BULGARIAN ACADEMY OF SCIENCES

CYBERNETICS AND INFORMATION TECHNOLOGIES • Volume **17**, No 4
Sofia • 2017 Print ISSN: 1311-9702; Online ISSN: 1314-4081
DOI: 10.1515/cait-2017-0048

ISAR Image Recognition Algorithm and Neural Network Implementation

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Abstract: *The image recognition and identification procedures are comparatively new in the scope of ISAR* (*Inverse Synthetic Aperture Radar*) *applications and based on specific defects in ISAR images, e.g., missing pixels and parts of the image induced by target's aspect angles require preliminary image processing before identification. The present paper deals with ISAR image enhancement algorithms and neural network architecture for image recognition and target identification. First, stages of the image processing algorithms intended for image improving and contour line extraction are discussed. Second, an algorithm for target recognition is developed based on neural network architecture. Two Learning Vector Quantization* (*LVQ*) *neural networks are constructed in Matlab program environment. A training algorithm by teacher is applied. Final identification decision strategy is developed. Results of numerical experiments are presented.*

Keywords: *Inverse synthetic aperture radar, ISAR imaging, image processing, neural network recognition.*

1. Introduction

In latest years producing of high quality Inverse Synthetic Aperture Radar (ISAR) images of moving targets becomes a great challenge for researches in radar world. ISAR measurements are used for image reconstruction, geometric feature definition and target identification. In addition, ISAR imaging is becoming a powerful tool for Automatic Target Recognition (ATR) of non-cooperative targets. Recently many ISAR ATR techniques have been suggested [1]. Algorithms for multi-feature based ISAR image recognition of ship targets and automatic polarimetric ISAR image recognition based on a model matching are discussed in [2, 3]. Automatic target recognition of ISAR images of multiple targets and ATR results, and algorithms for automatic ISAR images recognition and classification are presented in [4-6]. Based on a comparison of range-Doppler imagery to 3D ship reference models an ISAR image classification is discussed in [7]. A parametric system identification method is proposed in [8] to estimate signal model parameters for the short dwell time and extrapolation of the radar data outside this time, to reduce smeared Doppler shifts, and improve image resolution. An application of the compressive sensing methods in the recovery of heavily corrupted signal and radar images is proposed in [9].

The prospective instrument for target image recognition is neural networks [10, 11]. An integrate ATR approach with a three-feed forward neural network is proposed in [12]. It includes images pre-processing, feature extraction and automatic target recognition and classification of ISAR object. Automatic aircraft target recognition by ISAR image processing based on neural network classifier composed by a combination of 20 feed-forward artificial neural networks is described in [13].

The main problem in the automatic image recognition process is the ambiguity in respect of the object position and scale in the image frame. To find the solution of this drawback, algorithms removing ambiguity problem have been developed [14, 15]. One possible solution of this problem is a great data base to be created that comprises all possible variants of the object position [16]. Another approach is objects to be considered as an assembly of elementary geometrical segments, and then the recognition is accomplished independently of the object position and scale [17]. Similar principal is applied in Fukushima's cognitron and neocognitron neural network architecture [18]. Both approaches require complicated multi-layer neural networks consisting of great number of neurons [19, 20].

There exist three different type of neural networks invariant with respect to the target position [13]. In the first type the invariance is achieved by training of different pattern shifts, the number of possible variations of patterns makes the training set too large, increasing at the same time the computational complexity of the learning system. In the second type the invariance is achieved by structure, i.e., outputs of neural networks are always invariant to certain transformations, and it requires high-order neural networks with too complicated implementation. In the third type the invariance is achieved by feature vectors as inputs for the neural networks. In this case the number of features can be reduced to realistic levels, but long processing time is required to extract the features before the classifier can be employed [21, 22].

Automatic target recognition of ISAR images based on neural network classifier and combined neural networks for target recognition from radar range profiles are described in [13, 23, 24]. Object recognition using wavelet and neural network approach is presented in [25] Application of a neural network as target identification instrument requires the image position in the frame to be exactly determined. In other words, the image data have to provide for invariant recognition procedure concerning the position of the object's image in the frame. One of the methods to solve this problem consists in tracking out the contour line of the image by choosing the pixels with maximum intensities, assuming that they are from the contour line of the image. Contour pixels form an image vector, which is processed by a neural network with radial basis function of activation [26].

The main goal of the present study is to develop an algorithm for ISAR target recognition constituted on neural network architecture. Two Learning Vector

Quantization (LVQ) neural networks are built and program implemented. The training algorithm by teacher is applied. Final identification decision strategy is developed.

In the first place, the suggested target identification and recognition algorithm has a logical structure and provides for the necessary reliability of identification in the presence of disturbances in the image and corruption in the contour line of the image being displayed. In the second place, the number of neurons in the first layer is defined by the number of the models, but not by the number of pixels or segments in the image.

Thus, the selected architecture of the neural network has the following advantages. It possesses a property of an associative memory which guaranties the correct classification of the object in the presence of high level of noise background and incomplete and distorted shape of images. Substantial advantage of the suggested algorithm for neural network learning is the training process. It comprises one single epoch, and it is completely determined, fast and flexible. The layers' weight matrices of both neural networks are completely known. Thus, the results can be unambiguously defined. Another advantage is that the complementation of new etalon models in the neural network is reduced to addition of new neurons in the first layers of the neural network and extension of the input training matrix. Finally, the suggested neural network can be easily realized in a hardware setting.

At the first step of the recognition process constrains relevant to the ambiguity of the image position have to be overcome. In that sense an algorithm to cope with the ambiguity of the image position and contour line extraction is generally described and graphically illustrated is Section 2.

It is important to emphasize that many of image recognition procedures using neural networks require one neuron to each pixel or segment of the image to be assigned (back-propagation network, self-organized map), which makes these neural architectures too bulky. In contrast, the suggested ISAR image recognition and identification procedure requires simpler neural architecture to be implemented in order to recognize the contour line of the object silhouette.

The remainder of the paper is organized as follows. In Section 2 data model and all stages of the ISAR image processing are outlined. In Section 3 an algorithm for automatic ISAR image recognition based on a neural network is created. In Section 4 neural network architectures, training algorithms, and final identification decision are described. In Section 5 numerical results of the automatic target recognition with two-layer neural network are provided. In Section 6 conclusions are made.

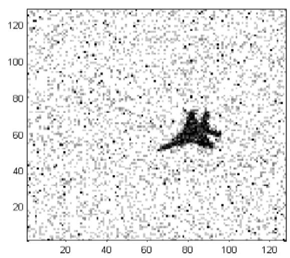
2. ISAR image processing – main stages

2.1. ISAR data formation

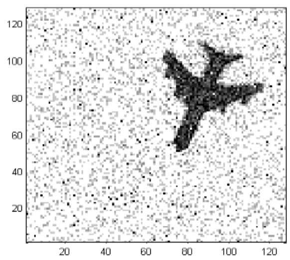
Suppose that the inverse aperture synthesis is carried out through illuminating a moving target by a Linear Frequency Modulated (LFM) transmitted signal, and ISAR image reconstruction including range and azimuth compressions is completed [27].

Based on the analytical description of the ISAR scenario, target's kinematical parameters and images obtained by signal modelling and image reconstruction, an algorithm is developed removing the ambiguity in respect of the object position and scale. By precise determination of the emitted pulse parameters and the synthetic aperture length mutual unambiguity between scales of the real object, which should be compared to, and the object image in the frame can be achieved. By adaptive alteration of the object position in the frame and its orientation with respect to the horizontal direction, invariability concerning rotation of the image in the frame can be ensured. The procedures developed, including image rotation, optimal filtration, and contour line extraction allow a centered image of the object in the frame to be obtained. Consider ISAR scenario, described in a two-dimensional (2D) coordinate system *Oxy*. The target, object of observation, is depicted in a 2D coordinate grid with dimensions $\Delta X = 0.5$ m, $\Delta Y = 0.5$ m, and moving rectilinearly at a constant speed.

ISAR transmitter illuminates the object by LFM pulses with parameters: pulse timewidth $T = 10^{-6}$ s, pulse repetition period $T_p = 10^{-3}$ s, wavelength $\lambda = 0.03$ m, frequency bandwidth $2\Delta F = 3\times10^8$ Hz. The real ISAR signal is a sum of the deterministic signal and additive Gaussian noise, with signal to noise ratio $S/N > 5$ dB. The intensities of the reconstructed image are normalized in the interval from 0 up to 1. The reconstructed image is blurred with additional additive Gaussian noise with zero mathematical expectation and variance 0.03 and pulse noise with probability distribution density 0.02. Targets to be imaged and recognized are Mig-29 with velocity $V = 800$ m/s, velocity angle $\alpha = 170°$, initial slant distance $R = 1.2\times10^5$ m, initial azimuth angle $\Phi = 50°$, and Boeing-707 with velocity $V = 700$ m/s, velocity angle $\alpha = 100°$, initial slant distance $R = 9\times10^4$ m, initial azimuth angle $\Phi = 300°$. The target images with cross-range resolution $\Delta L = 0.5$ m and range resolution $\Delta R = 0.5$ m are placed in a frame with dimensions 128×128 pixels (Fig. 1).



(a)



(b)

Fig. 1. ISAR images with additive Gaussian noise: ISAR image of Mig-29 (a); ISAR image of Boeing-707 (b)

2.2. ISAR image processing

The geometric characteristic used for neural network recognition, the target's contour line are extracted from the ISAR image improved based on the following image processing steps [27].

1. Rotation of the image in the frame based on a preliminary defined rotating angle and the image in the frame is placed in a particular (horizontal) position.

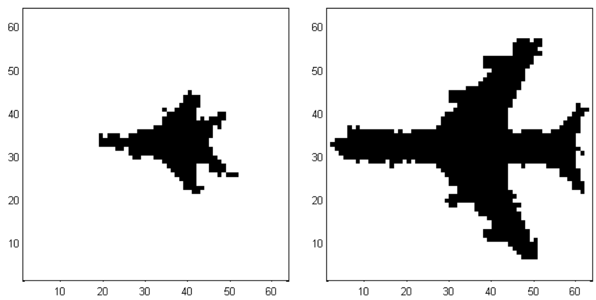
2. Adaptive Winner filtration of the background noise and preserving the silhouette of the target.

3. Intensity segmentation with total removing of the background noise by Otsu's thresholding, and binary image conversion.

4. Injection-rejection filtrating with a variable aperture to remove isolated noise patches (resulting from remaining impulse disturbances) in the image without causing damages to the original image and removing some defects from the silhouette of the object.

5. Sub-area extraction of dimensions with a centered image of the targets.

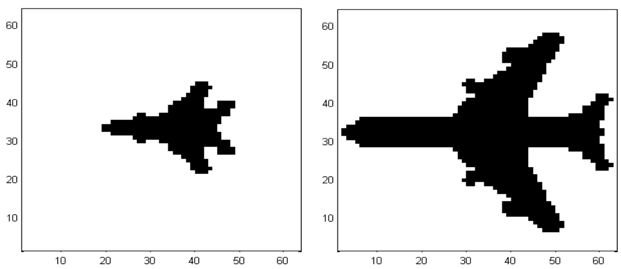
Results after image rotation, adaptive Winner filtration, intensity segmentation, Otsu's thresholding and binary image conversion, injection-rejection filtration, and subarea extraction are presented in Fig. 2.



(*a*) (*b*)

Fig. 2. Images of MiG-29 and Boeing-707 after image rotation, adaptive Winner filtration, intensity segmentation, Otsu's bi-level thresholding and binary image conversion, injection rejection filtration, and subarea extraction: Mig-29 (*a*); Boing-707 (*b*)

6. Adding missing pixels to the silhouette of the target and removing defects from horizontal silhouette contour line by image reconstruction procedure based on symmetry of the object (Fig. 3).



(*a*) (*b*)

Fig. 3. Improved images of MiG-29 and Boeing-707 by smoothing of contour horizontal lines: Mig-29 (*a*); Boing-707 (*b*)

7. ISAR image's contour line extraction

The following expressions applied to each (i, j)-th pixel's intensity of the object silhouette are exploited to implement the contour line extraction:

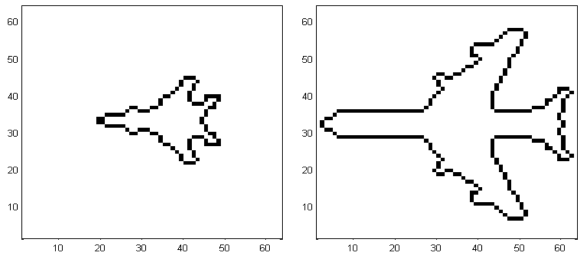
$$(1) \qquad A_{i,j} = \operatorname{sign}\left[a_{i,j} \operatorname{floor}\left(\frac{3}{W} \right) \right],$$

where

$$\operatorname{sign}\left[a_{i,j} \operatorname{floor}\left(\frac{3}{W} \right) \right] = \begin{cases} 1 \text{ if } \left[a_{i,j} \operatorname{floor}\left(\frac{3}{W} \right) \right] \ge 1, \\ 0 \text{ if } \left[a_{i,j} \operatorname{floor}\left(\frac{3}{W} \right) \right] < 1, \end{cases}$$

$$W = \begin{bmatrix} a_{i-1,j-1} & a_{i-1,j} & a_{i-1,j+1} \\ a_{i,j-1} & a_{i,j} & a_{i,j+1} \\ a_{i+1,j-1} & a_{i+1,j} & a_{i+1,j+1} \end{bmatrix} \otimes \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix},$$

where $i = \overline{2.63}$, $j = \overline{2.63}$, $a_{i,j}$ is the current value of the (i, j)-th pixel intensity; W is the sum of the intensities of four neighboring pixels in horizontal and vertical directions; $A_{i,j}$ is the recalculated intensity of the (i, j)-th pixel. In Fig. 4 results after contour line extraction of MiG-23 and Boeing-707 silhouettes are presented.



(*a*) (*b*)

Fig. 4. Contour line extraction of the image silhouettes MiG-23 (*a*) and Boeing-707 (*b*)

Contour lines extracted from silhouettes of MiG-23 and Boeing-707 fully describe real images of the aircrafts and can be used for further identification of the targets by applying of two layer neural networks.

3. Algorithm for automatic ISAR image recognition

3.1. ISAR recognition strategy

Assume the ISAR image as a contour line (Fig. 4) is described by the binary matrix **S**. The target identification is performed through comparison of the obtained ISAR image contour line of the target with a priory defined contour lines of aircrafts' etalon models.

It is assumed that there are M etalon models. The data base is formed by $M{\times}N$ binary matrices with dimension equal to image matrix dimension, where N is the number of accepted etalon subsidiary matrices for each model. These matrices consist of ones for elements that correspond to the pixels of the etalon models contour line. The remaining elements of the matrices are zeros.

In essence, the recognition process implies estimation of the number of coincident elements (pixels) not equal to zero. The maximal value of coincident pixels is the condition for decision making process of the object identification. The detection of coincident elements can be implemented by any linear evaluation operation. This linear operation is performed over the binary matrix of the ISAR image **S** and each subsidiary matrix $\mathbf{W}_{m,n}$, i.e.,

(2) $$\mathbf{S}_{m,n} = \mathbf{S} \oplus \mathbf{W}_{m,n},$$

where $\oplus$ denotes the linear evaluation operation, $m = \overline{1, M}$ is the number of the current model, which is compared to, $n = \overline{1, N}$ is the number of serial subsidiary etalon matrix of this model. If there is not any ambiguity or the ambiguity is fully removed, N is equal to one.

In case the evaluation operation is multiplication of **S** and $\mathbf{W}_{m,n}$, the resultant matrix $\mathbf{S}_{m,n}$ has elements not equal to zero in the positions, where both matrices have elements not equal to zero. This way the addresses of subsidiary matrix elements for a certain model are registered. The subsidiary matrix elements coincide with elements of the original image matrix (silhouette contour line). The elements of each calculated matrix $\mathbf{S}_{m,n}$ are summed according to the expression

(3) $$\hat{\mathbf{S}}_{m,n} = \sum_{i=1}^{I} \sum_{j=1}^{J} \mathbf{S}_{m,n}(i, j),$$

where I = 64 and J = 64 are the dimensions of the image matrix. The result $\hat{\mathbf{S}}_{m,n}$ renders an account for all number of coincident pixels. For each $m = \overline{1, M}$, i.e., for each model the maximum value among all received values $\hat{S}_{m,n}$ is defined by the expression

(4) $$\hat{S}_m^{\max} = \max(\hat{S}_{m,n}),$$

where $n = \overline{1, N}$.

The received M values $\hat{S}_m^{\max}$ stand for the best results for each competitive model. The maximum value among obtained M values is defined by

(5) $$\hat{S}^{\max,\max} = \max\left(\hat{S}_m^{\max}\right),$$

where $m = \overline{1, M}$.

The index m for which the maximum value $\hat{S}^{\max,\max}$ is received and it defines the “winner” – the number of the model that resembles the original image mostly.

3.2. Neural network architecture synthesis

In compliance with the requirements of the criteria, the chosen neural architecture is Learning Vector Quantization (LVQ) Network. LVQ is a method for training competitive layers in a supervised manner. A competitive layer automatically learns to classify input vectors. The classes that the competitive layer finds depend on the distance between input vectors, which performs function of an associative memory.

LVQ networks can be easily learned in order to classify input vectors into output classes chosen by the user [28].

LVQ networks consist of two layers (Fig. 5): the first one consists of neurons with competitive transfer function, which is trained according to Kohonen's learning rule; the second layer contains neurons with linear transfer function, which is trained according to Grossberg's learning rule.

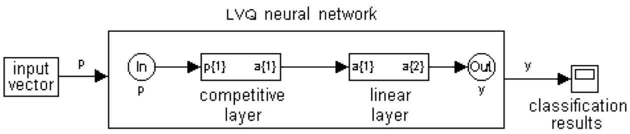


Fig. 5. LVQ neural network architecture

The Kohonen's layer works in conformity with the principle "the winner takes all". The weight matrix and activation function for each neuron are organized so that by input of the input vector onto the output of a layer, only one neuron is activated. On its output this neuron returns value one. The other neurons returns on their outputs value zero [29].

The competitive transfer function accepts an input vector for a layer and returns neuron outputs of zeros for all neurons except for the winner – the neuron associated with the most positive element of the input vector. The winner's output is 1. If all biases are 0, then the neuron whose weight vector is closest to the input vector has the least negative input and, therefore, wins the competition to output.

Kohonen's layer forms as many subclasses as the number of neurons in the layer. In the layer a priory clustering is accomplished, in which the input vector relates to some of the preliminary formed subsidiary subclasses.

The number of neurons in Grossberg layer is determined in accordance with a finite number of desired classes. Only one of the neurons returns 1 and all of the remaining neurons generate on their outputs 0. The number of the neurons in this layer corresponds to the desired final classes. The role of this layer is to accomplish an additional classification of the results from the first layer according to desired final requirements [30].

LVQ neural networks are mostly used for vector classification. The weights of the neurons of the Kohonen's layer form vectors that present the rows of the weight matrix $\mathbf{IW}_{1,1}$ (Fig. 6). This layer accepts input vector $\mathbf{p}$ and forms the differences between elements of the input vector $\mathbf{p}$ and the rows of the weight matrix according to

$$\mathbf{n}_1(q,:) = -\left|\mathbf{IW}_{1,1}(q,:) - \mathbf{p}\right|, \tag{6}$$

where $q = \overline{1,Q}$, and Q is the number of neurons in the layer.

The elements of the matrix $\mathbf{n}_1$ are summed by rows

$$N_q = \sum_{q=1}^{Q} \mathbf{n}_1(q,:). \tag{7}$$

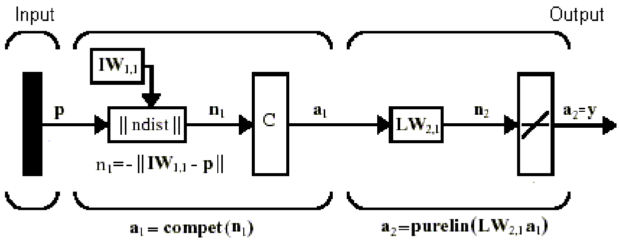


Fig. 6. Transfer functions of the LVQ neural network architecture

For each neuron, the values N_q are negative (less than zero). The transfer function (competitive function) of this layer returns an output vector $\mathbf{a}_1$ that consists of 0's corresponding to negative values, except one element equal to 1 – this is the element with value nearest to 0. This way a preliminary classification in subclasses is accomplished.

The linier transfer function of Grossberg's layer performs multiplication of the vector $\mathbf{a}_1$ by weight matrix $\mathbf{LW}_{1,2}$ and returns an output vector $\mathbf{a}_2 = \mathbf{y}$ consisting of $M - 1$ elements equal to 0, where M is the number of the final classes, except one element equal to 1, which is the "winner" neuron. The position of this element in output vector signifies the number of the final class, with which the input vector is associated.

4. Neural network implementation

4.1. Image database generation

In order to generate an image database eight models of aircrafts are used and presented as binary matrices, elements of which are digital expressions of aircrafts' contour line. The models are described in a 64×64 pixels grid with dimension of the resolution cell $\Delta X = \Delta Y = 0.5$ m (Fig. 7).

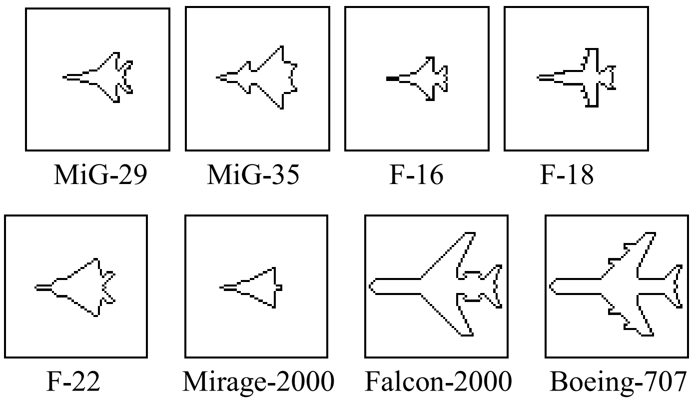
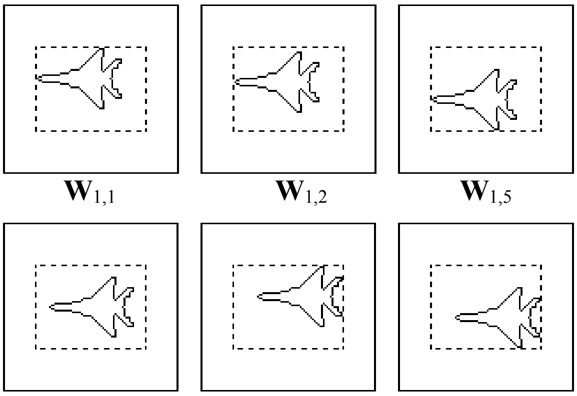


Fig. 7. Eight models of aircrafts that form a database

The elements of the model matrix that belong to the target contour line are accepted equal to 1; otherwise, they are equal to (–1). It is necessary to note that the size of the model of Boeing-707 is especially reduced for the purpose of achieving maximal resemblance of the models of Boeing-707 and Falcon-2000. This way the two models are distinguished only by the position of the engines.

It is assumed that by applying algorithms, discussed in Section 2.2 (rotation, optimal filtration, centering and contour line extraction) it is possible an error to occur in respect of centering of the object in the frame. That error is accepted to be in the boundary of ± 2 pixels in any of the eight directions. Therefore, the data base is formed by generation of 200 subsidiary matrices $\mathbf{W}_{m,n}$ with dimension 64×64 elements, where $m = \overline{1,8}$, and $n = \overline{1,25}$. It means for each of the 8 aircraft models 25 subsidiary matrices are created. These matrices define 25 horizontal object positions in the frame, which are distinguished by ±2 pixels in reference to the center of the image. The described principle of creation of matrices with image displacement is illustrated in Fig. 8, where some of the considered 25 positions in the frame for the etalon model of an aircraft MiG-29 are depicted.



$\mathbf{W}_{1,1}$ $\mathbf{W}_{1,2}$ $\mathbf{W}_{1,5}$

$\mathbf{W}_{1,13}$ $\mathbf{W}_{1,21}$ $\mathbf{W}_{1,25}$

Fig. 8. Some of the assumed 25 positions in the frame for the etalon model of an aircraft MiG-29

4.2. Neural network architecture synthesis

Assume that the received object image is placed in the middle of the frame with dimension 64×64 pixels. An error in the boundaries of ±2 pixels in any of the eight directions is possible. To remove the ambiguity concerning disposition of the object for each etalon model of aircrafts, 25 subsidiary matrices are formed. For eight etalon models, 200 etalon matrices are created. Each etalon matrix is conformed in vector with dimension 1×4096, taking the elements column wise. These vectors form rows of a combined general matrix   with dimension 200×4096. To reduce the number of arithmetic operations the columns, containing only (–1), are removed, because these elements do not take part in the contour line formation of the aircraft for all 200 matrices. The indices of the removed columns are memorized. In the case being considered the reduced general matrix $\mathbf{S}_{in}$ has a dimension 200×1617 and consists of elements 1 and (–1). Hence, the architecture of chosen LVQ neural network includes two layers – first Kohonen's layer composed of 200 neurons corresponding to the number of all etalon matrices (Fig. 9), and second Grossberg's layer composed of 8 neurons corresponding to the number of etalon models (Fig. 10).

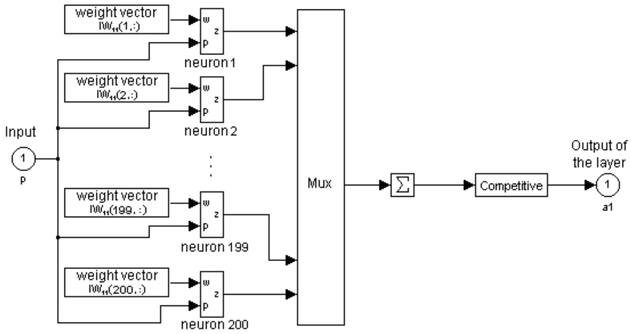


Fig. 9. Architecture of Kohonen's layer

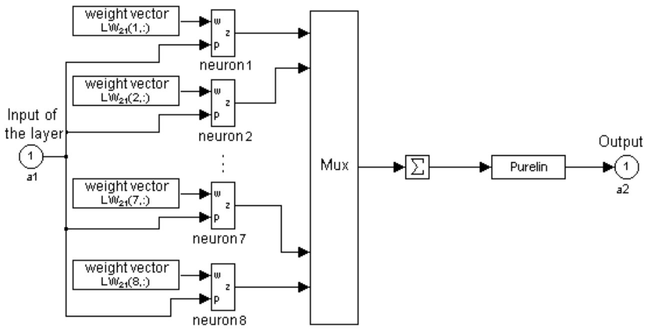


Fig. 10. Architecture of the Grossberg's layer

4.3. Training algorithm for the 2-layers neural network

LVQ learning in the competitive layer is based on a set of input/target vector pairs. In this case, the data base of input training vectors consists of 200 vectors with dimension of 1617 elements – 25 vectors for each of the eight classes. Accordingly, 200 target vectors are created. The target vectors have eight elements that correspond to the number of the classes. Each target vector has a single 1. The rest of its elements are 0. The position of 1 in the vector tells the proper classification of the associated input. In this case, for the first 25 input vectors the corresponding target vectors have 1 placed on the first position. For the next 25 input vectors, the corresponding target vectors have 1 placed on the second position and so on.

Commonly, the learning process of LVQ neural architecture without "teacher" initiates by assigning the average of minimal and maximal values of the elements of the input training matrix to the weight matrix of the first layer $\mathbf{IW}_{1,1}$. During training process, the elements of the weight matrix alter by certain step, usually 0.01 per epoch, until satisfactory result is obtained.

The suggested LVQ neural networks are realized in program environment. The training-blue MMSE (Minimum Mean Square Errors) diagram of output values of the LVQ neural network is presented in Fig. 11.

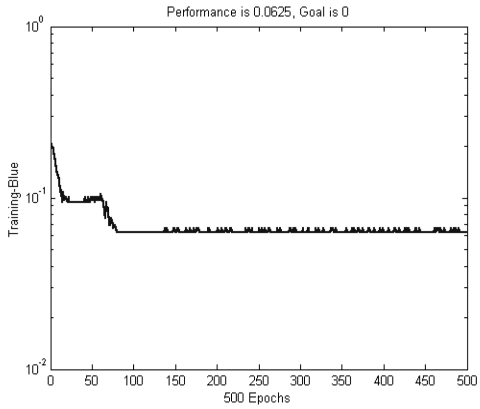


Fig. 11. MMSE of the training process

As can be seen the standard training process converges too slow. In the present study, the training process is suggested to be accomplished by "teacher", based on the recognition strategy presented in Section 3.1. The essence of the proposed idea consists in assigning immediately the values of elements of the input training matrix $\mathbf{S}_R$ to the elements of the weight matrix of the first layer $\mathbf{IW}_{1,1}$. It is reasonable, because the criterion of affiliation of the following input vectors to the certain class is completely contained in the input training matrix. In this way, the training process of the neural network extends only one epoch.

The decision rule, containing in present LVQ architecture, is simple – maximum number of detected coincident pixels defines the class that the current object has to be assigned to. Actually, this rule is not perfect, because the contour line of different aircrafts is described by different number of pixels in dependence of geometry of the aircraft. To overcome this obstacle a second LVQ neural network with exactly the same architecture is suggested. The decision rule of the second neural network is noted as follows. The class that the current object has to be assigned to is defined by the maximum ratio of the number of detected coincident pixels related to general number of pixels that form the contour line of the corresponding model.

For instance, let as result two neural networks render an account of 100 coincident pixels for the object contour of certain image and the model of the aircraft Boeing-707, and 80 coincident pixels for the model of the fighter F-22. In this case, LVQ-1 recognizes the target as Boeing-707, because the absolute number of coincident pixels is greater. In the meantime, LVQ-2 prefers F-22 because the model contour of F-22 is described by 96 pixels, whereas the model contour of Boeing-707 is described by 218 pixels, i.e., the probability the target to be F-22 is greater.

The realization of the second rule requires the input training matrix to be changed. The alteration of the input training matrix influences only on these elements equal to 1, which describe the contour line of the models. The values of these elements of the new matrix $\mathbf{S}'_R$ are recomputed by division of corresponding elements of the matrix $\mathbf{S}_R$ to the full number of pixels, which form the contour line of the relevant model. This rule is more efficient in probabilistic meaning.

Based on the recognition algorithm described in Section 3.2 the training process is suggested to be accomplished by "teacher" again. Similarly to the previous neural network, in the beginning the values of the input training matrix $\mathbf{S}'_R$ are assigned to the elements of the weight matrix of the first layer $\mathbf{IW}'_{1,1}$ of the second neural network. This way, the training process of the neural network lasts one epoch again.

Although the Kohonen and Grossberg neural networks have identical architecture, with the described organization of the weight matrices $\mathbf{IW}^1_{1,1}$ and $\mathbf{IW}^2_{1,1}$ these neural networks possess different decision rules. The first neural network LVQ-1 associates the input vector with this etalon model for which the greatest number of coincident pixels is found. The second neural network LVQ-2 associates the input vector with this etalon model for which the maximum ratio of coincident pixels related to the general number of pixels that form the contour line of the respective model.

4.4. Final identification decision strategy

In practice, the ISAR images are expected to be of low quality, blurred and with presence of different kind of disturbances. As a result, after preliminary image processing the extracted contour line could be deformed. For this reason in this paper, an algorithm for final identification decision is suggested using results of both of the neural networks. Algorithm is based on the particular decisions of the object affiliation formed by the LVQ-neural networks, and on the application of special additional logical rules. The logical rules have the meaning of constrain conditions. The choice of the final decision is accomplished following next sequence of operations.

1. First step is performed in accordance with the following logical rule. If the maximum number of coincident pixels for all models is less than a certain minimal permissible value the decision is the target is not recognized. The motive is, it is not possible to exist a target resembling all models, simultaneously. The most probable reason for such an event is the bad image quality due to the high noise level. If the number of coincident pixels exceeds the minimal permissible value continue with the next step of the algorithm.

2. The second logical rule is, in case the number of coincident pixels for the winner model is less than a certain minimal permissible value the decision is the object is not recognized. The motive is there is not enough number of coincident pixels to guarantee an unambiguously correct recognition. The most probable reason for such an event is that the observed target is unknown (the model does not present in the data base). If the number of coincident pixels exceeds the minimal permissible value continue with the next step of the algorithm.

3. The third logical rule requires examination of the output results of the neural networks. If the results, obtained by LVQ-1 and LVQ-2 are different, the decision is

the object is not completely recognized. As a most probable result is chosen the one, received by LVQ-2, but a message is displayed that resemblance exists with another model. If the results, obtained by LVQ-1 and LVQ-2 are identical the decision is the object is completely and unambiguously recognized. The rules of the final decision strategy are presented in Table 1.

Table 1. Final decision strategy: “0” – the rule is not performed; “1” – the rule is performed; “–” denotes the rule is not examined

Rule 1	Rule 2	Rule 3	Final decision
0	–	–	The object is not recognized
1	0	–	The object is not recognized
1	1	0	The object is not completely recognized
1	1	1	The object is completely recognized

It is necessary to note that formally both of the neural networks can be integrated in one common general neural structure. In this case another approach by applying additional final decision strategy is preferred. The reason is that the neural networks are not flexible in making decision in principle. The main idea is based on using of several different neural networks with different decision criteria and then the final decision to be formed on the ground of more flexible algorithms, for instance fuzzy logic algorithms [31].

5. Neural network automatic recognition – experimental results

Numerical experiments that prove the correctness and illustrate the capabilities of the developed neural networks automatic target recognition system are carried out. The stages of the recognition process applied to identify two targets MIG-29 and Boeing-707 are graphically illustrated on the panels in Fig. 12 and Fig. 13, respectively.

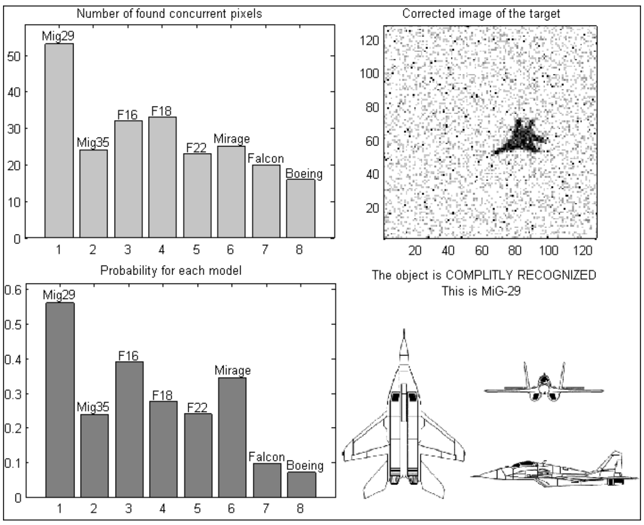


Fig. 12. Diagram with the results of the recognition process for aircraft MiG-29

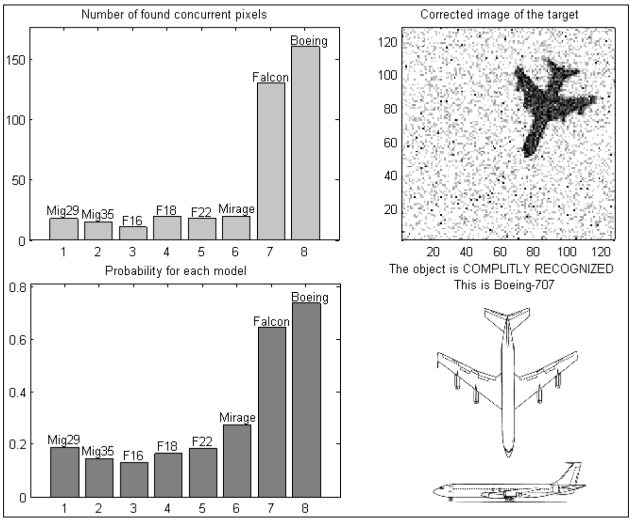


Fig. 13. Diagram with the results of the recognition process for aircraft Boeing-707

On the left part of each panel diagrams with results of the recognition process for 8 targets are depicted. A diagram that illustrates the functionality of the LVQ-1 neural network is pictured up side. It presents the maximum number of coincident pixels for each of the eight models. A diagram that illustrates the functionality of the LVQ-2 neural network is pictured down side. It presents the recognition process in a probability form as a ratio of the same number of coincident pixels to the full number of pixels from the contour line of the relevant model.

In the right part of the panel, the original reconstructed and focused image of the object is presented, that is used for contour line extraction, necessary for the realization of the image recognition algorithm.

The final decision is automatically displayed as a text string, explaining the inference, accomplished by the identification system. In case the target is identified, the type of aircraft is specified and a graphic map appears that presents the object from different point of view. If additional information exists as the geometric dimension, tactical and technical data, nationality or weapon equipment of the recognized target, it is presented on the display. Otherwise, the motives of the accepted decision are indicated, and the most probably reasons for this decision, are specified. The experiments are carried out in Matlab program environment.

6. Conclusion

In this paper, an image processing algorithm and system for ISAR target recognition are considered. The recognition system is created by using neural network's architecture. Two LVQ neural networks are constructed and implemented in program environment. A training algorithm by teacher is preferred. Final identification decision strategy based on the inferences of the two neural networks is formulated. Results of numerical experiments that prove the correctness and effectiveness of the suggested recognition system are graphically illustrated.

The suggested algorithm for target identification has logical structure and provides for the necessary reliability of the identification in the presence of the disturbance in the image and corruption in contour line of the displayed image. On the second place, the number of neurons in the first layer is defined by the number of the models, but not by the number of pixels in the image.

The selected architecture of the neural network has the following advantages. It possesses a property of associative memory, which guarantees the correct classification of the object in the presence of high level of noise background and incomplete and distorted images. Substantial advantage of the algorithm preferred for neural network learning is the training process. It comprises one single epoch, completely determined, fast and flexible. The weight matrices of the layers of both neural networks are completely known. Thus, the results can be unambiguously defined. Another advantage is that the complementation of new etalon models in the neuron network is reduced to addition of new neurons in the first layers of the neural network and extension of the input training matrix. The training process lasts only one epoch as well. Finally, the suggested neural network can be easily realized in a hardware setting.

Generally, the neural networks are not flexible in decision making. It requires a different approach in neural networks' implementation, e.g. based on using of many neural networks with different decision criteria. Then, the final decision can be formed on the ground of more flexible algorithms, for instance fuzzy logic algorithms [31] which are the aim of the authors' future work.

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