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Extraction of urban network from high spatial resolution imagery

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ABSTRACT: This paper presents a new strategy to extract, fully or semi-automatically, quadrangular urban network from high spatial resolution imagery. A quadrangular network is generally composed of different classes of streets in a hierarchical system. The developed strategy is based both on the multiresolution analysis and on the wavelet transform. The multiresolution analysis allows a multiscale analysis of images and thus to focus on the streets of one class at once. The wavelet transform enables the modelling of information at different characteristic scales. In the problem, it allows to model the topology of streets. These two mathematical tools are combined in the "à trous" algorithm. The application of this algorithm to images of urban areasis used to develop fully or semi-automatic multiresolution processing in order to extract a hierarchical urban network from high spatial resolution imagery. These methods will bring a help to the photo-interpreter in his work.

1 INTRODUCTION

Urban mapping by the means of satellite images is a promising market for Earth observation in the next decade. It is usually realised by a manual photo-interpretation. In order to help the photo-interpreter in his work, a fully or semi-automatic process is developed to extract the urban network from satellite images with high spatial resolution, included between 2 m and 20 m.

Although the first works about the extraction of the network of roads, railways or rivers from satellite images have been initiated in the seventies, few of them has been concerned by urban areas. Indeed, the production of reliable algorithms is difficult because of the complexity of urban landscape. This complexity depends both on the spatial resolution of images and the inner organisation of the studied towns (Weber 1995). Then, the finer the spatial resolution, the easier the discrimination between two neighbouring urban objects, and thus the richer the cartography of urban network (Couloigner *et al.* 1997). But more little objects (like cars, buses or trees along streets) would disturb the fully or semi-automatic extraction of urban network. Moreover, towns with large areas and quadrangular network (like in North America) are easier to analyse from remotely-sensed images than towns with dense urban structure and sinuous network (like in Europe or Asia).

This paper presents a new strategy to extract, fully or semi-automatically, the urban network from high spatial remotely-sensed data. It concerns, for the moment, the towns with large urban areas and a quadrangular network

The new strategy is based on the "à trous" algorithm which combines the multiresolution analysis and the wavelet transform. After a short presentation of some fundamentals of these two mathematical tools, the "à trous" algorithm will be demonstrated. Afterwards, the new method, which allows to extract a hierarchical urban network, will be exposed. The multiresolution processing developed to extract the topology of the streets of the studied network will be finally discussed.

2 THE WAVELET TRANSFORM

In order to facilitate the understanding, the wavelet transform will be presented in its continuous version and in the mono-dimensional case. The main property of the wavelet transform is to adapt the analysis window to the phenomena under study, providing a local information. The wavelet transform leads to a time-frequency representation. In the case of images, the wavelet transform leads to a scale-space representation. Some examples will be provided in order to illustrate this main property.

As the Fourier transform, the wavelet transform is equivalent to a decomposition of the signal into a base of elementary functions: the wavelets. The base is generated by dilatation and translation of a single function called the mother wavelet:

$$\psi_{a,b} = |a|^{\frac{-1}{2}} \psi\left(\frac{x-b}{a}\right) \tag{1}$$

where $a, b \in \Re$ and $a \neq 0$. a is called the dilation step and b the translation step.

Many mother wavelets exist. They are all oscillating functions, that are well localised both in time and frequency. All the wavelets have common properties such as regularity, oscillation and localisation, and satisfy an admissibility condition. For more details about the properties of the wavelets, one may refer to Meyer (1990) or to the book of Daubechies (1992). Even if they have common properties, each of them brings to a single decomposition of the signal related to the used mother wavelet. In the one dimension case, the continuous wavelet transform of a function f(x) is :

$$WT_f(a,b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(x) \overline{\psi(\frac{x-b}{a})} dx \tag{2}$$

where $\psi_{a,b}$ is defined as in Eq. 1, $\overline{\psi(\frac{x-b}{a})}$ is the complex conjugated of ψ. $WT_f(a,b)$ represents the information content of *f(x)* at scale *a* and location *b*. For fixed *a* and *b*, $WT_f(a,b)$ is called the wavelet coefficient. The computation of the wavelet transform for each scale and each location of a signal provides a local representation of this signal. The process can be reversed and the original signal reconstructed exactly (without any loss) from the wavelet coefficients by :

$$f(x) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} WT_f(a,b) \psi_{a,b}(x) \frac{dadb}{a^2} \tag{3}$$

where C_ψ is the admissibility condition of the mother wavelet. This last equation can be interpreted in two ways :

- *f(x)* can be reconstructed exactly if one knows its wavelet transform ;
- *f(x)* is a superposition of wavelets.

These two point of views lead to different applications of the wavelet transform. In the first case, the processing of the signals and in the second their analysis. A discrete version of the wavelet transform, the dyadic wavelet transform, exists and an algorithm for applications is proposed. The discrete wavelet transform is applied to signals by means of filters.

3 THE MULTIRESOLUTION ANALYSIS

The association of the wavelet transform and of the multiresolution analysis leads to a powerful and comprehensive analysis and processing of remotely sensed images.

The concept of multiresolution analysis introduced by Mallat (1989) derives from the Laplacian pyramids (Burt and Adelson 1983). In this approach, the size of a pixel is defined as a resolution of reference to allow a measure of local variations in the image. Note that the resolution is related to the inverse of the scale used by cartographers. Hence, the larger the resolution of an image, the smaller the size (or the characteristic length or characteristic scale) of the smallest visible object.

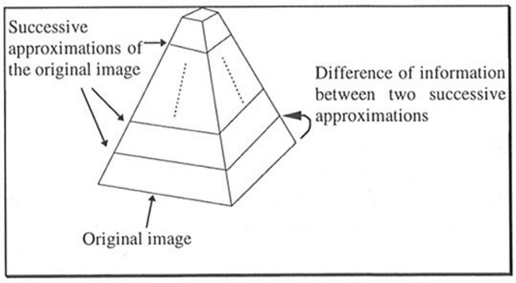

Figure 1. Representation of the successive approximations of an image by the means of a multiresolution algorithm.

Figure 1 is a very convenient description of the multiresolution analysis and more generally of pyramidal algorithms. The multiresolution analysis computes successive, coarser and coarser approximations of the same original image. The basis of the pyramid corresponds to the original image. Climbing the pyramid, the different floors represent the successive approximations of the image. The theoretical limit of these algorithms is the top of the pyramid that corresponds to an unique pixel. The difference of information existing between two successive approximations of the same image is described by the wavelet coefficients.

For the description of the pyramidal algorithms, (Meyer 1993, page 45) uses the example of the cartography :

"We can see from this example the fundamental idea of representing the image by a tree. In the cartographic case, the trunk would be the map of the World. By travelling toward the branches, the twigs and the leaves, we reach successive maps that cover smaller regions and give more details, details that do not appear at lower levels.

To interpret the cartographic representation using the pyramid algorithm, it will be necessary to reverse the roles of top and bottom, since the pyramid algorithm progresses from 'fine to coarse'".

The mathematical foundations of multiresolution analysis are described in Mallat (1989). From a practical point of view, the computation of the multiresolution analysis is done by applying low-pass filters on the signal and the computation of the difference of information between two successive approximations is done by a pass-band filter.

For more details on the mathematics of wavelets and multiresolution analysis, one can refer for example to the very complete book of Daubechies (1992). A good review on wavelets can also be found in Rioul *et al.* (1991). This list is far from being exhaustive.

4 THE "A TROUS" ALGORITHM

In the "à trous" algorithm (Dutilleux 1987), only a scale function is used. The approximation of the original image is obtained by filtering the original image and the wavelet coefficient image is obtained by subtracting the approximation to the original image in a pixel-to-pixel basis. This algorithm provides at each step one context and one non-directional wavelet coefficient image. To perform a dilation of the scale function, one adds zero between each coefficient of the filter. Hence no subsampling of the image is performed and all images have the same size. The reconstruction is done by summation of the last context and the wavelet coefficient images computed.

Figures 3a to 3c represent the approximation, the context image, computed from the original one Figure 2 using the "à trous" algorithm.

Figure 2. Extract of the panchromatic band of the KVR-1000 russian sensor at 2 m of spatial resolution on Jedda (Saudi Arabia).

The original image was acquired, in March 1991, by the Russian analogic sensor KVR-1000 with a spectral range included between 0.51 and 0.71 μm equivalent to a panchromatic band and digitally scanned at 2 m of spatial resolution. Figure 2 represents an extract of the city of Jedda in Saudi Arabia. Its urban network is quadrangular and consists of four classes of streets: the primary streets with a 68 m of width and a central and two secondary reservations, the secondary streets with a 34 or 54 m of width and a central reservation and the tertiary streets with a 15 m of width. In Figure 2, one can see a primary street in the right of the image from North to South, two secondary streets (one perpendicular to the primary one with 54 m in width and one with 34 m of width in the left part of the image) and a lot of tertiary streets.

Figure 3a represents the first context image. In this image, the small structures between 2 and 4 m have between filtered out. Figure 3d represents all the structures in all directions with scales comprised between 2 and 4 m. This image exhibits the difference of information between Figure 2 and Figure 3a. It models the components of the original image at these scales and enhances the fact that even a big structure, like the primary street, has a component in the small scales. This structure is visible from the spatial resolution of the image up to its characteristic scale that can be greater than the size of the image.

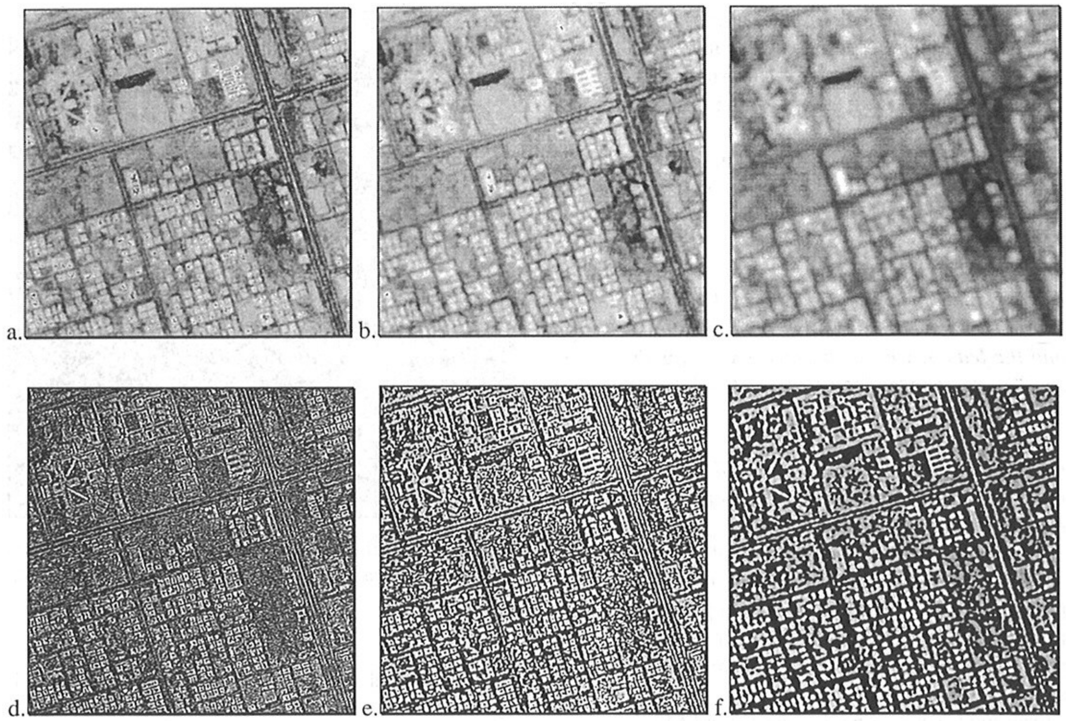

Figure 3. (a) First context image of Figure 2 using the "à trous" algorithm ; (b) Second and (c) Third context images ; (d) First wavelet coefficient image of Figure 2 ; (e) Second and (f) Third wavelet coefficient images.

Figures 3b and 3c represent respectively the context images with structures with scales greater or equal to 8 and 16 m. One can see the progressive smoothing of the original image and the disappearance of the small structures in the approximation images. In Figure 3b, the secondary reservations of the primary street are no more visible. In Figure 3c, the central reservation of the two secondary streets have disappeared. Moreover, the tertiary streets are more difficult to distinguish than in Figure 3b.

Figures 3e and 3f represent all the structures with scales respectively comprised between 4 and 8 m, and 8 and 16 m. In Figure 3e, the central reservations of the primary and secondary streets are well perceptible like the secondary reservations of the primary street. In Figure 3f, only the central reservations of the primary street and of the secondary street with 54 m in width are well drawn. Moreover, the tertiary streets are better enhanced than in Figure 3e.

Because the images are not re-sized, this algorithm is most suitable for analysis of images. It enhances all the features in the original image and allows a scale by scale interpretation. This decomposition allows to focus on the different scales of the different structures composing the original image.

5 A NEW METHOD TO EXTRACT A HIERARCHICAL URBAN NETWORK

As explained in the previous section, the streets of a specified class and their characteristic lines disappear when the spatial resolution of the context images becomes coarser. This analysis allows to introduce a new strategy to extract the studied urban network in a hierarchical system.

5.1 *The developed strategy*

The extraction of the cross sections of different streets allows to understand the evolution of the representation of these streets when the spatial resolution decreases. The cross section of a considered street depends both on its class and on the observed scale as shown in the following diagrams.

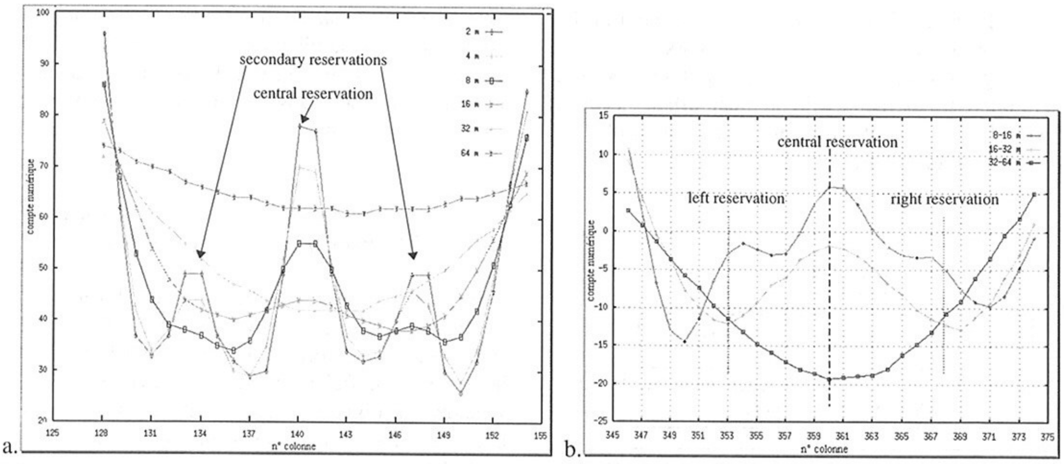

Figure 4. Cross section of a primary street at different spatial resolution on the context images (a) and on the wavelet coefficient images (b).

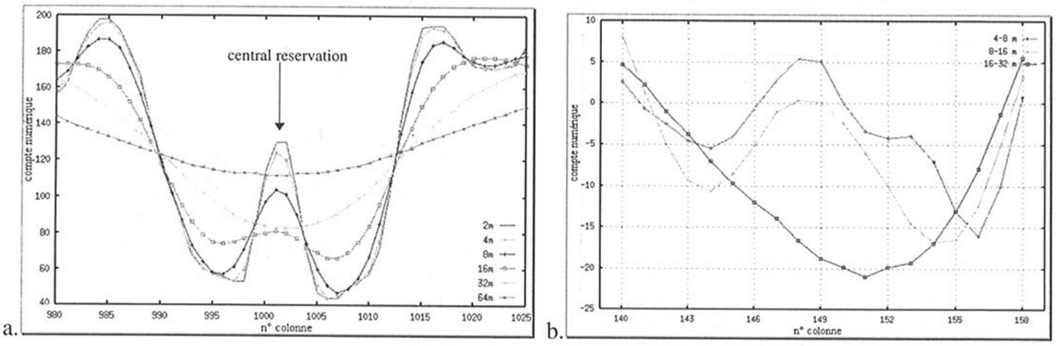

Figure 5. Cross section of a secondary street at different spatial resolution on the context images (a) and on the wavelet coefficient images (b).

Figures 4a and 5a display the evolution of the cross section of a same street with the spatial resolution of context images. In Figure 4a, the secondary reservations disappear for a spatial resolution greater or equal to 8 m and the central reservation for a spatial resolution greater or equal to 32 m like in Figure 5a.

Moreover, on these two figures, two typical points emerge. They are the points of intersection of each cross section at different scales. These two points represent the positions of the two sides of the considered street.

Figures 4b and 5b allow to indicate and verify the positions of the characteristic lines of the considered street. In Figure 4b, three wavelet coefficient images could be observed. In the cross section with the lower scale (32-64 m), only the position of the axis of the considered primary street is marked. It corresponds to the mimimum of the cross section included between the two sides of the street. At the medium scale (16-32 m), this position is characterised by a maximum and one observes the positions of the two secondary reservations marked by two minima. In the high scale (8-16 m), these two minima become two maxima of the cross section included between one side of the street and its axis. Figure 5b shows that, for secondary streets, two wavelet coefficient images are only necessary to indicate the position of the axis, *i.e.* the central reservation: one at medium scale (16-32 m) to estimate the position and one at a higher scale (8-16 m) to verify and adjust the position of the axis. The wavelet coefficient images with the highest scales (2-4 m and 4-8 m) present the same cross sections than in the high scale wavelet coefficient image. Hence, it is not necessary to use them in the extraction of a hierarchical urban network.

In regard of these points, a new strategy has been developed to extract a hierarchical urban network from high spatial imagery. Its principle is summarised on Figure 6.

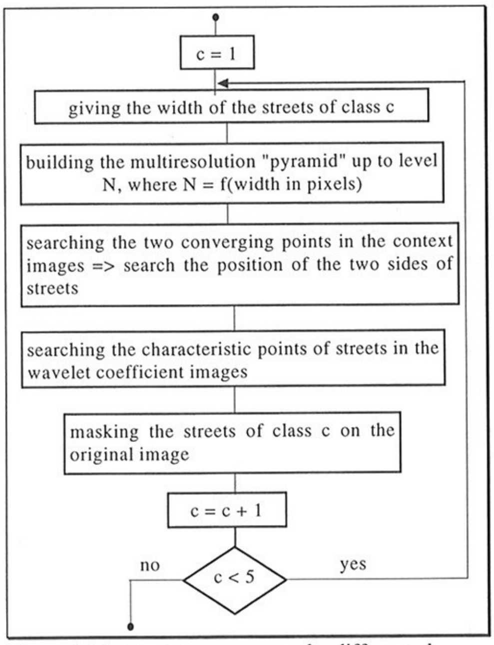

Figure 6. The strategy to extract the different classes of street of the studied urban network.

The new method is based on the application of the "à trous" algorithm to urban imagery at high spatial resolution. It extracts the streets class by class and specifies their topology as well.

The first step of this method is the fully or semi-automatic search of the two sides of the streets of the considered class. The streets width is known. This is carried out by the search of the two points of intersection of the cross sections of a same street at different scales acquired in the context images. The second step allows to extract the characteristic lines, *i.e.* the topology, of streets in searching these lines in the wavelet coefficient images at the appropriate scales. Before extracting streets of an another class, the extracted streets of the considered class are masked. This multiresolution method starts with the extraction of the primary streets, because if the tertiary streets are extracted firstly, the roads of primary and secondary streets will be extracted too.

A hierarchical skeleton of the urban network results from the application of this method to the images of the studied cities. To obtain an accurate network, the right angle intersections would be processed separately.

5.2 *The developed method to extract the characteristic lines of streets for each class*

A multiresolution processing has been developed to specify the topology of streets for each class of the studied urban network. This processing is based on the wavelet coefficient "pyramid" of original images. As shown in Figures 4b and 5b, the crossing section of a same street is different according to the scales.

For the primary streets, three wavelet coefficient images are necessary to specify their topology. One begins by searching the position of the axis of the observed street. This is achieved by:

$$pos\_axe_1 = \min_{x \in [ls, rs]} f(x) \qquad (4)$$

where *f(x)* represents the cross section of the street on the low scale wavelet coefficient (see Figure 4b) between the position of the left side, *ls*, and of the right side, *rs*, of the street. The medium scale wavelet coefficient image is used to verify and adjust the previously measured position. This is realised by:

$$pos\_axe_2 = \max_{x \in [ls, rs]} g(x) \qquad (5)$$

where *g(x)* represents the cross section of the street on the medium scale wavelet coefficient between the position of the left side, *ls*, and of the right side, *rs*, of the street. Then, the positions of the two secondary reservations are computed by:

$$pos\_tpg_1 = \min_{x \in [ls, pos\_axe]} g(x)$$

$$pos\_tpd_1 = \min_{x \in [pos\_axe, rs]} g(x) \qquad (6)$$

where pos_tpg_1 is the position of the left secondary reservation and pos_tpd_1 of the right one. And, in order to verify and accurate the two previously measured positions, the equations 7 are computed.

$$pos\_tpg_2 = \max_{x \in [ls, pos\_axe]} h(x)$$

$$pos\_tpd_2 = \max_{x \in [pos\_axe, rs]} h(x) \qquad (7)$$

where *h(x)* represents the cross section of the street on the high scale wavelet coefficient between the position of the left side, *ls*, and of the right side, *rs*, of the street.

The extraction of the characteristic lines for the secondary streets uses the equations 4 et 5 but where *f(x)* and *g(x)* represent the cross sections on the medium and high scale wavelet coefficient images respectively (see Figure 5b).

For the tertiary streets, only one wavelet coefficient image is necessary to extract their axis. It is the high scale image where the search of the minimum of the cross section of the considered street included between its two sides is computed.

To obtain the characteristic lines of the observed street, it is necessary for the positions of the two sides of the street to be accurate. These positions depend both on the initial points of the two sides and on the orientation taken by the observed street on the original image. These points are defined at the present time by the user.

Figure 7. Application of the processing of the extraction of the characteristic lines of primary and secondary streets to Figure 2.

The processing to extract the topology of streets was applied to a primary and a secondary street of the urban network of Jedda (Figure 2). The results of this processing are presented Figure 7. One can see that the characteristic line of the secondary street is fitted to its central reservation on the image. For the primary street, there is an artefact for the three reservations in the end of characteristic lines (right lower part of image). Indeed, the central reservation is less perceptible in this area of the observed street. So, the algorithm failed. In order to resolve this problem, the parameters of the processing has been adjusted. The contrast has been enhanced using multiscale representation (Lu *et al.* 1997)

6 CONCLUSION

In order to help the photo-interpreter, a new strategy has been developed to extract, fully or semi-automatically, a hierarchical urban network from high spatial resolution images. This strategy is based both on the multiresolution analysis and on the wavelet transform combined in the "à trous" algorithm. As a quadrangular urban network consists on different classes of streets, multiresolution processing allows to extract the streets class by class as well as their topology.

The extraction of the characteristic lines of the streets, *i.e.* their topology, of each class present in the studied urban network has been developed.

The next milestones of the method are the validation of the previous extraction and the extraction, fully or semi-automatic, of the two sides of streets in a hierarchical processing.

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