# An Application of ANN to Automatic Ship Berthing under Disturbances and Motion Identification

Namkyun Im.* and Kazuhiko Hasegawa**

* Graduate School of Engineering, Osaka University, 2-1,Yamada-Ok,Suita-shi,Osaka, Japan
(Tel 81-6-6877-5111,Ext.3504, Fax : 81-6-6879-7594; E-mail:im@naoe.eng.osaka-u.ac.jp )
**Graduate School of Engineering, Osaka University, 2-1,Yamada-Ok,Suita-shi,Osaka, Japan
(Tel 81-6-6879-7588; Fax : 81-6-6879-7594; E-mail:hase@naoe.eng.osaka-u.ac.jp)

**Abstract**: This paper deals with motion identification using artificial neural network (ANN) and its application to automatic ship berthing. As ship motions are expressed by multi-term non-linear model, it is very difficult to find optimal methods for automatic ship berthing especially under environmental disturbances. In this paper, motion identification was used to estimate the effect of environmental disturbances and then the differences between values of identification and state variables are used to estimate the effect of environmental disturbances. A rule based-algorithm using the difference is suggested to cope with the effect of the disturbances. The algorithm adjusts the value of input units of ANN, which control a ship to keep desired route and to induce the ship to berthing point. The algorithm also control rudder angle according to the result of identification. Numerical simulations are carried out with this control system to confirm its improvement under environmental disturbances.

**Keywords:** automatic ship berthing, control, motion identification, environmental disturbances, artificial neural network

## 1. Introduction

Studies on automatic ship berthing have been considered as one of difficult problems in ship control fields. Until now a great number of researches[1-3] have been carried out for automatic ship berthing by many researchers. But many problems still should be solved and overcome. As ship motions are expressed by multi-term and non-linear model, it is very difficult to find optimal methods for automatic ship berthing especially under environmental disturbances.

In this paper, a neural controller will be introduced, which has a parallel command system. It consists of two artificial neural networks (ANN) each controls engine revolution and rudder angle respectively. In other hands, anther problem of ship operation in berthing is how to overcome environmental disturbances. As ship motion in berthing operation is very slow, it is easy to be affected by slight environmental disturbances such as wind and current. It is easy to find researches[4] concerning motion identification using neural networks and its application to motion control. Likely that in this paper, motion identification was tried to estimate the effect of environmental disturbances and then the differences between values of identification and state variables are used to estimate the effect of environmental disturbances. A rule based-algorithm using the difference is suggested to cope with the effect of the disturbances. Finally numerical simulations for automatic berthing are carried out to verify this controller.

## 2. Automatic Ship Berthing Using ANN

Tow multi-layer feed-forward networks are adopted as a controller in automatic ship berthing. As they are particularly suitable for approximating non-linear and multivariable functions.

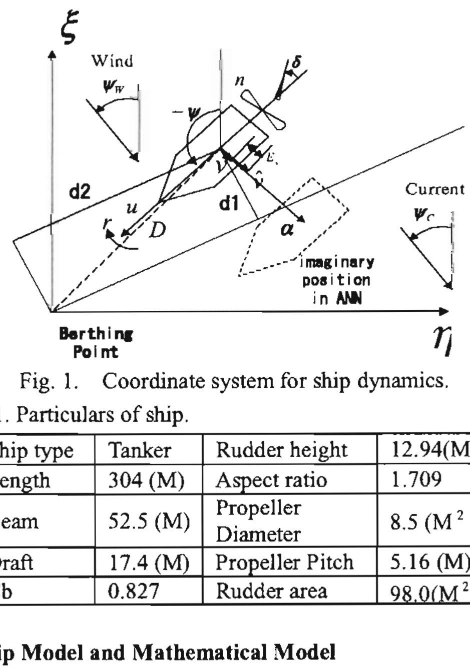


Fig. 1. Coordinate system for ship dynamics.

Table 1. Particulars of ship.

| | | | |
|---|---|---|---|
| Ship type | Tanker | Rudder height | 12.94(M) |
| Length | 304 (M) | Aspect ratio | 1.709 |
| Beam | 52.5 (M) | Propeller Diameter | 8.5 (M$^2$) |
| Draft | 17.4 (M) | Propeller Pitch | 5.16 (M) |
| Cb | 0.827 | Rudder area | 98.0(M$^2$) |

### 2.1 Ship Model and Mathematical Model

A 260,000 ton of tanker is adopted as a model, of which coordinate is depicted in Fig. 1 and details are well explained in other research[5]. Particulars of the ship are presented in table 1 and mathematical ship model can be drawn briefly like Eq. (1)-(6), which are believed to be suitable to maneuvering motions of ships in low speeds. A non-dimensional symbol is expressed by " ` ". The variables are defined in the appendix.

$$(m+m_x)\dot{u}-(m+m_y)vr = X_H + X_P + X_R + X_W \quad (1)$$

$$(m+m_y)\dot{v}+(m+m_x)ur = Y_H + Y_R + Y_W \quad (2)$$

$$(I_{ZZ}+J_{ZZ})\dot{r} = N_H + N_R + N_W \tag{3}$$

$$X_H' = X_{vr}v'r' + X_{uu}'|u'|u' + X'_{vv}u'v'^2/U' + X'_{v|v|r}v'|v'|r'/U' \tag{4}$$

$$Y_H' = Y'_v U'v' + Y'_{vv}|v'|v'\ Y'_{5v}v'^5/U'^3 + Y'_r r' + Y'_{ur}u'r' + Y'_{vvru}v'^2u'r'/U'^2 + Y'_{vrr}v'r'^2/U' \tag{5}$$

$$N_H' = N'_{uv}u'v' + N'_r r' + N'_{rrr}r'^3 + N'_{ur}u'r' + N'_{vvr}v'^2 r' \tag{6}$$

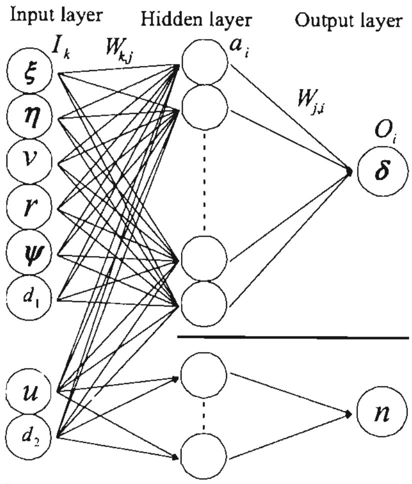

Fig. 2. Neural network adopted as a controller.

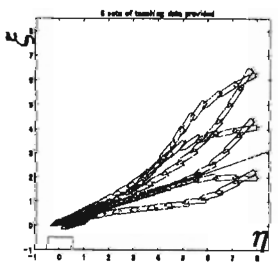
Fig. 3. Simulation samples for teaching data.

## 2.2 Neural Controller

Fig. 2 shows a structure of artificial neural networks (ANN), which was adopted in controller for automatic ship berthing. As it is shown, two ANNs were used to control output units such as engine revolution and redder angle respectively. Inputs units was a 8x1 vector consisting of location information ($\xi, \eta$), $u, v, r$, $\psi$, and additional location information ($d_1, d_2$). Output is a vector consisting of engine revolution ($n$) and rudder angle ($\delta$). Fig. 3 shows samples of teaching data consisting of 6 sets of manual berthing cases. For learning method, back propagation learning is adopted. The sum of the squared errors over the output values is used to evaluate efficiency of learning. As two ANNs were used, two training procedures were needed and two sets of weights and biases were produced. Automatic berthing mentioned in this paper means that a ship stops near the goal point within 0.2m/s of speed and between 250-270deg of heading angles.

## 2.3 Simulation Results

Fig. 4 shows the results of simulations in which a neural controller was used and cross marks mean initial starting positions of teaching data. As it is shown in that figure, it is easy to understand that even if ships started in different positions with teaching data provided, successful automatic berthing control was accomplished. It is assumed that this is due to the interpolation ability of neural controller.

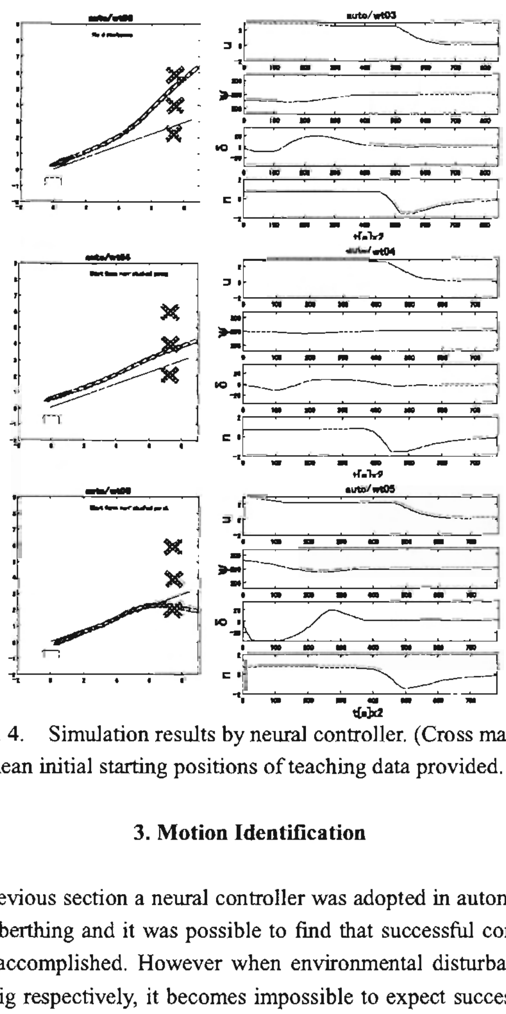
Fig. 4. Simulation results by neural controller. (Cross marks mean initial starting positions of teaching data provided. )

# 3. Motion Identification

In previous section a neural controller was adopted in automatic ship berthing and it was possible to find that successful control was accomplished. However when environmental disturbances are big respectively, it becomes impossible to expect successful control.

So motion identification using ANN is suggested. Under no environmental disturbances, state variables of a ship are identified and then they will be compared with real state variables that can be measured in real time under environmental disturbances. Among $u,v,r$ two items ($v$ and $r$) are identified as a first step just to confirm how the proposed system can cope with the effect of environmental disturbances.

## 3.1 Identification Neural Network (INN)

A structure of ANN used in identification is shown in Fig. 5. Input units are consisted of control inputs at time $t$ ($n, \delta$), integrated control inputs at time $t$ ($\int\delta, \int n$) and the difference of integrated control inputs between time $t$ and $t+\Delta t$ ($\Delta\int\delta, \Delta\int n$). Output unit are consisted of state variables at time $t+1$, $S(t+1)$. In this paper, two items of $\hat{v}$ and $\hat{r}$ are expressed as $S(t+1)$.

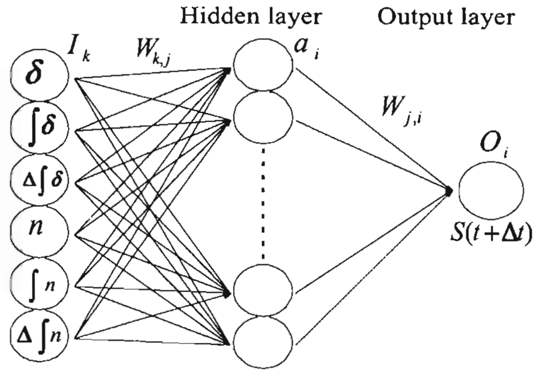


Fig. 5. INN for motion identification.

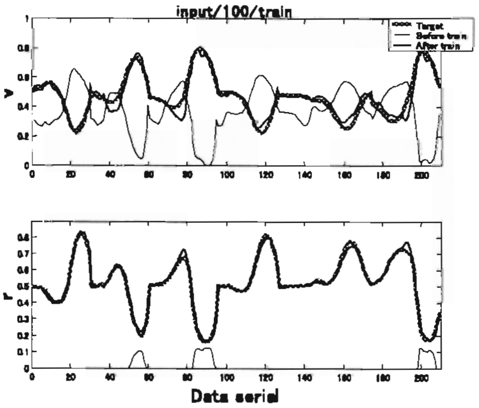


Fig. 6. Result of learning for identification.

### 3.2 Learning Results

For procedure of learning, teaching data were obtained from automatic ship berthing simulations under no environmental disturbances which are carried out by neural controller described in previous section. Fig. 3 is showing the results of learning. It is easy to find good agreements between targets (desired value) and values after learning.

### 3.3 Concept to Cope with Environmental Disturbances

The flow of control using INN to cope with environmental disturbances is depicted in Fig. 7. As shown in that figure, the $E_v, E_r$ can be obtained form the difference between state variables and identified state variables. These differences are used to cope with environmental disturbances. The $Ev$ means that a ship deviated form expected course due to lateral disturbances. If this value can be obtained, the lateral deviation distance can be calculated like Eq. (7)-(10) and then imaginary position in ANN can be calculated using the *Dist* like a vector $a$ in Fig. 1. This imaginary location means how a ship will be deviated due to present disturbances at berthing point, so input of these data to ANN induces a controller to cope with the effect of environmental disturbances in advance.

$$Dist = \frac{D}{u} E_v \tag{7}$$

$$f = \begin{cases} 0, & if\ |E_v| \le 0.05 \\ |E_v| & if\ 0.05 < |E_v| < 0.2 \\ 0.2 & if\ |E_v| \ge 0.2 \end{cases} \tag{8}$$

$$|\alpha| = \begin{cases} 0, & if |E_v| \le 0.05 \\ \frac{D}{u} \times f, & if |E_v| > 0.05 \end{cases} \tag{9}$$

$$\psi_s = \begin{cases} \psi + 90^\circ, if\ E_v > 0 \\ \psi - 90^\circ, if\ E_v \le 0 \end{cases} \tag{10}$$

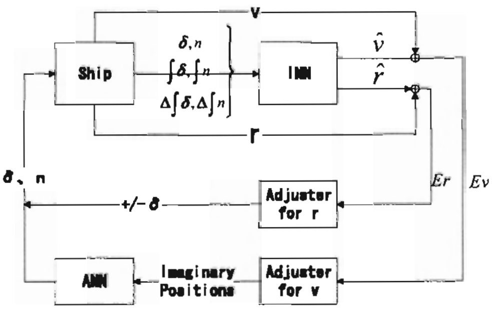


Fig. 7. Control concept using INN.

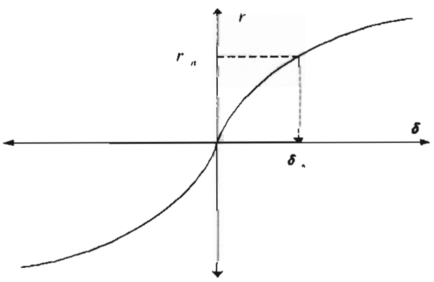


Fig. 8. Diagram of turning characteristics.

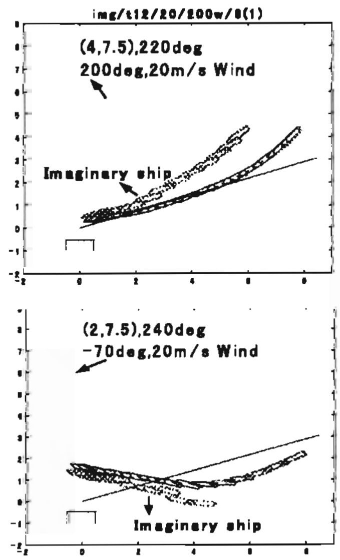


Fig. 9. Simulation results when identification for $v$ only was adopted.

In other hands, with disturbances on bow or astern, the variation of $E_v$ might not be conspicuous. However a ship's heading will tend to come up into, or pay off from the disturbances, depending on the design so angular velocity will be changed comparing to when disturbances are zero. This difference, $E_r$, can be used to cope with environmental disturbances. If identified value of angular velocity, $\hat{r}$, is less than real value, $r$, it means that disturbances caused the ship the change of $r$. In this situation, appropriate action is needed to decrease the $r$. Using difference between identified value and real value of $r$, appropriate rudder angle can be calculated. Diagram of turning characteristics can be adopted to determine rudder angle like in Fig. 8. If $E_r$ is $r_n$ at time $t$, $\delta_n$ is added to present rudder angle to increase or decrease angular velocity like Eq. (11).

$$\delta_{t+1} = \delta_t + \delta_n \tag{11}$$

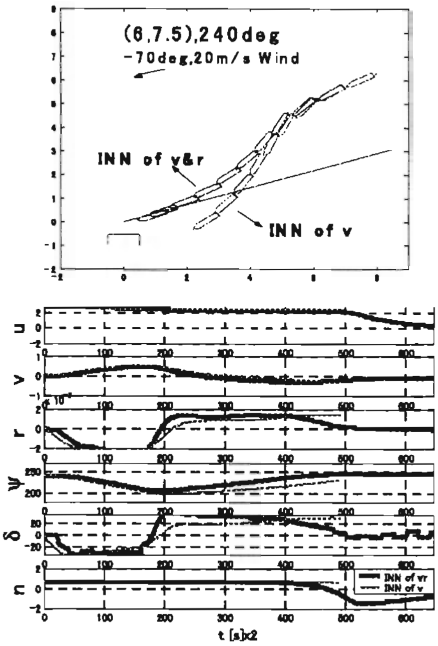


Fig. 10. Comparison simulations when identification for $v$ was adopted and when identification for $v$ and $r$ was adopted.

### 3.4 Simulations Results

Fig. 9 indicates one of simulation results in which only lateral speed is identified and its algorithm is applied to cope with environmental disturbances. A wind is on ship' portside beam (top) and the rear (bottom). The dot line of ships indicates imaginary ships, which are calculated by $E_v$. It is easy to understand that successful berthing are accomplished because the $E_v$ would be conspicuous when a wind is on port beam. In other hands, with a wind on the rear of a ship, berthing failed because this algorithm would not cope with the change of angular velocity. Fig. 10 shows the comparison when identification for $v$ was adopted and when identification for $v$ and $r$ was adopted. In this case, a wind is on astern of the ship, so the ship will tend to come up into the wind with no conspicuous change of lateral speed. It can be found that appropriate rudder action is taken to prevent the ship come up into the wind when INN for $v$ and $r$ is adopted.

## 4. Conclusions

As ship motions are expressed by multi-term non-linear model, it is very difficult to find optimal methods for automatic ship berthing especially under environmental disturbances. In this paper, motion identification using ANN was discussed to cope with the effect of environmental disturbances in automatic ship berthing. Conclusions can be drawn as follows.

1) A neural controller was adopted in automatic ship berthing.
2) A method was suggested which estimates the effect of environmental disturbances with motion identification.
3) The control algorithm using INN of $v$ was applicable to lateral disturbances, which cause a ship lateral deviation
4) The control algorithm using INN of $r$ was applicable when ship's angular velocity is changed due to disturbances.

## 5. Acknowledgements

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## APPENDIX

Nomenclature

$m$ - mass of ship
$m_x$ - added mass in surge direction
$m_y$ - added mass in sway direction
$I_{zz}$ - mass moment of inertia
$J_{zz}$ - added mass moment of inertia
$X_H, Y_H, N_H$ - hydrodynamic forces acting on ship hull
$X_P$ - forces due to a propeller.
$X_w, Y_w, N_w$ - forces and moment due to winds
$X_R, Y_R, N_R$ - forces and moment due to a rudder