# SELF-ORGANIZING MAP FOR CLUSTERING OF REMOTE SENSING IMAGERY

Radu-Mihai STOICA[1], Victor-Emil NEAGOE[2]

*We present a neural unsupervised pattern recognition approach for two applications related to significant topics of Earth Observation (EO) imagery: (a) EO image region classification; (b) multispectral pixel classification. The proposed model is based on the Self-Organizing Map (SOM) clustering, which is compared to two benchmark unsupervised classifiers: k-means and fuzzy c-means. We propose to apply the Davies-Bouldin index for cluster separation measure. The best classification scores are obtained by the proposed SOM approach for both applications. The experimental results prove the efficiency of the Davies-Bouldin measure to automatically detect the number of clusters in an unclassified dataset.*

**Keywords**: Unsupervised pattern recognition, Earth Observation (EO) imagery, multispectral pixel clustering, Self-Organizing Map (SOM), cluster separation measure

## 1. Introduction

In recent years, the analysis and classification of satellite/aerial images has become an important area of research in the field of image processing. Two of the most common classification problems found in this area are the classification of Earth Observation (EO) images [21] and the classification of multispectral pixels [16]. While in the past, these tasks have been done manually by technicians, as the number of available images has increased this approach has become unfeasible. Numerous automatic classification algorithms have been proposed [4], [13], [14], [15], [16], [17], [18]. Such algorithms can be applied either at the pixel level (each pixel is classified individually) or at the patch/region/image segment level, by splitting the image in pixel regions, then by extracting representative features from each region and finally by classifying them based on these features.

A category of these algorithms is that of unsupervised algorithms [1], [2], [5], [12], [19], [20]. A pattern recognition algorithm is considered to be unsupervised if the classification is done based on the intrinsic traits of the classified dataset, without using a labeled training dataset. In general, such

[1] PhD. student, Depart. of Applied Electronics and Information Engineering, University POLITEHNICA of Bucharest, Bucharest, Romania, e-mail: radumstoica@gmail.com
[2] Prof., Depart. of Applied Electronics and Information Engineering, University POLITEHNICA of Bucharest, Bucharest, Romania, e-mail: victor.neagoe@upb.ro

algorithms are used for three categories of applications [10] :

- Discovering the underlying structure of the dataset: for example, to generate hypotheses or detect anomalies
- Natural classification: to identify degrees of similarity among forms
- Compression: summarizing the data using cluster prototypes

The biggest advantage of unsupervised methods is the fact that they do not require a pre-labeled training set. In this way, the degree of automation is increased and the inadvertent errors, caused by human intervention, can be avoided.

A particular class of models that have emerged as a solution for the classification of satellite images is that of Artificial Neural Networks [3], [6], [14], [16]. ANNs have several advantages over classical statistical algorithms, such as the fact that they can be used as universal functional approximations and they do not require initial hypotheses regarding the data distribution.

This paper investigates the application of SOM (Kohonen) neural network as an unsupervised classifier for EO image region classification as well as for multispectral pixel classification. The SOM has been first described by T. Kohonen [11] and it has been inspired by the human sensorial system. Our experimental results for EO clustering obtained by SOM classifier are compared with two benchmark unsupervised classifiers: k-means and fuzzy c-means.

For the classification of EO image regions according to predefined categories, we have used a set of images extracted from the UCMerced dataset [21], split into four classes: agricultural, chaparral, buildings and forests.

A second application for which we have investigated the proposed model is the classification of multispectral pixels from satellite images. We propose to apply SOM unsupervised classifier at pixel level, for the analysis of multispectral LANDSAT images. The database used for testing has been acquired in the Kosice region (Slovakia) by a LANDSAT 7 ETM+ satellite and contains 7 spectral bands.

Section 2 presents the proposed clustering model, based on SOM, and the reference classifiers k-means and fuzzy c-means. Also, the Davies-Bouldin index for the partition evaluation is considered. Section 3 discusses the experimental results and section 4 presents the concluding remarks.

## 2. Clustering Model

### 2.1. Proposed Clustering Algorithm

The proposed unsupervised classification model has the following steps:

1. Feature selection (optional)
2. Clustering, using the SOM network or one of the benchmark classifiers

3. Apply the Davies-Bouldin index to the partitions obtained in the previous step and select the best partition
4. Evaluate the classification score for each algorithm, based on the partition obtained at step 3.

Based on the above model, we have evaluated the performances of the SOM neural classifier, which has been then compared with those obtained by k-means and fuzzy c-means algorithms. A problem specific to the unsupervised classification is the automatic detection of the number of clusters. For this, we have used the Davies-Bouldin index [7].

Figures 1 and 2 show the proposed model in the two considered versions: image region clustering and multispectral pixel clustering.

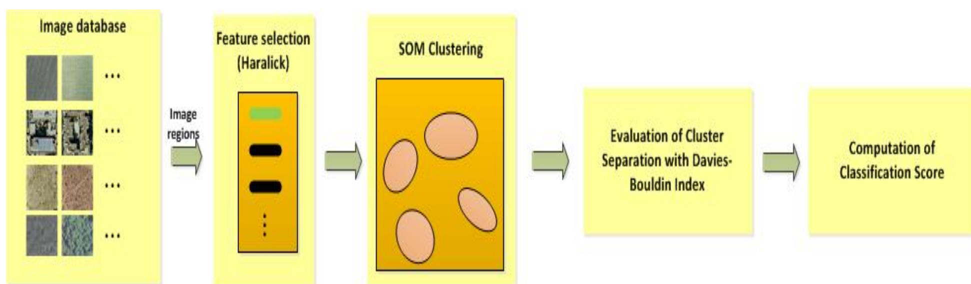


Fig. 1. Proposed model for EO image region clustering

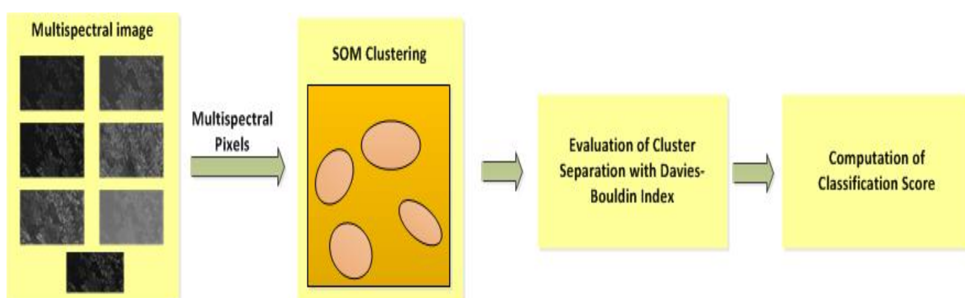


Fig. 2. Proposed model for multispectral pixel clustering

## 2.2 Self Organizing Map (SOM)

The Self-Organizing Map (SOM) is an exciting unsupervised neural network, proposed by Kohonen [11] inspired by the human sensory system. The SOM network creates a mapping of the input vector space onto a one or two-dimensional grid of neurons. Each neuron is described by a weight vector, having the same dimensions as the input space. When an input vector is applied to the SOM input, it is compared to each of the weight vectors and the best match is selected as the response. A competitive, unsupervised algorithm is used for training of the network.

We have used the following algorithm to apply a SOM network with *M* neurons for clustering in *C* classes:

1. Each SOM neuron is initially considered as centroid for a cluster. Each data vector *V* is assigned to the cluster with the nearest centroid
2. Only the clusters containing at least one element are kept
3. The distances between the centroids of the classes are computed
4. The classes which have the closest centroids are fused and the value of the new centroid is computed as

$$\boldsymbol{v} = \frac{\boldsymbol{v_1} + \boldsymbol{v_2}}{2} \qquad (1)$$

   The new class will contain the vectors from both original classes.
5. If the number of remaining clusters is greater than *C*, the algorithm is repeated from step 3.

## 2.3 Benchmark Classifiers

### 2.3.1 K-means algorithm

The well-known K-means algorithm attempts to minimize the cost function

$$J = \sum_{j=1}^{K} J_j = \sum_{j=1}^{K} \sum_{X_i \in \omega_j} \| X_i - \mu_j \|^2 \qquad (2)$$

where $X_i$ is the *i*-th vector from the dataset and $\mu_j$ is the centroid of cluster *j*, calculated with the formula

$$\mu_k = \frac{1}{|S_k|} \sum_{X_i \in S_k} X_i \qquad (3)$$

where *K* is the number of clusters.

### 2.3.2 Fuzzy C-Means algorithm

Hard clustering algorithms, such as k-means, assign exactly one cluster to each data point. In fuzzy clustering, membership grades are associated to each data vector, indicating the degree to which the data vector belongs to different clusters.

One such algorithm is Fuzzy C-Means, also known as Fuzzy ISODATA. In this case, the cost function that is minimized has the following formula [8]:

$$J(U,V) = \sum_{i=1}^{N}\sum_{j=1}^{C}(u_{ij})^m \left\|X_i - V_j\right\|^2 \qquad (4)$$

where:
$X_i$ is the ***i***-th vector from the dataset
$V_j$ is the centroid of cluster *j:*

$$V_j = \frac{\sum_{i=1}^{N}(u_{ij})^m X_i}{\sum_{i=1}^{N}(u_{ij})^m} \qquad (5)$$

$u_{ij}$ is the membership degree of vector $X_i$ to cluster *j*, calculated with the formula:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}},\ d_{ij} = \left\|X_i - V_j\right\| \qquad (6)$$

*m* is the fuzziness index; there is no theoretical basis for the selection of *m;* the value of 2.0 is usually chosen.

### 2.4 Cluster Separation Measure with Davies-Bouldin Index

Because the number of classes is considered unknown before applying the clustering algorithms, one needs a metric to determine the optimum partition obtained. We have used the Davies-Bouldin index [7] to evaluate the clustering algorithms that have been tested.

The Davies-Bouldin index uses two metrics, one to measure the within cluster scatter and one for the separation between clusters:

$$S_i = \sqrt{\frac{1}{N_i}\sum_{j=1}^{N_i}\left|X_j - A_i\right|^q} \qquad (7)$$

where:

- $A_i$ is the centroid of cluster $C_i$
- $N_i$ is the number of vectors in cluster *i*
- $X_j$ is a vector from cluster *i*
- *q* is a parameter, usually chosen as 2.0, so that the formula becomes the Euclidean distance

$$M_{i,j} = \|A_i - A_j\| = \sqrt{\sum_{k=1}^{n} |a_{k,i} - a_{k,j}|^2} \qquad (8)$$

where $A_i$ is the centroid of cluster $i$.

Based on this, the following metrics are defined:

$$R_{i,j} = \frac{S_i + S_j}{M_{i,j}} \qquad (9)$$

And

$$D_i = \max_{j,i \neq j} R_{i,j} \qquad (10)$$

Lower values of $D_i$ indicate a better clustering. The Davies-Bouldin index is defined as

$$DB = \frac{1}{N} \sum_{i=1}^{N} D_i \qquad (11)$$

The clustering with the lowest value is considered the best. However, this index does not necesarily indicate the clustering with the best information retrieval.

### 2.5 Feature Selection for EO Image Classification

For applying the SOM to the problem of EO image unsupervised classification, an important step is feature selection. We have used the Haralick textural descriptors [9], which are applied as follows.

For an image with $N$ different color levels, one considers $p(i,j)$ the normalized color co-occurrence matrix for the given image and $p_x(i)$ the marginal probability matrix obtained by summing the rows of $p(i,j)$.

The following formulas are used to extract the features from each image. The descriptors are applied independently for each color channel and the results are concatenated.

1. Angular Second Moment

$$f_1 = \sum_i \sum_j \{p(i,j)\}^2 \qquad (12)$$

2. Contrast

$$f_2 = \sum_{n=0}^{N-1} n^2 \left\{ \sum_{i=1}^{N} \sum_{j=1, |i-j|=n}^{N} p(i,j) \right\} \qquad (13)$$

3. Sum of Squares

$$f_3 = \sum_i \sum_j (i-\mu)^2 p(i,j) \qquad (14)$$

4. Inverse Difference Moment

$$f_4 = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \qquad (15)$$

5. Sum Average

$$f_5 = \sum_{i=1}^{2N} i p_{x+y}(i) \qquad (16)$$

6. Sum Variance

$$f_6 = \sum_{i=2}^{2N} (i-f_7)^2 p_{x+y}(i) \qquad (17)$$

7. Sum Entropy

$$f_7 = -\sum_{i=2}^{2N} p_{x+y}(i) \log\{p_{x+y}(i)\} \qquad (18)$$

8. Entropy

$$f_8 = -\sum_i \sum_j p(i,j) \log\{p(i,j)\} \qquad (19)$$

9. Difference Entropy

$$f_9 = -\sum_{i=0}^{N-1} p_{x-y}(i) \log\{p_{x-y}(i)\} \qquad (20)$$

## 3. Experimental Results

### 3.1 Databases

#### 3.1.1 UCMerced dataset for EO image patch clustering

We have tested the proposed model for EO image region unsupervised classification using a set of images selected from the UCMerced Dataset [21]. We have used four images classes: forest, chaparral, agricultural and buildings (Fig. 3). Each class contains 80 images with the dimensions of 256x256 pixels, and the resolution of these images is 3.5 meters/pixel. The selected images contain a large variety of spatial patterns, which makes them suitable for the experiments.

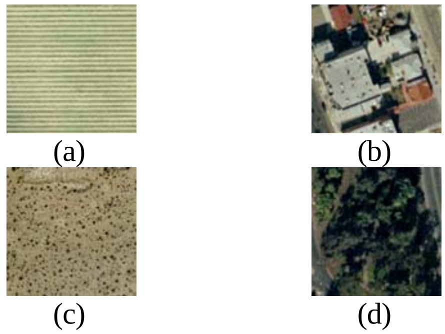

Fig. 3. Examples of EO images: (a) agricultural; (b) buildings; (c) chaparral; (d) forest

### 3.1.2 Kosice LANDSAT dataset for multispectral pixel clustering

For the classification of multispectral pixels, we have used a LANDSAT 7 TM+ image acquired in the Kosice region of Slovakia. The picture is composed of 7 spectral bands and it has a total of 368125 pixels (Fig.4). From these pixels, 6331 pixels have been classified by a human expert in seven thematic categories: bush, agricultural, meadows, forest, water, urban areas and empty areas.

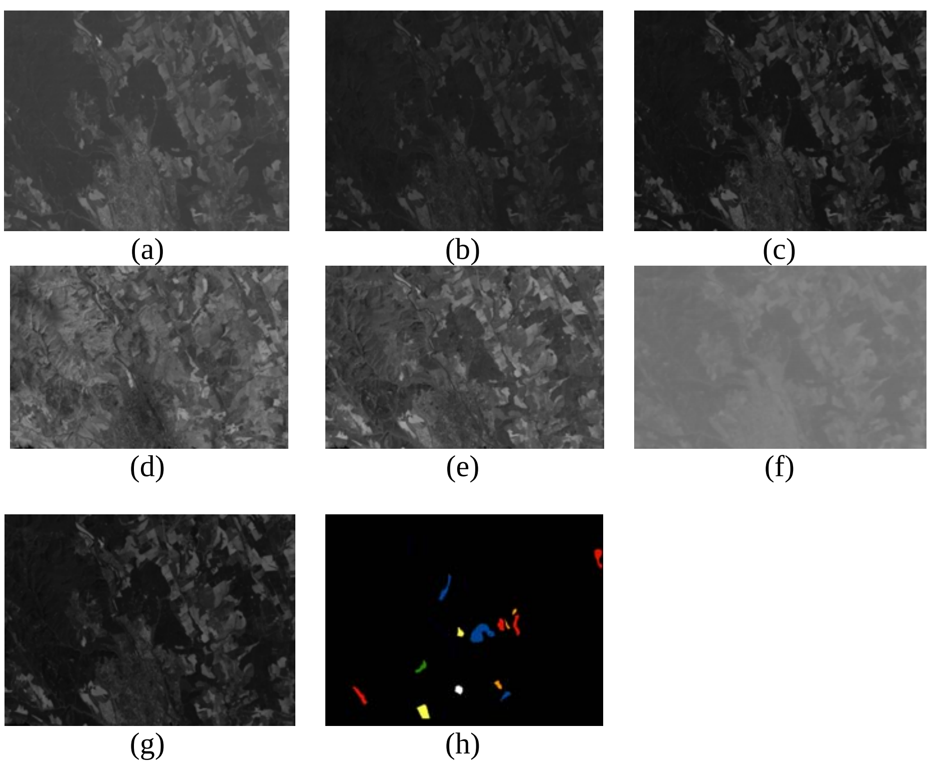

Fig.4. Kosice LANDSAT 7 TM image; (a)-(g) spectral bands; (h) reference map

## 3.2 Results

The next sections will discuss the experimental results obtained for each of the applications.

### 3.2.1 EO Image region clustering

For EO image region unsupervised classification, we have evaluated the Davies Bouldin index for a number of classes between 2 and 8. For the SOM network, we have used a rectangular cylinder topology and 100 training epochs. We have varied the dimensions between 5x5 and 15x15. Only the best results, which have been obtained for the 15x15 SOM, are presented in the Table 1.

*Table 1*

**Davies-Bouldin index for EO image region unsupervised classification (n=number of clusters)**

| n | k-means | Fuzzy c-means | SOM (dim 15x15) |
|---|---|---|---|
| 2 | 0.95 | 1 | 0.93 |
| 3 | 0.75 | 0.84 | 0.92 |
| **4** | **0.71** | 0.82 | **0.81** |
| 5 | 0.71 | **0.8** | 0.91 |
| 6 | 0.76 | 0.83 | 1 |
| 7 | 0.82 | 0.84 | 0.92 |
| 8 | 0.82 | 0.84 | 0.97 |

The Davies-Bouldin index has selected correctly the number of classes for the considered SOM classifier and also for the k-means classifier. For these two classifiers, we have also evaluated the correct recognition score, which are given in the tables 2.

*Table 2*

**Correct recognition score for EO image region clustering**

| Classifier | Correct recognition score [%] |
|---|---|
| k-means | 67.21 |
| **SOM** | **84.97** |

As we can see from the Table 2, the recognition score is much better for the SOM by comparison to K-means with about 20%. Regarding the confusion matrices in Tables 3 and 4, for SOM the buildings class has a correct recognition score of 97%; for k-means the chaparral class is best recognized (84.85%).

### 3.2.2 Multispectral pixel clustering

We have used the Davies-Bouldin index, combined with the three studied classifiers (SOM, k-means and fuzzy c-means) on the LANDSAT multispectral image presented in section 3.1.2. We have varied the number of clusters between 2 and 13. The results are given in table 3.

*Table 3*

**Davies-Bouldin index for multispectral pixel clustering (n=number of clusters)**

| n | k-means | Fuzzy c-means | SOM (dim 15x15) |
|---|---|---|---|
| 2 | 0.75 | 0.77 | 1.01 |
| 3 | 0.74 | 0.75 | 1.04 |
| 4 | 0.72 | 0.76 | 0.98 |
| 5 | 0.73 | 0.77 | 0.96 |
| 6 | 0.86 | 0.75 | 0.96 |
| **7** | **0.67** | **0.72** | **0.92** |
| 8 | 0.78 | 0.8 | 1.03 |
| 9 | 0.7 | 0.82 | 1.1 |
| 10 | 0.85 | 0.91 | 1.06 |
| 11 | 0.76 | 1.03 | 1.16 |
| 12 | 0.82 | 0.91 | 1.1 |
| 13 | 0.82 | 1.04 | 1.13 |

The Davies-Bouldin index selects the correct number of classes for all the considered classifiers. The correct recognition scores for each classifier are given in Table 4 .

*Table 4*

**Correct recognition score for multispectral pixel unsupervised classification**

| Classifier | Correct recognition score [%] |
|---|---|
| k-means | 84.74 |
| Fuzzy c-means | 84.84 |
| **SOM** | **86.2** |

All the considered unsupervised classifiers have obtained decent scores. The best score, which is 86.2%, is obtained by a square SOM of 15x15 neurons.

## 4. Concluding Remarks

1. This paper investigates a neural network approach using the Self-Organizing Map (SOM) for the unsupervised classification of EO images. The Davies-Bouldin measure on the SOM partition has been chosen to automatically select the optimum number of clusters.

2. The proposed SOM-Davies-Bouldin clustering model has been applied for two different tasks: EO image regions clustering and multispectral LANDSAT pixel clustering.
3. For EO image region classification, the feature selection stage uses the Haralick textural descriptors.
4. The EO image clustering performances of the proposed model are compared with those of the k-means and fuzzy c-means algorithms.
5. The Davies-Bouldin index, applied to the partitions obtained by SOM, selects correctly the optimum number of clusters both for the task of EO image region clustering (4 classes, see Table 1) and also for multispectral pixel clustering (7 classes, see Table 5). For comparison, one can see that by applying Davies-Bouldin measure on the Fuzzy c-means partition of image regions leads to an erroneous class number (see Table 1).
6. The best clustering scores are also obtained by SOM for both variants of the proposed model, by comparison to the results of the chosen benchmark algorithms.
7. For EO image region clustering, the SOM correct recognition score is of 84.97%, compared to a score of 67.21% for the k-means clustering (Table 2) ; the fuzzy c-means clustering is not considered in Table 2 for score comparison since this algorithm fails to identify the correct number of classes (see Table 1). For multispectral pixel clustering, the best score is of 86.2% (with SOM), compared to ~84.8% for k-means and fuzzy c-means algorithms (Table 6).

**Acknowledgments**

The authors would like to thank Alexandru Iosup. This work is funded by the Sectoral Operational Programme Human Resources Development 2007-2013 of the Romanian Ministry of Labour, Family, and Social Protection through POSDRU ID76813.

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