Journal of
Ship&Ocean Technology

SOTECH Vol. 6, No. 1, pp. 16~26, 2002

Motion Identification using Neural Networks and Its Application to Automatic Ship Berthing under Wind

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Abstract

In this paper, a motion identification method using neural networks is applied to automatic ship berthing to overcome disturbance effects. Motion identification is used to estimate the effect of environmental disturbance. Two rule-based algorithms have been developed to overcome disturbance. The first rule based-algorithm was designed to overcome lateral disturbance when a ship's lateral speed is affected by it. The second rule-based algorithm was also designed to overcome longitudinal disturbance when a ship's angular velocity is changed by it. Finally, numerical simulations for automatic berthing are carried out, and the suggested control system is proved to be more practical under disturbance circumstances.

Keywords: motion identification, neural networks, berthing

List of symbols

ANN	Artificial Neural Network
INN	Identificaion Neural Network
$\hat{v}$	Lateral speed identified by INN
$\hat{r}$	Angular velocity identified by INN
E_v	Difference between lateral speed and lateral speed identified$(v - \widehat{v})$
E_r	Difference between angular velocity and angular velocity identified$(r - \widehat{r})$
δ_{Corr}	Correction of rudder angle calculated by INN
δ_{ANN}	Rudder angle by output of ANN
α	A vector indicating estimated deviation of a ship at berthing point due to disturbance
α'	A vector indicating imaginary ship position according to
f	Adjust coefficient
ψ_s	Shift angle of imaginary ship from current position
d_{1i}	Distance to imaginary line by imaginary ship.
d_{2i}	Remained distance to berthing point by imaginary ship.
η_i	Horizontal distance to berthing point from imaginary ship's position.
ξ_i	Vertical distance to berthing point from imaginary ship's position.

1 Introduction

Studies on automatic ship berthing have been considered as one of the difficult problems in ship control fields. As ship berthing has requirements of multiple input and output parameters including data of environmental disturbances. Many obstacles are still be overcome to develop a successful automatic ship berthing. Until now there has been much research for automatic berthing carried out. Koyama T. et al(1987) applied feedback control to the problem. He found the conventional design method for the feedback controller was not easily applicable to this problem since ship motion is very difficult to represent in terms of the differential equations. Many studies also suggested a number of other controllers such as fuzzy theory, neural network, optimal control theory and expert system. For the first time, Yamato H.(1990) applied a neural controller to the automatic ship berthing problem. He included factors of disturbances, such as forces and directions, directly into inputs of the neural controller. However it is difficult to recognize all patterns of environmental disturbances and it can be very time consuming and tedious. Direction of environmental disturbance is especially difficult to work with since it is variable making it almost impossible to prepare data to satisfy the large range of variables.

Therefore, a new method must be developed to overcome disturbance effects without considering disturbance effect as input in a neural controller. Hasegawa K.(1993) suggested a neural network controller combined with an expert system in automatic ship berthing control. For the simplicity of making teaching data, he didn't consider disturbance effects as an input of the neural controller. Also it was found that successful automatic berthing was accomplished under slight wind effect. Hasegawa(1994) also applied tug operation to automatic ship berthing control. However, the accuracy and usefulness of the neural controller was only valid within the assumption of slight disturbance effect. Overcoming disturbance effects was not considered in a positive view.

Therefore in this paper, motion identification method is adopted to cope with disturbance effect. It is easy to find research concerning motion identification using neural networks and its application to motion control. Ura T.(1993, 1995, 1997) proposed an adaptive neural net controller for underwater vehicles where motion identification and a neural controller were adapted. In this paper, similarly motion identification method is applied to automatic ship berthing control. The motion identification method makes the neural controller more effective while disturbance is relatively strong. In addition to this, it appears to be more efficient for preparing teaching data for the neural controller. Two rule-based algorithms using the results of motion identification are developed to overcome disturbance. Finally numerical simulations for automatic berthing are carried out, and the suggested control system is proved to be more practical under disturbance circumstances. For a wind model, the Isherwood model(Isherwood 1973) is adopted

2 Motion identification using ANN

A neural network identifies a ship's motion to expect an effect of disturbance. Under conditions of no disturbance, state variable of a ship is identified and compared with the real state variable that can be measured in real time under disturbance. Comparatively important items among state variables might be u, v and r. All of them should be identified to express exact dynamics of a ship. However, this paper identifies only two items, lateral speed and angular velocity, to investigate how the proposed system can cope with the effect of disturbance. A 260,000 ton tanker is adopted as

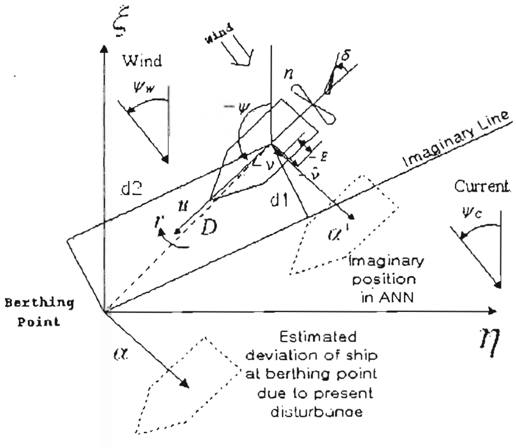

Figure 1: Ship dynamics

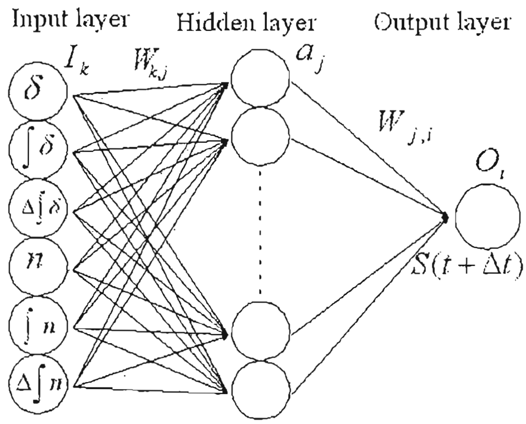

Figure 2: INN for motion identification

a model, the coordinates of which are depicted in Figure 1 and details are well explained in other research(Hasegawa and Kitera 1993).

2.1 A structure of identification neural network (INN)

To build up a motion identification method using neural networks, it is important to consider what kind of input units should be investigated. In this paper, integral and differential factors are considered to describe the changes with respect to time with greater effectiveness. A structure of neural networks used in identification is given in Figure 2. Input units consist of control inputs (n, δ) at time t, integrated control inputs ($\int \delta, \int n$) and the difference of integrated control inputs between time t and $t - \Delta t(\Delta \int \delta, \Delta \int n)$. Output units consist of state variables at time $t + \Delta t$, $S(t+\Delta t)$, which are lateral speed,$\hat{v}$, and angular velocity, $\hat{r}$. Sampling interval time for integration is set to 20 sec and the differences of integration between times at t and $t - \Delta t$ are expressed as $\Delta \int \delta$ and $\Delta \int n$.

2.2 Teaching data and learning procedure

Teaching data consists of 6 sets of automatic berthing simulation. Details are shown in previous research(Im and Hasegawa 2001). The Neural Network Toolbox from the MATLAB package is used to train a model. Back propagation method is adopted for learning procedures. Some results of learning are given in Figure 3. It is easy to find a good agreement between the target and after training. Outputs of INN show good agreement with the target after learning procedures, while they don't agree with the target value before the learning procedure. It indicates that learning of INN is successful.

2.3 Result of motion identification under disturbance

It is essential to confirm the INN can carry out motion identification effectively in order to apply the INN to automatic ship berthing control. Thus a number of free running simulations are designed, of which maneuvering patterns are given in Figure 4. When the ship is under way, states

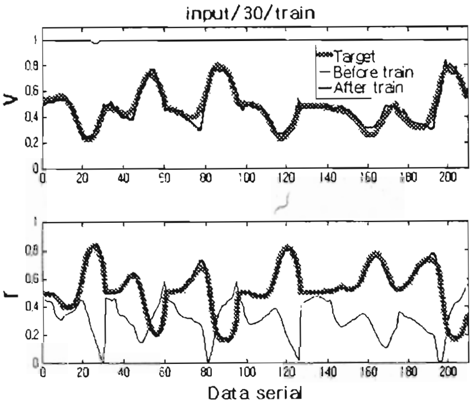

Figure 3: Result of learning for INN

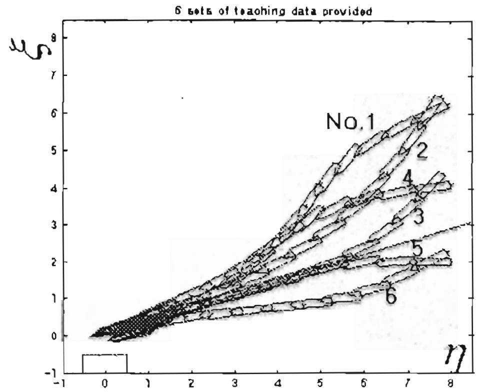

Figure 4: Free running to confirm the INN's efficiency

are identified by the INN, and then compared with the ship's present states. By analyzing the results, it becomes possible to confirm the INN's efficiency. The results are given in Figure 5. They show the results of identification concerning lateral speed when two different winds are added to a ship, i.e., ψ_w = 200 deg (left figure) and ψ_w = 110 deg (right figure). The figure on the left shows that most values of E_v are greater than zero. It indicates that v becomes larger than $\hat{v}$ due to disturbances coming from the port side of the ship. Therefore it is assumed that this INN reflects the effect of disturbance well. On the other hand, the right figure indicates situations when disturbance is added to a ship with parallel angle, i.e., ψ_w =110deg. As wind is directed to the front of the ship, values of E_v are given around zero. It indicates that variation of lateral speed might not be affected by longitudinal disturbance comparing with those when disturbance is added from a lateral direction. Therefore it becomes clear that the sign and variation of E_v are very sensitive to the direction of disturbance. It can also be said that the INN has the ability to identify lateral speed with efficiency.

To confirm how much INN can carry out motion identification concerning angular velocity effectively, additional free running are designed, the results are given in Figure 6. As shown in the figures, the ship started with constants δ and n, and 3 patterns of wind. When the ship is under way, angular velocity is identified and its value is compared with real angular velocity. The figure on the right indicates simulation results when the rudder angle is 0deg and engine revolution is 0.75. The ship started with -20deg and -90deg of wind and no wind respectively. When the wind is at -20deg, the ship will tend to make a right turn towards the wind direction, while the wind is at -90deg, the ship will tend to make a left turn. Thus, when we consider the ship's final heading angle or the variation of angular velocity, it is easy to find that the ship is affected by the wind and variation of the heading angle occurred. The result of E_r shows this fact clearly. When the wind is at -90deg, almost all values of $E_r(= r - \hat{r})$ are under zero, as the angular velocity is decreased due to the wind effect. While when the wind is at -20deg, almost all values of $E_r(= r - \hat{r})$ are greater than zero, as the angular velocity is increased due to the wind effect. It seems reasonable to think that INN suggested in this paper can also be used to express the deviation of angular velocity caused by wind effect.

When this section is summarized, it is observed that the INN can carry out motion identifica-

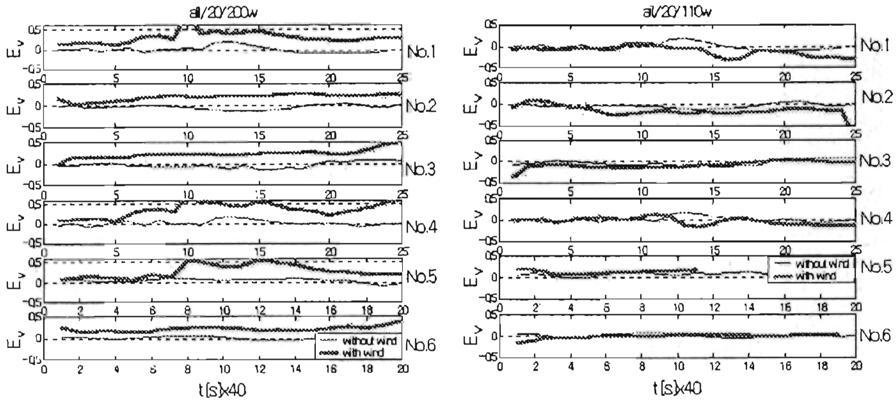

Figure 5: The results of identification concerning lateral speed. (Left: ψ_w=200 deg, Right: ψ_w=110deg)

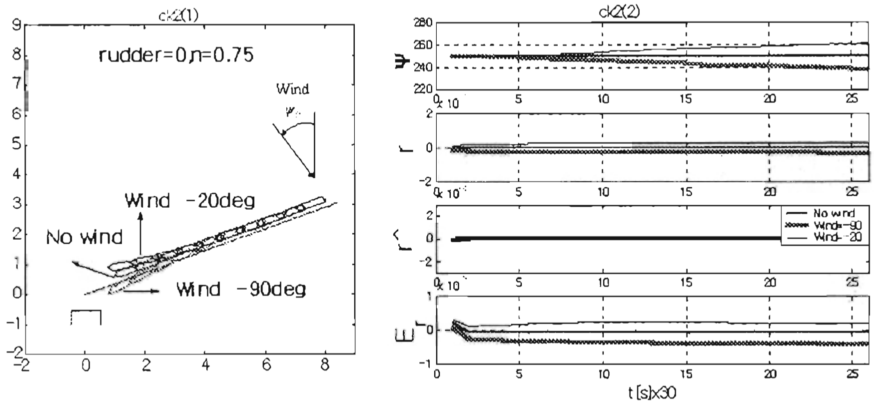

Figure 6: The results of identification concerning angular velocity. (Three patterns of wind are added to a ship)

tion concerning lateral speed and angular velocity even though disturbance is added to the ship. Moreover the INN is proved to be efficient to express the effect of disturbance. In the next section two algorithms to overcome disturbance effect using the INN will be discussed.

3 Control concept to overcome disturbance effect using INN

In order to overcome disturbance effect using INN in automatic berthing control, two rule-based algorithms are developed. As lateral speed and angular velocity are identified by INN in this paper, the two factors are adopted for algorithms.

3.1 Rule based-algorithm using deviation of lateral speed

In this section, rule based-algorithm using deviation of lateral speed will be discussed. If disturbance is added to a ship from the lateral direction, the ship's lateral speed change making it

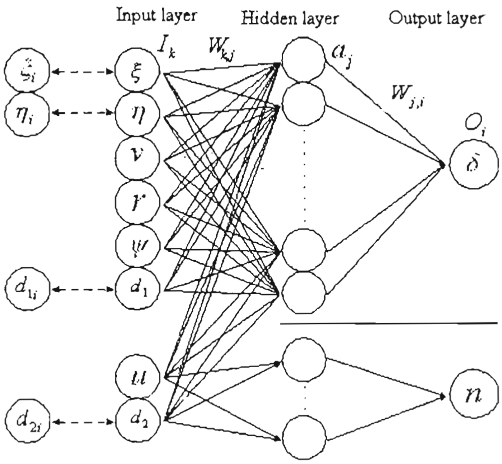

Figure 7: Replacement of input units by imaginary ship's data

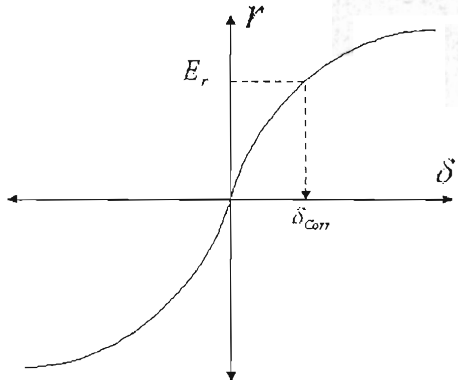

Figure 8: A diagram of ship's turning characteristics

necessary to use a new control algorithm to overcome this situation. Figure 1 represents a ship proceeding to berthing point with wind on its starboard side. So the ship will be deviated to port side due to the wind. Here if we can estimate how much the ship will be deviated, some action can be taken in advance to overcome disturbance effects. Thus, based on this concept, an imaginary position is suggested. This imaginary location indicates how a ship will be deviated in the future, due to its present disturbance at berthing point, so input of these data to ANN will make a controller cope with the effect of a disturbance in advance. Imaginary position in ANN can be calculated using α, as explained in (1), (2), (3) and (4). When an imaginary ship is obtained, some parts of input units in ANN are replaced by them. Details are well explained in Figure 7. As shown in the figure, information about position of a ship is replaced by imaginary ship position, i.e., ξ, η, d_1, d_2. So we can expect that the neural controller can take actions in advance to cope with disturbance effect.

$$|\alpha| = \frac{D}{u} E_v \tag{1}$$

$$f = \begin{cases} 0 & \text{if} \quad |E_v| \leq 0.05 \\ |E_v| & \text{if} \quad 0.05 < |E_v| < 0.2 \\ 0.2 & \text{if} \quad |E_v| \geq 0.2 \end{cases} \tag{2}$$

$$|\alpha| = \frac{D}{u} \times f \tag{3}$$

$$\psi_s = \begin{cases} \psi + 90^o & \text{if} \quad E_v > 0 \\ \psi - 90^o & \text{if} \quad E_v \leq 0 \end{cases} \tag{4}$$

3.2 Rule based-algorithm using deviation of angular velocity

In this section, rule based-algorithms using deviation of angular velocity speed will be discussed. When disturbances are on the bow or stern of a ship, the variation of $E_v(= v - \hat{v})$ may not be as variable. However the direction a ship is headed will tend to come up into, or pay off from the direction of disturbances, depending on the design of the ship, so angular velocity will change. This difference between r and $\hat{r}$ is used to cope with environmental disturbances. When a ship proceeds to berthing point with wind on its rear side, the ship tends to turn to the wind due to the wind effect. If the original angular velocity is $\hat{r}$, the angular velocity may be changed to r due to wind effect. Here original angular velocity can be identified by INN, so the difference between r and $\hat{r}$ can be easily obtained. Therefore $E_r(= r - \hat{r})$ indicates how much the angular velocity is affected by wind or other disturbance effects. If $\hat{r}$ is less than $r(E_r$ is more than zero), it means that environmental disturbances increased the ship angular velocity. While when $\hat{r}$ is greater than r, it means that the angular velocity is decreased. In these situations, appropriate action is required to decrease or increase the angular velocity to accomplish successful ship control in automatic berthing operations. However, a problem is how much rudder angle should be taken to decrease or increase current angular velocity. Some guidelines are required to meet this problem. A diagram of turning characteristics of a ship is adopted for the guide. As this well-known diagram of turning characteristics explains, angular velocity according to rudder angle is taken. So as shown in Figure 8, if E_r is given, which indicates the difference between r and $\hat{r}$, correction of rudder angle can be obtained by reading the diagram. We can control the angular velocity using the correction rudder angle to overcome disturbance effects appropriately. If the correction of rudder angle is added to current rudder angle, the ship's angular velocity will be changed. It means that angular velocity can be changed to the original angular velocity, by the addition of correction of rudder angle to the current rudder angle. The equation is given in (5). As it is explained, the correction of rudder angle, δ_{Corr}, is added to output of ANN to make E_r zero.

$$\delta = \delta_{ANN} + \delta_{Corr} \tag{5}$$

3.3 Total control flow

The whole loop of the control using INN for r and v is depicted in Figure 9. As shown in the figure, the INN receives input units, i.e., $n, \delta, \int n, \int \delta, \triangle \int n, \triangle \int \delta$, from a ship then carries out motion identification to calculate $\hat{v}$ and $\hat{r}$. These items are compared with real state variables, v and r, and then E_v and E_r are obtained. When a rule based-algorithm for v receives the E_v, imaginary ship is delivered into ANN. The ANN outputs control units, i.e., δ and n, based on the imaginary ship's location. On the other hand, when a rule based-algorithm for r receives E_r, the correction of rudder angle is calculated using the diagram of turning characteristics. This correction is added to output of ANN and final rudder angle is obtained. It means that a ship takes an action to overcome disturbance effect by the correction of rudder angle.

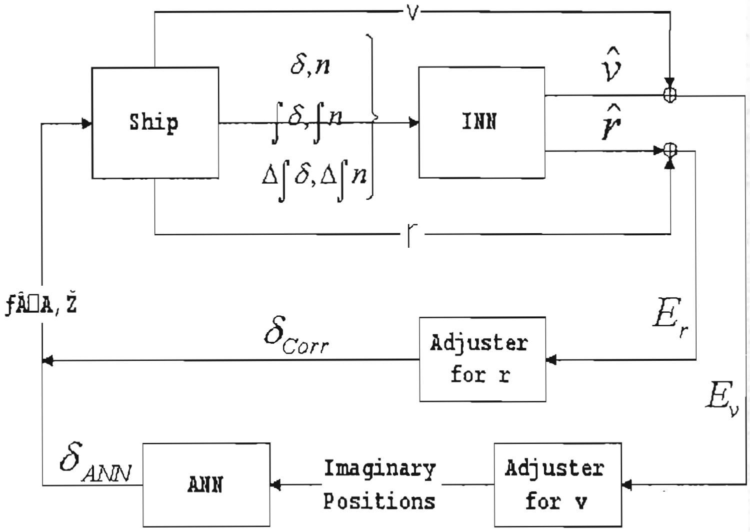

Figure 9: Total control flow using INN for v and r

4 Numerical simulation results

4.1 Simulation results with a rule based-algorithm for lateral speed

Figure 10 shows the details of simulation with 200 deg of wind. It can be assumed that the ship deviates to its starboard side due to the disturbance coming from the port side of the ship. Simulation results show that the ship is deviated starboard when INN is not adopted. The figure on the right shows that the control system using INN for v has more efficiency in inducing the ship to berthing point under environmental disturbance. When we look at the rudder control in the right figure, it is easy to see that the rudder is operated beforehand to shift the ship to the opposite direction of the effect of disturbance. It is reasonable to suppose that this comes from the imaginary ship's effect. In this situation, the position of the imaginary ship can be calculated with a position of starboard side of a ship, so the neural controller will try to make the ship proceed to the port side. As a result, the ship can proceed towards berthing point without being forced to the starboard side. Looking at the results, we can see that the ship deviated to the starboard side when INN is not adopted. Figure 11 displays the imaginary ship calculated using the based-algorithm rule for lateral speed when wind is on the starboard side, ψ_w=20deg. In this situation, the ship deviates to the port side as wind comes from the starboard side. As shown in that figure, imaginary ships are marked clearly at the port side of the ship. Since the neural controller considers these imaginary ship when considering the present ship's position, it is reasonable to assume that the ANN takes quick action in advance to cope with disturbance effects.

4.2 Simulation results with a rule based-algorithm for angular velocity

Figure 12 shows the comparison between two neural controllers with wind directed to the rear of a ship (ψ_w=-70deg). In one controller, the INN for v and r is adopted, while INN for v is included in another controller. In this case, as wind is directed to the stem of the ship, the ship

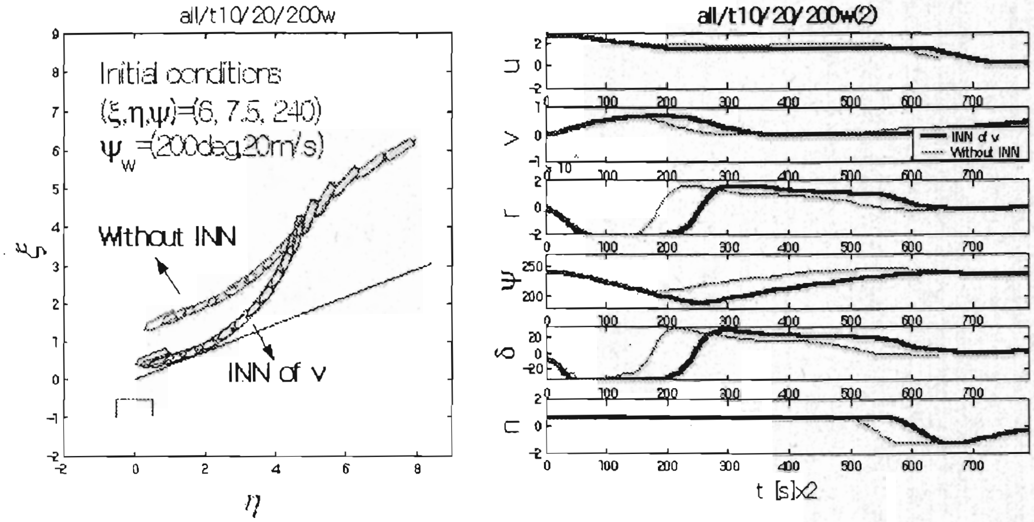

Figure 10: Comparison between normal neural controller and neural controller of INN. (Disturbance is at right angle to a ship, ϕ_w=200 deg)

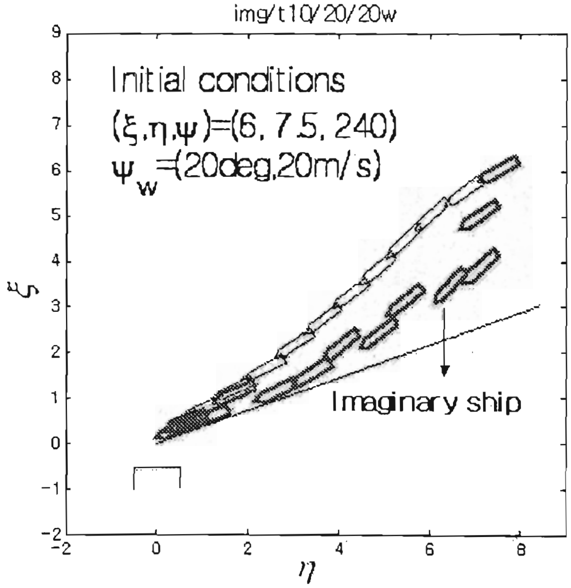

Figure 11: Simulation result and imaginary ship when INN for v is adopted. (Disturbance is at right angle to a ship, ϕ_w=20deg)

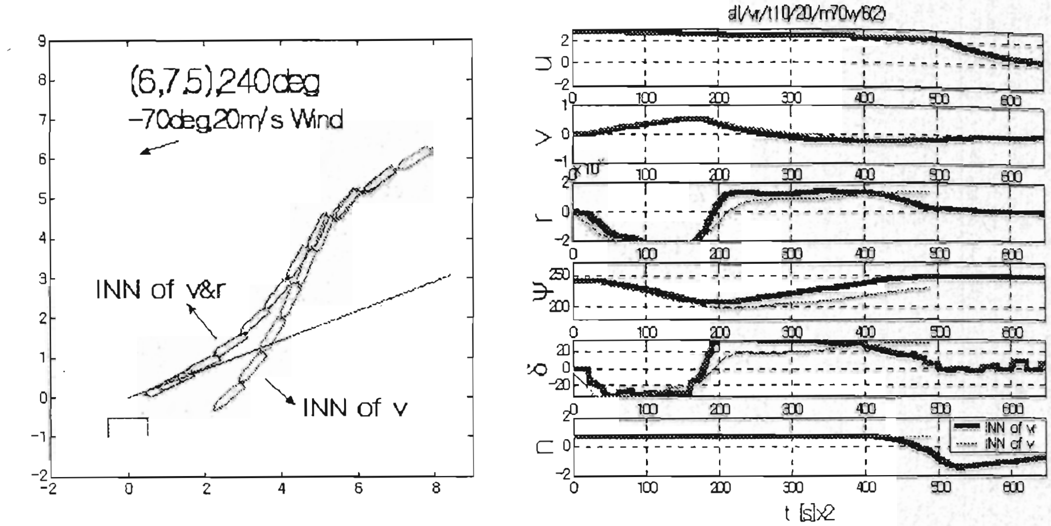

Figure 12: Comparisons of simulation result between two neural controllers. (Disturbance is at parallel angle to a ship, ϕ_w=-70deg)

will tend to come up into the wind without considerable change in lateral speed. As shown in the figure, successful berthing was accomplished when INN for v and r was adopted, while berthing failed when INN for only v was adopted. As the ship proceeds to berthing point with wind on its a stern, additional rudder action is required to prevent the ship turning into the wind. When we consider output of rudder angle, it is found that additive rudder angle is taken when INN for v and r is adopted. Also uneven control in rudder angle can be seen in last parts of time history, it is probably caused by the effect of changed angular velocity. These can be explained as follows; If a rule based-algorithm identifies the difference between r and $\hat{r}$, additive rudder angle is determined and it is added to the output of ANN.

When we make summary of simulation results, it is easy to find that appropriate rudder action is taken to prevent the ship coming up into the wind when INN for v and r is adopted. Quick rudder action is taken to prevent the ship turning into the wind direction when controlling the rudder when INN for v and r is adopted. It is reasonably assumed that a rule based-algorithm for r outputs corrects rudder angle appropriately to overcome environmental disturbance.

5 Conclusions and discussions for future works

So far we have outlined motion identification using ANN and its application to automatic ship berthing to overcome disturbance effect. Conclusions will be drawn as follows.

1) Motion identification method using neural networks was proposed in automatic ship berthing control to overcome disturbance.

2) The difference between identified lateral speed and real lateral speed was used to cope with lateral disturbance.

3) The difference between angular velocity identified and real angular velocity was used to cope with disturbance when the ship's angular velocity was changed by it.

4) Suggested control systems appeared to be more efficient and acceptable for automatic ship berthing compared to those when motion identification method is not adopted.

In this paper, it was found that the change of ship movement due to environmental disturbances was estimated by motion identification, and two rule-based algorithms were developed to cope with it. In case of a ship berthing, since ship movement is severe and the operation of a rudder is frequent compared with that of ordinary navigation, it is difficult to determine what kinds of control should be taken and what kinds of rule-based algorithms are required to cope with the disturbance. This paper has indicated that through motion identification methods, overcoming environmental disturbance in automatic ship berthing can be improved. This would be beneficial in the control system of automatic ship berthing and it could be also adopted in other ship control research such as course keeping research.

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