

COMPARISON OF CLASSIFICATION METHODS FOR URBAN IMAGES INTERPRETATION

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Résumé : Parmi les méthodes de reconnaissance des formes utilisables pour l'interprétation des données du satellite LANDSAT en zones urbaines, l'analyse des textures s'avère une des plus intéressantes. Deux essais sont exposés ici. A partir d'une analyse en composantes principales, on pratique tout d'abord une recherche de textures en mesurant les écarts entre la valeur d'un pixel et celles de ses voisins. On ne retient que les écarts inférieurs à un seuil fixé. Le deuxième essai consiste dans une troncature de l'histogramme du paramètre de texture afin de regrouper les classes faiblement représentées. On renforce ainsi les effets de contraste. Les deux méthodes sont appliquées à une étude des structures urbaines de la ville de Lubumbashi (Zaïre). Des conclusions en sont tirées qui montrent tout l'intérêt de la seconde technique pour une analyse plus fine du tissu urbain sur le plan de la morphologie des quartiers mais aussi de l'armature des voies principales de desserte.

Zusammenfassung : Bei den verschiedenen Methoden der Formen aufklärung für die Erläuterungen der Angaben des Satelliten "Landsat" für die bebauten Gebiete, erweist sich die Analyse der verschiedenen Texturen als äusserst interessant.

Vergleichen wir dazu zwei Versuche.

Beim ersten Versuch gehen wir von einer Analyse der prinzipalen Komponenten aus. Man praktiziert zuerst eine Suche der Texture indem man die Abstände zwischen den Werten eines Pixels und die seiner nachbaren misst. Dabei beachtet man nur die Abstände kleiner einer festen Begrenzung.

Beim zweiten Versuch stumpft man das Histogramm des Parameters der Texture ab und gruppiert die weniger vertretenen Klassen. Da durch ersetzt man die Kontrast Effekte.

Beide Methoden werden bei einer urbanistischen Studie der Strukturen der Stadt "Lubumbashi" in Zaïre (ex. Kongo) angewandt.

Die erhaltenen Resultate bevorteilen die zweite Methode und zeigen, dass eine feinere, genauere städtische Analyse ermöglicht for allem für die Formen der Stadtteile und den Aufbau der Hauptverkehrswege.

## INTRODUCTION

One of the pattern recognition techniques widely used in remote sensing is the classification of multispectral scanner (MSS) data on the pixel-by-pixel basis. It will be utilized here and will consist in examining several measured and / or computed characteristics of each pixel of an MSS image and in grouping pixels into a finite number of classes in order to produce some useful map such as a land-use map or thematic map. The problem can briefly be outlined by figure 1.

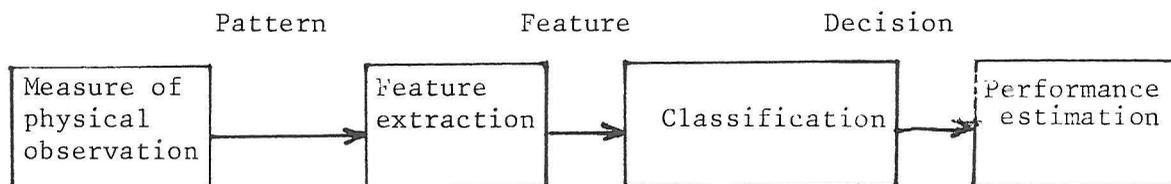


Fig. 1 Pattern recognition problem

The performance of the solution to the problem is depending :

- (i) on the quality of the measure of physical observations which must be able to provide sufficient information for the characterization of different classes
- (ii) on the extraction of information which cannot be directly measured
- (iii) on the classification method used.

In remote sensing, the user cannot directly act on the measure of physical observations. Quite often, his possibility amounts to the choice of a good image to be obtained on a compatible computer tape (CCT). Usually he directly uses the MSS data (i.e. spectral information) recorded on the CCT, chooses one or several available classification methods, and achieves limited success. This is due to the fact that spectral information is usually insufficient to fully characterize the different classes he is interested in. This case specially occurs when the actual size of observed objects (i.e. homogeneous regions) is too small when compared to the area represented by one pixel. In order to obtain better results, the user has two possibilities : post- and pre-classification processing. The post- classification processing implies the use of spatial information by means of spatial filtering [Goldberg et al., 1975] or the use of structural information by means of the technique of syntactic pattern recognition. The pre-classification processing- and this may be the most important - is the feature extraction problem. Several approaches are used and consist in combining spectral information with spatial information. The spatial information which is extracted from MSS data may be information on neighbouring properties (use of spatial filtering [Do Tu et al., 1979]), structural properties, and textural properties.

In this paper, a local textural parameter is proposed. Its value is then combined with spectral information in order to achieve a better classification of the pixels.

## 2. THE LOCAL TEXTURAL PARAMETER

Texture is a very important feature quite useful to human interpreters. Many different approaches to the quantitative characterization of texture have been attempted, for instance the autocorrelation function, grey-tone co-occurrence, edgeness per unit area, Fourier transform, autoregressive model and so on. Readers may refer to the survey article by Haralick [Haralick, 1978]. In most cases, a textural parameter is defined and computed considering pixels located within an  $m \times n$  window where  $m$  and  $n$  are sufficiently large (usually a  $16 \times 16$  or  $32 \times 32$  window). Such textural parameters are used in MSS pointwise classification but lead to limited success [Haralick and Shammugam, 1973; Swain, 1976; Wiersma and Landgrebe, 1976]. The main reason seems to be that these textural parameters are only well defined inside large objects which may entirely contain the  $m \times n$  window. These parameters have no significance for boundary pixels (see fig. 2). Properly speaking, the "global" texture concept may not be convenient for images containing small regions or complex boundaries such as urban images, because the ratio of boundary pixels to interior pixels is large.

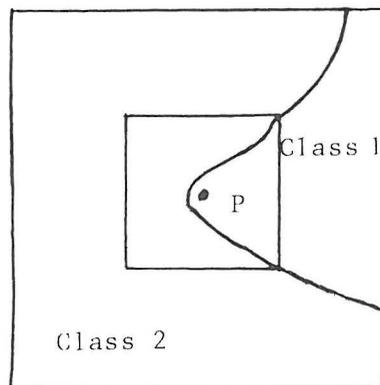


Fig. 2 Window centered on P has more pixels of class 2 than of class 1.

For these cases it is then necessary to define local textural parameters intended to represent characteristics of localized variations of pixel spectral values.

Some local textural parameters are studied in [Ramapriyan et al., 1978; Le Toan et al., 1978; Herzog and Sturm, 1975]. In this paper we propose a local textural parameter which reflects the local heterogeneity of an object at the examined pixel  $P_{ij}$ . By "local" we mean a small window centered on  $P_{ij}$ . We quantify the heterogeneity by the average sum of square differences of spectral values between  $P_{ij}$  and its neighbours assumed to belong to a same object. This assumption is met by means of a local contrast concept currently used by photo-interpreters; actually we measure the spectral distance between  $P_{ij}$  and each of its neighbours; if the distance is greater than a prespecified threshold, the two pixels concerned are assumed not to belong to a same object. Moreover, we attach a greater weight to the nearest neighbours than to the other ones. The proposed local textural parameter  $t_{ij}$  at pixel  $P_{ij}$  is then the following :

$$t_{ij} = \left( \sum_k w_k \| X_{ij} - X_k \|^2 \right) / \sum_k w_k \quad (1)$$

where :  $X_{ij}$  is the spectral value of pixel  $P_{ij}$   
 $X_k$  is the spectral value of pixel  $P_k$  located within a 5 x 5 window centered on  $P_{ij}$   
 $w_k$  is the weight attached to pixel  $P_k$  and defined as :  
 if  $\| X_{ij} - X_k \|^2 > \partial$  ( $\partial$  is a prespecified threshold)  
 then  $w_k = 0$   
 if  $\| X_{ij} - X_k \|^2 \leq \partial$  : if  $P_k$  lies in a 3 x 3 window centered on  $P_{ij}$ , then  $w_k = 1$  ; otherwise  $w_k = 0.5$ .  
 $\sum_k$  the summation is extended to all neighbours of  $P_{ij}$  which are located inside the 5 x 5 pixels window centered on  $P_{ij}$ .

The following rules are also adopted : (i) if all the squared differences are greater than threshold  $\partial$ , the value of  $\partial$  is taken as local textural parameter (upper bound estimation); (ii) if all the squared differences are equal to zero, the value of  $\partial$  is set at  $\partial = 0.25$  which is a very small value (lower bound estimation).

### 3. CLASSIFICATION TECHNIQUE

In the framework of the unsupervised classification of an image, we first define the feature vector  $Y_{ij}$  which characterizes pixel  $P_{ij}$  :

$$Y_{ij} = \begin{bmatrix} x'_{ij,1} \\ x'_{ij,2} \\ t_{ij} \end{bmatrix} \quad (2)$$

where  $X_{ij}$  is the Karhunen-Loeve transformed vector of  $X_{ij}$  (principal component analysis) and  $x'_{ij,1}$  and  $x'_{ij,2}$  are the first two components of  $X'_{ij}$  ; the reason for the use of the first two components is given in [Do Tu et al., 1979]. Moreover we know that :

$$\| X_{ij} - X_k \|^2 = \| X'_{ij} - X'_k \|^2 \approx \sum_{l=1}^2 (x'_{ij,l} - x'_{k,l})^2 \quad (3)$$

for almost all landsat images since the last two components of  $X'_{ij}$  have almost no significant value. Consequently and in order to save computing time, we suggest to use the following modified value  $t_{ij}^*$  obtained by replacing (3) in (1) :

$$t_{ij}^* = \left( \sum_k w_k \left[ \sum_{l=1}^2 (x'_{ij,l} - x'_{k,l})^2 \right] \right) / \sum_k w_k \quad (4)$$

In fact we use  $\ln t_{ij}^{**}$  instead of  $t_{ij}^{**}$  in order to reduce the impact of possible extreme values of  $t_{ij}^{**}$ . Vector  $Y_{ij}$  then becomes vector  $Y_{ij}^{**}$ . Each pixel  $P_{ij}$  being characterized by vector  $Y_{ij}^{**}$ , the unsupervised classification method presented in [Do Tu et al., 1979] is then applied. The resulting clustering is thus depending on two spectral values represented by the first two principal components, and on one local textural parameter expressed by  $\ln t_{ij}^{**}$ .

The influence of the local textural parameter on the classification can be modified : one tentative experiment has been implemented therefore. It consists in increasing the discriminating power of the textural parameter by reducing the interval subject to subdivision in 32 classes. The interval reduction is obtained by truncating the frequency histogram in such a way that each tail of the histogram (containing a small number of pixels) is considered as one class whereas the central part of the histogram (containing almost all the pixels) is subdivided with much more detail.

Finally two classifications are obtained :

- (i) the first one resulting from the combination of two spectral parameters (principal components) with one local textural parameter
- (ii) the second one resulting from the same kind of combination but where the effect of the local textural parameter is reinforced.

#### 4. APPLICATION TO URBAN INTERPRETATION IN THE TROPICAL REALM :

##### THE CASE OF LUBUMBASHI (ZAIRE)

The case study is a scene covering the town of Lubumbashi and a large surrounding area on september 8th 73 at 9.42 hour local time. The coordinates of the image center are  $11^{\circ}31'S$  and  $27^{\circ}47'E$ . The MSS tape is system corrected. Ground-truthes consist in aerial photographs, maps and a certain field experience in this region. Any accurate meteorological data could'nt be obtained for the day of overflight. Two textural procedures were tested on the town site and its neighbourhood, a matrix of 508 x 508 pixels. These procedures have been exposed above. They concern :

- a textural essay with threshold for the texture parameter ;
- the same textural attempt but with troncature of the texture parameter histogram.

Before undertaking these procedures we performed a post- assisted classification on spectral information only :

- of each channel separately ;
- of the four channels using principal components analysis (with 14 clusters).

Then imaging the results on a colour video screen for the questioned sample a comparison was established between the clustering on spectral information only and the textural procedures. The imaging was initiated with the assistance of the interpretor. Each class or group of classes had to correspond with one or several well defined elements of urban land use taxonomy.

Therefore landmarks were choosen which could be identified on each image. They gave a basis for implementing the taxonomical classification with help of aerial photographs and field experience .

### 1° Image of the 14 clusters -

Some classes had to be clumped for they corresponded to similar objects. So we did for the first two classes : dense woods and seasonal swamps ("dembos") which couldn't be distinguished. The same was done for classes 7 and 8 : less dense dwellings on individual plots planted with trees. Among the twelve remaining classes, five concern urban areas.

Among the latter one can point out :

- one class typical for suburban shelters stretched along roads and also central dwellings on individual plots with orchards and gardens ;
- one intermediary class representing less reflecting areas both in suburbs and core; they seem to be typical for agglomerated housing and also for some warehouses and equipments of inner city;
- one class of dense housing valuable for african cities built before the independance of Zaïre : for examples, the cities of Kenya, Ruashi, Gecamines compound and so on;
- one class with more reflecting surfaces summing up open spaces and less agglomerated dwellings in the ancient urban contexture ;
- very high reflecting areas typical for recent neighbourhoods of seized land occupied by slums and uncontrolled self-building. The corresponding high value of the cluster is assessed by the numerous high lighting areas of bare soils and corrugated iron roofs.

### 2° Texture Analysis with threshold at $\partial = 18$ .

The image content is relatively poorer : 9 classes can be set up.

The impoverishment is characterized by the clumping of several classes:

- class four displays several types of damaged "miombo" (deciduous tropical forest) ;
- class seven which represents several built-up densities.

The properly so called urban areas are compacted in three classes :

- the first one groups the suburbs and ancient green inner districts (as the cité Wangermee);
- the second one, most of planned and uncontrolled african cities as well as peripheral dwelling areas of ancient neighbourhoods with more scattered housing and a greater percentage of open treeless areas.
- the third one, a great part of the most reflecting areas of the recent urban expansion.

We observe that this procedure results into a better delineation of urban areas; nevertheless, it provides a very poor discrimination of their content.

### 3° Texture Analysis with threshold and troncature of texture parameter histogram.

The first 22 classes of the texture parameter were clumped into a single one. Moreover 9 among them were not present in the image area. This procedure has a very remarkable effect :

a - Physical landscape structures generally are poorly discriminated with the exception of varieties of shrubs and forest densities : 70 % of the pixels are contained in class 5 (Miombo).

b - On the other hand, analysis of urban structures is refined in respect with the results of principal component analysis. The town now includes 10 classes.

Let us point out, what seems to be of great importance, that the levels of the classes corresponding to well defined elements of the urban structure don't necessarily fill in a continuous sequence. The refinement of the procedure allows to make conspicuous some shades in the disposition of built up areas.

A second observation concerns the spatial distribution of several classes: they form a network corresponding to great lanes sided with continuous housing. On the contrary, some other levels of values are spatially distributed as patches. These represent the heavy reflectance of homogeneous dwelling units.

For example, the ancient colonial city appears on the image as divided into several patches connected by great crossing lanes. The colour hues between the patches on the video screen correspond to contrasts in housing densities.

We conclude that the texture analysis has so reached its purpose : to make more conspicuous connexions between urban units as well as some major elements of their inner structure.

## 5. CONCLUSION

The introduction of a local textural parameter led to a more powerful interpretation of the Landsat image. The strengthening of the influence of that parameter still improved the interpretation. These results invite to go on in that research direction. We intend to analyse the sensibility of the results to variations of the threshold  $\partial$ , of the weights  $w_k$ , and of the importance of the textural parameter in vector  $Y_{ij}^*$ .

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