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MEANS FOR A CLASSIFICATION TECHNOLOGY OF SYNTHETIC RADAR IMAGES OF OBJECTS HAVING COMPLEX SHAPES

Introduction. *Currently, research into the synthesis of wave images of reflected sound and radio signals has been actively carried out, due to the fact a successful attempt to determine the type of an object for which there is such an image requires either a very large sample base or an intelligent recognition tool. An attempt is made to analyze and recognize the type of an object of a complex shape (using ships as example) with the aim of its further use in applied tasks such as creation of homing heads for anti-ship missiles.*

The purpose of the paper *is to simplify and speed up the process of classifying objects having complex shapes based on their reflected radar images. For this purpose, we consider synthesized images generated on the basis of facet models. Then, on the basis of synthesized images, recognition is performed using neural networks.*

Results. *It is shown that the method developed for recognition of synthesized images has high reliability, and allows for building of a technology in the future. The elaborated model of image generation provides for a possibility of conducting experiments exclusively in a digital form, making thereby expensive live experiments unnecessary.*

Conclusions. *Despite very good results from a mathematical point of view, and in spite of the available convenient tools, such as faceted models for creating radar images, the task still requires further research, since the final product (technology) must be applied in the area where the cost of an error is very high. As for now, the development of the neural network approach looks the most promising.*

Keywords: *facet model, remote sensing, underlying surface, radar image.*

INTRODUCTION

Currently, research is actively being conducted in the field of synthesis of wave images for reflected sound waves and recognition of the resulting images [1]. These studies mainly concern systems and means of location, both passive and active, based on sound waves. The next stage in this line of inqury is the transition to active object location using radio waves.

Decimeter and centimeter range radars have wide practical applications in tasks related to onboard radar stations (RS) of aircraft and, most importantly, cruise missiles. At the same time, under the conditions of modern military confrontation anti-ship missiles (AShMs) are at the same time the most common and the most effective means for destroying ships.

Special attention should be paid to the complexity of the AShM electronics, which should allow target search and identification, and long-distance route planning without the need for prior course planning and/or external targeting. To these ends, the USA has adopted LRASM AShM (since 2018), which meets all the specified requirements. In Ukraine, the Neptune AShM was developed and consequently adopted in 2020 which is a subsonic low-altitude AShM designed to destroy not only ships with a displacement of up to 5,000 tons but also ground targets. It was developed by the Luch a State Kyiv Design Bureau, on the basis of the Soviet Kh-35 missile, in which development industrial enterprises of Ukraine once participated.

The key component of AShM electronics, which gives the misiles such capabilities, is a radar-based homing head (HH), owning to the use of phased array antennas (PAAs) [2]. It was the development of antenna arrays (AA) that led to increased AShM capabilities. Furthermore, the transition to digital antenna arrays (DAA) increased the capabilities of missile technology.

Compared to a similar task of the active location of high-speed objects using radio waves the task of location (targeting) of ships has a number of features that complicate the development and possible use of such means. This is most strongly manifested in the task of determining specific parameters, first of all the shape of high-speed maneuvering objects. In the case of air-borne object, a high-speed maneuvering object is usually an airplane, observing it for a certain period of time, in addition to the distance, speed, and maneuverability assessment gives the value of such parameters as the average value of the effective scattering surface or radar cross-section (RCS) and its dispersion [3]. The dispersion value is an important parameter for recognition, as it contains averaged information about the geometric properties of the aircraft. Yet, for both sea and river ships due to their much slower speed of movement and much lower maneuverability, the power of the reflected signal, which is a function of the RCS, has a much less informative variance since the objects are hit with waves mainly from one of the directions. In addition, there are other features requiring that the task of researching the radar image of ships must be set and solved as a separate task, and not just based on the results obtained for aircrafts.

PROBLEM STATEMENT

Let us consider the case when radio waves from the decimeter and centimeter ranges are used to find and track a target. The research approach for this case is based on the construction of models that reproduce the surface of the target, first of all, on faceted models [4]. It is expected that it will be possible to classify objects on the basis of emulating the signals reflected from these facet models.

A number of points are not considered in this paper, such as basic transformations [5] of the time-frequency image, generalized features [6, 7], and Doppler effects [8]. The main element of this study is the RCS of the target as in [4, 9–11].

However, as noted above, the average RCS and its variance are not always good sources of information. In our study, it is assumed that the reflectance calculated from the surface (facet) model can provide enough information for the identification of the characteristics of the object and, possibly, the complete identification of the object. For this purpose we developed a surface model of the object and a method of synthesizing the signal reflected from it.

To do this, an analysis of behavior of the value of the amplitude of the reflected signal from the surface of model was conducted. For convenience, it is assumed that the system of the emitter and sensor is monostatic, that is, the source of radio emissions and the receiver are so close that the distance between them can be neglected, or even the same physical antenna is used, which alternately works for emission and for reception at different time intervals.

It is furhter assumed that the distortions induced by the model do not destroy the effectiveness of the features that will be used for object recognition in the future.

The purpose of the paper is to create means for the technology of classification of synthetic radar images for objects having complex shapes. It is based on RCS and temporal characteristics of the amplitude of the synthesized radar image.

GEOMETRIC CHARACTERISTICS OF SURFACE MODELS

For many simple shapes, there are analytical formulas that allow obtaining RCS values for shape at a given angle. It is assumed that the final RCS can be constructed as the sum of elementary forms RCSs. Thus, Fig. 1 shows: a) a flat square plate perpendicular to the direction of emission, b) a cylinder, and c) a sphere. At the same time it is assumed that the wavelength (λ) is much smaller than the linear dimensions of the object (elementary form), and the distance D is so large that the wave can be considered flat.

The dependence of RCS on the angle of emission is called the scatter diagram of the target.

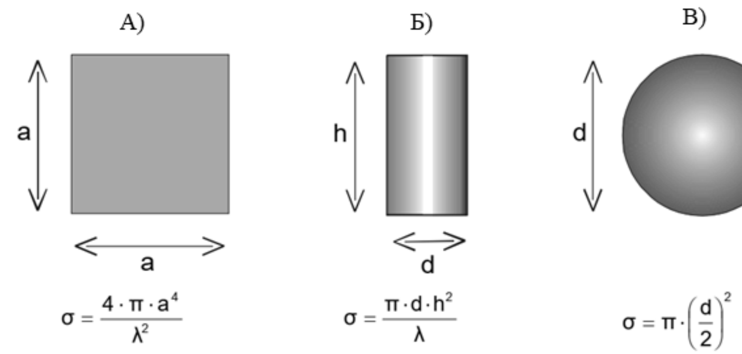

Fig. 1. Some simple forms and their RCS, where *a* is the side of the square, *h* is the height of the cylinder, and *d* is the diameter (of the cylinder or the sphere).

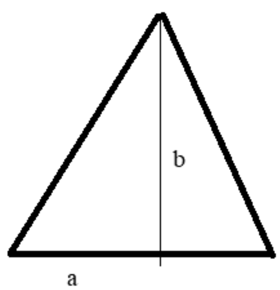

Fig. 2. Triangular plate: *a* is the base, b is the height.

When the angle of incidence of the wave is not the right angle (90^o), the formula for reflection from the plate at angle α takes the following form:

$$\sigma = \frac{4\pi a^4}{\lambda^2}\left(\frac{\sin(x)}{x}\right)^2 \cos^2 \alpha \tag{1}$$

$$x = \frac{2\pi\, a \sin\alpha}{\lambda}. \tag{2}$$

Since the surface model will most likely be formed as a faceted model, and will consist of triangles, it is necessary to give the formula for the triangular area (Fig. 2).

$$\sigma_{trg} = \frac{4\pi a^2 b^2}{\lambda^2}. \tag{3}$$

The value (3) is calculated for perpendicular exposure. However, under the condition where emission hits at an angle, the formula becomes much more complicated.

$$\sigma(\theta,\varphi) = \frac{\sigma_{trg}\cdot(\cos\varphi\cos\theta)^2}{[(ka\sin\varphi\cos\theta)^2-(kb\sin\theta)^2]^2}\times$$

$$\begin{bmatrix} [(\sin(ka\sin\varphi\cos\theta))^2-(\sin(kb\sin\theta))^2]^2 \\ +(kb\sin\theta)^2+ \\ \left(\frac{(\sin(2ka\sin\varphi\cos\theta)}{2ka\sin\varphi\cos\theta}-\frac{\sin(2kb\sin\theta)}{2kb\sin\theta}\right)^2 \end{bmatrix}, \quad (4)$$

where θ, φ are the corresponding angles at which wave falls at the facet, k – coefficient of multiplicity (k=1…n), a,b – dimensions of triangle, as before.

Using this formula it is possible to calculate the RCS of any faceted model element by element if all the facets are reduced to a triangular form. At the same time, the effects related to the phase of the reflected signal can also be taken into account since when RCS is calculated by this method, the exact spatial coordinates of each facet are known, along with the distances that affect the phase in which the signal will arrive at the antenna.

However, a better alternative would be to directly calculate the RCS by using the ray tracing method. In addition to the fact that exist ready-made free and commercial libraries for this method it, among other things, theoretically allows the use of non-triangular elements in the surface model, provided that there is a formula for them that describes reflection (scattering).

For example, for a square plate, when the projection of the beam onto the plane of the plate is parallel to one of the sides, the RCS values σ (depenfing on the angle α) obtained by the ray tracing method are shown in Fig. 3.

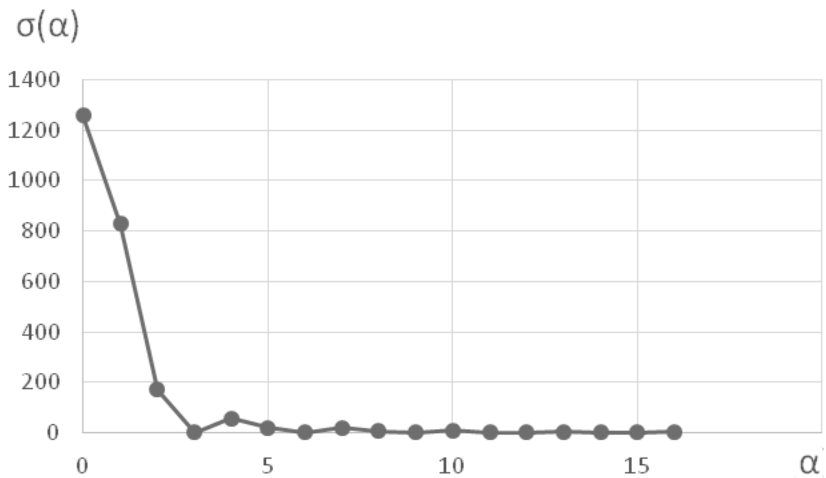

Fig. 3. An RCS (σ(α)) graph depending on the angle α.

A SHIP MODEL AND ITS REFLECTED SIGNAL

A number of features, such as basic transformations of the time-frequency image [5], generalized features [6, 7], and Doppler effects [8] are not considered in this work. The main element of this study is the RCS target as in [4, 9–11].

Fig. 4 shows a simplified faceted model of a ship, Fig. 5 dispalys visible reflective (scattering) points (minimum reflective elements) are displayed, and Fig. 6 presents the reflected signal, and Fig. 7 depicts the envelope of the signal.

As can be seen from Fig. 5, 6, and 7 there is a certain dependence between the angle from which the scanning wave enters and the shape of the reflected signal. The following parts of the signal corresponding to highly informative features are of particular interest:

- the time interval before the wave has completely covered the ship;
- the time interval when the wave has not completely covered the ship.

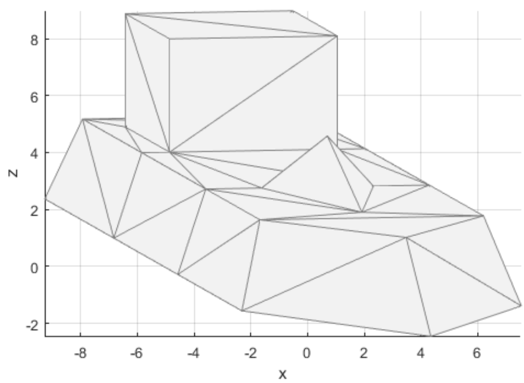

Fig. 4. A ship model.

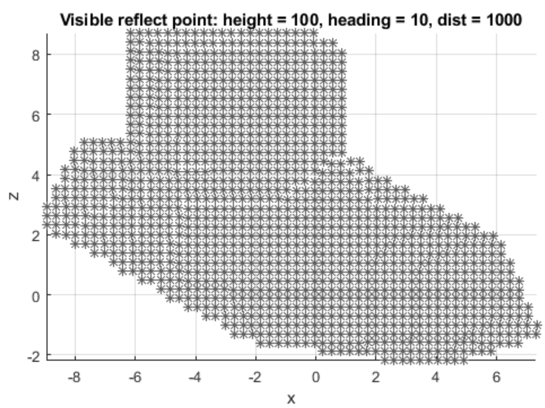

Fig. 5. Visible minimal reflection elements (reflection points).

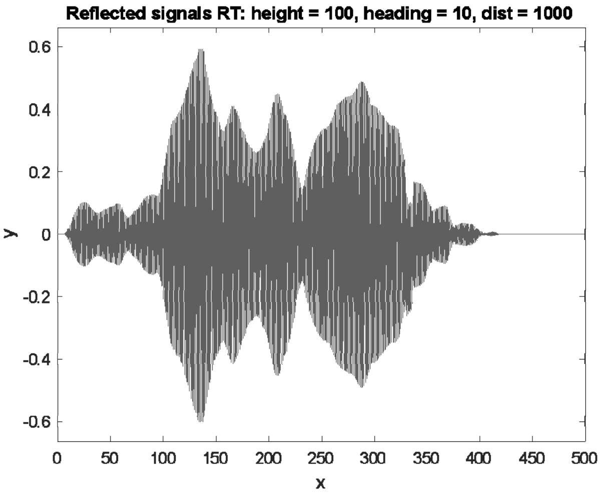

Fig. 6. Structure of the reflected signal.

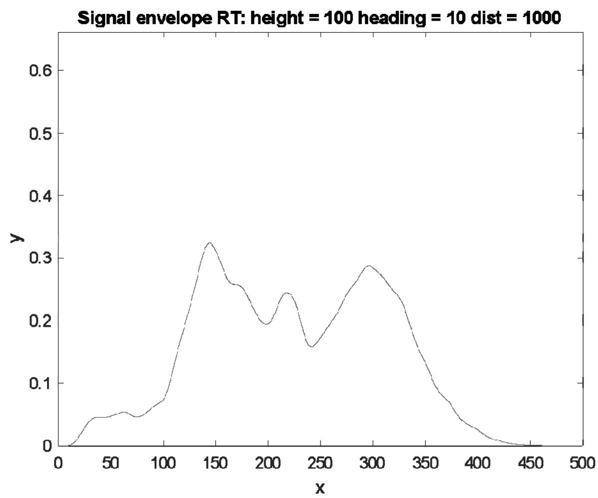

Fig. 7. Envelope of the reflected signal.

Potentially, these parts of signal contain significantly more information compared to the criterion that is based on the frequency correlation of fluctuations of the RCS of the target during discrete tuning of the emitter frequency (as proposed in [7]).

SIMULATED SIGNAL RECOGNITION

Recurrent Neural Networks (RNNs) are a special class of supervised machine learning models. They consist of a sequence of nodes with hidden states that have nonlinear interaction. RNNs are mainly used with time series such as: speech recognition [9], automatic anomaly detection in time series [10] etc. They serve a good alternative to the ARIMA model [11].

In a recurrent neural network, connections among nodes form loops. Every cell contains a hidden state that is updated at each iteration using its previous values. Such a structure creates the internal state of the network and works as a memory.

The RNN equation is:

$$\begin{cases} s_t = f(U \cdot x_t + W \cdot s_{t-1}), \\ h_t = g(V \cdot s_t) \end{cases} \tag{5}$$

where x is the input vector, s is the hidden vector of RNN layer values, lower indices t and t-1 represent moments of time, h — the output vector of RNN layer values, U — the weight matrix of the transition from the input layer to the hidden layer, V — the weight matrix of the transition from the hidden layer to the output layer, W — the weight matrix of the transition of the states of the hidden layer from the previous to the current moments of time, g and f — the activation functions for the initial and hidden layers, respectively.

Due to such architecture, RNNs are able to:

– recognize regularities, characteristics and dependencies in sequential and time series data;

– store, remember and process complex signals for a long period of time;

– match the input sequence with the output sequence at the current time step and predict the sequence at the next time step;

– reproduce any target dynamics after the training process, even with adjusted accuracy.

However, RNNs are prone to explosive growth (or vanishing) of gradient during training, making it difficult for such neural networks to learn long-term dependencies.

In order to solve this problem, Long Short Term Memory networks (LSTMs) were proposed in [12]. Their distinguishing feature is the existence of special memory blocks in the periodic hidden layer which accumulate information about the state. Each memory block has self-connected memory cells that store the temporary state of the network and special multiplicative units called gates that can control the flow of information. These cells and gates allow the LSTM to capture the gradient at a node and prevent it from disappearing. The structure of one LSTM cell is shown in Fig. 8.

By default, the activation function of all gateways is sigmoid. The output value ranges from 0 to 1 and represents the percentage of information that is allowed to pass out. The shape of the activation function is important and can significantly affect the efficiency of neural network.

The hyperbolic tangent function is the default activation function for the output gate of an LSTM cell. The main advantage provided by this function is that it is symmetric about the zero of coordinate system, which helps with the error backpropagation process.

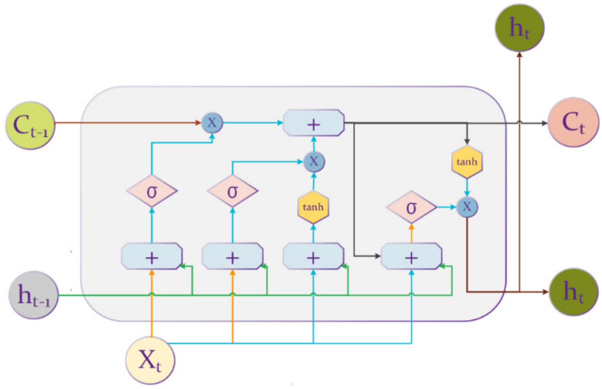

Fig. 8. LSTM node structure

Every LSTM layer is characterized by:
- the matrix W_f and vector b_f which are the parameters of the forgetting gate;
- the matrix W_c and vector b_c which are the parameters of the input gate;
- the matrix W_o and vector b_o which are the parameters of the output gate;
- subindices *t* and *t-1* denote moments of time for each element.

The detailed procedure of an LSTM cell can be explained as follows using notation from (5):

In the first step, the LSTM must decide what to forget. To this end, information about the previous state of the memory is processed through the forgetting gate f_t

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right). \tag{6}$$

In the second step, the input gate i_t decides what should be updated. In addition, the candidate vector C_t^* is updated:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right). \tag{7}$$

$$C_t{}^* = \tanh\left(W_c \cdot [h_{t-1}, x_t] + b_c\right). \tag{8}$$

In the next step, the memory state C_t is updated as a combination of the two parts above:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot C_t{}^*. \tag{9}$$

Finally, the output gate o_t is used to control the output h_t:

$$o_t = \sigma\left(W_o \cdot [h_{t-1}, x_t] + b_o\right). \tag{10}$$

$$h_t = o_t \times \tanh\left(C_t\right). \tag{11}$$

Therefore, every LSTM layer is characterized by:

the matrix W_f and vector b_f which are the parameters of the forgetting gate;

the matrix W_C and vector b_C which are the parameters of the input gate;

the matrix W_o and vector b_o which are the parameters of the output gate.

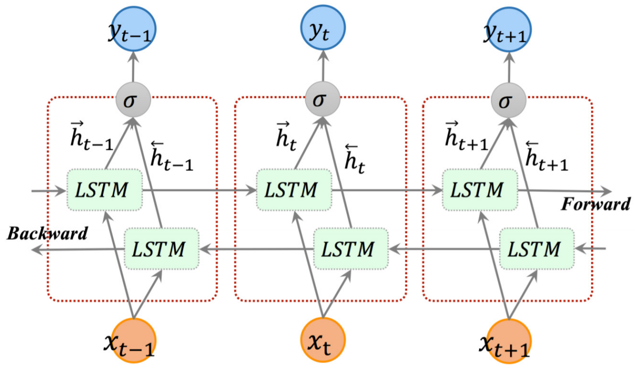

Fig. 9. A bidirectional LSTM Architecture [14]

To increase the performance and learning speed of LSTM neural networks, bidirectional LSTM neural networks were proposed in the study [13]; they can improve the performance of the model for sequence classification tasks. In tasks where all temporal states of the input sequence are available bidirectional LSTMs train two networks instead of one: the first network is trained on the input sequence and the second on the reverse copy of the input sequence. This can provide additional context for the network and lead to a more comprehensive study of the task.

The output sequence h^{fw} of the first network is iteratively computed using inputs in the forward direction in the time range from $t = 0$ to $t = T$. At the same time, the inverse sequence h^{bw} is computed using the inverse time range from $t = T$ to $t = 0$. Both forward and reverse sequences are calculated using the standard LSTM state update equations (6)–(11). The bidirectional LSTM layer generates an output vector y in which each element is calculated using the following equation:

$$y = \omega(h^{\mathrm{fw}}, h^{\mathrm{bw}}) \tag{12}$$

where function щ is used to concatenate the two output sequences. It can be a union function, a summation function, an averaging function, or a multiplication function.

Another extension of LSTM multilayer neural networks is the "Attention" mechanism [15]. The "Attention" mechanism in the deep learning model is a model that mimics the attention of the human brain. When people observe images, they are not looking at every pixel in the image. Instead, they selectively focus their attention on some important parts of the image while ignoring other unimportant parts of the same image.

THE CLASSIFIER INPUT

A set of reflected radar signals was generated for every ship model. For every angle of observation the reflected signal was simulated (in 2 degree increments), thus generating 180 samples for each ship. Table 1 provides information regarding the parameters of the output radar signal, as well as the location of the homing head relative to the ship.

Table 1. Simulation parameters

Name in code	Value Parameter	Description
Location		
dist	1000 m	Distance to the homing head
phi	-90°	Angle between the vector from the ship to the seeker head and the Ox axis
theta	5°	Angle between the vector from the ship to the seeker head and the plane OxOy
rotation_angle	Changes in 2° increments from 0 to 360	Ship course
Heading Signal Parameters (Stored in the global GP dictionary variable)		
w	1 GHz	Signal frequency
length	100 ns.	The duration of the signal
dt	0.05 ns.	Discretization
phi	0	Phase shift

The following steps were taken for data post-processing:

- All generated signals were aligned to the maximal of them to be in a matrix for training the neural network.

- All signals were replaced by their envelopes using an operator that calculates the absolute value of the Hilbert transformation [16] to eliminate high-frequency components of the signal that do not carry useful information.

- The discretization was reduced by a factor of 0.05 (by 20 times) to increase the learning speed of the neural network.

- The data is divided into a training set and a test data set randomly in a ratio of 4:1 to ensure the quality of the developed recognition algorithms.

THE CLASSIFIER NEURON NETWORK MODEL

A neural network model based on sequential bidirectional layers of the LSTM type (Bidirectional LSTM) was used. The last layer of the network consists of one neuron and determines the type of ship that the seeker head "sees" (civilian or military). The network architecture is shown in Fig. 10.

The optimizer "Adam" [17] was chosen with the learning speed parameter $lr = 10^{-4}$. The quality function is the root mean square error value. Its equation has the form

$$\mathrm{MSE}\ (y, y^*) = \frac{1}{n}\sum_{i=1}^{n}(y_i - y_i{}^*)^2 \tag{13}$$

where y and y^* are the expected and available output vectors, y_i and y_i^* are components of vectors, n — the number of values in each of vectors. The optimizer tries to make MSE as small as possible. The major advantage of the MSE function is that it is differentiable, so instead of subgradients one can use normal gradients.

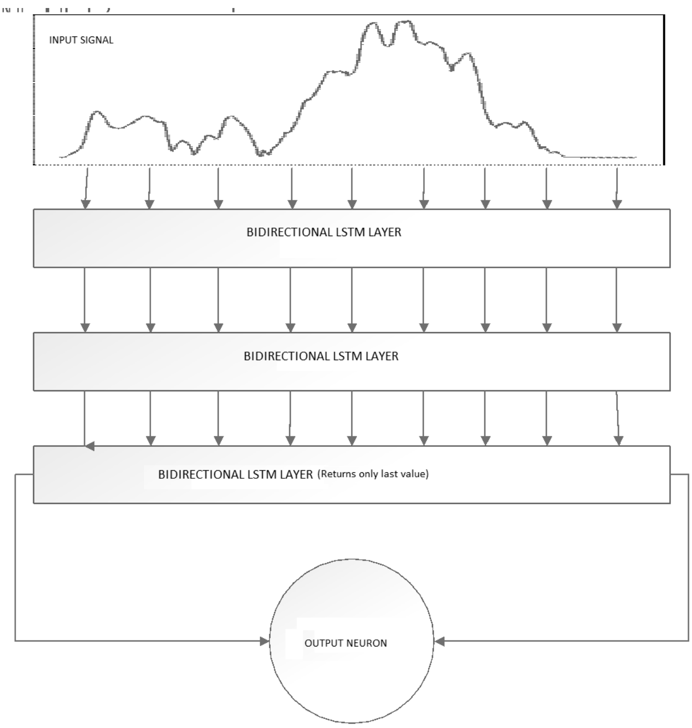

Fig. 10. Architecture of the developed model

CLASSIFICATION RESULTS

Neural network training was conducted on 10 ship models. A military ship is considered a positive class ("1") and a civilian ship is considered a negative class ("0").

As characteristics of classification quality, we will use the following:

ROC curve – a graph that is created by plotting the true positive rate (TPR) against the false positive rate (FPR). To quantify the ROC curve we also calculated the area under it (50% means a random guess, 100% is a 100% guess). This curve shows how the false positive and false negative rate will change when the cutoff threshold is changed.

A cutoff threshold T_{cut} must be determined to calculate accuracy, sensitivity, and specificity. If the output of the last neuron of the model is less than T_{cut} we believe that the model has recognized the signal as belonging to the negative class. If the output of the last neuron of the model is greater than or equal to T we believe that the model recognized the signal as belonging to the positive class. We used a standard cut-off threshold of $T_{cut} = 0.5$, which provides a balance in the recognition of both positive and negative classes.

Maximum correlation criterion was chosen as the control method of classification.

Table 2. Classifier quality assessment

Parameter	Neural network	Maximum correlation
Accuracy	94.4%	55%
Sensitivity	100%	54%
Specificity	89%	56%
Area under the ROC-curve	98%	Not calculated

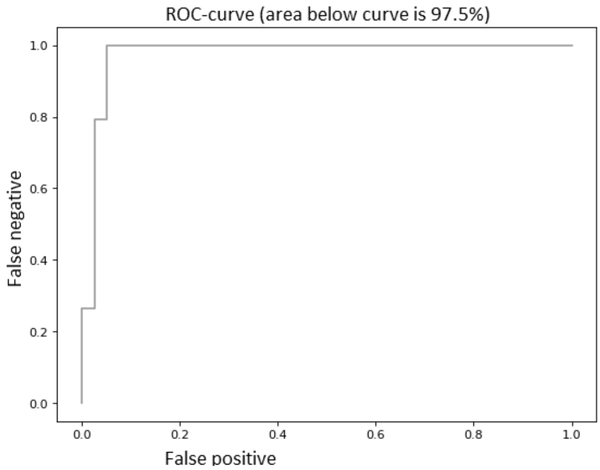

Fig. 11. ROC curve and the area under it for the neural network.

Maximum correlation criterion showed very poor performance so the area under the ROC-curve was not calculated.

As can be seen from the table all reflected signals from warships were correctly recognized by the neural network, and therefore these ships were potentially destroyed. At the same time, only 89% of signals from civilian ships were correctly recognized and remained afloat. Another 11% of civilian ships were mistakenly identified as military.

Fig. 11 displays the ROC curve of the recognition results of two ships. This curve is convex and is close enough to the ideal recognition curve. Therefore, we consider the recognition result to be satisfactory.

The biggest problem in the recognition experiment was created by the civilian ship model "Her Majesty's Hospital Ship Britannic". This is probably due to the large number of different components of noticeable size on the upper deck. They cause a complex envelope shape and complex envelopes are more typical for modern warships.

In accordance with the given task the article demonstrates the method of constructing a model of objects and radar reflections from them and considers the general principles of the synthesis technique of reflective characteristics of complex surfaces for short wavelengths. It is shown why and exactly how such a model is built, and the existence of a significant difference in signal characteristics for different angles is clearly demonstrated. The main advantage of such a model is the possibility of conducting experiments exclusively in digital form, without the need for expensive field experiments.

CONCLUSIONS

According to the results of the software experiments, it is possible to assert the success of the approach for the available data and under the introduced restrictions, however we believe that it is necessary to continue the research in order to increase the accuracy because the conditions of use of the systems that will utilize this developing technology (or its elements) have a very high price of mistake. Further research should continue in the direction of creating an optimal recognition system, most likely it will be based on neural networks.

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ЗАСОБИ ДЛЯ ТЕХНОЛОГІЇ КЛАСИФІКАЦІЇ СИНТЕЗОВАНИХ РАДІОЛОКАЦІЙНИХ ОБРАЗІВ ДЛЯ ОБ'ЄКТІВ СКЛАДНОЇ ФОРМИ

Вступ. *Наразі активно проводяться дослідження синтезу хвильових образів відбитих звукових та радіосигналів, оскільки успішне визначення типу об'єкта, для якого є такий образ, вимагає або дуже великої бази зразків, або інтелектуального засобу для розпізнавання. Проводиться спроба виконати аналіз та розпізнавання типу об'єкта складної форми (на прикладі кораблів) з розрахунку на подальше використання у прикладних задачах, як то створення головок самонаведення для протикорабельних ракет.*

Метою статті *є спрощення та прискорення процесу класифікації об'єктів складної форми за їхніми відбитими радіолокаційними образами. Для цього вводяться до розгляду синтезовані образи, згенеровані на основі фацетних моделей. На основі синтезованих образів виконується розпізнавання за допомогою нейромереж.*

Результати. *Показано, що розроблений метод розпізнавання для синтезованих образів має високу надійність та дає змогу у подальшому будувати технологію на його основі. Наявна модель генерації образів надає можливість проведення експериментів виключно у цифровому вигляді, без необхідності дорогих натурних експериментів.*

Висновок. *Попри дуже хороші результати з математичної точки зору та наявність зручних засобів, як то фацетних моделей для створення радіолокаційних образів, задача вимагає подальшого дослідження, оскільки кінцевий продукт (технологія) має застосовуватись у галузі, де ціна помилки дуже висока. На поточний момент часу найперспективнішим може вважатись розвиток нейромережевого підходу.*

Ключові слова: *фацетна модель, дистанційне зондування, сентизований образ об'єкта, радіолокаційне зображення*