CARTOGRAPHIC DATA EXTRACTION FROM AIRBORNE IMAGERY BY HIERARCHICAL-BASED MORPHOLOGIC IMAGE PROCESSING

F. Soares [a, *], A. Navarro [a], T. Santos [b], S. Freire [b], A. Fonseca [c], N. Santos [c], J. Tenedório [b]

[a] ITU, University of Lisbon, Faculty of Sciences, LATTEX-IDL, Portugal-(fsoares, acferreira)@fc.ul.pt
[b] e-GEO, Geography and Regional Planning Research Centre, New University of Lisbon, Portugal-(teresasantos, sfreire, ja.tenedorio)@fcsh.unl.pt
[c] National Laboratory for Civil Engineering (LNEC), Lisbon, Portugal-(afonseca, nafonso)@lnec.pt

KEY WORDS: Hierarchical Segmentation, Urban Feature Extraction, Watershed segmentation, Waterfall segmentation

ABSTRACT:

This paper presents a comprehensive approach to effectively extract cartographic urban data from high resolution satellite imagery. It consists of a sequence of image processing techniques, for image segmentation, based on RGB band separation, analysis and pre-processing, followed by a morphological-based approach for data segmentation. The chosen image objects for this study are roof-tile buildings and road network. The first step of this approach consists of a spectral response evaluation for roof-tile building objects in a dense urban environment, being those enhanced through proper sequence of standard arithmetic operators, applied to RGB bands, segmented and generalized. The second step aims at urban road network segmentation for cartographic representation purposes, by combining *watershed* and *dual reconstruction* morphological transformations, which characterize the hierarchical *waterfall* concept. For the latter concept, a new approach is developed in order to improve hierarchical segmentation procedure, to better induce object discrimination. Each one of the referred objects will be segmented in separate. The road network segmentation will have in consideration the previous result of roof-tile buildings extraction. Finally, segmented objects will be compared with other extraction results in order to do proper validation. The method is applied over high-resolution ortho-rectified images, taken from satellite, of the city of Lisbon. Results will show the practicality of the method for purposes of cartographic data structures acquisition, from high-resolution satellite imagery, aiming urban management and GIS applications.

1. INTRODUCTION

Urban land cover data extraction is an important research topic under the major activities of the municipal authorities. Within municipal organization environment, land information systems have to be able to produce detailed and high precision technical maps. A central role is played by the large scale base maps including base topography and objects such as buildings, roads, facilities, and distribution networks. Tangible products of municipal planning highly depend on regular updated cartography, which in the present time, is mandatory for the Portuguese municipalities to produce, within the PDM's framework, thematic and base cartography at 1:10000 (urban municipalities) and 1:25000 (rural municipalities) scales. The PDM is legally valid for 10 years. However, regarding the cartography for these plans, and in municipalities with great urban demands, like the city of Lisbon (Portugal), such periodicity is not suitable. Changes in land use occur due to building, street maintenance and construction, new sidewalks, etc., meaning that digital expedite cartography in large scale is a constant demand for the municipalities. Nowadays, the main drawbacks to a rapid municipal cartography production / updating are the complexity of the technical specifications and the cost and time consuming of the updating, leading to maps that do not reflect the actual land use and, consequently, not suitable for municipal uses. New VHR satellite sensors provide images equivalent to orthophoto products. These images can be used to extract land cover objects by image processing methods, and to monitor changes in yearly bases, maintaining the land information updated. At the European level, the operational use of satellite imagery in urban areas has been evaluated by a large survey (Puissant and Weber, 2002, SCOT-Conseil, 1997). The most common procedure to derive thematic maps from remote sense data is the use of pixel based classifiers. However, no technique operating at the pixel level seams to satisfy all the needs for producing precise and robust maps from remote sensing images (Blaschke et al., 2000). In order to derive useful thematic maps from VHR images of urban areas, other approaches than the traditional pixel based classification are used. Recently, classifiers that operate at the object level rather than the pixel one were developed. A multiresolution segmentation algorithm was proposed (Baatz and Schape, 2000), using a region-growing technique to create image segments based on four criteria: scale, colour, smoothness and compactness. The image objects are then classified into thematic classes, based on sample objects (training areas) or according to class descriptions organized in an appropriate knowledge base. The knowledge base itself is created by means of inheritance mechanisms, concepts and methods of fuzzy logic, and semantic modelling. Automatic methodologies for Earth surface data extraction are also a hot research image processing topic. An automatic methodology, aiming road extraction from aerial images combines multi-scale detection with edge detection by snakes, overcoming existing road intensity gaps like shadows, or other image turbulence (Laptev et al., 2000). An approach for road extraction from aerial image is proposed by combining region growing techniques with road neighbourhood pixel analysis, and classifying them through a

* Corresponding author. Tel.: + 351 21 750 08 35; fax: + 351 21 750 08 07. E-mail address: fsoares@fc.ul.pt.

process indicated as "region competition" (Amo et al., 2006). In the scope of morphological image processing techniques, edge-based skeleton extraction, passing through several optimization procedures, is used to detect curvilinear structures like roads, or rivers, in grey level images (Jang and Hong, 2002). Preliminary histogram analysis and segmentation, trivial openings and granulometry tools are used to develop a morphologic-based method of automatic road network detection from digital images (Zhang et al., 1996). An overview through morphologic-based methodologies is made for extracting structural information in spatial data, as well as discussion of recent theory advances like directional and levelling transformations (Soille and Pesaresi, 2002). Although many studies focus automatic data extraction methods (Amini and Seradjian, 2001, Dial et al., 2002, Zhu and Yeh, 1986, Mena and Malpica, 2005), there are still limitations concerning the effectiveness of full automatic methods, especially if one aims to be applied over global landscape containing many different classes of objects having themselves also different radiometric representations.

2. IMAGE DATA AND AREA OF STUDY

2.1 Image Data

This work was developed in the scope of the project "Methodologies to extract large scale GEOgraphical information from very high resolution SATtellite images" (PTDC / GEO / 64826 / 2006), funded by the Portuguese Foundation for Science and Technology. A four band pan-sharpened (PS) QuickBird image (60 cm spatial resolution) was used in this study. Image data was acquired on 13 April 2005 and is referred to the area of the Municipality of Lisbon. The three data set channels of the RGB colour composite image were read, at first, in a 16-bit radiometric resolution. Enhancement pre-processing was applied to each, using histogram contrast stretching, followed by a quantization to 8-bit radiometric resolution. The developed work was done using the programming language environment of the Matlab software (version R2007b).

Figure 1. Image sample for testing

2.2 Area of Study

The case-study image sample presented in this paper was cropped from the PS image and corresponds to an urban area from the East part of the city of Lisbon, with the approximately geographical coordinates of Latitude = 38.73 N and Longitude = 9.11 WG (Figure 1). This sample was chosen for having the characteristics of a dense urban tissue, populated with roof-tile buildings and a road network inside the urban perimeter. Also, a prior paper (Santos et al., 2009) presented extraction results regarding the same area of study, to which the present results will be put against to.

3. THEORETICAL BACKGROUND

In the field of mathematical morphology, the transformation known as *watershed* (Beucher and Lantuéjoul, 1979) is often used as a first step segmentation of a region growing procedure (Yang et al., 2008) and it characterizes the morphology of a grey scale image, as if it was a topographic surface. All image "valleys" are often designated as *catchments basins* and are represented as 2D binary objects. The separation lines are known as *watershed lines*. If the image radiometry is complex, the watershed transformation gives an over-segmented image result. In most practical cases, even if a certain image region seems to be homogeneous, there will be certainly many low amplitude catchments basins that are also detected by watershed. Based on this transformation, a hierarchical image segmentation method known as *waterfall* (Beucher, 1994) was developed, in which larger regions are created by filling and merging image "valleys". Next, the method will be explained in more detail and further framed under the scope of the present study.

3.1 Waterfall method

The morphological waterfall method is inspired on the natural event of water falling from a slope into a dip and consequently filling it. Although some new algorithmic approaches for waterfall have been tested (Marcotegui and Beucher, 2005, Hanbury and Marcotegui, 2006), the method following described will be the standard one. The first thing to mention is that, given a grey level image as input, the waterfall application will also produce a grey level image as an output. Morphological operators such as *watershed* and *dual reconstruction* by *erosion* are used in waterfall computation. The algorithm, applied to a image $f(x)$, can be divided in two parts: the first part consists on watershed segmentation of the grey image in order to create a function $s(x)$ such as $s(x) = f(x)$ for all pixels x belonging to the watershed lines of $f(x)$, and $s(x) = \max(f(x))$ otherwise. The binary marker image used by default for watershed computation is defined as the *regional minima* of the image f. The second part results from morphologic dual reconstruction of $f(x)$ from $s(x)$ (*geodesic erosion* of s), until the condition of *idempotence* is satisfied, as described by expressions (1) and (2).

$$R_f^*(x) = e_f^i(s(x)) \qquad (1)$$

$$e_f^i(s(x)) = e_f^{i+1}(s(x)) \leftarrow \textit{idempotence} \qquad (2)$$

Waterfall ends when a new grey level image is achieved, or in other words, when R_f* is finished. After the first waterfall execution, the hierarchical scheme is established by applying again the same algorithm, over the preceding waterfall output image. The hierarchical sequence stops when the waterfall output image is entirely filled by a single grey value correspondent to the maximum grey value of the original grey image. The hierarchical sequence with j steps can be described as following, pointing also the most relevant output binary images as well:

f_0 : initial grey level image;
m_0 : w_0 : reg. minima and watershed of f_0;

f_1 : dual reconstruction of f_0
m_1 ; w_1 : reg. minima and watershed of f_1;
…

f_j : dual reconstruction of f_{j-1}
m_j ; w_j : reg. minima and watershed of f_j ;

3.2 Waterfall-Plus method

The watershed of a grey image, executed from its regional minima, often produces region over segmentation (many and very small regions). The described waterfall works as a region growing technique, in a morphological basis. The over segmentation is reduced every time each hierarchical step is executed. On this basis, the method has already proved to be suitable in some image based applications (Beucher and M. Bilodeau, 1990, Marcotegui and Beucher, 2005). However, in some cases of a high image radiometric complexity, like in urban scenes, the region growing evolution, seen in each watershed image, seems to stop making sense in terms of the segmentation of the real-world scene. In general, the waterfall filling runs quickly towards the maximum image grey level, for which the hierarchical process is finished after a few steps. The reason for this performance stands on the watershed marker image used in each waterfall hierarchical stage, being it always the regional minima of the preceding grey image of the running hierarchy. Each new minimum, given as an input for the watershed leading to waterfall, correspond to the grey spot where were two adjacent CB only. In all other filled CB, the waterfall filling is done and minima have disappeared at those spots. Hence, in the hierarchical process, region growing will never segment the CB corresponding to those minima. Thus, the fast growing tendency of the segmented areas increases from one step to another. As an example, the top illustration of Figure 2 represents an original grey level 2D function f_0, on which CB are filled according to the binary marker image imposition (regional minima shown as arrows).

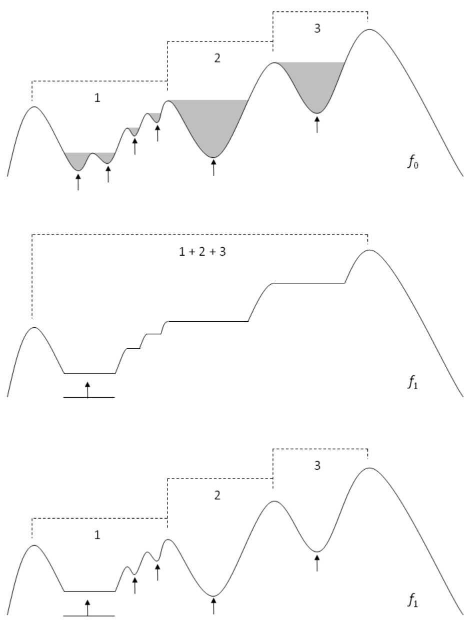


Figure 2. Beucher waterfall vs. WFP: First waterfall application (top), using *f regional minima* (vertical arrows); Beucher waterfall new minima (middle); WFP new minima (bottom)

Also, three relevant CB are suggested as major regions to be segmented, one of them containing some minor CB inside. The first waterfall step creates a new f_1 function (middle illustration) having only one minima spot (adjacent CB location), to enter as a watershed marker on the next waterfall stage. The new CB will be a unique large CB containing all existing ones. So, the first large CB (1) was never entire segmented along the hierarchical segmentation process. Driven by this drawback and also based on the general structure of the standard waterfall hierarchical algorithm (Beucher, 1994), a new approach for merging CB in a more local context is suggested. The method is designated as *waterfall-plus* (WFP). As seen earlier at Section 3.1, watershed lines are computed from the regional minima of *f*. The proposal changes the image marker data set, which feeds the watershed segmentation in each waterfall hierarchical stage, in order to slow down the region growing process. Instead of give as an input for watershed, the regional minima from the new computed grey image, it is given as an input a new marker set, defined as the logical sum between both new and preceding regional minima binary images; in other words, being m_k and m_{k-1} the regional minima sets of two consecutive waterfall output images, the binary set m_k to enter in watershed k-step will be replaced by $m_k \cup m_{k-1}$. This way, CB which aren't adjacent to others remain intact in each new segmentation step (bottom illustration of Figure 2).

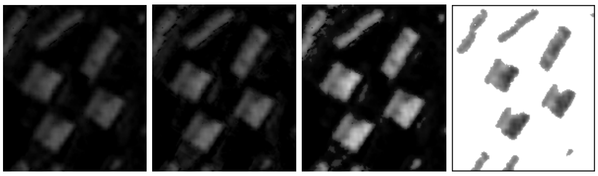
4. IMAGE SEGMENTATION METHODOLOGY

The proposed work aims at the extraction of two feature types: roof-tile buildings and roads crossing building tissue. The motivation for the first one was induced by a mere observation process of the grey radiometric response of the roof-tile buildings on each one of the three RGB channels. The connection between a high occupation percentage of buildings with tile-roof coverage in urban zones and that coverage radiometric response in different RGB bands, gave meaning to the purpose of developing a new extraction methodology for those features. For road-network, the same observation was made, but no relevant radiometric differences were seen. However, the roads radiometric stability had influence on deciding to do segmentation by a morphological-based approach. Further, it is suggested for the first roof-tile buildings extraction output to become integrated as a constraint for the methodology of road-network segmentation. However this procedure hasn't been examined thoroughly in this study.

4.1 Roof-tile buildings segmentation and generalization

In this work, roof-tile building (RTB) extraction is implemented by following a radiometric based image analysis, using Red (R), Green (G) and Blue (B) radiometric channels of a pan-sharpened image, followed by morphological segmentation approach. Then a simple shape generalization method, based on the raw segmented first results, is applied. Initially, the pan-sharpened image was read in a 16-bit radiometric resolution. The three spectral components were then separated, enhanced by linear contrast stretching and quantized into an 8-bit radiometric resolution. By computing the arithmetic differences $D_{12} = | R - G |$, or $D_{13} = | R - B |$, RTB become enhanced over homogeneous background. However, while in D_{12} the background is more homogeneous (Figure 3-a), in D_{13} the RTB radiometric response is higher with a less homogeneous background (Figure 3-b). In order to preserve the background of D_{12} as well as RTB response of D_{13} (foreground), the pixels of D_{13} with grey values higher than the maximum of $\Delta D = | D_{12} - D_{13} |$ (expression (3)) were added to D_{12}. The correspondent image result is shown in the sequence Figure 3-a/b/c.

$$X = D_{12} + [D_{13} > \max(\Delta D)] \times D_{13} \qquad (3)$$



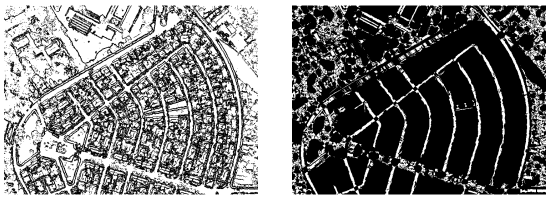
a) b) c) d)

Figure 3. RTB enhancement and generalization

The segmentation of the raw RTB image shapes is done by a simple histogram threshold. The histogram of this image has two peaks (bimodal histogram), being one narrow and high and the other wide and low. The location of the threshold value was generalized to the minimum value between both peaks, separating the background from the foreground objects. By now, the raw shapes of the RTB are segmented. Then, a simple shape generalization method is applied to each. Given an irregular binary raw shape, one is cropped from the original image window, by the minimum sized rectangular window that includes all its pixels. All the pixels of the cropped image window are space referenced to the global (x_0,y_0) coordinates of the correspondent main window central pixel. The shape is rotated by an angle succession (i = 1º…90º). For each angle i, the rotated shape is cropped again within its both minimum and maximum rows and columns respectively and is estimated the sum of both two window sizes (number of rows and columns). Thus, this value is assigned to the position i of a first vector v_1. Also, in order to classify the wanted shape in terms of its general geometry (either a square/rectangle or U-shape), the ratio between empty and non empty pixels inside the rotated window is estimated and assigned to the same position i of a second vector v_2. The shape exclusion criteria adopted was fixed on 35%, for which all shapes having a percentage value higher than that were excluded, which in this case, the algorithm passes to the next raw segmented shape automatically. For each accepted raw shape, the orientation angle of the building is given by i vector positions for both v_1 and v_2. The generalized shape is formed by filling the rotated raw shape window entirely with one-value pixels; then it is rotated by the same i angle but in the inverse way, returning to the original spatial orientation. Finally, after cropping it again all the pixels are assigned with the correspondent coordinates with relation to (x_0,y_0), at the global window. Generalization results are shown for all RTB shapes of an exemplification sample at Figure 3-d.

4.2 Road-network segmentation

In this section is presented the proposed methodology for urban road-network extraction based on a morphologic hierarchical approach. Unlike the spectral RGB response o RTB, the road areas response is quite similar for all RGB bands. A similar extraction strategy could be done, in this case to obtain only the less radiometric variations within RGB bands; however, the existence of a wider number of urban events with radiometric characteristics similar to roads, causes the method to fail. Unless the landscape is of a simple cross-country road, which would be the case of an object and a background (not compatible with an urban landscape), the alternative is to approach segmentation in other ways. The proposed approach is based on the application of the morphological waterfall method. The strategy behind this approach is to explore the radiometric homogeneity of the areas occupied by such objects. The morphology of an image surface can be characterized by applying the watershed transformation from its regional minima as the binary marker image, returning all surface catchments basins (CB) (or the watershed lines instead). Both homogeneous and heterogeneous area types often return approximately the same quantity of regional minima. However, in the first case, the difference on height between both CB minimum and watershed line is low and also about the same for all CB belonging to that area. This means that a small increase in the flooding process (small grey interval) will merge most of those CB at one time. Waterfall algorithm fills CB until the minimum level of the correspondent watershed line is reached; meaning that, in each step, the flat surface of the filled area is not the CB itself, but a CB sub-area instead. The earlier explained WFP segmentation method (Section 3.2) induces a detailed evolution of the segmentation process and, therefore, higher homogeneous areas get to be merged before connecting themselves to the heterogeneous ones. Using the morphological gradient (Rivest et al., 1992) for WFP hierarchical scheme computation, homogeneous areas are merged before heterogeneous areas and, therefore, can be easily identified and further segmented into binary format. After WFP execution, a segmented image result is chosen from the correspondent hierarchical regional minima scheme, with the aimed objects filled (Figure 4-a). In order to isolate those, a morphological opening (γ) filtering routine is applied, using two orthogonal directional structuring elements (SE) combined. The aim of that is to preserve all objects which are simultaneously large on a given direction and thinner in the correspondent orthogonal direction. Analyzing the roads wideness, both $SE_{(10)}$ and $SE_{(30)}$ were defined as line-shapes with lengths of 30 and 10 pixels respectively, having always a 90 degree angle between them. Those sized SE were taken in order to provide the extraction of aimed structures, by intersecting $[\gamma_{(10)}]^c$ with $\gamma_{(30)}$ for each angle within the range from 1º…180º. For each angle of the opening operation, a cumulative binary image was updated then. The resulting image is shown on Figure 4-b.



a) b)

Figure 4. Road network segmented images

5. RESULTS AND DISCUSSION

Inside a chosen study perimeter, there are 133 roof-tile spots recognized as buildings and also manually identified as single objects belonging to the aimed RTB class (Figure 6-a). Some of these are small groups of connected houses; however, due to their physical roof adjacency, they were considered as being single objects. Other buildings don't have a general squared/rectangular shape. In these cases, the methodology will either accept or reject a raw RTB spot according to the ratio between empty and non empty pixels inside its cropped window, once rotated to the state of empty pixels minimum quantity (Section 4.1). Despite this shape criteria aims at U-shaped spots detection, some L-shapes, or even triangular shapes, are affected also. As an immediate solution, empty vs. non empty ratio commitment can be taken in order to partially overcome these aspects. However, since shape resolution is beyond the scope of this study, it will be left for a posterior work. Concerning the proposed image sample, also a total of 133 raw RTB spots were extracted which means a 100% percentage of number equivalence. However there are certain objects in the output which haven't been manually marked as RTB. For that score achievement, have contributed both cases of merged raw RTB during segmentation and other roof-tile spots not initial recognized and identified as buildings (e.g. outbuildings). However, a clear high percentage of RTB spots have been well spotted. The global positional accuracy was measured by the computation of the normalized cross-correlation index between both the present method and manual extraction output images; also the same index was computed individually for each extracted single object from the generalized image, being both indicators above 0.8 (to refer that, concerning the generalized image output, the referred global index was computed considering only the correspondent manual extracted ones). After generalization procedure, a total of 108 RTB were fixed as squared/rectangular shapes, which indicates an extraction percentage of 81.2%. Comparing these last results with a previous non manual extraction result (Santos et al., 2009) from the same area, which was based on a supervised classification by area sample selection, we can see that our method becomes as accurate as the referred one, segmenting though 3% more raw RTB building spots, which is a reliable indicative for the proposed method's usage. RTB values are listed in Table 1. In what respects to road network extraction, the main difficulty stood on the differentiation between similar spectral responses of both asphalt and vegetation and neighbourhood terrain. However, the adequate chosen of morphologic operators can make a difference. For this study, and based on a registered waterfall-plus minima image from its hierarchical segmentation scheme, there were chosen morphologic line structuring elements with sizes adequate to the plane morphology of the road features, so that other features than those would be eliminated in its majority. That procedure sequence has returned an adequate segmentation result. From this step forward, the correspondence of those results with the RTB results is an important role to be played on further segmentation improvements. Early, this idea was already been practiced when the acquisition of image b) from Figure 4 for which remaining binary spots from the directional segmentation were suppressed at generalized RTB locations. The final proposed result is presented at Figure 6-b.

Ext. process	RTB units	Perc. (%)	cc index
Manual	133	100	1
Raw	133	100	0.79
Raw (*FA soft.)*	129	96.9	0.79
Generalized	108	81.2	0.81

Table 1: RTB extraction scores

a) b)

Figure 5: a) Raw segmented roof-tile spots; b) Raw building extraction results with Feature Analyst software (Santos et al., 2009)

a) b)

Figure 6: Extraction outputs: a) RTB manual extraction; b) RTB and RN extraction results

6. CONCLUSIONS AND FUTURE WORK

The work presented in this study aimed at urban feature segmentation from very-high resolution remote sensing images, for purposes of municipal high-scales cartography update. Two extraction approaches were described: one for roof-tile buildings (RTB) and the other for road network inside (RN) dense building tissue. The first approach was simply based on the radiometric variations of the RTB, in RGB image composition, followed by the implementation of a geometric generalization algorithm. The first raw RTB extraction results were very satisfactory, working as a motivation to go further in the exploration of the subject. The technique turned out to be as powerful as simple for the present work established purposes. At this stage, the main conclusion is that the first raw extraction results are very reliable when put against to the aimed features, since their image spectral signature allows a secure radiometric presence just by doing very simple arithmetic operations with the RGB bands. Later, for purpose of cartographic representation of those objects, several extraction improvements are presently under study: the first aimed improvement will be studied at the level of the raw shape itself, isolating each first, and then study its radiometric morphology, spatial geometry and neighbourhood context (either spatial or spectral), in order to get information about if the building corresponds effectively to one or several adjacent house buildings. This has also particular interest for the problem of knowing if the object is a single building covered by other features (e.g. vegetation), or if it is a U-shape or another shape kind. Future assessment of results can be achieved also by comparison with LIDAR (LIght Detection And Ranging) data, which provide elevation for the top roof buildings. The second aimed improvement to be worked under the RTB extraction is to extend building extraction to others than roof-tile covering. For this matter, hierarchical segmentation procedure will have a significant role, meaning that other representation classes must be previously recognized and entered in the segmentation process as fixed objects. Concerning the RN extraction task, the achieved results are much acceptable but yet incomplete in terms of final cartographic characterization. However, the morphological algorithmic approach tested over the presented image sample has showed a good performance on detecting homogeneous regions which are according to the RN areas. The segmentation by waterfall is a non supervised method, being its results guided just by the relief characteristics of the radiometric image surface. Sense roads have many grey level variations either in the neighbourhood of their edges (sidewalks, vegetation, houses, etc.), or inside it (traffic, asphalt discontinuities, guide lines, painted traffic lines, etc.), a morphological segmentation approach may give some less objective results concerning features geometry. The exploration of the roads texture properties, as well as knowledge context, inferred by previous data extraction can give significant improvements for the segmentation results. Prior insertion of that knowledge as a fixed condition in the execution of the morphological waterfall is the future proposal for road network segmentation improvement. As a final comment, the methodologies presented either for roof-tile buildings, or road network, can be considered tangible in the effectiveness of cartographic data extraction from VHR remote sensing images, for purposes of Municipal cartography production and GIS updating.

REFERENCES

Amini, J. and Seradjian, M. R., 2001. Automatic identification of cartographic objects. The Photogrammetric Journal of Finland by The Finnish Society of Photogrammetry and Remote Sensing and Institute of Photogrammetry and Remote Sensing, Helsinki University of Technology Vol. 17, no. 2, pp. 3–12.

Amo, M., Martnez, F. and Torre, M., 2006. Road extraction from aerial images using a region competition algorithm. IEEE Transactions on Image Processing.

Baatz, M. and Schape, A., 2000. Multiresolution segmentation - an optimization approach for high quality multi-scale image segmentation. Angewandte Geographische Informations verarbeitungXII, Ed. J. Strobl et al. AGIT Symposium, Salzburg, Germany pp. 12–23.

Beucher, S., 1994. Watershed, hierarchical segmentation and waterfall algorithm. Proc. Mathematical Morphology and its Applications to Image Processing in Serra, J. and Soille, P., Mathematical Morphology and Its Applications to Image Processing, Kluwer Ac. Publ., Nld pp. 69–76.

Beucher, S. and Lantuéjoul, C., 1979. Use of watersheds in contour detection. International Workshop on Image Processing, Real-time edge and motion detection/estimation, CCETT/INSA/IRISA, IRISA Report 132, Rennes, France pp. 2.1–2.12.

Beucher, S. and M. Bilodeau, X. Y., 1990. Road segmentation by watersheds algorithms. Centre de Morphologie Mathmatique, ENSMF, France.

Blaschke, T., Lang, S., Lorup, E., Strobl, J. and Zeil, P., 2000. Object-oriented image processing in an integrated gis/remote sensing environment and perspectives for environmental applications.

Cremers, A. and Greve, K. (eds.): Environmental Information for Planning, Politics and the Public. Metropolis, Marburg Vol. 2, pp. 555–570.

Dial, G., Gibson, L. and Poulsen, R., 2002. Ikonos satellite imagery and its use in automated road extraction. Optical Engeneering.

Hanbury, A. and Marcotegui, B., 2006. Waterfall segmentation of complex scenes. Lecture Notes in Computer Science (Computer Vision ACCV 2006), Springer Berlin / Heidelberg Vol. 3851, pp. 888–897.

Jang, J.-H. and Hong, K.-S., 2002. Detection of curvilinear structures and reconstruction of their regions in gray-scale images. Pattern Recognition 35, Elsevier Science Ltd pp. 807–824.

Laptev, I., Mayer, H., Lindeberg, T., Eckstein, W., Steger, C. and Baumgartner, A., 2000. Automatic extraction of roads from aerial images based on scale space and snakes. Machine Vision and Applications, Springer-Verlag Vol. 12, pp. 23–31.

Marcotegui, B. and Beucher, S., 2005. Fast implementation of waterfall based on graphs in mathematical morphology. 40 Years On Proceedings of the 7th International Symposium on Mathematical Morphology, Edited by Christian Ronce, Laurent Najman and Etienne Decencire, Springer pp. 177–186.

Mena, J. B. and Malpica, J. A., 2005. An automatic method for road extraction in rural and semi-urban areas starting from high resolution satellite imagery. Pattern Recognition Letters Vol. 26, no. 9, pp. 1201–1220.

Puissant, A. and Weber, C., 2002. The utility of very high spatial resolution images to identify urban objects. Geocarto International Vol. 17, no. 1, pp. 31–41.

Rivest, J. F., Beucher, S. and Soille, P., 1992. Morphological gradients. Proc. SPIE Image Science and Technology, San Jose, California.

Santos, T., Freire, S., Boavida-Portugal, I. and Tenedório, J. A., 2009. Accuracy assessment of features extracted from quickbird imagery for urban management purposes. Proceedings of the 33rd International Symposium on Remote Sensing of Environment, Stresa, Italy.

SCOT-Conseil, 1997. User workshops to define the requirements of town/city local government departments. Ispra, Space Applications Institute Joint Research Center: 48.

Soille, P. and Pesaresi, M., 2002. Advances in mathematical morphology applied to geoscience and remote sensing. IEEE Transactions on Geoscience and Remote Sensing Vol. 40, no. 9, pp. 2042–2055.

Yang, H.-H., Liu, J. and Zhong, T.-C., 2008. Anisotropic diffusion with morphological reconstruction and automatic seeded region growing for color image segmentation. ISISE 2008: International Symposium on Information Science and Engineering, Shangai, China Vol. 2, pp. 591–595.

Zhang, C., Murai, S. and Baltsavias, E., 1996. Road network detection by mathematical morphology. Proceedings of ISPRS Workshop, Paris-France, April 7-9 pp. 185–200.

Zhu, M. L. and Yeh, P. S., 1986. Automatic road network detection on aerial photographs. Computer Vision and Pattern Recognition (CVPR86) pp. 34–40.