EXTRACTION AND UPDATE OF STREET NETWORKS IN URBAN AREAS FROM HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT:

Among possibilities of remote sensing for urban uses, extraction of street networks is an important topic. A good knowledge of the street network is necessary for urban planning, map updating or estimation of atmospheric pollution. Moreover, an assisted street extraction from remotely sensed data can highly help cities which do not have a cartography of their road network.
However, if road extraction from rural or semi-rural area images has led to encouraging results, the urban context, because of its complexity and the numerous artefacts encountered, is still a new and challenging topic.
The context of our current work is urban area and high spatial resolution imagery. In order to help image interpreters, we are concerned about extracting and updating street networks. In this paper, we present a complete methodology adapted to those aims. It includes the definition of a reference object for quantitative evaluation and also the processing algorithm. The extraction process is then applied on a high resolution IKONOS image. Results and future prospects are finally discussed

RÉSUMÉ:

Parmi les apports possibles de la télédétection en milieu urbain, l'extraction automatisée de réseaux de rues est un sujet important. En effet, une bonne connaissance du réseau de rues est nécessaire pour l'aménagement de la ville, la mise à jour de cartes ou l'estimation de la pollution atmosphérique. De plus, une assistance à l'extraction manuelle de rues peut grandement aider les villes ne disposant pas d'une cartographie de leur réseau routier. Cependant, si l'extraction de routes en milieu rural ou peri-urbain a mené à des résultats encourageants, le contexte urbain, du fait de sa complexité et du grand nombre d'artefacts qu'il engendre, est encore un nouveau domaine à explorer. Notre travail se situe dans le domaine de l'imagerie spatiale à haute résolution de scènes urbaines. Dans le but d'aider les photo-interprètes, nous souhaitons extraire et mettre à jour les réseaux de rues.
Dans cet article, nous présentons une méthodologie complète adaptée à ces objectifs. Elle comprend l'établissement d'une référence pour l'évaluation quantitative des résultats, ainsi que l'algorithme de traitement. Ce procédé d'extraction est ensuite appliqué à une image haute résolution du satellite IKONOS. Enfin, les résultats ainsi que les améliorations futures sont discutés.

1. INTRODUCTION

1.1 Context

Among possibilities of remote sensing for urban uses, extraction of street networks is an important topic. A good knowledge of the street network is necessary for urban planning, map updating or estimation of atmospheric pollution. Moreover, an assisted street extraction from remotely sensed data can highly help cities which do not have a cartography of their road network.

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 mathematical morphology (Destival, 1987), linear filtering (Wang and Howarth, 1987; Wang *et al.*, 1996), or on more specific tools using Markov fields (Merlet and Zerubia, 1996; Stoica *et al.*, 2000), neural networks (Bhattacharya and Parui, 1997), cooperative algorithms (McKeown and Denlinger, 1988), dynamic programming (Jedynak, 1995; Gruen and Li, 1995), or multiresolution (Baumgartner *et al.,* 1996; Couloigner and Ranchin, 2000; Laptev *et al.,* 2000). Promising studies try to take the context of the road into account in order to focus the extraction on the most promising regions (Baumgartner *et al.,* 1999 ; Ruskoné, 1996). Efficiency of all of these methods depends on the use they are targeting. For instance, for operational constraint, semi-automatic approaches are prefered.

In order to overcome all problems raised by an automatic or semi-automatic road extraction, most of those works focused on rural or semi-rural areas, where artefacts are less numerous than in cities. However, the recent possibility to have high resolution satellite images (1 meter or less) has increased the interest in satellite images for urban use.
Figure 1 is a good example of artefacts generated both by the urban context and the high spatial resolution. Vehicles (circled), the bridge and its shadow disturb the road

extraction process. Other artefacts encountered can be trees, tarred areas (parking, airport) or buildings with a radiometry similar to roads and with an important contrast to their environments.

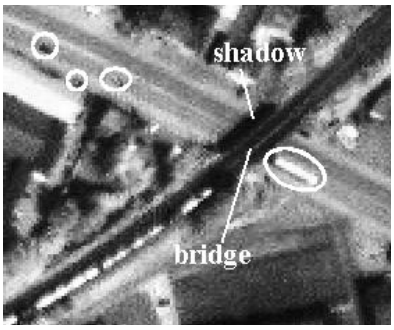

Figure 1. Artefacts encountered in urban context and high resolution images. Copyright 2000 Space Imaging Europe. *Courtesy of GIM - Geographic Information Management*

Baumgartner *and al.* (1996), and Couloigner (1998) have shown the interest of using multiresolution algorithms, especially on high resolution images: small details, such as shadows or vehicles do not disrupt the numerical processing.
In high resolution satellite images, a road is represented as a surface element which was not the case with lower resolution where streets were seen as linear elements. This increase of the spatial resolution leads to a more complex scene but also enables a more accurate extraction.

1.2 Objectives

The context of our current work is urban area and high spatial resolution imagery. In order to help image interpreters, we are concerned about street extraction.
In the case where a road database already exists, we also aims at updating street networks. Indeed, with the rapidly changing environment and increasing amount of new information, remotely sensed images provide the perfect media for keeping a geographic information system (GIS) up-to-date. Research on this topic have been carried out in (Agouris *et al.* 2001a), incorporating accuracy information to identify local or global change to the prior information given by the initial GIS.

In the next sections, the proposed methodology is presented and applied on an IKONOS image of the town of Hasselt, Belgium.

2. METHODOLOGY

2.1 Description

In order to extract urban street networks from high resolution satellite images, we propose a methodology, aiming at helping operational users.
For operational purposes, the main constraint is the reliability of the result: false detection or over detection are banned. To fit to this goal and increase the robustness, a semi-automatic approach has been chosen (see Figure 2): the inputs of the algorithm are linear elements coming from a database or manually given by the user. In both cases, it provides an initialization of the graph representing the road network, which vertices are street intersections and ridges are street axis. Models of streets (using roads properties defined by Couloigner 1998) and properties of street network (such as connexity) are introduced to perform the extraction.

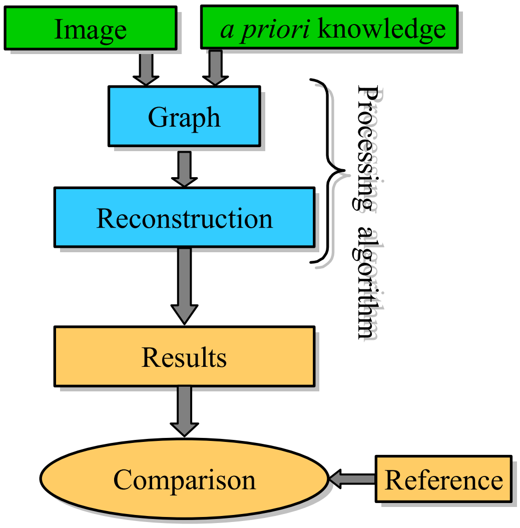

Figure 2. The methodology including topology management and street reconstruction

As for (Airault and Jamet, 1995), our approach is decomposed in two sequential parts.
Firstly, a topologically correct graph of the street network is extracted. This step aims at giving correct spatial connections between streets as well as an approximation of their location. If available, road database is updated.
The next step is the actual street reconstruction. Due to the high resolution of the images, a surface reconstruction has to be performed. This step uses the previous step of graph management as an initialization for the reconstruction.
Finally, results are quantitatively characterized, using mathematical criteria (Heipke *et al.*, 1997; Couloigner and Ranchin, 1998).
An important point of the methodology is to separate the process in a step of topological management and an other of street reconstruction as surface element. First of all, it enables to focus separately on each step which are both of them very challenging. An other advantage of separating the algorithm is that it will enable potential user to check if the road network topology is correct during the process.
In the next sections, we describe more precisely the different parts of the process.

2.2 Evaluation and reference

As an operational image processing system has to be validated and its limits quantified, we aim at obtaining a measure of the quality of the results delivered by our method. This purpose needs the definition of a reference in order to compare it with extracted objects.

Despite the fact that a reference based on ground truth enables an accurate location of the object in the geographical space, a reference based on image interpretation is, in our case, preferable. Indeed, the comparison of the algorithm with visual interpretation enables to evaluate only the automatic process and not the whole image acquisition chain. Moreover, the image interpreter is an efficient pattern recognition system, able to use the context to extract the searched pattern. Though, considering a team of image interpreters and their subjective interpretations of the context, there is an important variability of such an estimation. This variability of interpretation has an effect when it comes to evaluate the efficiency of a method.

We have defined a methodology to extract a reference, in order to take the mentioned variability into account. Its implementation is currently under development and will not be presented in the real case study.
Our choice is an *a priori* reference, in a vector representation, based on statistics over several image interpreters, which leads to an "average" object (Péteri and Ranchin, 2002).
As the average can be not representative of a manual extraction, we also define a reference area which gives an *acceptance zone* for the result of an automatic extraction. An extraction method could then be considered as efficient as an human interpreter if the extracted object is included in this region.

2.2.1 Acceptance zone

Several image interpreters acquire the road contour in a vector representation via polylines. Figure 3 exhibits an acceptance zone, representative of the interpretation discrepancies between different interpreters.

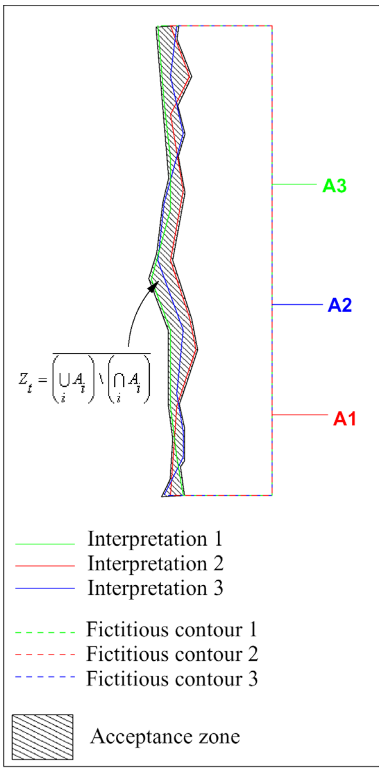

Figure 3. Acceptance zone

One consider the A_i surface inside the object contour acquired by the interpreter *i*. If the contour is open, it will be closed by a fictitious contour (see Figure 3).
The acceptance zone is then defined as:

$$Z_t = \overline{\left(\bigcup_i A_i\right) \setminus \left(\bigcap_i A_i\right)} \qquad (1)$$

where A_i is the surface of one interpretation *i*, and the bar above is the closure of the set.
The quantitative evaluation is done by calculating what percentage of the extracted contour is included in this acceptance zone.

2.2.2 Extracted contour reference

We aim here at defining a "reference" object, representative of the different interpretations. For each polyline *i*, each segment *j* is represented by a slope vector $\mathbf{V_{ij}}$ (vectors are written in bold font).

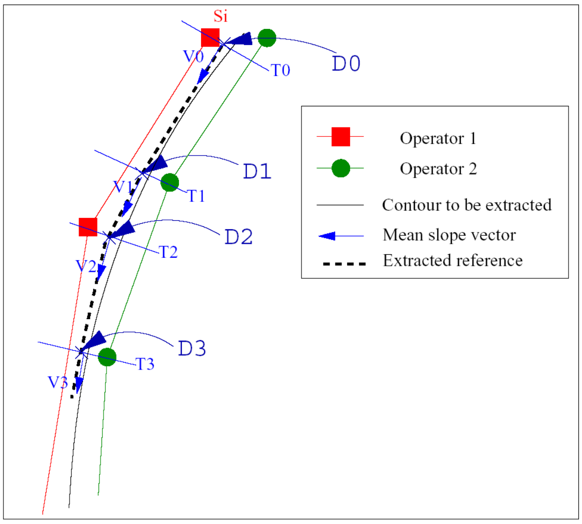

Figure 4. Extraction of a reference from the different interpretations

Figure 4 represents the method used for extracting the reference contour (for clarity reason, only two interpretations are represented).
The extraction of a reference polyline is the following:

- Firstly, the average vector $\mathbf{V_0}$ of the N slope vector is computed : $\vec{V}_0 = \frac{1}{N}\sum_i \vec{V}_{0i}$.

We then consider the transect (To) orthogonal to this vector and located to the extremity of the last polyline met in the $\mathbf{V_0}$ direction (vertice S_i on Figure 4).

- An average is computed between points located at the intersection between (To) and the different polylines (rejecting external modes). The point D_0 is obtained and will be a vertice for the reference polyline.
- The transect (To) is "propagated"(in the direction of $\mathbf{V_0}$) to the first vertice met. The mean slope vector $\mathbf{V_1}$ is re-evaluated, as well as the transect (T_1) and the point D_1.

– This procedure is repeated till the final vertices of one of the polylines is met.

Quantitative criteria for comparing the extracted object to this "reference" object will be applied using (Heipke *et al.,* 1997 ; Couloigner and Ranchin, 1998).
For more details, see (Péteri and Ranchin, 2002)

2.3 The processing algorithm

As mentioned in section 2, the processing algorithm is composed in two sequential parts: a graph management step extracting the correct "skeleton" of the network, and a reconstruction step using active contours (snakes) initialized by the previous step.

2.3.1 Topology management of the graph

2.3.1.1 Graph management
At this step, a topologically correct graph of the street network is extracted. It aims at giving correctly spatial connections between streets as well as an approximation of their location. If available, road database will be updated at this step.
Polylines are currently entered by the user (Figure 5), without strong constraints on the segment location and on the number of vertices. The use of road databases is under development.

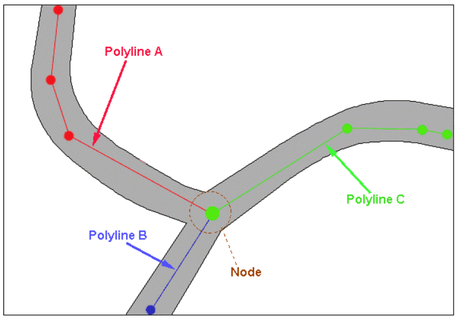

Figure 5. Graph of the road network

2.3.1.2 Initialization of the snake
This step also enables to initialize the contour of the reconstruction process: it is simply obtained by thickening the polyline (propagation of two parallel sides). More sophisticated approach could be to register the propagated contour by evaluating the gradient next to the polyline segment.

2.3.2 The reconstruction step: combining snakes and multiresolution

2.3.2.1 Snake model
Active contours (snakes) are suitable for road extraction, as they allow to overcome certain inherent problems like occlusions, width changes, surface material variations, and the effect of overpasses and intersections (Agouris *et al.,* 2001b). They have been first introduced by (Kass *et al.*, 1988).
As a snake seeks to minimize its overall energy, its shape will converge on the image gradient contours.
We use the greedy algorithm for contour extraction described in (Williams and Shah, 1992). This greedy approach claimed to have a significant speed advantage over the dynamic programming model introduced by (Amini *et al.*, 1990).

Energy in a snake can be represented by three energy terms: E_{con}, E_{curv} and E_{image}.

The total energy is therefore:

$$E_{snake} = \sum_i \alpha E_{cont}(i) + \beta E_{curv}(i) + \chi E_{image}(i) \qquad (2)$$

where E_{Cont} is minimal when the points are evenly spaced and E_{Curv} is minimal when the snake has a constant first derivative (C^1 continuity, change in slope between any two segments is minimized).
E_{image} is the image force attracting the snake to contours with large image gradients. More precisely, $E_{image}(v) = -|\Delta I(v)|$, where I(v) is the image intensity at point v.

For computation, the greedy algorithm takes an initial snake and iteratively refines the location of its points by looking at a "neighborhood" of pixels surrounding each and selecting the pixel of this neighborhood where the energy is minimized (see Figure 6).

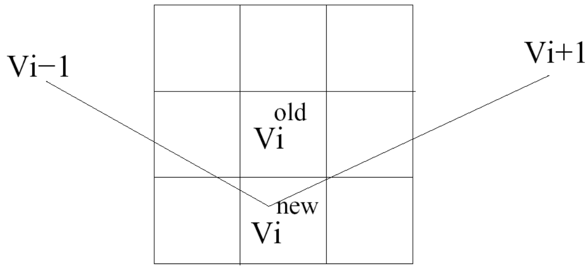

Figure 6. Optimization procedure

2.3.2.2 Combining snakes and multiresolution
As it was mentioned in the first section, artefacts such as vehicles or shadows, often encountered in the urban context may disturb the extraction process.
An approach to prevent the snake from being trapped by little artefacts such as vehicles or reservation is to use multiresolution. Multiresolution was indeed previously successfully used in (Baumgartner *and* al., 1996), (Couloigner, 1998) and (Péteri *et al.,* 2001).
The algorithm includes this multiresolution approach: the snake is first applied on the coarsest resolution image, then on each intermediate resolution images until it runs on the original resolution.
An important point is to adapt the coefficients of the different energy terms 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.

3. REAL CASE STUDY

Here is presented the result of the extraction algorithm on an image from the IKONOS satellite of the region of Hasselt,

Belgium. The resolution of one pixel is 1 meter in the panchromatic band.
The road to be extracted is in fact a portion of a motorway crossing a railway station. This road presents a slightly curve (see Figure 7).

Figure 7. Original image for Hasselt

An operator has drawn a polyline very roughly (the dash and dot centerline on Figure 8). From this polyline, a contour was propagated with a width of 26 meters (the two dash and dot sidelines).

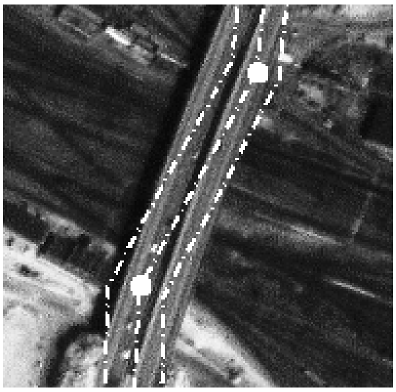

Figure 8. The polyline and the initial contour derived from it

The snake algorithm was applied on the image from this initialization of the contour. In the multiresolution scheme, the snake was first applied at the coarsest resolution of 8 meters. Figure 9 presents the result with the extracted contour (in plain line).
Compared to the rough initialization of the contour, the snake fits quite well to the motorway sides. The multiresolution has prevented the snake from being trapped by little artifacts with gradient of high magnitude (vehicles for instance).

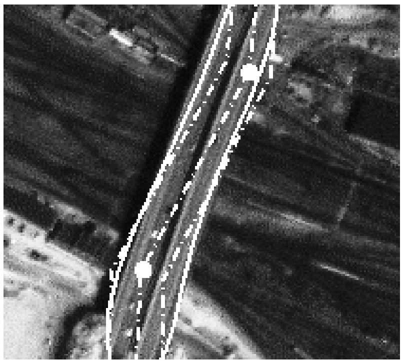

Figure 9. Result of the extraction (in plain line)

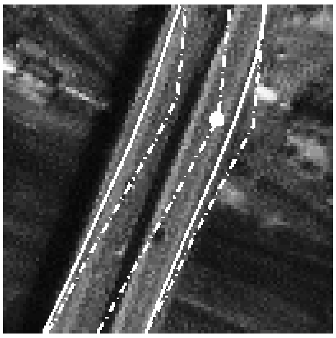

Figure 10. Zoom area

Nevertheless, it is noticeable on the zoom area (Figure 10) that the left side of the active contour was trapped by the inside line of the road, whereas the right side has succeeded. It can be explained by the similar properties (gradient and length) of the inside line and the road side. It underlines the need for energy functionals more adapted to the context.

4. CONCLUSION AND PROSPECTS

In this paper, a complete methodology for extracting streets from high resolution images was presented. To reach the reliability required by operational uses, a semi-automatic approach was chosen.
The first step of this method aims at extracting a topologically correct road network. In the second step, a reconstruction of roads as surface elements is proceed, using snakes combined with multiresolution. Snakes are initialized by the graph obtained at the first step of the algorithm.
The algorithm was then applied on an IKONOS image, leading to promising results. Due to the multiresolution approach, the reconstruction process in not disrupted by the numerous artefacts such as vehicles encountered in the urban context.
A way for improvement is to introduce more contextual information for constraining the reconstruction process to converge to the actual street sides. An important effort is currently held to find for the active contours some energy functionals proper to the urban context.

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