Fuzzy Logic Identifying of Air Targets with Two-Coordinate Radars

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***Abstract* — The paper is devoted to the identifying of air targets with measuring systems based on two-coordinate radars. The solution is based on estimation of the targets height by measuring the range and azimuth. The resulting targets height processed by neuro-fuzzy network, which determines air targets. The configuration of such a neuro-fuzzy network is described in paper. Computer simulation shows the constructive approach proposed for typical situations.**

Keywords* — *traffic control, air target, radar, measurement, target height, neuro-fuzzy network

I. Introduction

Coastal vessel traffic service (VTS) are high-tech and organizationally complex center [1, 2], the main purpose of which is to improve the safety and efficiency of vessel traffic and protect the environment in the area of responsibility.

The main coast based VTS sensors for attitude important navigation information is two coordinate marine radar, to detect other ships and land obstacles, to provide bearing and distance around the water surface surrounding the horizon. In additional as a sensor VTS include Automatic Identification System transponder (AIS).

Estimation of the parameters of each ships trajectory (position, speeds, etc.) and their prognosis is a methodological basis for collision avoidance [3]. If ships are identified as dangerous approaching, the VTS system generates an alarm and recommendations for changing the course or speed.

They are low-altitude low-speed air crafts (helicopters) over the busy water area in the VTS responsibility zone can fundamentally distort the view of the navigational situation. The problem is that the error conclusion of the navigator or VTS operator about an air target as a sea target (when their speeds are comparable) can lead to the generation of false alarms and error management decisions. This problem is partially solved by using AIS at an air craft (AIS information in additional also allows to uniquely identify the type of target). At the same time, there are not all capable of flying over the water area aircrafts are equipped with AIS transponders. This moment requires solving the problem of identifying aircraft objects based on measurements obtained by two-coordinate radars.

In this paper, we study the possibility creating a measuring system using ideas, underlying a neuro-fuzzy system, which provides accurate identification of air targets on the basis of two-coordinate radar.

II. Model Representation and Problem Statement

The problem of three-coordinate observation of airborne objects by two-coordinate radar has repeatedly attracted the attention of researchers [4–9]. The fundamental possibility (however with a limited effect) of solving the three-coordinate task using only one two-coordinate radar was shown [6, 7]; the result was demonstrated with the multi-position observation, when a system of several two-coordinate radars is used [6, 8]; the prospects of estimating the coordinates of objects in a spherical system have been proved: φ, λ, R - respectively, the geographical latitude, longitude and distance from the center of the Earth to the object (as a model of the Earth's surface the sphere is taken) [9].

A feature of external observation of objects over sea surface carried out by radar is the unavailable to measure the forces and moments that determine the movement of the object. Therefore, when describing the evolution of the position of the observed objects, traditionally turn to kinematic models of a polynomial form [10]. For low-maneuverable with constant speed and at a constant height objects, it is enough to restrict of the first degree polynomial for angular components and zero degree polynomial for radial:

$$\varphi_{k+1} = \varphi_k + a^{\varphi} T, \quad \lambda_{k+1} = \lambda_k + a^{\lambda} T, \quad R_{k+1} = R_k, \quad k = \overline{1,m}, \tag{1}$$

where φ_k, λ_k, R_k - the values of the corresponding position of the object at time t_k; a^{φ}, a^{λ} - polynomial coefficient, identified with the rate of change of the corresponding positions; $T = t_{k+1} - t_k$; $t_k \in [t_1, t_m]$.

The information about navigation situation provided by a network of L radars is described by a model of the form:

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$$z_k^{(j)} = \begin{bmatrix} r^{(j)}(k) \\ \psi^{(j)}(k) \end{bmatrix} + \begin{bmatrix} \xi_r^{(j)}(k) \\ \xi_\psi^{(j)}(k) \end{bmatrix}, \quad (2)$$

where $z_k^{(j)}$ – vector of the k-th measurement by the j-th radar station, $r^{(j)}(k)$ – distance from the object to the j-th station at the time $t_k^{(j)}$ (the time of k-th measurement by the j-th station), $\psi^{(j)}(k)$ - is the azimuth of the object with respect to the j-th station at the time $t_k^{(j)}$; $t_{k+1}^{(j)} - t_k^{(j)} = T^{(j)}$; $T^{(j)}$ - period of rotation of the j-th radar station; $\xi_r^{(j)}(k)$, $\xi_\psi^{(j)}(k)$ - instrumental measuring errors, moreover $M[\xi_r^{(j)}(k)] = 0$, $M[\xi_r^{(j)}(k), \xi_r^{(i)}(m)] = D_r^{(j)}\delta_{ji}\delta_{km}$, $M[\xi_\psi^{(j)}(k)] = 0$, $M[\xi_\psi^{(j)}(k), \xi_\psi^{(i)}(m)] = D_\psi^{(j)}\delta_{ji}\delta_{km}$; $j = \overline{1,L}$; M[*] – is the operator of mathematical expectation, δ_{ij} - is the Kronecker symbol.

Having regard to the above model described by equations (1) and (2), an inverse trajectory problem can be posed. The purpose of it is to determine the vector $s_k = (\varphi_k, a^\varphi, \lambda_k, a^\lambda, R_k)^T$ from measurements $z_k^{(j)}$, $j = \overline{1,L}$.

III. The Method of Solving the Problem

A general method for solving such inverse problems is to linearize them around some support solution that characterizes a priori ideas about an object movement. Assuming the presence of a support solution, we will talk about reducing the original problem to the "in small" problem with the desired vector $\delta s_k = (\delta\varphi_k, \delta a^\varphi, \delta\lambda_k, \delta a^\lambda, \delta R_k)^T$ where δs_k - vector of errors of a priori representations. Linearization of the original problem (1), (2) leads it to the following form "state-measurement":

$$\begin{aligned} &\delta s_{k+1} = A_k \delta s_k + q_k, \\ &\delta z_k^{(j)} = H_k \delta s_k + \xi_k^{(j)}, \\ &j = \overline{1,L}. \end{aligned} \quad (3)$$

where q_k is the vector of non-simulated motion parameters, and A and H are matrix coefficients (matrices of partial derivatives). The transformation of equations (3) to the finite-dimensional form characteristic of the problems of the least squares method leads the original problem to the model

$$\delta Z = \widetilde{H}\delta s_i + \widetilde{q}, \quad (4)$$

where δZ is the full vector of measurements on the observation interval, δs_i is the vector of errors of a priori representations at the time t_i, $\widetilde{q}$ is the vector of reduced errors of measurements, $\widetilde{H}$ is the matrix dimension coefficient, which is the composition of the matrices A and H, N is the total number of processed measurements (from all radar stations).

If $a^\varphi(i)$ and $a^\lambda(k)$ are not equal to zero at the same time, system (4) is not already degenerate for one radar (L=1), and if there are several radars in the system (L>1), the problem is in principle solvable for any possible trajectories of the observed object [9].

A characteristic property of the considered problem (1), (2) is the irregularity of the estimates of the radial coordinate (i.e., height) of low-altitude distant objects, which is associated with poor conditioning of system (4), the initial nonlinearity of the problem, and the finite measurement accuracy. This feature of the problem is shown in Fig. 1, which gives an estimate of the height of a surface object (Fig. 1a) and airborne objects moving at an altitude of 100 m (Fig. 1b) and 200 m (Fig. 1c) for the case of two radars measuring the distance from error ± 5 m and azimuth with an error of ± 0.1°. It can be seen that, starting from a certain distance from the radar system, the airborne object (according to the height estimate) becomes indistinguishable from the "sea surface object": in this case, it is 5 km for an object with a height of 100 m and 9 km for an object with a height of 200 m. The height estimates themselves are "rugged" character with random emissions. This makes it necessary, along with assessing the actual height of the object, to additionally determine the range of heights to which the object's trajectory belongs. In the framework of this work, the possible ranges of heights are limited by the concepts of "marine" and "air". With this view of the problem, learning ideas that are currently identified with the concept of artificial neural networks turn out to be productive.

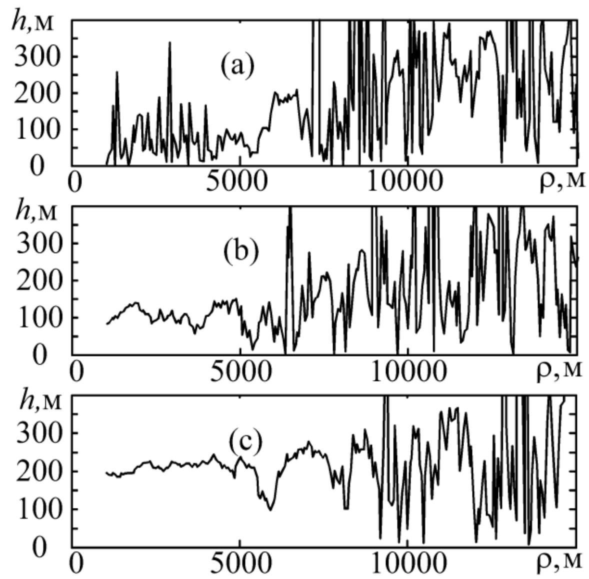

Fig. 1. Evaluation of the height of the object as the distance from the radar. ρ is the distance from the radar system to the object

Let be $\hat{h}_i = \hat{R}_i - R_E$ the estimate of the height of the object above sea level ($\hat{R}_i$ is the estimate of the radial component of the s_i vector, R_E is the radius of the Earth at sea level). Taking into account the features of the problem, we will consider that the main informative features that give an idea of the range of heights of the object are the assessment of its height and the comparative nature (the degree of "ruggedness", "irregularity") of the height estimates at different points in time t_i. We introduce the linguistic variable P_h "object height estimation" with the terms "large" and "small" and membership functions of the type "addition"

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$$\mu_{\text{small}}(h) = 1 - \frac{1}{1+\exp(-a_h(h-c_h))}, \quad (5)$$
$$\mu_{\text{large}}(h) = \frac{1}{1+\exp(-a_h(h-c_h))}.$$

Let be $\Delta_i = 2\left|\hat{h}_i - \hat{h}_{i-1}\right| / \left|\hat{h}_i + \hat{h}_{i-1}\right|$ the relative difference between adjacent height estimates. We introduce the linguistic variable P_Δ "the difference of neighboring estimates of the height of object" with the terms "large" and "small" and the membership functions of terms of the type "addition":

$$\nu_{\text{small}}(\Delta) = 1 - \frac{1}{1+\exp(-a_\Delta(\Delta - c_\Delta))}, \quad (6)$$
$$\nu_{\text{large}}(\Delta) = \frac{1}{1+\exp(-a_\Delta(\Delta - c_\Delta))}.$$

The values $\hat{h}_i$ and Δ_i (input) are processed by a neural-fuzzy network, shown in Figure 2. The output of this network is a numerical value is formed u_i - the degree of belonging of the observed object to the "air" range of heights at a t_i time (it is believed that u_i=0 for sea-surface objects and u_i=1 for air objects). The network consists of three layers.

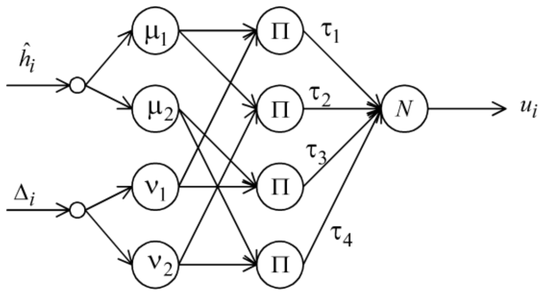

Fig. 2. Neuro-fuzzy network scheme for recognizes aerial objects

The nodes of the first layer μ_1, μ_2, ν_1, ν_2 calculate the values of membership functions μ_{small}, μ_{large}, ν_{small}, ν_{large} respectively.

The nodes Πof the second layer (four nodes) correspond to the premises of four possible fuzzy rules:

1. P_h = "small" AND P_Δ = "small",
2. P_h = "large" AND P_Δ = "small",
3. P_h = "small" AND P_Δ = "large",
4. P_h = "large" AND P_Δ = "large".

Each node of the second layer is connected to those nodes of the first layer that form the premises of the corresponding rule. The output of each node of the second layer is the degree of *j*-th fulfillment of the τ_i rule, which is calculated as the product of the input signals.

We assume that an object can be identified as airborne if the estimate of its height is sufficiently large and at the same time stable enough, that is, the difference between adjacent estimates of the height of the object is small. This corresponds to only one - the second - fuzzy rule. Therefore, the third layer of the neuro-fuzzy network consists of a single node that calculates the relative degree of fulfillment of the second fuzzy rule by the equation

$$u_i = \frac{\tau_2}{\sum_{k=1}^{4} \tau_k}. \quad (7)$$

Training a neuro-fuzzy network (Fig. 2) consists in setting the coefficients of membership functions a_h, c_h, a_Δ, c_Δ. Training can be carried out by an expert method (all coefficients are assigned by an expert), and on a training sample formed by modeling the solution to problem (1) and (2). In the case of training sample, after accumulating data for various heights of the object's movement and the set of possible trajectories, using well-known methods of training networks of this type, on the basis of which a neuro-fuzzy network is trained (Fig. 2), a common training sample is formed [11, 12].

IV. Results of Numerical Simulation

In the forming of problem, it was assumed that the VTS information base is a two round-looking scan radars (for example, of Raytheon type) located at a distance of 5 km from each other, with a rotation period of 3 sec. and error in measuring the angle and range, respectively $\xi_\psi^{(j)}(k) \in [-0.1^\circ, 0.1^\circ]$, $\xi_r^{(j)}(k) \in [-5м, 5м]$. The number of measurements *m* from each station was taken equal to *m*=10 and *m*=20 (that is, measurements are collected within 30 seconds and one minute).

The system was trained on a training sample, the volume of which amounted to about 10,000 "input-output" values obtained by simulating the movement of an object along various trajectories. In this case, the parameters of membership functions took the following values: $a_h = 0.12$, $c_h = 20.32$, $a_\Delta = 2.71$, $c_\Delta = 0.41$.

Figure 3 shows the trajectory of the movement of an air object, modeled to demonstrate the solution of the problem of recognition of air objects using a pre-trained neuro-fuzzy network (Fig. 2).

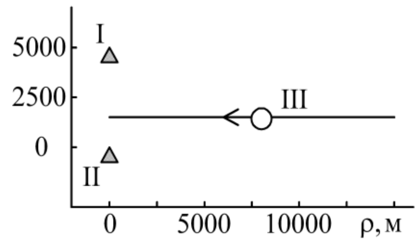

Fig. 3. Simulated configuration of a system with two radars and the trajectory of the object

Here I and II are radar stations, III is the trajectory of the object. The object moves from a distance in a straight line at a speed of 20 m/s, approaching the radar. The ρ - the distance from the object to the line connecting the radar stations.

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Figure 4 shows the results of solving the problem of estimating the height of an object (left column of figures) and evaluating its altitude range with a fuzzy system (right column of figures). Here ρ - the distance from the object to the line connecting the radar, *h* - the height of the object, *u* - the degree of belonging of the object to the status "air".

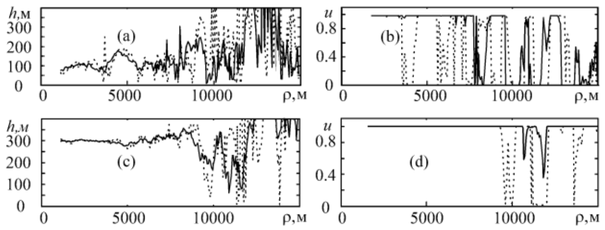

Fig. 4. The result of solving the problem

The task was simulated for objects moving at a height of 100 m (Fig. 4a and 4b) and 300 m (Fig. 4c and 4d). Solid plots correspond to the number of measurements m=20, points correspond to the number of measurements m=10. It can be seen from the figure that, for example, a reliable separation of an air object moving at a height of 100 *m* is possible up to a range of ≈ 3000 *m* at and up to a range of ≈ 7000 *m* at (Fig. 4b). For an object moving at an altitude of 300 *m*, its isolation as air is possible up to a range of ≈ 9,000 *m* at m=10 and up to a range of over 15,000 *m* at m=20 (Fig. 4d). That ranges (in fact, the limits of applicability of the method) are consistent with the size of the areas of responsibility in the waters of seaports, which suggests the suitability of the proposed method for identifying airborne objects for navigation practice.

The results of the work are aimed to expansion of the navigation functions of modern Vessel traffic service.

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