A-PRIORI INFORMATION DRIVEN MODEL FOR ROAD SEGMENTATION IN HIGH RESOLUTION IMAGES

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ABSTRACT:

The problem of road segmentation in high resolution images is addressed in this paper. We present an extension of the active contour model that includes a-priori knowledge about the width of the roads being extracted. In order to improve the segmentation performance of the algorithm, the proposed model also contains a modified external energy term. The problem of the contour energy minimization is solved by using genetic algorithms, which makes it possible to use random initialization of the contours. The proposed segmentation method is validated on a series of high resolution images. The results show that by using the modified external energy term the new model performs better than the typically used gradient-based version.

1. INTRODUCTION

Accurate road extraction is an integral part of the process of automatic interpretation of satellite and aerial images. One of the major applications of this task lies in the field of transportation applications, where the tools capable of populating, maintaining and continuously updating GIS databases of complex transportation networks are of high importance, for the purposes such as road traffic management, automated navigation systems or critical decision support systems. The problem of road extraction has been the topic of numerous research papers and still remains a challenging problem. The existing research in this field explored generic tools of image processing such as searching for linear features (Fischler et al. 1981), Markov fields (Merlet 1996), neural networks (Bhattacharya et al. 1997), multiresolution analysis (Baumgartner et al. 1999), profile matching (Vosselman et al. 1995), or various combinations of these methods. With the increasing availability of high resolution images giving us spatial resolutions of 1m or even better, methods able to accurately extract roads as surfaces on the pixel level are of the highest importance to us.

The novel segmentation method proposed in this paper follows these two stages: (1) random initialization of the model's parameters within a rectangular search region (2) refinement of the road contour described by a set of parameters. We aim to search for the best set of parameters by exploring the high-dimensional space of all possible solutions.

Conventional local search minimization techniques are time-consuming and tend to converge to whichever local minimum they first encounter. Such methods are unable to continue the search after a local minimum is reached. Therefore, the key requirement of any global optimization method is that it should be able to avoid being trapped in local minima and continue the search to give a near-optimal final solution whatever the initial conditions. Genetic algorithms were applied to solve this problem.

2. GENETIC ALGORITHMS

Genetic algorithms present a tool for exploring a parameter space to find an optimal solution; with respect to an "objective function". If we intend to find a solution of a problem by the means of genetic algorithms, we must:

1. Define and represent each solution of a problem as a chromosome.
2. Define and implement the objective function. The objective (fitness) function plays the role of a universal measure of a solution.
3. Define and implement the genetic operators. The essential genetic operators are initialization, mutation and crossover. The initialization operator generates the initial population of solutions. The crossover operator defines a method of combining different solutions, while the mutation operator defines a way of modifying a single solution.

3. THE NEW MODEL

The input of the presented algorithm is a topologically correct graph of the road network. The graph gives us approximate road locations and can come as an output of a road database, it can be extracted via an automatic algorithm (Airault 1995) or it can be generated manually. The extracted graph is topologically correct, but the roads are not well registered on the pixel level. Each leaf of the graph serves us as a base for generating rectangular search regions on which is our genetic algorithm executed. In order to describe the algorithm, we show how it executes on an arbitrary search region that contains one road segment.

Our method extends the traditional active contour model in three ways. Firstly, since roads in high resolution images typically have two boundaries, not one, but two contours at once, bound by an additional energy term, are refined at a time. This additional energy term allows inclusion of a-priori information about the expected road width. Secondly, a different technique for the computation of the external energy term, which is responsible for the binding of the contours and the image, is developed. Lastly, the parameters of the extended model are refined by a genetic algorithm, which allows for a random initialization of the model parameters and so the typical problems associated with the contour initialization are avoided.

3.1 Active contour models

Active contour models (Kass et al. 1988) have been widely used for the purposes of boundary delineation in image processing. The planar active contour model is an energy minimizing spline, whose energy changes based on its shape and position in the image. In the case of the contour v being parameterized by $v(s) = (x(s), y(s))$ for $s \in [0,1]$, the total contour energy functional E_v can be written as

$$E_v = \alpha \cdot E_{\text{int}}(v) + \beta \cdot E_{ext}(v) \tag{1}$$

$$E_{\text{int}} = \int_0^1 e_{\text{int}}(s) ds \tag{2}$$

$$E_{ext} = \int_0^1 e_{ext}(s) ds \tag{3}$$

where

E_{int} = the internal energy, which is a smoothness driven component that constraints the geometry of the contour

E_{ext} = the external energy term, which is a data-driven component and binds the image and the contour together.

The internal energy term (2) is according to (Kass et al. 1988) given by the following expression:

$$e_{\text{int}}(s) = \frac{1}{2}\left[\alpha(s)\left|\frac{\partial v(s)}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial^2 v(s)}{\partial s^2}\right|^2\right] \tag{4}$$

The first term of this equation constraints the stretching of the contour whilst the second term constraints the bending of the contour. Denoting the image intensity as $I(x, y)$, the external energy responsible for attracting the contour to the image is usually based on the image gradient and typically has the following form

$$e_{ext}(s) = -\left|\nabla I(x(s), y(s))\right| \tag{5}$$

Under these conditions, the goal is to minimize the total contour energy (1).

3.2 Extended active contour models

Firstly, in contrast with (Ballerini 1999) we don't use a polar representation of the contour points. Instead, as shown in Figure 1, in each rectangular search region, which contains two road contours U and V, we establish an orthogonal local coordinate system, where the x-axis and y-axis (the dashed lines) are parallel to the sides of the search region. The entire y-axis is subsequently uniformly sampled by n points, so that any contour in the search region, with respect to this sampled y-axis (the double dashed lines), can be represented solely by a set of x-coordinates, making this representation suitable for the later genetic optimization. Therefore, each road segment consisting of two contours $U = \{u_i\}_{i=1}^N$ and $V = \{v_i\}_{i=1}^N$, is modeled by two sets of x-coordinates $U_x = \{\alpha_1, \alpha_2, ..., \alpha_n\}$ and $V_x = \{\beta_1, \beta_2, ..., \beta_n\}$, respectively.

In order to be able to apply the active contour model on the task of road segmentation in high resolution images, we extend it by reflecting the generic road model properties, in the form of constraints given by (Barzhohar et al. 1996). Such model assumes that both road width variance as well as road direction variance are likely to be low. Since the constraint being put on the road direction variance has already been reflected by the choice of active contours as our base model, we have to deal only with the first constraint, by introducing an additional energy functional E_p which reflects the road width variance and is defined as

$$E_p = \sum_{j=1}^{N}\left(\left|u_j - v_j\right| - d_a\right)^2 \tag{6}$$

where

$d_a = \frac{1}{n}\sum_{j=1}^{n}\left(\left|u_j - v_j\right|\right)$ is the mean road width.

The choice of replacing d_a with a-priori known value d_e, corresponding to the expected width of the road, reduces by a great deal the search space of all possible solutions that needs to be explored, resulting into increased noise resistance as well as speed improvement of the algorithm.

Since in our model each contour is assumed to be a polyline, we have to work with discrete versions of equation (1) and (2), which are obtained by simple substitution of the derivates with differences.

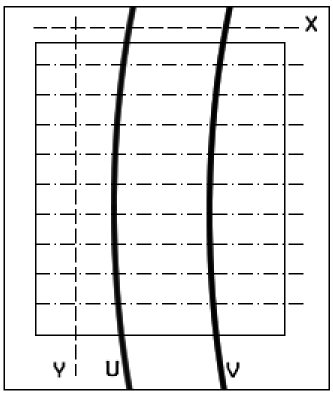

Figure 1. A rectangular search region overlaying the road segment

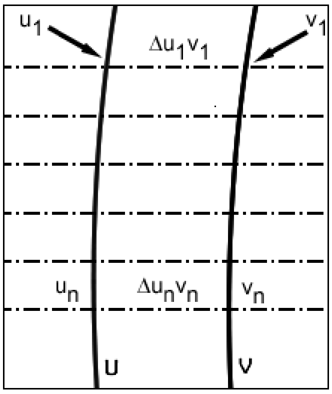

Figure 2. Neighbourhood used for the computation of the external energy term

In the new model we also deal with the external energy term. As we have already noted, in most methods the calculation of the external energy term is based on the magnitude of the gradient of the image and under these conditions, the contour is during the energy minimization process attracted to most salient edges of the image. However, we can observe that in many images due to noise and/or scene complexity, the variation of the magnitudes of the gradient along the road sides is high, which leads to undesirable behavior and the results can be unsatisfactory. To counter this problem we propose to use a different feature. We propose to compute the external energy term based on the assumption that the variation of gray levels of the road pixels tends to be low. Also, to our model we add the constraint that the road pixels should have a typical gray level, which is known in advance and therefore is also used as a-priori information.

The new external energy term is computed for each pair of the corresponding contour points u_i and v_i and is given by the following equation:

$$E_{ext} = \sum_{i=1}^{N} \sum_{(x,y)\in\Delta u_i v_i} \left(I(x,y) - \mu_a\right)^2 \tag{7}$$

where $\Delta u_i v_i$ = the set of pixels on the line segment $u_i v_i$

μ_a = the expected mean gray level

This new energy term should perform better than the gradient-based term since the homogeneity of the gray levels within the road segment is obviously a feature, which is much more consistent within the road segment than the magnitude of the gradient along the sides of the road. Therefore, the new model should exhibit increased robustness.

To sum up, the new total energy functional, for an arbitrary road segment, is given as:

$$\begin{aligned} E_{seg} &= \alpha \cdot (E_{\text{int}}(u) + E_{\text{int}}(v)) + \\ &+ \beta \cdot E_{ext}(u,v) + \gamma \cdot E_p(u,v) \end{aligned} \tag{8}$$

4. EXPERIMENTAL RESULTS

In this section we present some details and results of our implementation. The genetic algorithm used in this work follows the principles of the simple genetic algorithm, as described in (Goldberg 1989), thus each of its iterations produces non-overlapping populations. Moreover, elitism was implemented, ensuring the best individual is always moved into the next generation, speeding up the convergence.

With regard to the chromosomal representation of an arbitrary solution, each chromosome contains *2n* alleles, each represented by $\lceil \log_2 s \rceil$ bits, where *s* is the maximal dimension of the search region. The objective function being minimized corresponds to the total road segment energy, defined by (7). With respect to genetic operators used, a one-point crossover with the probability $p=0.59$ and mutation with the probability $p=0.0005$ were used. The population size was 10 000. The initial population which serves as the baseline of the evolutionary process was generated via random generation of points within the rectangular search region. This is in strong contrast with road segmentation methods based on the standard active contours model, which required initial inititialization in the proximity of the road sides.

In Figure 3 we can see a satellite image of a part of road, which has a mean width of 25 pixels, and in Figure 4 we can see the result of the segmentation. On each image we ran the algorithm twice. In the first run, we used the external energy term based on the gradient, and in the second run, we used the proposed external energy term (7). The accuracy of the segmentation process was measured via Euclidean distances between the road boundary points given by our algorithm and the corresponding real boundary points, which were selected manually. Mean square errors are shown in Table 3. The results show that the accuracy of the segmentation process increased when we used the modified external energy term, as opposed to the computation of the external energy term based on the image gradient.

Image	Gradient-based model	The extended model
1	12.4	3
2	15.2	4.8
3	9.8	2.5
4	25.9	14.5
5	11.5	3.8
6	12	8.6
7	8.9	2.7
8	46.7	5
9	35.8	4.7
10	23	5.4

Table 3. MSE comparison

CONCLUSION

We have implemented a new road segmentation method in high resolution images, which is based on the active contour model. The new method extends the standard active contour model by incorporating an additional energy term. This term allows inclusion of a-priori information about the road width. We have also modified the external energy term, which is the data-driven component of the active contour model. We have validated that when compared to the gradient-based approach, our modified energy term leads towards more accurate segmentation. The results obtained indicate a promising direction for further research of road segmentation in high resolution images.

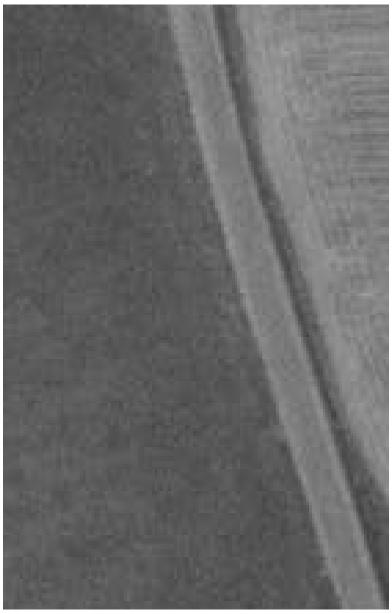

Figure 3. A satellite image of a road segment.

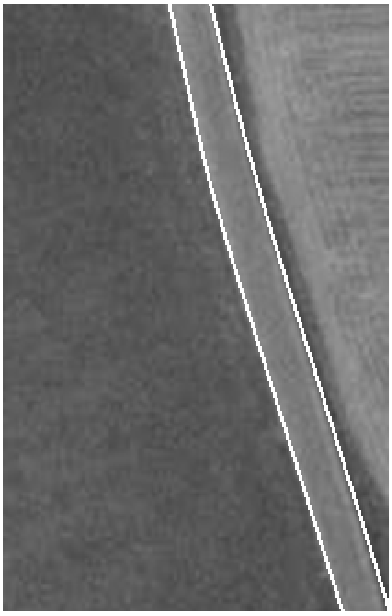

Figure 4. The result of segmentation.

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