Comparison between Conventional and Fuzzy Classification Methods for Urban Area and Road Network Characterization

Elena Console (*), Marie-Catherine Mouchot (**)

(*) T.E.A. sas, Via Bruno Chimirri n. 28, 88100 Catanzaro (Italy)
e-mail: console_e@abramo.it
(**) Département I.T.I., ENST de Bretagne
Technopole de Brest-Iroise, BP 832, 29285 Brest Cedex (France)
e-mail: mc.mouchot@enst-bretagne.fr

Abstract:

In this work we have compared the results of different classification techniques applied to a Landsat TM image acquired over an area of Southern Italy. The image has been classified at first using the algorithms of Maximum Likelihood and Minimum Distance, referred to as conventional techniques. A second type of classification was performed based on fuzzy techniques. Membership value of pixels to a given class was computed according to a pre-defined membership function. The Euclidean distance of each pixel to its class of assignment, obtained by conventional classification, has then been computed for comparison with the membership values, obtained by fuzzy techniques. The different results are evaluated according to the ground truth, with special emphasis on urban areas and road networks.

1 Introduction

Although classification techniques have been used for a long time in remote sensing, questions still remain concerning their interpretation in non homogeneous areas. When the ground truth does not statistically represent the occurrence of the different classes, it becomes legitimate to wonder if the

Maximum Likelihood Probability algorithm or other statistical algorithms are really the best possible choice among all the classifiers. It becomes especially obvious in areas of mixed pixels, such as urban areas and road networks, where many grey levels patterns may occur without being represented in the test sample. In this case, when modelling is made difficult by imprecision or by the lack of information about the training data, we can rely on *fuzzy set theory* [6].

About twenty years ago, Zadeh introduced the idea of *fuzzy set*. This concept has since been applied to many fields of Science and Technology and Remote Sensing Image Classification is one of the fields of application of this theory.

As in the case of conventional classification techniques, fuzzy classification allows us to identify and recognize heterogeneous pixels. It is possible to compute a membership value of each pixel to each considered class using a pre-defined function and then to determine mixed classes. The choice of a suitable function is done by analysing the spectral signatures of the considered class.

In this work, the emphasis has been put on the determination of urban area and road networks, which have proved in the past to be very difficult to identify on TM images, due to their mixed nature. A Landsat TM image has been classified with conventional and fuzzy classification techniques. Then the standardized Euclidean distances computed from each class center derived from conventional classifications have been compared with fuzzy membership values in order to determine which technique was most appropriate for identifying these two particular classes.

The considered image has been acquired over an areas of Southern Italy covering 432 km^2 (800x600 pixels, Fig. 1). This area is extremely heterogeneous and presents a highly rough topography. The urban settlements are very scattered through the territory and road networks are blended into the background.



Figure 1: County of Catanzaro - Georeferenced image, TM band 5 Copyright (C) ESA/EURIMAGE 1988 - Courtesy Nuova Telespazio

The steps of the applied methodology have been the following:

- *a) legend definition and spectral signature computation;*
- *b*) conventional classification (minimum distance and maximum likelihood);
- c) computation of standardized Euclidean distances;

d) *fuzzy classification;*

e) comparison of results.

2 Methodology

2.1 Legend definition and spectral signature computation

In order to compute the spectral signatures we have defined 8 classes, selected according to the typology used in the official documentation of ISTAT (Italian National Institute of Statistics). These classes are: *orchards* (olives, oranges), *cultivated area* (wheat, oats), *forest* (deciduous and evergreen; this class has been divided into *forest on sunny slopes* and *forest on shady slopes*) grass covered area (pasture, fallow), *non vegetated area* (beach, riverside), *urban area* and *road network*.

The spectral signatures have been computed on a training sample of 127 pixels. The nature of these pixels has been checked during a field campaign using a GPS.

The minimum, maximum, mean and standard deviation values of the classes in each band have been summarized on the table 1 and successively used for conventional and fuzzy classifications.

CLASS	BAND 1				BAND 2					
	MIN	MAX	MEAN	ST.DEV.	MIN	MAX	MEAN	ST.DEV.		
Orchards	72	120	87.47	11.1871	34	56	41.42	5.9471		
Cultiv. a.	73	123	89.27	13.4245	32	67	44.36	9.2981		
Shady F.	59	67	62.68	2.3930	23	29	25.56	1.6852		
Forest	62	112	79.00	13.8420	27	59	36.94	9.0882		
Gr. cov. a.	79	110	88.88	9.5490	35	58	43.94	6.8359		
Urban a.	94	135	109.05	9.4999	45	68	51.81	5.5283		
Non veg. a.	113	159	139.54	12.4026	61	84	73.92	6.0066		
Road net.	79	103	93.33	8.1946	36	54	44.58	5.5671		

Table 1: Spectral signatures

CLASS	BAND 3				BAND 4					
	MIN	MAX	MEAN	ST.DEV.	MIN	MAX	MEAN	ST.DEV.		
Orchards	29	71	46.68	9.3693	64	93	78.47	7.3513		
Cultiv. a.	30	100	52.18	18.2747	65	115	93.27	16.4018		
Shady F.	18	27	20.48	2.8449	44	159	90.2	35.3695		
Forest	21	66	37.44	13.716	62	132	91.38	22.4407		
Gr. cov. a.	34	78	51.5	13.7113	77	107	90.56	9.8045		
Urban a.	50	79	60.38	7.3721	41	74	62.33	7.8124		
Non veg. a.	74	102	87.96	7.5382	62	86	79.54	4.8183		
Road net.	35	68	50.17	10.0257	58	94	76.17	11.1993		

CLASS	BAND 5				BAND 7					
	MIN	MAX	MEAN	ST.DEV.	MIN MAX		MEAN	ST.DEV.		
Orchards	70	120	99.84	13.8414	27	65	50.05	9.5422		
Cultiv. a.	69	162	100.18	23.3659	23	71	45.18	11.8728		
Shady F.	36	81	55.32	13.2121	12	23	17.68	3.3382		
Forest	61	109	83.75	15.4984	18	59	34.63	13.6425		
Gr. cov. a.	73	164	106.06	21.7178	29	69	45.88	11.4535		
Urban a.	60	117	95.24	15.5721	39	75	58.9	11.1844		
Non veg. a.	100	153	127.42	15.0879	57	95	76.54	9.2735		
Road net.	67	115	89.42	16.2786	32	72	47.83	13.5970		

2.2 Conventional classifications

The image was classified using the Maximum Likelihood (M.L.) and Minimum Distance (M.D.) algorithms. The overall accuracy of results was verified calculating the error matrix on a second sample of 127 test pixels (Tab. 2.A and 2.B.)

CLASSES	ID	1	2	3	4	5	6	7	8	Total	ErrorC (*)
Non classified	0	5	1	0	2	2	0	11	0	21	1
Orchards	1	7	0	0	1	4	0	2	2	16	0.5625
Cultivated area	2	3	1	0	0	0	0	0	1	5	0.8
Shady forest	3	1	0	19	3	0	0	0	1	24	0.2083
Forest	4	3	1	2	8	4	0	2	0	20	0.6
Grass covered area	5	5	5	0	1	2	0	1	3	17	0.8824
Urban area	6	0	1	0	1	0	1	1	0	4	0.75
Non vegetated area	7	0	0	0	0	0	1	5	0	6	0.1667
Road network	8	1	2	0	1	2	2	0	6	14	0.5714
Total		25	11	21	17	14	4	22	13	127	
ErrorO (*)		0.72	0.91	0.09	0.53	0.85	0.75	0.77	0.54		0.6142

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(*) Error O/C: errors of Omission/Commission (expressed as proportions)

Table 2.B:	Error matrix	computed of	on Minimum	distance	classification
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CLASSES	ID	1	2	3	4	5	6	7	8	Total	ErrorC (*)
Non classified	0	6	3	2	13	6	1	15	3	49	1
Orchards	1	3	0	0	0	1	0	0	0	4	0.25
Cultivated area	2	6	4	0	0	0	0	1	3	14	0.7143
Shady forest	3	0	0	19	0	0	0	0	0	19	0
Forest	4	8	3	0	4	4	0	1	2	22	0.8182
Grass covered area	5	1	0	0	0	0	0	0	0	1	1
Urban area	6	0	0	0	0	0	1	2	0	3	0.6667
Non vegetated area	7	0	0	0	0	0	1	2	0	3	0.3333
Road network	8	1	1	0	0	3	1	1	5	12	0.5833
Total		25	11	21	17	14	4	22	13	127	
ErrorO (*)											0.7008

(*) Error O/C: errors of Omission/Commission (expressed as proportions)

Moreover the following coefficients of agreement have been computed in order to synthesize with some indices the accuracy of classifications [1, 5]:

a) *global K*, in order to test the overall accuracy:

$$K_{g} = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}{N^{2} - \sum_{i=1}^{r} (x_{i+} \cdot x_{+i})}$$
(1)

where:

N = total number of test pixels

- r = number of lines in the error matrix
- x_{ii} = number of pixels on the main diagonal of the matrix

 x_{i+} , x_{+i} = total of lines and columns

b) *conditional K*, in order to test the individual accuracy of each considered class:

$$K_{c} = \frac{Nx_{ii} - (x_{i+} \cdot x_{+i})}{Nx_{i+} - (x_{i+} \cdot x_{+i})}$$
(2)

The global K was equal to 0.31 for Maximum likelihood and to 0.24 for Minimum distance. The conditional K values have been reported on table 3.

CLASSES	Conditional Kappa	Conditional Kappa		
	Max. Likelihood	Min. Distance		
Non classified	0	0		
Orchards	0.2996	0.6887		
Cultivated area	0.1241	0.218		
Shady forest	0.7504	1		
Forest	0.3073	0.0554		
Grass covered area	0.0083	-0.1239		
Urban area	0.2256	0.3117		
Non vegetated area	0.7984	0.5968		
Road network	0.3634	0.3501		

Table 3: Conditional K values for each class

2.3 Computation of standardized Euclidean distances

The Euclidean distance of a pixel to its class of assignment has been calculated as:

$$d_{e} = \sqrt{\sum_{p=1}^{6} \left(x_{i,p} - \bar{x}_{c,p} \right)^{2}}$$
(3)

where:

i = i-th considered pixel

$$p = p-th$$
 band, $(p = 1, 6)$

$$c = c-th$$
 class ($c = 1, 8$)

 $\bar{x}_{c,p}$ = mean of c-*th* class in p-*th* band

These distances have then been normalized using the standard deviation of each class:

$$\mathbf{d}_{\mathrm{es}} = \sqrt{\sum_{p=1}^{6} \left(\frac{x_{i,p} - \bar{x}_{c,p}}{\sigma_{c,p}} \right)^2} \tag{4}$$

where:

 $\overline{\sigma}_{c,p}$ = standard deviation of c-*th* class in p-*th* band

The standardized Euclidean distance computation has allowed us to verify the accuracy of the results obtained with conventional algorithms. The distance to the class center can be considered as an index showing how close a pixel is to a nominal class definition. Expressed in this form, it was thereafter easier to compare results of conventional classification and fuzzy techniques performed in the following section.

2.4 Fuzzy classification

Regarding fuzzy techniques, the pixels membership values to each class have been computed using trapezoidal membership functions, chosen after analysis of the spectral signatures, as follows:

$$\begin{array}{ll} \text{if } Min_{c,p} < x_i < Max_{c,p}, & \text{then } \mu_c(x_i) = 1 \\ \\ \text{if } 0 \leq x_i \leq Min_{c,p}, & \text{then } \mu_c(x_i) = f_1(x_i) \\ \\ \text{if } Max_{c,p} \leq x_i \leq 255, & \text{then } \mu_c(x_i) = f_2(x_i) \end{array}$$

$$\begin{array}{ll} \text{(5)} \end{array}$$

where:

 $\mu_c(x_i)$ = membership value of the *i*-*th* pixel to *c*-*th* class

 $Min_{c,p}$, $Max_{c,p}$ = minimum/maximum value in the p-th band for c-th class

$$f_{1}(x_{i}) = \frac{1}{Min_{c,p}} x_{i}$$

$$f_{2}(x_{i}) = (\frac{1}{Max_{c,p} - 255}) x_{i} - (\frac{255}{Max_{c,p} - 255})$$

The final membership value of a pixel to a given class has been defined according to the Zadeh definition (Fig. 2):

$$\begin{aligned} & 6 \\ \mu_c(\mathbf{x}_i) = \operatorname{Min} \, \mu_{c,p} \, (\mathbf{x}_i) \\ & p = 1 \end{aligned} \tag{6}$$

where:

c = c-th class, (c = 1, 8)

p = p-th band, (p = 1, 6)

considered pixel



Figure 2: Final membership value computation: an example

In order to compute the error matrix assessing the fuzzy classification results, it has been necessary to define the mixed classes. Surveying the county, it was noticed that mixed classes are generally a combination of two typologies of ground coverage.

Thereafter, in order to represent mixed coverage, the first two highest membership values to all classes were computed for each pixel. These values were codified as shown in Table 4. Two images were obtained: *IMAX*, representing the first coded maximum membership value to a class, and

2MAX, representing the second coded maximum membership value to another class. The codified images were added and the resulting image represents the mixed classes.

Classes	Codes of 1 st maximum membership value (1MAX)	Codes of 2 nd maximum membership value (2MAX)
Orchards	10	1
Cultivated area	20	2
Shady forest	30	3
Forest	40	4
Grass covered area	50	5
Urban area	60	6
Non vegetated area	70	7
Road network	80	8
Non classified	90	9

Table 4: Codes of 1st and 2nd maximum membership values

The following sixteen types of mixed classes have been identified by combination of the two highest membership values:

orchards +	cultivated area			
	forest			
	urban area			
cultivated area +	forest			
	grass covered area			
	urban area			
	non vegetated			
	road network			
forest +	shady forest			
	road network			
grass covered area +	forest			
urban area +	forest			
	non vegetated			
	road network			
road network +	orchards			
	grass covered area			

Table 5: Mixed classes

The pure pixels, i.e. belonging to one class only, were represented by pixels which second maximum value is equal to 0 and first maximum is greater than 0. If the first maximum value is equal to 0, then the considered pixel is non classified.

The global K computed on a test sample of mixed and pure pixels was equal to 0.60. We can immediately notice that this value is significantly higher than the one obtained using conventional classifiers. The conditional K was equal to 1 for "Urban area" class and to 0 for "Road network" class.

2.5 Comparison of results

The analysis of the obtained results (Tab. 6) clearly establish that fuzzy techniques perform better than conventional ones for urban area recognition. One can see that the number of pixels belonging to this class (in the sense of fuzzy membership) is by far superior to the number of pixels which normalized distance tends towards zero.

Unfortunately, the technique did not lead to the expected results for road network extraction. The number of pixels assigned to this class by fuzzy technique tends to exceed the real number of pixels, while the results obtained with conventional techniques seem closer to reality.

Table 6: Comparison between standardized Euclidean distances and fuzzy membership val	lues
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STANDA	RDIZED EU	CLIDEA	N DISTA	NCES		FUZZY MEMBERSHIP VALUES				
		Maximum		Minimum						
	likel	ihood	dist	ance						
	des	Road	Urban	Road	Urban		$\mu(\mathbf{x})$	Road N.	Urban a.	
		N.	А.	N.	A.					
min.dist. from	0.01-25	11158	10	14444		full member-	100	52781	10966	
class center						ship				
	26-50	4577	5387		3082	_	99-76	5872	1224	
	51-75	339	2423		1409		75-51	6010	3983	
	76-99		285				50-26	12624	3309	
max.dist. from	100 - > 100		6				25-0.01	6978	3972	
class center										
no membership		638006	645966	639636	649589	no membership		578384	636691	

3 Conclusion

The overall result shows that the tested fuzzy algorithm is more adequate than conventional classifiers to describe the heterogeneity of a given target in general and for extracting urban areas in particular. On the other hand, for road networks, fuzzy techniques do not seem to be an improvement on conventional ones.

In the future, a study will be carried out to eliminate spectral bands inducing a bias in fuzzy classification, in order to improve the extraction of urban areas and road networks. In addition, contextual analysis will be taken into account to reduce the impact of mixed pixels.

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