AUTOMATIC ROAD EXTRACTION FROM AERIAL IMAGES BY PROBABILISTIC CONTOUR TRACKING

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ABSTRACT

In this paper a new automatic approach to road extraction from aerial images is proposed. This method improves a recently introduced promising approach to probabilistic contour tracking, originally semi-automatic, by adding a fully automatic initialization strategy and a merging methodology, able to combine the different obtained results. The initialization strategy is based on the Hough transform and on some topological considerations, and the merging step is based on a new introduced quality measure, based on color and gradient information. Experimental results on real highly complex images show that the proposed approach is a promising and fully automatic method for extracting roads from images, even in presence of highly urbanized areas, occlusions or shadows.

1. INTRODUCTION

The extraction of roads from aerial images is an interesting problem, which has grown in importance in the last years, due to its wide applicability in different research area, as, for example, Geographic Information System (GIS). If manually performed, road extraction is a time-consuming operation, thus, much effort is devoted to search for solutions to this problem [1]. Among the several proposed techniques, great attention has been paid to the so-called edge trackers, which are based on the criterion of "following" the road in the image. More specifically, starting from an initial point, the next point to be linked to the road is searched for. The approaches may involve a heuristic methods [2, 3, 4], graph searching (minimal path [5, 6, 7]), dynamic programming [8] or stochastic modelling [9].

The JetStream algorithm [10] belongs to the latter family and addresses the road extraction problem by using a probabilistic contour tracking strategy. JetStream implements a space version of the well-known CONDENSATION algorithm [11], a probabilistic Bayesian approach to tracking recently introduced. This Monte Carlo technique, based on sequential importance sampling/resampling, provides a statistical framework for propagating sample-based approximations of posterior distributions, with almost no restriction on the ingredients of the model. This kind of approach outperforms Kalman approaches [9], because of its ability to perform multi-hypothesis tracking, which is a necessary condition for dealing with noisy situations. Algorithms based on the Kalman filter have also the disadvantage of being unimodal, i.e., only one contour can be followed at each time step.

Even if this approach provides quite accurate results, its practical application is limited by its intrinsic semi-automatic nature, since it needs to be initialized for each road extracted. In other words, it needs a starting point. Even if this step is often manually solved [10], some automatic initialization systems have been proposed, based on GIS or geographical databases [12, 13], on heuristics [4, 7], or on stochastic assumptions [14]. Another problem of the JetStream approach is that the definition of the ingredients of the model does not take into account color information, but only gradient, neglecting the fact that roads are uniform inside. Finally, this method is not able to go behind small occlusions, as cars, isolated trees, or shadows.

In this paper a new automatic system for road extraction is presented, based on the JetStream algorithm. The system is completely automatic, since initial seeds are automatically identified in the image. This search is based on the observation that roads have precise topological characteristics, as smoothness of the curve, opposite gradient directions on borders etc., that could be effectively used to find the "true" pieces of roads. The proposed method uses a simple segmentation method, together with the Hough Transform and gradient operators, for initializing the JetStream algorithm.

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Moreover, the proposed system englobes color information and an inertial mechanism into the basic method, and proposes a probabilistic measure used to merge results from different extractions. All these features makes the proposed approach an effective and completely automatic system for extracting road from aerial images.

The system has been tested on images regarding a highly urbanized area, where the high density of houses and buildings, and the complex road networks, together with the occlusions due to cars and shadows, makes the extraction of these entities very difficult.

The rest of the paper is organized as follows. In Section 2, the fundamentals of the probabilistic contour tracking are given, while the proposed approach is detailed in Section 3. Experimental results are given in Section 4, and in Section 5 conclusions are drawn.

2. THE PROBABILISTIC APPROACH TO CONTOUR TRACKING

Tracking of contours in images could be considered as an unconventional tracking problem, where the concept of time should be substituted by a concept of space. Moreover, in the time-tracking problem data arrive frame by frame, while in this space case all data are available at each step. Thus, some adaptations of the standard CONDENSATION algorithm should be accomplished. This section summarizes the fundamentals of the probabilistic approach to contour tracking proposed in [10].

The main idea under the JetStream algorithm is to approximate the posterior probability, representing all the information of the model obtainable from the image, as a set of samples $S^t = \{s_1^t ... s_N^t\}$, or particles, each featured with a weight $\{\pi_1^t ... \pi_N^t\}$. Each particle represents a path in the image (the road), while the weight is the "reliability" of the path (the probability). In particular,

$$s_i^t = (x_{i,0}, m_{i,0}), (x_{i,1}, m_{i,1}), ..., (x_{i,t}, m_{i,0})$$

where $x_{i,t}$ represents the middle point of a road large m_i pixels. In other words, m_i is the distance between the two side points $x_{i,t}^+$ and $x_{i,t}^-$. The point $x_{i,0}$ is the first road point (given), and $x_{i,1}, ..., x_{i,t}$ represent the evolution of the road (*i.e.* the subsequent middle points). The distance between two consecutive points represents the "space step", and denotes the "speed" with which the algorithm follows the road in the image.

Supposing that N samples are maintained during all evolution, at each step t the following operations are performed:

1. *Sampling.* N particles are sampled from the set S^{t-1}, based on the weights $\{\pi_i^{t-1}\}$: the higher the weight π_i^{t-1}, the larger the probability of the sample s_i^{t-1} to survive (to be extracted). Let us denote this set as $\tilde{S}^{t-1}$
2. *Prediction.* In this step a dynamic (prediction) is applied to the selected set of particles $\tilde{S}^{t-1}$, in order to predict the next position in the road and obtain the set S^t: this dynamics encodes the a priori knowledge on the possible evolution of the road contour, defined as
$$s_i^t = \tilde{s}_i^{t-1}, (x_{i,t}, m_{i,t})$$
with $x_{i,t} = x_{i,t-1} + R(\theta_i)(x_{i,t} - x_{i,t-1})$. $R(\theta_i)$ denotes a rotation of an angle θ_i. The angle θ_i is drawn from two different distributions, depending from the value taken by the corner function $c(x_{i,t})$, defined as
$$c(x_{i,t}) = \begin{cases} 1 & \text{if there is a corner in } x_{i,t}^+ \text{ or in } x_{i,t}^- \\ 0 & \text{otherwise} \end{cases}$$
The angle θ_i is then drawn from:
   - an uniform distribution in $(-\frac{\pi}{2}, \frac{\pi}{2})$, if $c(x_{i,t}) = 1$
   - a Gaussian distribution $\mathcal{N}(0, \sigma_\theta^2)$, otherwise.

   The evolution of the width of the road m_i is driven by
$$m_{i,t} = m_{i,t-1} + v_{i,t} \qquad (1)$$
with $v_{i,t}$ drawn from a Gaussian of zero mean and fixed small variance.
3. *Weighting.* These predictions are then validated using information from the image (likelihood), obtaining the new weights. The likelihood is computed by using image gradient information (both direction and magnitude), taking into account also the corners. More in detail, the likelihood ℓ of a sample s_i^t is determined by the following formula
$$\ell(s_i^t) = \frac{p_{\text{on}}(x_{i,t}^+) p_{\text{on}}(x_{i,t}^-)}{p_{\text{off}}(x_{i,t}^+) p_{\text{off}}(x_{i,t}^-)} \qquad (2)$$
where p_{on} and p_{off} are the probabilities of the "on contours" and the "off contours", respectively. These quantities are computed for both the points $x_{i,t}^+$ and $x_{i,t}^-$, with the use of the gradient ∇I and the corner function c, and are defined as (removing the i-th index and the +/- apex for readability):
$$p_{\text{on}}(x_t) \propto \frac{c(x_t)}{\pi} + (1 - c(x_t)) \mathcal{N}\left(\psi(x_t); 0, \frac{\sigma_\psi^2}{|\nabla I(x_t)|}\right) \qquad (3)$$
and
$$p_{\text{off}}(x_t) \propto \exp - \frac{\nabla I(x_t)}{\lambda} \qquad (4)$$
where $\psi(x_t)$ is the angle between the gradient normal $\nabla I(x_t)^\perp$ and the segment (x_{t-1}, x_t), λ is the average gradient norm over the image, and σ_ψ^2 has experimentally been fixed to 1.36.

At each step, the extracted road is represented by the most probable sample.

3. AUTOMATIC EXTRACTION OF ROADS

The approach proposed in this paper starts from [10], adding three important contributes: first, we modify the basic Jet-Stream algorithm, in order to use color information and to deal with small occlusions. Second, we propose an automatic tool for extracting the points from which starting the contour tracking, based on the Hough transform and some topological considerations. Finally, we propose a method for merging the results obtained from different runs of the algorithm, based on a measure able to quantitatively assess the goodness of the extracted roads.

Regarding the first contribution, we modify the Jetstream algorithm by changing the weighting step (step 3) in a twofold manner. First, we propose to augment the information used in the likelihood computation (i.e., gradient) by considering also the color information (roads are typically homogeneous inside). Color information are obtained by segmenting the image in the HSV (Hue Saturation Value) color space. This space has been chosen as it permits to separate the chroma information from the luminosity, resulting in a more effective segmentation. This results in a change of the definition in eq. (2):

$$\ell(s_i^t) = \frac{p_{\mathrm{on}}(x_{i,t}^+)p_{\mathrm{on}}(x_{i,t}^-)U(x_{i,t}^+, x_{i,t}^-)}{p_{\mathrm{off}}(x_{i,t}^+)p_{\mathrm{off}}(x_{i,t}^-)} \tag{5}$$

where $U(x_{i,t}^+, x_{i,t}^-)$ measures the color uniformity of the pixels between $x_{i,t}^+$ and $x_{i,t}^-$.

The second change to the weighting step proposes to add an inertial term to the likelihood computation procedure, that allows a particle to survive along its direction for few additional steps, even if not supported by high likelihood. This permits to go beyond small occlusions like isolated trees or cars. This is obtained by defining the new likelihood $\hat{\ell}(x_{i,t})$ as:

$$\hat{\ell}(s_i^t) = \alpha\ell(s_i^t) + (1-\alpha)\ell(s_i^{t-1}) \tag{6}$$

where α is the parameter driving the decay of the process memory. In this way also older likelihood is taken into consideration. When $\ell(x_{i,t})$ is zero (sure non-contour point), we force the $R(\theta)$ function of the prediction step (step 2) to 0. By means of these two modifications, a particle can continue to survive (along its last good run direction) for few more iterations, even if not supported by a high likelihood, allowing to overcome from small occlusions.

Regarding the initialization, initial seeds are automatically found with a method based on the Hough transform and on some topological road properties. The main idea is the following: the Hough transform (the well known line extractor) could not be used in the whole image, due to the fact that roads are not perfect straight lines. But it should be noted that streets are composed by straight segments, that could be extracted by the Hough transform by analyzing only small neighborhoods of pixels. So the idea is to seek for parallel straight lines in small subimages, using the Hough transform, and to choose points lying on these lines having high gradient and uniform color in the points between them. These small segments are then used for initializing the contour following algorithm, that starts the tracking in a direction perpendicular to the gradient.

Every execution of the contour tracker can find a road, or a small part of a road, and can also extract the same road more times. To obtain an accurate and homogeneous result from the original photo, only the best part of each result is considered. To this aim a new measure is introduced, able to quantitatively assess the quality of the extracted roads. This measure is based on color information (as roads are typically quite homogeneous inside) and gradient information (gradient on the road boundaries is typically high and the directions on both sides is parallel). The quality of a fragment $x_0 \ldots x_T$ is measured with the following formula:

$$Q(x_0 \ldots x_T) = \sum_{t=0}^{T} \frac{U(x_t^+, x_t^-)\nabla I(x_t^+)\nabla I(x_t^-)}{|\nabla I(x_t^+) \times \nabla I(x_t^-)|} \tag{7}$$

where $\times$ represents the vector product. This measure is directly proportional to the uniformity of the points lying between the two borders and to the magnitude of the gradient, and inversely proportional to the perpendicularity of the gradient directions (vector product).

The resulting extracted roads are then formed by only high quality segments.

4. EXPERIMENTAL RESULTS

The proposed approach has been tested on several real images[1], regarding a highly urbanized city zone. An example of the results obtained from the road extraction process is proposed in Fig. 1, in which one can notice that the task is quite difficult, due to the high urbanization of the area, shadows and car occlusions. Nevertheless, the proposed approach is able to correctly extract all the relevant roads in the image. Another example is proposed in Fig. 2, confirming the goodness of the proposed approach.

5. CONCLUSIONS

In this paper a fully automatic approach to road extraction from aerial images has been proposed, based on a probabilistic contour tracking approach.

The method is able to deal with small occlusion, and include color information in the validation process. The initial

[1] All images are courtesy of CO.GE.ME. Informatica - Rovato (Brescia).

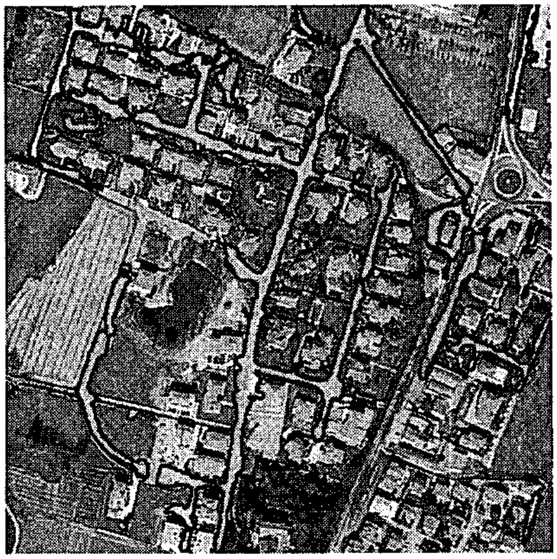

Fig. 1. Extracted Roads.

Fig. 2. Extracted Roads.

points from which to start the contour tracking are automatically found, using a Hough transform based approach. All the obtained results are effectively merged with a strategy able to deal with possibly overlapping roads. Experimental evaluation on highly complex real images has shown the validity of the proposed approach.

6. REFERENCES

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