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An efficient neural-network based approach to automatic ship docking

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ABSTRACT

Automatic ship docking is one of the applications of autonomous ships. How to realize autonomous low-speed maneuver under environmental disturbances for docking is the fundamental problem at present. This paper presents an efficient approach based on artificial neural network (ANN) for automatic ship docking. The problem is formulated and well-modeled for simulating ship docking operation. A joystick implementation in simulation provides manual maneuvering and thus enables collection of sufficient and reliable data from successful maneuvers. To keep consistent with the manual control, an ANN with two parallel structure is proposed to control the ship's thrust and rudder, respectively. Feature selection technique and genetic algorithm (GA) are utilized to optimize the structure and reduce the training cost. Numerical simulations under different environmental disturbances, including no wind, constant wind and dynamic wind are carried out. The results show the ship is able to reach the dock smoothly, which confirms the effectiveness of the proposed approach.

1. Introduction

Digitization is a major agenda in the development strategy of the European shipbuilding industry, which promotes technological innovation and economic growth. This agenda points out that the first task is to achieve ship autopilot characterized by strong adaptability to sea conditions, low energy consumption, and high safety performance. Automatic ship docking is considered an essential application of ship autopilot. Ship docking is a challenging maneuvering task for captains. During the docking process, the captain needs to know the ship's current state and estimates its future state based on the maneuverability of the ship. The ship is suggested to be sailed at low speed to avoid collision with the dock and other vessels; but low speed will sharply reduce the ship's maneuverability and increase control complexity.

To address the above challenges, attempts have been made to design advanced controllers using knowledge of nonlinear control theory (Katayama and Aoki, 2014; Li et al., 2016; Mizuno et al., 2016) and fuzzy theory (Yingjie et al., 2019; Tran et al., 2017). However, it is hard to construct nonlinear mathematical models and define fuzzy rules for ship docking since any unpredictable situations including weather influences and other vessels' disturbances may arise. In such a case, an ANN-based approach with the ability to learn the underlying nature from maneuvering data, provides a potential solution for automatic ship docking. In principle, the robustness of this approach depends not only on the ANN's structure but also on the training data. The training data can be either from real ship docking operation, or from reliable simulation. The former has high reliability, but is difficult to be collected under different environmental disturbances; the latter is most frequently used because of its high efficiency, and as long as the fidelity of modeling ship docking operation is good enough, the reliability of the training data is guaranteed.

In this paper, we propose a new ANN-based approach to achieve automatic ship docking under different environmental disturbances. The main contributions of this paper can be summarized as follows:

(1) A ship docking simulation module with complete ship-environment models is established for generating reliable docking data.
(2) The feature selection technique is applied to provide optimal inputs for the ANN.
(3) The ANN-based approach with two parallel structure optimized by genetic algorithm is verified to be able to dock the ship under different environmental disturbances.

The present paper is organized as follow. Section 2 is a brief overview of related work. In Section 3, a ship docking simulation module including ship mathematical model and wind disturbance model is established. In Section 4, the proposed ANN-based approach, from data collection, feature selection, to ANN construction and optimization, is introduced in detail. Section 5 presents the docking results of the

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approach under different environmental disturbances. Conclusions and future work are given in Section 6.

2. Related work

The first automatic ship berthing system based on ANN was demonstrated in the 1990's by Yamato (1990). Later, Zhang et al. developed an automatic ship-berthing system using a multivariate neural network based controller (Zhang et al., 1997). The pre-planned birthing path was determined as the input of the controller. However, the authors did not introduce how to set the berthing path. In 2001, Im and Hasegawa proposed a parallel neural network based controller to control ship thrust RPM and rudder (Im and Hasegawa, 2001). The experimental results demonstrated the proposed parallel neural network-based controller could eliminate the effects of slight wind and current, but failed to manipulate the ship to the destination in harsh environment. To address this challenge, a motion recognition method was utilized to cope with environmental impacts (Im et al., 2002). The method succeeded to compensate the crosswind disturbance, but still failed when the wind comes from the direction of the bow. Nguyen and Jung explored the adaptive neural networks to achieve automatic ship berthing (Nguyen and Jung, 2007). Recently, Zhang et al. proposed a robust adaptive neural network approach based on the navigation dynamic deep-rooted information to reconstruct the lumped uncertainties caused by unknown ship dynamics and external disturbances (Zhang et al., 2019).

The above researches focused more on the structure design of the ANN controller; whilst none of them tried to generate training data with different constraints by using an algorithm to improve the applicability of the ANN controller. In fact, there have been attempts in training data generation. In 2007, Ohtsu et al. proposed a new solution using nonlinear programming method to generate minimum time ship maneuvering data (Mizuno et al., 2007). Hasegawa et al. first attempted to use a nonlinear programming language (NPL) to generate ship berthing data with restricted conditions (Xu and Hasegawa, 2012). Ahmed and Hasegawa followed the research and first proposed the concept of virtual windows which is used to ensure the consistency of training data (Ahmed and Hasegawa, 2012; Ahmed et al., 2013; Ahmed and Hasegawa, 2014, 2015). The NPL method allows the user to define non-equal constraints by setting rudder angle as the optimal variable and the time as an objective function. However, excessive restrictions are defined as termination conditions in these researches when using the NPL method, which causes fluctuation of rudder angle commands.

Nonlinear model prediction algorithm is another solution for optimal berthing data generation, but requires higher computational resources to obtain the optimal maneuver path (Mizuno et al., 2003). However, taking advantages of graphics processing unit, the method can be executed in parallel, which makes real-time optimal control feasible (Mizuno et al., 2012). For example, Mizuno et al. proposed a quasi-real-time optimal control system composed of a multiple shooting algorithm for docking data generation and a nonlinear model predictive controller for path following under wind disturbance (Mizuno et al., 2015).

There are also researches that directly use real ship docking data obtained by experienced captains who successfully maneuver the ship into the berth, to train neural network based controllers (Im and Nguyen, 2018; Nguyen et al., 2018). But the method is not applicable to general docking operation, as it is difficult to collect large number of real ship docking data under different cases of environmental disturbances for training. To achieve the generality of ANN based docking in different environment disturbances, we propose a new automatic ship docking strategy that employs a ship docking simulation platform to generate reliable docking data and an ANN-based approach with optimized parallel structure to maneuver ships into the dock.

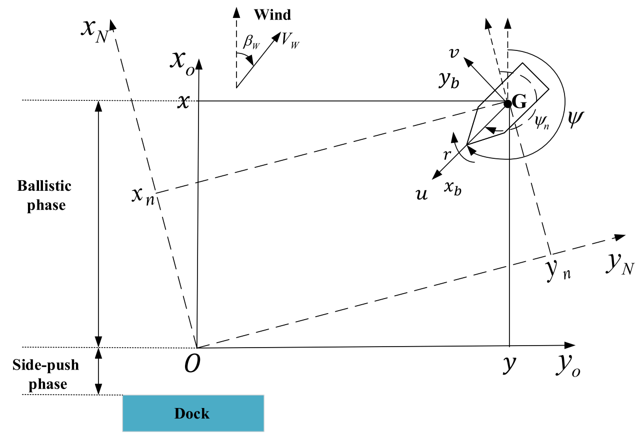

Fig. 1. Coordinate systems for ship docking.

Table 1
The notation for marine vessels.

Symbol	Description
G	The center of gravity
β_w, V_w	Relative wind direction and speed expressed in $\{d\}$
u, v, r	Surge, sway and yaw velocities expressed in $\{b\}$
x, y, ψ	Position and heading expressed in $\{d\}$
x_n, y_n, ψ_n	Position and heading expressed in $\{n\}$

3. Docking problem statement and simulation model

3.1. Docking problem statement

Slow speed, planning, on-board sensing equipment and control approach play key roles in ship docking. Kose et al. proposed two requirements to ensure ship safety according to the maneuvering procedures followed by the captain in the actual docking of ships (Kose et al., 1986). The first one is that the destination for docking should be at some distance away the dock instead of completely at the dock. The second one is that the captain has enough time to plan a good maneuver in any critical situation. To meet these two requirements, the whole process can be divided into two phases as shown in Fig. 1. The first is the ballistic phase. It utilizes the main thrusters and rudder for course changing, speed adjustment, and stopping. The second phase is to use tunnel thrusters to achieve side push.

In this paper, we focus on the first phase of the docking operation. It is assumed that the ship starts from a stationary state and maneuvers towards the port in low speed. The ship will dock in parallel to the port with zero velocities when it arrives at the destination. Moreover, three different sea conditions, including no wind, constant wind and dynamic wind, are considered for the docking problem.

In Fig. 1, $\{n\} = (x_N, y_N)$ is the North-East coordinate system, and its coordinate values can be obtained from the Global Positioning System (GPS). $\{d\} = (x_o, y_o)$ is called the north-up coordinate system which includes the heading angle and distance from ship to dock (Nguyen et al., 2018). In this paper, all simulations are performed in the north-up coordinate system. The merit of using the north-up coordinate system is to control the ship into other different docks without retraining the controller. $\{b\} = (x_b, y_b)$ represents the body coordinate system. The notation for the marine vessel in Fig. 1 is shown in Table 1.

3.2. Ship mathematical model

The study of ship dynamics consists of two parts: kinematics, which overcomes geometrical problems of motion; and kinetics, which analyzes the relationship between force and motion. Ship movement is expressed in six degrees of freedom (DOF) which includes surge,

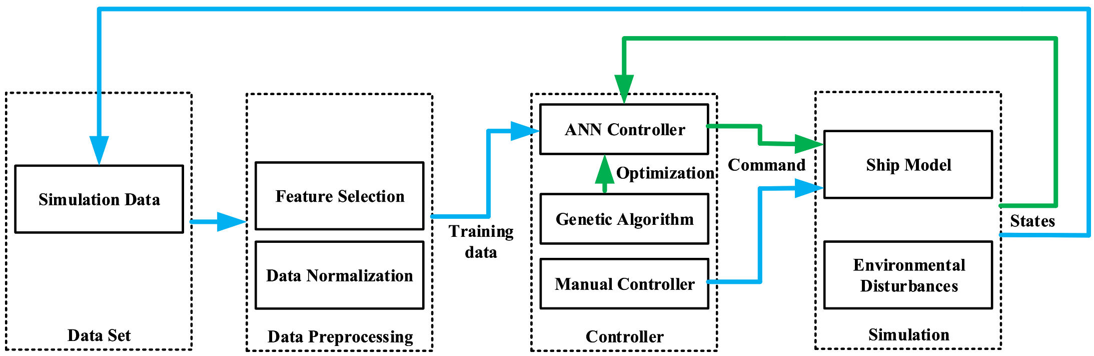

Fig. 2. A neural-network based control strategy for automatic ship docking. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

sway, heave, roll, pitch and yaw (Fossen, 2011). For a surface ship, as shown in Fig. 1, it is only necessary to study the motion in three DOF, namely, the surge, sway and yaw. In this study, the maneuver model group (MMG) is used to describe ship motion, in which the hydrodynamic forces and moments acting on the ship are divided into modular components such as hull, rudder and propeller. The following is an MMG-based mathematical model considering wind influence (Committee et al., 2002):

$$\begin{aligned}(m+m_x)\dot{u}+(m+m_y)vr &= X_H+X_P+X_R+X_W\\ (m+m_y)\dot{v}+(m+m_x)ur &= Y_H+Y_P+Y_R+Y_W\\ (I_{ZZ}+J_{ZZ})\dot{r} &= N_H+N_P+N_R+N_W\end{aligned} \tag{1}$$

where m is the ship mass; m_x, m_y are the added mass in surge, sway direction; I_{ZZ} is the mass moment of inertia; J_{ZZ} is the added mass moment of inertia; X, Y and N denote surge force, sway force and yaw moment; H, P, R and W are the symbols that represent hull, propeller, rudder and wind.

X_h, Y_h and N_h represent the hydrodynamic forces and moment acting on the ship hull, which are defined as (Katsuro et al., 1990):

$$\begin{aligned}X_H &= \frac{\rho}{2}LdU^2(X'_{\beta r}\sin\beta + X'_{uu}\cos^2\beta\frac{rL}{U})\\ Y_H &= \frac{\rho}{2}LdU^2(Y'_\beta + Y'_r\frac{rL}{U} + Y'_{\beta\beta}\beta|\beta| + Y'_{rr}\frac{rL}{U}|\frac{rL}{U}|\\ &\quad + Y'_{\beta\beta r}\beta^2\frac{rL}{U} + Y'_{\beta rr}\beta|\beta|(\frac{rL}{U})^2)\\ N_H &= \frac{\rho}{2}LdU^2(N'_\beta + N'_r\frac{rL}{U} + N'_{\beta\beta}\beta|\beta| + N'_{rr}\frac{rL}{U}|\frac{rL}{U}|\\ &\quad + N'_{\beta\beta r}\beta^2\frac{rL}{U} + N'_{\beta rr}\beta|\beta|(\frac{rL}{U})^2)\end{aligned} \tag{2}$$

where ρ is the water density; L denotes the length over all of ship; d is the draught of ship; U represents the speed of ship. The hydrodynamic coefficients ($X'_{\beta r}, X'_{uu}, \ldots, N'_{\beta rr}$) can be estimated with the method described in Katsuro et al. (1990).

The propeller mainly produces longitudinal force, and its lateral force is negligible. Thus propeller hydrodynamic model can be written as:

$$\begin{aligned}X_p &= (1-t_P)T\\ Y_P &= 0\\ N_P &= 0\end{aligned} \tag{3}$$

where t_P is a coefficient, and the propeller thrust force T is defined:

$$T = \rho n^2 D_p^4 k_T \tag{4}$$

where n is propeller speed (rpm); D_p is diameter of the propeller; k_T is the thrust coefficient.

Table 2
Parameters of wind force model.

Symbol	Physical meaning
ρ_a	Air density
A_F	Frontal projected area of ship
A_L	Lateral projected area of ship
V_r	Relative wind speed
X_W	Fore-aft component of wind force
Y_W	Lateral component of wind force
N_W	Yawing moment
C_X, C_Y, C_N	Coefficients calculated using Isherwood72

The hydrodynamic forces and moment generated by the rudder can be calculated by the following formula:

$$\begin{aligned}X_R &= -(1-t_R)F_N\sin\delta\\ Y_R &= -(1+a_H)F_N\cos\delta\\ N_R &= -(x_R+a_Hx_H)F_N\cos\delta\end{aligned} \tag{5}$$

where t_R, a_H are coefficients; x_R and x_H are the distances from the rudder and the propeller to the ship's center of gravity, respectively; F_N is the rudder pressure; δ denotes the rudder angle.

As a result, the control inputs of the MMG model are the propeller speed n and rudder angle δ; the ship velocities u, v, and r represented as the state variables in Eq. (1) are the control outputs of the model.

3.3. Wind force model

The wind has a significant effect on the ship, which will affect heading and sway movement. Failure to compensate correctly for wind during docking is one of the main factor of docking accidents. Here, the wind forces and moments acting on the ship are estimated as (Fujiwara et al., 1998):

$$\begin{aligned}X_W &= \frac{1}{2}C_X\rho_aV_r^2A_F\\ Y_W &= \frac{1}{2}C_Y\rho_aV_r^2A_L\\ N_W &= \frac{1}{2}C_N\rho_aV_r^2A_LL\end{aligned} \tag{6}$$

The physical meaning of each symbol in Eq. (6) is shown in Table 2.

4. Proposed approach

Fig. 2 schematically depicts the ANN-based ship docking control strategy for ship docking under environmental disturbances. First, the ship docking simulation module is constructed. It consists of a ship model and environmental disturbance models, which is fundamental to both manual control and ANN-based control. Based on that, training data set can be generated, as indicated by the blue arrow. The "data set" is the collection of ship maneuvering data from the simulation. The

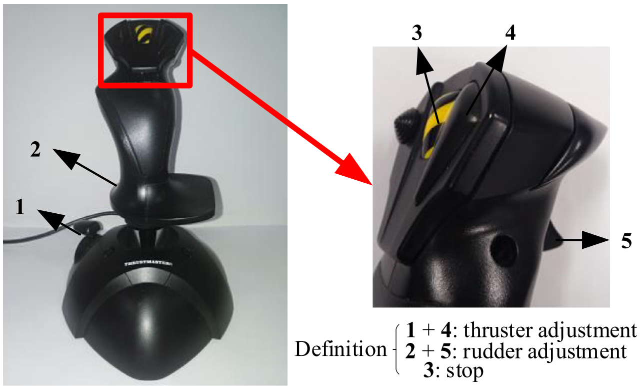

Fig. 3. Definition of Joystick.

data is pre-processed through feature selection to find optimal input parameters for ANN construction, and further normalized before the training of the ANN. The green arrow illustrates the implementation of the ANN-based approach. The ANN is optimized by a genetic algorithm and trained using the data set. As a result, the trained ANN model can be applied to steer the ship to dock under external disturbances.

4.1. Data generation

In this research, training data is created through "manual controller", i.e., by a skilled captain using a joystick to control ship's rudder and thrust. The usage of the joystick is shown in Fig. 3. "Button 4" is used to enable the control of thruster speed. Only when it is pressed, can "Button 1" be used to adjust thruster speed within the range of $[-130, 130]RPM$. Similarly, "Button 5" enables the use of rudder control, and "Handle 2" can adjust rudder angle between $-45°$ and $45°$ only if "Button 5" is pressed. "Button 3" is the stop key. When the ship arrives at the dock safely, the captain can press the button to stop the maneuver.

4.2. Data pre-processing

The data pre-processing mainly contains two parts: feature selection and data normalization. The purpose of feature selection is to choose an optimal subset from the training data for ship control. In this paper, a step-wise feature selection method is developed. First, those constant variables would be deleted. In addition, to remove the redundant information between input parameters, Pearson correlation analysis (Bolboaca and Jäntschi, 2006) is applied. Then ANN-based variance-based sensitivity analysis is used for identifying the importance of each feature (Cheng et al., 2019). Assume any two input parameters x and y, the Pearson correlation of these two parameters can be defined as follows:

$$\rho_{xy} = \frac{\sigma_{xy}^2}{\sqrt{\sigma_x^2 \sigma_y^2}} \tag{7}$$

where σ_x is the standard deviation of x; σ_x^2 is the variance of x; σ_y is the standard deviation of y; σ_y^2 is the variance of y; σ_{xy}^2 is the co-variance of the variables x and y. The Pearson coefficient can be used to detect the dependency of two input parameters. In this paper, one of the two parameters would be removed, if the Pearson coefficient of the two parameters is large. If the model form is $f(\boldsymbol{X}) = f(x_1, \ldots, x_M)$, where $\boldsymbol{X} = (x_1, \ldots, x_M)$ represents the model input which contains M independent parameters. Based on the theory of Sobol (Saltelli and Sobol', 1995), the variance-based sensitivity index can be described as the ratio of partial variance and total variance. The influence of the ith variable x_i to the output can be defined by

$$S_{Ti} = 1 - \frac{V_{\sim i}}{V} \tag{8}$$

where S_{Ti} is the influence of input parameter to output; V stands for the total variance; and $V_{\sim i}$ represents the influence excluding the ith variable. If the S_{Ti} is close to zero, the parameter can be considered to be non-important.

In addition, it is necessary to normalize all parameters to speed up the training convergence and improve accuracy of the ANN model. All the parameters would be normalized:

$$\hat{\boldsymbol{x}} = \frac{\boldsymbol{x} - E(\boldsymbol{x})}{\sqrt{Var(\boldsymbol{x}) + \epsilon}} \tag{9}$$

where $E(\boldsymbol{x})$ represents the mean of $\boldsymbol{x}$; $Var(\boldsymbol{x})$ stands for the variance of $\boldsymbol{x}$; ϵ is a positive infinitesimal to make the calculation possible when $\boldsymbol{x}$ is a constant; ϵ is set to 10^{-6} in this paper.

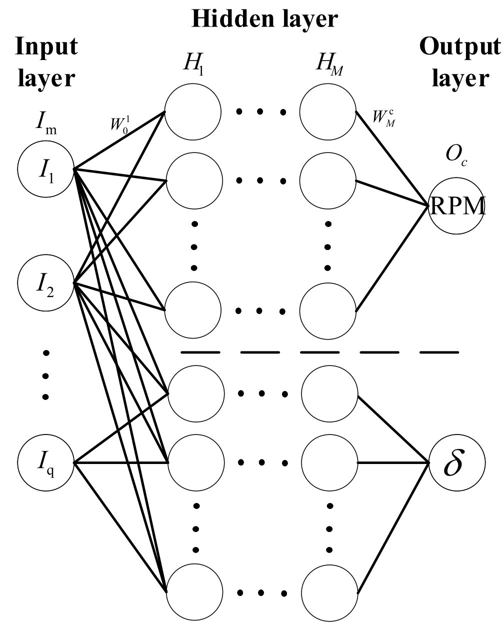

Fig. 4. Multi-layer ANN with two parallel architecture.

4.3. ANN-based controller

Since the automatic ship docking system is a multi-input and multi-output system, it is important to design a neural network that can learn the underlying nature relationship between inputs and outputs autonomously. An ANN-based controller with two independent parallel structure is designed. The inputs of the ANN are the parameters selected from data analysis, and the outputs are the ship's propeller speed and rudder angle. The construction of the two parallel multi-layer ANN is demonstrated in Fig. 4. The ANN is a multilayer feedforward network that can be trained by error backpropagation. The principle of the training algorithm is the gradient descent method that is used to minimize the mean square error (MSE) between the actual output value of the network and the desired output value. Assume the neural network in Fig. 4 consists of an input layer, M hidden layers and an output layer. The output of each hidden layer can be written as:

$$H_i = f(W_{i-1}^i H_{i-1} + b_i), i = 1, 2, \ldots, M \tag{10}$$

where $H_0 = I_m$, W_i^{i+1} is the weight between the hidden layers; b_i is the offset of the hidden layer; and f is activation functions. Here we choose

Table 3
Specification of model ship.

Parameter	Length (m)	Beam (m)	Draught (m)	Dead weight (tonnes)
Value	93.79	23.04	8	4925

Table 4
Initial and termination states for ship docking.

Ship states	Initial	Termination
Position x (m)	122	0
Position y (m)	600	0
Heading ψ $(^{o})$	[0,360]	270
Surge velocity u (m/s)	0	0
Sway velocity v (m/s)	0	0
Yaw velocity r (rad/s)	0	0

the Tansig function as the activation function, and its mathematical expression is expressed as:

$$f(x) = \frac{2}{1 - exp(-2x)} - 1 \tag{11}$$

Similarly, the output layer of ANN uses linear function, and its formula is expressed as following form:

$$O_c = purelin(W_n^c H_n + b_c) \tag{12}$$

where W_n^c is the weight between the last hidden layer and output layer; b_c is the offset; and H_n is the input of the output layer. The performance of the trained network is determined by calculating the value of the MSE. Suppose there are k samples in the training data, $(x_1, y_1), (x_2, y_2), \ldots, (x_k, y_k)$, where (x_k, y_k) represent the inputs and outputs of the samples. The objective function of the network training is written as:

$$MSE = \frac{1}{k} \sum_{i=1}^{k} (y(i) - O_c)^2 \tag{13}$$

where $y(i)$ can be either rudder angle or propeller speed. The Levenberg–Marquardt algorithm is used to minimize the MSE. The weights of the ANN are updated as follows:

$$\begin{aligned} W_{i-1}^i(t) = & W_{i-1}^i(t-1) - [J^T(W_{i-1}^i(t-1))J(W_{i-1}^i(t-1)) \\ & + \mu I]^{-1} J^T(W_{i-1}^i(t-1)) MSE(W_{i-1}^i(t)) \end{aligned} \tag{14}$$

where J is Jacobian matrix; and I is identity matrix.

In this paper, GA is used to optimize the ANN based controller. The chromosome consists of integers, representing the number of hidden layers and the number of neurons in each hidden layer (Phan et al., 2017). The fitness function is designed as the performance of ANN in Eq. (13). Through GA operation including crossover and mutation, individuals with high fitness values will be selected to form a new generation. The process is repeated until termination condition is satisfied. As a result, the ANN structure is optimized to fit the training data.

5. Experiments

This section is devoted to the validation of the proposed ANN-based approach. First, a simulated offshore vessel represented by the MMG model with parameters derived from the marine systems simulator (MSS) (Perez et al., 2006) is set up, as shown in Table 3. Next, a docking scenario is built up, as listed in Table 4. The task is to steer the vessel from the initial state to the final state under a zero velocity constraint of the respective state. After that, data with three different environmental conditions, including no wind, constant wind and dynamic wind, is collected for training the ANN-based controller introduced in Section 4.3. All experiments are conducted in a computer equipped with 2.60 GHz i7-6700K CPU and 16 GB RAM.

Fig. 5. Correlation analysis of 12 input parameters.

5.1. Feature selection

To obtain the optimal input parameters for the ANN shown in Fig. 4, the proposed feature selection method is performed. There are 16 parameters are logged in the simulated scenarios, mainly including two categories: state of vessel and environmental information. The vessel's state includes its position and heading, the speed of vessel in each DOF, the force of vessel in each DOF, and the state of thrusters; environmental information includes the force of wind in each DOF, the wind speed and the wind direction. Since wind speed and wind direction are constant values, they are removed for analysis. Thus, the correlation of 12 parameters excluding two output variables, i.e., rudder and thruster speed, are used for correlation analysis, as shown in Fig. 5. We further use a threshold $\rho_{xy} = 0.84$ to eliminate redundant information among parameters, which results in the removal of parameters "yaw speed", "surge force", "sway force", "yaw force", "wind force of surge", "wind force of sway", and "wind force of yaw". An ANN used for sensitivity analysis is built on the basis of the rest 5 parameters. A variance-based Sobol method with a distribution sampled from the original data is performed on the ANN (Cheng et al., 2019). Fig. 6 shows the sensitivity index of the 5 parameters.

According to the results of sensitivity analysis, three input parameters, i.e., the relative distances x and y between the ship and the dock, and heading angle, are selected as the inputs of the ANN; the output of the ANN, as shown in Fig. 4, are the rudder angle δ and thruster speed n introduced in Section 3.2.

5.2. Configuration of ANN

It is necessary to determine the structure of ANN, as there are no existing rules that can be used to accurately select the number of layers of the hidden layer and the number of neurons. In this study, the structure was determined by trial and observation of the minimum MSE employing GA. The search for the number of hidden layers is set as $M \in [2, 3, 4, 5, 6]$, and the search for the number of neurons in each hidden layer is set as $N \in [0, 3, 6, 9, 12]$. The optimized hidden number M_o should meet the requirement $M_o \in M$. For GA, each chromosome contains the above two parameters, i.e. number of hidden layers and neurons. The crossover probability and mutation probability of GA are set to 0.3, and the stopping criterion is that the number of generations reaches 50. Table 5 lists the optimized hidden layers and

Table 5
Parameters for hidden layers using GA optimization.

M	δ			Rpm		
	M_o	N	MSE	M_o	N	MSE
2	2	12, 12	1.100×10^{-3}	2	12, 12	3.800×10^{-3}
	2	12, 12	1.100×10^{-3}	2	12, 12	3.800×10^{-3}
3	3	12, 12, 12	8.388×10^{-4}	3	12, 12, 12	3.400×10^{-3}
	3	9, 9, 12	8.514×10^{-4}	3	12, 12, 12	3.400×10^{-3}
4	3	9, 12, 3	7.088×10^{-4}	4	12, 6, 12, 12	3.100×10^{-3}
	4	9, 9, 12, 6	7.547×10^{-4}	4	12, 6, 12, 12	3.100×10^{-3}
5	**4**	**12, 12, 12, 12**	$\mathbf{5.976 \times 10^{-4}}$	**4**	**12, 6, 12, 6**	$\mathbf{3.100 \times 10^{-3}}$
	5	12, 9, 12, 12, 12	5.673×10^{-4}	4	12, 6, 12, 12	3.100×10^{-3}
6	4	12, 12, 6, 12	6.430×10^{-4}	4	12, 12, 12, 12	3.200×10^{-3}
	4	12, 3 , 12, 12	7.419×10^{-4}	5	12, 6, 3, 12, 12	3.200×10^{-3}

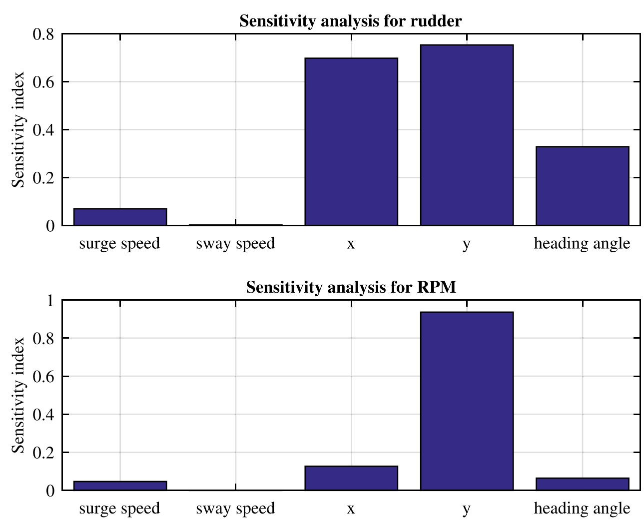

Fig. 6. Sensitivity analysis for rudder and RPM.

the neuron number of each hidden layer. Considering a metric among MSE, number of neurons and training time, four hidden layers with the corresponding neuron number shown in bold in Table 5 are used for the experiment.

5.3. Verification of ANN in no wind condition

Fig. 7 illustrates some successful maneuvers without wind perturbation in dotted lines using the ANN-based approach. Note the two paths one in red representing the trajectory using the same initial heading in training data; and the blue one representing a completely new initial heading different from the training data. The rudder angle and thruster speed generated completely by the ANN are expressed in Fig. 8. Fig. 9 illustrates the variation of the ship's surge velocity, sway velocity, yaw velocity and heading angle during the docking process. When the ship arrives at the dock, its velocities are very close to zero (less than 0.01 m/s), and the ship's heading angle is also approximately 270°. In this case, the ship successfully stopped at the dock and terminal states also meet the requirements in Table 4.

5.4. Verification of ANN in constant wind condition

Here we test the ANN-based controller in different initial states under constant wind condition of $V_w = 3$ m/s and $\beta_w = 0°$.

Fig. 10 illustrates the automatic docking trajectory starting from different initial headings. The red curve and the blue curve are two successful maneuvers, with the same initial states and different initial

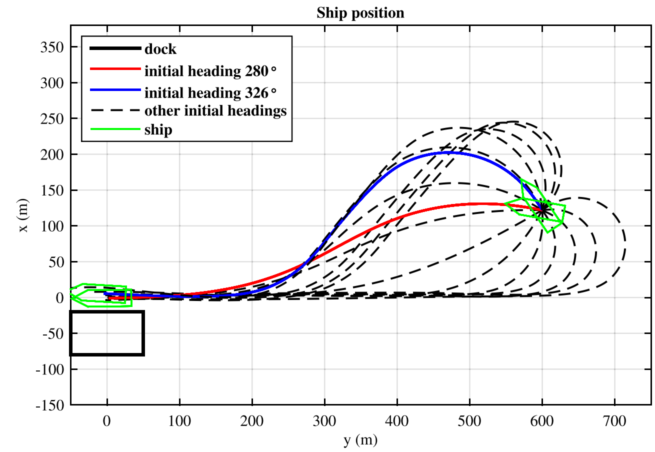

Fig. 7. Docking results for different initial headings without wind. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

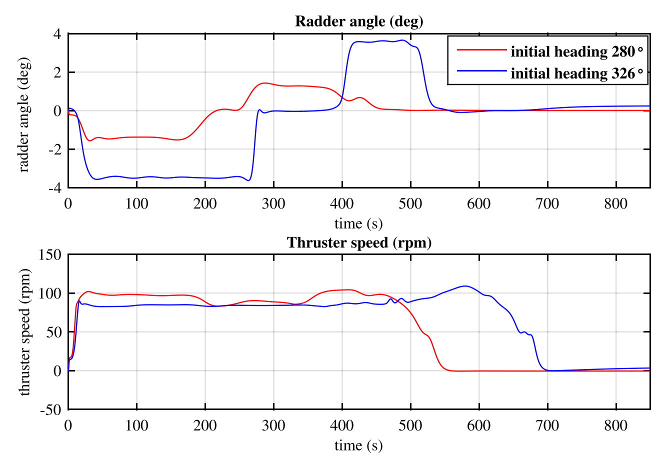

Fig. 8. Rudder angle and thruster speed for maneuvers with initial heading of 280° and 326° under no wind.

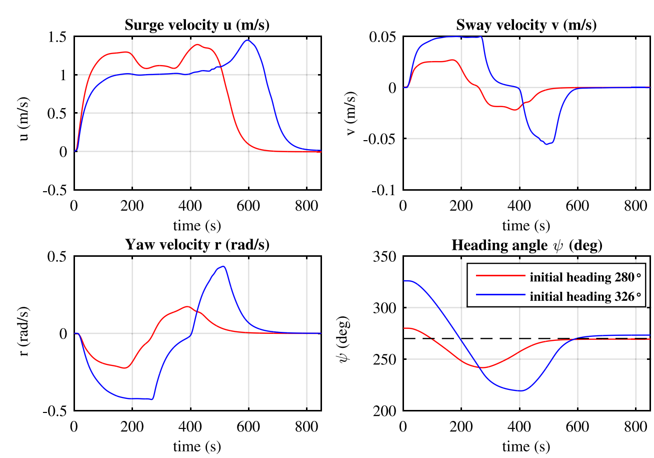

Fig. 9. Ship velocities and heading angle for maneuvers with initial heading of 280° and 326° under no wind.

states from the training set, respectively. Fig. 11 shows the control commands used for the docking. The thruster speed dramatically fluctuates between 300 and 400 s, which may be caused by speed adjustment. It can be seen from Fig. 12 that when ships arrive at the dock, the

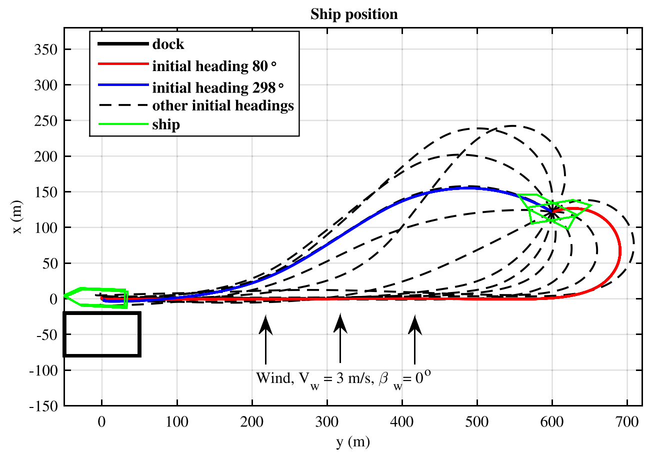

Fig. 10. Docking results with different initial headings under constant wind. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

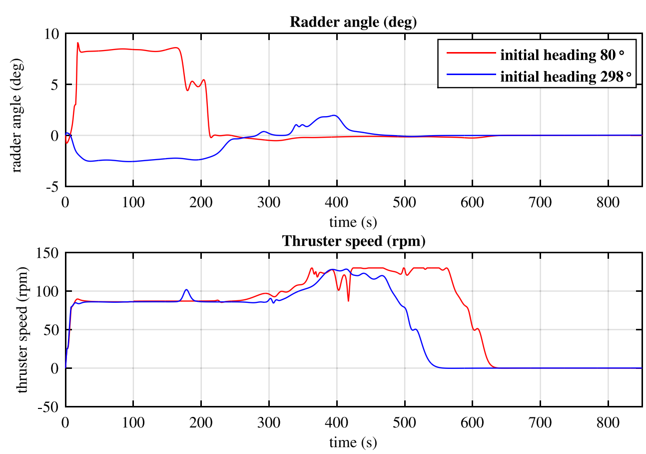

Fig. 11. Rudder angle and thruster speed for maneuvers with initial heading of 80° and 298° under constant wind.

surge velocity and yaw velocity are close to zero, and the heading angle is also close to 270°. Due to the disturbance of wind, the ship's sway velocity is not zero.

5.5. Verification of ANN in dynamic wind condition

The ANN-based controller is tested under different wind speeds. Fig. 13 shows the results of different ship initial states. The red curve represents a ship docking path starting from heading 300° which is included in training data. The blue curve is a maneuver that the ship starts from a random heading. It shows that the ANN cannot navigate the ship to move straight when arriving at position (0, 500), even though the ship is heading towards the dock. The reason is that the wind is becoming stronger at the moment. In the simulation, wind direction is constant ($\beta_w = 0°$), and speed changes randomly from 1.5 m/s to 4.5 m/s per minute, as demonstrated in the bottom panel of Fig. 14. The change of surge velocity, yaw velocity, and heading angle can converge to zero at last, but the sway velocity fluctuates periodically with the wind disturbance, as shown in Fig. 15.

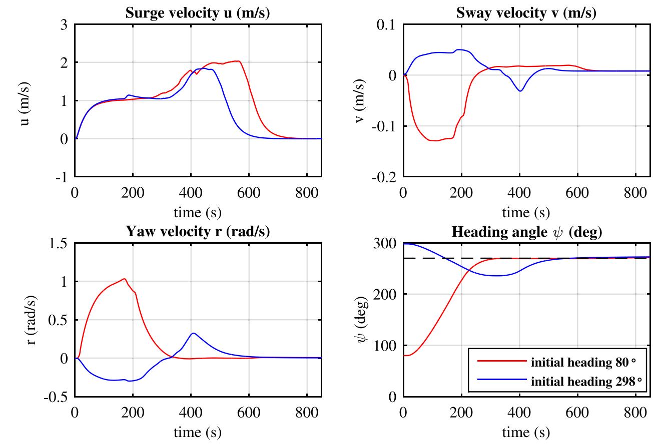

Fig. 12. Ship velocities and heading angle for maneuvers with initial heading of 80° and 298° under constant wind.

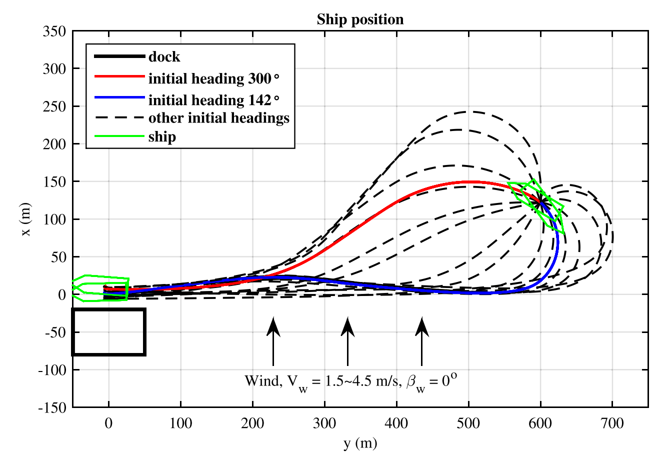

Fig. 13. Docking results with different initial headings under dynamic wind. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

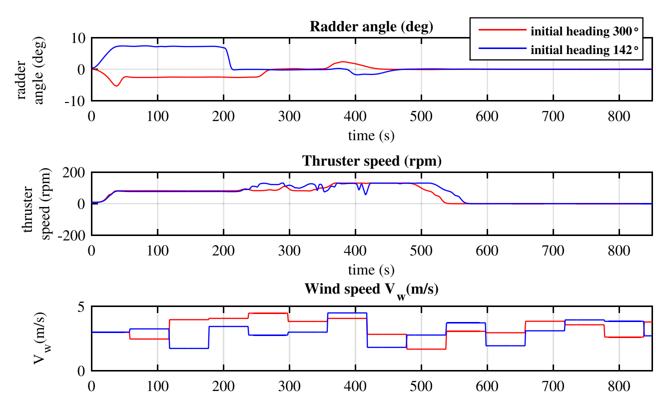

Fig. 14. Rudder angle and thruster speed for maneuvers with initial heading of 300° and 142° under dynamic wind.

5.6. Discussion

The simulation results show that in no wind condition, the ANN controller works very well, with only small fluctuations in command of rudder angle and thruster speed. Moreover, the ship states are in full compliance with the requirements in Table 4 when the ship arrives

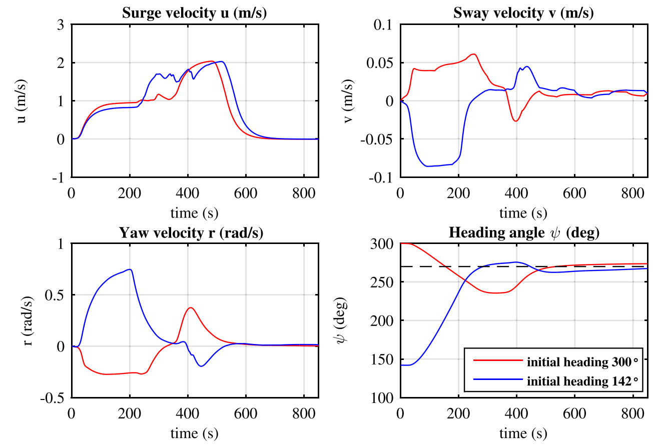

Fig. 15. Ship velocities and heading angle for maneuvers with initial heading of 300° and 142° under dynamic wind.

at its destination. Ships can also dock safely in the constant wind environment, but there is a slight error in the final heading angle (less than 2°) and the yaw speed is not fully zero. The main reason for this problem is that the ship is required to sail at low speed when it approaches the berth, which greatly reduces the ship's maneuverability. In the dynamic wind condition, the control results of the ANN are not as good as these in the previous conditions due to the randomness of the wind. The rudder angle and propeller speed fluctuate drastically and the path is not smooth enough. In addition, the ship cannot successfully arrive the dock when it departs from initial heading angles between 5° and 23°. Because at these initial heading angles, the ANN is very sensitive to the disturbance of dynamic wind.

6. Conclusion

This research proposes a novel way to generate reliable ship docking data and finds the optimal variables for training a new neural network by employing feature selection technique and genetic algorithm which were not considered in previous studies. The conclusions of this work are summarized as follows:

(1) A ship docking simulation module is established, which provides both manual and algorithm-based interface for ship docking operation.
(2) Feature selection is applied to eliminate redundant information between input parameters and identify their importance to ship's control parameters.
(3) To ensure the stability of the ANN-based approach, the neural network structure is optimized by using GA. Two parallel forward neural networks with four hidden layers are established to control ship's rudder angle and the propeller speed, respectively.
(4) Numerical results show that under no wind and constant wind conditions, the feasibility of the ANN-based approach is fully reflected; while under the dynamic wind environment, the performance is inferior but can still steer the ship into dock.

For future study, the degree of sensitivity of the trained ANN-based controller to the initial and termination states will be investigated. Furthermore, it is critical to improve the proposed approach to effectively compensate for dynamic wind disturbances. Advanced mechanisms will be set up to create versatile control strategies that meet different requirements, such as minimum time maneuver, lowest energy consumption, and collision avoidance with dynamic obstacles.

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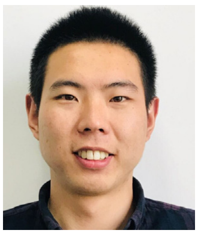

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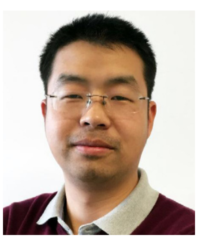

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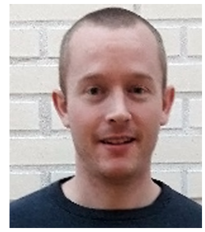

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