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NAVIGATION SYSTEMS

Fuzzy Collision Avoidance System for Ships

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Abstract—The paper discusses the problem of maritime traffic control. A model of the relative motion of two vessels is considered. An algorithm for the generation of alarms of various types in accordance with the verbal ship–ship danger level is considered. Navigation situations are separated into levels based on the ship's maneuvering intensity and time to collision. A fuzzy decision-making system about the motion's danger level that combines Mamdani and Sugeno fuzzy inference systems is proposed. The results of the numerical experiment that demonstrates the system's operation under standard conditions and the results of the system's field tests based on real ship traffic data in the waters adjacent to the port of Vladivostok are given.

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INTRODUCTION

Maritime traffic control is an exceptionally large scientific and technical challenge. The corresponding problems formed a separate independent part of the science of management [1–3].

In practice, such control is implemented by onshore vessel traffic control systems (VTCSs), i.e., by specialized companies, whose main task is to prevent dangerous situations, such as ship collisions [4–6]. Two-coordinate all-round looking radars supported by satellite navigation, transponders of the An Automatic Identification System (AIS), serve as the information base for a modern VTCS [7].

The estimation of the parameters of the path of the motion of each vessel (coordinates, velocities, etc.) and their extrapolation are the methodological basis for the recognition of the dangerously close approach of vessels. If the vessels are identified to be approaching each other dangerously, the traffic control system generates an alarm and recommendations to modify the path of the motion.

The control decision that ensures the safety of the traffic depends on a number of factors: the velocity of the vessels, the distance between them, their size, maneuverability, and the characteristics of the path. The prediction of shipping traffic always has an element of uncertainty, which requires the formalization of the verbal concept of a "dangerous situation" with the identification of different danger levels such as "very dangerous," "dangerous," and "safe." Danger levels are determined based on experience and navigation practice. This approach allows the ship driver and the coastal VTCS operator to regulate their actions: to make different types of decisions in situations with different danger levels and, thereby, to reduce the degree of uncertainty in making specific decisions.

In [8], the author examined the three-level system of decision-making about the dangerous proximity of ships. In this system, the shipping traffic (maneuvering ships are considered less dangerous than those moving rectilinearly and uniformly) is a feature that affects the decision about the level of danger. A significant drawback of the system [8] is the discrete nature of the value that describes the danger level, which makes it difficult to use it in the case of high vessel traffic density: too many ships have the same danger level at the same time.

This paper is devoted to the study of a collision avoidance system for ships that makes it possible to detect dangerous situations and estimate the danger level by a continuous value using the ideas of fuzzy logic systems.

1. MODEL IDEAS AND PROBLEM FORMULATION

Let us use traditional approximations when simulating the navigation safety of vessel traffic. Firstly, the ship traffic safety will be interpreted by the ship–ship safety model for each pair of vessels. Secondly,

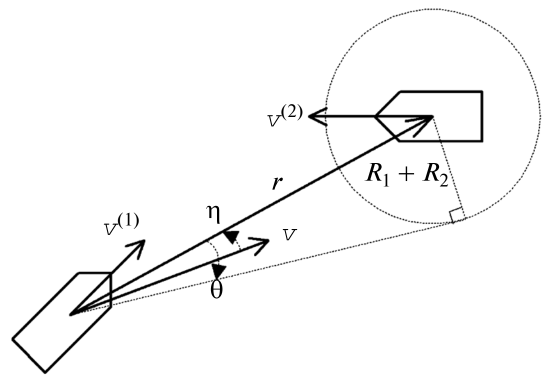

Fig. 1. The model of the relative motion of the ship–ship pair.

because of the fact that the water area controlled by the VTCS is limited to 20–30 km, all the simulations will be carried out in a local Cartesian coordinate system. This approach is used in many well-known collision avoidance algorithms [9–11].

If the GPS/GLONASS is used as the VTCS information base, the measurement of the trajectory of each ship includes its coordinates, velocity, and course [7].

Let oxy by the right orthogonal coordinate system with the y axis directed to the North and the x axis directed respectively to the East. Let us consider two vessels with coordinates $x^{(1)}$, $y^{(1)}$ and $x^{(2)}$, $y^{(2)}$, velocities $v^{(1)}$ and $v^{(2)}$, and courses $k^{(1)}$ and $k^{(2)}$ (in this case, the course of the ships is measured from the direction to the North in a clockwise manner, as is customary in navigation). We will describe all the traffic by the following set of values:

$$s = (r_x, r_y, v_x, v_y)^{\mathrm{T}} \tag{1.1}$$

is the state vector of the motion of two ships, where

$$r_x = x^{(2)} - x^{(1)},$$

$$r_y = y^{(2)} - y^{(1)}$$

are the components of the relative position of ships r, and

$$v_x = v^{(1)} \sin k^{(1)} - v^{(2)} \sin k^{(2)},$$

$$v_y = v^{(1)} \cos k^{(1)} - v^{(2)} \cos k^{(2)}$$

are the velocity vector components of the relative motion of ships v (Fig. 1).

Let us assume the following model representations about the evolution of the state vector of collective motion:

$$\begin{aligned} r_x(t_{i+1}) &= r_x(t_i) - v_x(t_i)\tau + q_{rx}(t_i), \\ r_y(t_{i+1}) &= r_y(t_i) - v_y(t_i)\tau + q_{ry}(t_i), \\ v_x(t_{i+1}) &= v_x(t_i) + q_{vx}(t_i), \\ v_y(t_{i+1}) &= v_y(t_i) + q_{vy}(t_i). \end{aligned} \tag{1.2}$$

Here, $\tau = t_{i+1} - t_i$ is the difference between neighboring points in time, in which the measurements are carried out, while $q_{rx}(t_i)$, $q_{ry}(t_i)$, $q_{vx}(t_i)$, and $q_{vy}(t_i)$ are random nonmodelable motion parameters. The accepted model of the relative motion of ships (1.2) is a kinematic model. Such models are typical of problems of monitoring moving objects when there is no information about the forces and moments that determined the motion.

We have the following measurement equations:

$$\begin{aligned}
&z_{rx}(t_i) = r_x(t_i) + p_{rx}(t_i),\\
&z_{ry}(t_i) = r_y(t_i) + p_{ry}(t_i),\\
&z_{vx}(t_i) = v_x(t_i) + p_{vx}(t_i),\\
&z_{vy}(t_i) = v_y(t_i) + p_{vy}(t_i),\\
&i = \overline{1, N}.
\end{aligned} \tag{1.3}$$

Here, $z_{rx}(t_i)$, $z_{ry}(t_i)$, $z_{vx}(t_i)$, and $z_{vy}(t_i)$ are the measurements of the corresponding projections of the vector of the relative position of the ships and the vector of the relative velocity of ship traffic obtained at time t_i; $p_{rx}(t_i)$, $p_{ry}(t_i)$, $p_{vx}(t_i)$, and $p_{vy}(t_i)$ are occasional instrumental measurement errors; and N is the number of measurements. The solution of (1.2, 1.3) is the estimate of the state vector of the collective motion of two ships (1.1) at each time t_i.

The set of variables (1.1) indicates a potentially dangerous motion of two ships if the following informal conditions are fulfilled:

The direction of the velocity vector of the relative motion of ships v is close to the direction of the vector of the relative position of ships r.

The time remaining until the closest approach of the vessels is allowed below.

The formalization of these conditions is determined by the particular interpretation of the concept of a dangerous situation. Experience of practical navigation shows that a “security area” around the vessel, also called the “domain of the ship” [1, 9, 11, 12], which other vessels try to avoid, is of the greatest importance for safe navigation. In this paper, the static domain of the ship strictly assigned to vessel no. n and interpreted by a circle of a given radius R_n is considered.

Let us introduce the following values (see Fig. 1):

$$|r| = \sqrt{r_x^2 + r_y^2}$$

is the distance between the vessels.

$$|v| = \sqrt{v_x^2 + v_y^2}$$

is the relative velocity of the ships.

$$\theta = \arcsin\frac{R_1 + R_2}{|r|}$$

is the angle determined by the distance between the vessels and the size of their domains. It is believed that under safe conditions ship domains should not overlap.

$$\eta = \arccos\frac{r_x v_x + r_y v_y}{|r||v|}$$

is the angle between the vectors r and v.

$$\frac{d|r|}{dt} = -\frac{r_x v_x + r_y v_y}{|r|}$$

is the rate of change of the distance between the vessels.

$$T = -\frac{|r|^2}{r_x v_x + r_y v_y}$$

is the approximate time remaining before the closest approach of the ships.

A potentially dangerous approach of the two vessels can be formalized as follows (it is assumed that all the functions are defined for the correct calculation of the angles and their differences):

$$\eta < \theta, \tag{1.4}$$

$$0 < T < T^*, \tag{1.5}$$

where T^* is the threshold for time T. Condition (1.4) formalizes a dangerous situation during the subsequent uniform and rectilinear motion of the ships. Condition (1.5) selects from the common array only vessels with an approaching time that is less than the threshold.

With regard to maneuvering ships, the experience of practical navigation shows that in the case of external observation, maneuvering and not maneuvering vessels differ fundamentally in terms of the security of their motion. Firstly, under external observation it is impossible to reliably predict the trajectory of a maneuvering ship [13, 14]. Secondly, in practice maneuvers usually indicate the attempt of the ship's pilot to make the motion safe and their control over the situation. Therefore, from the point of view of external observation for maneuvering vessel the verbal danger level is clearly lower than for a nonmaneuvering ship. This feature of the problem encourages not only the estimation of the set of variables (1.1), as well as conditions (1.4) and (1.5), but also the additional definition of the nature of vessel traffic (uniform and rectilinear or maneuvering).

Thus, in this paper, the objective is to find by coordinate measurements the velocity and course of each ship of the state vector of the motion of two vessels (1.1), to determine the nature of ship traffic, and in conclusion to formulate the danger level of the existing navigation situation.

2. METHOD OF PROBLEM SOLUTION

Let us write Eqs. (1.2) and (1.3) in a generalized form of "state–measurement":

$$\begin{aligned} s(t_{i+1}) &= \Phi s(t_i) + q(t_i), \\ z(t_i) &= Hs(t_i) + p(t_i). \end{aligned} \tag{2.1}$$

The model for estimating the state vector $s(t_i)$ by measurements $z(t_i)$ can be represented by the following equation:

$$\hat{s}(t_{i+1}) = \Phi\hat{s}(t_i) + K(z(t_{i+1}) - H\Phi\hat{s}(t_i)). \tag{2.2}$$

Here, $\hat{s}(t_i)$ is an estimate of the state vector and K is the matrix coefficient.

There are many approaches to the assignment of matrix K. In this paper, the choice is made in favor of the Kalman algorithm popular in practical applications [15]. In this algorithm, coefficients of the matrix K depend on the serial number of the point in time elapsed since the beginning of the iterative procedure (2.2). With regard to the considered problem, the coefficients of matrix K will decrease from iteration to iteration. It will lead to the fact that with an increasing number of iterations algorithm (2.2) will estimate the parameters of the trajectory of vessels moving rectilinearly and uniformly, but it cannot be used to qualitatively estimate the trajectories of the maneuvering ships. This feature of the algorithm makes it possible to determine the nature of the ship's motion. The idea of such a maneuver determinant was proposed by the authors in [16–18].

Let $\hat{s}^{(J)}(t_i)$ be the estimation of the state vector $s(t_i)$ obtained by iterative algorithm (2.2) when processing J recent measurements. If this problem is solved simultaneously for J, $J-1$, $J-2$, ..., and, finally, for only one measurement, then at time t_i we will have a sequence of estimation vectors

$$\hat{S}^{(J)}(t_i) = \{\hat{s}^{(1)}(t_i), \hat{s}^{(2)}(t_i), \ldots, \hat{s}^{(J-1)}(t_i), \hat{s}^{(J)}(t_i)\}. \tag{2.3}$$

Let us introduce the vector $\delta z(t_{i+1}) = z(t_{i+1}) - H\Phi\hat{s}(t_i)$, which characterizes the residual of the measurement in the estimation of the state vector by Eq. (2.2). Let $\delta z(t_i)^{(J)}$ be the residual vector obtained at time t_i in the implementation of iterative algorithm (2.2) that processes recent measurements. Thus, when the plant is monitored at any given time t_i, along with a sequence of estimation vectors (2.3), we will have a sequence of residual vectors

$$d^{(J)}(t_i) = \{\delta z(t_i)^{(1)}, \delta z(t_i)^{(2)}, \ldots, \delta z(t_i)^{(J-1)}, \delta z(t_i)^{(J)}\}. \tag{2.4}$$

The elements of sequence (2.4) are the main informative feature that characterizes the estimation quality by algorithm (2.2) with value J. For further analysis of the estimation quality, it is advisable to go to the sequence of relative values

$$\Delta^{(J)}(t_i) = \{L^{(1)}(t_i), L^{(2)}(t_i), \ldots, L^{(J-1)}(t_i), L^{(J)}(t_i)\}, \tag{2.5}$$

Table 1. The system of rules of the Sugeno fuzzy inference machine

No.	$Q^{(1)}(t_i)$	$Q^{(2)}(t_i)$	$Q^{(3)}(t_i)$	...	$Q^{(J-1)}(t_i)$	$Q^{(J)}(t_i)$	m
1	Good	Good	Good	...	Good	Good	J
2	Good	Good	Good	...	Good	Bad	$J-1$
3	Good	Good	Good	...	Bad	Bad	$J-2$
...	...	...	...	...	...	...	...
$J-1$	Good	Good	Bad	...	Bad	Bad	2
J	Good	Bad	Bad	...	Bad	Bad	1
$J+1$	Bad	Bad	Bad	...	Bad	Bad	1

where $L^{(J)}(t_i) = \sigma^{\mathrm{T}} \cdot \delta z(t_i)^{(J)}$, and

$$\sigma = \left(\frac{1}{\sigma_{rx}}, \frac{1}{\sigma_{ry}}, \frac{1}{\sigma_{vx}}, \frac{1}{\sigma_{vy}}\right)^{\mathrm{T}}$$

is the vector that describes the standard deviation of the measurement error vector $p(t_i)$ in (1.3).

3. PROBLEM FUZZIFICATION

Let us introduce functions

$$\varphi(x,a,c) = [1 + \exp(-a(x-c))]^{-1},$$

$$\omega(x,a,c) = \exp\left(-\frac{(x-c)^2}{a}\right).$$

Let us introduce a linguistic variable $Q^{(j)}(t_i)$ of the "estimation quality by algorithm (2.2) by the j latest measurements" with Good and Bad terms. Let the terms have the following complement membership functions defined on the universal set $L = [0,3]$:

$$\mu_{Good}(L) = 1 - \varphi(L, a_L, c_L),$$

$$\mu_{Bad}(L) = \varphi(L, a_L, c_L),$$

where a_L and c_L are configurable parameters.

Let the variables $Q^{(j)}(t_i)$ be processed by the Sugeno fuzzy inference machine [20]. A sequence of values (2.5) is fed to its input and at the output the numeric value $m \in [1,J]$ is generated. This value is a real number corresponding to the maximum number of measurements which provide a qualitative estimation of the state vector, $s(t_i)$, and is characterized by the maneuvering intensity of ships (the smaller m the more intense the maneuvering). The fuzzy inference machine operates according to the system of rules shown in Table 1. For example, according to the first rule of Table 1 "if all values of $Q^{(j)}(t_i)$ correspond to the term Good, then the number m is equal to J" (i.e., it is necessary to take algorithms with the maximum number of measurements), and, according to Rule $J-1$, "if values $Q^{(1)}(t_i)$ and $Q^{(2)}(t_i)$ correspond to the term Good and other values, to the term Bad, the number m is 2" (i.e., it is necessary to take the algorithm with two measurements). Here, a feature of the model of the considered maneuver determinant should be noted. If $Q^{(j)}(t_i)$ corresponds to the term Good, then $Q^{(j-1)}(t_i)$ also corresponds to the term Good, and if $Q^{(j)}(t_i)$ corresponds to the term Bad, then the $Q^{(j+1)}(t_i)$ also corresponds to the term Bad. Therefore, Table 1 is "diagonal" and contains only the $J+1$ rule.

Let us introduce the linguistic variable $P(t_i)$ "the nature of the vessel's motion at time t_i" with the terms Maneuverable and Constant. Let the terms have the following complement membership functions defined on the universal set $m \in [1,J]$:

$$\mu_{Maneuverable}(m) = 1 - \varphi(m, a_m, c_m),$$

$$\mu_{Constant}(m) = \varphi(m, a_m, c_m),$$

where a_m and c_m are configurable parameters.

Let us determine $\alpha = \eta/\theta$, the estimated ratio of the angle between vectors r and v to the angle θ. Let us introduce a linguistic variable $D(t_i)$ "the estimation of the ratio α at time t_i" with the terms Large and Little and complement membership functions defined over the universal set $\alpha \in [0, 2]$:

$$\mu_{Little}(\alpha) = 1 - \varphi(\alpha, a_\alpha, c_\alpha),$$

$$\mu_{Big}(\alpha) = \varphi(\alpha, a_\alpha, c_\alpha).$$

Here a_α and c_α are configurable parameters. The term Little corresponds to the case where the dangerous approach of vessels is possible and the term Large corresponds to a safe situation.

In order to describe values of T (the approximate time remaining before the closest approach of the ships), let us introduce the linguistic variable $F(t_i)$ "the estimation of T at time t_i" with the terms Little, Average, and Large, and cluster membership functions defined over the universal set $T \in [0, 2000]$ with

$$\mu_{Little}(T) = 1 - \varphi(T, a_1^T, c_1^T),$$

$$\mu_{Average}(T) = \omega(T, a_2^T, c_2^T),$$

$$\mu_{Large}(T) = \varphi(T, a_3^T, c_3^T).$$

Here, a_1^T, c_1^T, a_2^T, c_2^T, a_3^T, and c_3^T are configurable parameters. The description of the linguistic variable $F(t_i)$ by three terms corresponds to the three states of the closest approach time adopted in practice [20]. The term Little determines the time when it is possible to make only one decision that can help avoid a collision. The term Average determines the time necessary to make the optimal maneuver, i.e., the time when it is not too early to start the maneuver but there is still time to "fix" the result of an incorrect maneuver; there is time for a second attempt; this is the time when a critical situation has not yet occurred. The term Large describes the time when there is no sense in taking any action, because the situation can change, and a completely different maneuver will probably be required.

The danger level of situation U we will describe by the linguistic variable $A(t_i)$ "the danger level at time t_i" with the terms Green (safe), Yellow (almost safe), and Red (dangerous) and cluster membership functions on a universal set $U \in [0, 2]$:

$$\mu_{Green}(U) = 1 - \varphi(U, a_1^U, c_1^U),$$

$$\mu_{Yellow}(U) = \omega(U, a_2^U, c_2^U),$$

$$\mu_{Red}(U) = \varphi(U, a_3^U, c_3^U).$$

Here, a_1^U, c_1^U, a_2^U, c_2^U, a_3^U, and c_3^U are configurable parameters. Variables $P(t_i)$, $D(t_i)$, and $F(t_i)$ are processed by the Mamdani fuzzy inference machine [19]; values m, α, and T are fed to its input; and at the output, a numerical value of $U \in [0, 2]$ is formed, which is the danger level of the ship–ship navigation situation; $U = 0$ corresponds to the lowest danger level and $U = 2$, to the greatest. The machine operates according to the system of fuzzy inference rules shown in Table 2.

For example, Rule 8 in Table 2 is as follows: if $D(t_i)$ corresponds to the term Little, $P(t_i)$, to the term Constant, and $F(t_i)$, to the term Average, then $A(t_i)$ corresponds to the term Yellow. In practice, it implies a situation where vessels will dangerously approach each other, if they do not change their motion trajectory, but there is enough time to choose the most appropriate maneuver. Rule 9 states that if $D(t_i)$ is Little, $P(t_i)$ is Constant, and $F(t_i)$ is Little, then $A(t_i)$ is Red. This is a situation where it is necessary to begin evasive action as quickly as possible. Rule 12 states that if $D(t_i)$ is Little, $P(t_i)$ is Maneuverable, and $F(t_i)$ is Little, then $A(t_i)$ is Yellow. It means that the vessel can dangerously approach each other if they do not change their trajectories; however, most probably they have already begun evasive maneuvers.

The operation of a fuzzy ship collision avoidance system can thus be finally introduced by the diagram shown in Fig. 2. The data measured on the relative motion of vessels $z(t_i)$ are fed to the input of the algorithm that estimates the state vector $s(t_i)$ of system (2.2) and generates sequence (2.5). Next, the Sugeno fuzzy inference machine S estimates the maneuvering intensity of vessels m. Given this value, the vector

Table 2. The system of rules of the Mamdani fuzzy inference machine

No.	$D(t_i)$	$P(t_i)$	$F(t_i)$	P_U
1	Big	Constant	Large	Green
2	Big	Constant	Average	Green
3	Big	Constant	Little	Green
4	Big	Maneuverable	Large	Green
5	Big	Maneuverable	Average	Green
6	Big	Maneuverable	Little	Green
7	Little	Constant	Large	Green
8	Little	Constant	Average	Yellow
9	Little	Constant	Little	Red
10	Little	Maneuverable	Large	Green
11	Little	Maneuverable	Average	Green
12	Little	Maneuverable	Little	Yellow

$\hat{s}^{(m)}(t_i)$ is selected from sequence (2.3), based on which α and T are calculated. Then values m, α, and T are input to the Mamdani fuzzy inference machine M, whose output is the danger level $U \in [0,2]$ of the situation.

The setting of the described system consists in setting the maximum number of measurements J; parameters of membership functions a_m, c_m, a_α, c_α, a_1^T, c_1^T, a_2^T, c_2^T, a_3^T, c_3^T, a_1^U, c_1^U, a_2^U, c_2^U, a_3^U, and c_3^U; and components of the vector σ that characterize the measurement error.

The proposed inference mechanism for the danger level is based on precedents. Such mechanisms are used in systems whose complexity does not allow them to be completely formalized but that have precedents of their successful solution [21]. In this case, values $D(t_i)$, $P(t_i)$, and $F(t_i)$ are the coordinates of the situational vector, and their relation to specific precedents $A(t_i)$ (Table 2) is established by the experts.

4. RESULTS OF THE NUMERICAL SIMULATION OF THE PROBLEM

In order to demonstrate the operation of the described system, let us consider a model example for the three vessels. Two of them (I and II) are moving uniformly at a speed of 5 m/s and the third (III) is carrying out maneuvers (Fig. 3).

It is assumed that measurements are received every $\tau = 3$ s. Given the typical GPS measurement errors the vector σ is set at $\sigma = ((1/10\text{ m}, 1/10\text{ m}, 1/1\text{ m/s}, 1/1\text{ m/s})^{\mathrm{T}}$. The maximum number of measurements for estimating the trajectory J is taken to be 10. The coefficients of the membership functions are taken so that the functions took the form shown in Fig. 4. Here in Fig. 4a there are functions $\mu_{Good}(L)$ (solid line) and $\mu_{Bad}(L)$ (dotted line); in Fig. 4b there are functions $\mu_{Maneuverable}(m)$ (solid line) and $\mu_{Constant}(m)$ (dotted line); in Fig. 4c there are functions $\mu_{Little}(\alpha)$ (solid line) and $\mu_{Big}(\alpha)$ (dotted line), in Fig. 4d there are func-

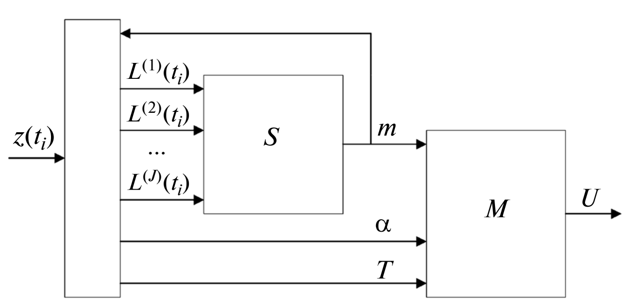

Fig. 2. The diagram of the operation of the fuzzy collision avoidance system for ships.

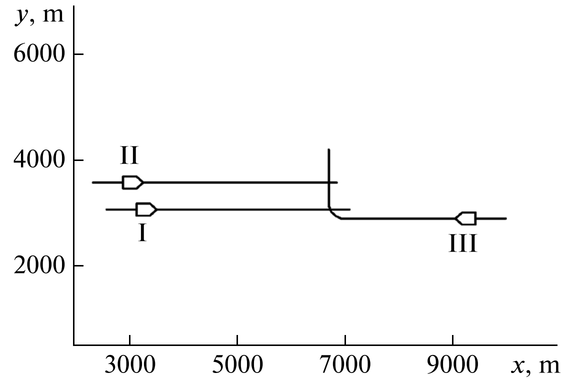

Fig. 3. Simulated ship motion trajectories.

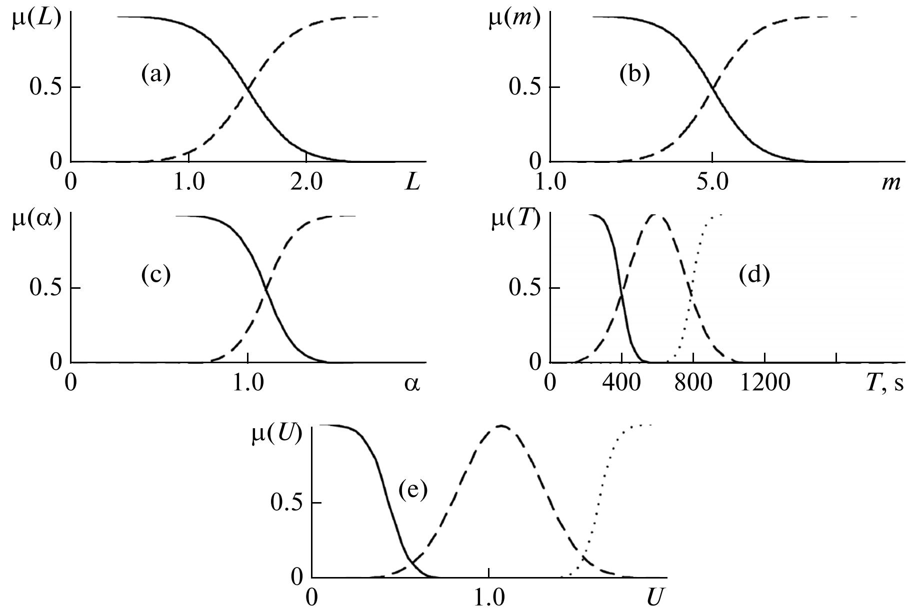

Fig. 4. Membership functions of the fuzzy system.

tions $\mu_{Little}(T)$ (solid line), $\mu_{Average}(T)$ (dotted line), and $\mu_{Large}(T)$ (dots); and in Fig. 4e there are functions $\mu_{Green}(U)$ (solid line), $\mu_{Yellow}(U)$ (dotted line), and $\mu_{Red}(U)$ (dots). In this case, all membership functions are set by the expert. The fuzzy system is not adjusted using the training sample, although this training option is basically possible.

The ensemble of membership functions in Fig. 4 is selected so that standard situations that the interpret input and output variables of the fuzzy inference machine (clusters) are clearly distinguishable (except for certain points where the membership function values are equal). In this case, the system of fuzzy inference rules describes all combinations of clusters of the input and output variables, and hence the fuzzy inference machine will work consistently and correctly, which is confirmed by the computational experiments (see below). If the universal intervals are set where all membership functions are zero the fuzzy inference machine will not operate properly by Hadamard. If the universal intervals are set where the values of at least two maximum membership functions are close to each other (the clusters are indistinguishable), the fuzzy inference machine will be poorly conditioned.

Figure 5 shows the result of the solution of the problem for vessels I–III (left column in the figures) and II–III (right column in the figures). The shading in Figs. 5g and 5h denotes the Yellow danger level zone. The Green level zone is below it and the Red level zone is above it. Figures 5a and 5b show the calculated values of α. Figures 5c and 5d indicate the values of m. Figures 5e and 5f show the values of T

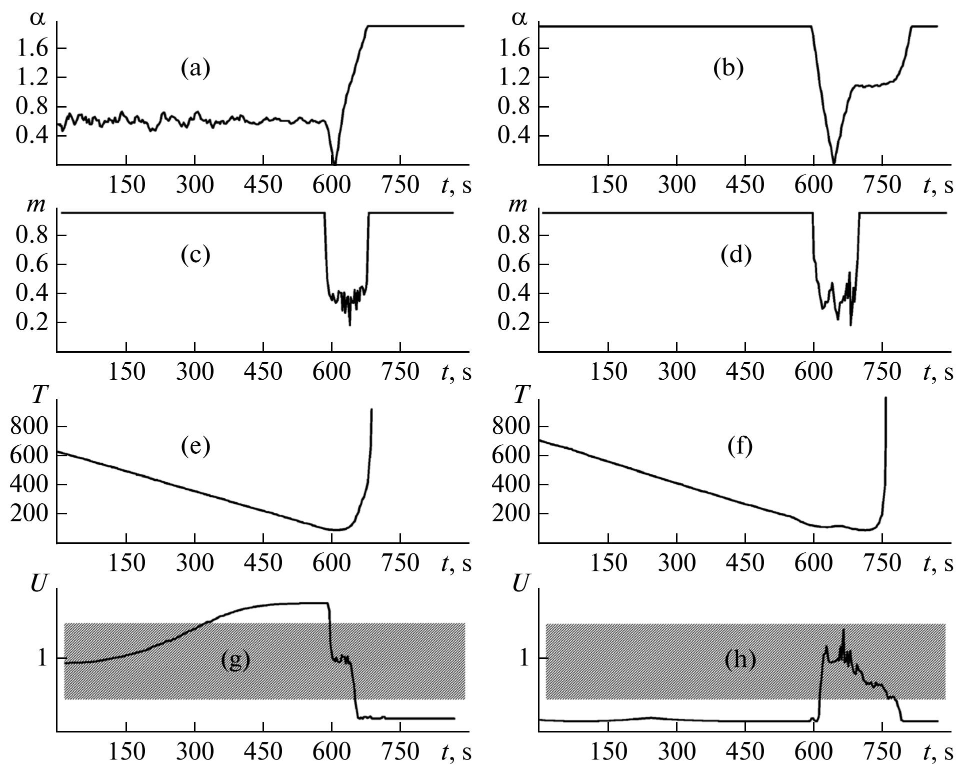

Fig. 5. The operation of the fuzzy collision avoidance system for ships.

(M system input, Fig. 2). Figures 5g and 5h indicate the values of U (the system output, Fig. 2). Thus, Fig. 5e shows that the danger level for the pair of ships I and III constantly increases as they approach each other and reaches the Red level at $t = 350$ s. At $t = 600$ s, vessel III begins evasive action by turning to the right, then the danger level for the pair of ships I and III is rapidly reduced to the Yellow level and then to the Green level. Figure 5h shows that at first vessels II and III are moving safely. However, when ship III starts to maneuver the danger level for the pair of ships II and III abruptly increases to Yellow, and then, as vessel III continues to rotate, it reduces to the Green level.

The alarm level declines from the maximum Red to Yellow almost immediately after the maneuver (Fig. 5g). For ships II and III the generation of the Yellow alarm level also occurs in advance (Fig. 5h). It demonstrates the ability of the proposed fuzzy system both in warning about the danger and filtering false alarms. The expected effect of the separation of danger levels depending on the trajectory properties of the vessel's motion is confirmed.

5. RESULTS OF FIELD STUDIES

The developed system was tested on the real data of ship motion in the waters adjacent to the port of Vladivostok. The following typical example was obtained from the analysis of ship traffic data during a single day in summer in 2013. At this time simultaneously there were about 80 vessels in the VTCS responsibility area. Figure 6 shows the position of vessels in the waters at the times when Yellow (crosses) or Red (ovals) level alarm signals were generated for them. It can be seen that the largest number of alarms occurs in the inner harbor waters, where vessels are located close to each other and the traffic of small boats is high (motor boats and tugs). Both alarm levels also occur when vessels move outside port waters: in the Amur (left) and Ussuri (right) bays and in the Eastern Bosphorus Strait. The share of Yellow level alarms is around 20%. The locations of their generation are not stable.

For VTCS operators (dispatcher) the generation of the Red level alarm means that they must immediately pay attention to the situation and decide whether the pilot of the ship requires their assistance. The generation of the Yellow level alarm means that although the situation is not completely secure, there is no need for immediate intervention: most likely, the ship's pilot is in control of the situation. In other words, if there are Yellow and Red level situations at the same time, the VTCS operators must pay attention

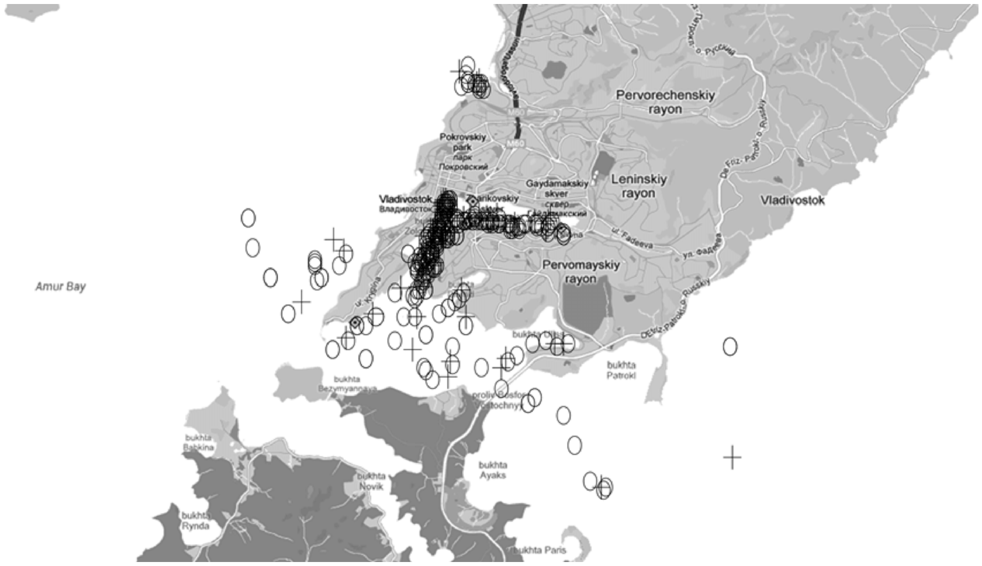

Fig. 6. Motion of vessels in the waters of the port of Vladivostok.

to the latter first. The fact that the share of Yellow level situations is quite significant (20%) in the water area means that their separation can significantly reduce the burden on VTCS operators and shows the relevance of this problem in practice.

CONCLUSIONS

The test of the developed system on the data from real ship traffic confirmed its efficiency and the prospects for practical use. The proposed color interpretation of the alarm levels is intuitive and can be easily understood by the pilots of the ships and VTCS operators. It promotes the adoption of adequate administrative decisions and improves traffic safety. The authors plan to dedicate an independent study on the considered systems using training samples: the problems of generating such a sample, a variety of learning strategies, and the correctness and stability of training methods.

The study aims to expand the navigation features of traffic control systems for modern vessels.

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