IMAGE CLASSIFICATION BASED ON FUZZY LOGIC

I. Nedeljkovic

MapSoft Ltd, Zahumska 26 11000 Belgrade, Serbia and Montenegro igor.n@sezampro.yu

Commission VI, WG VI/1-3

KEY WORDS: fuzzy logic, classification, if-then rules, digital, imagery, remote sensing, land cover

ABSTRACT:

Fuzzy logic is relatively young theory. Major advantage of this theory is that it allows the natural description, in linguistic terms, of problems that should be solved rather than in terms of relationships between precise numerical values. This advantage, dealing with the *complicated* systems in *simple* way, is the main reason why fuzzy logic theory is widely applied in technique. It is also possible to classify the remotely sensed image (as well as any other digital imagery), in such a way that certain land cover classes are clearly represented in the resulting image. *If that's so, can we use fuzzy logic technique to diminish the influence of person dealing with supervised classification? Can we eliminate the prejudice?* These questions were the light motive for this paper. In this paper, *a priori* knowledge about spectral information for certain land cover classes is used in order to classify SPOT image in fuzzy logic manner. The later was done with ©Matlab's Fuzzy Logic Toolbox. Some information, needed for membership function definition, was taken from supervised maximum likelihood classification. Also, the idea for result comparison came from ©PCI's ImageWorks used for supervised procedure. Results of two procedures, both based on pixel-by-pixel technique, were compared and certain encouraging conclusion remarks come out.

1. INTRODUCTION

1.1 About fuzzy logic

Over the past few decades, *fuzzy logic* has been used in a wide range of problem domains. Although the fuzzy logic is relatively young theory, the areas of applications are very wide: process control, management and decision making, operations research, economies and, fot this paper the most important, pattern recognition and classification. Dealing with simple 'black' and 'white' answers is no longer satisfactory enough; a degree of membership (suggested by Prof. Zadeh in 1965) became a new way of solving the problems. A fuzzy set is a set whose elements have degrees of membership. A element of a fuzzv set can be full member (100% membership) or a partial member (between 0% and 100% membership). That is, the membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in-between. Mathematical function which defines the degree of an element's membership in a fuzzy set is called *membership function*. The natural description of problems, in *linguistic* terms, rather than in terms of relationships between precise numerical values is the major advantage of this theory.

An idea to solve the problem of image classification in fuzzy logic manner as well as comparison of the results of supervised and fuzzy classification was the main motivation of this work. Behind this idea was also the question if the possible promising results can give the answer to the question of diminishing the influence of person dealing with supervised classification.

1.2 Algorithm

In this paper, *a priori* knowledge about spectral information for certain land cover classes is used in order to classify SPOT image in fuzzy logic manner. More specifically,

- ➔ input (image channels) and output variables (land classes) are introduced in Matlab's environment,
- membership functions are defined using results from supervised classification,
- Matlab's Fuzzy Logic Toolbox was used in definition of fuzzy logic inference rules,
- these rules are tested and verified through the simulation of classification procedure at random sample areas and at the end,
- SPOT image classification was conducted.

2. SUPERVISED CLASSIFICATION

2.1 Input data

The procedure of supervised image classification was conducted with PCI ImageWorks software. As the source for classification procedure, SPOT Image recorded in "XS" multispectral mode was used. This image contains three channels recorded in following bands:

- \rightarrow band **B1** covering 0.50 to 0.59 µm (green),
- \rightarrow band **B2** covering 0.61 to 0.68 µm (red) and
- \rightarrow band B3 covering 0.79 to 0.89 µm (near infrared).

In order to use them further in different software (PCI ImageWorks, Matlab), SPOT image channels (named 701, 702, 703) are first *converted* from original SPOT format into *tif*, and then *exported* from *tif* into *pix* format in Geomatica Focus module (Figure 1.). The images were taken over the city of Cologne. The size of images is 3593x2990 pixels.

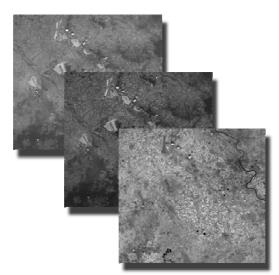


Figure 1. SPOT image converted into three separated images

2.2 Definition and verification of the training areas

As it was later used for fuzzy logic classification, the process of supervised image classification will be given in brief. Selected land cover classes are: deciduous trees, coniferous trees, urban area, water, crop1 and crop2. For these classes, training areas were pointed on the image (Figure 2.)

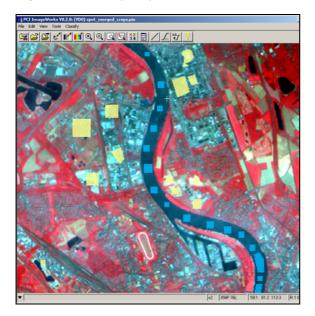


Figure 2. Training areas shown in display window

Since the *signature separability* showed that deciduous trees and coniferous trees are very poorly separated (low values of *Transformed Divergence* and *Bhattacharrya Distance;* big overlap between the signatures of two classes) and considering that this separability cannot be improved by a different channel combination, those classes were merged into the one single class: vegetation. Accepted combination of three images (with the biggest signature separability between the classes), in terms of RGB channels, was 702(red) \bullet 703(green) \bullet 701(blue).

The *signature statistics* gave a list of each of the classes, with the mean values and standard deviations for each channel for the class selected. These data were used later in the definition of the membership function. Also, the listing contained the class correlation matrix, the covariance, inverse covariance and triangular inverse covariance matrices for the signature.

In determination whether the training areas that have been selected are well represented, histogram was used: if the histogram has a single peak, then the training area is distinct and there is no confusion between it and another training area. A histogram with a bimodal distribution would indicate that there is an ambiguity between the current and some other class.

2.3 Classification procedure

In the classification process, the *maximum likelihood classifier* without NULL class was used. It assumes a normal (Gaussian) distribution and evaluates the variance and correlation of spectral response during the classification of the unknown pixel. In cases of overlapping areas, this method uses 'apriori' probabilities or a weighting factor to delineate.

The NULL class option determines whether every pixel should be classified. If this option is selected, then a pixel is assigned to a class only if it is within the Gaussian threshold specified for the class. If it is not within any threshold, it is assigned to the NULL (0) class.

Report about the results of the image classification contains: number of classified pixels, average and overall accuracy, statistics for the each of the classes and confusion matrix. This matrix gives the information how much of original training areas pixels was actually classified as being in the class that the training areas was meant to represent. If many of training areas pixels were classified into different classes, it is likely that the training areas were not so well determined.

2.4 Result evaluation

One way of the result evaluation was through the *accuracy assessment*. The classification results are compared to the raw image data and the report is created. This process is done during the *random sample selection*. The idea of the accuracy assessment is: point is highlighted in the sample list and observation was done where it is located on the image. This position should be compared to the class list and select the class that one believes it should belong. This idea was taken and applied in the fuzzy logic classification verification.

3. FUZZY LOGIC CLASSIFICATION

3.1 Matlab's Fuzzy Logic Toolbox

In the lack of precise mathematical model which will describe behaviour of the system, Fuzzy Logic Toolbox is a good "weapon" to solve the problem: it allows using *logic if-then rules* to describe the system's behaviour.

This Toolbox is a compilation of functions built on the MATLAB® numeric computing environment and provides tools for creating and editing *fuzzy inference systems* within the framework of MATLAB.

The toolbox provides three categories of tools:

- ➔ command line functions,
- ➔ graphical interactive tools and
- → simulink blocks and examples.

The Fuzzy Logic Toolbox provides a number of interactive tools that allow accessing many of the functions through a graphical user interface (GUI). Fuzzy Logic Toolbox allows building the two types of system:

- → Fuzzy Inference System (FIS) and
- Adaptive Neuro-Fuzzy Inference System (ANFIS).

3.2 Fuzzy inference system

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. The process of fuzzy inference involves: *membership functions, fuzzy logic operators* and *if-then rules*. There are two types of fuzzy inference systems that can be implemented in the Fuzzy Logic Toolbox:

- ➔ Mamdani-type and
- → Sugeno-type.

Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology and it expects the output membership functions to be fuzzy sets. After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification. Sugeno-type systems can be used to model any inference system in which the output membership functions are either linear or constant. This fuzzy inference system was introduced in 1985 and also is called Takagi-Sugeno-Kang. Sugeno output membership functions (z, in the following equation) are either linear or constant. A typical rule in a Sugeno fuzzy model has the following form:

If Input
$$1 = x$$
 and Input $2 = y$, then Output is $z = ax + by + c$

For a zero-order Sugeno model, the output level z is a constant (a=b=0).

3.2.1 Membership function

Membership function is the mathematical function which defines the degree of an element's membership in a fuzzy set. The Fuzzy Logic Toolbox includes 11 built-in membership function types. These functions are built from several basic functions:

- ➔ piecewise linear functions,
- → the Gaussian distribution function,
- \rightarrow the sigmoid curve and
- → quadratic and cubic polynomial curve.

Two membership functions are built on the *Gaussian* distribution curve: a simple Gaussian curve and a two-sided composite of two different Gaussian curves (Figure 3.)

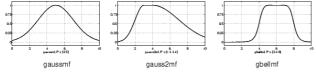


Figure 3. Membership functions built on the Gaussian distribution curve

This type of membership function will be used later on, according to the results coming from PCI.

3.2.2 Fuzzy logic operators

The most important thing to realize about fuzzy logical reasoning is the fact that it is a superset of standard Boolean logic. In other words, if the fuzzy values are kept at their extremes of 1 (completely true) and 0 (completely false), standard logical operations will hold. That is, A AND M operator is replaced with minimum - min (A,M) operator, A OR M with maximum - max (A,M) and NOT M with 1-M.

3.2.3 If-Then rules

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. Usually the knowledge involved in fuzzy reasoning is expressed as rules in the form:

If
$$x$$
 is A Then y is B

where x and y are fuzzy variables and A and B are fuzzy values. The if-part of the rule "x is A" is called the *antecedent* or premise, while the then-part of the rule "y is B" is called the *consequent* or conclusion. Statements in the antecedent (or consequent) parts of the rules may well involve fuzzy logical connectives such as 'AND' and 'OR'. In the if-then rule, the word "is" gets used in two entirely different ways depending on whether it appears in the antecedent or the consequent part.

3.3 Classification procedure

Since the goal of both procedures, maximum likelihood (ML) and fuzzy logic, is to classify the image, input data must be the same. That is, three SPOT channels are used as the starting point for the image classification based on fuzzy logic (Figure 1.).

The *Fuzzy Inference System* (FIS) *Editor* displays general information about a fuzzy inference system: a simple diagram with the names of each input variable (green, red and NIR channel) and those of each output variable (water, urban area, crop 1, crop 2 and vegetation). There is also a diagram with the name of the used type of inference system (Sugeno-type inference).

The *Membership Function Editor* is used to display and edit all membership functions associated with all of the input and output variables for the entire fuzzy inference system.

Because of the smoothness and non-zero values, in order to define a membership function, in the process of image classification simple Gaussian curve (gaussmf) is used (Figure 3a). In this case, Matlab's Fuzzy Logic Toolbox needs two parameters for the valid membership function definition: mean and standard deviation values. Values given in the Table 1 (mean gray value and standard deviation for each class in green, red and near infrared channel) come from PCI's 'Signature statistics' panel. These values are used as the pattern (parameters) in FIS ('fuzzy inference system') membership function design. In this table, values in cursive (mf_i) represent membership functions. That is, mfl represents membership function for water in green input variable. For some reasoning, sampled areas used for testing showed that results are much better if in membership function definition half of standard deviation values is used, instead of values given in the Table 1. Reason can be found in large overlap (Figure 4.) between very close range of membership functions (mf1, mf2, ..., mf5). This close range was also the reason why specific names for membership functions (linguistic hedges) like: not very light, light, middle tone, dark, very dark,... are not given (wider range may be found just in NIR channel). The names of membership functions remained the same: mf1, mf2, ..., mf5.

channel	mean	st. deviation		
water (from 12792 samples)				
Green (mfl)	93.35	14.04		
Red <i>(mf1)</i>	62.47 13.53			
NIR (mfl)	37.6	16.37		
urban area (from 5548 samples)				
Green (<i>mf2</i>)	125.23	17.15		
Red <i>(mf2)</i>	99.76	18.79		
NIR <i>(mf2)</i>	88.40	19.30		
crop 1 (from 6121 samples)				
Green (<i>mf3</i>)	112.23	6.4		
Red <i>(mf3)</i>	76.20	6.2		
NIR <i>(mf3)</i>	197.66	16.08		
crop 2 (from 3461 samples)				
Green (<i>mf4</i>)	121.82	12.97		
Red <i>(mf4)</i>	111.01	17.43		
NIR <i>(mf4)</i>	124.50	22.00		
vegetation (from 10231 samples)				
Green (<i>mf5</i>)	76.57	11.90		
Red <i>(mf5)</i>	47.37	12.34		
NIR <i>(mf5)</i>	109.88	28.03		

Table 1. Mean and standard deviation values of training areas

As it can be seen in following figure, similar values (overlap) can be found in the green channel for crop 1, crop 2 and urban area classes. This is due to the similar characteristics in the spectral response (reflectance) of these classes in the wavelength range $0.5-0.59 \mu m$. Fortunately, they can be better separated cause of the bigger difference in other two channels, especially in NIR where vegetation cover plays an important role.

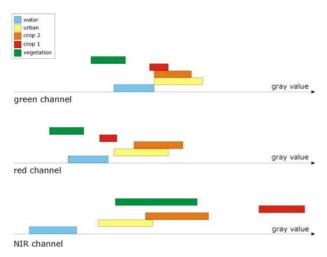


Figure 4. Channel's overlap

Gray values in image channels are strongly influenced by the presence of the clouds, since they are a little bit 'shifted' (lighter) comparing to the clear, non-cloudy areas.

Creation of the membership functions for the output variables is done in the similar manner. Since this is Sugeno-type inference (precisely, zero-order Sugeno), *constant* type of output variable fits the best to the given set of outputs (land classes). When the variables have been named and the membership functions have appropriate shapes and names, everything is ready for writing down the rules.

class	parameter/output variable	
water	1	
urban	2	
crop1	3	
crop2	4	
vegetation	5	

Table 2. Parameter values for output variables

Based on the descriptions of the input (green, red and NIR channels) and output variables (water, urban, crop1, crop2, vegetation), the rule statements can be constructed in the *Rule Editor*.

Rules for image classification procedure in verbose format are as follows:

IF (GREEN is mf1) AND (RED is mf1) AND (NIR is mf1)
THEN (class is water)
IF (GREEN is mf2) AND (RED is mf2) AND (NIR is mf2)
THEN (class is urban)
IF (GREEN is mf3) AND (RED is mf3) AND (NIR is mf3)
THEN (class is crop1)
IF (GREEN is mf4) AND (RED is mf4) AND (NIR is mf4)
THEN (class is crop2)
IF (GREEN is mf5) AND (RED is mf5) AND (NIR is mf5)
THEN (class is vegetation)

At this point, the fuzzy inference system has been completely defined, in that the variables, membership functions and the rules necessary to calculate classes are in place.

Classification is conducted by the Matlab's m-file. Resulting image is showed in the Figure 5.

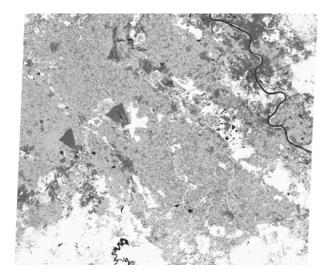


Figure 5. Classified SPOT images (fuzzy classifier)

Output images coming from PCI maximum likelihood and fuzzy classification can be compared. These grayscale images are produced in such way that pixels coming from the same class have the same digital numbers in both images: water (50), urban (100), crop 1 (150), crop 2 (200) and vegetation (250). This is the basis for image comparison. Percentage of classified pixels in both methods is given in the Table 3 (overall number of pixels is 10743070).

method class	PCI	fuzzy	difference
water	1.25	1.39	0.14
urban	15.62	13.95	1.67
crop 1	13.1	17.24	4.14
crop 2	28.82	34.11	5.29
vegetation	37.90	29.99	7.91

Table 3. Percentage of classified pixels in ML and fuzzy classification

Large number of misclassified pixels (black pixels) can be found in the areas covered by clouds (yellow circle regions in Figure 6).

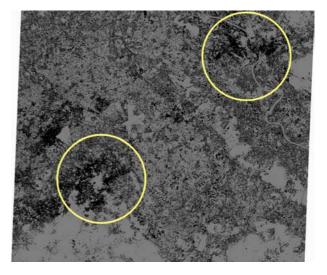


Figure 6. ML and fuzzy classification comparison image

3.4 Accuracy assessment

Idea for accuracy assessment of fuzzy logic classification results comes from the manner the maximum likelihood accuracy assessment was performed: select random sample areas with known classes and then let fuzzy logic 'say' what these samples are. With 100 random selected samples, results were as following:

- ➔ correctly classified samples: 89
- ➔ misclassified: 11
- → accuracy: 89%

3.5 Concluding remarks

Considering chosen land cover classes, results from image classification (Figure 5) and accuracy assessment can be good starting point for certain analysis:

- ➔ in the knowledge base, it must be well known whether selected sample is vegetation (forested area) or vegetated crop area
- ➔ around 30% of misclassified samples represent classes with small signature separability
- classification procedure is strongly influenced by the presence of clouds. These regions are lighter, so they cannot be properly classified. Since several samples, during accuracy assessment, were taken in this area with intention, overall classification procedure is probably of higher accuracy
- → at first sight, time necessary for fuzzy classification is longer comparing to maximum likelihood procedure, which takes several seconds to classify an image. But, if in ML procedure possible image transfer to recognizable format for certain software, formulation of the training areas, analysis concerning signature separability take place, than situation is quite different: *fuzzy logic takes advantage of already created simple rules and image classification (started from the scratch in both procedures) equal or even less time consuming.* Of course, different conditions during image capture must be taken into account.
- considering the level of classification accuracy, fuzzy logic can be satisfactory used for image classification.

4. REFERENCES

References from books: Lillesand M. T., Kiefer W. R., *Remote sensing and image interpretation*, John Wiley & Son Ltd, 1999

Terano T., Asai K., Sugeno M., Fuzzy systems theory and its applications

Mather P., Computer Processing of Remotely-Sensed Images, John Wiley & Son Ltd, 1999

Yan J., Ryan M., Power J., Using fuzzy logic; towards intelligent systems

Patyra M.J., Fuzzy logic; implementation and applications

Tizhoosh H., Fuzzy image enhancement /Kerre E., Nachtegael M., Fuzzy techniques in image processing/

Hildebrand L., Reush B., Fuzzy color processing /Kerre E., Nachtegael M., Fuzzy techniques in image processing/

References from other literatures:

Zhan Q., Molenaar M., Gorte B., Urban land use classes with fuzzy membership and classification based on integration of remote sensing and GIS, ISPRS 2000 Amsterdam

Kojima H., Chung C., Westen C., Strategy on the landslide type analysis based on the expert knowledge and the quantitative prediction model, ISPRS 2000, Amsterdam

Samadzadegan F., Rezaeian M., Hahn M., A robust automatic digital terrain modelling method based on fuzzy logic, ISPRS 2000 Amsterdam

Bellone T., Giacobbe L., Mussio L., *Classification by a proximity matrix*, ISPRS 2000 Amsterdam

Porwal A., Sides E., A predictive model for basemetal exploration in a GIS environment, ISPRS 2000 Amsterdam

Kok R.d., Buck A., Schneider T., Ammer U., Analysis of image objects from VHR imagery for forest GIS updating in the Bavarian alps, ISPRS 2000 Amsterdam

Hahn M., *Remote sensing and feature extraction I*, lecture notes, University of Applied Sciences Stuttgart, 2002

Jung J-S.R., Neuro-Fuzzy Modelling: Architecture, Analysis and Applications, PhD, 1992

Ghosh J.K., Godbole P., Ghosh S.K., Mapping of tea gardens from satellite images – a fuzzy knowledge-based image interpretation system, ISPRS 2000 Amsterdam

Willhauck G., Comparison of object oriented classification techniques and standard image analysis for the use of change detection between SPOT multispectral satellite images and aerial photos, ISPRS 2000 Amsterdam

Growe S., Schroeder T., Liedtke C.E., Use of Bayesian networks as judgement calculus in a knowledge based image interpretation system, ISPRS 2000 Amsterdam

PCI Geomatics, Getting results with Geomatica Image Works, 2001

References from websites:

www.mathworks.com

aria.arizona.edu/courses/tutorials/class/html/class.html

http://www.ch172.thinkquest.hostcenter.ch/fuzzy-logic7.html

http://www.dementia.org/~julied/logic/sets.html

http://www.geocities.com/rockyrami/

http://members.aol.com/wsiler/intro.htm

http://processsafety.tamu.edu/Research/Inherent%20Safety/FLogic.htm#HIS TO

http://www.spot.com