NEURAL PROCESSING OF MULTISPECTRAL AND MULTITEMPORAL AVHRR DATA

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ABSTRACT

In this work a mixed NDVI data processing method has been developed. It uses both statistical algorithm and neural network techniques to process and analyse the large historical archive of NDVI data being acquired by the NOAA/AVHRR sensor and developed by FAO-ARTEMIS jointly with NASA-GSFC. The archive contains ten years of data, so that it is possible to analyse, within this wide temporal range, the spatial and temporal variation of the vegetation index. The Principal Component Analysis has been used to reduce the amount of data to be processed. A neural network has been used to produce the clustering map. Some statistical parameters have been extracted from each cluster and the results have been compared with the ones obtained by statistical clustering (ISODATA algorithm).

1. INTRODUCTION

In the last years a large amount of multisensor data has been generated in consequence of the development of remote sensing techniques for the analysis of the Earth's surface. The study of the evolution of the vegetation status is particularly useful in planning agro-ecological operations and in the estimation of the vegetation development (Maselli et al. 1992).

In this paper normalized vegetation index data (NDVI) collected by the AVHRR sensor on the NOAA satellite are processed. These multitemporal data belong to a historical archive composed of ten years of ten-day images of the whole African continent. This archive has been implemented in the framework of a cooperation between NASA-GSFC and the FAO Remote Sensing Centre (ARTEMIS project). The archive started from August 1981 to June 1991 and it is composed of 356 georeferenced images. This set of NDVI data collected over a so long period of time is extremely useful when the annual and seasonal variations of the reflectance of the Earth's surface have to be investigated.

In this work a new approach to NDVI data processing is presented: it is composed of both statistical techniques and neural algorithms. The large number of images in the archive makes extremely difficult to analyse the whole data set and this is particularly true when personal computer are used for processing: in this case it becomes important the reduction of the amount of data to be processed whilst keeping control on the loss of information.

The method can be summarized in two fundamental steps: i) the reduction of the number of images to be processed while controlling the loss of information by statistical techniques; ii) the use of a neural network for clustering the scene in order to highlight areas showing similar vegetation index variability.

The results obtained by the neural network have been compared with those ones produced by statistical clustering performed by the ISODATA algorithm.

2. THE FAO/ARTEMIS DATASET

The dataset used in this work has been collected by the NASA Goddard Space Flight Center in cooperation with the FAO Remote Sensing Centre in the framework of ARTEMIS project (Africa Real Time Environmental Monitoring Information System). The archive consists of 356 ten-day images collected from August 1981 to June 1991. The images are produced by processing the data being collected by the AVHRR sensor flown on the NOAA satellite and represent NDVI values. The image format is GAC (Global Area Coverage), and the spatial resolution is 7.6 Km by 7.6 Km. Image data are generated by an 8 bit quantization of the NDVI values computed by combining the spectral channel 1 (red) and 2 (near infrared) of the sensor according to the following relationship:

$$NDVI = \frac{(NIR - R)}{(NIR + R)} \qquad [1]$$

The spatial resolution of the available image data allows the analysis on a continental scale: each image covers in fact the whole African continent. The study started with the selection from the whole scene of the region of the Western Africa from the Sahara desert to the Guinea gulf as shown in figure 1.

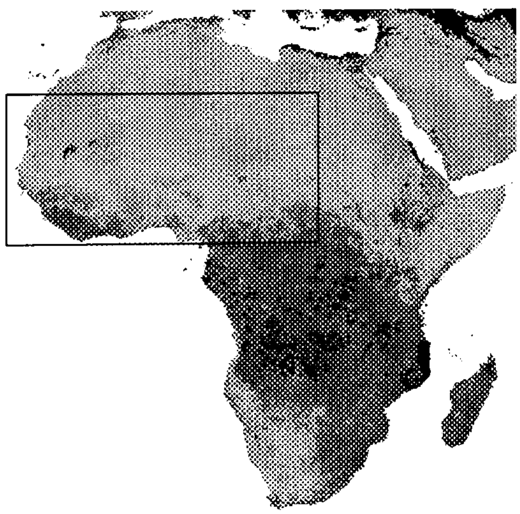

Figure 1- FAO-ARTEMIS archive image: the box shows the selected study area

The FAO-ARTEMIS archive makes available a very long time-series and in this way the analysis of ten years of image data allows a statistically reliable study on the spatial and temporal variations of the vegetation index.

3. THE METHODOLOGY

The methodology can be divided into three phases: the first phase where the data are statistically preprocessed in order to reduce their size while preserving their information contents; the second phase where a neural network is used to produce the cluster map; the third phase where vegetation index temporal profiles are generated and the statistical analysis of the results obtained is carried out. The temporal profiles of each cluster have been compared with the ones obtained by the statistical ISODATA algorithm. In figure 2 a block diagram of the whole processing is drawn.

3.1 Principal Component Analysis

The large amount of data collected in the FAO-ARTEMIS dataset makes the simultaneous processing of all the images almost impossible. Thus it is necessary to apply a "block" data processing so as to reduce the amount of data to be processed concurrently.

For the examined images it can be noted that, due to the high temporal frequency of data acquisition and to the spatial scale a high correlation exists between each image and the next one. The correlation among data produces redudancy in the information collected in the data set.

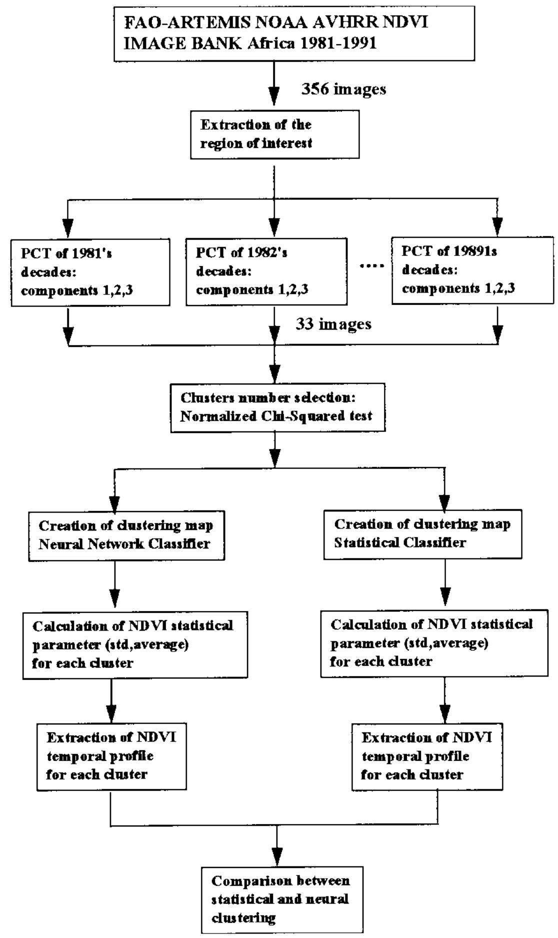

Figure 2 - Block diagram of the applied methodology.

In order to reduce both the data amount and the redudancy the multivariate statistical technique (Eklund et al. 1993) known as principal component trasformation (PCT) has been applied. For each picture element of the observed scene a feature vector can be defined: its components are the NDVI values computed for that pixel in each image of the set. By means of PCT taking into consideration the variance of data set, a transformation of coordinates can be computed and the data set described in a new hyperspace where the components of the feature vectors are de-correlated. Moreover in the new hyperspace the information brought by each component decreases with the increase of its order (in the first component the maximum quantity of information can be found).

Because of the high correlation degree in the original images, it is reasonable to suppose that a few number of components could be sufficient to describe almost completely the whole data set. When the PCT has been applied to images acquired in the same year the first 3 components of each year (33 images in total) have been sufficient to reach the 90% of the original information.

Because the PCT technique gives the possibility to enhance the changes of spectral values of a given pixel among the different images, the NDVI seasonal variations during the 10 years analyzed (Fung et al. 1987) have been pointed out.

The ISODATA algorithm (Richards 1993) has been applied as a statistical unsupervised classification technique to be compared with the neural one. ISODATA is based on an iterative non hierarchical method where pixels are grouped according to their euclidean distance with respect to predefined centroids (Richards 1993, Thomas et al. 1987).

3.2 Optimal selection

One of the principal problems of the unsupervised classification techniques is the choice of the optimal number of clusters which must be set as an initial parameter. This value should be as close as possible to the number of "natural" classes in which the observed scene can be sub-divided. This estimation has been done by the statistical chi-squared test, suitably modified:

$$\tau = \sqrt{\frac{\chi^2}{(Nc-1)Nt}} \qquad [2]$$

where:

χ^2 comes from the table of contingency

Nc is the number of classes

Nt is the number of pixels

The value of τ ranges from 0 to 1 and can be considered as an index of the stability of the different clusters (which is maximum when τ=1) between two consecutive clustering steps.

The optimal selection has been obtained with a variation of the number of clusters between 5 and 12. The best results have been achieved with 7 clusters.

3.3 The neural approach

The classification techniques based on neural networks (Benediktsson et al. 1990) have the advantage that no a priori hypothesis on data distribution is necessary and that is due to the behaviour of neural networks which tipically learn by experience.

Unfortunately, one of the major problems when dealing with remotely sensed data is due to the acquisition and the processing of ground truth data, which represent, for all supervised algorithms, the training set. As a matter of fact several steps are necessary for the acquisition and the use of the training data: i) the identification, on site, of the coverage present on the scene ii) the identification, on the remote sensed image data, of the areas previously investigated; iii) the extraction of the spectral signatures for the pixels falling into the training regions.

It is thus easy to understand that supervised training algorithms have, in remote sensing applications, a considerable drawback: the landcover classification task cannot be accomplished, even in part, without the ground truth data.

In this paper the Counterpropagation newtwork (Hecht-Neilsen 1984) has been used as unsupervised classifier. The architecture of the network is shown in figure 3. It is composed of two layers: a first unsupervised trained layer (Kohonen layer) and a second supervised trained layer (Grossberg layer). The two layers can be trained in different times. In this way the two different training phases allow us to obtain some preliminary, but still acceptable, results even without the ground data..

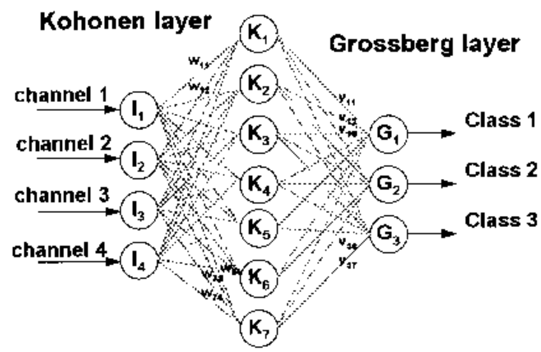

Figure 3 - Counterpropagation network topology

The discrimination of the classes on the scene generated by the first Kohonen layer is not a classification but rather a clustering because the network groups pixels with similar characteristics. The output produced by the first layer becomes a classification of the area when the supervised Grossberg layer is added and when it is trained by ground truth data. In this way clusters are changed in land cover classes (Chiuderi et al. 1994).

In more detail the training procedure used for the Kohonen layer is the following:

- for each pixel on the image the feature vector **x** is determined;
- for each weight vector **w** of the network the dot product s =**x w** is computed;
- $\mathbf{s}_{max}$ the max of dot products is evaluated;
- the weight **w** corresponding to $\mathbf{s}_{max}$ is modified according to the following law:

$$\mathbf{w}(t+1)= \mathbf{w}(t)+a(t)(\mathbf{x}(t)-\mathbf{w}(t)) \qquad [3]$$

where:

w(t+1) is the weight vector at the $(t+1)^{th}$ iteration

w(t) is the value of the weight at the t^{th} iteration

x(t) is the input vector

a(t) is the parameter which determines the learning speed

The procedure used to modify the weights makes the weight vector "as close as possible" to the input vector. The end of the unsupervised training procedure is regulated by convergency criteria.

At the end of this first unsupervised training phase, when an input vector is presented to the network, the unit of the first layer which achieves the maximum scalar product is activated: this means that the pixel is discrimated by the activated neuron. All the pixels whose feature vectors activate the same neuron belong to the same cluster. The clusters are as many as the neurons that composing the Kohonen layer. Figure 4 shows the 7 clusters map produced for the study area.

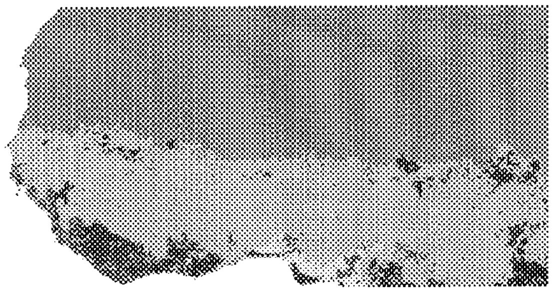

Figure 4 - Seven cluster map generated by neural network processing.

4 ANALYSIS AND RESULTS

The clustered maps generated with both the methods show a subdivision in bands of latitude which is analogous to the distribution observed for rainfall (Malo and Nicholson 1990). The two methods enhance in the same way the desertic region, while they produce different results in the southern sahelian and tropical region. The statistical method produces a more evident separation in bands of latitude, while the neural network generates more spread classes. For each cluster the average and the standard deviation of NDVI have been computed by processing all the images of the dataset.

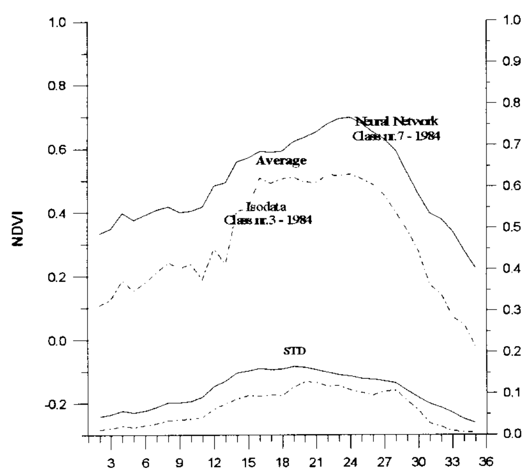

Figure 5 - Example of annual average NDVI profiles computed with neural and statistical methods

The profiles thus obtained show a monomodal behaviour for every class except the desertic one where NDVI has a very low value which is costant in time. The profiles obtained with the two methods are similar even if the neural newtork produces higher NDVI values.

In figure 5 annual average profiles computed for overlapping clusters obtained by the two different methods is reported.

5. CONCLUSIONS

The objective of this work is the study of a methodology in order to subdivide the Western Africa territories on an agro-ecological basis by the spatial-temporal analysis of the normalized vegetation index. The results being obtained show how a reclustering phase for each generated class is necessary in order to characterize in more detail the different types of territory belonging to a so wide region.

6. REFERENCES

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