Fast Road Network Extraction in Satellite Images using Mathematical Morphology and Markov Random Fields

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ABSTRACT

This paper presents a fast method to extract road network in satellite images. A pre-processing stage relies on mathematical morphology to obtain a connected line which encloses road network. Then, a graph is constructed from this line and a Markovian Random Field is defined to perform road extraction.

1 INTRODUCTION

In the particular field of satellite imagery, many different methods have been proposed to extract roads. Let us just recall some of them: a tracking by active testing based on information theory [2], a differential geometry scheme [9], a Markovian field on a set of segments [11], a Markov point process [10], an active contour based method [4].

Most of these methods fortunately rely on a global optimization process but suffer from drawbacks. Many methods are close to tracking-like approaches and cannot take into account features extracted from image regions. Many methods consider that a road is a set of straight lines so road accuracy is quite poor. Last, most of these methods take several minutes to detect roads in rather small satellite images.

In this paper, we propose a detection method for road network that overcomes these drawbacks.

This paper is organized as follows. First, section 2 recalls some classical tools used in pattern recognition. Then, section 3 presents the method we propose and section 4 discusses the results we obtain. Last, section 5 concludes and gives perspectives.

2 PRELIMINARIES

2.1 Watershed Transform

The watershed transform (WT) [12] is a morphological algorithm usually used for the purpose of segmentation. Considering a gray level image as a topographic map, let us denote by catchment basin associated with a regional minimum of this map, all points whose steepest slope paths reach this minimum. The watershed line is a closed one-pixel thick crest line which separates every adjacent catchment basins, i.e., regions. Since numerous minima populate images, applying the watershed transform to an image leads to an over-segmentation.

2.2 Region Adjacency Graph and Markov Random Field

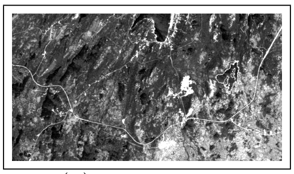
A now common framework [8] to segment an image I or to extract objects from I is the following. First, one applies an over-segmentation method to I, which gives S. Please note that this method can be the watershed transform (WT) applied to the gradient norm image of I, as in [3]. Then, one computes from S the region adjacency graph (RAG) R and fills this graph with information from I. Last, one defines a Markov Random Field (MRF) on R and runs a Markovian relaxation to get a final segmentation.

This framework is powerful since it is general and since the final segmentation results from a global process on high-level image primitives (regions in that case). Moreover, it enables operational segmentations even when images are over-sized as it is the case in satellite imagery.

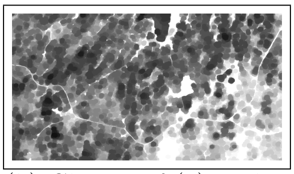
2.3 Minima Suppression and Area Closing

A classic algorithm to suppress minima in images is the morphological closing operator with a structural element being a disk for isotropic purpose. However, artifacts appear in resulting images: in particular, crest lines can strongly move when one wants to remove many minima, that is, when filtering strength (i.e., the disk radius) increases.

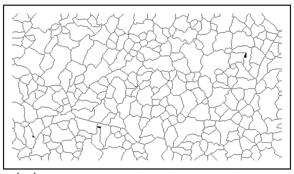
An area closing operator [7, 5] is a “connected filter” that removes minima whose area is less than a given threshold. Area closing does not present the crest lines shifting drawback that appears while clos-



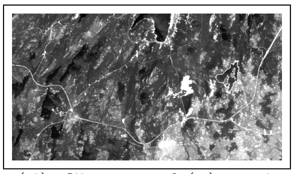
(a) Test image.



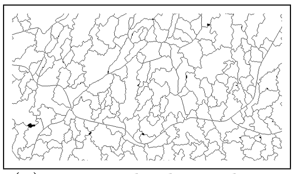
(b) Closing of (a) with a disk s.a. radius = 5.



(c) Watershed resulting from (b).



(d) Closing of (a) with area = 500.



(e) Watershed resulting from (d).

Figure 1: Morphological Closings and Crest Lines.

ing with a structural element. This property is depicted by figure 1 thanks to the watershed algorithm which points out resulting crest lines.

3 PROPOSED METHOD

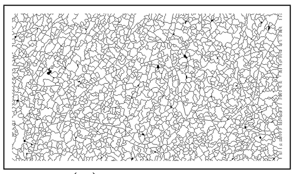
The method we propose is composed of four steps. They are illustrated with a small part (700×380 pixels) of a Landsat image from St-Johns city, Canada, having a 25 m resolution and 7 spectral channels. This original image is under the following copyright: " © *2000. Government of Canada with permission from Natural Resources Canada*"; it can be fetched from `http://geogratis.cgdi.gc.ca/`. A natural image, build from the three natural color channels red-green-blue, is depicted in figure 4 (a).

3.1 Pre-Processing

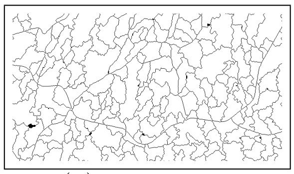
From a satellite image compute a gray level image where pixel values denote their potential of belonging to a road. Roads are thus located on crest lines of this "potential" image. We have chosen a very simple potential image, the red channel $(0,63 - 0,69\mu m)$; it is depicted in figure 4 (b). In the following the potential image is denoted by V.

3.2 Filtering

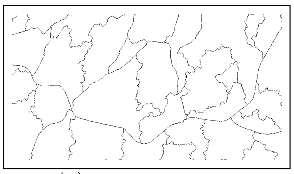
The filtering step consists in computing an area closing of the potential image and then running the watershed transform. The potential image, once closed (figure 4 (c)), has much less minima than the "original" potential image (figure 4 (b)) while properly retaining crest lines location. Therefore, the resulting watershed line (figure 4 (d)) includes the road network.



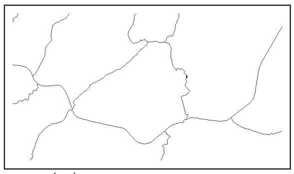
(a) *area = 10*



(b) *area = 100*



(c) *area = 1000*



(d) *area = 10000*

Figure 2: Different Strengths of Filtering.

In figure 2, we depict the watershed lines resulting from different values of area. Multi-scale properties of this morphological filtering can be observed: new curves (features) do not appear when area (scale) increases and a feature which is present at a given scale (a piece of watershed line obtained with a given area) is still present at a lower scale (in the watershed line obtained with a smaller area). This property is very important for us since the only parameter of this filtering step is the *area*; even with a large value of area, we are guaranteed to have important roads be included in watershed line.

3.3 Curve Adjacency Graph

From the watershed line, we build a curve adjacency graph (CAG). A node of this graph (red bullets in the picture below) represents a shed, that is, a connected part of the watershed line separating two adjacent basins. An edge (green lines in the picture below) is drawn between two nodes/sheds if one end of the first shed is connected with a end of the second one through the watershed line.

For every node we make the distinction between edges coming from connections to one shed end (yellow anchors) and those coming from connections to the other shed end. This distinction, symbolized by yellow and blue anchors in figure 3, allows to properly handle in the next step (section 3.4) some geometrical constraints upon the road network.

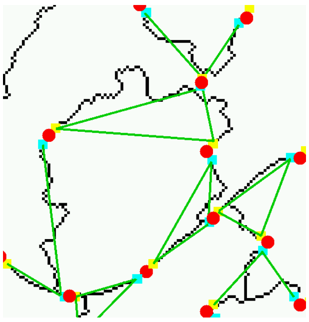


Figure 3: CAG Definition From Watershed.

3.4 Markovian Relaxation

Extracting road network now turns out to be a graph labeling problem. Upon the graph structure, we can define a Markov random fields. Let us denote by X the observation field, by Y the result field, by x_s and y_s their respective restriction to a given node s, by Y_{V_s} the restriction of Y to the neighborhood of s. The variable y_s has a Boolean realization where 1 means *road* and 0 means *not road*. Under the Markovian assumption we have:

$$p(y_s|X, Y - y_s) = \frac{1}{Z}\exp(-(U(x_s, y_s) + U(Y_{N_s}))),$$

and we can express road extraction as an energy minimization problem.

The first energy term, $U(x_s, y_s)$, models *a priori* knowledge about roads. As a node designates a small piece of the watershed line, that is, a set of points, we can have measures associated with every nodes, such as the curvature of this piece of line, its "potential" mean value (measured from the potential image), its contrast with respect to adjacent regions, its saliency [6], and so on.

For instance, an *a priori* energy based on curvature κ can be:

$$U_\kappa(x_s, y_s) = \begin{cases} \kappa(s)/\sum_s \kappa(s) & \text{if } y_s = 1 \\ 0,5 & \text{otherwise,} \end{cases}$$

favoring road when curvature is low. Please note that the parts of the watershed line which do not correspond to roads look like "chaotic" paths because they join up high potential points that are not correlated. This phenomenon is clearly observable in figure 2 (c) because the watershed line is very simple thus readable: the smooth parts belong to road network whereas chaotic parts do not.

The second energy term, $U(Y_{N_s})$ deals with labeling contextual information. We use a model rather close to the Potts model. In this model, *when* $y_s = 1$ (that is, when s is labeled as a road), we favor e.g. the configuration "two sheds are connected to one end of shed s and one shed is connected to the other end" to express that roads can fork. Conversely, when $y_s = 1$, the configuration "both ends of shed s are not connected to any other piece of road" is strongly penalized.

Last, a relaxation process is performed by Metropolis algorithm.

4 COMMENTED RESULTS

We have validated our method on about a dozen of Landsat images. Applying the whole road extraction process to an image having 2.10^6 pixels takes less than 20s on a 1,7 GHz personal computer running GNU/Linux. A representative result is depicted in figure 4 (f).

We observe that road extraction results with our method is comparable to literature results except that road extraction is much faster and road description is more accurate. In particular, our method is speeded-up when the area parameter increases since the CAG is becoming smaller. Filtering often leads to information loss but, with *area = 500* for our 25 m resolution test image, we obtain a very lightweight graph (about 400 nodes; see table below) and the filtering step only prevents us from extracting loops in road network whose area is less than 0,3 km^2. Put differently, our method is rather poorly sensitive to data simplification.

area	number of bassins (regions)	number of sheds (nodes)	number of crosses (links)
10	15797	42956	27523
50	3359	10218	7010
100	1772	5613	3927
500	415	1643	1120
1000	232	1046	687
5000	58	223	187
10000	36	146	126

About implementation issues. We have developed our method with our C++ image processing library Olena [1]. Olena is a free software under the GNU Public Licence (GPL) and can be downloaded from our web site `http://www.lrde.epita.fr` Olena provides a wide range of objects: images structures —1D, 2D or 3D images, graphs—, safe data types —integers, floating values, different color encodings— and utility objects —points, iterators, etc. Olena also provides fast implementation of algorithms and can be considered as a *generic* library —an algorithm is written once while accepting various input types. Olena can thus be used in different fields of image processing and pattern recognition.

5 CONCLUSION

We have presented a method to extract road network from satellite images. We have transposed the recognition scheme "WT + RAG + MRF", described in section 2.2 and which is dedicated to image segmentation, to the problematic of road network recognition. To that aim, we propose a recognition scheme that is, as far as we know, original: "area opening + WT + CAG + MRF".

This recognition scheme is a global optimization process so it provides robust and reproducible results. Moreover, it is general and can easily be adapted to other image processing fields where the recognition of curvilinear structures is involved.

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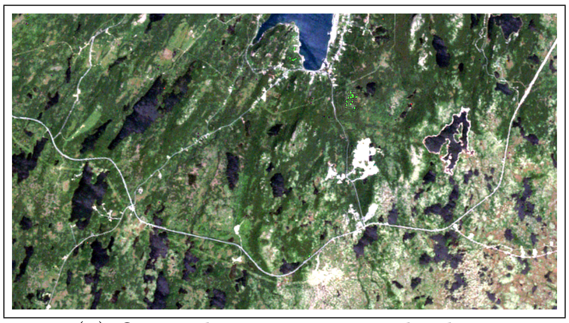
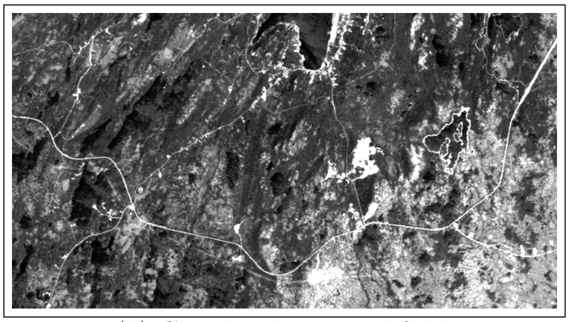
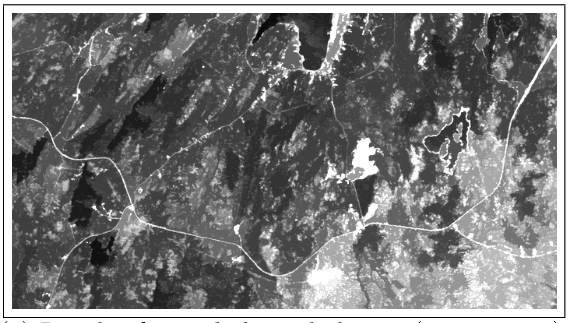


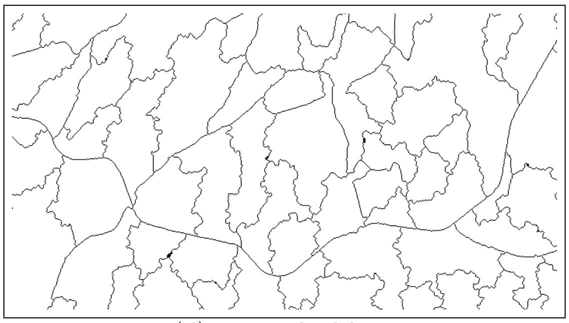
(a) Original image in natural colors.



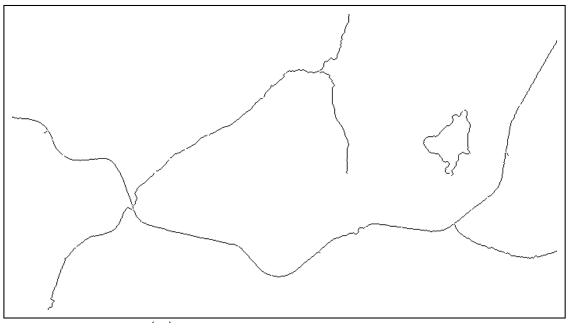
(b) Gray level potential field.



(c) Result of morphological closing (*area* = *500*).



(d) Watershed line.



(e) Final MRF labeling.

Figure 4: Different Steps of Road Network Extraction.