# A Concurrent Neural Module Classifier for Automated Target Recognition in SAR Imagery

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*Abstract:* - The paper presents an original approach for automated target recognition (ATR) in the synthetic aperture radar (SAR) imagery using the neural network classifier called Concurrent Self-Organizing Maps (CSOM), previously introduced by first author of the present paper. The ATR algorithm has the following stages: (a) image preprocessing (median filtering, histogram equalization, binarization); (b) feature selection using Gabor Filtering (GF); (c) neural classification with CSOM, representing a winner-takes-all collection of neural network modules. The algorithm has been applied for the recognition of three classes of military ground vehicles represented by the set of 2759 images of the MSTAR public release database. The experimental results obtained using CSOM has led to the best total success rate of 95.31%.

*Key-Words:* - automated target recognition (ATR), SAR Imagery, Concurrent Self-Organizing Maps (CSOM), Gabor Filters, MSTAR database

## 1 Introduction

Defence forces rely upon a variety of sensor information to locate and track oppositional forces; the surveillance problem becomes particularly difficult over large land areas with sparse population centres and over the great expanse of the seas. The modern war fighter is dependent upon several types of image data to aid in the surveillance task including optical data, infrared data, and radar data. Radar imagery enjoys the advantage of independence from a passive illumination source, such as sunlight or starlight, thus offers imaging capability at night and through clouds. Modern day radar imaging systems are capable of comparatively high resolution by utilising synthetic aperture radar (SAR) imagery.

The area of Automatic Target Recognition (ATR) for SAR imagery is an ongoing research in many branches of the military and large research institutions. The U.S.A. Defence Advanced Research Agency (DARPA) has made part of the Moving and Stationary Target Acquisition and Recognition (MSTAR) data set available to the public. We shall further present an ATR algorithm with applications for the recognition of three categories of military ground vehicles of the former Soviet Union with 0 to 360 degrees azimuthal angle and depression angle of 15 to 17 degrees.

There has been increasing interest in using artificial neural networks (ANN) for pattern recognition [1]. Neural networks have been successfully applied to classification problems in the areas of industry, business, science and defense. A classifier is considered to be good or not according to its ability to generalize. The investigation of sample size problem for neural network classifiers leads the conclusion that the generalization error decreases as the training sample size increases. However, in contrast to statistical pattern recognition, neural networks have a good behavior regarding small size problem and they also are faster than statistical classifiers. An approach to the application of the Multi Layer Perceptron (MLP) for ATR of military vehicles of the MSTAR database is reported by Sandirasegaram [9]. A similar ATR approach based on Radial Basis function (RBF) neural network has been performed by Sun et al [10].

Self-Organizing Map (SOM) (also called Kohonen network) [3] is an artificial unsupervised neural network characterized by the fact that 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. Similar input vectors correspond to the same neuron or to neighbor neurons.

Starting from the idea to consider the SOM as a cell characterizing a specific class only, Neagoe *et al* proposed [5] and evaluated for satellite imagery [6], [7] a new neural recognition supervised model called Concurrent Self-Organizing Maps (CSOM), representing a collection of small SOM modules, which use a global winner-takes-all strategy. Each SOM is trained to correctly classify the patterns of one class only and the number of neural network modules equals the number of classes. For feature selection, we have considered the

Gabor wavelet filters [2], [4], [8]. The CSOM model proved to have better performances than the other statistical and neural classifiers considered in our experiments, both for the recognition rate and also for reduction of the training time.

The proposed ATR algorithm applied for several military vehicle categories of the MSTAR database has the following processing stages (Fig. 1):

a. Image preprocessing
   a1. Median filtering
   a2. Histogram equalization
   a3. Binarization
b. Feature selection using Gabor Wavelet Filtering (GWF)
c. Neural classification using Concurrent Self-Organizing Maps (CSOM)

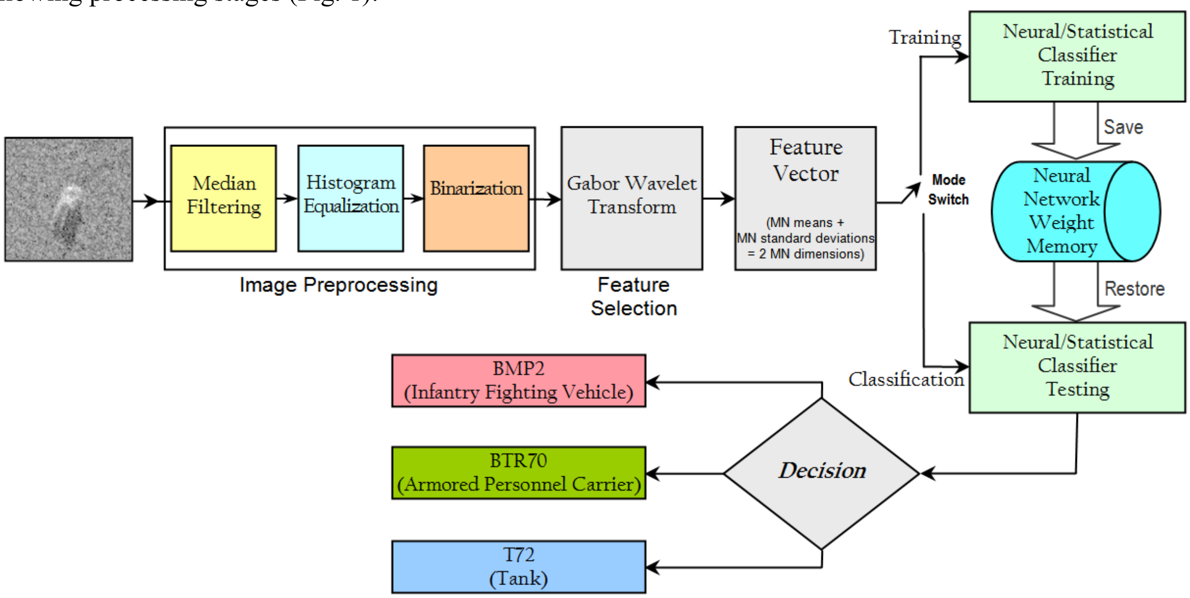


Fig. 1. Flowchart of the ATR cascade.

## 2 Feature Selection Using Gabor Filters (GF)

The feature selection is based on the two-dimensional Gabor filters (2D GF). A distinct advantage of the Gabor functions is their optimality in the space–spatial-frequency planes, providing the smallest possible pieces of information about time-frequency events (Gabor, 1946). In the spatial domain, a 2D GWF is defined as a complex sinusoidal plane wave function modulated by a Gaussian

$$\psi(x,y) = e^{-(\alpha^2 x'^2 + \beta^2 y'^2)} e^{j2\pi f x'}, \qquad (1)$$

$$x' = x\cos\theta + y\sin\theta, \qquad (2)$$

$$y' = -x\sin\theta + y\cos\theta, \qquad (3)$$

while the 2D GF is represented in the frequency domain by a Gaussian centered at the point (fcosθ, fsinθ)

$$\psi(u,v) = \frac{\pi}{\alpha\beta} e^{-\pi^2\left(\frac{(u\cos\theta + v\sin\theta - f)^2}{\alpha^2} + \frac{(u\sin\theta - v\cos\theta)^2}{\beta^2}\right)}, \qquad (4)$$

where f is the central frequency of the sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian and the plane wave, and α and β are the sharpness values of the major and minor axes of the elliptic Gaussian. The response of the above 2D Gabor filter for an image ξ(x,y) can be calculated via the convolution

$$resp_{\xi}(x,y) = \psi(x,y) * \xi(x,y). \qquad (5)$$

By denoting γ = f / α and η = f/ β, one obtains a normalized response

$$r_{\xi}(x,y) = \frac{f^2}{\pi\gamma\eta} \psi(x,y) * \xi(x,y). \qquad (6)$$

The response of the Gabor filter is a low level Gabor feature. In a feature space constructed from the Gabor filter responses, invariant search operations can be established based on the rotation, scale, and translation invariance properties of the Gabor features [4]. Furthermore, the Gabor feature space provides robustness to noise and illumination changes. One uses features at a single location (x; y), and thus, by combining the responses of several filters in different orientations and frequencies, complex objects can be represented.

*Sampling filter parameters*

A filter bank, consisting of several filters, needs to be used, as the relationships between responses of filters provide the basis for distinguishing objects. Next, it is considered how the filter parameters should be chosen for the bank of filters. The selection of discrete rotation angles $\theta_k$ has been chosen so that orientations to be spaced uniformly in the interval [0, π), that is,

$$\theta_k = \frac{k\pi}{N}, k = \{0,\dots,N-1\}, \qquad (7)$$

where $\theta_k$ is the $k^{th}$ orientation and $N$ is the number of orientations to be used. We have considered the following values for N: 3, 6, 9, 12, 15 and 18. For example, for N = 3, the corresponding discrete orientations are: $0, \frac{\pi}{3}, \frac{2\pi}{3}$.

In the selection of discrete frequencies $f_k$, the following exponential sampling is used [4] that is,

$$f_k = a^{-k} f_{\max}, k = \{0, \ldots, M-1\}, \tag{8}$$

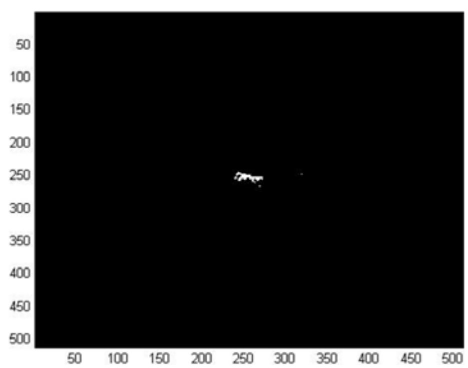
where $f_k$ is the $k^{th}$ frequency, $f = f_{max}$ is the highest desired frequency, and $a$ is the frequency scaling factor ($a > 1$). Useful values for a include $a = 2$ for octave spacing and $a = \sqrt{2}$ for half-octave spacing; $M$ is the number of considered scales.

By choosing $a = \sqrt{2}$, $f_{max} = \frac{1}{2}$ cycles/pixel (Nyquist frequency) and the number of scales $M = 11$, one obtains the following set of central frequencies:

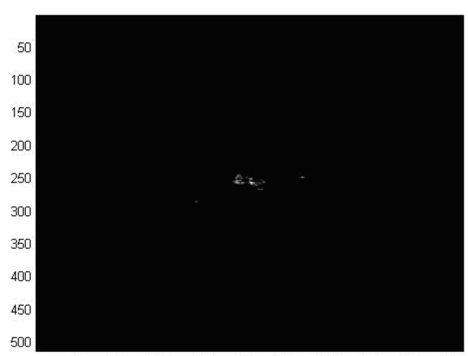
$$\frac{1}{2}, \frac{1}{2\sqrt{2}}, \frac{1}{4}, \frac{1}{4\sqrt{2}}, \frac{1}{8}, \frac{1}{8\sqrt{2}}, \frac{1}{16}, \frac{1}{16\sqrt{2}}, \frac{1}{32}, \frac{1}{32\sqrt{2}}, \frac{1}{64}. \tag{9}$$

To provide a smooth behavior of the features, the sharpness parameters γ and η have been adjusted to obtain a sufficient overlap of the Gabor filters in the feature space. For a good performance in the experiments of military vehicles recognition, one has chosen $\gamma = 1$ and $\eta = 0.5$.

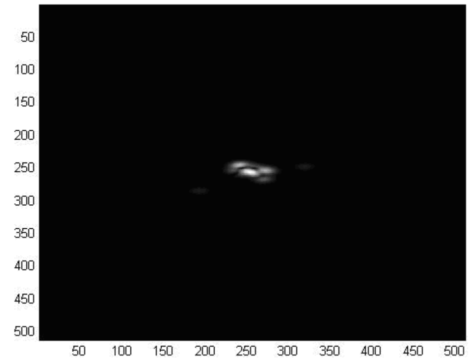
In Fig. 2 there are shown the responses of several 2D Gabor filters for an input binarized image.



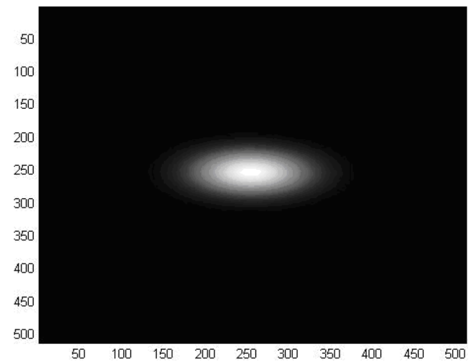
*(a)*



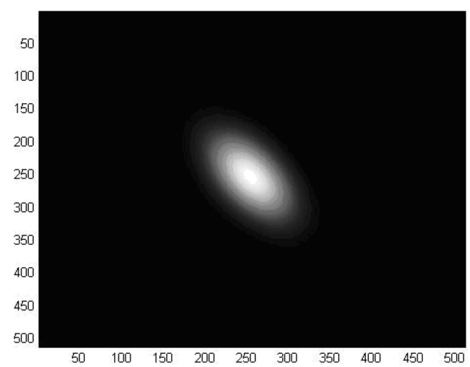
*(b) $f = 1 / 2$, $\theta = 0$, $\gamma = 1$, $\eta = 0.5$.*



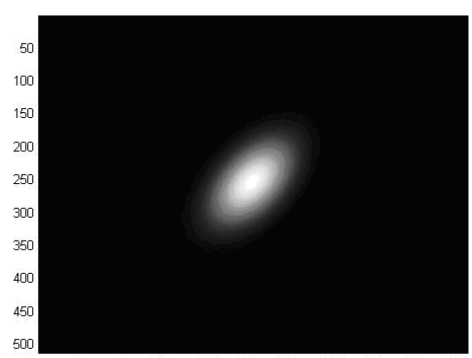
*(c) $f = 1 / 8\sqrt{2}$, $\theta = 0$, $\gamma = 1$, $\eta = 0.5$.*



*(d) $f = 1 / 64$, $\theta = \pi / 3$, $\gamma = 1$, $\eta = 0.5$.*



*(e) $f = 1 / 64$, $\theta = 2\pi / 3$, $\gamma = 1$, $\eta = 0.5$.*



*(f) $f = 1 / 64$, $\theta = 2\pi / 3$, $\gamma = 1$, $\eta = 0.5$.*

Fig. 2. (a) Binary input image. (b)-(f) Responses of the corresponding 2D Gabor filters, whose parameters are specified for each case.

For the M frequencies of interest and the N orientations of the desired angular discrimination, one can construct a set of M x N 2D Gabor filters. For each filter of indices {(i,j) $0 \le i \le$ M-1; $0 \le j \le$N-1}, one computes the filter response $G = resp(x, y; f_i, \theta_j)$ }, $0 \le$ x,y $\le$ P-1. Then, one computes the following three statistical parameters: mean, variance and skewness (measure of the asymmetry of the data around the sample mean) of response magnitudes for the square central zone of P x P pixels. Hence, we have a vector of 3 MN features, which is led to the classification processing stage.

## 3 Neural classifier with concurrent self-organizing modules

*Concurrent Self-Organizing Maps (CSOM)* [5] is a collection of small SOM modules, which use a global *winner-takes-all* strategy. Each module is trained to correctly classify the patterns of one class only and the number of networks equals the number "M" of classes.

The CSOM training technique is a supervised one, but for any individual net the SOM specific unsupervised training algorithm is used. We built "M" training patterns sets and we used the SOM training algorithm independently for each of the "M" neural units. Namely, each SOM module is trained with the patterns characterized by the corresponding class label. The CSOM models for *training and classification* are shown in Figs. 3 and 4.

### 3.1 Training of each $SOM^{(k)}$ module (k=1,…,M)

Assume that the module $SOM^{(k)}$ has $J^{(k)}$ neurons; particularly, one can choose

$$J^{(1)} = \ldots = J^{(M)} = \frac{J}{M} \qquad (10)$$

where $J$ is the number of CSOM neurons and $M$ is the number of classes.

For each $SOM^{(k)}$ module, a specific training data subset is prepared containing all the training vectors having the label "*k*", as shown in Fig.3.

Assume also that the number of vectors having the class label "k" is $N^{(k)}$, so that

$$\sum_{k=1}^{M} N^{(k)} = N \qquad (11)$$

where $N$ is the total number of training vectors. Usually, $J^{(k)} >> N^{(k)}$, to use the interpolation capacity of CSOM.

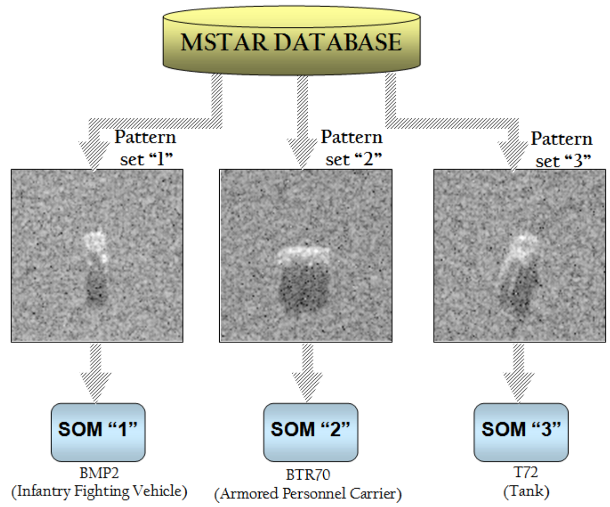



Fig. 3. The training phase of the CSOM model.

### 3.2 Recognition Phase

For the ***recognition,*** the test pattern has been applied in parallel to every previously trained SOM module. 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. 4).

In fact, CSOM is a **system of systems** having improved performances over a single big SOM with the same number of neurons, both from the point of view of recognition accuracy and for reducing the training time as well [5], [6], [7].

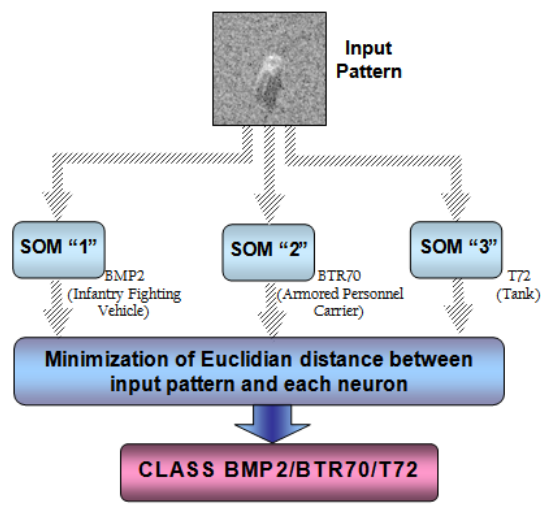



Fig. 4. The classification phase of the CSOM model.

### 3.3 Example

Consider the two class 2D dataset "Palm" shown in Fig. 5; 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.

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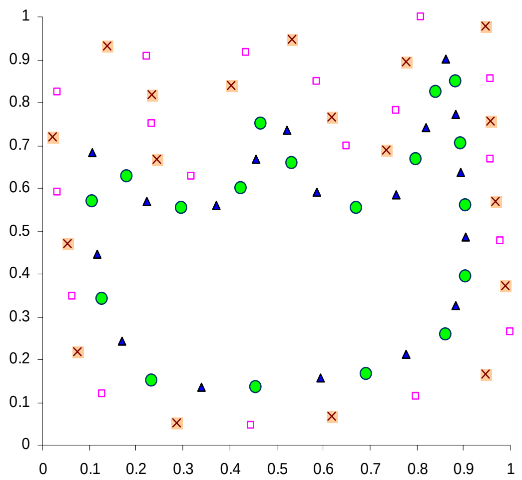


Fig. 5. A two-class data subset "Palm"; = training vector of the first class; = test vector of the first class, = training vector of the second class; = test vector of the second class.

We further present a comparison of several classifiers for PALM database: Concurrent Self-Organizing Maps (CSOM) with linear and circular architecture, Multilayer Perceptron (MLP), Radial Basis Function (RBF) neural network, Support Vector Machine (SVM), nearest neighbor (NN), and K-Means.

Table 1. Recognition score (%) for several classifiers (PALM dataset).

| *Number of neurons per module* | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| *CSOM with linear modules* | 66.67 | 80.56 | 80.56 | 75.00 | 77.78 | **83.33** | 80.56 | 72.22 | 80.56 | 80.56 |
| *CSOM with circular modules* | 61.11 | 80.56 | 91.67 | 86.11 | 88.89 | **91.67** | 75.00 | 80.56 | 72.22 | 80.56 |
| *MLP (20 neurons on the hidden layer)* | 75.00 | | | | | | | | | |
| *RBF* ($\sigma \in [0{,}076{,}1]$) | 77.78 | | | | | | | | | |
| *SVM (linear)* | 58.33 | | | | | | | | | |
| *NN* | 66.67 | | | | | | | | | |
| *K-Means* | 55.56 | | | | | | | | | |

# 4 Experimental Results

## 4.1 MSTAR database

The MSTAR (*moving and stationary target recognition*) data is a standard dataset for *automatic target recognition (ATR)* tasks, using *Synthetic Aperture Radar (SAR)* imagery Three types of military ground vehicles of the former Soviet Union which are BMP2 (tank), BTR70 (armored car), and T72 (tank) in MSTAR database are used for our experiments. We have considered 2759 images of 128 x 128 pixels, using two depression angles: $15^0$ and $17^0$. The number of images for each category is shown in Table 2.

One considers 1394 images corresponding to the depression angle of $17^0$ for training, while the other 1365 pictures corresponding to the depression angle of $15^0$ are considered for test.

Table 2. Number of pictures for each of the military vehicle class and version in the considered MSTAR dataset.

| class | ***BMP2*** | | | ***BTR70*** | ***T72*** | | |
|---|---|---|---|---|---|---|---|
| version | **9563** | **9566** | **c21** | **c71** | **132** | **812** | **s7** |
| 15° | 195 | 196 | 196 | 196 | 196 | 195 | 191 |
| 17° | 233 | 232 | 233 | 233 | 232 | 231 | - |

## 4.2 Recognition performances

We have considered the following classifiers for the considered application of ATR of the selected MSTAR pictures:

a. *Neural classifiers* : Concurrent Self-Organizing Maps (CSOM) and Radial Basis Function (RBF) neural network.

b. *Statistical classifiers* : Nearest Neighbor (NN) and K-Means.

For CSOM classifier, we have considered two categories of experiments. The model **CSOM I** uses three SOM modules; each module is trained with the MSTAR images (taken under $17^0$ depression angles) of the corresponding class of military vehicles having one of the three labels: *BMP2, BTR70,* and *T72.* The model **CSOM II** contains six neural modules; each SOM module is trained with the images corresponding to the corresponding version of vehicles (see Table 1): 9563, 9566, c21, c71, 132, and 812. However, the decision is given according to the group (class) level whose the vehicle version of the module belongs. For example, a winner neuron of any of the modules 9563, 9566, and c21 implies the decision corresponding to the class BMP2.

We further present the results of our experiments by considering the following parameters:

– number of scales: M=11;

– number of orientations N=15.

Consequently, we obtained a number of MN= 165 Gabor filters as well as a number of 3MN=495 statistical Gabor features for each image.

Table 3. Recognition score (%) for **1D CSOM I** architectures (MSTAR database).

| *Number of neurons per module* | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Total number of neurons* | 30 | 60 | 90 | 120 | 150 | 180 | 210 | 240 | 270 | 300 |
| *CSOM I with 3 linear modules* | 82.05 | 83.44 | **84.25** | 83.30 | 71.94 | 69.82 | 69.82 | 72.01 | 69.60 | 73.19 |
| *CSOM I with 3 circular modules* | 78.83 | 80.73 | 80.81 | 79.49 | 73.19 | 73.92 | 76.12 | 74.43 | 73.11 | 75.31 |

Table 4. Recognition score (%) for **2D CSOM I** architectures (MSTAR database).

| *Number of neurons per module* | 10x10 | 20x20 | 30x30 | 40x40 | 50x50 | 60x60 | 70x70 |
|---|---|---|---|---|---|---|---|
| *Total number of CSOM neurons* | 300 | 1200 | 2700 | 4800 | 7500 | 10800 | 14700 |
| *CSOM I with 3 square modules* | 82.93 | 93.26 | 93.48 | 93.70 | 93.63 | 93.63 | 93.26 |
| *CSOM I with 3 cylindrical modules* | 90.11 | 93.55 | 93.92 | **94.65** | 94.29 | 94.14 | 93.77 |
| *CSOM I with 3 toroidal modules* | 83.88 | 92.31 | 94.07 | 94.58 | 94.07 | 94.36 | 94.43 |

Table 5. Recognition score (%) for **1D CSOM II** architectures (MSTAR database).

| *Number of neurons per module* | 10 | 20 | 30 | 40 | 50 | 60 | 70 | 80 | 90 | 100 |
|---|---|---|---|---|---|---|---|---|---|---|
| *Total number of neurons* | 60 | 120 | 180 | 240 | 300 | 360 | 420 | 480 | 540 | 600 |
| *CSOM II with 6 linear modules* | 84.10 | 87.77 | 88.42 | 87.40 | 87.91 | 87.99 | 89.45 | 90.04 | **90.77** | 89.74 |
| *CSOM II with 6 circular modules* | 81.47 | 85.79 | 85.57 | 84.98 | 88.86 | 88.94 | 89.74 | 89.74 | 90.62 | 90.26 |

Table 6. Recognition score (%) for **2D CSOM II** architectures (MSTAR database).

| *Number of neurons per module* | 10x10 | 20x20 | 30x30 | 40x40 | 50x50 | 60x60 | 70x70 |
|---|---|---|---|---|---|---|---|
| *Total number of CSOM neurons* | 600 | 2400 | 5400 | 9600 | 15000 | 21600 | 29400 |
| *CSOM II with 6 square modules* | 91.28 | 94.14 | 94.58 | 94.80 | 94.80 | 94.58 | 94.95 |
| *CSOM II with 6 cylindrical modules* | 92.16 | 94.58 | 95.09 | **95.31** | 95.02 | 94.14 | 94.87 |
| *CSOM II with 6 toroidal modules* | 91.21 | 93.63 | 94.80 | 94.43 | 94.95 | 94.73 | 94.43 |

Table 7. Best recognition scores (%) of the experimented classifiers (MSTAR database).

| *Type of classifier* | 2D CSOM II *(6 cylindrical SOM modules of 40x40 neurons each)* | Radial Basis Function (RBF) net (σ = 1.10) | Nearest neighbor (NN) | K-Means |
|---|---|---|---|---|
| *Recognition score (%)* | **95.31** | 93.19 | 92.23 | 54.87 |

## 5 Concluding Remarks

1. The paper proposes an ATR algorithm based on the neural network classifier of the Concurrent Self-Organizing Maps (CSOM).
2. We have experimented the presented algorithm for a set of 2759 SAR images of 128 x 128 pixels belonging to the MSTAR database corresponding to three military vehicle classes: BMP2 (infantry fighting vehicle), BTR70 (armored car), and T72 (tank). The implemented neural CSOM classifier is evaluated for various architectures and sizes of the SOM modules. Namely, we have taken into account both the 1D architecture (linear and circular) and also the 2D one (square, cylindrical, and toroidal).
3. The best recognition score of 95.31 % is obtained using a CSOM with 6 cylindrical SOM modules of 40x40 neurons each. By comparison, the RBF neural network leads to the recognition score of 93.19 %, the NN method obtains a score of 92.23 %, and the K-means leads to the score of 54.87 %.

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