MAPPING OF BUILT–UP AREA DENSITY FROM SATELLITE IMAGES USING MORPHOLOGICAL GRANULOMETRIES

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ABSTRACT:

The overall objective of this work is to provide maps based on the spatial organization of built-up areas and to achieve the comparative spatial analysis of built-up areas on east of Algiers in 1985 and 1996. Landsat TM images from both dates are processed here in order to characterize spatial and temporal change in built-up areas. Contextual supervised classification method is used for built-up areas extraction. Built-up density mapping is provided by local granulometric analysis, based on binary mathematical morphology. This method enables the classification of entities according to their granulometric descriptors generated by opening granulometries.

1. INTRODUCTION

Built-up areas in Algiers have markedly increasing during the last decades. Growth of urban built-up area is accompanied by an evolution of land use. Remote sensing images are relevant materials for observation and thematic mapping by multispectral and multi-textural classification. The objective here consists in mapping the spatial organisation of one single component of the landscape under study, such as built-up areas. Many techniques have been developed for built-up analysis (Zhang, 2002; Zha, 2003). Different parameters can be used to define the spatial organisation of a set: the size of convex entities forming the set, their form or their ordering. Texture is the characterizing feature of built-up areas in satellite imagery. For some researchers (Matsuyama, 1983; Wood-1996), there exist two categories of methodologies to analyze the textures, a statistical and a structural one. The former model the textures as a random function without a regular structure and are utilized for the detailed textures. The structural methods describe the textures produced by the regular structure of textural elements (Philipp, 1994).

In the local or global analysis of the texture, the textural parameters computed from the local or global statistics of the image with grey tone images are used as classifying descriptors. However, computation of the texture parameters from grey-tone values is not relevant for the feature extracted data used in this study. The work presented in this paper is about the development of a methodology for the quantification of the spatial organization of built-up areas from binary images. Such spatial organization is called macro-texture. On a binary image, Busch *et al*. (Busch, 1998) define the feature density as the number of pixels matching this feature that are contained in an image window. The proposed approach is based on mathematical morphology (Serra, 1982; Soille, 2003), and has been used successfully in vegetation density mapping (Kemmouche, 2004). In a first step, after extraction of the built-up areas by multi-spectral analysis, we define the descriptors of the macro-texture from the concept of the granulometric analysis of binary images representing built-up areas. To describe the macro-texture around a pixel of the image, we have calculated the local granulometric density over a window centred on the pixel. The result of this granulometric computation is a vector associated with each pixel and new grey level images generated.

In a second step, all the pixels of the original, described by the macro-texture parameters are classified by the K-means method to produce the final map, which can be considered as a map of the density of the built-up areas. The method has been applied to map built-up areas density from satellite data on east of Algiers in 1985 and 1996. Such maps are efficient tools to study the spatial dynamics of built-up areas.

The paper is organized as follows. In section II, the classification of satellite data with high spatial resolution from urban areas is described. The proposed mathematical morphology approach to built-up areas density mapping is discussed in section III. Experimental results are given in section IV.

2. BUILT-UP AREAS EXTRACTION

In this section image analysis methods used for extraction of built-up areas from Landsat images are described. The first part is devoted to image processing adapted to urban areas classification from multispectral images, and the second part describes built-up areas extraction. Landsat images corresponding to seven band multispectral mode (Thematic Mapper) were explored over eleven-year period.

2.1 Classification of urban areas from satellite data

There are many different approaches to classifying remotely sensed data. They all fall under two main topics: unsupervised *and* supervised classification. Supervised classification methods are two kinds: punctual or blind methods and contextual methods (Pieczynski, 1989; Richards 1993). Punctual classification methods are conventional classification techniques which classify each pixel independently by considering only its observed intensity vector. The result of each method has often a "salt and pepper" appearance characterizing misclassification. It means that intensity vector is insufficient and then leads to incorrect classification of pixels. In particular of remotely sensed data, adjacent pixels are related or correlated, both because imaging sensors acquire significant portions of energy from adjacent and because ground cover types generally occur over a region that is large compared with the size of a pixel. Using coherent contextual information for classification efficiency and accuracy in remote sensing has long been desired. Contextual information is important for the interpretation of a scene. When a pixel is considered in isolation, it may provide incomplete information about the desired characteristics. However, the consideration of the pixel in its context, more complete information might be derived. The basic idea of spatial context is that the response and class of two spatially adjacent pixels are highly related. For example, if *(i, j)* and *(m, n)* are two neighbouring pixels and if *(i, j)* belongs to class *k*, then there is a high possibility that pixel *(m, n)* also belongs to the same class *k*. Therefore, the decision for a pixel is taken based not only on the observation at *(i, j)* but also on all observations at *(m, n)* where *(m, n)* is neighbour of *(i, j)*. Among contextual methods, the most widely applied to remote sensing images is the Markov random Field (MRF) approach , which has given very promising results (Schistad 1999a; Schitad 1996b, Khedam 2001). MRF is given as the best methodological framework to describe the correlation of neighbouring pixels.

2.2 MRF contextual classification model

We assume that a classified image X and observed data Y are realisations of stochastic processes $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively. $Y = \{Y^1, Y^2, ..., Y^K\}$ are multispectral data observed through K spectral bands and are supposed to be acquired on a finite rectangular lattice $W = \{s = (i, j) : 1 \le s \le S\}$, s is the site of the *ijth* pixel and S is lattice's area. The multispectral data can be described with $Y = \{y_s,\ 1 \le s \le S\}$ where $y_s = \{y_s^1, y_s^2, ..., y_s^K\}$ is a feature vector observed on the site s. Our goal is to find the optimal classified image $X^* = \{x_s, ..., x_S\}$ based on the observed data Y. Each site of the segmented image is to assigned into one of M classes; that is, $x_s = \{1,\ 2, ..., M\}$ where M is the number of classes assumed to be known in supervised classification process. This optimisation is executed from the view point of the maximum *a posterior* (MAP) estimation as follows:

$$X^* = X_{MAP} = \underset{X \in \Omega}{argmax}\{P(X/Y)\} \tag{1}$$

Where Ω is labelled configurations set. Following Bayes theorem, equation (1) becomes:

$$X_{MAP} = \underset{X \in \Omega}{argmax}\left\{\frac{P(Y/X)P(X)}{P(Y)}\right\} \tag{2}$$

The modelling of both class conditional distribution *P(Y/X)* and prior distribution *P(X)* becomes an essential task. *P(Y)* is the probability distribution of the observed data and doesn't depend on the labelling X. Note that the estimate (2) becomes the pixel–wise non–contextual classifier if the prior probability doesn't have any consequence in formulating (2). *P(Y/X)* is the conditional probability distribution of the observation Y given the labelling X. A commonly used model for *P(Y/X)* is that the feature vector observed Y_s is drawn from a "*Gaussian distribution*". For a Markov random field X and so, according to the Hammerslay-Clifford theory, *P(X)* can be expressed as a Gibbs distribution with "*Potts model*" as energy function model. The global MAP estimate given by equation (1) is equivalent to the minimisation of the followed *a posterior* global energy function:

$$X_{MAP} = \underset{X \in \Omega}{\arg\min}\left\{U\left(X/Y\right)\right\} \tag{3}$$

Once MAP classification problem is formulated as an energy minimisation problem, it can be solved by an optimisation algorithm. Among the most effective algorithms for optimisation in the framework of image MRF modelling are Simulated Annealing (SA) (Geman, 1984) whose the computational demands are well known and Iterated Conditional Modes (ICM) (Besag, 1986) which is a computationally feasible alternative of the SA with a local minimum convergence of the energy function. To use ICM algorithm, global minimisation energy function of equation (3) must be transformed on the followed local minimisation energy function:

$$U(x_s/y_s) = \left\{\left\{\frac{1}{2}(y_s - \mu_{x_s})^T \cdot \Sigma_{x_s}^{-1} \cdot (y_s - \mu_{x_s}) + \frac{1}{2}ln\left\{\left|\Sigma_{xs}\right|\right\}\right\}\right. \\ \left. + \beta \sum_{r \in V_S} (1 - \delta\ (x_s, x_r))\right\} \tag{4}$$

Where μ_{xs} and Σ_{x_s} are class xs are respectively mean vector and covariance matrix of class x_s estimated during training process. β is a regularisation parameter and is frequently user specified. δ is Kroeneker symbol calculated on the neighbourhood *Vs* of site *s*.

ICM algorithm can be resumed on five steps as follows:

Step 1: Estimate statistic parameters set (μ_{xs}, Σ_{x_s}) from the training samples of each class from M classes

Step 2: Based on μ_{xs} and Σ_{x_s}, estimate an initial classification using the non-contextual pixel-wise maximum likelihood decision rule. We use the first term of equation (4)

Step 3: Choose an appropriate value of β, an appropriate shape and size of neighbourhood system *Vs* and an appropriate convergence criterion.

Step 4: Perform the local minimisation defined by equation (4) at each pixel in specified order: update *ys* by the class *xs* that minimises equation (4)

Step 5: Repeat step (3) until convergence.

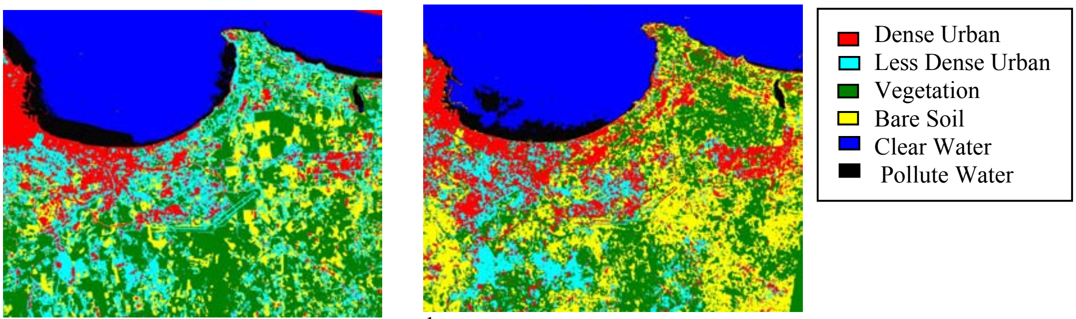
2.3 Built-up area extraction from classified urban areas

The described algorithm is applied to classify satellite images of the selected region of interest. Multispectral and multitemporal images were acquired in 1985 and 1996 by

ETM+ sensor of Landsat-7 satellite. The images cover the north-eastern part of Algiers (Algeria). The RGB compositions of these two images are given on figure 1. Six thematic classes dominate the study site: Dense Urban (DU), Bare Soil (BS), Less Dense Urban (LDU), Vegetation (V), Clear water (CW), and Pollute Water (PW). Using a 2-D scatterogram of ENVI software, data samples are selected automatically from each class for training and testing the proposed classifier. The MRF contextual classification results (8-connexity and β = 0.75) are shown on figure 2. Statistical assessment of these results relatively to the considered test data gives an appreciate KHAT parameter of 91.6% for data acquired on 1985 and 90.2% for data acquired on 1996.

a b

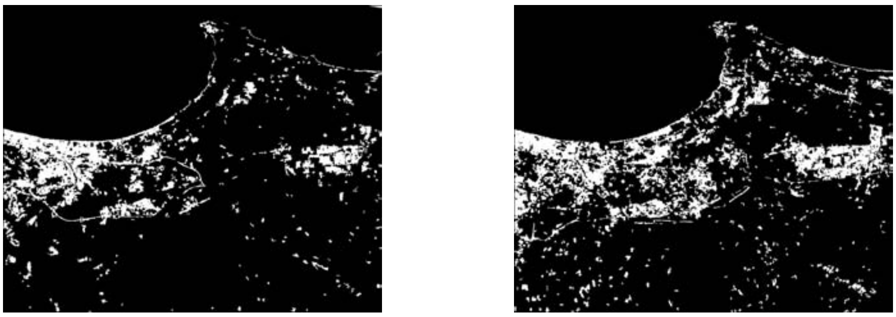
Figure 1. RGB composition of ETM+ images for 1985(a) and to 1996(b) scenes



a b

Figure 2. MRF classification result for 1985(a) and to 1996(b) scenes

From the obtained classified images (Figure 2), built-up area is extracted using a simple masking operation. Except dense urban (DU) class, all the other classes (BS, LDU, V, CW, PW) are masked which means that except DU pixels, all other pixels are assigned label “0”. The resulting binary images are presented in figure 3 (a and b) for both dates 1985 and 1996.



a b

Figure 3. Built-up areas extracted from TM scene corresponding 1985(a) and to 1996(b)

3. GRANULOMETRIC ANALYSIS FOR QUANTIFICATION OF THE BUILT-UP DENSITY

The process of built-up areas density mapping is organised in two parts. In the first one, granulometric analysis is computed on binary images with built-up areas in order to define the macro-texture parameters. In the other part, a density map is built by automatic classification of granulometric images.

3.1 Granulometric analysis on binary images

A binary image can be described as a set of the Euclidean space R^2. Such a set consists of many subsets, which are the connected components of the image. We choose here a criterion, which is the size distribution of the subsets in order to perform the textural analysis of the set. It is obtained by global transformations and measurments on the image. This analysis called Granulometric analysis is very similar to quantitative analysis of soil granulometry by sieving and weighting. The concept of granulometry for Euclidean set analysis was introduced by Matheron (Matheron, 1967) as a new tool for studying porous media. The principle of binary morphological granulometric size distributions was conceived by Matheron (Matheron, 1975) as a way to describing image granularity. The sieving of grains within the image was accomplished by a series of morphological openings with convex structuring element of increasing size.

A series of openings $O^{\lambda B}$ with a family of structuring elements B_1, B_2, ... B_n, is a granulometry if it satisfies the following axiom:

$$\forall (i,j)\; i \leq j \Rightarrow O^{B_i} \geq O^{B_j} \tag{6}$$

Many parameters are provided by granulometric analysis, such as *granulometric distribution.* In order to assess the size distribution of the connected components of a set X, we use the method of granulometry by opening with a convex structuring element B. It consists in a successive application of morphological openings on the set X using an increasing structuring element B. As the size of the structuring element B increases, more and more details in the image are suppressed. The connected components, which are smaller than B, are eliminated. By increasing the size λ of B, the elements of size $(\lambda - 1)$ are successively eliminated as though they were sieved. Computation of the area of elements suppressed at each opening step on the whole image leads to the evaluation of the size distribution $G_\lambda(X)$ of the set X, which is:

$$G_\lambda(X) = \left[A(X) - A\left(O^{\lambda B}(X)\right)\right] / A(X) \tag{7}$$

where, $A(X)$ indicates area on the initial image and $A\left(O^{\lambda B}(x)\right)$ is the area of the set X opened by structuring element of size λ.

Experiments such as studies on porosity of rocks from thin section images (Serra 1982) show that, in case of finite sequence of openings (i.e. for finite values of λ), the granulometric density is more relevant than the granulometric distribution for providing-g efficient descriptors of the size of the components of the binary image. The granulometric density $g_\lambda(X)$ of a binary image $X \subset R^2$ relative to a convex structuring element B is defined as:

$$g_\lambda(X) = \left[A\left(O^{\lambda B}(X)\right) - A\left(O^{(\lambda+1)B}(X)\right)\right] / A(X) \tag{8}$$

Granulometric density $g_\lambda(X)$ represents the fraction of total area of X that is rejected between two successive openings of respective radius λ and $(\lambda + 1)$. It provides a statistical evaluation of the area of the components of X : the maxima of $g_\lambda(X)$ indicate that there are a high proportion of subsets of X having a radius inferior to λ.

This analysis generates a finite and homogeneous set of quantitative descriptors $g_\lambda(X)$ that can be easily used to quantify the density.

3.2 Computation of macro-textural descriptors

The application of granulometric analysis has focused on taking local granulometric density around individual pixels. The use of local granulometric analysis to define texture descriptors was introduced by Dougherty et al (Dougherty, 1992; Chen, 1992). Rather than computing granulometric density across an entire image, as the global granulometry, pixel counts are only taken locally in windows about each pixel, thereby generating local granulometric density at each pixel: for each pixel of the binary image the *local granulometric density* $g_\lambda(X)$ was measured over a window centred on the pixel P at each stage of the granulometry**.**

This value is computed for the windows $F(P)$ around all the pixels P. The resulting texture representation is a vector $\{V_i(P)\}$. The texture variables describing a pixel P will be $\{V_i(P)\}_{i=1,2,.....,I}$ where,

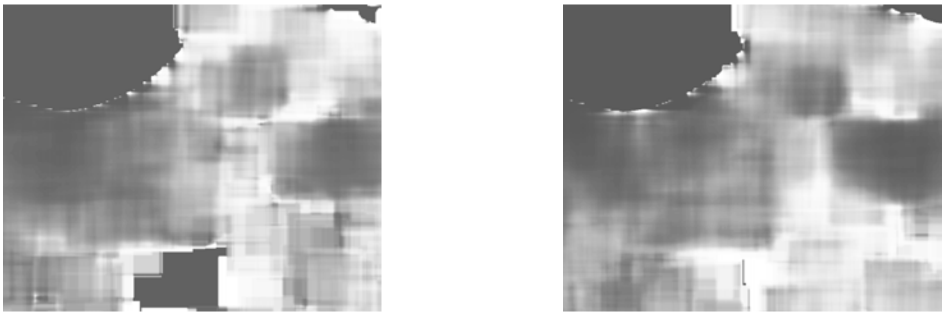
$$V_i(P) = g_i(F(P)) \tag{9}$$

$g_i(F(P))$ is the value of the local granulometric density computed inside the window $F(P)$ centred on pixel P at opening step i.

I is the size of B such that all the pixels of $F(P)$ are eliminated after the opening by B_I.

By this way, each pixel P of the binary image is described by the I values of Vi where, $i = 1,2,....,I$. Local granulometric densities for all the pixels of the binary image were computed and results were reassembled to form an image. Such a processing is performed for $i = 1,2,....,I$ then I gray-tone images are generated. This set of images will then be used as input for the classification step.

Seven images of granulometric density were obtained by this way. An example is shown on figure 4, which corresponds to the image of the granulometric density of size $\lambda = 1$ computed from the binary images of built-up areas of figure 3.



a b

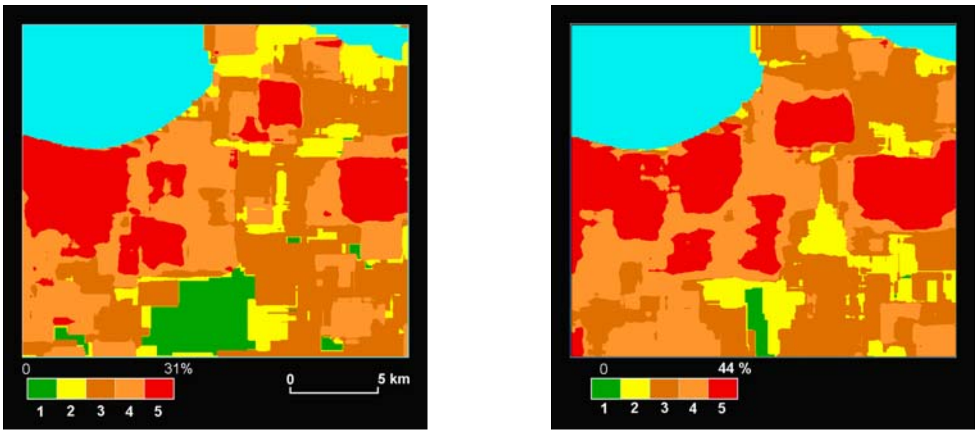
Figure 4. granulometric density images computed from binary images of built-up in figure 3

3.3 Built-up density mapping from macro-textural indicators

In order to obtain a built-up density map, we applied granulometric image processing and produced I gray tone images from binary images of built-up areas extracted on section 2.3. The map is then obtained by a multi-channel classification on density ganulometric images. An unsupervised classification of each pixel is performed by a K-means method (Diday, 1974). Classification of macro-texture at a pixel P is based upon the descriptor vector of granulometric densities at P. The 'macro-textural descriptors' are the input variables for the classification process. The result is a k-colours image. Each class is interpreted according to the mean granulometric density values and it contains pixels having similar macro-textural signatures. When the neighbouring contains only small components, it corresponds to high values for smaller size of sieving. At the opposite, it may correspond to high value for biggest size of sieving, if the neighbouring contains mainly large components. Such an analysis leads to the legend of the map in terms of density. The classes are coloured with a red to green colour scale to show the progressive decreasing in the density of built-up zones. For both dates green colour represents the smaller built-up areas while red colour corresponds to the bigger areas.

4. RESULTS

We have analysed the macro-texture of the two binary images (figure 3 a and b) and mapped the different types of macro-texture. K-means classification was performed for both dates into five classes of built-up density. The result of these maps according to the density is represented in figure 5 (a and b).



a b

Figure 5- Built-up density map computed from binary images in figure 3 for 1985 (a) and 1996 (b)

The five classes show that progressive decreasing density can be summarized as follow:
Class 1: this class corresponds to nearly bare soils.
Class 2 : this corresponds to sectors of transition between areas essentially of bare soil to those with weak density.
Classes 3, 4 and 5: representing areas from intermediate to highest built-up density.

To differentiate the classes which represent the different densities of urban zones in Algiers, it is possible to use the notion of covered area over each of the two classes, the mostly dense and the least dense, for both dates. The area of the least dense class covers only 7.68% of the territory for the year 1996, while in 1985 it covers 11.5%. The occupation of the dense class represents only 13% in 1985 compared to areas occupying

16% in 1996 (see Table 1). The result of these analyses shows that the method of quantification of the density of the urban space using satellite images makes it possible to separate urban zones based on their density.

Class	Very dense	Least or not dense	
Number of structures	17	44	Algiers 1985
Number of pixels	75034	64567	
Percentage	13 %	11.5 %	
Number of structures	11	29	Algiers 1996
Number of pixels	93017	43033	
Percentage	16 %	7.68 %	

Table 1 Comparative result of the highest and lowest dense classes

5. CONCLUSION

The above-described method maps the built-up areas organizations by using the macro-textural descriptors of the classified images. In the produced map, the patterns are characterized by their relative macro-textures. The method has been applied for analysing and mapping the spatial variations of built-up areas using Landsat TM multispectral data. It provides a striking illustration of spatial organisation of urban zones from binary images. The produced maps for two dates leads to the analysis showing the evolution of built-up density during the period under study. The works will be focused in reproducing this method at a regional scale, in order to study built-up growth on the Algerian littoral by satellite image processing.

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