DETECTION AND EXTRACTION OF ROAD NETWORKS FROM HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT

This article addresses the problem of road extraction from new high resolution satellite images. The proposed algorithm is divided in two sequential modules : a topologically correct graph of the road network is first extracted, and roads are then extracted as surface elements. The graph of the network is extracted by a following algorithm which minimizes a cost function. The extraction algorithm makes use of specific active contours (snakes) combined with a multiresolution analysis (MRA) for minimizing the problem of geometric noise. This reconstruction phase is composed of two steps : the extraction of road segments and the extraction of road intersections. Results of the road network extraction are presented in order to illustrate the different steps of the method and future prospects are exposed.

1. ROAD NETWORK EXTRACTION

1.1. State of the art

Road extraction from remotely sensed images has been the purpose of many works in the image processing field, and because of its complexity, is still a challenging topic. These methods are based on generic tools of image processing, such as linear filtering ([1]), mathematical morphology ([2]), Markov fields ([3]), neural networks ([4]), dynamic programming ([5]), or multiresolution analysis ([6]; [7]). Road models are common for all authors, *i.e.* the radiometry along one road is relatively homogeneous and contrasted compared to its background. Moreover the width of the road and its curvature are supposed to vary slowly, and the road network is supposed to be connex. Promising studies try to take the context of the road into account in order to focus the extraction on the most promising regions ([6]; [8]).
The recent possibility to have satellite images with a high spatial resolution (1 meter or less) has re-boosted the interest for road extraction (especially for the applications in urban areas). This increased resolution enables a more accurate localization of the road sides as well as its extraction as a surface element. In return, it generates a higher complexity of the image and an increase of geometric noise (vehicles, trees along the road, occlusions, ...).

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2. THE PROPOSED APPROACH

2.1. Description

A method has been developed in order to extract and characterize the road network from high resolution images. Inputs of the algorithm, besides the high resolution satellite image, are models of roads (using roads properties defined by [7]) and properties of road network (such as connexity). Our algorithm is composed of two sequential modules (fig.1).

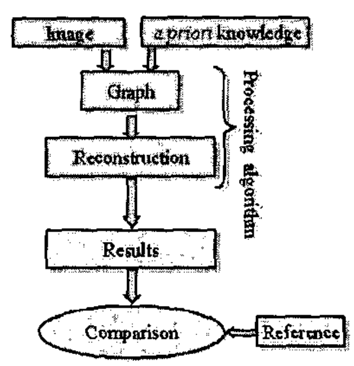

Fig. 1. The methodology including topology management and road reconstruction

Firstly, a topologically correct graph of the road network is extracted. This step aims at giving correct spatial connections between roads as well as an approximation of their location. The next step is the actual road reconstruction. Due to the high resolution of the images, a surface reconstruction has to be performed. This step uses the previous step

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of graph management as an initialization for the reconstruction.
In the next sections, the different modules of the process are more precisely described.

2.2. Graph management

This module intends to extract a topologically correct graph of the road network. It aims at giving correctly spatial connections between roads as well as an approximation of their location. The graph can come from a road database or be extracted automatically. In this second case, the graph extraction algorithm is based on the work of [9] : a following algorithm selects the best path for the potential road by minimizing a cost function. The cost function evaluates the homogeneity of the local radiometry variance for several propagation directions. In order to overcome noise which may disturb the process, a decrease of the image resolution can be performed by applying a blurring filter.
At this step, the extracted graph is topologically correct but the different polylines are not necessary well registered.
From the extracted graph, polylines are then sampled and propagated along their normal direction in order to initialize the surface reconstruction module.

2.3. Reconstruction module

2.3.1. Description

The goal of this module is to reconstruct roads as surface elements from the graph provided by the previous step. This module makes use of specific active contours (*snakes*) combined with a multiresolution analysis (*MRA*). The snake implementation is based on the *greedy algorithm* described by [10]. The use of the *MRA* with the Wavelet Transform enables to perform a multiresolution edge detection (*see* [11]). It also increases the algorithm convergence by minimizing the problem of noise (vehicles, ground markings,...).
Two sequential steps compose this reconstruction phase : the extraction of road segments with parallel sides and the extraction of road intersections. Indeed, these two objects present too many differences in both topology and shape to be processed in the same way. The frontier between the two kinds of process is defined by a circle including the whole intersection (fig. 2).

2.3.2. Extraction of parallel road sides

For extracting portions of road with parallel sides, a new object has been defined : the *DoubleSnake*. It is composed of two branches which are two snakes evolving jointly. The *DoubleSnake* energy functional has a new term $E_{//}$ that constrains the *DoubleSnake* to maintain a local parallelism between its two branches. Moreover, their extremity points are forced to minimize their energy staying on the intersection circle.

The snake energy functional is :

$$E = \sum_i \left[\alpha^i E^i_{cont} + \beta^i E^i_{curv} + \gamma^i E^i_{2^j{}_{image}} + \delta^i E^i_{//} \right] \tag{1}$$

where i represents the point i of one of the branch.
E^i_{cont} and E^i_{curv} are internal energies that control the snake's shape. A special attention is paid on the image energy term $E^i_{2^j{}_{image}}$, as it the one that attracts the snake to the object of interest. The image energy is computed with the wavelet coefficients at different spatial resolutions :

$$E^i_{2^j{}_{image}} = -\sqrt{|W^1_{2^j} f(i)|^2 + |W^2_{2^j} f(i)|^2} \tag{2}$$

where $W^{1,2}_{2^j} f(i)$ are the coordinates of the wavelet transform and j is the resolution in a dyadic analysis.

A more detailed description of the different energy terms can be found in ([12])

2.3.3. Extraction of road intersections

Once road segment extraction is finished, the intersection extraction starts. They are extracted by simple snakes which are initialized by pairing extremity points of the *DoubleSnakes* (see fig. 2). This *IntersectionSnake* has its extremities fixed and is constrained not to go out of the circle.

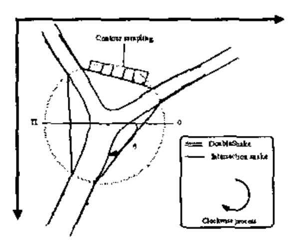

Fig. 2. Initialization of the intersection snakes

2.3.4. Reconstruction algorithm flowchart

Fig. 3 represents the different steps of the reconstruction algorithm. From the original image, a multiresolution analysis is performed, giving several approximation images at coarser resolutions and several wavelet coefficient images. *DoubleSnakes* are first applied on the coarsest resolution image, then on each intermediate resolution images until they run on the original resolution image. Coefficients of

the different energy terms are adapted to the image resolution. For instance, at the coarsest resolution, a high value of the image term allows the snake to be attracted from far. Refining the estimation on a finer resolution image is then done by releasing image constraints and increasing the importance of the internal energy.
Once *DoubleSnakes* have all minimized their energy, the *IntersectionSnakes* are initialized and the extraction starts in the same multiresolution process.

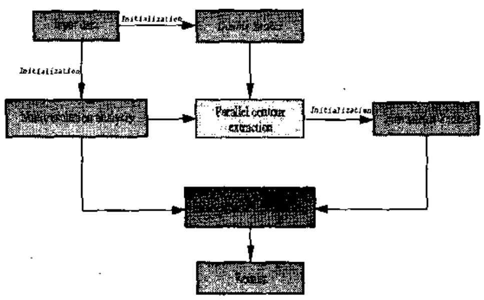

Fig. 3. Reconstruction algorithm

The algorithm stops when all snakes are in an equilibrium state.

3. RESULTS AND PROSPECTS

3.1. Real-case study

As the graph module is currently under integration, only the reconstruction module will be illustrated in the following example. Image of figure 4 comes from the IKONOS satellite which has spatial resolution of 1 meter in the panchromatic mode.

Fig. 4. Original image with the road graph

This image includes a crossroad composed of two main roads on which the input graph (coming from a database or manually given) has been superposed.
Images 5, 6 and 7 represent the different steps of the algorithm. On image 5, polylines of the input graph have been sampled and propagated. The circle delimiting the two types of the reconstruction process is also drawn.

Fig. 5. After propagation of the polylines

At step of image 6, portions of roads with parallel sides have been extracted by *DoubleSnakes* after running on the different resolution images.

Fig. 6. After the parallel contour extraction

The extraction final result after the intersection process is represented on image 7.
Contours have globally been extracted with a good precision (except the sharp edge of the intersection, partly due to its poor image force). The use of the multiresolution approach has prevented the snakes from being trapped by the geometric noise such as ground marking.

Fig. 7. After the intersection extraction

3.2. Conclusion and future prospects

This article describes a new method for extracting the road network from high resolution satellite images. A topologically correct graph of the road network is first extracted, and roads are then extracted as surface elements. The graph of the network is extracted by a following algorithm [9] which minimizes a cost function. The extraction algorithm makes use of specific snakes combined with a multiresolution analysis. Current works aim at increasing the robustness of the algorithm, particularly in noisy environments such as urban areas. The use the wavelet coefficients deriving from the MRA for extracting texture information proper to roads could constraint the snake evolution. Some contextual information (such as building or car alignment) can also be a clue for the extraction.
Results on test images are encouraging. However, results should be validated and characterized using quantitative criteria described in [13].

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