AN ALGORITHM FOR ISAR IMAGE CLASSIFICATION PROCEDURE

Assist. Prof. PhD Slavyanov K.[1], Assist. Prof. M.Sc. Nikolov L.[2]
Faculty „Artilery, Air defence and CIS“ – Shumen, National Military University, Bulgaria

k.o.slavyanov@gmail.com[1]
linkonikolov@abv.bg[2]

Abstract: *This article offers a neural network architecture for automatic classification of Inverse Synthetic Aperture Radar objects represented in images with high level of optimization. A full explanation of the procedures of two-layer neural network architecture creating and training is described. The neural network is experimentally simulated in MATLAB environment.*

Keywords: NEURAL NETWORKS, ETALON MODEL, TRANSFER FUNCTION

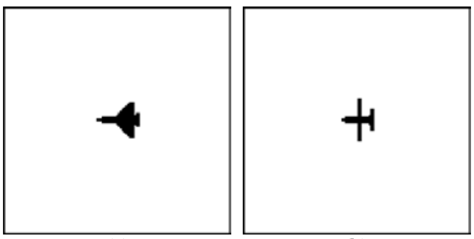
1. Introduction

In the time of globalization, many aircraft models are produced and thus the main ISAR (Inverse Synthetic Aperture Radar) systems task is more complicated because the planes are constructed with relatively small differences in product design for aircraft of a given class of different manufacturers. The neural networks technologies can be implemented in the classification and recognition process in different SAR and ISAR systems [1, 2, 3].

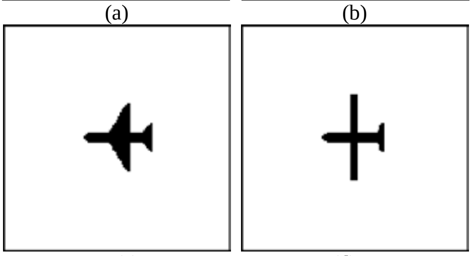
In this paper, a new procedure for ISAR objects classification in the recognition stage is proposed based on several main classes or sets of flying objects gained by the specifications in the structural models of the aircrafts. Different types of mobile objects can be easily distinguished by their size [4]. The algorithm in this paper can be used for a simple classification of the observed ISAR object to small, middle or big size.

2. Preconditions

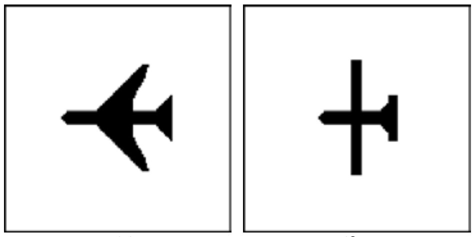
For the simulation environment is assumed that the process of obtaining a horizontal orientation of the observed object in a network of 256x256 pixels is completed with linear resolution at azimuth and distance, respectively $\Delta L = 0.5\,[m]$ and $\Delta R = 0.5\,[m]$. Procedures for filtering the resulting image and extraction of 128x128 pixels subarea containing the object‘s silhouette and image optimization are also preconditions for the binary matrix *S* with the aircraft object [6,7,8]. That object is to be compared with *L* etalon models representing the size classes “Small”, “Middle” and “Big”. The etalon models are designed to be binary matrices, whose elements are a numerical representation of graphically described dense models of sample airplanes of different sizes. Two models are used for each airplane size classes definition in relation with the most popular wing shapes for them. The exemplary graphically detailed dense aircraft models that form the model base in the numerical experiments are shown on figure 1. On Fig. 1 (a), (b) models of "Small" class are presented, on Fig. 1 (c), (d) - models of “Middle” class and on Fig. 1 (e), (f) -models of the "Big" class.



(a) (b)



(c) (d)



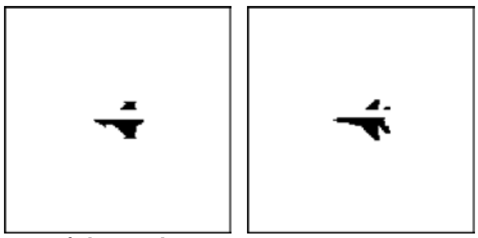
(e) (f)

Fig. 1 *Images of graphic dense reference models of classes "Small" (a, b), "Medium" (c, d) and "Big" (d, e).*

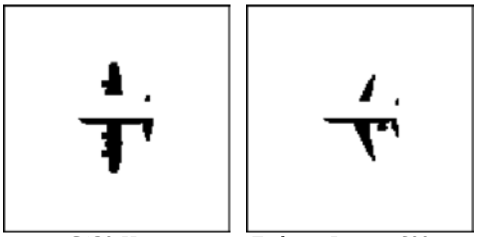
Dense object patterns are placed exactly in the middle of the frame, both horizontally and vertically. Model matrices with the size of 128x128 elements are formed as follows: If the pixel of the graphical dense model is part of the dense model, the value of 1 is assigned to the corresponding matrix element, otherwise the element is 0.

For the simulation experiment, sixteen airplane models are defined in a rectangular network of 128x128 pixels with network dimensions $\Delta X = \Delta Y = 0.5\,[m]$. Sixteen exemplary graphical dense models are used: Eurofighter Typhoon, Pilatus 9M, Rafale, Mirage 2000, MiG-29, Gripen, Falcon 2000, F-22, F-18, F-16, C-130 H, Bombardier Q400, Boeing-747, Boeing-737, Boeing-707 and Embraer Legacy 600. The reference models are created based on detailed graphical maps, accompanied by precise data on the geometric dimensions of objects in the three dimensions. Graphics cards and data are published on the FAS website (Federation of American Scientists). The models are designed to be scale copies of the actual planes. Exceptions are made to the Boeing 747 and Boeing 707, whose models are especially diminished geometrically, as they are much larger than the rest. The proportional reduction of the model is aimed to create difficult recognition conditions to assess the reliability of decisions taken by the classification system.

The modeling is carried out under the following initial conditions. Objects are observed with ISAR, their movement is simulated in a rectilinear trajectory at constant speed and at constant altitude during observation. The object is modeled in its own two-dimensional coordinate system with network dimensions on both coordinates [2]. The all sixteen models of actual aircraft database are processed with added shading effect applied to parts of their structure (Fig.2).



Eurofighter Typhoon MiG-29



C130-H Embraer Legacy 600

Fig. 2. *Standard airplane models with added shading effect attached to parts of their structure.*

It is assumed that High resolution at a distance $\Delta R = 0.5\,[m]$ is realized in the Inverse Synthetic Aperture Radar by usage of impulses with linear frequency modulation. The geometry in modeling a 3D coordinate system of observation from the ISAR system and geometry of the 3D System of a flying object are shown on figure 3. The initial parameters of the flying object trajectory are defined in MATLAB environment as follows: $V = 600\,[m/s]$, $f = 10^{10}$ [Hz] is the carrier frequency, $\varepsilon = \arccos\left(\frac{R_{proj}}{R}\right)$, $\beta = \frac{\pi}{2}$, $\gamma = 0$, $H = 5000$ [m], $R = 50000$ [m], $T = 10^{-6}$ [s] is the duration of each impulse in the sequence [5].

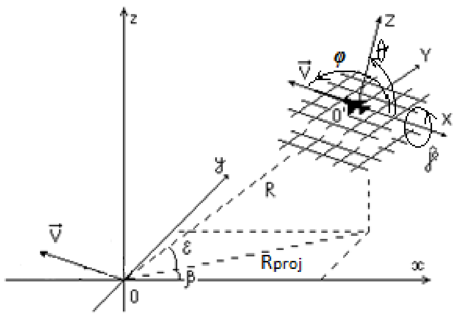


Fig. 3. *Geometry in modeling a 3D coordinate system of observation from the ISAR system and geometry of the coordinate system of a 3D model of a flying object[5].*

ISAR pulses are designed with linear frequency modulation of duration $T = 10^{-6}\,[s]$, repetition period $T_p = 10^{-5}\,[s]$, high frequency oscillation $f = 10^{10}\,[GHz]$, wavelength $\lambda = 0.03\,[m]$ and full frequency deviation $2\Delta F = 3.10^{8}[Hz]$.

3. Algorithm for the classification procedure

The processes for determining the parameters and the realization of the synthesized aperture in the modules of the automated system of ISAR are modeled. To the resulting complex matrix of the trajectory signal is added additive Gaussian noise, with the signal to noise ratio not exceeding 5 dB. The image is restored by applying spectral processing. The pixel intensities in the restored image are normalized in the range of 0 to 1. The image is additionally overwhelmed by additive Gaussian noise with constant zero mean and variance 0.01 and "salt and pepper" noise with density 0.015. It is assumed that the image has been preassigned through the autofocus and optimization procedures of the final image [6, 7, 8]. In this Algorithm for each reference model, the binary matrix of the original image S is multiplied by each of the matrices G_L, ($L = \overline{1,6}$) corresponding to the reference models from the size classes database:

$$S_m = SG_m \tag{1}$$

where $m = \overline{1, L}$ is the number of the current comparison model.

The resultant matrices are constructed with non-zero elements only at the positions in which both the S and G_m matrices have both non-zero elements. In this way, pixel address registration is performed by the matrices of a given reference model that match the pixels of the image of the object compared. The resulting L values are compared, and one of them that has the maximum value is chosen. Its number is related to the model number (model size) with which the compared object is processed with a maximum match between the non-zero positions of the matrices S and one of the G_m matrices.

4. Neural network classification procedure

The main idea in the proposed classification approach is concluded in the comparison of the intensity of the observed image pixels with a set of predefined reference models of different sized objects with a size-specific geometry. In the process of this approach realization, the task is put into conversion of the recognizable image into an input vector to be classified by a neural network as similar to one of the classes in the formed database.

During the second approach designing stage, the reference matrices with the pixel intensity values of the reference images are converted into vectors of 16384 elements by taking the corresponding column members. The resulting vectors form a common matrix „training", named Training1. The matrix is designed to have dimension 16384x16 - 16 pillar, as is the number of objects in the database subject to the recognition procedure and 16384 lines as the number of pixels in one Image. At this stage, a matrix of the "desired result" named Target1 is also built, necessary for the neural network training process. The matrix is dimensioned 3x6 - 3 rows for the three types of objects, classified by their size and 6 columns, because for each size (small, medium and large) two sample models are applied. The location of the non-zero element in the main diagonal of each column is corresponded to the class number that associates the corresponding recognition result.

In the third stage of the design, a neural architecture consisting of two layers, which is built with the tools of the Matlab programming language (fig. 4) and modeled in the Simulink environment (fig.5), is constructed according to the assigned task.

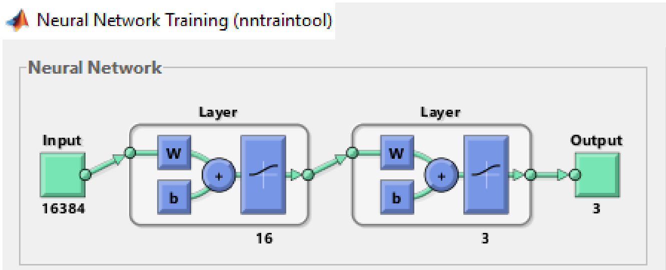


Fig. 4. *Block diagram of Neural Network I designed in MATLAB.*

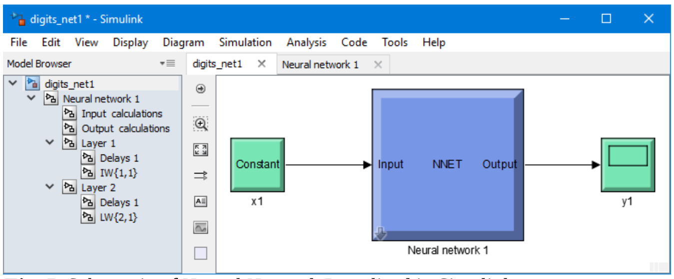


Fig. 5. *Schematic of Neural Network I, realized in Simulink.*

According to the algorithm, a neural network architecture of back propagation type with two layers is selected. Thus the associative memory functions in the presence of interference in the input Sequence are performed (Figure 6). In a theoretical aspect, the learning process for this type of neural network is proven to coincide, and therefore, over a sufficiently long period of self-learning, the weights of the neurons should be suitably adapted to solve the task of properly classifying the vectors from the trainee sample. The first layer of the neural network is "hidden" and is made up of 16 neurons with logarithmic-sigmoidal transfer function. the subclasses to which some of the input vectors are classified are formed by these neurons. The inner structure of this layer is depicted in figure 7.

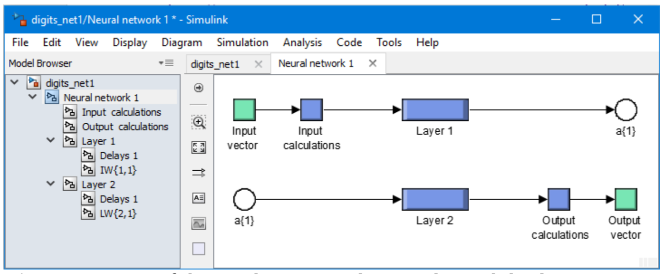


Fig. 6. Structure of the two-layer Neural Network I with back propagation of the error.

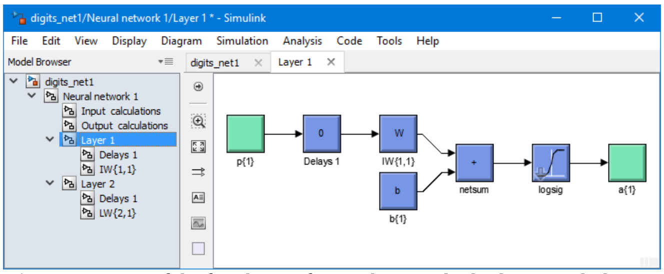


Fig. 7. Structure of the first layer of Neural Network I built in Simulink.

A delay line "Delays 1" is included in the layer structure for conversion of the input sequence elements into an input vector. The logarithmic-sigmoidal transfer function provides high sensitivity and high-resolution ability in the recognition process (Fig. 8).

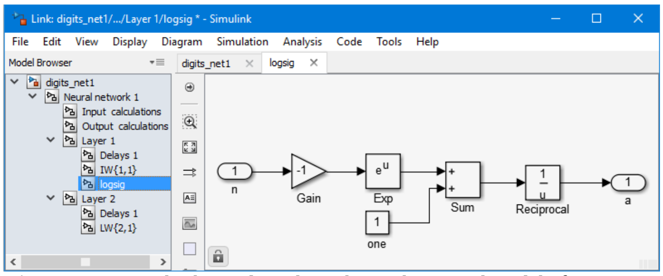


Fig. 8. A structural scheme describing the mathematical model of Logarithmic-sigmoidal transmission function in Simulink.

The structure of the mathematical model and the physical realization of the logarithmic-sigmoidal transfer function is presented - the structure of the neuron inputs in the layer where the weight matrix IW is formed from sixteen weighing vectors, the specific values of which are determined at the stage of learning of the neural network (Fig. 9).

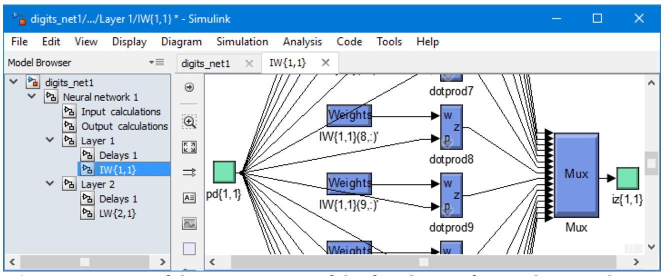


Fig. 9. Structure of the input matrix of the first layer of Neural Network I.

The second layer is made up of neurons again with a logarithmic sigmoidal activation function - the number of neurons in this layer is set according to the final number of desired classes, in this case the number is 3. The number of the neuron "winner" is corresponded to the class ("small", "medium" or "big") to which the current input vector is associated. The role of this layer is designed to classify the results of the first layer and to summarize and reduce them to the user-defined number of classes. Its structure is analogous to the structure of the first layer with the indicated differences. The structure of the mathematical model and the physical realization of the logarithmic-sigmoidal type function is presented - the unfolded structure of the neuron inputs in the layer where the weight matrix LW consists of three weight weights, the specific values of which are determined at the stage of training of the neural network (Fig.10).

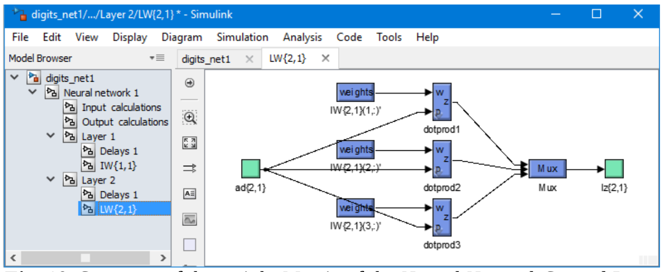


Fig. 10. Structure of the weight Matrix of the Neural Network Second Layer Input.

The fourth stage of the neural architecture is described as a neural network training process, which essentially consists of adjusting the coefficients of the weight matrices of the neurons of the two layers. Toolbox algorithms and procedures for automated self-learning of Matlab neural networks are used to facilitate this task. A method of training a neural network with a teacher is applied, following the next sequence of actions. Initial training of the neural network is processed without interference. At the input of the network, the "training" matrix Training1 is provided, containing the pixel intensity values obtained from the reference models. At the output of the network a desired result is produced, indicated by the Target1 matrix. The learning algorithm is backpropagation of the error. The goal for the possible error is selected to be 0.1 and the error calculating function is of the type sse (sum squared error - accumulated value of the square error). The training process is limited to 1000 epochs. The training results are shown on Figure 11 (a). The Network training is continued with higher requirements - the threshold for the level of permissible error is reduced ten times to 0.01. The learning outcomes are presented in Figure 11. (b). According to the graphs presented, the desired limit value is reached in two training cycles, where the training process is considered complete. Modeling the synthesis process of this neural architecture is executed In MATLAB environment.

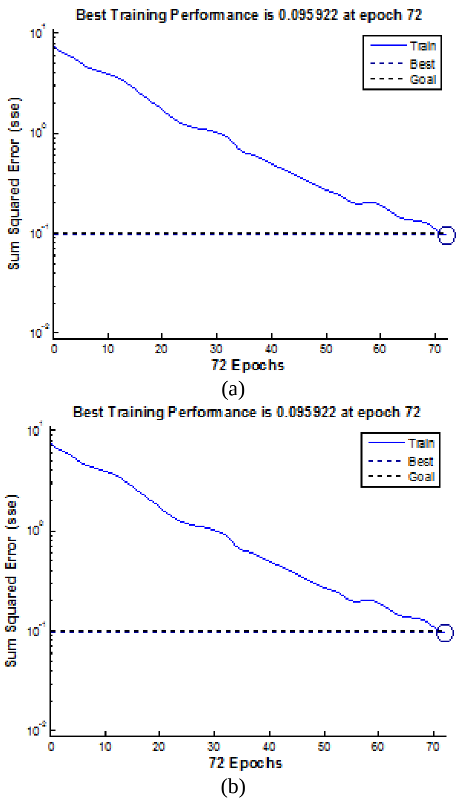
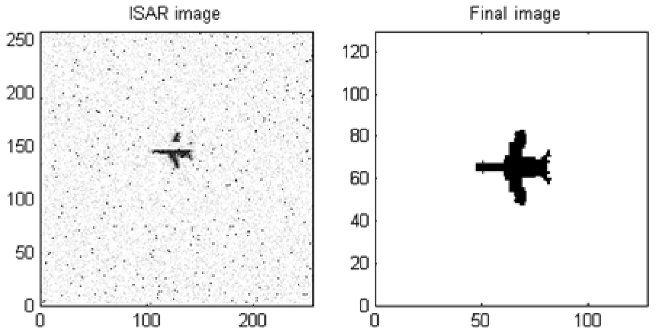
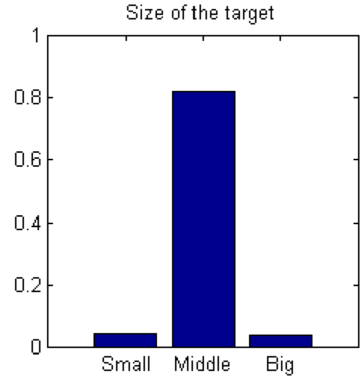


Fig. 11. Graphs describing the achievement of the desired permissible error of 0.1 (a) and 0.01 (b) in the no-noise training reached for 72 and 117 epochs respectively.

The results of a numerical simulation experiment of observation of a model Falcon 2000 are presented on Figure 12. Figure 12 (a) shows the image of the object obtained from ISAR. The radar image processed by the digital filtration and optimization-processing algorithms for quality improvement is shown in Figure 12 (b). The work of the Neural Network I is illustrated on Figure 12 (c) - the plane is classified as Middle.



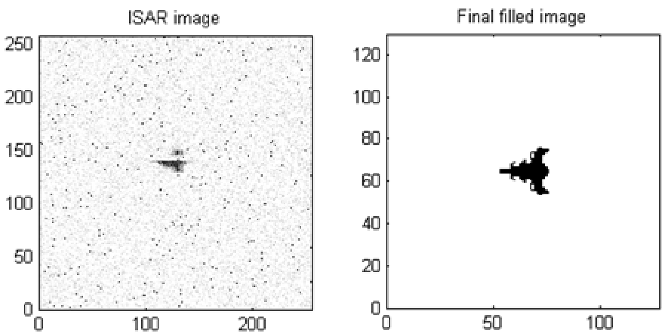
(a) Radar image (b) Optimized radar image



(c) Size of the object

Fig. 12. *Observation (a), optimization (b) and neural network processing (c) for the model Falcon 2000.*

The results of a numerical simulation experiment of observation of a model Rafale are presented on Figure 13. Figure 13 (a) shows the image of the object obtained from ISAR. The radar image processed by the digital filtration and optimization-processing algorithms for quality improvement is shown in Figure 13 (b). The work of the Neural Network I is illustrated on Figure 13 (c) - the plane is classified as Small.



(a) Radar image (b) Optimized radar image

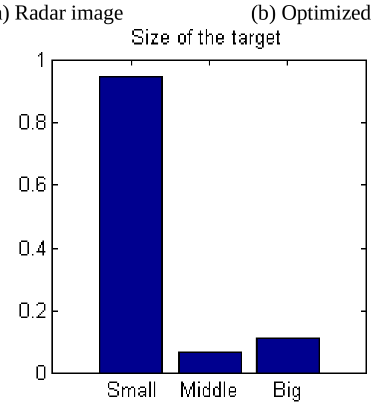


Fig. 12. *Observation (a), optimization (b) and neural network processing (c) for the model Rafale.*

4. Conclusions

As a result of the analysis and the carried out experiments the following conclusions can be made.

The chosen decision making algorithm is logical and accurate for the class belonging of the observed object.

The described neural network operates like an associative memory and makes correct classification of the ISAR objects in high level of noise environment as well as if the objects are not full or heavy damaged.

The used number of neurons in the first layer is smaller than in other networks because it depends of the chosen models in contrast to the image pixel number.

ISAR image classification procedures with similar algorithms can be implemented together for some specific aircraft analysis, leading to ISAR object's fast and complete recognition.

5. Literature

1. Inggs,M.R., Robinson,A.D. Ship target recognition using low resolution radar and neural networks. IEEE Trans., AES, vol.35, No2, April 1999.
2. Kaplan L.M., Improved SAR target detection via extended fractal features, IEEE Transactions on Aerospace and Electronic Systems (Volume: 37, Issue: 2, Apr 2001), 436 – 451.
3. Ning W., Chen W., Zhang X., Automatic target recognition of ISAR object images based on neural network, Neural Networks and Signal Processing IEEE, 2003.
4. Chenchen J. L., Ling H., Wide-angle ISAR imaging of vehicles, Antennas and Propagation (EuCAP), 2015 9th European Conference on, 13-17 April 2015.
5. Minchev, C.N., Slavyanov, K.O., An opportunity for improved modeling and information analysis in ISAR systems, “Engineering.Techologies.Education.Security”, Veliko Tarnovo, May 2015.
6. Image Processing Toolbox User's Guide, Mathworks, 2015.
7. Minchev, C.N. Modeling an automated ISAR information processing system. PhD dissertation, National Military University, Shumen, Bulgaria, 2002.
8. Minchev, C.N., Slavyanov, K.O., An algorithm for ISAR image optimization procedure, Bulgaria, National Military University, Internatinal scientific conference 2015.