

A Marine Autopilot With a Fuzzy Controller Computed by a Neural Network

Nelly Sedova

Automatic and Information Systems
Maritime State University named after G.I.Nevelskoy
Vladivostok, Russian Federation
nellyfish81@mail.ru

Viktor Sedov

Electrician Theoretical Bases
Maritime State University named after G.I.Nevelskoy
Vladivostok, Russian Federation
sedov@msun.ru

Ruslan Bazhenov

Information Systems and Mathematics
Sholom-Aleichem Priamursky State University
Birobidzhan, Russian Federation
r-i-bazhenov@yandex.ru

Irina Ledovskikh

Mathematics and Information Technology
Pacific National University
Khabarovsk, Russian Federation
ledovskih_irina@mail.ru

Abstract—The paper proposes simulation findings for an autopilot IC-2005 on a signal simulator developed by the authors of an intelligent control system to steer a sea vessel. The principle of the intelligent control system operation consists of generating a data vector with values of the yaw angle of the vessel, the rate of the angle change, the rudder displacement values and the rate of angling the rudder blade change during the ship heading. The features of the seaway provided by current wind and wave conditions are defined through spectral analysis. Then the intelligent classifier of the control system selects the optimal pre-trained neural network model of the seaway from a series of them. The fuzzy logic controller settings are computed after that. 120 search patterns for six types of vessels in various navigation conditions were developed using the simulator as a result of modeling. 79 neural networks were trained, and 2518 neural network way models of them were obtained for a representative sample of search patterns. The top settings of neural networks to develop search pattern models of the seaways were identified in response to statistical manipulation. As exemplified by a trawler ship type, computer and simulation methods were carried out that proved the efficiency of the approach proposed to apply to an intelligent sea craft automatic heading control system

Keywords—marine autopilot, fuzzy controller, neural network

I. INTRODUCTION

The level of ship automation has increased greatly over the last few decades, and tends to grow further. The development of ship automation facilities mostly deals with the requirements of cost efficiency and safety ensuring. For example, the studies in the field of automation of ship heading control systems are related to these two very factors, since the use of autopilots contributes to ensure an economy mode of a vessel heading, thus decreasing the rate of fuel consumption and reducing the wearing process of final control elements of the control system [1]. Safety matters are also in a major focus, in particular, paper [2] examines the strategies of onshore personnel's actions in case of autopilot failure.

Despite the substantial progress in developing ship heading control systems, a proportional-integral-differentiating (PID) controller is still used as the main approach to designing autopilots. PID is characterized by extensive overshooting values. A number of authors are working out the methods that enable to reduce disadvantages of PID controller. For example, the findings of simulating a model of an autopilot with PID controller and a compensation device are shown in paper [3]. They allow reducing overshooting, as well as turn away a vessel at a constant angular velocity. Paper [4] observes PID regulation used to control a vessel, however, the system includes a model for generating the path of the vessel heading taking into account the International Rules for Preventing Collisions at Sea (COLREG), especially modeled decision diagrams according to Rule 8 and 14 of COLREG. The researchers of paper [5] designed a simulator, including a model of an autopilot, applied successfully for ship's crew training. They used MATLAB / Simulink mathematical software to develop the simulator. The simulation was performed using Nomoto mathematical model for a sea craft heading.

There are a number of autopilots designed for certain types of vessels. Such autopilots tend to take into account the characteristics of the vessel types. For example, the outcomes of mathematical control modeling of a tanker heading based on deviations from a given seaway are presented in paper [6]. The study also highlights the formulation of nonlinear symbolic models counting a maneuvering ability of large tankers in deep and enclosed waters.

The researchers of paper [7] solve the optimization issue of adjustment the output feedback coupling features using a special multi-operated controller structure. The authors present the application and efficiency of the proposed approach in the study through the example of the sea autopilot designing construction. Paper [8] focuses on the issue of deviation of external disturbances for marine control systems controlled by autopilots under the influence of wind and wave disturbances. The author searches for mathematical models of adjustable members for the law of control with a special structure capable of achieving the desired values of

corresponding composed functions characterizing the accuracy and intensity of the steering vessel control. Paper [9] devoted to the same subject points out a new applied method for synthesizing control laws for autopilots, which is based on feedbacks with a multiple-purpose structure with the introduction of a generating filter for disturbance. It is nominally represented by Gaussian white noise having equal intensity at different frequencies. Finally, a computational algorithm is given based on the idea of H_∞ -infinity stabilization method, which allows ensuring guaranteed filtering quality for the autopilot operation when navigating under sea waves conditions. This approach has several advantages in contrary to the options. One of them is its flexibility in coming to terms with real navigation conditions.

In paper [10], the PID controller is one of the elements of an intelligent transportation control system (ITCS). The proposed intelligent transportation control system (ITCS) applies a wavelet neural network (WNN) controller, while the PID controller parameters are drawn from Lyapunov's stability theorem. They are also used to adjust the parameters of the wavelet neural network, ensuring stability and fast autopilot convergence. In [11], the authors show the findings of solving the problem of forecasting a marine vessel heading pattern using an artificial neural network.

In a number of papers, the authors solve the problem of steering the vessel heading through the fuzzy set theory. The authors of paper [12] considered the model of a large-scale copy of the tanker Esso Osaka, for which a controller based on the fuzzy logic theory was proposed. The simulation results obtained by the authors show that the proposed controller, based on the fuzzy logic theory, is more efficient than well-established controllers.

In paper [13] an autopilot is proposed for oil tankers using the neuro-fuzzy stabilization model of the ship heading. In paper [14], they offer a backstepping method diagram with non-linearity compensation using fuzzy logic. The simulation carried out by the authors proves the efficiency of the proposed control diagram. In paper [15], an autopilot model is given based on the fuzzy logic theory, which contains Takagi – Sugeno fuzzy inference system. In [16], an autopilot model is observed using the fuzzy logic theory. Such an autopilot can respond to various external disturbances influencing a vessel properly. In this paper, a numerical simulation of the proposed autopilot is performed on the Cybership II model vessel, and the findings of a comparative analysis of the proposed controller with traditional backstepping and PID controllers are shown. The paper also proves the stability of the proposed approach using Lyapunov's stability criteria. There is an autopilot for autonomous maritime vessels, combining the advantages of variable structure systems with a self-regulating scheme based on the fuzzy logic theory presented in paper [17].

The authors of paper [18] suggest an approach based on the extended state observer (ESO) technique for controlling the ship yaw. The reliability of the autopilot is ensured by the fact that the level of external influences on the vessel is estimated using ESO, which also evaluates the parameters of the controller. So the simulation was performed to confirm the efficiency of the ESO technology. In the studies [19], which are to be a further survey of the previous one [18] there is an approach featured using the Generalized Extended

State Observer (GESO). The paper presents a structural diagram consisting of a controller, supplemented by the term GESO disturbance compensation. The efficiency of the proposed controller system is illustrated by modeling considering different real situations.

There are also developments aimed at developing control systems for next-generation unmanned surface vehicles (USV) that can steer efficiently, based on limited sensory information on the underwater environment surrounding a vessel. In paper [20], the authors put up a system that revitalizes the behavior pattern of the sea surface according to the information from LiDAR (light Identification, detection and ranging (LiDAR), which provides a foundation for the development of ship control systems operating in rise and fall of the waves seas and limited information on the surrounding sea surface. Also, in paper [21] the authors submit a model predictive controller, and the forecast is based on one of the following optimization algorithms: the gradient descent method, the least squares method or the weighted least squares method.

II. AN AUTOMATIC CONTROL INTELLIGENT SYSTEM OF A SEA CRAFT HEADING

The problem of steering a sea vessel is difficult to formalize, not having an appropriate mathematical formulation. Therefore, the application of conventional approaches is considered to be ineffective. The attractiveness of artificial intelligent systems for steering a ship lays in their positive properties such as the ability to operate with fragmentary data, the information with no exact analytical description, with big data, i.e. data that are large in size and having difficulty in finding a certain correlation among the separate elements.

Increasing demands for navigation systems, the deficiency of methods for modeling the process of steering a ship heading using artificial intelligent systems reasoned the relevance of this survey. The aim of the study is to develop and simulate testing a universal ship control system of a vessel heading involving theoretical and applied foundations of artificial intelligent systems.

The intelligent system of automatic vessel heading control is presented in the given study. The functional flow diagram of it is shown in Fig.1. The intelligent systems, which are the best at performing specific functional purposes, are used for its development. When the vessel is heading as a controlled object (CO) of an intelligent automated control system (IACS) in the operation mode, the vessel generates a data vector with the values for the vessel yaw angle, the rate of this angle change, the values of rudder shifts and the rate of rudder blade change.

Subsequently, a spectral analysis of this vector occurs, highlighting eight over tones for each signal plus a linear value of the vessel speed, which are characteristics of the vessel heading under current weather conditions. These values are displayed onto the input of the neural network classifier (NNC) that determines which of the neural networks fits these characteristics best of all according to statistic data. The data from the NNC is received in the unit containing the neural network models of the patterns of marine vessels seaways, where the optimal neural network model is determined based on the input data. The determined

neural network model of the sea vessel heading path constitutes the optimal parameters of the neural network classifier, i.e. adjusts the fuzzy logic controller according to the neural network model in the optimizer. The best parameters are selected for the current wind and wave conditions, navigation mode and sea craft features.

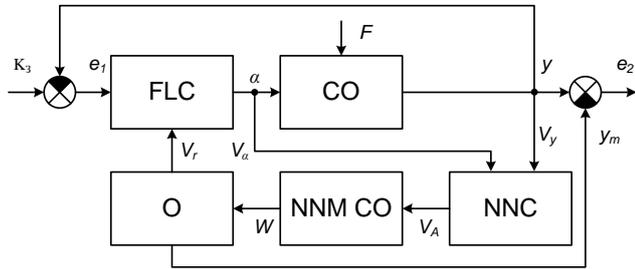


Fig. 1. Functional flow diagram of an intelligent vessel automatic heading control system

FLC—a fuzzy logic controller, CO—a controlled object, O—an optimizer, NNM CO—a neural network model of the controlled object (neural network model of the marine vessel heading pattern), NNC—a neural network classifier, K_3 —a specified heading, e_1 —a control error, e_2 —an identification error, α —the control action (angle of the rudder blade), K —the value of the actual vessel heading, y_m —the value of the actual model of the vessel heading, F —external effects, W —the vector of neural network parameters, V_r —the vector of adjustable control parameters, V_α —the vector of control action data, V_y —the data vector of the actual vessel heading, V_A —the vector of criteria signs of vessel heading.

III. AN EXAMINATION OF THE DEVELOPED INTELLIGENT SYSTEM OPERATIONAL CAPACITY OF AUTOMATED VESSEL HEADING CONTROL

The performance check of the vessel heading designed by IACS was run in two stages. The first stage was to conduct computer modeling to fill the knowledge base of the neural network classifier with models of ships under various wind and wave conditions. The second stage consisted of carrying out simulation modeling for a model of a trawler type vessel at different speeds and changing weather conditions in order to test the adaptation process of the fuzzy logic controller. For simulation, a certified IC-2005 simulator (Manufacturer: Engineering Center of Information and Control Systems, St. Petersburg, Russia) was used to simulate signals of a GLONASS / GPS receiver, a chip log, mariner's compass and rudder position sensor for testing and setting modern autopilots. The mathematical model of heading for 6 types of vessels has 4-degree-of-freedom and provides modeling of the aheading only (more than 1 knot) in deep and shallow water (regular shallowness) by winds, stream current and irregular sea waves.

A. Computer modeling for filling the knowledge base of a neural network classifier

First, a simulation on a certified signal simulator for an autopilot IC-2005 was carried out to obtain neural network models of the ship heading patterns. More than 120 patterns of six different models of ships were received. They are a passenger coastal craft, a trawler, a transport refrigerator, an automobile and passenger vessel, a tanker, and a supertanker.

Marine Ship Characteristics used in simulation are shown in Table 1.

Computer simulations were carried out for the following different navigation conditions:

- wind speed from 0 to 2 m/s, wave height of 0.25 m,
- wind speed from 2 to 5 m/s, wave height 0.85 m,
- wind speed from 5 to 8 m/s, wave height 1.25 m,
- wind speed from 8 to 10 m/s, wave height 1.25 m.

TABLE I. SHIP CHARACTERISTICS

Parameter	Ship Type		
	Trawler Ship	Automobile and Passenger vessel	Passenger Coastal craft
Length, m	85	158	35.5
Width, m	15.9	25	7.2
Draft, m	5.6	6.5	2.15
The ratio of the overall completeness	0.64	0.58	0.63
Rudder area, m ²	11.7	23.9	1.5
Engine Type	Diesel	Diesel	Diesel
Speedmax, knots	8; 12; 15	15	8
Parameter	Ship Type		
	Tanker	Transport Refrigerator	Supertanker
Length, m	179.9	107.8	325
Width, m	31	18.2	53
Draft, m	10	7.5	22
The ratio of the overall completeness	0.813	0.638	0.81
Rudder area, m ²	25.7	42.8	124.2
Engine Type	Diesel	Diesel	Turbine
Speedmax, knots	15	15	15.6

79 neural networks, which are different in architecture and learning algorithm, were trained for several of the selected possible patterns of a vessel heading under various weather conditions. In conclusion, 2518 neural network models of sea vessel heading patterns were obtained. After reviewing a root-mean-square error (RMS error), 8 NN were selected out of 79. They allow approximating the vessel heading patterns with the lowest RMS values. The results that the authors have arrived at are brought all together in the diagram and introduced in Figure 2. An observation of computer simulation results allows the authors to sum up that it is more beneficial to use the feed forward propagation NN with the Levenberg–Marquardt learning algorithm as a neural network model of a vessel heading pattern.

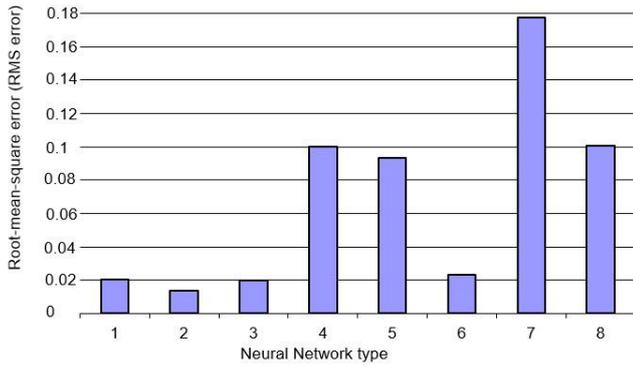


Fig. 2. Standard error dependence on the NN type

1-3 – feed forward propagation neural networks with the Levenberg–Marquardt learning algorithm (100, 500 and 1000 learning cycles, respectively),

4 – feed forward propagation NN with the Möller learning algorithm (combination of the nonlinear conjugate gradient method and the Quasi-Newton method) (500 learning cycles),

5-7 – a recurrent Elman neural network with the Levenberg–Marquardt learning algorithm (500 and 1000 learning cycles, respectively),

8 – a recurrent Elman neural network with the Möller learning algorithm (1000 learning cycles).

The cost function of the identification algorithm of the neural network model of the vessel pattern was to minimize the standard deviation of the instantaneous e output value of the marine vessel model from the corresponding actual vessel heading.

$$I_1 = \min \frac{1}{T_{\max}} \int_0^{T_{\max}} |Y - Y_m| dt \quad (1)$$

To avoid the astatism effect, it is proposed to use the squared difference of the error derived from the heading of the neural network model of the vessel pattern and its actual heading as a cost function.

$$I_2 = \min \frac{1}{T_{\max}} \int_0^{T_{\max}} |Y' - Y'_m| dt \quad (2)$$

In this case, the search algorithm tends to minimize the discrepancy between the derivatives of the output signals at current times.

Figure 3 shows the behavior patterns of the trawler ship model heading and entering a new one with an adapted and unadapted fuzzy logic controller by wind of 8 to 10 m/s and a wave height of 1.25 meters.

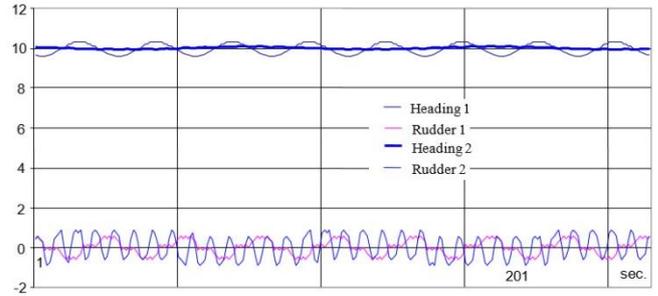


Fig. 3. Trawler ship type heading at the rate of 10 degrees before and after adaptation

The review of the findings showed that the fuzzy logic controller requires additional configuration when the weather is bad, which confirms that introduction of a neural network classifier with the intelligent database of neural networks with the best identification of the sea vessel heading patterns for various weather conditions is quite reasonable. The adaptation of the fuzzy logic controller resulted in new values of the setting parameters

B. Simulation for a trawler ship type model

A trawler ship type was taken as a model for further IACS investigation. The parameters of this model are presented in Table 1.

After conducting a series of simulation experiments, 12 neural network models of the trawler heading patterns for various weather conditions and different speeds were kept in the intelligent database of the neural network classifier. The model behavior of the trawler ship type simulator before and after adaptation is shown in Figure 4.

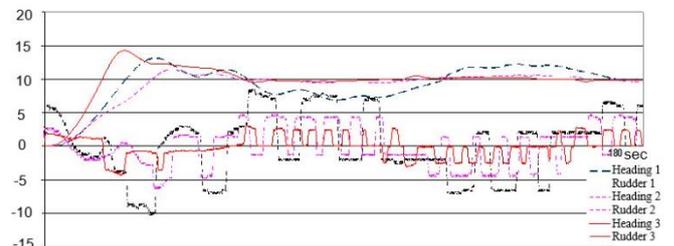


Fig. 4. Sailing of the trawler ship type heading of 10 degrees at wind speeds of 8-10 m/s, a wave height of 1.25 m

Figure 5 shows the adaptation for a trawler during the extreme weather events (wind speed from 0 to 2 m/s, wave height of 0.25 m; wind speed from 8 to 10 m/s, wave height of 1.25 m).

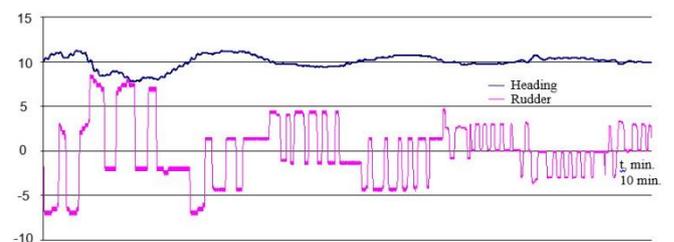


Fig. 5. Adaptation of the trawler heading of 10 degrees at wind speeds of 8-10 m/s, wave height of 1.25 m

The root-mean-square integral performance criterion for the deviation of the trawler from the heading decreased from

2.43 (for the first three minutes) to 0.16 (for the last 3 minutes). The criterion was optimized while ensuring the autopilot actuator could operate no longer than 2/3 of the studied period (Fig. 6, heading 1). When adapting the RNN, other objective functions are available to minimize the load upon a steering gear, if conditions for maintaining the appropriate vessel steering are met. If the requirements of the operating time are to be relaxed to 1/2 (Fig. 6, course 2), i.e. enter the cost function in the optimization condition of fuzzy logic controller parameters in the following form:

$$\min_{k \in K} I = \frac{1}{T_{\max}} \int_0^{T_{\max}} \alpha' dt \quad (3)$$

where k is the fuzzy logic controller settings, α' is derived from the angle of the masonry of the rudder blade (for a steering machine with a solenoidal control system $\alpha' = \pm 3$ degrees / s = const). Thus the load on the steering machine is relaxed, the operating time of the machine reduces but the quality of steering the ship is getting a bit worse. The integral criterion is 0.31 in this case.

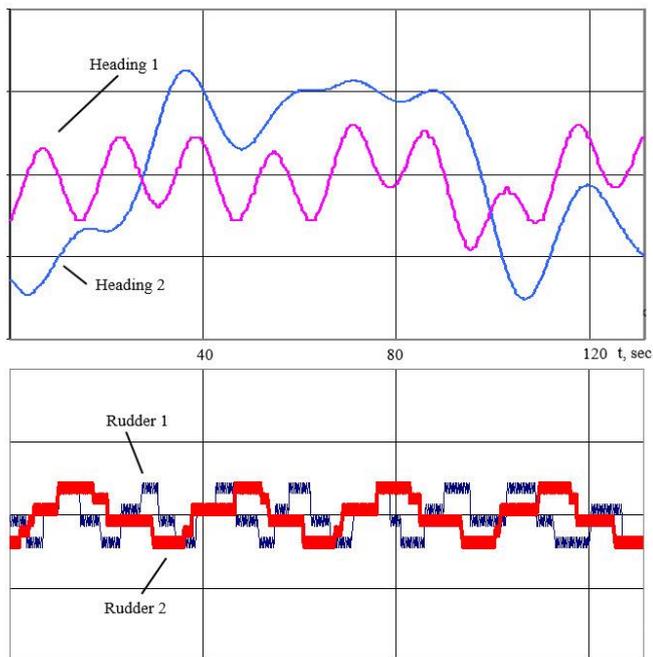


Fig. 6. Changing the quality of the vessel heading at 10 degrees and the operation mode of the steering vehicle when changing the objective function of the fuzzy logic regulator optimization

Keep in mind that the authors used genetic algorithms to optimize the parameters of the predicate rules of the fuzzy logic controller in this study, which allows the authors to avoid stopping the algorithm at a local extreme value (extremum) and not depending on the problem dimension.

IV. CONCLUSION

The review of the findings of a simulation showed the high-quality vessel heading using a fuzzy logic controller and at a given load on the steering gear. According to the research, it should be also admitted that the adapted fuzzy logic controller steers the vessel heading for the given yaw limits (1 degree) for all studied navigation conditions.

Moreover, the tested vessel is extremely difficult to navigate because of its small size. The high-quality operation of the fuzzy logic regulator on such a vessel confirms that it is working on ships that are much larger and therefore less sensitive to external wind and wave effects. The carried out computer and simulation modeling proves the efficiency of the given intelligent vessel automatic control heading system.

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