CONCURRENT NEURAL CLASSIFIERS 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 the 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 7 ETM+ image. One takes in considerations both the interband and intraband pixel correlation using a 63-dimensional representation of the 7-band pixels. There is a subset containing labeled pixels, corresponding to seven thematic categories. The best experimental result leads to the recognition rate of 99.11%.

Key-Words: multispectral satellite imagery, 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 use 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. Neural networks learn whatever distribution present in the training data; consequently, they can be successfully 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 Landsat 7 Enhanced Thematic Mapper Plus (ETM+), using \( n = 7 \) spectral bands and \( M = 7 \) 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 (CSOM)

2.1 CSOM for Training and 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 pattern 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).

2.2 Example

We have built the two class dataset “Palm” shown in Fig. 3; the training set contains 36 vectors (18 vectors for each class); the test set has the same number of vectors as the training lot. We have tested a CSOM with \( M = 2 \) modules having a circular architecture using the above dataset “Palm”: \( N(1) = N(2) = 18 \) training vectors / class.

One can remark the very good interpolation capacity of the CSOM (see Fig. 4, circular with \( J(1) = J(2) = 25 \) neurons / module). For the “Palm” dataset, from Fig. 5 one deduces that the correct recognition rate obtained by CSOM model (91.67%, for two circular neural modules with the total number of neurons = 50) is better than SOM (77.77%) and far
better than the other non-neural (statistical) considered classifiers: quadratic Bayes (69.44%), k-Means (55.56%), Nearest Neighbor (1NN, 66.67%).

3 CSOM Classifier of Multispectral Landsat Imagery

3.1 Satellite Image Database: Landsat 7 ETM+ Data Set over Kosice (Slovakia)

The data for this study consists of a Landsat Thematic Mapper (TM) image of the city of Kosice (located in Eastern Slovakia) and its environs. The whole image consists of 368,125 7-dimensional pixels, out of which 6,331 pixels were classified by an expert into seven thematic categories. Fig. 6 shows the original image along with the seven categories identified by expert. The following classes are defined in the figure: A – urban area, B – barren fields, C – bushes, D – agricultural fields, E – meadows, F – woods, G – water.

The considered multispectral image is shown in Fig. 7 with 3 bands (Red=B5, Green=B4, Blue=B3).

3.2 Multispectral Pixel Representation

To classify the multispectral pixels (M=7 bands), one chooses one of the following two models.

A. Representation of the M-band pixel as an M-dimensional vector (1 multispectral pixel)

Each multispectral pixel (with M=7 bands) is characterized by the corresponding M-dimensional vector containing the pixel projections in each band (see Fig. 8).

B. Representation of the M-band pixel as a 9M-dimensional vector (using 9 multispectral neighbor pixels).

One proposes to use both the interband and the intraband correlation by representing the M-band pixel by the corresponding hyper rectangle centered in the current multispectral pixel (see Fig. 9). This hyper rectangle has
a square base of 3x3 and a height of M, corresponding to the 9M-dimensional vector representation. (For our case, 9M=63).

Fig. 8. Representation of the M-band pixel by the M-dimensional vector containing pixel spectral signatures (M=7).

Fig. 9. Representation of the M-band pixel by the corresponding 9M-dimensional vector corresponding to the 3x3xM hyper rectangle centered in the current pixel (9M=63).

3.3 Experimental Results of CSOM Satellite Image Classification

Each multispectral pixel (M=7 bands) is characterized either by a corresponding 7-dimensional vector or by a 63-dimensional vector according to the models shown in Figs. 8 and 9. Such a vector is applied to the input of the neural/statistical classifier. We have tested the following classifiers: CSOM, Bayes (by assuming the seven classes have normal distribution), 1-NN (Nearest Neighbor), and K-means. In the figures given below we denoted by 7D the case of 7-dimensional pixel representation and by 63D the case of 63-dimensional representation.

Figure 10. 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).

The results of simulation (corresponding recognition score for the test lot) are given in Figs. 10-11, as well as in Tables 1 and 2. The CSOM classified multispectral image (7 classes) is given in Figs. 12 and 13, for each of the multispectral pixel representation considered here: 7D and 63D models. 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.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Architecture</th>
<th>No. Neurons / module</th>
<th>Correct recognition rate [%] (7D representation)</th>
<th>Correct recognition rate [%] (63D representation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSOM 1D</td>
<td>Linear</td>
<td>100x1</td>
<td>95.22</td>
<td>98.64</td>
</tr>
<tr>
<td></td>
<td>Circular</td>
<td>100x1</td>
<td>94.40</td>
<td>98.38</td>
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<tr>
<td>CSOM 2D</td>
<td>Planar+Rect.neigh.</td>
<td>10x10</td>
<td>95.00</td>
<td>98.41</td>
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<td>Cylindrical+Rect.neigh.</td>
<td>10x10</td>
<td>94.75</td>
<td>98.38</td>
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<td>Toroidal+Rect.neigh.</td>
<td>10x10</td>
<td>94.31</td>
<td>98.10</td>
</tr>
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<td></td>
<td>Planar+Hexa.neigh.</td>
<td>10x10</td>
<td>94.81</td>
<td>98.48</td>
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<td>10x10</td>
<td>94.50</td>
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<td>Toroidal+Hexa.neigh.</td>
<td>10x10</td>
<td>94.24</td>
<td>98.13</td>
</tr>
<tr>
<td>k-Means</td>
<td></td>
<td>100x1</td>
<td>90.20</td>
<td>94.78</td>
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<tr>
<td>l-NN</td>
<td></td>
<td>100x1</td>
<td>95.60</td>
<td>98.07</td>
</tr>
<tr>
<td>Bayes</td>
<td></td>
<td>100x1</td>
<td>95.32</td>
<td>94.84</td>
</tr>
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</table>

Table 1. Correct recognition rate [%] for 100 neurons/module.

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Architecture</th>
<th>No. Neurons / module</th>
<th>Correct recognition rate [%] (7D representation)</th>
<th>Correct recognition rate [%] (63D representation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSOM 1D</td>
<td>Linear</td>
<td>361x1</td>
<td>95.44</td>
<td>169x1</td>
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<tr>
<td></td>
<td>Circular</td>
<td>625x1</td>
<td>95.57</td>
<td>484x1</td>
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<td>CSOM 2D</td>
<td>Planar+Rect.neigh.</td>
<td>19x19</td>
<td>95.51</td>
<td>24x24</td>
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<td></td>
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<td>19x19</td>
<td>95.89</td>
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<td>24x24</td>
<td>96.04</td>
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<td></td>
<td>100x1</td>
<td>95.32</td>
<td>94.84</td>
</tr>
</tbody>
</table>

Table 2. Best Recognition Rate [%] for CSOM modules with various architecture.

Figure 11. Best recognition rate [%] (Representation of the results given in Table 2).
Figure 12. Classified multispectral pixels (7 categories) using 7D multispectral pixel representation and CSOM with 7 toroidal modules of 24 x 24 neurons (recognition rate 96.04 %).

Figure 13. Classified multispectral pixels (7 categories) using 63D multispectral pixel representation and CSOM with 7 toroidal modules of 24 x 24 neurons (recognition rate 99.11 %).

4 Concluding Remarks

• By considering the training and the test sets of the multispectral image Landsat-7 (ETM+), with labeled pixels, we have evaluated the high accuracy score of multispectral satellite image classification for all the experimented classifiers, both neural ones [based on the model of Concurrent Self-Organizing Map (CSOM)] and also statistical ones [Bayes, nearest neighbor (1-NN) and nearest prototype (K-means)]. Since the multispectral image has M=7 land-cover categories, the number of CSOM modules is equal to 7.
• We have considered several CSOM variants, with different architectures and neighborhoods. For each case, we have retained the neural module size with the best performance and then we have compared the best solutions.
• One can remark that the CSOM model leads to better results than statistical techniques for almost all of the considered variants.
• One can also remark the significant advantage of the new extended 63-dimensional representation of the multispectral pixel over its conventional 7-dimensional representation.
• The best result (a multispectral pixel classification rate of 99.11% for the test lot) is obtained by using the 63-dimensional pixel representation followed by a 2D CSOM model containing 7 toroidal SOM modules with 24x24 neurons each and rectangular neighborhood.
• By comparison, the same concurrent neural classifier leads to the pixel recognition rate of only 96.04 % by using the classical 7-dimensional pixel representation.
• The classification performance does not depend significantly on the architecture of the neural modules.

References: