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Neural nets classification techniques for the tutelage of cultural and natural resources

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ABSTRACT: The multispectrality of satellite images and the continuing improvement in the resolving power of the last generation of satellites makes satellite images useful not only for land cover classification but also for identification and classification tasks at a detail useful for archaeology, urban classification and relative risk assessment. The availability of multi-scalar and multi-spectral images asks for power tools for processing this kind of data. In this paper we investigate the use of unsupervised artificial neural networks like Self-Organizing Maps and supervised neural nets like Multi-Layer-Perceptron for feature extraction and classification of satellite images. The study area is a coastal plain in the southern part of Italy, which is of high interest for the Cultural and Natural resources there preserved. Firstly we employ the Kohonen's Self Organizing Map (SOM) as a strategy for an unsupervised analysis of an IKONOS scene, employing in our analysis both the spectral information from its four MultiSpectral channels together with the spatial information extracted from the Panchromatic band. Secondly, we implement a supervised strategy on the same dataset, based on two steps: (1) features extraction step, which exploits the previous unsupervised results, (2) the discrimination step which uses a Multilayer Percepetron (MLP) neural network. The training of the Multlayer Perceptron is carried out using a training dataset which has been built mainly on the basis of information extracted by visual inspection of the Panchromatic image, but also using the results of the previous segmentation step over Ikonos data and other ancillary information available to us.

1 STUDY AREA, DATASET, PROCESSING TOOLS

The study area is a coastal plain in the southern part of Italy, which is of high interest for the Cultural and Natural resources there preserved. The area is located in the alluvial plain of the Salerno Gulf, more precisely on the left bank side of the Sele River. Within its boundaries is also situated an archaeological site, the ancient city of Poseidonia-Paestum, that preserves ruins dated 600 BC.

Land use is primarily agricultural, but during the last sixty years an urbanization phenomenon has arisen, associated not only to farm practice, but also to the growing tourist interest concentrated on this area. Consequently, the principal types of land covers are agricultural fields (both fallow fields and crop covered ones), rural fabrics (greenhouses), sea water, a coniferous wood strip along the coastline, small urban areas made up of discontinuous fabric mixed with vegetation.

For this study we employed both the four multispectral bands (spanning from Visible Blue to Near Infrared frequencies and at a spatial resolution of 4 m) and the panchromatic band (a single wide band spanning from Visible Green to Near Infrared frequencies and at a resolution of 1 m) of an Ikonos 2 scene from January 2004, licensed from Planetek Italia (www.planetek.com). The product is at GEOretification level, i.e. it is rectified to a Geographic Projection System; in this case to UTM projection, zone 33N, with WGS84 Ellipsoid and Datum. The cloud coverage is zero percent. Data are quantized at 11 bits. The Area Of Interest (AOI) is identified by Upper Left Corner(m): 497395.3882329; 4478054.4263542, Lower Right Corner(m): 504518.6571163; 4473130.9317472.

In this study we used Idrisi Andes (Release 15) as main environment for managing our geo-referenced images; the Neural Nets Algorithms (both SOM and MLP) were performed in a Matlab Environment (Release 12) and a PCI Geomatica (Release 10) Free Viewer was adopted to ease interpretation of the SOM results.

2 CLASSIFICATION METHODS, EXPERIMENT SETTINGS

The Self-Organizing Map (SOM) (Kohonen 1997) is an unsupervised neural network algorithm that has turned out to be an efficient tool, in various applications, for data exploration tasks. Recently it has been used also for the analyses of remote sensing multispectral images (Pugliese *et al*. 2005), (Villmann *et al*. 2003), (Ji 2000) with quite successful results. It carries out a nonlinear mapping of multidimensional input data onto a two-dimensional grid of neurons (or nodes). The output grid is organized so that similar inputs are represented by nodes that lay topographically close to each other over the output grid. This ordering facilitates the understanding of data structures. Moreover, displaying on the map the Euclidean distances between prototype vectors of neighbouring nodes through grey levels (Figure 1), the SOM gives a good representation of the cluster structure, graphically depicting the data density, too. Finally, by exploiting the SOM similarity property exposed above, a Colouring Procedure based on the Sammon's Projection (Borg & Groenen 1997) of the prototypes was performed. The obtained projection allows to assign similar colours to similar neuron-prototypes on the SOM map. The idea to transfer the prototypes similarity information into an equivalent palette of colours, and then of colouring accordingly the pixels of the classified image, was suggested by the technique used by photo interpreters in analysing RGB composites.

The Multi-Layer Perceptron (MLP) is a well known supervised neural network algorithm, that has long been employed also in remote sensing classification tasks (Mather 2001). In particular we concentrate our study on three-layered architectures (McClelland 1989).

The SOM experiment was conducted with the following settings: for each pixel of the multispectral bands, the input to the Neural Net is a five components vector, composed by

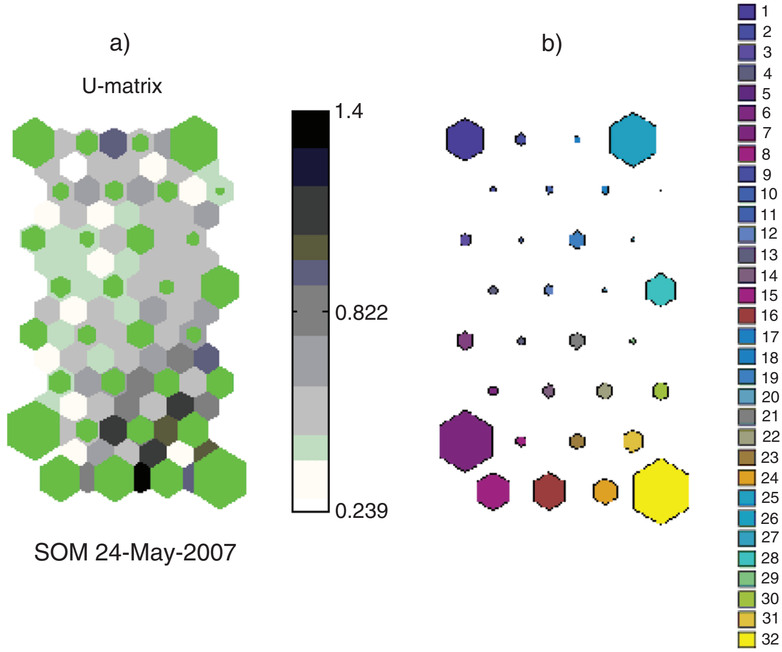


Figure 1. a) the so called U-matrix for our SOM experiment involving 32 output neurons. The Green hexagons areas are proportional to the number of input vectors (hits) which are represented by the corresponding output node (prototype vector). The hexagons interconnecting the green ones are grey scaled according to the level of similarity between couples of neighbouring nodes; white stands for strong similarity and black for weak similarity. b) The Sammon's colouring procedure generates a colour-equivalent representation of the distances between nodes. On the right side the Colour palette that was built from Sammon's projection results.

the four spectral values relative to that pixel plus a textural information relative to the same pixel area but extracted from the panchromatic band. The textural information consists in the standard deviation calculated over a 4×4 window of the panchromatic band, which covers the area of a single pixel of the multispectral band. The output of the SOM is set to 32 nodes, due to our a priori information of the territorial variability; as it will be seen later, the number of informative classes are less than 32 (they are in the order of ten- fifteen); but we prefer not to try to obtain directly informative classes from the SOM nodes, as it is also suggested in literature (Mather 2001). The other SOM parameters (neighbourhood radius and learning rate functions) are not critical and they were settled in agreement with the prescriptions reported in Kohonen *et al.* (1996).

The MLP experiment is done under these conditions: a three layered architecture (one hidden layer) is selected; the hidden layer is composed of nine nodes; the output nodes, one for each target class, are also nine. The number and types of target classes were in part determined by our a priori knowledge of the study area, but they were also selected on the basis of the exploratory results obtained through the SOM experiment. We were looking for four types of agricultural fields, sea water, coniferous trees (in particular the pine wood near the coast line), artificial surfaces (subdivided into two classes: greenhouses, buildings), the sea shore. The training sites were selected by visual inspection of the panchromatic band and they were digitised in Idrisi environment. The input vector to the MLP net is the same as the one used for the SOM experiment.

3 RESULTS AND CONCLUSIONS

Starting with the SOM results, it has been said in the previous paragraph that the idea to transfer the prototypes similarity information into an equivalent palette of colours, and then of colouring accordingly the pixels of the classified image, was suggested by the technique used by photo interpreters in analysing RGB composites. In this domain is common practice to recognize under a group of similar colours the same land cover, only with differences in physical state (for example, consider the different state of vegetation revealed by different tones of red in a Infrared false colour composition). The SOM result with the colouring procedure applied to the classification product is reported in Figure 2. We have already said that generally the SOM classes don't coincide with informative classes. It is more frequent, though, that a group of few neighbouring nodes of the SOM map represents a meaningful class. Thus, a colour-driven gathering of SOM

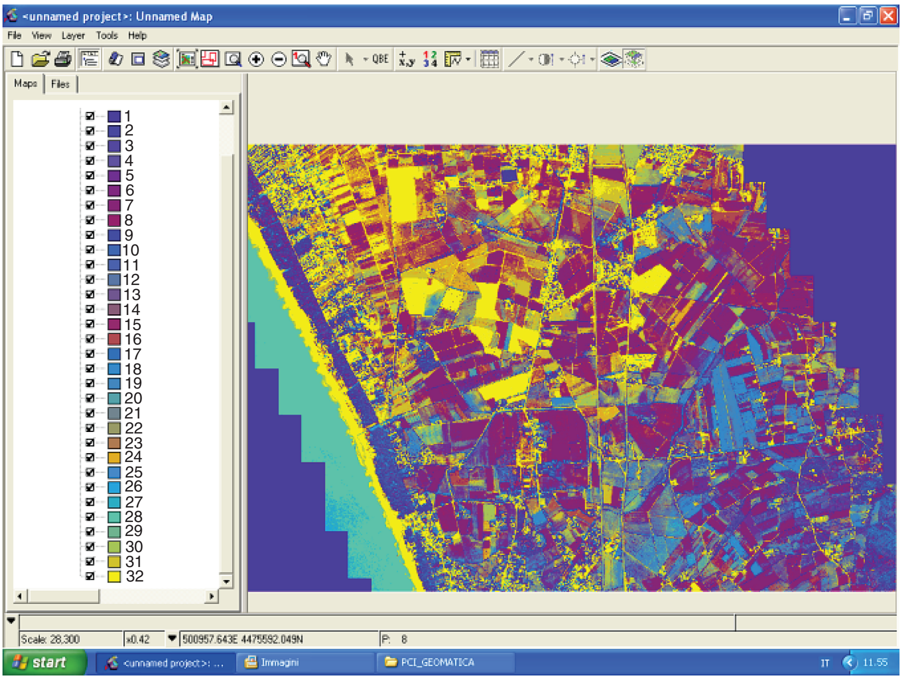
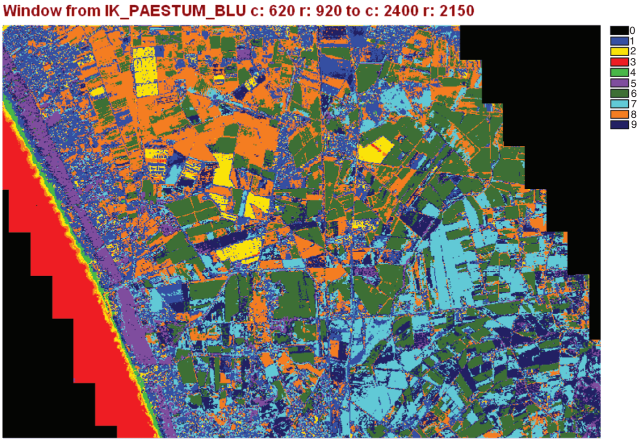


Figure 2. SOM classification results. The Sammon-driven colouring procedure eases a successive photointerpretation task (see below, Figure 4).

nodes has produced the semiautomatic classification in Figure 4, with more informative classes than those present in the original 32 classes segmentation.

For the MLP experiment, we used our a priori knowledge combined with information extracted by visual inspection of the panchromatic band, in order to define the training



Network Confusion Matrix (98.6547%)

True / Predicted

123	1	0	1	1	0	1	0	0
0	69	0	0	0	0	0	0	0
0	0	202	0	0	0	0	0	0
0	0	0	69	0	0	0	0	0
0	0	0	0	123	1	0	0	8
0	0	0	0	0	279	0	0	0
0	0	0	0	0	0	240	0	0
0	0	0	0	0	0	0	103	0
0	0	0	0	5	0	0	0	112

Figure 3. The MLP classification result. On the right side is reported the confusion matrix relative to this experiment.

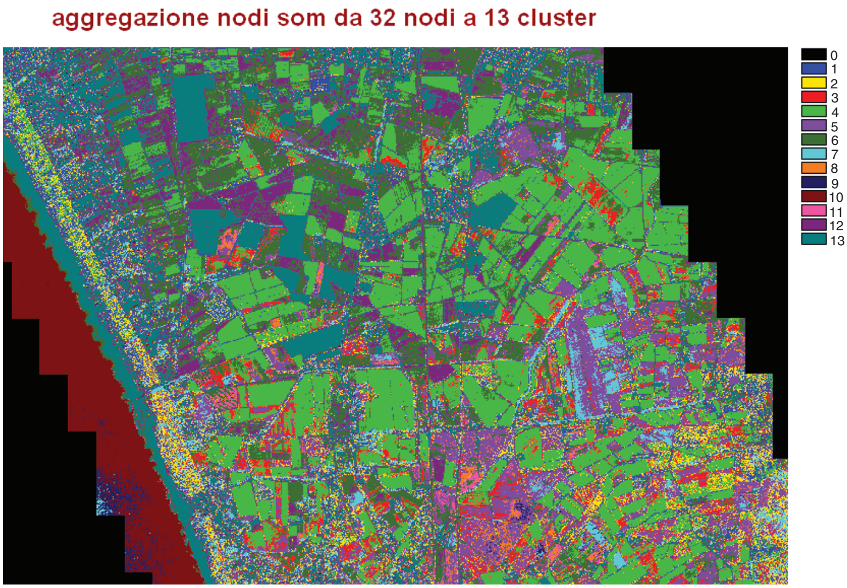


Figure 4. A semi-automatic classification, obtained by manually combining the 32 SOM clusters produced by SOM in a 13 information classes classification.

(and testing) set. But the first results of classification were not so good, especially for two "simple" classes like pine wood and sea water. The confusion matrix contained too many errors in correspondence of these two classes. We consider these classes not difficult to classify on the basis of our previous experiments of environmental factors classifications conducted on the same area, but with medium resolution satellite data (Landsat, Aster,..) (Pugliese *et al.*). Also in consideration of the SOM results (considered here as an exploratory tool about the data structure) which were also bad for these two classes, we decided to downscale artificially the spatial resolution of the multispectral bands, considering, for each pixel, the mean of a 3×3 matrix of spectral values in the neighbourhood of the pixel, instead of the single pixel value. The textural information remained the one used in the SOM experiment. This modification of the input vector (mean of the four spectral values plus textural information) increased the MLP classification results in relation to the selected target classes (see Figure 3, also containing the confusion matrix that now presents an overall accuracy of 98,6%).

Our experiments have confirmed the utility of unsupervised methods (in particular the SOM method) as exploratory tools to drive successive supervised analysis. Moreover, an improvement in autonomous classification capacity of the SOM net was proposed, by the semi-automatic classification of SOM results.

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