Object-oriented analysis applied to high resolution satellite data.

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Abstract: - The aim of this contribute is to examine an application of Object Oriented Image Analysis on very high resolution data, on Ikonos images - multispectral and panchromatic – of Bagnara Calabra, in the province of Reggio Calabria. Our objectives are to show as an automatic analysis as we implemented in a unitary package for segmentation and classification Neuro Fuzzy – with a minimal manual participation - can get a good classification also in presence of high and very high resolution data of small cities, where higher is an error possibility.

Key-Words: - Object-Oriented Image Analysis - Morphological Based Segmentation – Fuzzy Classification.

1 Introduction

The pixel-oriented analysis of satellite data as main limit has the acknowledgment of semantic low level information, as the amount of energy emitted from the pixel, while the context does not assume any role. In the object oriented analysis [1] the semantic level is raised: relation rules join space are added, topological information and statistics and so the context is defined. Recognition is based on concepts of Mathematical Morphology applied to the image analysis and elements of Fuzzy Logic for classification. In the explained example, was partially used the software eCognition of Definiens Imaging GmbH, that operates a segmentation of the entire scene on more levels [2], and an experimental software being completed and reviewed properly, implemented for integrating segmentation and classification. The segmentation Multiresolution [3] obtains the automatic creation of vectorial polygons, directly extracted from the raster (with the remarkable advantage of having therefore a perfect coincidence in the superimposition on raster) and subsequently the final classification predisposing an adapted hierarchy of classes that hold account of the relations between the produced segmentation levels.
The aim of this contribution is to examine an application of Object Oriented Image Analysis on very high resolution data, particularly on Ikonos images - multispectral and panchromatic – of Bagnara Calabra, in the province of Reggio Calabria. Our objectives are to show as an automatic analysis – with a minimal manual participation - can get a good classification also in presence of high and very high resolution data of small cities. A comparison of the results obtained with some others classification algorithms shows a strong improvement of classification results.

2 Multiresolution Segmentation

It is a bottom up region-merging technique starting with one-pixel objects. In subsequent steps, smaller image objects are merged into bigger ones. Throughout this clustering process, the underlying optimization procedure minimizes the weighted heterogeneity *nh* of resulting image objects, where *n* is the size of a segment and *h* an arbitrary definition of heterogeneity. In each step, that pair of adjacent image objects is merged which stands for the smallest growth of the defined heterogeneity. If the smallest growth exceeds the threshold defined by the scale parameter, the process stops. Doing so, multiresolution segmentation is a local optimization procedure.
Spectral or color heterogeneity is the sum of the standard deviations of spectral values in each layer weighted with the weights for each layer are used:

$$h_s = \sum_{c=1}^{q} w_c \sigma_c \quad (1)$$

where h_s is spectral heterogeneity; q = bands number; σ_c = standard deviation of *digital number* in c spectral band; w_c = weight assigned to c spectral band.

But the exclusive minimization of spectral heterogeneity leads to branched segments or to image objects with a fractally shaped borderline. This effect is even stronger in highly textured data, such as radar data.

For this reason it is useful in most cases to mix the criterion for spectral heterogeneity with a criterion for spatial heterogeneity, in order to reduce the deviation from a compact or smooth shape. Heterogeneity as deviation from a compact shape is described by the ratio of the border length l and the square root of the number of pixels forming this image object.

$$h_{g\_smooth} = \frac{l}{\sqrt{n}} \quad (2)$$

where: h_{g_smooth} = fractal factor of spatial heterogeneity; l = border length; $\boldsymbol{n}$ = number of pixels of the image object..

The second is a compactness f*actor* ($h_{g\_compact}$) that depends from dimensional ratio of polygon axis:

$$h_{g\_compact} = \frac{l}{b} \quad (3)$$

where: $h_{g\_compact}$ = compactness factor; l = berder length; b = the shortest possible border length given by the bounding box of an image object parallel to the raster.

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The segmentation algorithm proceeds fusing adjacent polygons beginning from every pixel of the image until the change of observable heterogeneity between the two original polygons and the new generated polygon does not exceed the threshold defined from the customer (scale factor). If the change of heterogeneity already does not exceed the threshold defined the fusion is effectively realized, otherwise the two polygons remain separated. Heterogeneity difference (overall fusion value) between resultant object and the two original polygons is:

$$f = w_f \Delta h_s + (1 - w_f) \Delta h_g \quad (4)$$

where: f = *overall fusion value*; w_f = the user defined weight for color (against shape). For w can be chosen a value between 0 and 1, while 0 and 1 is also possible: for w_f =1 only the shape heterogeneity is valued, and for w_f = 0 only the color heterogeneity is valued.

The difference of spectral heterogeneity (Δh_s) between the resultant polygon and the two polygons before the merge is:

$$\Delta h_s = \sum_{c=1}^{q} w_c \left[n_{merge} \sigma_{merge_c} - \left(n_{obj1} \sigma_{obj1_c} + n_{obj2} \sigma_{obj2_c} \right) \right] \quad (5)$$

where: n_{merge} = resultant polygon pixel number; σ_{mergec} = standard deviation of *digital number* in c -spestral band of the resultant polygon; n_{obj1} = pixel number in the first of the two polygons before the merge; σ_{obj1c} = standard deviation of *digital number* in c -spestral band of the first of the polygons before the merge; n_{obj2} = pixel number in the second polygon before the merge; σ_{obj2c} = standard deviation of *digital number* in c -spestral band of the second polygon before the merge.

Again, the change in shape heterogeneity (Δh_g) caused by the merge is evaluated by calculating the difference between the situation after and before the merge. This results in the following methods of computation for smoothness and compactness:

$$\Delta h_g = w_g \Delta h_{g\_compact} + (1 - w_g) \Delta h_{g\_smooth} \quad (6)$$

w_g being the user defined weight for smoothness (against compactness). For w can be chosen a value between 0 and 1, while 0 and 1 is also possible: for w_f =1 only smoothness is valued, and for w_f = 0 only compactness is valued.

$$\Delta h_{g\_compact} = n_{merge} \frac{l_{merge}}{\sqrt{n_{merge}}} - \left\{ n_{obj1} \frac{l_{obj1}}{\sqrt{n_{obj1}}} + n_{obj2} \frac{l_{obj2}}{\sqrt{n_{obj2}}} \right\} \quad (7)$$

$$\Delta h_{g\_smooth} = n_{merge} \frac{l_{merge}}{b_{merge}} - \left\{ n_{obj1} \frac{l_{obj1}}{b_{obj1}} + n_{obj2} \frac{l_{obj2}}{b_{obj2}} \right\} \quad (8)$$

n being the object size, l the object perimeter and b the perimeter of the bounding box

The choice of the scale factor allows to calibrate the largeness of the resultant polygons, and its definition is tied to the cartographic scale reference that the customer must obtain. The segmentation process is multiresolution because, beginning from a same image, is possible to generate various hierarchical levels of polygons with various scale factors. Reducing the scale factor the polygons generated become more and more small because smaller it must turn out the spectral variability intra-polygons, and whereas increasing the scale factor.

2.1 Segmentation procedures

The particularity of the multiresolution consists in the existing connection between the polygons of the various hierarchical levels of the segmentation. When a first level of polygons is generated is possible to generate n new upper hierarchical levels if the scale factor is larger (greater polygons) or n inferior levels if the scale factor is smaller (smaller polygons). Polygons of inferior hierarchical level are always geometrically consisting with those of upper hierarchical level, so every polygon of inferior level only belongs to one polygon of upper level. All the polygons of the various levels of segmentation constitute an only database in which are all the existing connections between the polygons of the same or various hierarchical levels. For every polygon are therefore known the polygons in contact on the same hierarchical level, the polygons that constitute an eventual inferior hierarchical level and the polygon in which it is contained in the eventual upper hierarchical level

The procedure for the realization of a good classification passes through a fine-resolution segmentation creating more segmentation levels, with the parameters indicated in the following table holding account of characteristics of the IKONOS dataset with availability of panchromatic:

Segmentation level	Bands					Scale	Criteri di omogeneità			
									Shape Settings	
	PAN	RED	GREEN	BLUE	NIR		Color	Shape	Smoothness	Compactness
Preliminar	Yes	No	No	No	No	4	0.8	0.2	0.9	0.1
Level I	No	Yes	Yes	Yes	Yes	4	0.8	0.2	0.9	0.1
Level II	No	Yes	Yes	Yes	Yes	10	0.8	0.2	0.9	0.1
Level III	No	Yes	Yes	Yes	Yes	1	0.8	0.2	0.9	0.1
Level IV	No	Yes	Yes	Yes	Yes	45	0.7	0.3	0.2	0.8

Table 1

The preliminary level of segmentation works on panchromatic image, has the aim of realizing objects at the best resolution. The level I characterizes the main classes. Level II must be more detailed for it is based on the relations with the sublevel. Level IV instead has to classify great areas based on the city density in sublevels. At last level III it takes advantage of the relations of all the three described levels in order to obtain the refined and corrected final classification with a minimum of unskilled labour. The preliminary segmentation level is realized with the parameters of homogeneity enunciated, and operating the preliminary segmentation on the panchromatic image using the parameters in table 1. This segmentation makes objects at the best resolution, based on the multispectral dataset blue, green, red and nir, in a composition 4,3,2 and has the level of segmentation on the added layers assigning weight 0 to layer pan and 1 to others. It corresponds to the level of the table and has the same parameters already used. Level II has the same weights attributed to the layers in the level but parameters of scale are modified from 4 to 10, and for level IV from 10 to 45. The last level of segmentation is the III, visible only with a zoom, since scale factor assumes the pixel. The visualization for pixel in previous level IV shows that there is maximum heterogeneity. There a course segmentation identifies wider areas unifying sublevels objects.

It will follow the classification procedure.

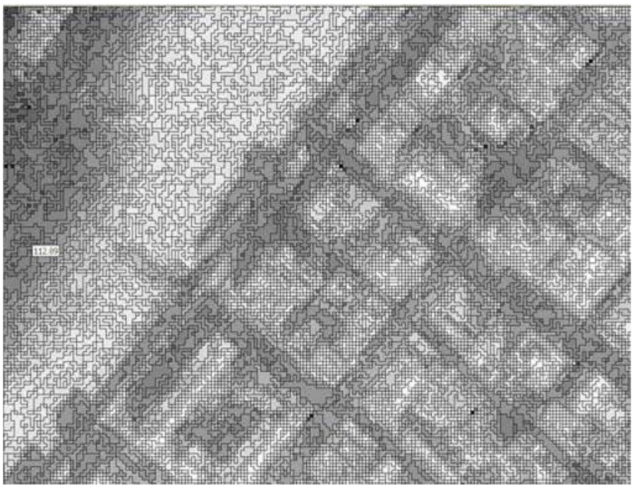

Fig.1: Preliminary level of segmentation.

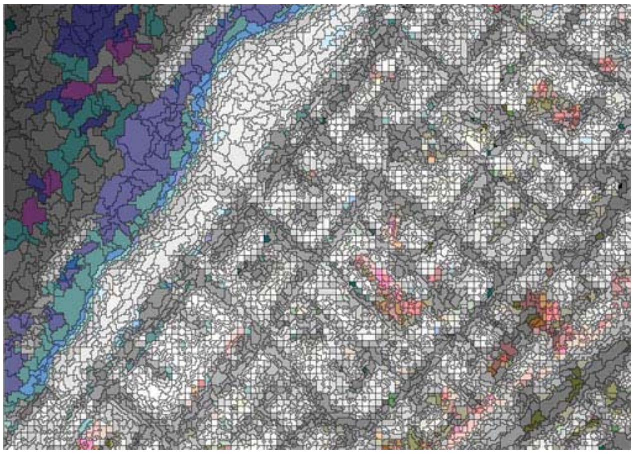

Fig.2: Level 1: zoom.

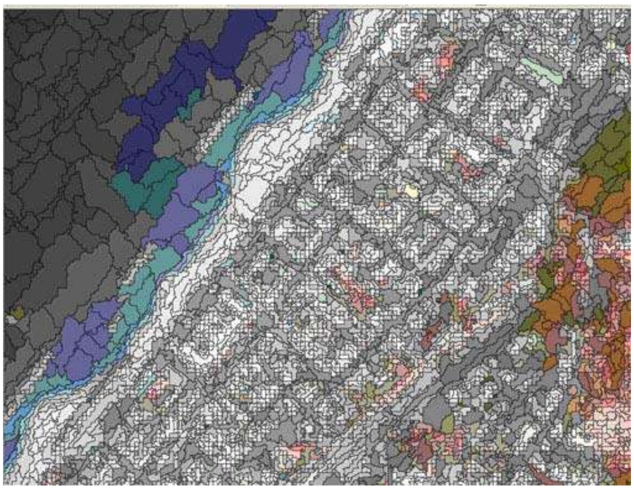

Fig.3: Segmentation, level II.

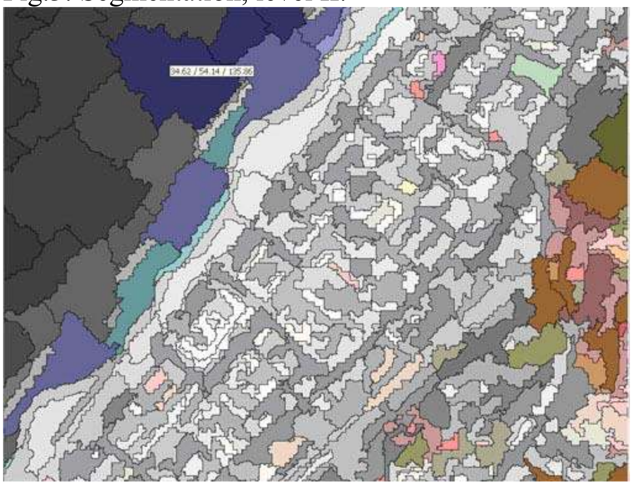

Fig.4: Segmentation, level IV.

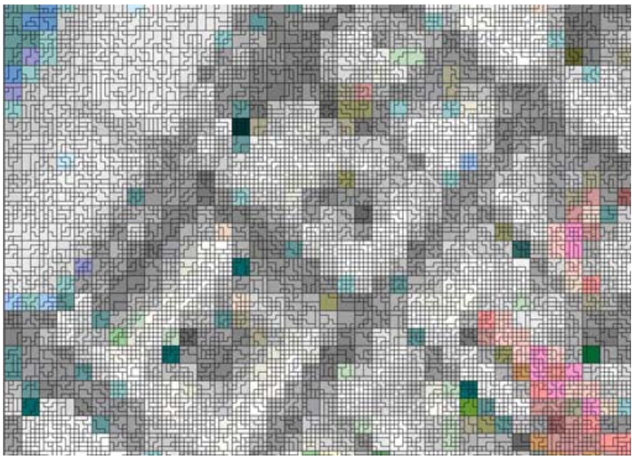

Fig.5: Segmentation, level III.

Fig.6: Level IV, pixel visualization.

This segmentation is partially known in literature (software eCognition of Definiens Imaging GmbH). In our job we propose the integration of segmentation and classification Neural Fuzzy in a unitary package for final classification of image.

3 Fuzzy Classification

Fuzzy logic, a mathematical approach to quantifying uncertain statements, replaces the two strictly logical statements “yes” and “no” by the continuous range of [0…1], where 0 means “exactly no” and 1 means “exactly yes.”. All values between 0 and 1 represent a more or less certain state of “yes” and “no”.

More recently, fuzzy sets have been employed in the classification of land terrain covers [9]. Fuzzy sets theory, [10] which has been developed to deal with imprecise information, can provide a more appropriate solution to this problem. In fact, it provides useful concepts and tools to deal with imprecise information. It allows each region to have partial and multiple membership in several classes. A region’s membership grade function with respect to a specific class indicates to what extent its properties are akin to that class. The value of the membership grade varies between 0 and 1. Closer the value is to 1 more that region belongs to that class. Partial membership allows that the information about more complex situations, such as cover mixture or intermediate conditions, can be better represented and utilized.

Fuzzy logic emulates human thinking and takes into account even linguistic rules.

Fuzzy classification systems are well suited to handling most vagueness in remote sensing information extraction. Parameter and model uncertainties are considered as using fuzzy sets defined by membership functions. Instead of the binary “true” and “false” multivalued fuzzy logic allows transitions between “true” and “false”.

There are more or less strict realizations of the logical operations "and" or "or".
The output of a fuzzy classification system is a fuzzy classification, where the membership degree to each land cover or land use class is given for each object. This enables detailed performance analysis and gives insight into the class mixture for each image object. This is a major advantage of soft classification. The maximum membership degree determines the final classification to build an interface to crisp systems.

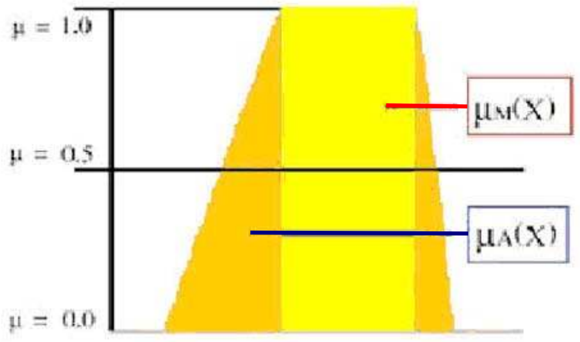

Fig. 7: Rectangular and trapezoidal membership functions on feature x to define crisp set M (yellow) $\mu_M(X)$ and fuzzy set A (orange) $\mu_A(X)$ over the feature range X;.

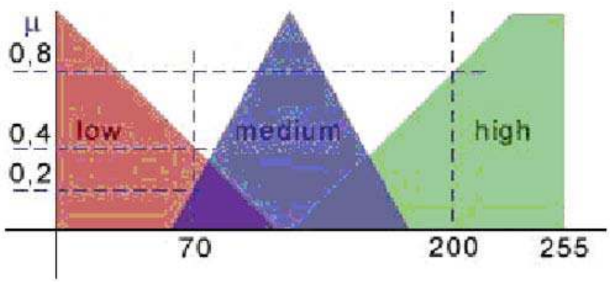

Fig. 8: The membership functions on feature x define the fuzzy set low, medium and high for this feature.

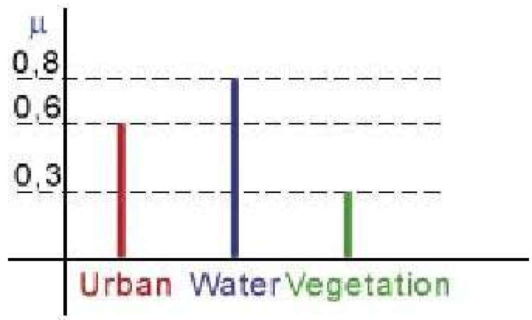

Fig. 9: Fuzzy classification for the considered land cover classes urban, water and vegetation. The image object is a member of all classes to various degrees:

$$\mu_{urban}(object) = 0.6,$$
$$\mu_{water}(object) = 0.8,$$
$$\mu_{vegetation}(object) = 0.3$$

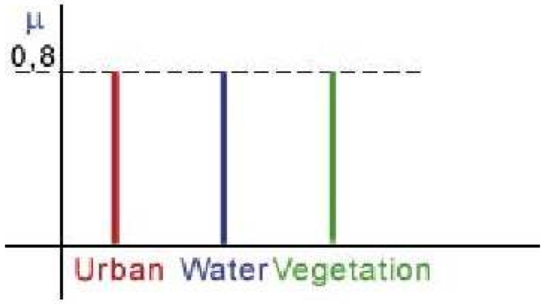

Fig.10: Fuzzy classification for the considered land cover classes Urban, Water and Vegetation. The equal membership degrees indicate an unstable classification between these classes for the considered image object. If the land cover classes can usually be distinguished on the data set, this result indicates that all land cover classes are within the image object to a similar degree. The high membership value shows that the assignment to this class mixture is reliable

$$\mu_{urban}(object) = 0.8,$$
$$\mu_{water}(object) = 0.8,$$
$$\mu_{vegetation}(object) = 0.8$$

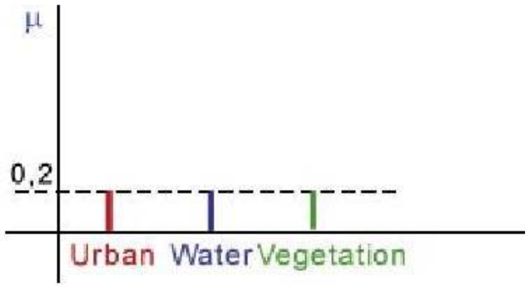

Fig. 11: Fuzzy classification for the considered land cover classes Urban, Water and Vegetation. The equal membership degrees again indicate an unstable classification between these classes for the considered image object, as in fig. 4. However, the low membership value indicates a highly unreliable assignment. Assuming a threshold of a minimum membership degree of 0.3, no class assignment will be given in the final output.

$\mu_{urban}(object) = 0.2,$
$\mu_{water}(object) = 0.2,$
$\mu_{vegetation}(object) = 0.2$

A fuzzy rule base is a combination of fuzzy rules, which combine different fuzzy sets. The simplest fuzzy rules are dependent on only one fuzzy set.
Fuzzy rules are “if – then” rules. If a condition is fulfilled, an action takes place. Referring to fig. 8, the following rule could be defined: “If ” feature x is low, “then” the image object should be assigned to land cover *W*. In fuzzy terminology this would be written: If feature x is a member of fuzzy set *low*, then the image object is a member of land cover *W*. According to the definition in fig. 8, in case feature value x = 70, the membership to land cover *W* would be 0.4, in case x = 200, the membership to land cover *W* would be 0.
To create advanced fuzzy rules, fuzzy sets can be combined. An operator returns a fuzzy value that is derived from the combined fuzzy sets. How this value is derived depends on the operator. The basic operators are “and” and “or.” “and” represents the minimum, meaning that the minimum value of all sets defines the return value. “or” represents the maximum value, meaning that the maximum value of all sets defines the return value. The results are very transparent and ensure independence of the sequence of logic combinations within the rule base (A “and” B gives the same result as B “and” A). In addition a hierarchic structure following common logic (e.g., A “or” (B “and” C) equals (A “or” B) “and” (A “or” C)) can be created easily.
A fuzzy rule base delivers a fuzzy classification, which consists of discrete return values for each of the considered output classes (see fig. 9). These values represent the degree of class assignment.
Must be considered that fuzzy classification gives a possibility for an object to belong to a class, while classification based on probability give a probability to belong to a class. A
The higher the return value for the most possible class, the more reliable the assignment. In the example above, the membership to water is rather high and in most applications this object would therefore be assigned to the class *Water*. The minimum membership value an object needs to have in order to be assigned to a class can be defined.
Fuzzy classification with its enhanced analysis of classification performance of class mixture, classification reliability and stability is possible, because fuzzy classification is one powerful approach to soft classification. The results of the fuzzy classification are an important input for information fusion in current and future remote sensing systems with multidata sources. The reliability of class assignments for each sensor can be used to find the most possible and probable class assignment. A solution is possible, even if there are contradictory class assignments based on different sensor data..

3.1 Neural fuzzy systems

Neural fuzzy systems of prediction (SIF) and neuro fuzzy (RNF) are known in literature. Our contribution is the creation of an integrated package implementing totally the classification and partially the segmentation.
As known, the Neural Nets are born from the idea of being able to get intelligence and ability to decision. Substantially these are adaptive systems “learning”, through examples, to execute correctly a determined task involving complex, not linear and multivariable relations. Our net can be outlined like a black-box that has inside some neuronal layers: the first of them is the input layer, and is made from many neurons how many are the incomes of the system; then there are from 0 to 2 inner layer; a Neural Net with 2 inner layer can approximate whichever type of function; at the end there is an output layer, with many neurons how many are the escapes of the system. The neurons are connected each other by synaptic links (Inter and intra-layer) having some opportune weights, whose value is used in the learning algorithm. The Neural Net, therefore, is a system Multiple Input Multiple Output (MIMO). Referring to the wide bibliography for an exhaustive description of the Neural Nets, we can say that a classic example of Net Neural is Multi-Layer Perceptron, trained with the Backpropagation algorithm. The signal object of predictive analysis is found and processed; the final numerical series is the sampled version. It works subsequently in the simulation environment. The predictive systems based on MLP Neural Nets are strongly used in literature. These do not need of pre-cognized information on the structure of the model characterizing the phenomenon to analyze; therefore they are ideal for systems that must be processed with a low level of acquaintance. The Neural Nets are therefore useful for functional predictions and modelling systems where the physical processes are not known or are highly complex. So their use is simple and highly suitable for phenomena whose complexity and/or structuring are known, for this acquaintance is useful to the research worker structuring Neural Net.
Is already common knowledge that a RNF consist in the representation of a Fuzzy system through a Neural Net. This tendency developed in the last

years. In fact, if a Fuzzy system is fused with a neural net and if are available (from "backpropagation" to the other genetic algorithms), effective methods of learning for the net, then the Fuzzy system become very more efficient. Regarding develop environments for traditional Fuzzy systems, this approach supplies the possibility to realize systems that "they learn", taking advantage of all developed the theoretical and applicative baggage available for Neural Nets. The inspirer idea, taking advantage of the tolerance towards uncertainty and imprecision, is the possibility of sturdier solutions at a low cost. This contribute don't give an exhaustive description of the Fuzzy logic, for which we refer to wide bibliography in scientific literature; but it wants to emphasize a difference between Fuzzy logic and conventional logic (binary).

4 Results of the algorithm proposed

As previously explained, our contribution is the creation of an integrated package implementing classification (RNF) and segmentation (as we described in previous chapter) useful for automating classification procedure, getting higher accuracy for applications like that we are now proposing.
Of course an automated package is very useful for processing great many data in a short time.
We carried out a RNF classification on a segmentation with a preliminary level on the panchromatic image and four levels on the multispectral data, obtaining a first level of classification in four classes.
We intend to make a careful study for obtaining a classification in other three levels, getting it deeper until 12 18 and 23 classes.

Fig. 12 Classification

Fig. 13 Class Hierarchy: at the first level.

We compared confusion matrix of our Fuzzy Set with some classification algorithms as Mahalanobis Distance, Maximum Likelihood, Neural Net.
Table 2 shows how Neural Fuzzy Set has the higher accuracy and the best results.

		Algorithm			
		Mahalan. Distance	Maximum Likelihood	Neural Net	Neural Fuzzy Set
Overall Accuracy		74.4589%	84.6320%	95.6284%	97.2678%
Unclassified		0	0	0	0
class	impervious	103/149	103/149	134/149	135/149
	water	112/135	122/135	135/135	135/135
	agriculture	81/141	111/141	141/141	141/141
	rural	66/124	100/124	115/124	123/124
	Total	362/549	436/549	525/549	534/549

Table 2

The future perspectives expect to refine the classification. As described previously, we are realizing a Class Hierarchy structured, on the base of the nomenclature indicated previously, on 4 levels respective with 4, 12, 18 and 23 classes

5 Conclusion

Classification and multiresolution segmentation object-oriented techniques distinguish structural methodology from classic spectral analysis. The pixel-oriented analysis increases ambiguity in statistics definition of the land use classes increasing resolution in remote sensing images. With object-oriented analysis is instead possible to using better information from remote sensing data with an immediate integrability in the GIS allowing the direct realization of vectorial maps, the used software, eCognition of the Definiens Imaging, that it applies to concepts of Mathematical Morphology and principles of logic fuzzy, organizes the data hierarchically and it concurs to arrange of different typology, integrating also raster and vectorial data. The possibility to introduce rules for the location of the context and the relations between the objects meaningfully increases the acknowledgment possibility automatic rifle of the objects on the land surface. Also imitating therefore the approach followed in manual photo interpretation, such methodology exceeds the limits of a subjective classification, by making a process that can be reproduced and homogenous, and exceeds the problems of the traditional classification techniques.

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