Fuzzy Classification Techniques in the Urban Area Recognition

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Abstract -- Determination of scattered urban areas in very heterogeneous environment can prove to be quite difficult using conventional classification techniques of remotely sensed images. On the other hand, fuzzy logic methods enable this difficulty to be overcome by assigning one pixel to more than one class according to a membership grade, determined using a pre-defined function.

In this study, urban area have been classified using fuzzy logic methods. The analysis was performed on a Landsat-TM sub-scene (800X600 pixels) acquired over the province of Catanzaro (Calabria, Italy). The intrinsic characteristics of the ground coverage, as well as the rough topography, contribute to make this area a very heterogeneous one.

The image was classified using a Fuzzy Parallelepiped classifier and membership values, associated to each pixel, were calculated. For each pixel, the classes, which contributed the most, were kept for the determination of the final pixel assignment. Global accuracy of fuzzy classification, estimated on mixed test area (chosen during a 2nd ground truth campaign) reached a level of 0.75

Urban areas were identified analysing the images that represent the combinations of "Urban" class with the other classes.

The fuzzy classification results were compared to image classified using the traditional techniques, minimum distance and maximum likelihood. In terms of global accuracy, fuzzy technique appeared to be more accurate than conventional techniques.

INTRODUCTION

One difficult, although interesting, aspect of remotely sensed images classification is the extraction of urban areas when they appear as heterogeneous scattered patches. Being able to clearly describe these areas is however mandatory for adequate land planning and monitoring.

In the present work, the analysis was performed on a Landsat5 TM sub area of 800x600 pixels (432 km2) acquired over the county of Catanzaro (Calabria, Italy). This area is highly representative of scattered urban settlement, characterized by a mixture of modest inland housing, often abandoned or altered, and more recent coastal housing anarchically erected without any foreseen planification.

Topographically speaking, the area is mainly covered by steep hills quite hard to cultivate. The best arable fields are then intensively used by combining up to three different types of culture at the same location. The radiance reaching the sensor is then modulated by the spectral signature of more than one type of ground cover. In such a very heterogeneous area, conventional methods obviously fail to adequately represent this ground cover; the pixel is authoritatively assigned to the class whose spectral characteristics are the closest, without taking into account the possibility of mixed signatures. On the other hand, fuzzy logic classifiers allow to assign each pixel to more than one class in a proportion given by the membership value of this pixel to all the considered classes.

METHODOLOGY

The first step of a fuzzy logic classification is then to describe the membership functions to each desired class. These classes have been selected according to the one present on the official Italian maps produced by the Istituto Nazionale di Statistica (ISTAT). In our study area, the most representated classes are: *cultivated area* (wheat, oats), *orchards* (olives, oranges), *forest* (deciduous, evergreen), *grass covered area* (pasture, fallow), *non vegetated area* (beach, riverside), and *urban area*. Due to the topographical constraints, it has been necessary to split the forest class into two sub-classes: forest on sunny slopes and forest on shady slopes.

Thereafter, 103 training sites were identified in the field and their spectral signatures calculated. The mixed nature of these pixels was strictly reported for further evaluation of the method. Trapezoidal membership functions were chosen with the core of the function being represented by the interval bounded by the minimum and the maximum values determined for each class using the spectral signatures of the training sites. The functions were defined like this:

if $Min_{i,p} < x_j < Max_{i,p}$, then $\mu_i(x_j) = 1$
if $0 \le x_j \le Min_{i,p}$, then $\mu_i(x_j) = f_1(x_j)$ (1)
if $Max_{i,p} \le x_j \le 255$, then $\mu_i(x_j) = f_2(x_j)$

where:
$\mu_i(x_j)$ = membership value of the j*th* pixel to i*th* class
$Min_{i,p}$, $Max_{i,p}$ = minimum/maximum value in the p*th* band for i*th* class

$$f_1(x_j) = \frac{1}{Min_{i,p}} x_j$$

$$f_2(x_j) = \left(\frac{1}{Max_{i,p} - 255}\right)x_j - \left(\frac{255}{Max_{i,p} - 255}\right)$$

In order to belong to a class, a pixel must comply with the membership function of this class in all spectral bands. The final membership value of a pixel to a given class is then obtained by a t-norm, chosen here according to the Zadeh definition and such as:

$$\mu_i(x_j) = \min_{p=1}^{6} \mu_{i,p}(x_j) \quad (2)$$

where:
i = i*th* class, (i = 1, 7)
p = p*th* band, (p = 1, 6)

RESULTS

Membership values of each class being calculated for all pixels, we first ranked them in descending order and extracted the first two values. The two most contributing classes and their respective contribution are now attached to each pixel. In order to visualize this result, two different types of images were produced. The first one representing the mixed classes and the second one representing, for each mixed class, the degree of mixture.

In the first case encoding was performed as follows. The number of classes being less than 10 each pixel is attributed a 2 digit number. The first digit corresponds to the most contributing class M1 and the second to the second most contributing class M2. If M1=0 the pixel is non classified and, if M2=0, the pixel is considered as being *"pure"*.Using this method a number of 11 mixed classes, among a potential of 15, were identified. They effectively correspond to possible occurrence in the field. As this image does not reflect the degree of membership to each class, 11 more images were created representing the mixed classes. The degree of membership has been reduced to 5 levels in order to ease the interpretation. Each pixel has been assigned to a 2 digit number. The first digit corresponds to the membership value of class M1 and the second to the membership value of class M2.

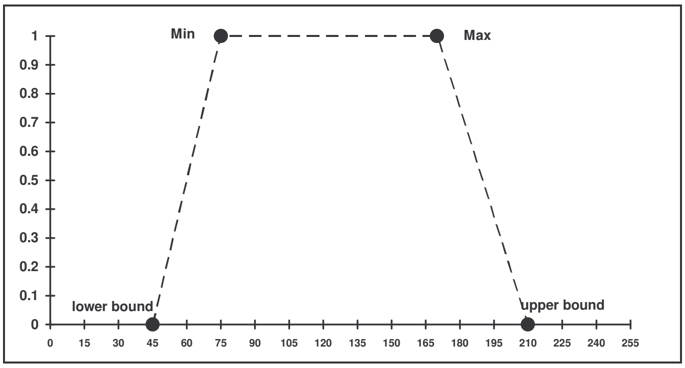

Figure 1: Example of chosen membership function

In order to verify the overall accuracy of the classification the confusion matrix was calculated on a sample of pixels extracted according to the simple sampling method. The global precision index K was equal to 0.75 while it reached 1 for all pure and mixed urban classes.

Finally, the image was also classified using more traditional algorithms such as maximum likelihood and minimum distance. In this case accuracy was evaluated on pure pixels only.

For maximum likelihood, global accuracy was 0.29, going down to 0.17 for the urban class. In the case of the minimum distance, these numbers became 0.23 and 0.30 respectively. Table 1 summarizes the results obtained with the three methods. In the figure 2 there is a subset of the entire image (the urban area of Catanzaro Lido), classified through the maximum likelihood algorithm (figure 2.a) and fuzzy technique. Figure 2.c represents a combination of classes (Non vegetated area + Urban area).

CONCLUSION

Fuzzy logic methods have proven to be more adequate than conventional methods for the classification of mixed areas. Both the overall accuracy and the level of intrinsic information have been substantially increased by using fuzzy logic. It should therefore be preferred in all cases of mixed classes interpretation. In the special case of urban area interpretation where mixture is inherent to the class (a town is not a giant block of concrete) it should allow the wider use of remote sensing images for urban planning and monitoring.

Table 1: Comparison between results

PURE CLASSES	MAX.LIK.	MIN.DIST.	FUZZY P.
Orchards	73191	18920	45
Cultivated area	37526	77439	10606
Forest (shady area)	18878	12005	17325
Forest	108156	150650	45127
Grass covered area	91524	10306	-
Urban area	9364	4680	3001
Non vegetated area	5235	1739	4493
MIXED CLASSES			
Orchards+Cultiv. a.	-	-	5517
Orchards+Forest	-	-	6278
Orchards+Urban a.	-	-	143
Cultiv.area+Forest	-	-	96190
Cultiv.a.+ Grass c.a.	-	-	53331
Cultiv.a.+Urban a.	-	-	4171
Cult.a.+Non veget.a.	-	-	1446
Forest+ F.Shady a.	-	-	17981
Forest+Urban area	-	-	4295
Grass cov.a.+Forest	-	-	82827
N. veg.a.+Urban a.	-	-	597
Total pure pixels	**343874**	**275739**	**80597**
Total mixed pixels	**-**	**-**	**272776**
Non classified	**310206**	**378341**	**300707**
Total	**654080**	**654080**	**654080**
Global accuracy (K index)	**0.29**	**0.23**	**0.75**

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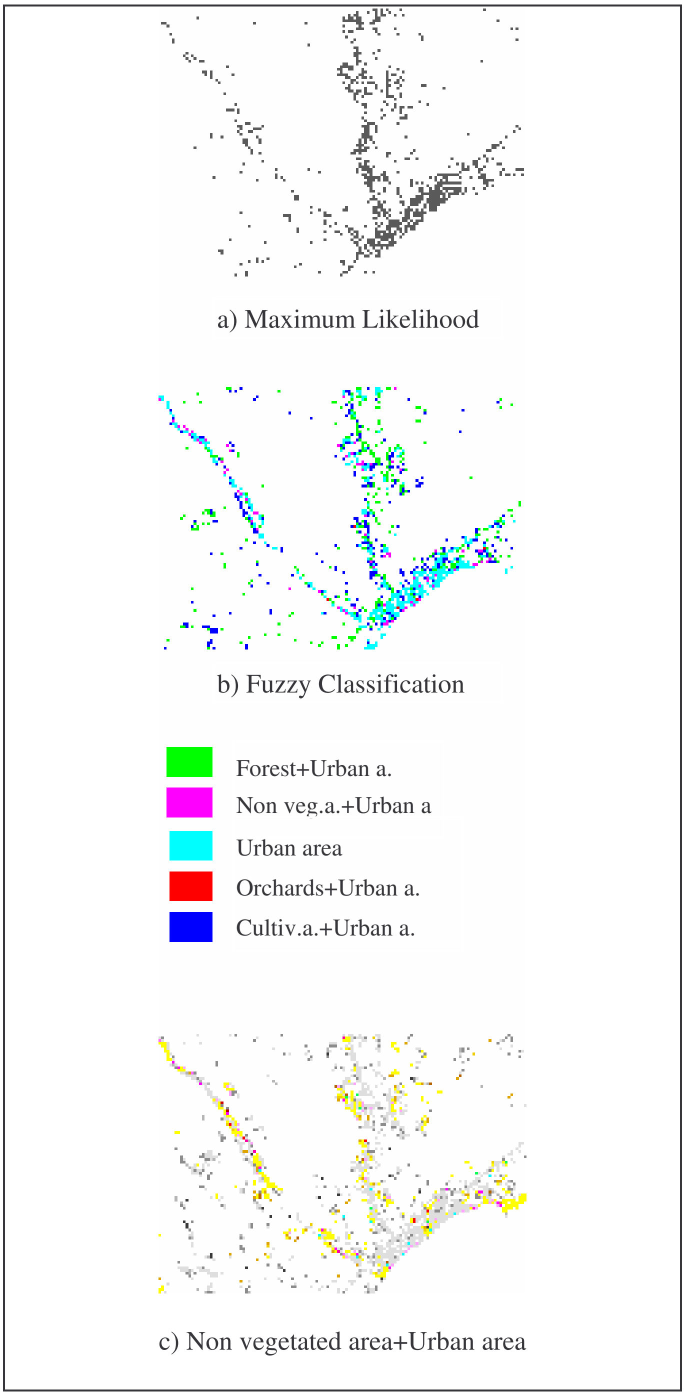

Figure 2: Comparison of results