ARTIFICIAL NEURAL NETWORK CONTROLLER FOR AUTOMATIC SHIP BERTHING USING HEAD-UP COORDINATE SYSTEM

Dr. Manh-Cuong Nguyen
Dr. Van-Suong Nguyen

Faculty of Navigation, Vietnam Maritime University, Vietnam
e-mail: nguyenvansuong@vimaru.edu.vn

Abstract: The Artificial Neural Network (ANN) model has been known as one of the most effective theories for automatic ship berthing, as it has learning ability and mimics the actions of the human brain when performing the stages of ship berthing. However, existing ANN controllers can only bring a ship into a berth in a certain port, where the inputs of the ANN are the same as those of the teaching data. This means that those ANN controllers must be retrained when the ship arrives to a new port, which is time-consuming and costly. In this research, by using the head-up coordinate system, which includes the relative bearing and distance from the ship to the berth, a novel ANN controller is proposed to automatically control the ship into the berth in different ports without retraining the ANN structure. Numerical simulations were performed to verify the effectiveness of the proposed controller. First, teaching data were created in the original port to train the neural network; then, the controller was tested for automatic berthing in other ports, where the initial conditions of the inputs in the head-up coordinate system were similar to those of the teaching data in the original port. The results showed that the proposed controller has good performance for ship berthing in ports.

Keywords: Automatic ship berthing; ANN controller; Head-up coordinate system; Low speed; Relative bearing.

1. Introduction

Because a neural network has learning ability and mimics the actions of the human brain when performing the stages of ship berthing, many researchers have used this theory for automatic ship berthing. The first study on berthing control using a neural network as the main controller was conducted by Yamato et al. (1990) [2]. In that work, the inputs of the ANN controller included the ship position, ship heading, ship velocities, and beam distances. Although this suggestion obtained excellent results, this approach was replaced by an expert system proposed by Yamato (1992) [3]. Zhang et al. (1997) [10] suggested a multivariable neural controller for ship berthing with inputs that included the ship state, desired states, and the control signal at previous steps and with parameters that could be adapted by an online training process. Later, Im and Hasegawa (2001, 2002) [5] proposed a neural network with parallel structure in a hidden layer to obtain better results than a centralized network. Subsequently, Im (2007, 2009) [6] applied a selective ANN controller for ship berthing considering that the ship starts from any point around the berthing area. On the other hand, Nguyen (2007) [4] proposed two ANN controllers using an adaptive interaction learning technique and a predetermined berthing route to control the ship heading and ship speed simultaneously. Recently, the auxiliary devices used to support ship maneuvering, such as the side thruster and tugboat, have been incorporated in automatic berthing by Tran and Im (2012) [9]. In that research, the bow thruster and stern tugboat were added simultaneously into the ANN controllers as new outputs. With four outputs consisting of the rudder angle, propeller, bow thruster, and stern tugboat, the ship was controlled to the first goal area by the rudder angle and propeller, as in previous studies; then, the ship was guided to the final goal area by the bow thruster and stern tugboat. In addition, nonlinear programming methods and virtual windows have been suggested by Ahmed and Hasegawa (2013) [1] to create consistent teaching data for training the network, and the ANN controller was later verified for ship berthing with no disturbance cases. In the case of gusty winds, the PD controller was used to keep the ship on an imaginary line after the course changing process was performed by the ANN controller. As summarized above, the neural controllers that have been proposed by previous studies only control a ship into a berth of a certain port, and the ANN inputs are the same as those of teaching data created in advance. When arriving at new ports, either these ANN controllers must be retrained by other teaching data or the ship must install different controllers for each port. This requires time-consuming, expensive, and computationally complex control systems. In this research, by using the head-up coordinate system, which includes the relative bearing and distance from the ship to the berth, a novel ANN controller is proposed to control a ship into a berth in different ports without retraining the ANN structure. Numerical simulations were performed to verify the effectiveness of the proposed controller. The results showed that the proposed controller has good performance for ship berthing in ports.

2. Mathematical Model of Ship Maneuvering

In this research, the Maneuvering Modeling Group (MMG) model was applied to represent the ship motion, in which the hydrodynamic forces and moments acting on the ship were divided into modular components such as the hull, rudder, and propeller.

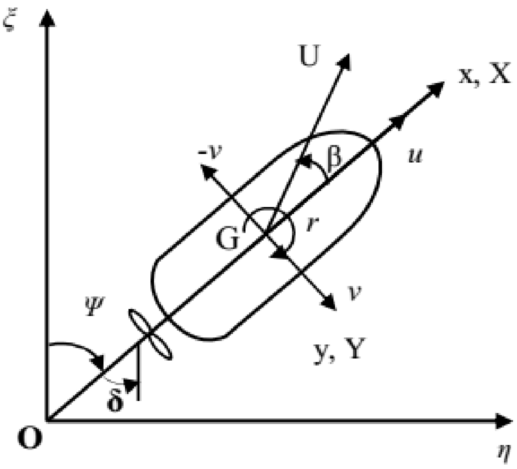

Fig. 1 Coordinate system for ship dynamic motion

According to MMG model, the maneuvering equation of the ship is expressed in the following form:

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

The subscripts *H, P,* and *R* represent the hull, propeller, and rudder components, respectively. The hydrodynamic forces and moments acting on the ship are expressed by by Kijima et al. (1990).

In this study, the training ship SAE NURI of Mokpo National Maritime University was adopted as the model ship whose parameters were used to predict the hydrodynamic coefficients. The ship's principle particular is shown in Table 1.

Table 1 Principle particular of the ship

Type	Training ship
Length overall	103[m]
Length between perpendicular	94[m]
Breadth	15.6[m]
Draft	5.4[m]
Thruster (Bow)	49000[N]
Transverse projected area	183.3[m^2]
Lateral projected area	1053.7[m^2]

3. ANN controller for automatic ship berthing using head-up coordinate system

3.1. Head-up coordinate system

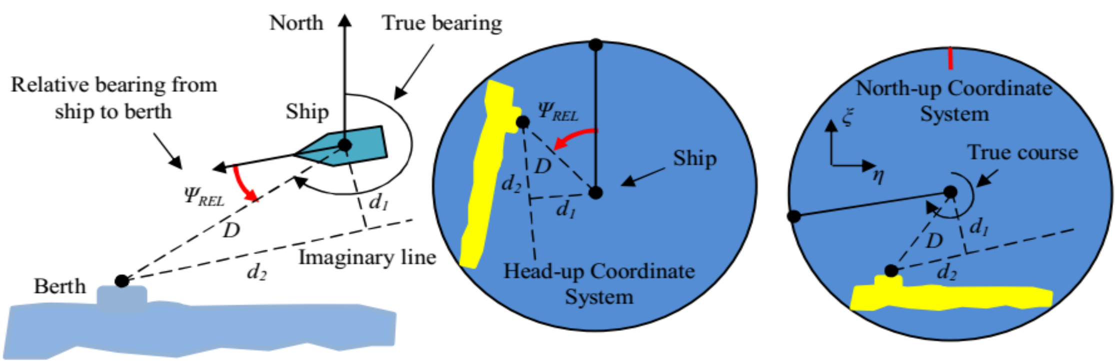

Fig. 2 Relative bearing from ship to the berth in head-up coordinate system

The inputs used in previous controllers were the parameters in the North-up coordinate system, namely, the geographical coordinates (η, ξ) and ship heading (Ψ). In this research, two new parameters expressed in the head-up coordinate system, the relative bearing (Ψ_{REL}) and the distance from the ship to the berth (D), were introduced to obtain suitable actions for the rudder (δ_{ord}) and propeller (rps) by the proposed ANN controller, as shown in Fig. 2. The combination of these parameters with the distance to the imaginary line (d_1) and the remaining distance to the berth (d_2) created four parameters (Ψ_{REL}, D, d_1, d_2) for the proposed controller.

3.2. Formula for data converter

In every case, the ship dynamics data (u, v, r) are originally kept, the data converter is used to convert the ship states (η, ξ, Ψ, d_1, d_2) in the North-up coordinate system into inputs for the proposed ANN controller, such as (Ψ_{REL}, D, d_1, d_2), in the head-up coordinate system. The detailed formula for the data converter is expressed as in Eq. (2).

$$
\begin{aligned}
&D = \sqrt{\left(\xi_{ship} - \xi_{berth}\right)^2 + \left(\eta_{ship} - \eta_{berth}\right)^2} \\
&BA = kD \ \ (k > 1) \\
&\lambda = \cos^{-1}\left(\frac{\overrightarrow{BS}\overrightarrow{BA}}{|\overrightarrow{BS}||\overrightarrow{BA}|}\right) \\
&d_1 = D\sin(\lambda) \\
&d_2 = D\cos(\lambda) \\
&\psi_{REL} = \angle\left(Heading\ line, \overrightarrow{SB}\right)
\end{aligned}
\tag{2}
$$

where the relative bearing to the berth ψ_{REL} is the directional angle (in degrees) from the heading line of the ship to a straight line drawn from the observation position on the ship $S(\eta_{ship}, \xi_{ship})$ to the berth $B(\eta_{berth}, \xi_{berth})$, and λ is the angle between the vector $\overrightarrow{BS}$ and the vector $\overrightarrow{BA}$.

3.3. Concept and control flow of automatic ship berthing for different ports based on ANN

In previous studies, the inputs of the teaching data consisted of the ship velocities (u_1, v_1, r_1), the ship heading (Ψ_1), and the geographical coordinates of the ship in the port area (η_1, ξ_1). The neural network has no ability to calculate well when the initial inputs of the network are entirely different from those considered in the teaching data. Because the geographical coordinates of the ship (η_1, ξ_1) in the original port are always different from those (η_2, ξ_2) in other ports, these ANN controllers cannot be applied to other ports. In this research, the ship maneuvering process used to create the teaching data was performed similarly to previous studies, but the ship states, including the relative bearing (Ψ_{REL}) and distance from the ship to the berth (D, d_1, d_2), were used as the main key for the proposed ANN controller. By using a data converter, the geographical coordinates of the ship at the port (η, ξ) and the ship heading (Ψ) are cancelled out from the teaching data. This means that the teaching data for the proposed ANN that were created in the original port consist of the inputs ($\Psi_{REL1}, D_1, d_{1(1)}, d_{2(1)}, u_1, v_1, r_1$) and outputs such as the rudder angle (δ_{ord}) and propeller speed (rps). In other ports, where the initial states ($\Psi_{REL2}, D_2, d_{1(2)}, d_{2(2)}, u_2, v_2, r_2$) of the ship are the same as those ($\Psi_{REL1}, D_1, d_{1(1)}, d_{2(1)}, u_1, v_1, r_1$) used in the teaching data created in the original port, the proposed ANN controller will control the ship automatically into the berth, as illustrated in Fig. 3.

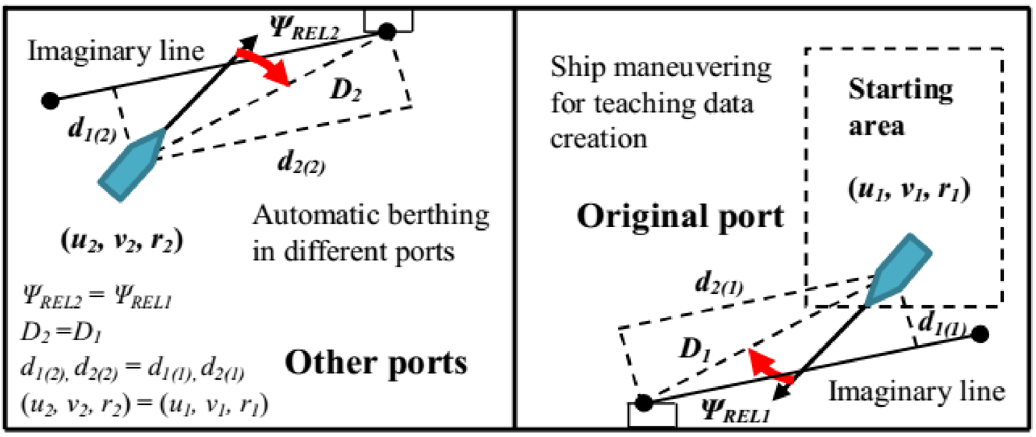

Fig. 3 Automatic ship berthing in different terminals and different ports

3.4. ANN controller using head-up coordinate system

In previous research on automatic ship berthing control using neural networks, such as Yamato et al. (1990), Yamato (1992), Im and Hasegawa (2001, 2002), Im (2007, 2009), Tran and Im (2012), and Ahmed and Hasegawa (2013), the neural network was used as the main controller and was designed based on the direct learning method of teaching data. In this research, we used the same approach to design the proposed ANN controller, as shown in Fig.9. In this study, a neural network of multi-layer perception was applied to the proposed ANN controller, which had seven inputs, the relative bearing (Ψ_{REL}), distance from the ship to the berth (D), beam distances (d_1, d_2), surge velocity (u), sway velocity (v), and yaw rate (r), and two outputs, the command rudder angle (δ_{ord}) and propeller speed (rps). The structure of the controller is shown in Fig. 4.

The back-propagation technique, in which the weights and bias of the network move along the negative direction of the gradient of the performance function, was employed to train the ANN structure. The objective of network training is to minimize the error between the outputs of the network and the outputs of the teaching data. After training the neural network, the control law $[\delta_{ord(t+1)}, rps_{(t+1)}]^T$ determined by the proposed ANN controller was derived as:

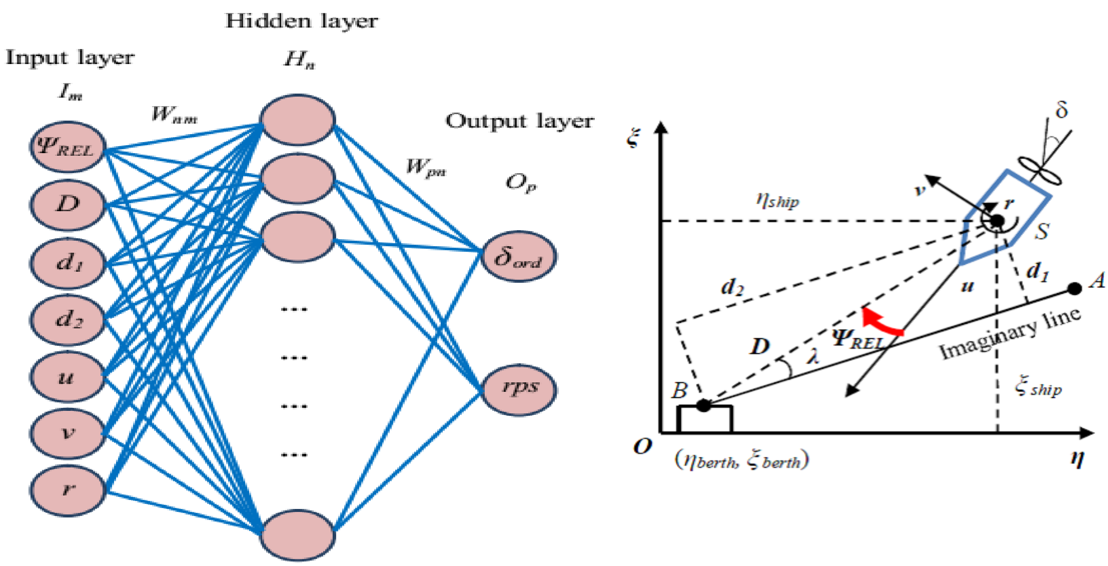

Fig. 4 The structure of neural network controller

$$\left[\delta_{ord(t+1)}, rps_{(t+1)}\right]^T =$$

$$f_2\left(\sum_{n=1}^{n} W_{pn} f_1\left(\sum_{m=1}^{m} W_{nm}\left[\psi_{REL(t)}, D_t, d_{1(t)}, d_{2(t)}, u_{1(t)}, v_{1(t)}, r_{1(t)}\right]^T + b_n\right) + b_p\right) \qquad (3)$$

The training process of the neural network began by selecting the number of nodes in the hidden layer. This procedure must ensure that the learning error converges to zero in the shortest time. The structure of the hidden layer in the ANN controller was chosen to consist of 25 nodes. The trained ANN controller guarantees that the outputs of the network always follow up the outputs of the teaching data. This means that the ANN controller adjusts the rudder angle and propeller speed to control the ship into berth as a human brain when the initial states of the ship in the port are identical or similar to the inputs of the teaching data.

4. Numerical simulations and results

This section describes numerical simulations performed to verify the effectiveness of the proposed controller for different ports. The ship was controlled automatically into a berth in two different ports: the first one was the original port, where the teaching data were created, and the second one had different geometrical coordinates inform the original port.

4.1. Numerical simulation results for original port

This section describes the ship berthing simulation in the original port, which was performed to validate the learning ability of the neural network controller. Generally, the proposed ANN controller is believed to be a very useful tool when faced with a situation that mimics that of a trained one. As shown in Fig. 5, the ability of controlled ship to stop near the wharf and reach the berthing point was good. In particular, the stopping ability was good, as it was possible to reach the wharf within 0.2 m/s in all cases. Furthermore, the final heading angles were in the range 250–270 deg.

In Fig. 5, the initial conditions of the ship at the starting time are the same as those in the teaching data. The results show that the proposed controller performs successful actions for controlling the ship into the berth in this area.

In Fig. 6, the simulations are performed for the original port, where the initial conditions of the ship are different from those in the teaching data. The results show that the interpolation ability of the proposed controller is good for initial states that are not included in the teaching data.

4.2. Numerical simulation results for other port

This part describes the simulations performed for the second port, where the geographical coordinates of the ship and the ship heading at the starting time were entirely different from those of the original port. The non-dimensional coordinates of this port were between -20 and -4 in the horizontal range and from 22 to 35 in the vertical range, and the berth position was (-10, 33.5). In Fig. 7, the initial states of the ship in this port are (-17.1, 25.4, 64, 1.5, 0, 0, 0, 0.75), (-18.6, 26.5, 34, 1.5, 0, 0, 0, 0.75), (-15, 25.5, 14.1, 1.5, 0, 0, 0, 0.75), and (-18.6, 29.4, 74, 1.5, 0, 0, 0, 0.75). The time history of the rudder angle and revolution speed shown in Fig. 7 was appropriately calculated by the controller to bring the ship into the berth.

Although the initial ship position and the ship heading in this port were different from those in the teaching data, the results show that the numerical simulations were successful. Particularly, the initial conditions of the ship in Fig. 7 are different from those in Fig.6. Therefore, the proposed controller can be applied to the second port, as well as other ports, where the initial conditions of the ship, such as the relative bearing and distance to the berth, are different from the teaching data in the original port.

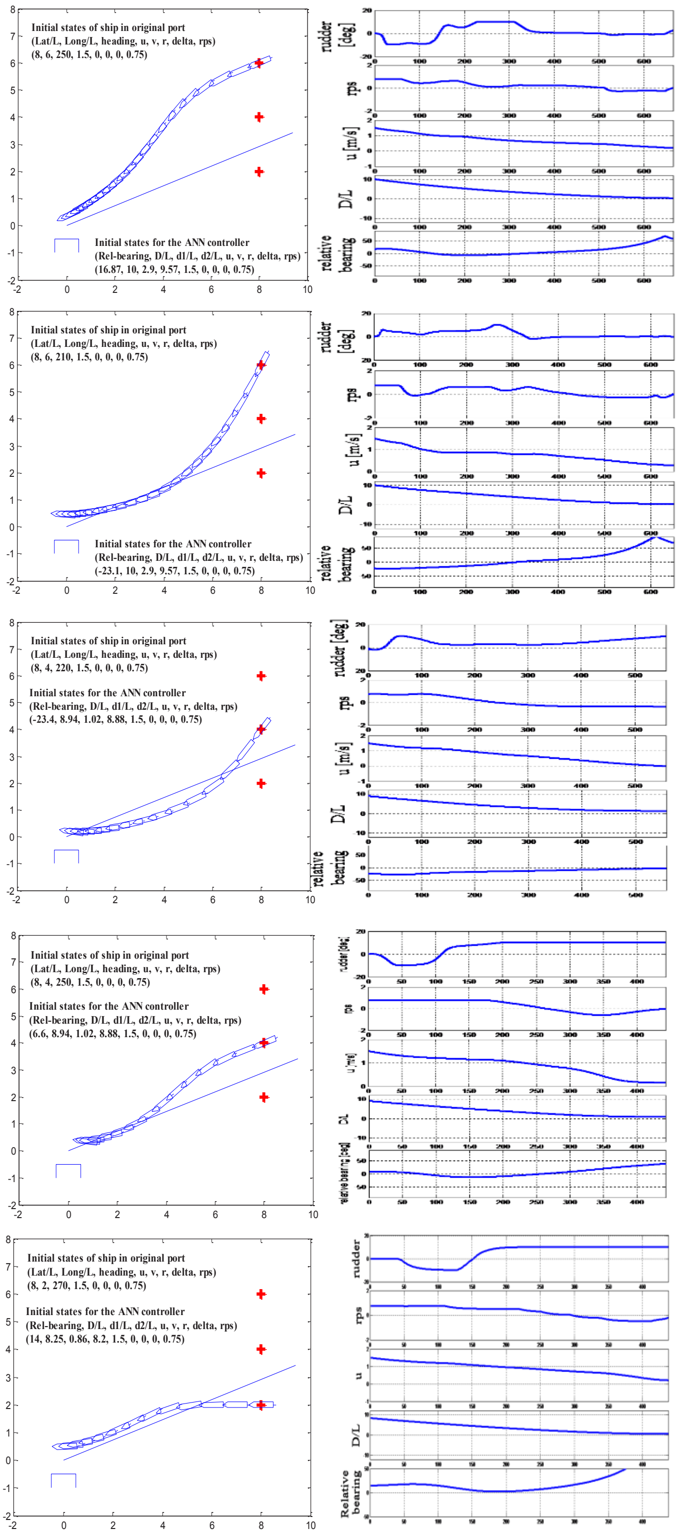

Fig 5. Simulation results in original port having same initial conditions with teaching data

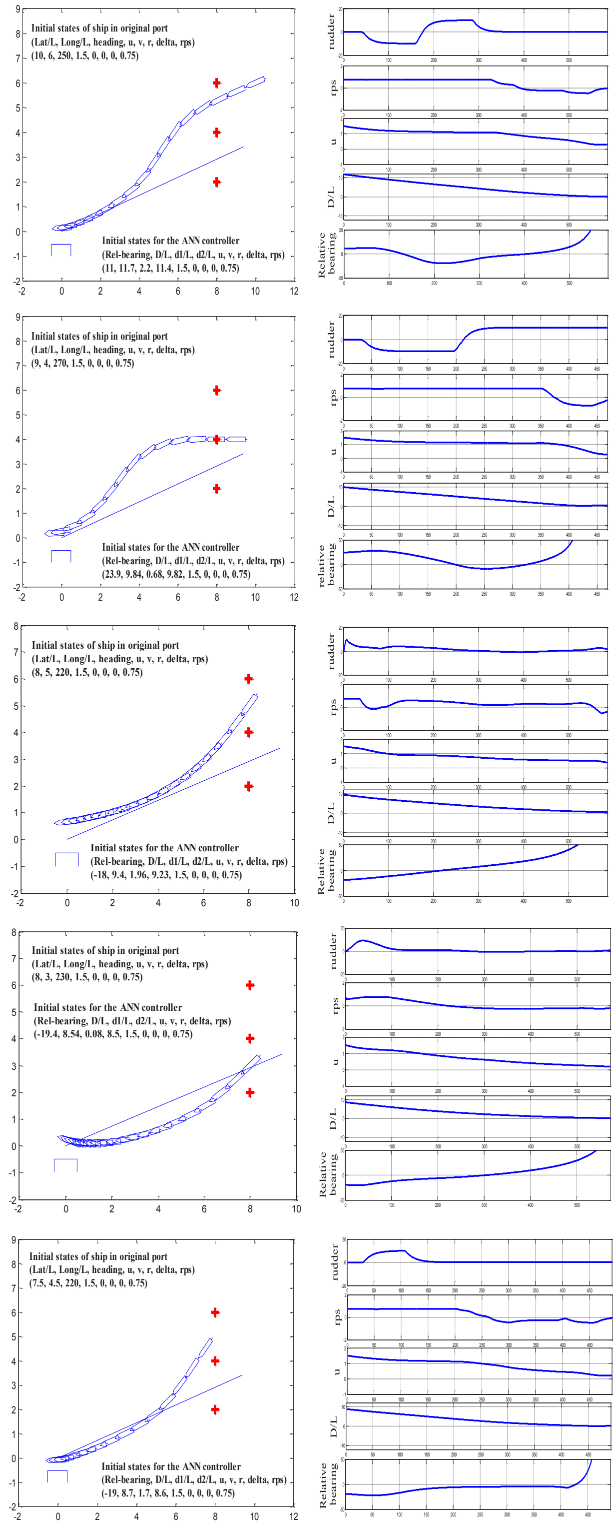

Fig 6. Simulation results in original port having initial conditions different with teaching data

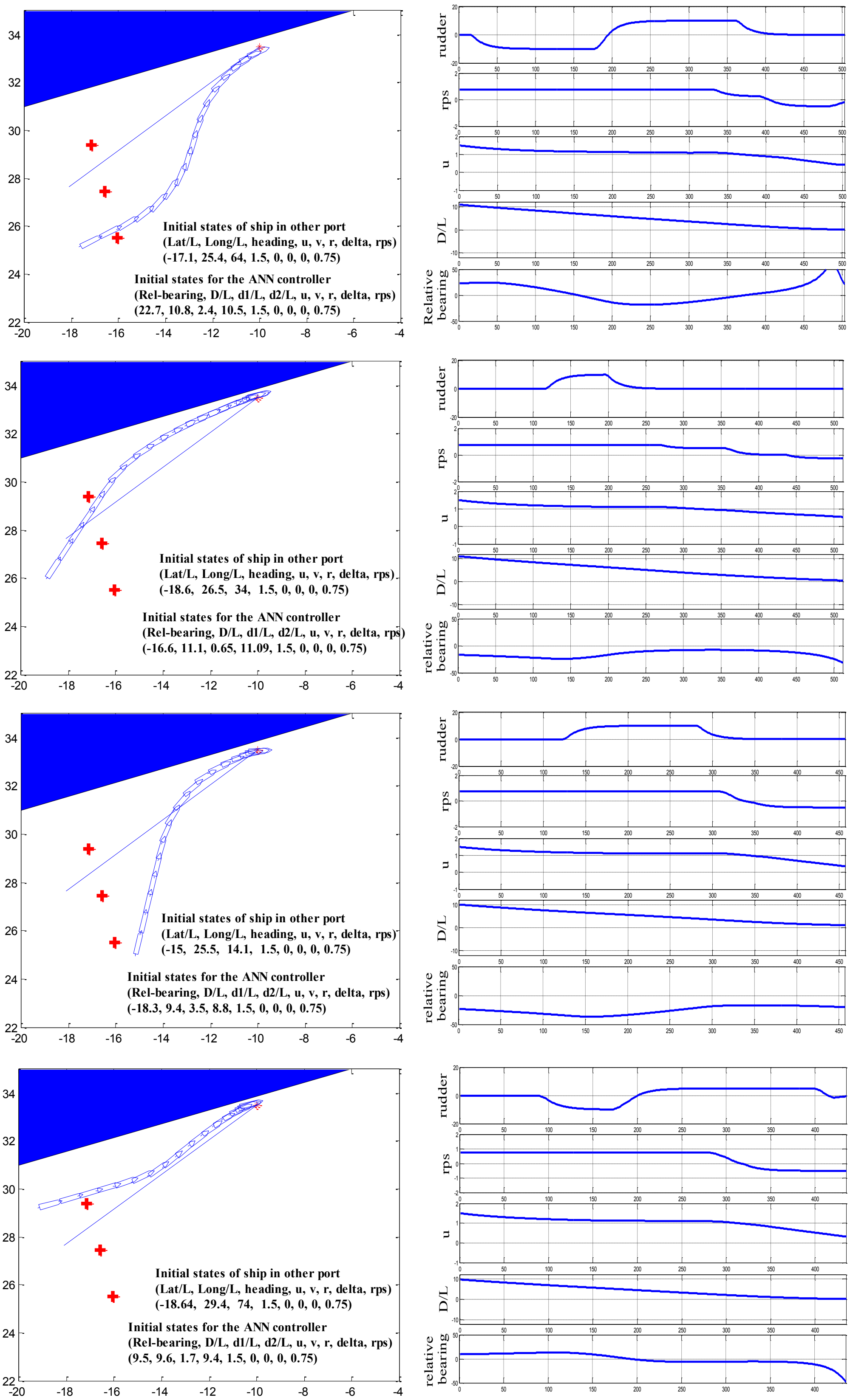

Fig. 7 Simulation results in other port having different initial conditions with teaching data

The simulation results verify that the proposed ANN controller can automatically control the ship into the berth in the original port and different ports or multi-terminals adaptively and without retraining the ANN structure. By using new inputs for the neural network, the contribution of this research is to propose the new neural controller for automatic ship berthing. The advantage of the proposed controller in comparison with previous ones is the omission of the retraining stage when applying the controller to multi-ports and multi-terminals. Therefore, this controller is more time- and cost-effective than previous ones.

5. Conclusions

In this paper, a novel research on the automatic ship berthing problem is proposed. The conclusions of this research can be summarized as follows.

- The head-up coordinate system is proposed to express the new inputs for the ANN controller. In previous research, the North-up coordinate system was usually employed to represent parameters such as the ship position and ship heading. A data converter was used to convert parameters expressed in the North-up coordinate system to the head-up coordinate system in this research.
- The relative bearing and distance from the ship to the berth were used as key inputs in the proposed ANN controller. These parameters were used as main factors in the head-up coordinate system to allow the ANN controller to adapt to different ports without retraining.
- The ANN controller was trained by teaching data created in an original port. Subsequently, the ship could be controlled automatically in different ports and multi-terminals without retraining the controller.
- Numerical simulations were performed for two ports to verify the effectiveness of the proposed controller.

For further work, It may be interesting to see the behaviour of the proposed controller in simulator studies. The manoeuvres ordered by controller could be assessed on energy saving aspect for different ports at different conditions.

Although the proposed automatic ship berthing system has some advantages, it still has some limitations. For example, the ship is only controlled into the berth from one approaching direction and the relative bearing must be within 180 deg. In the future, additional suggestions for the ANN controller will be presented to overcome the above drawbacks.

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