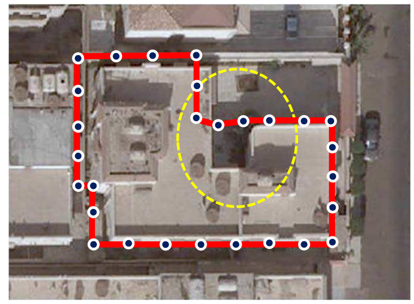

Figure 2 concave region in a building problem

Overall, the presented approaches used ACM in different building extraction approaches, quality and level of results differentiate from one approach to another. We find that the aforementioned related works have achieved high performance in extracting buildings but suffered low accuracy in cases where the buildings had deep concavities because snake model cannot converge inside deep concavity regions as you can see in Figure 2. This shortcoming is an intrinsic problem in the ACM model itself which needs more research work. Therefore, in our research we introduce modification to the ACM model and method that make it more useful for automatic building extraction.

The details of our method are given in Section 3, but first we present some background on the ACM model in Section 2. Evaluation and Results are presented and discussed in Section 4, and the conclusion is given in Section 5.

II. Active Contour Model and Process

As mentioned in Section 1, ACM is an energy minimization model. In the discrete formulation, the model is composed of a set of snake points $\boldsymbol{v_i} = (\boldsymbol{x_i}, \boldsymbol{y_i})$ for $i = 1,2, \dots, n$ where $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$ are the x and y coordinates, respectively, and $\boldsymbol{n}$ is the total number of snake points. The points are initialized around the object of interest as shown in Figure 3. Each snake point has an energy value determined by the effect of two types of forces: a) external forces based on image features such as edge gradient, and b) Internal forces based on snake features such as continuity and curvature. Overall, the snake's total energy is the sum of its points' energies, and is typically formulated as follows:

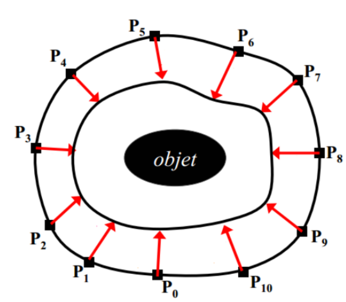

Figure 3 Active Contour Model (snake)

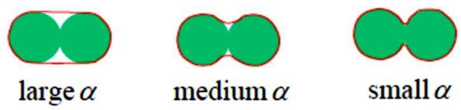

Figure 4: The effect of $\boldsymbol{\alpha}$ on snake stretch

$$E_{snake} = \sum_{i=1}^{n} (\alpha E_{cont}(v_i) + \beta E_{curv}(v_i) + \gamma E_{ext}(v_i)) \qquad \text{Eq. 1}$$

where α, β, and γ are relative weights,

$$E_{cont} = |\, v_s(s)|^2$$
$$E_{curv} = |\, v_{ss}(s)|^2$$

and E_{ext} is typically edge gradient or any other user interaction.

Through an optimization process the snake's energy is minimized and typically settles at the object's boundaries. The most commonly used algorithm for implementing the optimization process is the greedy techniques which leads to the greedy snake.

A. Greedy Snake

The greedy snake is called greedy because it looks for optimal solution locally at the snake point level. As Figure 5 shows, the movement of each snake point is determined by calculating the energy of candidate points in its $\boldsymbol{n \times n}$ neighborhood in terms of Eq. 1, and selecting the minimum energy location. This procedure performed for each snake point iteratively until the points stop moving to new locations [9].

The choice of coefficient values in Eq.**Error! Reference source not found.**, depends on what type of features to be extracted:

- Set α high if there is a deceptive Image Gradient.
- Set β high if smooth edged Feature, low if sharp edges.
- Set γ high if contrast between Background and Feature is low.

B. Gradient Vector Flow (GVF) Model

Many approaches where proposed to overcome traditional ACM shortcomings. Gradient Vector Flow (GVF) was proposed by Chenyang Xu et al. in [10] to solve the problem of boundary concavities and weak edges. GVF is computed as a diffusion of the gradient vectors of a gray-level or binary edge map derived from the image and used as an external force of snake and called a *GVF snake.*

The advantages of using GVF in snake model are:

- The snake become insensitive to the initial position of snake, if it's inside or outside object.
- The ability to move into boundary concavities.
- The large capture range, which means that, barring interference from other objects, it can be initialized far away from the boundary.

These advantages make the GVF snake more suitable for finding boundaries of buildings, and we find it the right choice to compare and evaluate our proposed method.

III. The Proposed Method

In this section we present our proposed improvements on the traditional ACM model which is composed of two parts: a) modifications on the ACM model, and b) modification on the iterative method of fitting the ACM to the object.

A. Proposed ACM Model Improvements

The idea of our improved ACM model is based on two remarks. First, as Figure 4 shows, the α coefficient of the internal energy affects the rigidity/elasticity of the snake and determines whether it is able to converge inside concavities. Second, as Figure 6 shows, for snake points in the concavity region the internal curvature force is high and the external energy is low.

Based on these two points, we propose to solve the problem of extracting deeply concave contours by adapting the ACM α coefficient during snake iterations based on a *concavity index* which indicates whether a snake point is located on a concave region or not. More specifically, α is increased when the index is high, and vice versa. The formula for the concavity index and its relationship with the alpha coefficient are expressed as follows:

$$\boldsymbol{ConcIndex\,(p_i) = mean(\,E_{ext}\,(p_i))/\,mean(E_{curv}(p_i))}$$
$$\boldsymbol{\alpha(p_i) = \alpha\,(p_i) * ConcIndex\,(p_i)}$$

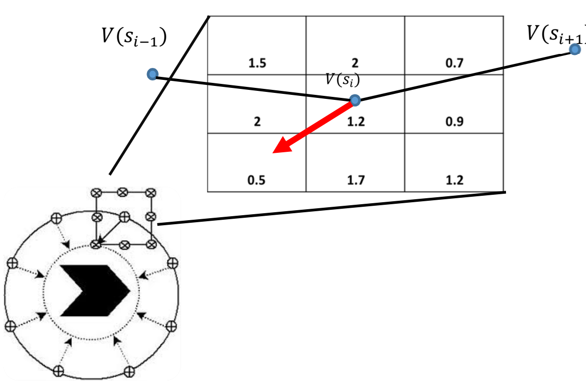

Figure 5: Greedy snake neighborhood energy minimization

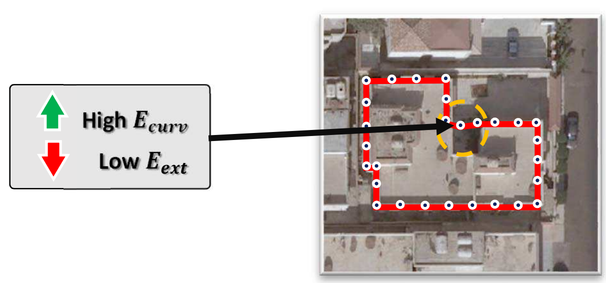

Figure 6: external and curvature energy in concavities

B. Proposed ACM Method

In this subsection, we present our improved ACM building extracting approach steps, Figure 7 shows a flowchart of the overall approach of our improved ACM model approach.

The used method for building extraction using ACM is the same steps of using the ACM model in other applications, a common step must be done first; such as preprocessing and extracting ROI, the complete method steps are as the following:

1) Step 1: Extraction of Region of Interest (ROI)

After loading the full aerial image, the user must define the sub image of the building, which is the region of interest, in this research; our improved model is applied on ROI, which contains one building only that contains concavity contour.

2) Step 2: Preprocessing

Our improved method is applied on manual preprocessed ROI image, so noise and other interrelated objects are removed Then Canny edge detector is used because it's considered to be optimal edge detection operator for building detection as Bhadauria et al. mentioned in their paper [15].

3) Step 3: Convergece of ACM on Object's Boundary

Apply modified ACM model, as follows:

Do the following, while ($\%\boldsymbol{X_i}$) of snake points still moving ($\%\boldsymbol{X_i}$ is a parameter which the user can change to control snake stopping criteria):

- Calculate internal and external forces of all snake's control point ($\boldsymbol{p_i}$) neighbors ($\boldsymbol{n_i}$).
- Calculate total energy E ($\boldsymbol{n_i}$) for ($\boldsymbol{p_i}$) and ($\boldsymbol{p_i}$) neighbors.
- In our modified ACM model, we attend to adapt coefficient of internal force (Alpha) during contour extraction process, depending on a new value called concavity index ($\boldsymbol{ConcIndex}$), which is a new parameter found in terms of external and internal energies values. Where:

$$\boldsymbol{ConcIndex}\ (\boldsymbol{p_i}) = \boldsymbol{mean}(\ \boldsymbol{E_{ext}}\ (\boldsymbol{p_i}))/\ \boldsymbol{mean}(\boldsymbol{E_{curv}}(\boldsymbol{p_i}))$$

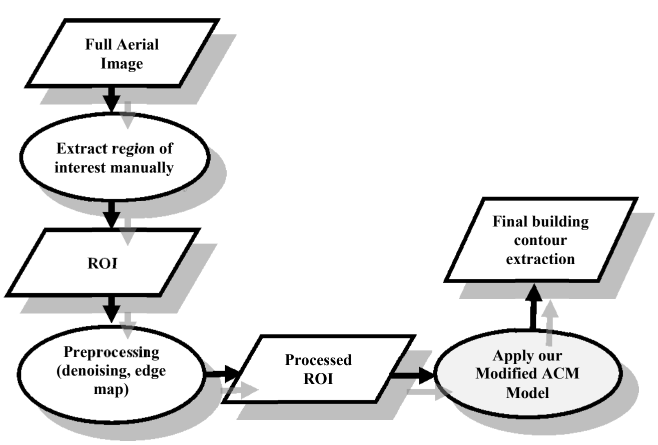

Figure 7: Overall approach for building contour extraction

- We used ***mean*** to prevent division by zero because external force and curvature force matrix values can be zeros
- If less than $\boldsymbol{Y_i}$ percentage of snake points still moving ($\boldsymbol{Y_i}$ threshold is set to 40%), then
  - check if ($\boldsymbol{p_i}$) is on contour or not, if not
    - recalculate $\boldsymbol{\alpha}\ (\boldsymbol{p_i})$ where

$$\boldsymbol{\alpha}(\boldsymbol{p_i}) = \boldsymbol{\alpha}\ (\boldsymbol{p_i}) * \boldsymbol{ConcIndex}\ (\boldsymbol{p_i})$$

    - recalculate total energy for ($\boldsymbol{p_i}$)
- Then, if less than $\boldsymbol{Z_i}$ percentage of snake points still moving ($\boldsymbol{Z_i}$ is set to 10%), do the following:
- Do the Insertion/Deletion refining contour shape process of snake points. This process done by adding new snake points and removing unnecessary points by computing the distances between these points until a threshold percentage of snake points still moving, the step of insertion/deletion snake points improves the final extracted contour shape.
- Finally, do the relaxation step, where if curvature and image energy of ($\boldsymbol{p_i}$) is more than the given threshold value, then set β to 0.

IV. Evaluation and Results

In subsection A we describe the evaluation setup, and in subsection B present and discuss the results.

A. Evaluation Setup

We implemented a testing application to test our improved ACM snake method using MATLAB 7.11.0, and used an open source code implementation of the GVF model [16]. We ran the tests on a laptop machine with a 2.40 GHz Core i3 processor and 2 GB RAM.

1) Evaluation Image Sets

We have tested 30 different images taken as parts of a high resolution, 5cm/pixel, complex aerial scene of Jeddah, Saudi Arabia, available from the Jeddah Geographic Eexplorer website. We categorized the collection into four different sets varying in complexity of building boundary as follows: 1) wide concavity regions, 2) narrow concavities, and 3) multiple narrow concavities. We also added a fourth set of custom shapes contain concavity regions. These four sets were used in testing and comparing the performance of our improved model with the GVF model on the basis of two criteria as explained next.

2) Evaluation Criteria

We evaluated our improved ACM model and compared it with the GVF model using two evaluation criteria: 1) accuracy precession, recall, and 2) total error distances between the resulting contour and the actual object's boundary.

a) Criterion 1: Precision, Accuracy, and Recall

For this criterion, the Confusion Matrix analyzing method is used to find the precession, accuracy, and recall of the final contour extraction results as defined bellow

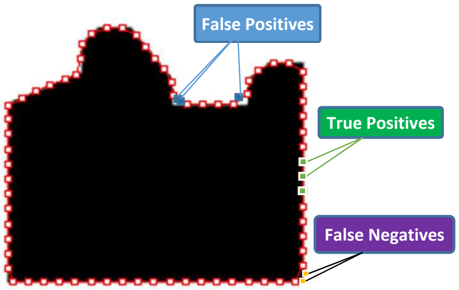

Figure 8: Illustration of evaluation criterion 1

- $Precision = TP/(TP + FP)$
- $Accuracy = (TP + TN) / (TP + TN + FP + FN)$
- $Recall = TP/(TP + FN)$

where ***TP (true positives)*** is the number of points correctly labeled as belonging to the extracted contour and edge map, ***FP (false positives)*** is the number of points incorrectly labeled as contour points but they are not, ***TN (true negatives)*** true negatives are the number of snake points that are not edge map points and are not labeled as contour points, and ***FN (false negatives)*** are the number of edge map points that are not labeled as a contour. Figure 8 shows a description of evaluation Criteria 1.

b) Criterion 2: Distance Error Ratio (ER_d)

This criterion measures an error ratio of the distances between each snake point and the true edge pixels. This ratio is calculated as follows:

$$ER_d = \frac{\sum_{i=1}^{n} d_i}{n} \qquad \text{Eq. 2}$$

where n is the total number of points in the final snake, and d_i is the distance between snake point i and the nearest edge pixel belonging to the building boundary inside an $N \times N$ window centered at point i.

B. Experiments Results

In this section we present the results of testing our improved ACM model in comparison with the GVF snake using the two criteria described earlier.

1) Results for Criterion 1:

Table 1 shows the results of testing our improved ACM model on the four categories of the image set based the three measures of Criteria 1: Precision, Accuracy, and Recall. From Table 1, we observe that we did not get a high precision and recall values, because the image processing classification is not purely true or false classification as numeric values, we can explain this by snake point can be too close to the edge map pixel but not exactly on the same coordinates, so it will be counted a false negative result. To assure and explain this, we used the second evaluation method which finds the ratio of distances between each extracted contour point and the truly edge map point.

Table 1: The proposed ACM model evaluation results using Criteria-1

Image Set	Image Set1	Image Set2	Image Set3	Image Set4
Average No. of iterations	101	104.7	93.4	106.8
Average Testing time in seconds	23.6	29.3	26.35	22.8
Average Precision	0.56	0.66	0.62	0.54
Average Recall	0.165	0.188	0.173	0.212
Average Accuracy %	97.5 %	98.3 %	98.2 %	97.87%

Table 2: GVF evaluation results using Criteria 1

Image Set	Image Set1	Image Set2	Image Set3	Image Set4
Average No. of iterations	721.67	672.7	635.7	770
Average Testing time in seconds	67.354	66.64	66.97	64.57
Average Precision	0.22	0.226	0.19	0.146
Average Recall	0.146	0.144	0.126	0.0952
Average Accuracy %	98.98 %	99.06 %	99 %	98.53 %

As we have mentioned before we compare our testing results with GVF model, because it is one of the most known approaches that solved the concavity contours problem. We tested the same four image sets with GVF model, and evaluate results with the two criteria methods. An open source implemented application [16] is used to test GVF using the two evaluation methods. Table 2 shows the results of testing GVF model with measures of Precession, Recall, and Accuracy.

2) Results for Criterion 2:

Firstly, to find **Error Distance Ratio (ER_d)**, we have tested different values of window size N to get minimum distances between each snake point and its neighbor edge map pixel. We got that when ***N=11*** the sum of distances does not change in more than N=11 and the distance ratio is the same.

Applying this criterion on our improved model and the GVF model showed that the average ER_d of our improved model is much lower than the average ER_d of the GVF model, which means that the snake points are closer to the correct contour points. Table 3 shows the average ER_d of the tested image sets with our improved model and the GVF model.

After applying our improved ACM model and GVF snake model on the same set of images, with these two described Criteria methods, the results showed that the final extracted contour by our improved ACM is much better than using GVF snake.

Table 3: Results of evaluating our improved ACM model and GVF model with Criteria 2

Image Set	Image Set1	Image Set2	Image Set3	Image Set4
Our improved model Average Error Distance Ratio (ER_d) (pixels)	**0.52**	**0.41**	**0.42**	**0.43**
GVF model Average Error Distance Ratio (ER_d) (pixels)	**1.8**	**1.79**	**1.78**	**1.81**

In addition, our improved model average execution time is faster than the average execution time of GVF model. Table 4 summarize the different average values for each of GVF snake and the improved ACM model using both testing criteria, and Table 5 shows three samples of extraction results using our improved model compared to using the GVF snake.

V. Conclusion

In this research, we have introduced an improvement on the Active Contour Model to solve the problem of extracting contours of concavity regions. The proposed improvements depend on the effect of the internal and external energies coefficients effect on snake movement. A concavity index parameter have been proposed to adapt internal force coefficient and make the snake converge inside narrow concavities.

The proposed method is tested using two evaluation criteria, the first criterion finds the Accuracy and Precision. The second criterion finds the Error Distance Ratio, which is the ratio of the distances between each contour snake point and the true contour point by pixels. Also, we have compared our improved ACM model with GVF model, which is one of the most used methods that solved the extraction of concavity contours problem.

The evaluation results of our improved ACM Model Accuracy is comparable with the GVF Model, where the average Accuracy of our improved ACM Model is 98% and GVF Model average accuracy is 98.8%. However, the Precision of our improved model is 60% while the GVF average precision value is 20%. In addition, the average execution time of our improved ACM model is much better than GVF Model, where the average execution time of our improved ACM Model is about 25.8 seconds, and GVF average execution time is 66 seconds.

Table 4: Overall comparison results of testing our improved ACM and GVF model

Testing criteria	Improved ACM	GVF snake
Average num. of iterations	**101**	**700**
Average ext. time (seconds)	**25.8**	**66**
Average Precision	**0.6**	**0.2**
Average Recall	**0.18**	**0.13**
Average Accuracy%	**98**	**98.8**
Distance Error Ratio	**0.46**	**1.79**

Table 5: Contour extraction samples using improved ACM and GVF snake

Smpl. image	Original ROI image	Improved extracted ACM contour	GVF extracted contour
1			
2			
3			

Evaluation based on the ER_d criterion gave an average of 1.79 pixels for the GVF and 0.46 for our improved ACM. This means that the resulted contour shape of our improved model is closer than the GVF model to the real contour. In general, satisfying results is shown after testing our improved ACM model in execution time and accuracy compared to the GVF model.

Having achieved such results with our enhanced ACM model in extracting building contours, we are looking forward to use our enhanced ACM model to improve the full process of automatic extraction of buildings from aerial images.

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