THEMATIC CLASSIFICATION OF A LANDSAT IMAGE USING NEURAL NETWORKS

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ABSTRACT:

Since the 60s we know the basic operation of artificial neural networks which are similar to the components of the human brain. The hardware and software necessary for the computation has become adequate just only nowadays.
It was proved in my experiment that the thematic classification by neural networks is possible. In the experiment I made the classification for a LANDSAT TM image with six bands containing Budapest in it by traditional (minimum distance and maximum likelihood) and neural methods. I used 2 and 3 layer neural networks with different number of neurons.
The classification results show that the operation is highly depending on the network structure and training vectors. It's possible to find such a structure which has the accuracy of the traditional methods. Inserting further information the accuracy can be increased.

1. THEORY OF NEURAL NETWORKS

There are many types of neural networks; I used the so-called feedforward and radial basis networks for thematic classification. Neurons build layers at these networks.
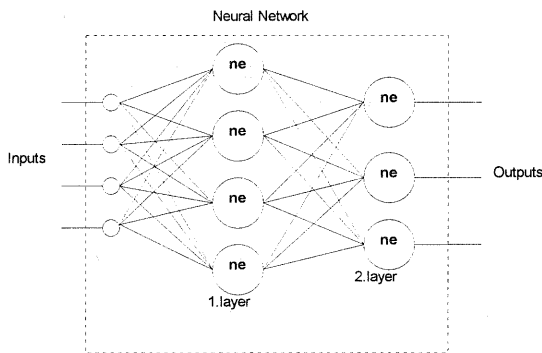

Figure 1. A 2 layer neural network

The operation of the neuron is the following:

1. The incoming signals are multiplied by the corresponding weights and are added.

2. The sum and bias are added.

3. The transfer function gives the neuron answer.

Important requirements of the transfer function to be differentiable relative easily. In the beginnings the logistic sigmoid was used almost exclusively:
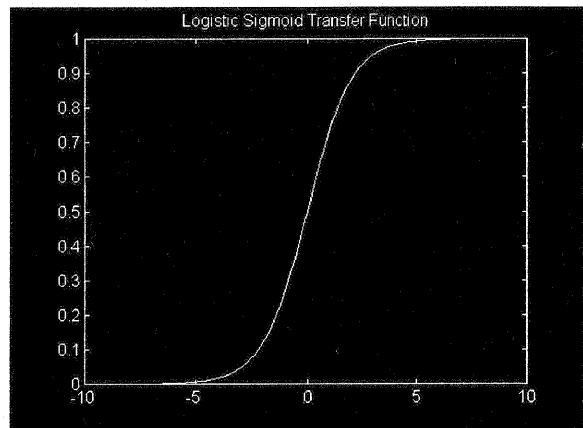

Figure 2. The logistic sigmoid transfer function

Equation of the function:

$$f(x) = \frac{1}{1+e^{-x}}$$

(1)

which has the derivative function:

$$\frac{df(x)}{dx} = f(x)[1-f(x)]$$

(2)

(Rojas, 1993).

Later the line, the tangenthyperbolic function and other curves were used as transfer function. Generally they are symmetric curves giving answers in a given interval (e.g. between 0 and 1, or between -1 and 1 etc.). Lately with the development of new methods a new function appeared, which is similar to the Gaussian curve. This is the so-called radial basis transfer function.
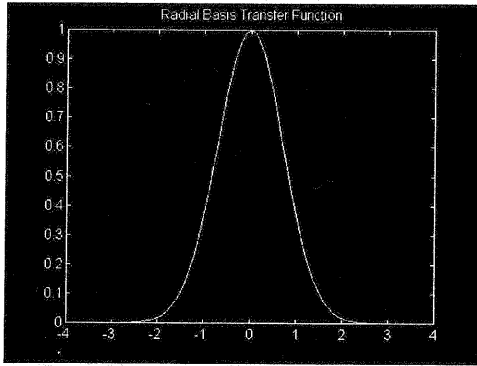
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Figure 3. The radial basis transfer function

Equation of the function:

$$f\left(c,x\right) = e^{-(cx)^2} \qquad (3)$$

The new transfer function and method caused revolutionary changes in the use of neural networks (see 2.3.) *(Demuth, 1995).*

Let's see how the network operates. The computations of a neural network can be solved as vector- and matrix operations. If we have S1 neurons in the first layer, S2 in the second one, and have R inputs, then the output is the following *(Barsi, 1995)*

$$O = \text{logsig}\left(W_2\ \text{logsig}\left(W_1 I + B_1\right) + B_2\right) \qquad (4)$$

where

O	the output vector (S2 × 1)
I	the input vector (R × 1)
W₁	the first weight matrix (S1 × R)
B₁	the first bias vector (S1 × 1)
W₂	the second weight matrix (S2 × S1)
B₂	the second bias vector (S2 × 1)
logsig	logistic sigmoid as transfer function.

For the previously described operation the network parameters (W1, B1, W2, B2) have to be defined. The training vectors contain the inputs and that, what the network should answer. The differences between the computed and the given answers are the errors, which are to be divided on the neurons, and the weights and biases are to be modified in order to decrease these errors. This phase is the backpropagation. The geometric meaning of the method is finding the minimum of the error hypersurface. This optimization could be computed in many steps, but today using the Levenberg-Marquardt method it takes only few epochs:
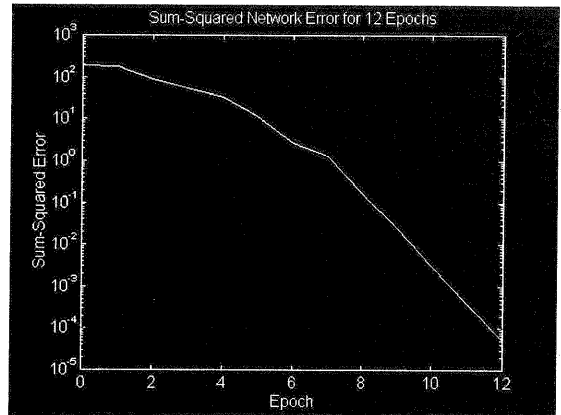

Figure 4. Network error during the training with Levenberg-Marquardt method

At the end of the training we get the weights and biases which we can see in Hinton-diagram:
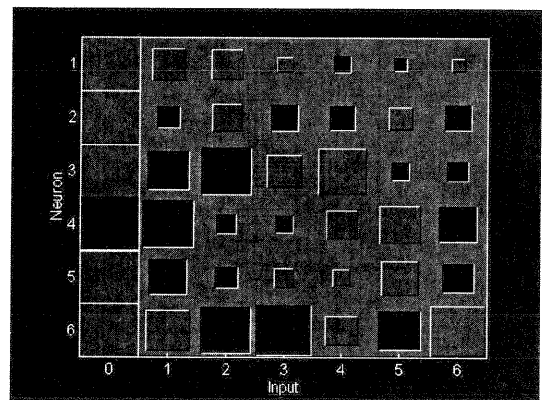

Figure 5. Hinton-diagram of the weights and biases of a layer

2. THEMATIC CLASSIFICATION

2.1. Traditional methods

Thematic map is a map on which we show the different thematics'. Thematics' are water, forest, meadow, street etc. At landuse classification we often use thematic maps.

One of the most efficient way of thematic mapmaking is the process of satellite images.

I used in my experiment six bands of a LANDSAT TM image taken in 1989 (Figure 9.).

I differentiated four thematics' in my research area:

- forest
- meadow
- water
- town.

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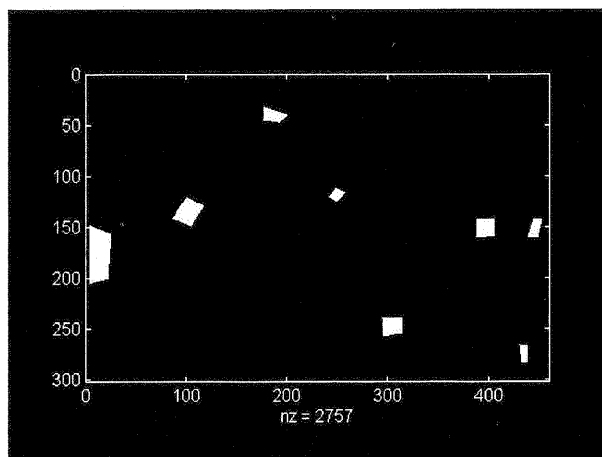The placement of the training area masks is this:

Figure 6. Mask of the training areas

My processing environment was the mathematical software package, MATLAB, developed by Mathworks Inc. I have written all the training area manipulating and classification procedures and the greatest part of the procedures of neural networks are also my products. Later the Neural Network Toolbox from Mathworks Inc. was available for me, so I used its procedures, too.

Let me begin with the minimum distance method. The essence of the method is sorting the pixels after the distance measured from the several classes. A pixel has a distance from the thematics water

$$d_{water} = \sum \left(\mathbf{X} - \overline{\mathbf{X}}_{water} \right) \qquad (5)$$

where

d_{water} distance from the class water

$\mathbf{X}$ intensity vector of the pixel

$\overline{\mathbf{X}}_{water}$ mean vector of the class water.

The maximum likelihood method decides after the highest probability. This method is the nowadays used best traditional method. During the calculation the mean values and covariances of the thematics' are to be considered *(Barsi, 1994)*.

The accuracy of the methods is shown in the comparison of traditional and neural techniques in chapter 3.

2.2. Classification by feedforward neural networks

Firstly the network had 6 neurons in the first layer, 4 in the second layer and the network error (Sum Squared Network Error – SSE) was 0.01 (ne2 model). The training material contained the mean vectors of the thematics'. Because of the bad classification results I analysed the bandwise distribution of the training vectors. The histogram of the class meadow has two peaks in band 5 *(Barsi, 1995)*.
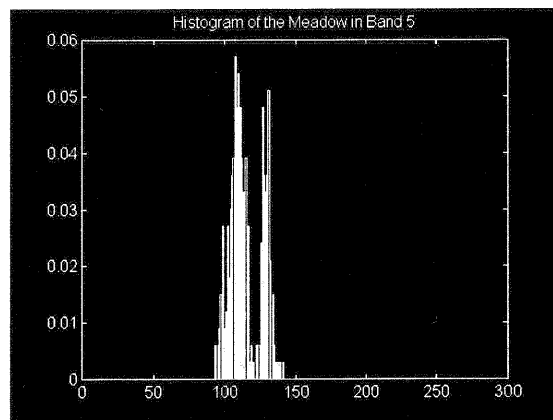

Figure 7. Histogram of the meadow pixels in band 5

The figure shows that the training area wasn't homogenous. If I split the area into two parts and train the network so, I get much less error (ne2_2).

The accuracy can be increased by using three neuron layers. The layers of the model ne3 contain 6, 5 and 4 neurons (SSE = 0.001).

But the increased amount of neurons doesn't cause increased accuracy, e.g. in the model ne3_2 (12, 6, 4 neurons) or in the model ne3_3 (6, 8, 4 neurons).

All the previously mentioned methods were trained by the mean vector of thematics'. Let me see what will happen if I'll use the pixels of the training areas as training vectors!

All training areas have altogether 2757 pixels. I've selected every tenth of them. I've done this selection for two reasons:

1. I can train the networks with the pixels, but the training material isn't so giant.

2. There will be such pixels, about which I know well their belongings, but they haven't taken part in the training. I can use these pixels for controlling the classification.

The model ne4 has 6, 5 and 4 neurons, SSE was 0.0001. This model shows so nice accuracy that I was interesting how does the classification a 2 layer neural network with the same training material. The result was surprising in model ne42 (12, 4 neurons) (Figure 10.) and in model ne43 (24, 4 neurons) (→ chapter 3.). In both cases the sum squared network error was 0.0001.

2.3. Classification by radial basis network

The design of a neural network with radial basis transfer function has a little difference from the customary backpropagation networks. In this case on purpose to get exact learning of the training vectors the algorithm defines also the necessary amount of neurons. My radial basis network had 2 layers, 275 neurons in the first layer with a transfer function like in Figure 3. In the second layer there were 4 linear neurons.

The training of radbas network was accelerated: while a backpropagation network needs 4123 epochs (nearly 21 million floating point operations) to learn the training material, a radial basis network require only 5 epochs (≈ 38000 flops) *(Demuth, 1995)*.

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3. COMPARATIVE ANALYSIS

At first in comparisons I studied how different were the testpixels classified by the different methods. Testpixels are the pixels of the training areas. (Important to know the models till ne3_3 have been trained with the means and covariances calculated from these pixels; afterwards the training material was every tenth pixels of them!)

In tableform the methods and their accuracy is the following (Table 1):

Model	Wrongly classified pixels	Classification accuracy in %
mini	61	2.21
maxi	8	0.29
ne2	244	8.85
ne2_2 *	41	2.56
ne3 *	95	5.93
ne3_2 *	221	13.79
ne3_3 *	115	7.17
ne4	26	0.95
ne42	11	0.40
ne43	11	0.40
ne5	9	0.33

Table 1. Accuracy of the methods (The * signals that the testfield had 1603 pixels, in all other models 2757 pixels.)
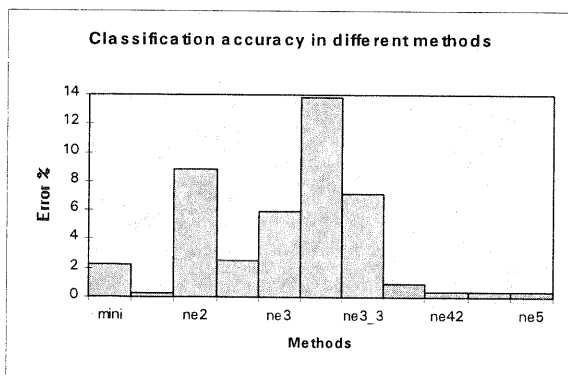

Figure 8. Barchart of the accuracy of the methods

Taken the whole image (301 × 460 pixels) in sight, it's different how the methods the pixels classified (Table 2.).

%	Forest	Water	Meadow	Town
mini	40.98	4.17	13.32	41.53
maxi	26.87	2.74	6.80	63.60
ne2	55.24	10.59	12.88	21.29
ne2_2	27.49	3.31	7.01	62.19
ne3	60.87	7.65	6.26	25.22
ne3_2	29.88	2.82	38.19	29.11
ne3_3	62.99	3.71	4.58	28.72
ne4	39.29	4.56	14.55	41.59
ne42	35.05	3.47	11.47	50.01
ne43	37.12	5.38	11.63	45.87
ne5	37.51	3.21	6.81	52.47

Table 2. Classification results for the whole image

The described experiment was an analysis of a single research area. In the future I would like to test the methods on other areas, too. I'd like to insert further information into the neural networks, so to get more accurate and efficient thematic classification. I want to expand my study on multitemporal images at the end.

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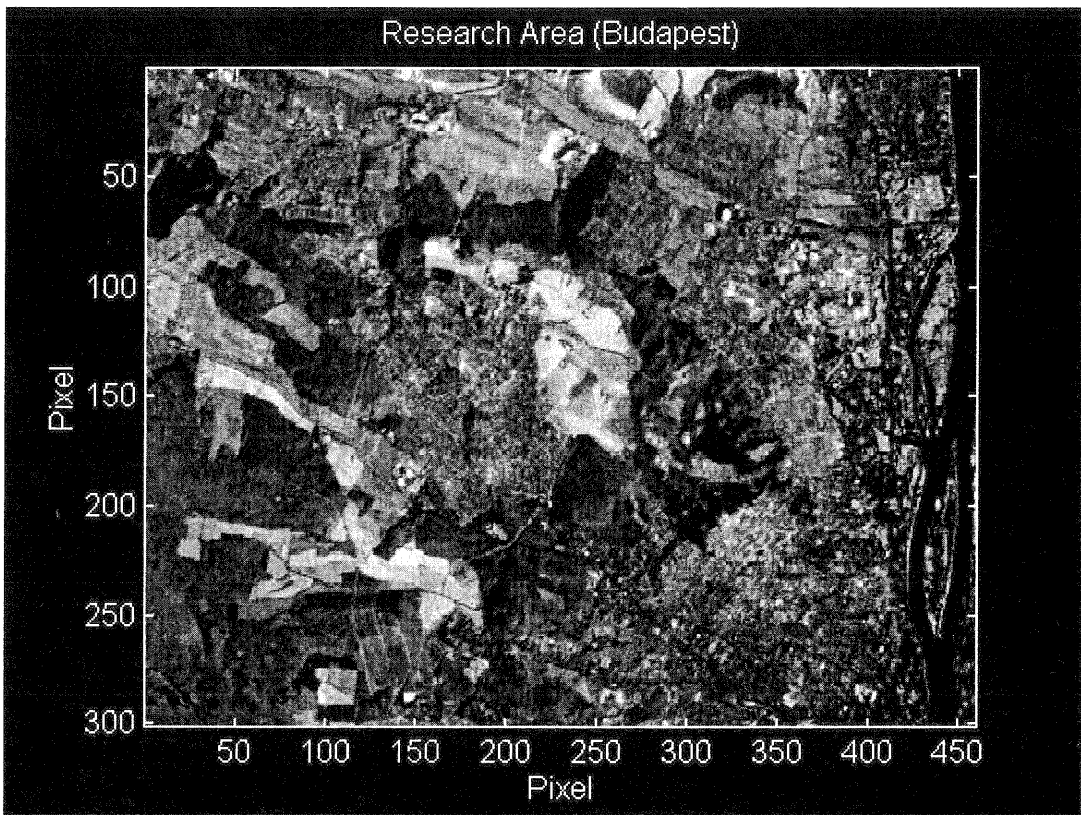Rojas, R. 1993 Theorie der neuronalen Netze Eine systematische Einführung Springer-Verlag, Berlin
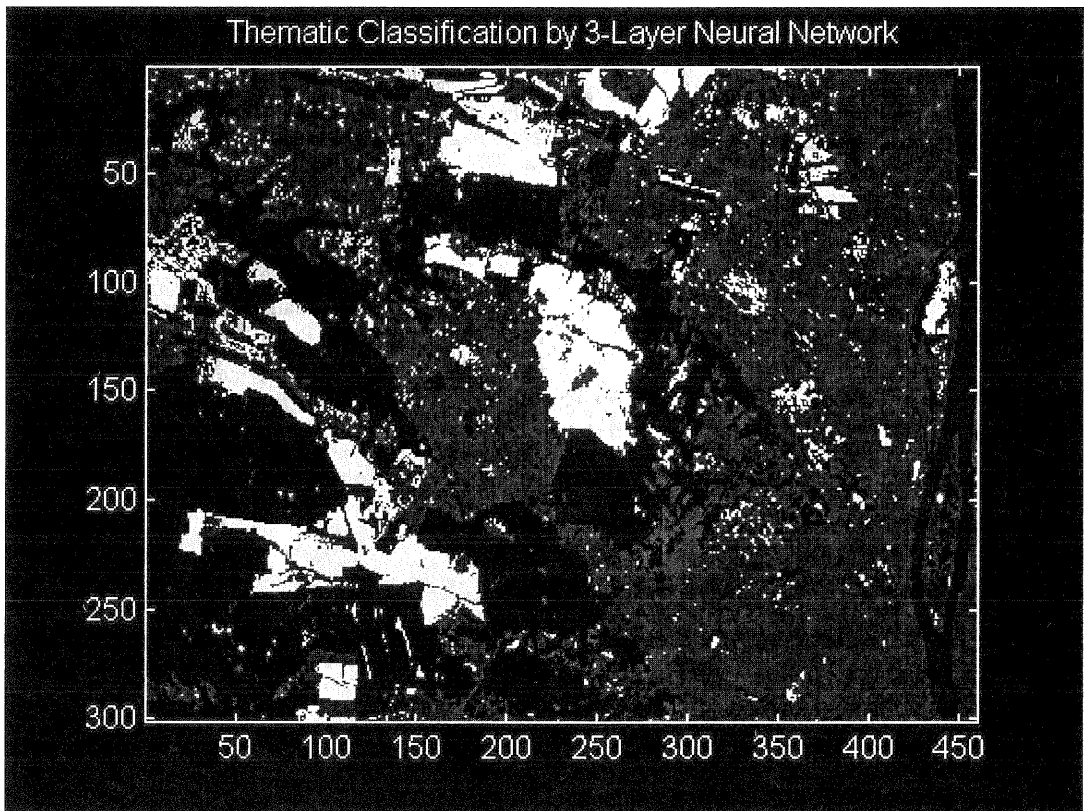
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Figure 9. The research area

Figure 10. Thematic map by 3 layer neural network trained the pixels

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