A HYBRID CLASSIFICATION METHOD BASED ON FUZZY LOGIC AND CONVENTIONAL TECHNIQUES

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The aim of this work is to improve classification results by mixing conventional and fuzzy techniques. The analysis, performed on Landsat-5 image (800x660 pixels), is divided into three parts:
* Step A: Conventional classifications;
* Step B: Fuzzy classification;
* Step C:Hybrid classification.

The comparison of results obtained with the differents techniques shows that:
1) fuzzy classification is more accurate than conventional classifications for describing the heterogeneity of geographical phenomena;
2) the accuracy of conventional classifications is improve by the use of training set selected among pure pixels.

1. Introduction

Conventional classification methods used in remote sensing data processing do not usually take into account the indetermination characterizing geographical phenomena. Using these methods, each pixel is assigned to a unique class, representing the best possible choice according to the spectral characteristics of the pixel. The natural heterogeneity of the pixel is, therefore, not preserved. On the contrary, fuzzy logic methods allow the assignment of each pixel to more than one class, according to its membership values in each class.

The objective of this work is to improve classification results by mixing both types of methods in a common classification scheme.

The analysis is performed on a Landsat 5 TM image of 800X600 pixels (24X18 km) acquired over Catanzaro in Italy. A training set of 103 pixels is used to extract the spectral characteristics of each class. The image was first classified using Minimum Distance (MD)and Maximum Likelihood (ML).

The analysis required three separate processing steps .

Step A: Conventional classifications

A1:Location of the pixels used in the first training set (103 pixels) and determination of the associated signature files.
A2: Classification of the image using ML and MD algorithms.
A3:Random extraction of 114 pixels used as a test set followed by their field location and characterization.
A4:Calculation of confusion matrices and determination of the global accuracy of both classification methods.

Step B: Fuzzy classification

B1:Determination of membership functions according to the analysis of the spectral signatures of the first training set.
B2:Classification by the fuzzy parallelogram method (FP).
B3:Assessment of the classification accuracy using a new test set of 38 mixed pixels. Comparison with ML and MD.

Step C:Hybrid classification

C1: Determination of pixels belonging to the core of one class only (i.e. having membership values of 1). They then form a new training set of 1790 pure pixels.
C2:Comparison between spectral signatures of training set 1 and training set 2 followed by ML and MD classification using the second training set.

2.Analysis

2.1 Conventional Classifications

The different classes used in the first training set were first determined according to the typology used in the official documentation provided by the Istituto Nazionale di Statistica (ISTAT)[1]. A first legend (table 1) has been defined and used for the elaboration of the training set. The TM image was geometrically corrected in order to be properly overlaid with the corresponding IGMI[2] maps at a scale of 1:50000.

Table 1: Legend

Cultivated area
Orchards (olives, oranges…)
Forest: -deciduous -evergreen -mixed deciduous/evergreen -macchia mediterranea
Grass covered area (fields, fallow,…)
Non vegetated area (beach, riverside,…)
Urban area

The first sample of training pixels (103 pixels) was positioned during a field campaign[3] and spectral signatures calculated for each considered class. The TM image was then classified using ML and MD algorithms. According to the first results, it was decided to merge all the forested classes into two classes: Forest (deciduous/evergreen) and Forest (shady area). This modification was made necessary by the topographic configuration of the area: very steep hills bounded by narrow flats carved by the *fiumare* (torrents often dry and having irregular and rapid flow).

In order to calculate the error matrices and to then establish the accuracy of the two classifications, a second set of sample pixels (114 pixels) have been identified in the field and used as a test set. Table 2 summarizes these results. Both methods performed obviously not very well, in term of global accuracy, and tended to under-estimate the urban area while over-estimating the orchard area. This error is partially due to the large number of mixed pixels induced by the agricultural practices combining two, or more, types of cultures: by example, wheat between olive trees rows.

Table 2: Accuracy of Conventional Classifications

Algorithm	**1st training set (103 pixels)**	**1st test set (114 pixels)**
Minimum Distance	0,35	0,23
Maximum Likelihood	0,81	0,29

It was then decided to improve the accuracy of the classification by using methods taking into account the mixed nature of the pixels.

2.2 Fuzzy Classification

The first requirement of a fuzzy classification consists, for each class, in the choice of appropriate membership functions.These functions were defined by the analysis of the spectral signatures calculated for the first training set. The retained algorithm, called fuzzy parallelogram, considers that a pixel belongs to a class if it carries the property of this class for all spectral bands. The membership value of a pixel to a given class is then given by a t-norm. The Zadeh t-norm was chosen for this experiment; it is defined as (Zadeh 1973):

$$\mu_A(x) = \operatorname*{Min}_{\lambda=1}^{n} \mu_{A,\lambda}(x)$$

[1] Ref.: 4° Censimento dell'Agricoltura 1990/1991, Caratteristiche strutturali delle aziende agricole, fascicoli provinciali, ISTAT.
[2] IGMI: Istituto Geografico Militare Italiano
[3] A Magellan Meridien GPS was used for pixels positioning through the whole experiment.

with for each λ :

$$\mu_{A,\lambda}(x)=1 \quad if \quad \min_\lambda \le x \le \max_\lambda$$

$$\mu_{A,\lambda}(x)=\frac{x}{\min_\lambda} \quad \text{if} \quad x \le \min_\lambda$$

$$\mu_{A,\lambda}(x)=\frac{255-x}{255-\max_\lambda} \quad \text{if} \quad x \ge \max_\lambda$$

The values $\min_\lambda$ and $\max_\lambda$ were chosen according to the spectral signatures in each spectral band.

Results of the fuzzy classification were represented by 3 images. The first one shows the hard classification performed using the fuzzy classification calculated just before. It has been produced by assigning each pixel to the class having the highest membership value.

$$x \in class\ A \quad \Leftrightarrow \mu_A(x) = \underset{i=1}{\overset{p}{Max}} \quad \mu_i(x)$$

This method assigns each pixel to a class, even if their membership value to this class is very low. In order to avoid this problem, a threshold value, under which the pixel is considered as non-classified, was defined.

The second image represents the cores of each class, i.e. the pixels having membership values of one. These pixels are considered as pure pixels.

The third image represents, for each pixel, the combination of the two classes having the highest membership. Eleven types of mixed pixels were then identified (Table 3). In order to verify the accuracy of this classification, a third sample of 38 mixed pixels were identified in the field. This time, the global accuracy of the classification reached 0,75 exceeding, by far, the previous results obtained with conventional classifiers.

Table 3: Mixed test area

Mixed classes	
forest +	shady forest grass covered area
cultivated area +	forest urban area non vegetated area grass covered area
urban area +	forest non vegetated area
orchards +	cultivated area forest urban area

2.3 Hybrid methodology

Although fuzzy classifications have proven to be an adequate tool for the classification of heterogeneous area, it sometimes remains necessary to generalize the obtained results under the form of hard classification. In our case, in order to improve classification, it was decided to modify the original training set by using the pure pixels found during the fuzzy classification process. This new set formed of 1790 pixels (Training set n°2) was used for ML and MD classifications. Table 4 shows the difference between the first and the second training sets.

Table 4: Signature Comparison

Signatures 1° training set

Nonveg	1° training set			
ID 1	MIN	MAX	MEAN	ST.DEV.
Band 1	113	159	139.54	12.4026
Band 2	61	84	73.92	6.0066
Band 3	74	102	87.96	7.5382
Band 4	62	86	79.54	4.8183
Band 5	100	153	127.42	15.0879
Band 7	57	95	76.54	9.2735

Urban a.	1° training set			
ID 2	MIN	MAX	MEAN	ST.DEV.
Band 1	94	135	109.05	9.4999
Band 2	45	68	51.81	5.5283
Band 3	74	102	87.96	7.5382
Band 4	62	86	79.54	4.8183
Band 5	60	117	95.24	15.5721
Band 7	39	75	58.9	11.1844

Orchards	1° training set			
ID 3	MIN	MAX	MEAN	ST.DEV.
Band 1	72	120	87.47	11.1871
Band 2	34	56	41.42	5.9471
Band 3	29	71	46.68	9.3693
Band 4	64	93	78.47	7.3513
Band 5	70	120	99.84	13.8414
Band 7	27	65	50.05	9.5422

F. Shady	1° training set			
ID 8	MIN	MAX	MEAN	ST.DEV.
Band 1	59	67	62.68	2.393
Band 2	23	29	25.56	1.6852
Band 3	18	27	20.48	2.8449
Band 4	44	159	90.2	35.3695
Band 5	36	81	55.32	13.2121
Band 7	12	23	17.68	3.3382

Cultiv. a	1° training set			
ID 6	MIN	MAX	MEAN	ST.DEV.
Band 1	73	123	89.27	13.4245
Band 2	32	67	44.36	9.2981
Band 3	30	100	52.18	18.2747
Band 4	65	115	93.27	16.4018
Band 5	69	162	100.18	23.3659
Band 7	23	71	45.18	11.8728

Signatures 2° training set
(Pure pixels selected on fuzzy classification)

Nonveg	2° training set			
ID 7	MIN	MAX	MEAN	ST.DEV.
Band 1	116	165	144.42	9.1480
Band 2	60	85	74.92	4.9234
Band 3	71	102	88.42	6.0713
Band 4	62	87	77.90	4.0734
Band 5	99	153	128.85	10.5415
Band 7	59	94	76.38	7.3013

Urban a.	2° training set			
ID 6	MIN	MAX	MEAN	ST.DEV.
Band 1	95	137	109.88	9.6762
Band 2	44	68	52.16	5.3583
Band 3	49	80	61.02	6.4604
Band 4	44	74	57.00	5.0062
Band 5	63	115	91.04	11.0969
Band 7	40	75	57.02	8.2953

Orchards	2° training set			
ID 1	MIN	MAX	MEAN	ST.DEV.
Band 1	70	99	80.21	8.684
Band 2	33	45	37.5	3.568
Band 3	33	54	43.71	6.2318
Band 4	63	79	66.29	6.5331
Band 5	99	120	113.07	6.8215
Band 7	51	66	59.5	4.9575

F. Shady	2° training set			
ID 3	MIN	MAX	MEAN	ST.DEV.
Band 1	55	71	64.08	2.9256
Band 2	21	31	25.86	1.5987
Band 3	17	28	21.11	2.7053
Band 4	43	159	82.55	16.7684
Band 5	35	81	50.86	8.1387
Band 7	11	24	16.31	2.4532

Cultiv. a	2° training set			
ID 2	MIN	MAX	MEAN	ST.DEV.
Band 1	88	122	109.54	6.0940
Band 2	46	67	59.33	4.6332
Band 3	53	97	77.91	8.8252
Band 4	67	116	104.06	11.3171
Band 5	110	165	146.58	12.4127
Band 7	45	73	65.62	5.2493

Table 4: Signature Comparison

Signatures 1° training set

Grass a.	1° training set			
ID 5	**MIN**	**MAX**	**MEAN**	**ST.DEV.**
Band 1	79	110	88.88	9.549
Band 2	35	58	43.94	6.8359
Band 3	34	78	51.5	13.7113
Band 4	77	107	90.56	9.8045
Band 5	73	164	106.06	21.7178
Band 7	29	69	45.88	11.4535

Signatures 2° training set
(pure pixels selected on fuzzy classification)

Grass a.	2° training set			
ID 5	**MIN**	**MAX**	**MEAN**	**ST.DEV.**
Band 1	84	110	95.95	8.3035
Band 2	37	58	47.29	5.2117
Band 3	42	78	56.20	10.3446
Band 4	78	107	90.95	9.2789
Band 5	100	164	115.56	18.5163
Band 7	45	69	54.05	6.2927

Forest	1° training set			
ID 7	**MIN**	**MAX**	**MEAN**	**ST.DEV.**
Band 1	62	112	79	13.842
Band 2	27	59	36.94	9.0882
Band 3	21	66	37.44	13.716
Band 4	62	132	91.38	22.4407
Band 5	61	109	83.75	15.4984
Band 7	18	59	34.63	13.6425

Forest	2° training set			
ID 4	**MIN**	**MAX**	**MEAN**	**ST.DEV.**
Band 1	64	88	72.1	5.6719
Band 2	27	46	33.95	4.7714
Band 3	21	47	30.71	5.2923
Band 4	61	133	106.38	20.4864
Band 5	61	109	78.05	9.2011
Band 7	19	50	28.28	5.2767

Classes are now described, not from a small number of pixels anymore, but from a larger number of pixels, randomly distributed over the entire image. It enables a better statistical distribution of the training set, free of sampling biases. This training set was subsequently used for classifying the image by ML and MD. Table 5 gives the global accuracy of each method.

Table 5: Accuracy of Conventional Classifications after increase of the training set

Algorithm	1° test set (114 pixels)	2° test set (104 pure pixels)
Minimum distance	0,34	0,86
Maximum likelihood	0,29	0,88

The methodology has not sensibly increased the accuracy of the classification of mixed pixels but it has allowed to drastically improve this classification on pure pixels.

3. Conclusion

This hybrid method has shown that, when the training set used, especially in situation of strong heterogeneity, is too small, it becomes possible to increase it by using fuzzy logic rules and, therefore, enhance the quality of the final classification. In very heterogeneous areas, fuzzy logic enables mixed pixels to be represented and thus to better interpret and classify the different soil coverage.

4. References

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leading to the result shown in Figure 6