EXTRACTION OF ROAD NETWORK USING A MODIFIED ACTIVE CONTOUR APPROACH

Said Mssedi\textsuperscript{1,2}, Mohamed Ben Salah\textsuperscript{2}, Riadh Abdelfattah\textsuperscript{3,4} and Amar Mitiche\textsuperscript{12}

\textsuperscript{1} Ecole Polytechnique de Tunis, \textsuperscript{2} Institut national de la recherche scientifique – Canada
\textsuperscript{3} URISA, École Supérieure des Télécoms, Université de Carthage – Tunisie
\textsuperscript{4} Institut Telecom ; Telecom Bretagne – France.

ABSTRACT
Road network extraction from digitized map consists in partitioning a map into two different classes (road and background) distinguished with their intensity values and geometric shape. In this paper, we propose a semi-automatic method where user intervention is minimal. We adopt a variational framework where a minimization energy is proposed. Roads are tracked by active contours which evolve according to evolution equations derived from the energy minimization. We consider that the energy is composed of three main terms which have never been combined and used in such application. The first term is the geodesic active contour (GAC) which is contour-based and which evolves toward high gradients in the image. The second term matches the intensity distribution inside the contour with a model distribution. The third term is a geometric constraint which describes the thin structure of routes. The user intervention is restricted to learning the road intensity model.

Index Terms— Road network, variational framework, active contour, minimization energy.

1. INTRODUCTION
Road extraction from digitized maps is a fundamental problem which has major practical importance for GIS update [1]. The classic manual techniques are time consuming. Besides, manual techniques are known to be dependent on the operator [2]. Thus, the solution may change even for the same map and is prone to human errors. Proposed solutions for road extraction can be classified among maps features extraction methods. However, all these methods almost use the same basic features which are intensity, geometry and topology. The intensity information is used, especially, in color images where roads have different color profile [3]. Geometry characteristics help the extraction process in the sense that, for example, roads are known to be elongated ribbons rather than other forms. However, the fact that roads are continues lines which form a network is rather topological information. Bases on these features, many automatic and semi-automatic methods have been published [4].

Regarding the amount of user intervention, the published methods are often classified into automatic and semi-automatic methods. A fully automatic method is theoretically supposed to take, as input, any kind of maps and provides, as output, the extracted road network. However, road characteristics vary significantly with map type, road type, image resolution, surrounding objects, presence of occluding objects, etc. Hence, a fully automatic method, as defined above, is quite impossible to achieve [3]. Moreover, the published automatic methods are known to work for a given range of images with specific conditions [5, 3].

In this paper, we propose a semi-automatic method where user intervention is minimal. We adopt a variational framework where a minimization energy is proposed. This framework allows embedding various constraints in the energy and, thus, solving many kinds of problems and various types of maps. Roads are tracked by active contours which evolve according to evolution equations derived from the minimization energy. We consider that the energy is composed of three main terms which have never been combined and used in such application. The first term is the geodesic active contour (GAC) [6] which is contour-based and which evolves toward high gradients in the image. The second term matches the intensity distribution inside the contour with a model distribution. The third term is a geometric constraint relative to the thin structure of routes, and which was developed to satisfy to our need. Hence, the contour evolution is guided locally by the GAC term, and globally by the distribution matching term and take finally the form of the geometric term. The user intervention is restricted to learning the road intensity model.

Indeed, this task is done only one time for a given map, then the same model is used for maps of the same class. However, other methods can be used for this task as clustering, or graph-cut methods.

The remainder of this paper is organized as follows: Section 2 describes the minimization energy terms, and explains the learning process for the distribution matching term. In section 3 we details the developed constraint proposed to describe geometrically the road network. Section 4 reports experimental results, and Section 5 contains concluding remarks.
where $\Omega$ is the image domain. In our application, the intensity energy functional is composed of two essential terms:

$$E_I = E_1 + \alpha E_2,$$  

(1)

where $\alpha > 0$ is a real constant. $E_1$ represents the local energy term which guides the active contour towards areas of high gradient and $E_2$ is the global energy which guides the active contour to areas which have a similar distribution to a model learned beforehand.

### 2.1. Local Energy

The first term of energy (1), the local term, is dependent on the contour $\gamma(s, t)$ as follow:

$$E_1 = \int g(I) ds,$$  

(2)

where $g$ is the edge indicator function. $g$ is a monotonically decreasing function which is often referred to as stopping function. A common choice of this function is:

$$g(I) = \frac{1}{1 + |\nabla G_\sigma * I|^p}, \quad p = 1, 2,$$

where $\nabla G_\sigma * I$ is a smooth version of the image $I$, and $G_\sigma$ is generally the Gaussian kernel $G_\sigma = \frac{1}{\sqrt{2\pi} \sigma} \exp(-\frac{|x|^2 + |y|^2}{2\sigma^2})$. The edge indicator function which depends solely on image gradient, stops the active contour on the edges of objects. Indeed, it vanishes on objects borders because image gradient is high. The curve flow minimizing this energy is known as the geodesic active contour (GAC) [6]. Although, efficient in many applications where objects are very well characterized by image gradient transitions, the GAC term is insufficient in our case. For instance, all road maps we consider contain various objects other than roads. Although unwanted, these objects attract the GAC because they have high image gradients along their boundaries. Hence, another term which biases the evolving contour towards only the object of interest is needed.

### 2.2. Global Energy

Let $z$ be the photometric variable of interest. For example, $z$ could be an intensity, color vector, or texture vector. Let $Y: \Omega \to Z$ be a mapping from the image domain to the space of the photometric variable and $x \in \Omega$. Thus, if $Z$ is the space of intensities, then $Y(x)$ is just a gray-scale image; if $Z$ is the space of color vectors, then $Y(x)$ is a color image. Denote by $R \subset \Omega$ the region surrounded by the contour i.e. $\gamma = \partial R$. The sample distribution within region R of the variable $z$ is estimated as follow: $d(z, R) = \int \frac{K(z - Y(x)) dx}{A(R)}$, where $A(R) = \int_R dx$ is the area of the region $R$, and $K$ is a kernel function. Most common choices of $K$ are the Dirac distribution and the Gaussian kernel function. The purpose of this part is to track the region $R$ where the probability density $d(z, R)$ most closely matches a model distribution $M$ learned beforehand. To do so, we measure the similarity between both distributions by the Bhattacharyya measure. However, other measures can be used such as the Kullback-Leibler distance [7]. This energy term is global because it references the intensity distribution in a given region and, as such, is not written in a pixel wise form. Hence, the global energy term is:

$$E_2 = -B(d, M) = - \int_\gamma \sqrt{d(z, R)M(z)} dz.$$  

(3)

This measure varies between 0 and 1, where 0 indicates complete mismatch, and 1, a complete match. In the next section, we derive evolution flows from the energies defined above.

### 2.3. Evolution Flows

We derive, in this part, the evolution equations of the active contour $\gamma$ minimizing $E_I$ in (1). These equations manage the movement of the active contour from its initial position to the borders of all roads in the map road network. Using functional derivative calculus, we obtain:

$$F_I = \frac{\partial E_I}{\partial \gamma} = -\frac{\partial E_1}{\partial \gamma} + \alpha \frac{\partial E_2}{\partial \gamma} = F_1 + \alpha F_2,$$  

(4)

where $F_1$ is the local force, called also the geodesic flow, which derives from the local energy and $F_2$ is the global force, we refer to it here by the Bhattacharyya flow, which derives from global energy: $F_1 = (gk - \nabla g, \nabla \nabla \tilde{n}) \tilde{n}$, $k$ and $\tilde{n}$ are respectively the curvature and the normal to the contour $\gamma$. ;

$$F_2 = \frac{1}{2A(R)} \left[ M^{1/2}(Y(\gamma)) \frac{d^{1/2}(Y(\gamma))}{d\gamma} - B(m, d) \right] \tilde{n}.$$
2.4. Level set implementation

Since its emergence, level set method has been widely adopted to implement active contour based methods \cite{8}. It makes no assumption about the topology of the objects. We use here the fact that, for a given evolution equation of the form $\frac{\partial \gamma}{\partial t} = \beta \nabla$, where $\beta$ is scalar function, the level set form is as follows $\frac{\partial \phi}{\partial t} = \beta |\nabla \phi|$. The total level set flow is thus derived ($F_T = \frac{\partial \phi}{\partial t}$).

$$F_T = \left[ \frac{1}{2A} \left( \frac{M^2}{d^2} - B(m, d) \right) + \left( g.k - \nabla g \cdot \nabla \phi \right) \right] |\nabla \phi|$$ (5)

3. GEOMETRIC TERM

The extraction of road network from digitized map cannot be reduced only to the recognition of objects boundaries and routes intensity distribution, but needs to specify their geometry. Take for example the presence of different objects on the digitized map which have the same intensity distribution as the road network as shown in Fig.2 (a). For this reason, adding to the intensity energy (1) a term which describes the geometric shape of the roads is necessary.

$$E_T = E_I + \beta E_3 = E_1 + \alpha E_2 + \beta E_3,$$ (6)

Fig. 2. first test image: (a) digitized map, (b) result of the extraction with the developed method.

3.1. The distance between pixels and the active contour

In our application, the level set is managed by the distance function between pixel and the zero level of the level set. Therefore, the value of level set at each point $x$ of the image $\Omega$ is the distance between $x$ and the contour $\gamma$. To distinguish between the region inside and outside the contour and to keep the concept of distance for all points of level set, we added a minus sign for any measure outside the contour $\gamma$. So, the distance function will be signed in our application: $d(x, \gamma) = d(x, \gamma)$ if $x \in R$ and $-d(x, \gamma)$ if $x \in R^c$. $R$ is area inside the contour $\gamma$ and $R^c$ is the complement of $R$ in the image domain $\Omega$. So, we remark that the maximum distance between pixels and the active contour corresponds to the centers of thick and convex objects. Since roads are structurally thin and not convex, the distance function can be a tool which distinguishes roads from thick and convex objects such as circles.

3.2. The developed distance function

This mathematical tool is used in the first step of segmentation with the calculation of gradient and measurement of Bhattacharyya. So after determining the initial position of our active contour, the level set is generated automatically by the geodesic term, Bhattacharyya measure and distance function. However, after several iterations, the level set no longer obeys to the distance function. Indeed several terms (geodesic, Bhattacharyya, smoothness) manage the new values of level set at each iteration. So it is impossible that the linear combination of these terms keep the distance notion in the structure of the level set. For this reason, the first challenge of this new method is to approach after each iteration the level set to the distance function. Li et al \cite{8} resolved the first issue. For more accurate computation involving the level set function, they need to regularize the level set function by penalizing its deviation from a signed distance function. They add to the overall energy a term which can be characterized by the following function:

$$P(\phi) = \int_{\Omega} \frac{1}{2} (|\nabla \phi(x)| - 1)^2 \, dx.$$ (7)

Retaining the concept of distance in the level set at each iteration, we added an additional term to the total energy to describe the structure of thin roads. This geometric term appears in the overall energy in the form of a Heaviside function:

$$E_3 = H \left( \phi - \frac{1}{2}m \right),$$ (8)

where $m$ is the maximum width of the road network. The user sets value $m$ in the initialization. Using the Heaviside function hides some objectives. Firstly, the function $H \left( \phi - \frac{1}{2}m \right)$ takes the value $1$ for all points distant more than $\frac{1}{2}m$ from the border $\gamma$ and $0$ otherwise. So the minimization of $E_3$ closes the curve until the distance between all pixels in region $R$ is less than $\frac{1}{2}m$ (the middle of the widest road in the network). Secondly, $H \left( \phi - \frac{1}{2}m \right)$ is discontinuous in a critical value which represents the geometric threshold between large and small objects. This discontinuity can significantly differentiate the two types of objects and avoid topological change of curve in uncertainty area. Indeed, if we use a continuous function, accumulation of small changes in pixels close to the critical value can change incorrectly the position of $\gamma$ in this area. Finally, Dirac function $\delta$, the derivative of the Heaviside function is very simple in the implementation level. The
derivation of $E_3$ gives a new term in the evolution equation:

$$F_3 = \delta \left( \phi - \frac{1}{2} m \right)$$

(9)

This new method extracts only the thin structure which resembles to roads independently of their shapes (straight, curved, ...) and their position (far, close to large objects). Fig. 1 which shows the position of the contour $\gamma$ few iterations after the extraction of objects having the same distribution of roads, explains the influence of $F_3(9)$ in evolution of active contour. This new term divides large objects into three parts. It eliminates, at the distance of $\frac{1}{2} m$ from contour $\gamma$, a very narrow area of the region $R$. After penetration of contour $\gamma$ in these large objects, the geodesic term looks again for new areas of high gradient until the complete disappearance of these objects in the region $R$.

Fig. 3. Second test image: (a) digitized map, (b) result of the extraction with the developed method.

4. EXPERIMENTAL RESULTS

To demonstrate the efficiency of the developed road network extraction approach, we present some experimental results tested on the digital maps depicted by Fig. 2 (a), Fig. 3 (a) and Fig. 4 (a). The result presented in Fig. 2 (b) contains some objects on the background with the same intensity distribution as roads. We also tested the developed approach on maps with road which are very curved and very close (stuck) with different widths which vary between 10 and 30 pixels (Fig. 3 (b)). Despite these difficulties, the new method was able to extract the majority of road network with few errors mainly due to the narrow width of the road as the difference between Fig. 3 (a) and (b). Moreover, considering the road network of a titled digitized map (Fig. 4 (a)), the extraction result (Fig. 4 (b)) is perfect. This is despite the roads are sometimes cut to display their names or other information. These obtained results show the rigidity of this method which extract accurately the entire road network and avoid two important problems: Firstly, the extraction of road network only even though it has the same intensity distribution with other objects. Secondly, the continuity of the road network even though it is cut by words and information panels.

Fig. 4. Third test image: (a) digitized map, (b) result of the extraction with the developed method.

5. CONCLUSION

In this paper, we presented a method for extracting road networks based on image segmentation by active contours and level set. This method gathers the contour information from the geodesic model, region information from distribution matching model and geometric information from the distance function. It improves the efficiency of road network extraction by the rapid detection of borders through the geodesic term, matches the segmented area with a model which contains accurate information about roads through the Bhattacharyya measure and distinguishes, by a geometric term, objects which have the same intensity distribution as roads and differ in geometric level.

6. REFERENCES