Българска академия на науките. Bulgarian Academy of Sciences
Аерокосмически изследвания в България. 15. Aerospace Research in Bulgaria
София.*1999. Sofia

Neural networks in classification of remotely sensed multichannel images—A case study

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In this paper are presented recently obtained results concerning the classification of remotely sensed multichannel data using neural networks. A structure of the neural network is proposed and it is chosen a training method among the well known methods. Moreover, the procedure applied for preparation of the training data is described as well as the initial conditions under which the training was performed. Also several configurations of the neural network with different number of neurons in the hidden layers ranging from three to eight are compared. The results obtained after classifying an image containing more classes than those included in training set are reported.

1. Introduction

A final stage in the classification of multichannel data obtained by remote sensing techniques is creation of "a digital image, a map of classified pixels" (Remote Sensing). Using statistical methods, as maximum likelihood, it is possible to aggregate each pixel from an image to some of the previously formed clusters based on its spectral signatures in the n-dimensional wavelength space. Following the statistical approach to achieve high accuracy first large sets of data have to be analyzed to find out statistically confident and significant features for each cluster. Afterwards, in the real data processing, it is necessary to compute the degrees of probability for belonging for each of the pixels to every one of the formed clusters and then to make the final decision. It is obvious that this procedure is a computationally hard and time consuming. In the following sections of this paper a neural network based classifier is proposed, which overcomes the above mentioned disadvantages in resolving the classification task. The advantages of the neural networks approach over the statistical one in resolving problems where *a priori* knowledge of the data processed is not available are discussed by many investigators [1]. Here should be outlined that "the neural network classifications are not the best possible, but probably no worse than typical ones" [2].

2. Theoretical background

In the recent years the development in the theory and practical implementation of the neural networks has proved their capabilities in pattern recognition, which could be "regarded as extension of the conventional techniques" in this field [3]. They offer very powerful general framework for representing non-linear mappings between multidimensional input and output. This mapping is accomplished by set of functions $Y_k(X,W)$, where X are the input parameters and W are parameters of the network called weights. In order to achieve particular mapping between an arbitrary input and its corresponding output a non-linear basis functions, called activation functions, which have to be differentiable, must be applied. The last property is extremely important for the network training, because it is the necessary condition which allows for conjugate gradient-based methods to be used in the training phase. In many cases a sigmoidal function, which has the form:

$$F(k) = \frac{1}{(1+\exp(-k))}$$

is utilized as activation function, because it fulfills the mentioned requirement. In some investigations the hyperbolic tangent has been used as activation function, but here only sigmoidal functions will be regarded.

Let's consider a neural network structure with two processing layers, called multi-layer perceptron (MLP) (Fig. 1), which is mathematically represented by the equation:

$$Yk(X) = \sum_{j}^{M} W_{kj} F(\sum_{i}^{I} W_{ji} X_i).$$

This structure can approximate any continuous mapping with accuracy compared with or higher than this achieved by other methods, if the number of hidden units M is large enough. One thing that must be outlined here is that this structure has generalization capabilities i.e. it can give reasonable output to the input not included in the set of patterns used during training. This means that it not only can interpolate the input data, but also to extrapolate them. This quality is essential when dealing with remotely sensed data, because the data used for training the network are only representative samples derived from a real scene and, as rule of the thumb, the spectral signatures of the land cover types vary between scenes even acquired by one the same sensor due to changes in atmospheric conditions, illumination etc.

3. Method and data

In this case study the main aim is to introduce the manner how a neural network was applied as a classification engine for several basic types of land cover based on their multispectral signatures received by remote sensing techniques. The procedure of training data preparation, network training and classification was divided in the following steps as shown on Fig. 1.

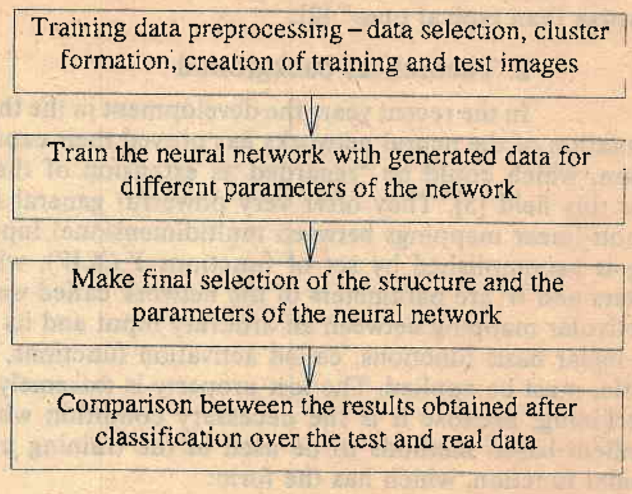

Fig. 1. Major steps used during the neural network training and classification

The main processing structure was chosen to be a multi-layer perceptron (MLP) with two hidden layers (Fig.2), with sigmoidal activation functions for processing elements, trained by backpropagation. This number of layers was considered to be sufficient since with this number of hidden layers a mapping with accuracy more than 95% between the inputs and the output was achieved [4].

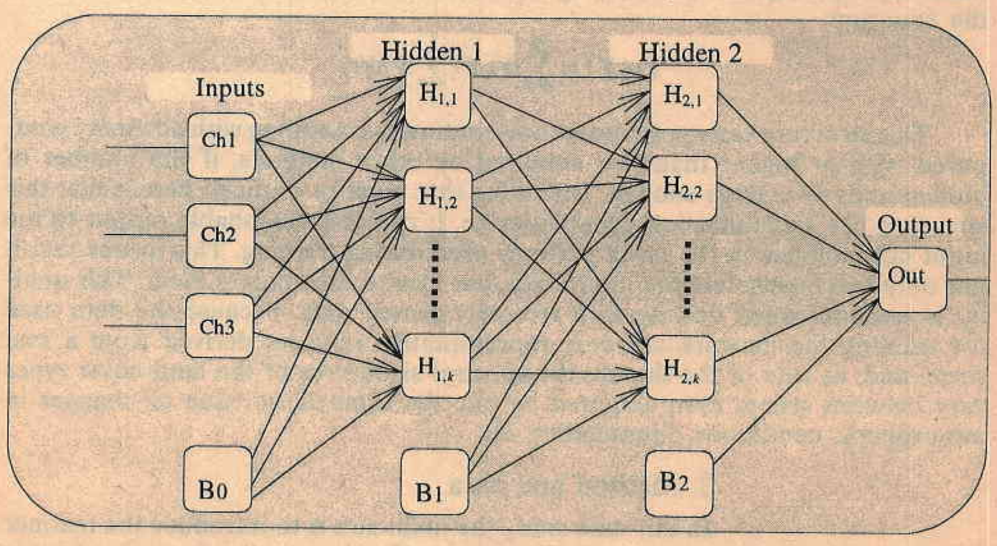

Fig. 2. Proposed neural network structure: input layer with three inputs for each of the spectral channels, two hidden layers with varying number of neurons (k=3,...,8), one output

The structure of the neural network and training method was selected according to the following criteria:

- convenient structure corresponding to the classification (pattern recognition) task;
- accuracy of the results after classification;
- adequate behaviour when data not included in the training set are presented for classification ;
- good speed of training;
- simplicity in software realization.

It has been reported that some other training methods (cf. LVQ) suit better for classification purposes than backpropagation, but this holds true only if all possible input patterns have been included in the training set.

One of the keys to successful implementation of neural networks is the selection of the training data i.e. to extract a set of representative feature vectors within the problem domain. In this case the training and the test data were taken from a pre-processed subscene with dimensions 512×512 pixels representing the North-West part of Bulgaria. This subscene is from the French satellite SPOT (instrument High Resolution Visible — HRV) in three spectral channels. Those training data were used to form the feature vectors during the training of the neural network, which had to perform the classification procedure. The training input patterns consists of a 4-tuple where the first three values are digital numbers (DN) representing the reflected by the Earth's surface solar radiation in the corresponding spectral channel and the last one is the number of the class to which this type belongs to.

In the subscene the following four types of land cover were present (bare soil, vegetation, water, limestone). The spectral signatures for this basic classes were obtained from a catalogue of SPOT imagery [5] and visual observations of the subscenes. After applying statistical methods for cluster formation on the data available for the three spectral channels four clusters were formed (Fig. 3).

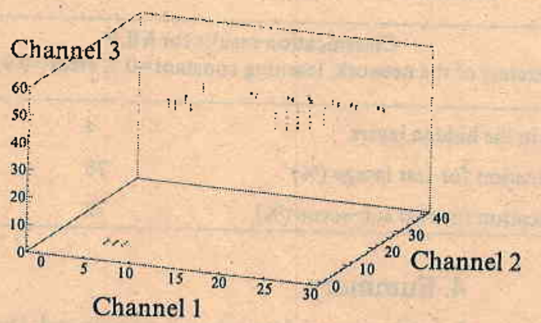

Fig. 3. Clusters used for training data creation (the values are percentage of the real DN, which vary from 0 to 255)

Using this spectral signatures one training and one test artificial images were created. They consist of arbitrary distributed non-overlapping rectangulars with random dimensions [4].

A comparison between the number of iterations for training and the speed of execution during the training phase both as a function of number neurons in the hidden layers, achieving one and the same accuracy, is presented on the Fig. 4. This picture clearly shows the reasons why we considered six to be the satisfactory number (in sense of above defined criteria) of neurons in every one of the hidden layers.

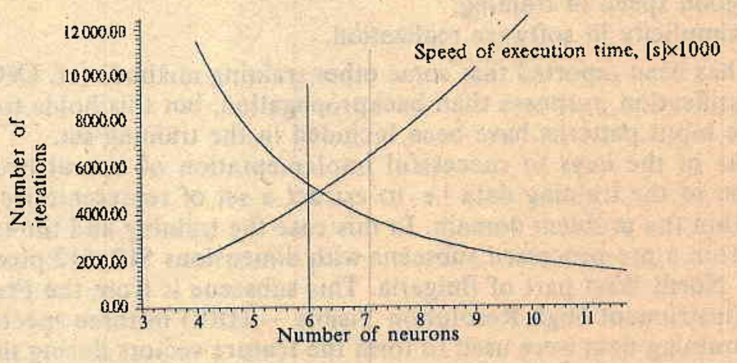

Fig. 4. Selection of the sufficient number of neurons based on iterations needed for training and execution time during training

In Table 1 the results of the performance of the neural network over the test and the real image are presented. In this table also are given the learning parameters used in the training phase.

Table 1. Comparison of the results after classification performed over the test and the real images

Classification results for MLP Training parameters of the network: learning constant=0.5; error=0.9; momentum=0.5			
Number of neurons in the hidden layers	4	6	10
Accuracy in classification for test image (%)	78	88	94
Accuracy in classification for real sub-scene (%)	72	83	88

4. Summary

In this paper have been presented the results from a recently completed project. An attempt has been made to introduce, step by step, the methodology applied to solve a real problem, namely classification, in remote sensing technology.

Acknowledgement. This work has been financially supported by the National Scientific Foundation, Ministry of Education, Science and Technology under grant No My-17/In.

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Received 18.VII.1997

Приложение на невронни мрежи при класификация на многоканални изображения, получени при дистанционни изследвания

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(Резюме)

В настоящата работа са представени резултати, получени при класификация на многоканални изображения от дистанционни изследвания на Земята, използвайки невронни мрежи. Предложена е топологична структура на невронната мрежа (НМ) и е обоснован изборът на метод за обучението ѝ между известни методи за обучение по дефинирани в статията критерии. Описани са също така процедурите за подготовка на множеството обучаващи данни и за избора на началните условия, при които е извършено обучението на НМ. Извършен е сравнителен анализ относно поведението и получаваните върху тестови данни резултати след обучение на НМ при различен брой (от 1 до 8) неврони (обработващи елементи) в скритите слоеве на НМ. Систематизирани са получените след класификация резултати, като в подлежащото на класификация изображение се съдържат по-голям брой класове от тези, включени в обучаващото множество.