

Neural Network Classification Method for Aircraft in ISAR Images

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Abstract — This article offers a neural network method for automatic classification of Inverse Synthetic Aperture Radar objects represented in images with high level of post-receive optimization. A full explanation of the procedures of two-layer neural network architecture creating and training is described. The classification in the recognition stage is proposed, based on several main classes or sets of flying objects. The classification sets are designed according to distinctive specifications in the structural models of the aircrafts. The neural network is experimentally simulated in MATLAB environment. Numerical results of the experiments carried, prove the correct classification of the objects in ISAR optimized images.

Keywords— artificial neural network, engine position, reference model.

I. INTRODUCTION

For the Inverse Synthetic Aperture Radar Systems (ISAR) the main purpose of the observed object's image is to be further classified and fully recognized as a type, model, specifications and owner even if the friend-foe system onboard or radio communications at all are not operational or used properly. In order to provide easy access to the ISAR principles of work a special dedicated airplane flight and ISAR simulation systems can be used to provide the environment for the ISAR system improvements ([1], [2], [3], [4], [5]).

Of particular importance for the proper recognition of objects in ISAR images is the classification of objects in the images according to particular details ([6], [7], [8], [9]). Several approaches can be used to analyse different data obtained for flying objects. The more successful classifications of the object, so they can be successfully merged with fuzzy logic tools to enable full recognition of objects according to specific rules [10].

II. MATERIALS AND METHODS

Preconditions and design.

For the purposes of the study, an ISAR simulation approach has been used ([1], [2], [6], [11]) in order to

generate simulated ISAR images with additive Gaussian noise with constant zero mean and variance 0.01 and “salt and pepper” noise with density 0.015 (figure 1).

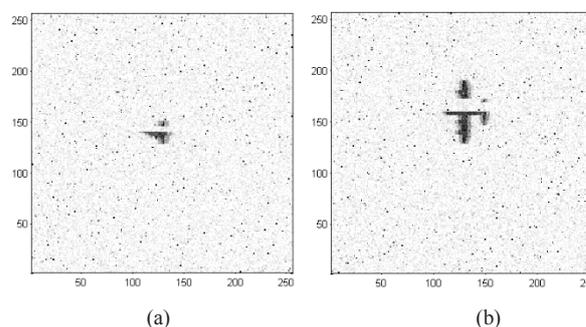


Fig. 1. Reconstructed images in presence of additive noise for the aircrafts Rafale (a) and C-130 H (b) [5].

To achieve the most accurate classification results, it is necessary for the experiments several optimization procedures to be applied to the ISAR image after its generation. It is of particular importance in this research to obtain the most detailed images ([11], [12], [13], [14], [15]), shown of figure 2 and to maintain a target-specific database with reference models [6].

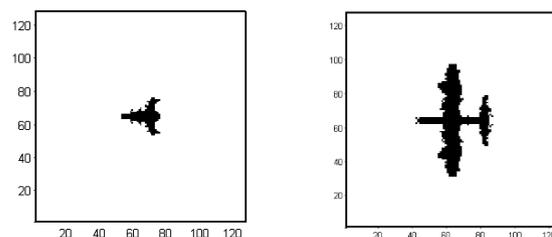


Fig. 2. Optimized ISAR images (128x128 pixels) of the aircrafts Rafale (a) and C-130 H (b).

This article proposes a method by which the observed aircraft is classified according to the location of its engines. R is the number of reference models to be compared. Patterns are binary matrices whose elements are a numerical representation of graphically described models of exemplary planes with different engine positions. With

Print ISSN 1691-5402

Online ISSN 2256-070X

<http://dx.doi.org/10.17770/etr2019vol2.4074>

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Published by Rezekne Academy of Technologies.

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three models, the three different engine versions available, respectively, at the rear of the aircraft, on its wings and the variant where the engines are embedded in the fuselage of the airplane front or rear and do not stand out in its profile. Fig. 3 presents 9 ($R=9$) exemplary graphically-detailed solid aircraft models that form the model base in the numerical experiments. On figure 3 (a), (b), (c) are presented models with the positioning of the wing motors, in Fig. 3 (d), (e), (f) - the position of the engines at the rear of the airplane and in Fig. 1 (g), (h), (i) - engines built into the fuselage.

The object patterns are placed exactly in the middle of the frame - horizontally and vertically. Model matrices with the size 128x128 elements are formed as follows: If the pixel (i, j) of the graphical solid model is part of the structure, then the corresponding element (i, j) of the matrix is assigned a value of 1, otherwise the element is 0.

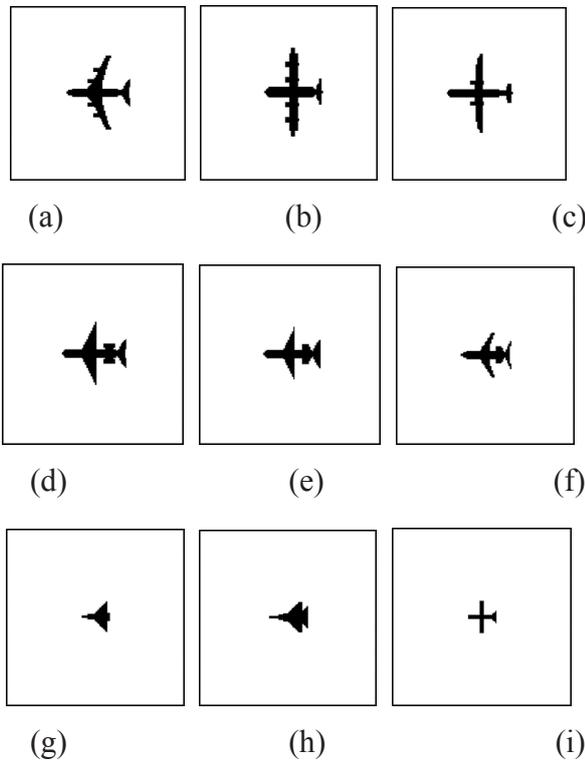


Fig.3. Graphical reference models of airplanes with engine position of types wing (a, b, c), rear (d, e, f) and built in fuselage (g, h, i).

For each reference model, a multiplication of the binary matrix of the original image S is performed with each of the R_F ($F = \overline{1,9}$) matrices.

$$S_m = SR_m \quad (1)$$

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

The resulting matrices S_m will have non-zero elements only at the positions in which the S and R_m matrices have both non-zero elements. In this way, pixel address registration is performed by the matrices of a given reference model that coincide with the pixels of the image of the object being compared. The resulting R counts S_m are compared, and one of them has the maximum value. Its number corresponds to the model number (engine

position) with which the object being compared has shown a maximum degree of matching between the non-zero positions of the matrices S and some of the matrices R_m .

A dataset is composed of 16 aircraft models (128x128 pixels) is used, the same like in [6] representing the planes: 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.

Neural network design and training

The basic idea in the proposed neural network classification approach is to compare the pixel intensity of the observed image with a set of predefined reference patterns of objects with different engine locations. In the process of realizing this approach, the task is to use the previously transformed and recognizable image in an input vector to be classified by a neural network as similar to one of the classes in the formed database.

To implement the described method, the training dataset shown on fig.1 is used. Reference matrices containing the pixel intensity values of the reference images are converted into vectors of 16384 elements by taking the respective column elements (128x128). The resulting vectors form a common "training" matrix called Training that is designed with dimension (16384x16) - 16 columns as the number of objects in the database subject to the recognition procedure and 16384 lines as the number of pixels in 1 image.

At this stage, a matrix of the "desired result" called Target, which is needed for the neural network training process, is built too. The matrix is with dimension 3x6 - 3 rows for the three types of objects classified by their size and 6 columns, because for each type of engine position (on the wings, rear and built in the fuselage) three exemplary reference models are designed. The location of the non-zero element in the main diagonal of each column corresponds to the class number that associates the corresponding recognition result.

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

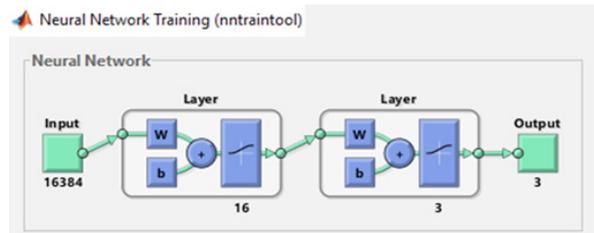


Fig.4. Neural network block diagram implemented in MATLAB.

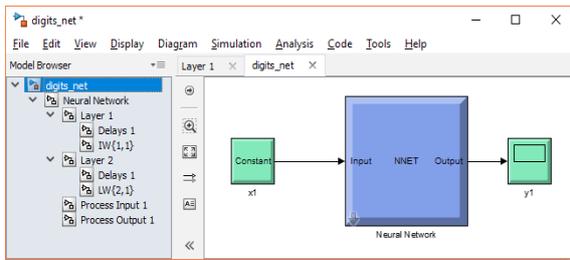


Fig.5. Schematic of Neural Network designed in Simulink.

According to the approach, the neural network is designed with backpropagation architecture of the two-layer error that performs associative memory functions in the presence of input sequence disturbances (Fig.6).

The first layer of the neural network is “hidden” and is made of 16 neurons with logarithmic-sigmoidal transmission function. These neurons form the subclasses, some of which are classified as the input vector. The inner structure of this layer is depicted in figure 7.

A delay line “Delays 1” is included in the layer structure, which converts the elements of the input sequence into an input vector.

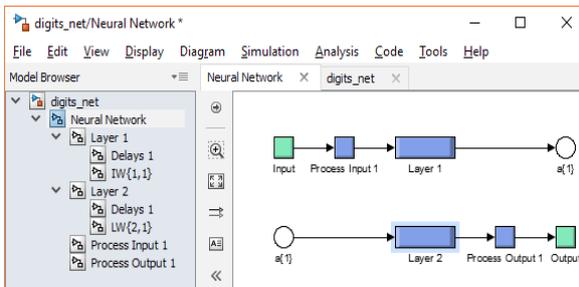


Fig. 6. Diagram of a two-layer Neural Network with right signal propagation and back propagation of the error realized in Simulink.

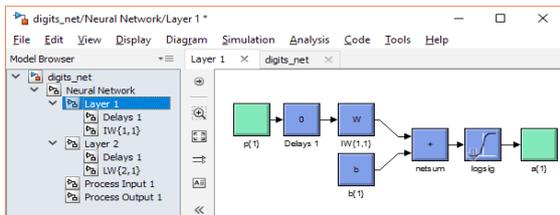


Fig.7. Structure of the first layer of Neural Network built in Simulink.

The logarithmic sigmoidal transmission function ensures high sensitivity and high resolution in the recognition process (Fig.8).

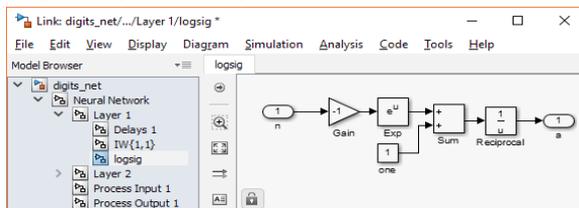


Fig.8. A structural scheme describing the mathematical model of Logarithmic-sigmoidal transfer function in Simulink.

On Figure 9 is presented the structure of the mathematical model and the physical realization of a logarithmic-sigmoidal type of function - the unfolded structure of the neuron inputs in the layer where the weight matrix IW is made by sixteen weighing vector weights whose specific values are determined at the stage of training of the neural network.

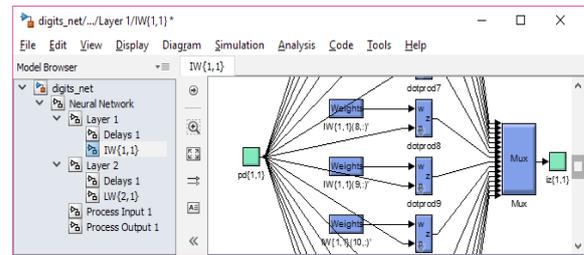


Fig.9. Structure of the input matrix of the first layer of Neural Network

The second layer contains 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” will correspond to the class (“on the wings”, “rear” and “built in the fuselage”) to which the current input vector is determined. The role of this layer is to classify the results of the first layer and to summarize and reduce them to the user-defined number classes. Its structure is analogous to the structure of the first layer with the stated differences. On Figure 10 is presented the structure of the mathematical model and the physical realization of a logarithmic-sigmoidal type function - 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.

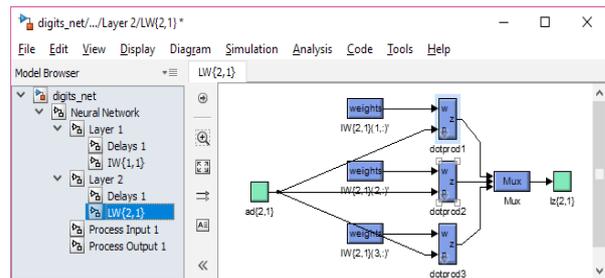
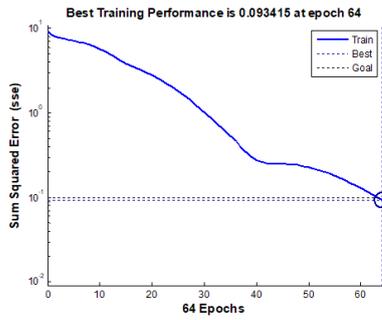
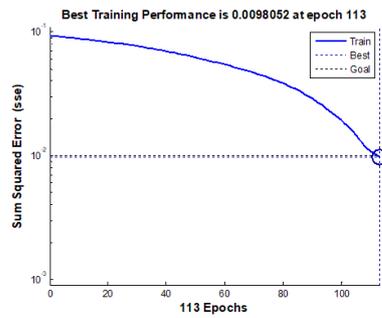


Fig.10. Structure of the input matrix of the second layer of the Neural Network

The fourth stage of the neural architecture realization involves a neural network training process, which essentially consists of adjusting the coefficients of the weight matrices of the neurons of the two layers. Inline algorithms and procedures for automated self-learning of Matlab neural networks are used to facilitate this task. The algorithm used for learning is backpropagation of the error. The admissible error level is 0.1, and the function of calculating this error is sse (sum squared error). The training is limited to 1000 epochs, and the results are presented in figure 11 (a). Network training is continued at higher requirements - the threshold for the permissible error level is reduced ten times to 0.01. The learning outcomes are presented in Figure 11 (b), the training process is considered complete.



(a)



(b)

Fig. 11. Graphics of learning - the desired permissible error 0.1 (a) and 0.01 (b) for noise-free learning reached for 64 and 113 epochs respectively.

III. RESULTS AND DISCUSSION

The evaluation for each object in the ISAR image is resulting in a number from 0 to 1, expressing the classification of the airplane /by its engine location/ according the neural network design and training. The results of 3 experiments with 3 aircraft models, carried out in Matlab environment are described on table 1. The results are improved advancing with repetitions of the experiments with the same airplane model according to the neural network's work.

Figure 12 (a) shows the graphical results of the third simulation with a C130 H reference model with initial parameters of the trajectory of the flying object as described in [10]. The result of the operation of the Neural Network - the position of the engines is on the wings (WingJet). The graphical results for the model Falcon 2000 (Rear Jet) and Rafale (Build In Jet) are depicted respectively on figure 12 (b) and (c).

TABLE 1 RESULTS

Aircraft model used	Simul. №1	Simul. №2	Simul. №3
C-130 H	0.72574	0.793476	0.823917
	0.142658	0.06961	0.059254
	0.014988	0.019725	0.019126
Falcon 2000	0.081169	0.07581	0.021735
	0.706703	0.796599	0.924063
	0.016546	0.012988	0.010172
Rafale	0.010236	0.015908	0.017213
	0.009062	0.003987	0.003661
	0.989968	0.993362	0.993443

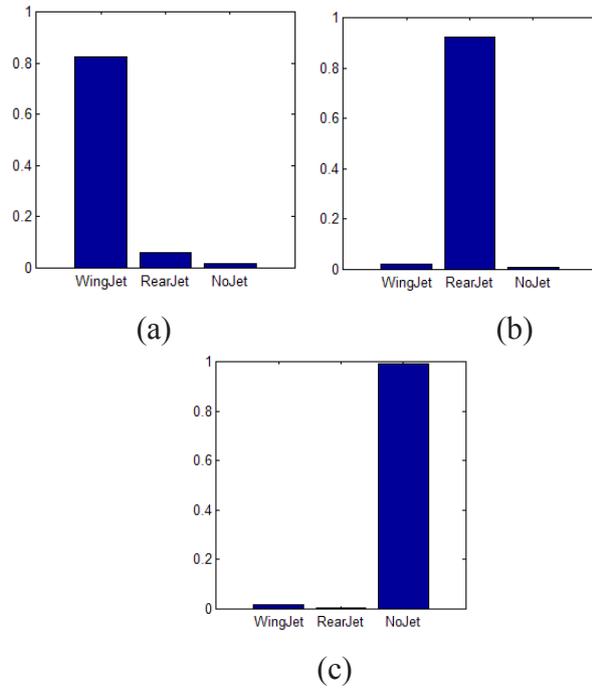


Fig. 12. Neural network graphical results (for simulation № 3) for the models: C-130 H (a), Falcon 2000 (b) and the Rafale (c).

IV. CONCLUSION

In this article, the decision-making processes concerning the type of object being identified are modelled by processing the results obtained from the proposed method. The resulting radar images can be classified into several larger groups or pluralities of planes, depending on the location of the engines, at the stage of their recognition. In this way, partial information about the observed object can be obtained even if it is not fully recognized.

The classification method can be used for any other silhouette distinguishable details in different type of aircraft structures analyzed in ISAR images. In combination with different classification approaches like speed and power detection, airflow and temperature variations etc. the problem of complete identification of an aircraft without any communication lines can achieve more grounded results.

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