

COMPARISON OF A BACK PROPAGATION AND A SELF ORGANIZING MAP NEURAL NETWORKS IN CLASSIFICATION OF TM IMAGES

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ABSTRACT

In this paper we report the results of an experimental analysis on the use of two neural models for the thematic classification of multispectral remotely sensed data. A Back Propagation network with two hidden layers and a Self Organizing Map network are used to classify a Landsat Thematic Mapper (TM) image. Firstly, we experimented with a number of the processing elements in the Back Propagation network's hidden layers. Secondly, we compared the classification accuracy of the supervised Back Propagation neural network with the classification accuracy of the unsupervised Self Organizing Map neural network. The first classifier is a little superior to the second one. The biggest drawback to the Back Propagation network is the large learning time when the sample size is large. The experiment has shown that this drawback can be overcome well, by using a Self Organizing Map network instead of a Back Propagation network.

KURZFASSUNG

In dieser Arbeit berichten wir über die Resultate einer experimentellen Analyse in der Anwendung von zwei Neuronalmodellen zur thematischen Klassifizierung von multispektral entfernten Messdaten. Das Back Propagation Netz mit zwei versteckten Trägern und das Self Organizing Netz sind angewandt worden, um den Landsat Thematic Mapper zu klassifizieren. Zuerst experimentierten wir mit einer Anzahl von Umlaufelementen (Bearbeitungselementen) der versteckten Träger im Back Propagation Netz. Wir verglichen die Klassifizierungsexakteheit des unkontrollierten Self Organizing Map Neuronalen Netzes. Der erste Klassifikator ist im Gegensatz zum Zweiten etwas überlegener. Das größte Hindernis des Back Propagation Netzes ist die hohe Lernzeit bei einer umfangreichen Mustergrosse. Das Experiment hat gezeigt, dass dieses Hindernis bewältigt werden kann, in dem man ein Self Organizing Map Netz an Stelle von einem Back Propagation Netz verwendet.

1. INTRODUCTION

The overall objective of image classification procedures is to automatically categorize all pixels in an image into land-cover classes. The classification process includes two types of classification methods: supervised and unsupervised. The supervised classification methods utilize your prior knowledge of material properties and land-cover types in the scene to guide the classification process. The unsupervised classification methods automatically classify raster objects on the basis of statistical grouping of spectral pattern determined with virtually no user intervention. In this paper we examine multispectral classification of Landsat TM images by using the both methods. Our primary objective is to examine a Back Propagation (BP) neural network with two hidden layers. Then, we compare the classification accuracy of the Back Propagation and Self Organizing Map (SOM) classifiers. The Back Propagation supervised net has been successfully applied to land-cover classification of satellite images. Unsupervised neural network has been successfully applied to recognize the patterns (like alphabetic characters), but very few has been applied to remotely sensed image. A short description of two classifiers are shown in Section 2. The data set used for experiments is detailed in Section 3. Results are reported in Section 4. Finally, conclusions are given in Section 5.

2. NEURAL NETWORK CLASSIFIERS

2.1 Back Propagation

A neural network consists of a set of nodes and the connections between them. Usually the nodes are grouped in layers with connections that go from one layer to a later layer. There is an input layer of nodes which are activated by the input image data. The output layer of nodes represents the output classes to train for. In between, there is usually one or more hidden layers of nodes. A node in one layer is connected to all nodes in the next layer. A node in a hidden layer receives input from all nodes in the previous layer. Output values from the hidden layer are distributed to an output layer, which

contains one node for each output class. Each node connection has a weight which multiplies the signal traveling along that connection. The nodes in the hidden and output layer sum the weighted signals they receive and apply a function to produce an output value. During a learning phase, sample spectral patterns are passed through the net in a number of iterations. The second phase in training is a backward pass through the network to reduce the error between the actual and the desired output.

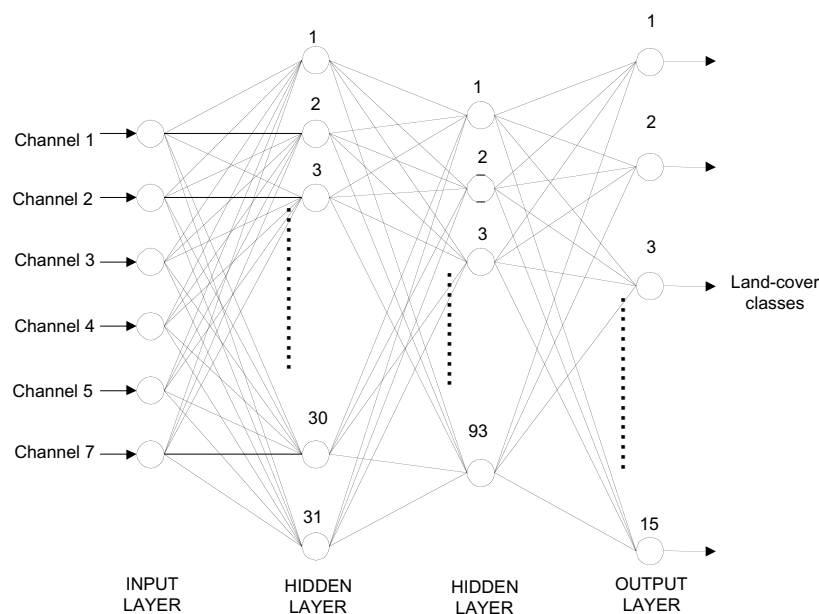


Figure 1. Four-layer Back Propagation neural network.

The neural network used in this study and shown in Figure 1, is designed as a Back Propagation network with two hidden layers. This network learns using the Generalized Delta Rule:

$$Dw_{jk} = hd_k s_j + aDw_{jk} \quad (1)$$

where h = learning rate, a = momentum, d_k = error at the k th layer, s_j is the output of layer j and w_{jk} is the connection weight between the j th and k th layer node.

2.2 Self Organizing Map

Self Organizing Map is an unsupervised classification method based on neural network computing techniques. The neural network used in this study is a three-layer net in which the hidden layer consists of nodes arranged in a two-dimensional matrix. The initial values of connection weights input nodes and hidden layer nodes are set randomly. The set of raster values associated with a single cell in the sample input are fed to each node in the hidden layer, where they are compared to the current set of weights for the node. The node with the closest match to the current values is determined on the basis of minimum Euclidean distance. The winning node and nodes in a surrounding local neighborhood have their weights updated to reduce the error in matching while other nodes remain static. With successive iterations of the sample data, different neighborhoods in the hidden layer are trained to recognize specific classes of input pattern. Connections between the hidden and output layers are modified so that the net produces the same output if any of the nodes in a particular neighborhood is activated. The learning phase continues until the conditions established by the user-defined parameters are met. The trained neural net is then used to classify the entire input image.

The learning algorithm of SOM consists of the following steps:

1. Initialize weights to small random values.
2. Select a training pattern and present it as an input to the network.
3. Compute Euclidean distance to all processing elements.
4. Select neuron j with the smallest distance, and update the weight vectors using following rule:

$$w_j(t+1) = w_j + a(t)(x(t) - w_j(t)), \tag{2}$$

where the learning rate a is smaller than 1.

3. DATA

The study area is situated in an agricultural area in Na_ice County, middle Slavonia, Croatia. One date of Landsat TM data were acquired on August 14, 1993. A 401x401 portion of the image was used for the classification. Six TM channels in the visible and infrared spectrum were selected to form an input vector for each pixel. Familiarity with area allowed for accurate class training and test side identification. Classes used in Back Propagation network training along with the number of pixels used for the training and testing of the classifier are shown in the Table 1.

Class #	Class	# of Train Pixels	# of Test Pixels
1	Water	293	64
2	Forest	233	42
3	New Forest	226	54
4	Old Forest	185	70
5	Arid soil	241	80
6	Maize I	317	108
7	Barley I	179	99
8	Oil rape	244	110
9	Dry vegetation	186	88
10	Stubble field	243	99
11	Wet soil	520	117
12	Wet vegetation	252	54
13	Indiv. parcels	223	70
Total		3342	1055

Table 1. Classes used for classification.

4. EXPERIMENTS

4.1 Experiment 1

In our experiments we tested a standard BP net composed of an input layer, two hidden layers and an output layer. The input layer consisted of six nodes, one for each of the TM nonthermal channels. The output layer consisted of thirteen nodes, corresponding to thirteen land-cover classes. We tested nets with from 2 to 31 nodes in the first hidden layer and from 6 to 93 nodes in the second hidden layer. Percentages of correctly classified pixels for these nets are shown in the Table 2. The best classification accuracy with a BP classifier was achieved using the combination of 7 nodes in the first hidden layer and 33 nodes in the second hidden layer. The next important increase of network performance was not achieved by increasing the number of nodes in both of hidden layers. The result of the classification correlates very well with the available ground truth data but is in some cases more detailed than existing maps.

# of nodes in the first hidden layer	# of nodes in the second hidden layer	Training set of data	Training set of data	Testing set of data	Testing set of data
		Average accuracy	Overall accuracy	Average accuracy	Overall accuracy
2	6	89.15%	89.00%	94.67%	93.85%
3	9	96.92%	96.87%	99.56%	99.53%
7	21	99.25%	99.25%	99.91%	99.91%

11	33	99.34%	99.35%	99.91%	99.91%
15	45	99.26%	99.28%	99.91%	99.91%
19	57	99.29%	99.28%	99.84%	99.81%
23	69	99.20%	99.22%	99.91%	99.91%
27	81	99.37%	99.38%	99.84%	99.81%
31	93	99.36%	99.38%	99.74%	99.72%

Table 2. Percentages of correctly classified pixels by using Back Propagation neural networks.

4.2 Experiment 2

The BP method has been shown to be an efficient and useful algorithm in classification of remotely-sensed data. However, this method has poor convergence rate and depend on parameters which have to be specified by the user. The training time for the BP classifier trained by 367 iterations was 2 hours and 10 minutes. The results of the classifications are shown in Table 3. At the same time, the SOM classifier spent a few minutes to classify the same TM scene. The results of the classification are shown in Table 4. Comparing the classification accuracy of the nets, it is obvious that the first classifier is a little superior to the second one. However, because of its fast convergence during training, and very good classification results, the SOM algorithm used in this study is an appropriate alternative to Back Propagation.

Segment	Name	Code	Pixels	Square meters	% Image
1	Water	10	13096	11786400.00	8.14
2	Forest	20	32489	29240100.00	20.20
3	New Forest	30	12747	11472300.00	7.93
4	Old Forest	40	13680	12312000.00	8.51
5	Arid soil	50	31309	28178100.00	19.47
6	Maize i	60	8974	8076600.00	5.58
7	Barley i	70	7228	6505200.00	4.49
8	Oil rape	80	5763	5186700.00	3.58
9	Dry vegetation	90	10473	9425700.00	6.51
10	Stubble field	100	6398	5758200.00	3.98
11	Wet soil	110	4917	4425300.00	3.06
12	Wet vegetation	120	9321	8388900.00	5.80
13	Indiv. parcels	130	4406	3965400.00	2.74
Total			160801	144720896.00	100.00

Table 3. Back Propagation Classifier

Group	# of Pixels	% Image
1	18250	11.35
2	28141	17.50
3	15067	9.37
4	9005	5.60
5	25117	15.62
6	8523	5.30
7	11096	6.90
8	8795	5.47
9	7719	4.80
10	8522	5.30
11	3538	2.20
12	11014	6.85
13	6014	3.74

Table 4.. Self Organizing classifier.

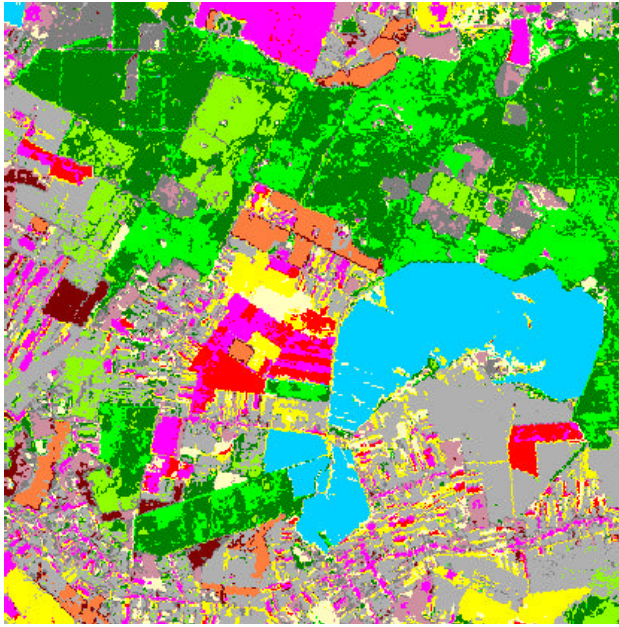


Figure 2. Classification map for the Back Propagation neural network classifier.

The resulting classification map for the Back Propagation classifier is shown in Figure 2. Mathematically, the difference in the overall test data accuracy between the classifiers mentioned above is 18%. It is evident that the BP output is a little accurate than the SOM output.

5. CONCLUSION

In this paper we report the results of an experimental analysis of the use of different neural models for the classification of multispectral remote-sensing images. In particular we consider two neural classifiers: the Back Propagation and the Self Organizing Map. Firstly, we experimented with a number of the processing elements in the Back Propagation network's hidden layers. Secondly, we compared the classification accuracy of the supervised Back Propagation neural network with the classification accuracy of the unsupervised Self Organizing Map neural network. The first classifier is a little superior to the second one. The primary computational difference between the algorithms is speed. The biggest drawback to the Back Propagation network is the large learning time when the sample size is large. The experiment has shown that this drawback can be overcome well, by using a Self Organizing Map network instead of a Back Propagation network. The results indicate that the SOM method can provide a successful discriminate between different spectral classes.

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