A CONCURRENT NEURAL NETWORK MODEL FOR PATTERN RECOGNITION IN MULTISPECTRAL SATELLITE IMAGERY

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ABSTRACT

We investigate multispectral satellite image classification using the neural model previously proposed by first author called Concurrent Self-Organizing Maps (CSOM), representing a winner-takes-all collection of self-organizing neural network modules. For comparison, we evaluate the performances of several statistical classifiers (Bayes, 1-NN, and K-means). The implemented neural versus statistical classifiers are evaluated using a LANDSAT ETM+ image composed by a set of 7-dimensional multispectral pixels, out of which a subset contains labeled pixels, corresponding to eleven thematic categories. The best experimental result leads to the recognition rate of 99.23 %.

KEYWORDS: multispectral satellite image, concurrent self-organizing maps, image classification.

1. INTRODUCTION

Analysis of satellite imagery has wide applications for generation of various kinds of civil or military maps: maps of vegetation, maps of mineral resources of the Earth, land-use maps (buildings, airports, agricultural fields, woods, rivers, lakes, and highways), and so on [1], [2], [3], [4].

Disaster management poses also significant challenges for space data analysis, particularly for multispectral satellite image classification. Geo-information technologies offer a variety of opportunities to aid management and recovery in the aftermath of natural or man-made disasters : earthquakes, tsunamis, fires, floods and similar catastrophes.

Multispectral image classification is one of the important techniques in the quantitative interpretation of remotely-sensed images. Satellite images usually involve multispectral pixels having their characteristics recorded over a number of spectral channels (bands). Such a pixel can be defined as a point in the n-dimensional feature (spectral) space. Multispectral imagery classification involves the grouping of image data into a finite number of discrete classes. Hence, the output from a multispectral image classification system is a thematic map in which each n-dimensional pixel in the original imagery has been classified into one of M classes. The standard approach to satellite image classification uses statistical methods. Conventionally, these statistical techniques widely uses the normal distribution assumption for remote sensing image classification. However, geographical phenomena do not occur randomly in nature and frequently are not displayed in the image data with a normal distribution. So neural networks with data distribution free have been applied instead of statistical methods. The advantages of applying neural networks for classification of satellite imagery are the following:

- neural classifiers do not require initial hypotheses on the data distribution and they are able to learn non-linear and discontinuous input data;
- neural networks can adapt easily to input data containing texture information;

- architecture of neural networks is very flexible, so it can be easily adapted for improving the performances of a particular application;
- the neural classifiers are generally more accurate than the statistical ones.

The Self-Organizing Map (SOM) (also called Kohonen network) is an artificial neural network characterized by the fact that its neighboring neurons develop adaptively into specific detectors of different vector patterns. The neurons become specifically tuned to various classes of patterns through a competitive, unsupervised or self-organizing learning. The spatial location of a neuron in the network (given by its co-ordinates) corresponds to a particular input vector pattern. Starting from the idea to consider the SOM as a cell characterizing a specific class only, Neagoe [4], [5] proposed and evaluated a new neural network recognition model called Concurrent Self-Organizing Maps (CSOM), representing a collection of SOM modules, using a global competition strategy. We further evaluate the application of CSOM for multispectral pixel classification on benchmark dataset grss_dfc_0009 Landsat 7 Enhanced Thematic Mapper Plus (ETM+), using n=7 spectral bands and M=11 land categories. For comparison, several statistical classification algorithms are considered: Bayes (assuming normal distribution for each category), 1-NN, and K-means.

2. CONCURRENT SELF-ORGANIZING MAPS FOR PATTERN CLASSIFICATION

Concurrent Self-Organizing Maps (CSOM) are a collection of SOM modules, which use a global *winner-takes-all* strategy [4], [5]. Each neural module (SOM) is used to correctly classify the patterns of one class only and the number of modules equals the number of classes. The CSOM *training* technique is a supervised one, but for any individual net the SOM specific *training* algorithm is used. We built "M" training patterns sets and we used the SOM training algorithm independently for each of the "M" SOMs. The CSOM model for *training* is shown in Fig. 1.

For the recognition, the test pattern has been applied in parallel to every previously trained SOM. The neural module providing the minimum distance neuron is decided to be the winner and its index becomes the class index that the pattern belongs to (see Fig. 2).

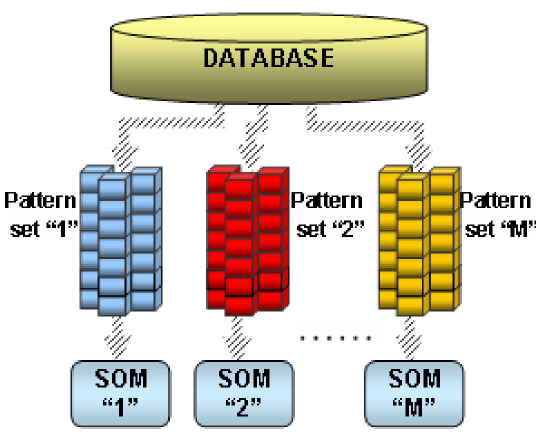


Figure 1. The CSOM model (training phase).

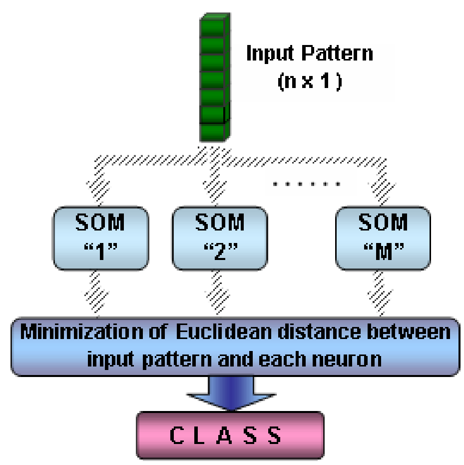


Figure 2. The CSOM model (classification phase).

3. CSOM CLASSIFIER OF MULTISPECTRAL LANDSAT IMAGERY

3.1 Satellite Image Database: Landsat 7 ETM+ Data Set Over Flevoland (Netherlands)

The CSOM classifier is applied to benchmark dataset grss_dfc_0009, obtained from the IEEE GRSS Data Fusion reference database [6]. The grss_dfc_0009 dataset consists of samples acquired by Landsat-7 Enhanced Thematic Mapper Plus (ETM+) with M=11 land-cover categories in Flevoland, Netherlands (Latitude = 52 21.8 N, Longitude=005 25.0 E). The numbers of training data as well as of test data are n_1=2891 and n_2=2890, respectively (Fig. 4.h); the dataset is a square region of size 512 x 512 multispectral pixels.

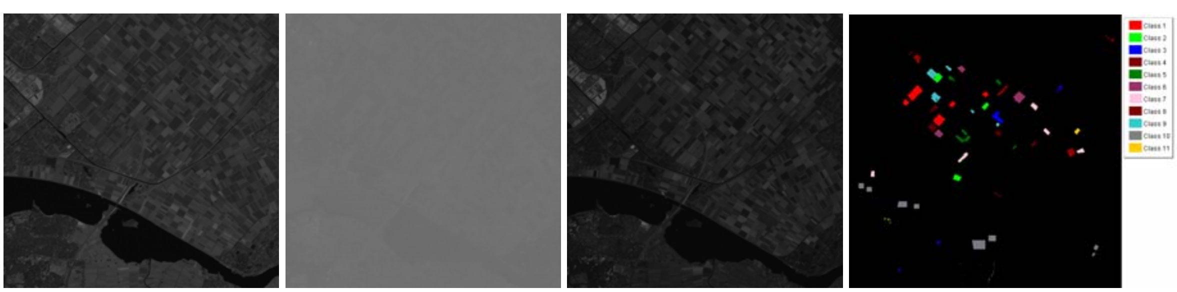
Landsat 7 carries the Enhanced Thematic Mapper Plus (ETM+) instrument - a nadir-viewing, multispectral scanning radiometer, and provides image data for the Earth's surface. The bands are for the visible and near infrared (VNIR), the mid-infrared (Mid IR), and the thermal infrared (TIR) regions of the electromagnetic spectrum, as well as the panchromatic region. Table 1 lists the ETM+ bands, spectral ranges, and nominal ground resolution and Fig. 4 (a-g) shows the seven bands. The considered multispectral image is shown in Fig. 3 with 3 bands (Red=B5, Green=B4, Blue=B3).

Band Number	**Spectral Range (μm)**	**Ground Resolution (m)**
TM1 (Vis. Blue)	0.450	30
TM2 (Vis. Green)	0.525	30
TM3 (Vis. Red)	0.630	30
TM4 (NIR)	0.750	30
TM5 (Mid IR)	1.550	30
TM6 (TIR)	10.40	60
TM7 (Mid IR)	2.090	30
TM8 (Pan)	0.520	15

Table 1. Landsat 7 ETM+ bands, spectral ranges, and ground resolutions.

Figure 3. ETM+ image (grss_dfc_0009) displayed with 3 bands (Red=B5, Green=B4, Blue=B3).

(a) B1 (b) B2 (c) B3 (d) B4



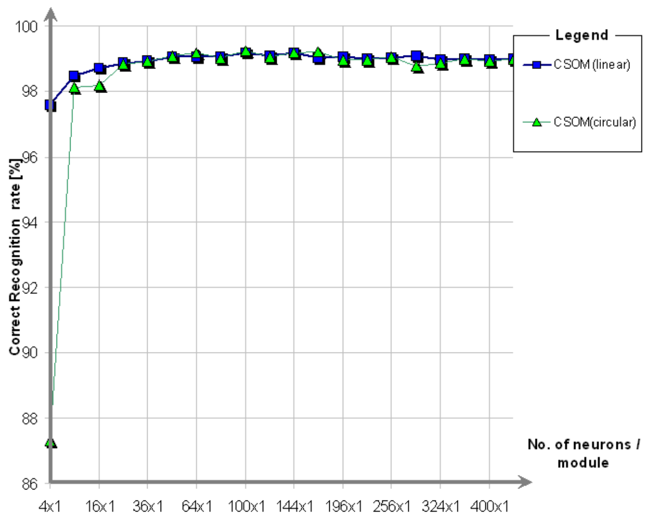
(e) B5 (f) B6 (g) B7 (h)

Figure 4. (a-g) The 7 bands of Landsat ETM+ image (grss_dfc_0009 [6]). (h) The 11 class labeled multispectral pixels of the training and test subsets (Landsat 7 image courtesy ESA 1999 - distribution Eurimage).

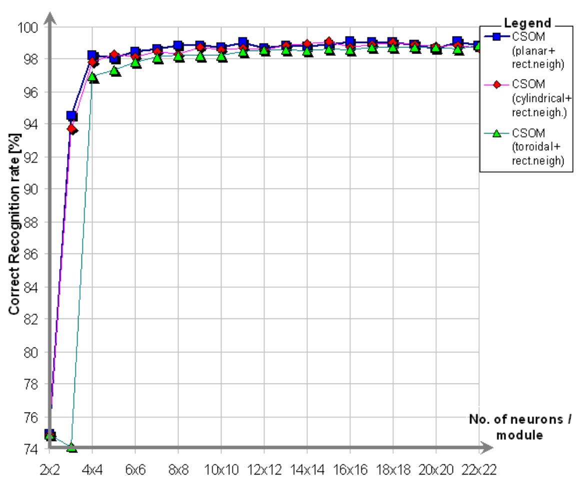
3.2 Experimental Results of CSOM Satellite Image Classification

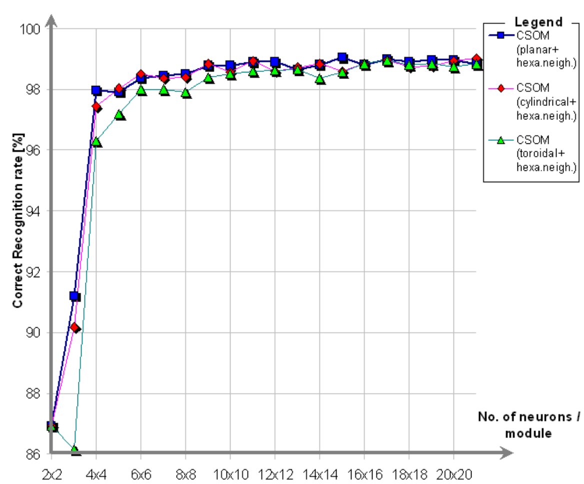
Each multispectral pixel (7 bands) is characterized by a corresponding 7-dimensional vector containing the pixel projections in each band. These vectors are applied to the input of the neural/statistical classifier. We have tested the following classifiers: CSOM, Bayes (by assuming the eleven classes have normal distribution), 1-NN (Nearest Neighbor), and K-means.

The results of simulation (corresponding recognition score for the test lot) are given in Figs. 5 and 6, as well as in Table 2. The CSOM classified multispectral image (11 classes) is given in Fig. 7. We have considered both the cases of 1D architecture of the SOM modules (linear and circular) and also those of 2D architecture (planar, cylindrical, and toroidal). For each of the above variants we have tested the rectangular and hexagonal neighborhoods.



(a)





(b) (c)

Figure 5. Pixel recognition rate on the test lot as a function of the number of neurons / module. (a) 1D architecture (linear and circular); (b) 2D architecture; rectangular neighborhood (planar, cylindrical, and toroidal); (c) 2D architecture; hexagonal neighborhood (planar, cylindrical, and toroidal).

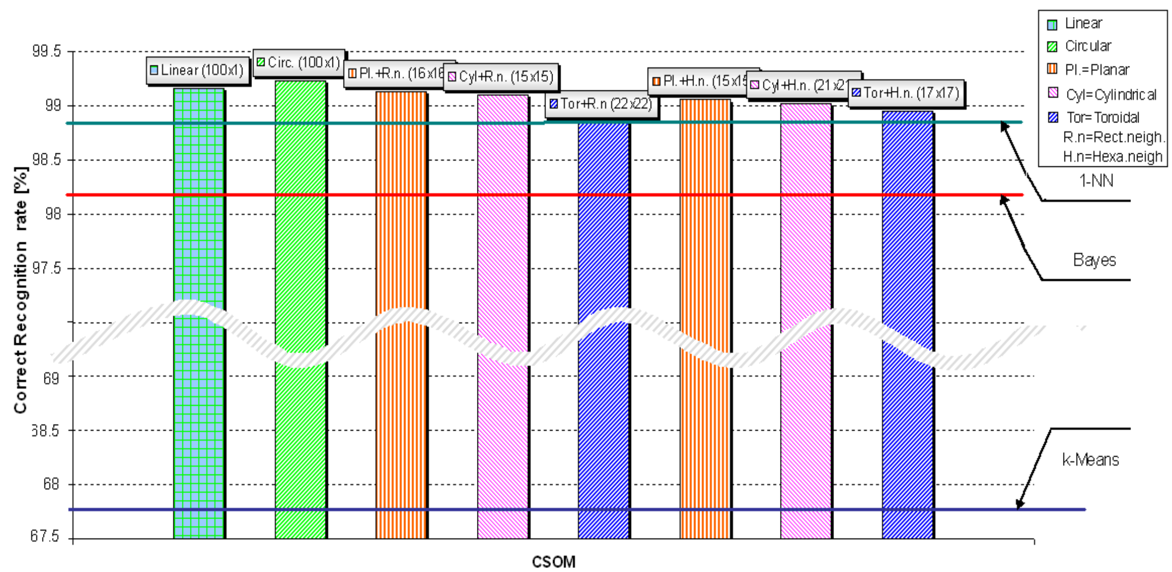


Figure 6. Comparison of the best variants.

Classifier	Architecture	No. of neurons /module	Best classification score
1D CSOM	Linear	100x1	99.16
	Circular	**100x1**	**99.23**
2D CSOM	Planar+ Rect.neigh.	16x16	99.12
	Cylindrical+ Rect.neigh.	15x15	99.09
	Toroidal+ Rect.neigh.	22x22	98.84
	Planar+ Hexa.neigh.	15x15	99.05
	Cylindrical+ Hexa.neigh.	21x21	99.02
	Toroidal+ Hexa.neigh.	17x17	98.95
K-means	67.99		
1-NN	98.95		
Bayes	98.25		

Table 2. Comparison of the best pixel classification scores obtained by CSOM, K-means, 1-NN and Bayes classifiers. (Rect. = rectangular, Hexa. = hexagonal, neigh. = neighborhood)

Figure 7. Classified multispectral pixels (11 categories) using a circular CSOM architecture with 100 x 1 neurons (recognition rate 99.26 %).

We can evaluate the very good recognition score of multispectral satellite image classification for all the experimented classifiers, both neural (CSOM) ones and also statistical (Bayes, 1-NN and K-means). One can remark that the CSOM model leads to better results than statistical techniques for all the considered variants.

The best result (a multispectral pixel classification rate of 99.23% for the test lot) is obtained by using a CSOM model containing 11 circular SOM modules with 100 neurons each of them.

4. ACKNOWLEDGEMENTS

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5. REFERENCES

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