International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:3, No:6, 2009

High Resolution Images: Segmenting, Extracting Information and GIS Integration

Erick López-Ornelas

***Abstract*—**As the world changes more rapidly, the demand for update information for resource management, environment monitoring, planning are increasing exponentially. Integration of Remote Sensing with GIS technology will significantly promote the ability for addressing these concerns. This paper presents an alternative way of update GIS applications using image processing and high resolution images. We show a method of high-resolution image segmentation using graphs and morphological operations, where a preprocessing step (watershed operation) is required. A morphological process is then applied using the opening and closing operations. After this segmentation we can extract significant cartographic elements such as urban areas, streets or green areas. The result of this segmentation and this extraction is then used to update GIS applications. Some examples are shown using aerial photography.

***Keywords*—**GIS, Remote Sensing, image segmentation, feature extraction.

I. Introduction

THE volume of Remote Sensing imagery is so large, its associated powerful image processing technology is used to manage geo-information with preprocessing analysis, accuracy assessment and information distribution.

GIS are more and more being used for the storage and analysis of geo-referenced data and also it handles the linkages between spatial entities and their discrete attributes. With the availability of high resolution satellite data and its processing technologies, integration of digital image analyzing systems with advance GIS systems permit compositing data sources as well as promoting a partnership between man and machine.

High resolution imagery gives a good indication of images in the future. Their impact in many areas like environment or civil security will be very important. Indeed, the arrival of these new images will allow a new perception and the study of a new range of non-observable objects until now. At the same time, these data will be productive only if they are exploited in a co-operative and interactive way like the geographical information, which is the main application system of the surface observation. The acquired information will have thus to be integrated in a geographical database which are now very important for knowledge and monitoring of land surfaces. From this point of view, the landscapes observed must be described by an object oriented approach for two reasons: 1) this description is adapted to the concept of spatial dynamics of the ecosystems by the land unit; 2) this expression is essential in order to be compatible with the knowledge extraction using the space analysis in a geographical information system.

Erick López-Ornelas is a Professor at the Universidad Autónoma Metropolitana in México city and works at the Department of Information Technology in Cuajimalpa campus (phone: (55) 52561028 e-mail: elopez@correo.cua.uam.mx).

II. Segmentation: An Overview

The segmentation is one of the most important processes among the different tasks on image processing (acquisition, preprocessing, segmentation, recognition, compression, etc.). Segmentation is the process of grouping an image into units that are homogeneous with respect to one or more characteristics [1].

A formal definition of image segmentation is as follows [2]: If P is a homogeneity predicate defined on groups of connected pixels, then segmentation is a partition of the set I into connected subsets or regions ($S_1, S_2, \dots, S_n$) such that $U\, S_{i=1,2,\dots,n}\; S_i = I$ *with* $S_i \cap S_j = \emptyset\ (i \neq j)$.

The uniformity predicate $P(S_i)$ is true for all regions S_i, and $P(S_i\, U\, S_j)$ is false, when $i \neq j$ and S_i and S_j are neighbors.

We can find in the literature some algorithms and segmentation methods. The technique used will depend on the problem to solve. The different techniques have its advantages and its limits; therefore the aim is to find the most adequate method with a specific application.

Segmentation techniques can be categorized into the following classes:

(i) **Thresholding** and clustering. It assumes that images are composed of regions with different ranges of gray level; the histogram of an image can be separate in a certain number of peaks, where each one corresponds to one region and there is a seed value, which separates two adjacent peaks [3].

(ii) **Edge detection**. This technique is extensively utilized for gray level image segmentation, which is based on the detection of discontinuity on gray level, and tries to locate points with abrupt changes in gray level [4]. This method is based on the first and the second difference operator.

(iii) **Region based approach**. This technique attempts to group pixels into homogeneous regions with similar properties. In the region growing approach, a seed region is first selected, and then expanded to include all homogeneous neighbors, and this process is repeated until all pixels in the

International Journal of Information, Control and Computer Sciences
ISSN: 2517-9942
Vol:3, No:6, 2009

image are grouped. One problem with region growing is its inherent dependence on the selection of seed region and the order in which pixels and regions are chosen [1], [3], [4].

(iv) **Fuzzy approach**. The regions in the image are not always crisply defined and uncertainty can arise, and fuzzy theory provides a mechanism to represent and manipulate uncertainty and ambiguity. Fuzzy subsets, fuzzy operators and rules have found considerable applications in image segmentation [5].

(v) **Neural networks approach**. This approach has been widely applied for pattern recognition. Neural networks are composed of many computational elements connected by links with variable weights; training time is usually very long, but after training, the segmentation is quite efficient. Different techniques have been used for example: Hopfield Neural Network (HNN), self-organizing map (SOM), the backpropagation, etc [6], [7].

(vi) **Others approaches**. There are many others approaches in the literature for example the fractal approach [8], cooperation approaches that mix techniques like region based with edge detection [4]. The use of snakes [9], the data mining [10], and the multiresolution approach had been used successfully [11].

The **mathematical morphology,** that belongs to region based approach, started at the end of the sixties and was proposed by Matheron and Serra [12]. Mathematical morphology rests in the study of the geometry and forms; the principal characteristic of morphological operations is image simplification and the features conservations from the objects. The main idea of mathematical morphology is to compare the objects to be studied with an object of known form: the structuring element. The principal morphological operators are erosion and dilation. From those we can define the operations of opening and closing. These operations define the form representation, the decomposition and feature extractions. Some applications can be found in [13].

Even if the segmentation method to explain rest in the use morphological operations, we will not enter in details with the theory of mathematical morphology and all the properties related. The interested reader is invited to read this reference [12].

III. Self-Adaptive Segmentation Using Mathematical Morphology

The morphological segmentation approach is based on a self-adaptive method that consists of the image description by adjacency graph using morphological methods to obtain appropriate and significant objects with regions growing.

A. Preprocessing

The finality of the preprocessing is to obtain images that are easier to handle. The process of quantification and sampling are made in order to reduce the noise caused to small zones or groups of pixels which can remain insulated during the segmentation process. This preprocessing makes the first pixel aggregation, and it will approximate the desired scene, which will permit a faster convergence of the morphological processing. This preprocessing step is optional and can be avoided; it depends on the degree of precision desired. To this preprocessing, we have added a nonlinear processing: the watershed, applied to the gradient of the filtered image. This method is based on a flood simulation process of the different areas. The general idea of this algorithm is [14]: (i) Flooding action, starting from the lower levels of gray; (ii) when one shock is produced by two various areas we will obtain a segment (dividing line) which we will maintain until the convergence of the algorithm and then we keep flooding the higher levels; (iii) these segments obtained will be the watershed, which in a similar way will be the closed contours of the objects contained in the image.

The finality is to obtain an initial image represented by the regions created by the preprocessing step. This image is over-segmented and has its own radiometry and it is constituted by iso-photometric regions $E_i = \{e_1, e_2, \dots, e_n\}$ of any size and forms that constitutes a good starting point to carry out the morphological processing.

B. Graph Construction

In order to apply the morphological operations, the space (set of regions E_i) will be modeled by *Vor(p)* (Voronoi diagram applied to regions *p*) and using their dual graph (Delaunay Triangulation *DT*) the final graph will be constructed.

The regions with the same radiometric value are labeled, and an image that contains *N* regions will have labels of the range from 0 to *N-1*.

In that way, for any $p \in V$, the Voronoi polygon *Vor(p)* associated with *p* is the locus of points that are closer to *p* than to any other point of *V*:

$$Vor(p)=\{m \in \mathfrak{R}^2\}, \text{ for all } q \in V\backslash\{p\},$$
$$distance(m,p) < distance(m,q)$$

Vor(p) is also called the "influence zone" of point *p* [16].

These regions partition the plane into a net called Voronoi diagram [Fig. 1c]. The Delaunay Triangulation (DT) is formed by the edges of this graph by all pairs of points (*p,q*) in *V*, whose Voronoi polygons Vor(p) and Vor(q) are adjacent (share an edge) [Fig. 1d].

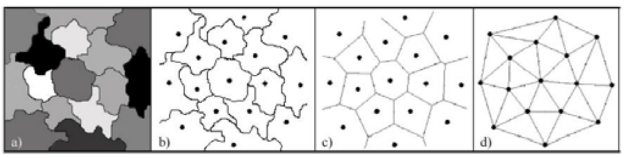

Fig. 1 Graph construction

This process permits to define the graph (*G*) using the Delaunay triangulation (*DT*) where a node p_i represents a polygon with the same photometric value e_i and is connected to another node p_j of e_j by an arc {a}, if and only if, there exists between e_i and e_j one common border [fig. 1d]. The graph (*G*) resulting of the *DT* describes the image I(x, y) on

(S, A) with: $S = \{p_1, p_2, \dots, p_n\}$, set of *N* nodes, and $A = \{a_1, a_2, \dots, a_n\}$, set of arcs with no intersection between the n nodes.

We also defines on *G* a subset $V_A(p) \subset G$ neighbors of p_i in *G* for any $p \in S$: $V_A(p) = \{p_i \in S, (p, p_i) \in A\}$, that gives the access to the neighbors p_i of with the same border. The decimal graph (S is mapped into $\Re$) is then constructed.

C. Morphological Processing

The proposed segmentation approach using the morphological operation will be applied in the graph (*G*) to get de desired regions and the structuring element will be the neighborhood $V_A(p)$.

In the image *I(x,y),* if the nodes (p_i) of the decimal graph constitute the digital grid and its neighbors the polygons e_i, then the process will compare and will affect the radiometric value of e_i on the decimal graph constructed using the morphological operations. These morphological operations will be the core of the segmentation.

The principle of region growing consists in transforming the *G(p)* value, by affecting the nearest radiometric value $val(p_i)$ present among the p neighbors, and the process of growth comes from union of regions $(e_i \ U \ e_j = e_n)$. The segment e_n is then the result of the growth of regions.

To carry out this transformation, the morphological operation on the graph will be applied. Furthermore they are defined par [16], [17] as follow:

$$\text{Dilation } D(G)(p) = \max\{G(p_i), p_i \in V_A(p) \ U \ \{p\}\}$$
$$\text{Erosion } E(G)(p) = \min\{G(p_i), p_i \in V_A(p) \ U \ \{p\}\}$$
$$\text{Opening } O(G)(p) = D(E((G)(p)))$$
$$\text{Closing } C(G)(p) = E(D((G)(p)))$$

In an algebraic way we can rewrite these operations of opening and closing:

$$\text{Opening} = \gamma(G)(p_i) = Min(G(p_i), Max(G(p)))$$
$$\text{Closing} = \varphi(G)(p_i) = Max(G(p), Min(G(p)))$$
$$\text{with } p = \{V_A(p)\} - p_i$$

The geometrical action of the algebraic openings and closings $\gamma(G)(p_i)$ and $\varphi(G)(p_i)$ respectively, will produce an enlarging of the regions size and remove the local limit of the decimal graph.

A loop is then required in order to alternate the used filters updating the decimal graph and to keep aggregating the regions [12], always applying the morphological algebraic operations $\gamma(G)(p_i)$ and $\varphi(G)(p_i)$ until their parameter value is reached (the idempotence has to be checked before the union $(e_i \ U \ e_j)$. Feature extraction is then calculated using the final graph and stored in a database in order to elaborate meanly queries. In Fig. 2 we show the original image. This is an aerial photography used to extract urban elements. The Fig. 3 shows the preprocessing step using watershed process and finally we show in Fig. 4 the segmented image after apply the morphological operations.

Fig. 2 Original image

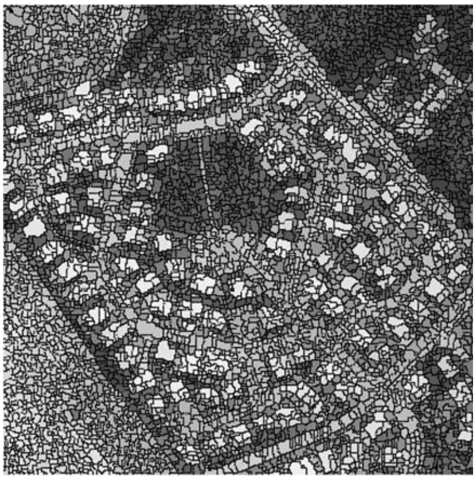

Fig. 3 Watershed process

Fig. 4 Segmented image

IV. Scene Interpretation Using Feature Extraction

The morphological segmentation step, previously described, produces a new image divided into *n* distinct regions *Ri*. So, we can define a new adjacency graph formed by a more complete set of intrinsic and extrinsic features.

A. Intrinsic Features

The set of the intrinsic features is constituted by the internal characteristics of the region, in relation with its geometric and morphologic nature. It's the first abstraction level of the image's knowledge.

Extract the internal information in each region of the image is based on the separation of the considered region from the others by building a binary image via the application of a mask. The usual morphological operations are then processed to get some features as:

- the value of the gray level *NdG(ri)* of the region,
- the surface of the region *Surf(ri),*
- the exterior perimeter *PerExt(ri),*
- the interior perimeter *PerInt(ri),*
- the perimeter *Per(ri)*; it's the average value calculated from the lengths of the two preceding perimeters,
- the opening cardinal *CardOp(ri);* it's the number of the pixels contained in the opening result.
- the closing cardinal *CardCl(ri),*
- the compactness *Comp(ri)*; it's the ratio between the two cardinals,
- the isoperimetric index *IsoPer(ri);* it's an index of the form that characterizes the connected objects: $IsoPer(ri)= 1 – (4\pi Surf(ri) / Per(ri)^2$
  This index varies from 0 (disk) to 1 (the object's surface equal to 0),
- the number of region's neighbors *NbVois(ri),*
- the contact length between a region and its neighbor *LoCont(ri,rj).*

These two last features are extracted from the exterior perimeter where the pixels don't belong to the considered region but to its neighborhood.

B. Extrinsic Features

Extrinsic features are extracted using the spatial information contained in the image. We need to define some spatial relations in order to define these extrinsic features. For this, we define the minimum bounding rectangle (MBR) that ensures, with its center of gravity and its dimensions, the identification of the concerned region.

Topological relations: The topology is certainly the most important aspect among the extracted spatial information.
Papadias and Theodoridis [18] define the *RCC-8* model that regroups the different cases existing between regions. Fig. 5 and the Table I illustrate this model.

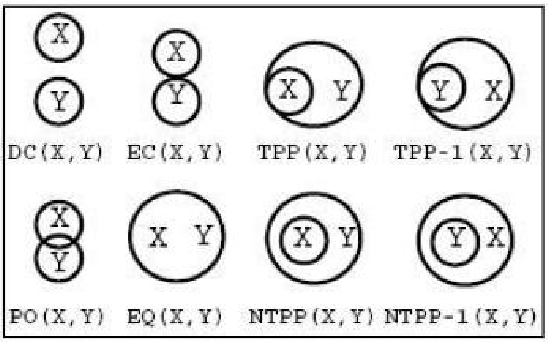

Fig. 5 RCC-8 model

TABLE I
TOPOLOGICAL RELATIONS

The RCC-8 relations	Significance
DC(X, Y)	X is disconnected from Y
EC(X, Y)	X is externally connected to Y
EQ(X, Y)	X is identical with Y
PO(X, Y)	X partially overlaps Y
TPP(X, Y)	X is a tangential proper part of Y
TPP-1(X, Y)	X contain the tangential part Y
NTPP(X, Y)	X is a non tangential proper part of Y
NTPP-1(X, Y)	X contain Y

Nevertheless, in the context of a segmented image and for defining topological relation for adjacent regions, just three relations are interesting:

- adjacency relation *EC(x,y),* given by the neighborhood,
- inclusion relation *NTPP(x,y),*
- and the relation of 'contain' *NTPP – 1(x,y).*

Angular relations: We calculate the angle between two adjacent regions. It's based on gravity's center of the MBRs previously defined.

$$\theta = \tan^{-1} \frac{y_j - y_i}{x_j - x_i}$$

(xi, yi) and *(xj, yj)* are the spatial coordinates of gravity's centers of the two regions *ri, rj*. From this angle, we estimate the direction of *ri* in relation to *rj* taken as landmark. The Table II illustrates the 8 possible directions.

TABLE II
ANGULAR RELATIONS

Direction	θ variation
$north(r_i)$	$60° \leq r_j \leq 120°$
$north - east(r_i)$	$30° \leq r_j \leq 60°$
$east(r_i)$	$330° \leq r_j \leq 30°$
$south - east(r_i)$	$300° \leq r_j \leq 330°$
$south(r_i)$	$240° \leq r_j \leq 300°$
$south - west(r_i)$	$210° \leq r_j \leq 240°$
$west(r_i)$	$150° \leq r_j \leq 210°$
$north - west(r_i)$	$120° \leq r_j \leq 150°$

Metric relation: It's the Euclidean distance between two regions.

$$dist = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$$

Features organization

Using spatial information is a real advantage. The fusion of information related to the relationships between objects enables the identification of complex objects for which the spectral attributes can be very variable. After the interpretation, a list of retained objects and their associated features can be stored in an XML (eXtensible Markup Langage) file that can be integrated into a geographic information system. An example is given in Fig. 6.


```
- <plateau>
   <Id>1</Id>
   <NdG>132</NdG>
   <Surf>118</Surf>
   <PerExt>119</PerExt>
   <PerInt>101</PerInt>
   <Per>110</Per>
   <CardOp>69</CardOp>
   <CardCl>121</CardCl>
   <Comp>0.57025</Comp>
   <IsoPer>0.87745</IsoPer>
   <NbVois>5</NbVois>
 - <REM>
     <x_min>27</x_min>
     <y_min>32</y_min>
     <x_max>39</x_max>
     <y_max>72</y_max>
     <x_center>33</x_center>
     <y_center>52</y_center>
   </REM>
 - <voisins>
     <Number>1</Number>
     <Id>19</Id>
     <LoCont>2</LoCont>
     <Topologie>Adjacent</Topologie>
     <Angle>105.94540</Angle>
     <Direction>nord</Direction>
     <Distance>36.40055</Distance>
   </voisins>
 - <voisins>
     <Number>2</Number>
     <Id>46</Id>
     <LoCont>43</LoCont>
     <Topologie>Adjacent</Topologie>
     <Angle>321.00901</Angle>
     <Direction>sud-est</Direction>
     <Distance>54.03702</Distance>
   </voisins>
```


Fig. 6 XML file

V. GIS INTEGRATION

The main obstacle when we want to deal with a raster map and the extracted information is to find a way coding this information. Obviously, we can scan this information manually but is time consuming even if this task is very important.

In our segmentation model and extraction of knowledge you can use vector model with this extracted information in an automatic way. This means that you can easily emigrate the extracted raster information in to the vector model which is commonly used by GIS to exploit the spatial information.

We use Freeman codes [19] to carry out this operation. During the segmentation process we can get different information: i) the segmented image, ii) intrinsic information, iii) the meta-information and finally iv) freeman codes of extracted elements which are vector files that can be read using a GIS software.

The main advantage of this coding is that information can be used rapidly any GIS software. When we store this information in vector format we can use all GIS functions and utilities of this specific software to generate different applications. In Fig. 7 we show the final result of integrate the extracted information using the segmentation process and how it can be integrated into GIS software.

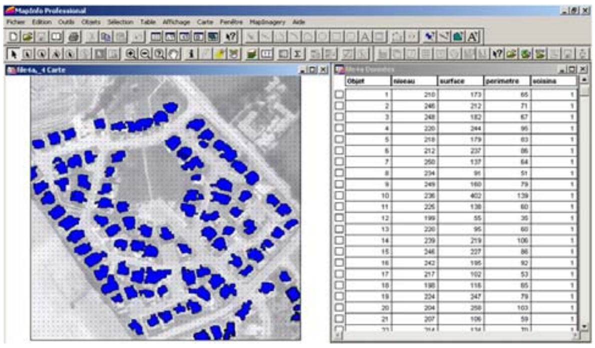

Fig. 7 Remote Sensing and GIS integration

VI. CONCLUSION

The results obtained above show that mathematical morphology presents a big interest in the Very High Resolution Spatial images interpretation. The neighborhood relations seem to be an important advantage and experiments show that the proposed methodology is particularly interesting. The geometric information used and integrated in the process has been chosen for their direct relationship to certain objects of interest. It is however important to note that the interpretation depend upon the quality of the segmentation obtained in the earlier processing steps. The last important result is this facility of integrates this extracted information into GIS information because you can use all GIS functionalities to exploit this extracted information.

REFERENCES

[1] R. Gonzalez, and R. Woods, *Digital Image Processing*, Addison-Wesley, 1993.
[2] S. K Pal et al., “A review on image segmentation techniques”, *Pattern Recognition*, 29, 1277-1294, 1993.
[3] A. Marion, *Introduction aux techniques de traitement d’images*, Ed. Eyrolles, 1987.
[4] R. Horaud and O. Monga, *Vision par ordinateur*, Ed. Hermes, 1993.
[5] A. Mohhaddamzadeh, and N. Burbakis, “A fuzzy region growing approach for segmentation color images”, *Pattern Recognition*, 30, 867-881, 1997.
[6] W. J. W Cheng, “Color image segmentation: advances and prospects ”, *Pattern Recognition*, 34, 2259-2281, 2001.
[7] S. H Ong et al. “Segmentation of color images using a two-stage self-organizing network”, *Image and Vision Computing*, 20, 279-289, 2002.

[8] R. Vuduc, "Image segmentation using fractal dimension", *Rapport Technique*, Cornell University, 1997.
[9] M. Kass et al. "Snakes: Active contour models", *Computer Vision Graphics and Image Processing*, 321-331, 1998.
[10] C. Soh, "Segmentation of satellite imagery of natural scenes using data mining", *IEEE Transactions on Geosciences and remote sensing*,37, 1086-1099, 1999.
[11] M. Baatz, and A. Shape, "Multiresolution segmentation: an optimization approach for high quality multi-scale segmentation", *Applied Geographical data processing*, 12-23, 2000.
[12] J. Serra, *Image Analysis and Mathematical Morphology*, Academic Press, London, 1982.
[13] J. Serra, and P. Soille, Mathematical Morphology and its applications to image processing, Kluwer Academic Publishers, 1994.
[14] L. Vincent. and. Soille, "Watersheds in Digital Spaces: An Efficient Algorithm based on Immersion simulations". *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 583-598, 1991.
[15] J. Chassery and A. Montanvert, *Geométrie discrète en analyse d'images*, Ed. Hermes, 1991.
[16] L. Vincent, "Graphs and mathematical morphology", *Signal Processing*, 16, 365-388, 1989.
[17] G. Flouzat and O. Amram, "Segmentation d'images satelitaires par analyse morphologique spatiale et spectrale", *Acta Stereologica*, 16, 267-274, 1997.
[18] D. Papadias and Y. Theodoridis. "Spatial relations, minimum bounding rectangles, and spatial data structures". International Journal of Geographical Information Science, 11(2) :111–138, 1997.
[19] J. Gero. Representation and reasoning about shapes : Cognitive and computational studies in visual reasoning in design. Spatial Information Theory, Springer, pages315–330, 1999

Erick López-Ornelas is a Professor of computer science at UAM (Universidad Autónoma Metropolitana) in México city. He is the author of a number of papers and has given talks on Geographical Information Systems and Remote Sensing Imagery at a variety of conferences.

López Ornelas received his Masters degree from University of Bourgogne in France and his Ph.D. from University Paul Sabatier in Toulouse France in 2005. He is a professor of Information Technology department at UAM.