

## Automatic Teaching Data Creation for Automatic Berthing Control System using Artificial Neural Network

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### ABSTRACT

Automatic berthing system using artificial neural network is discussed for the second phase development. It is already verified that the system works well by the simulation and by the model experiments. However, there remains the problem for the robustness and consistency for the circumstances with disturbances or the initial position of the ship where no teaching data is available. In this paper, automatic teaching data creation is proposed to overcome this problem. Based on the elemental manoeuvring method, berthing process is divided into some elementary manoeuvres and represented by the simple models. Some patterns of berthing are provided assuming these models and used for teaching data. Artificial neural network is configured with these teaching data and confirmed effective.

**KEY WORDS:** autopilot; artificial neural network; automatic teaching; automatic berthing.

### INTRODUCTION

Manoeuvring in harbour is considered as one of the sophisticated and difficult manoeuvres in ship's operation. Much experience and knowledge are demanded to accomplish the berthing. Automation of berthing is highly requested to meet the decrease of the number and aging of crew. Moreover, automatic berthing control is expected to meet the problems such as the shortage of experience and knowledge on berthing manoeuvring.

Many methods have been proposed to achieve automatic berthing control and found to be of some effective. Artificial Neural Networks (ANN) is considered as one of such methods, but the problem of this method is how to create teaching data. The inconsistency of human operator who creates the teaching data is also learned by ANN, which hurts the robustness of the system.

In this research teaching data is automatically made based on the standard procedure proposed by Endo (2003). The berthing manoeuvre consists of deceleration, course changing and stopping. The system of

automatic teaching data creation determines the control quantity and the timing of order for these manoeuvres. The structure of ANN is also considered to improve the system. One is the selection of the suitable input parameters for the input layer. The other is to choose the optimum number of units in hidden layer. The ANN system, thus optimized and associated with the consistent teaching data, is confirmed to work better than the previous works by numerical simulation.

### Model Ship

Esso Osaka is adopted in this paper. The ship is downscaled to 3m of model ship for the numerical simulation and experiment. Particulars of the model ship are presented in Table 1. The model test using the model ship is carried out to confirm several elementary manoeuvres.

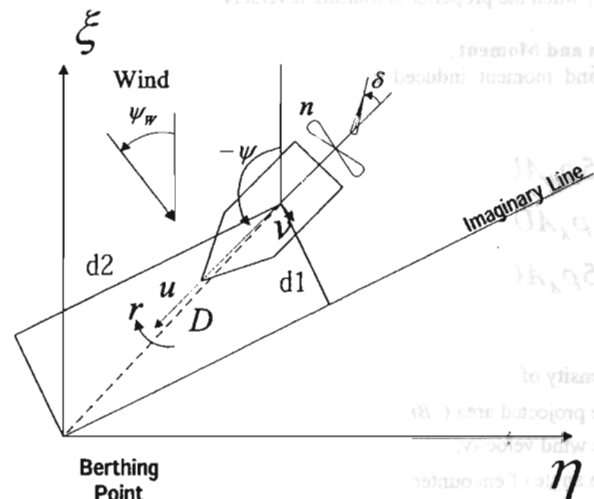


Fig. 1 Coordinate system and definition of parameters

Table 1. Principal particulars of model ship

$L_{BP}$	3.000m	$A_R/Ld$	1/56.66
$B$	0.489m	$\Lambda$	1.539
$d$	0.2011m	$D_p$	0.084
$x_G$	0.031m	$H_R$	0.1278
$Cb$	0.8306	$P$	0.06007

**Equation of Motion**

Surge, sway and yaw motion of a ship in winds are expressed by Eq. 1. Fig. 1 shows the coordinate system and definition of parameters.

$$\begin{aligned}
 m\dot{u} - mvr &= X \\
 m\dot{v} + mur &= Y \\
 I_{zz}\dot{r} &= N - x_G Y
 \end{aligned}
 \tag{1}$$

where  
 $m$  : ship mass,  
 $I_{zz}$  : moment of inertia of ship,  
 $u, v, r$  : velocity and angular velocity of ship,  
 $x_G$  : distance between ship's center of gravity and ship's center.

The external forces X, Y and moment N consist of hull, propeller, rudder and wind components that are noted with subscripts H, P, R and WD respectively.

$$\begin{aligned}
 X &= X_H + X_P + X_R + X_{WD} \\
 Y &= Y_H + Y_R + Y_{WD} \\
 N &= N_H + N_R + N_{WD}
 \end{aligned}
 \tag{2}$$

The equations and hydrodynamic coefficients of hull, rudder and propeller are expressed and estimated based on The 23<sup>rd</sup> ITTC (2002). SRAJ (1985) is also referred for estimating the forces of hull, rudder and propeller, when the propeller is rotating reversely.

**Wind Forces and Moment**

The forces and moment induced by steady wind are expressed as follows.

$$\left. \begin{aligned}
 X_{WD} &= 0.5\rho_A AU_A^2 C_{FX}(\Psi_A) \\
 Y_{WD} &= 0.5\rho_A AU_A^2 C_{FY}(\Psi_A) \\
 N_{WD} &= 0.5\rho_A AU_A^2 LC_{MZ}(\Psi_A)
 \end{aligned} \right\}
 \tag{3}$$

where  
 $\rho_A$  : mass density of air,  
 $A$  : effective projected area ( *Breadth* × *freeboard* ),  
 $U_A$  : relative wind velocity,  
 $\Psi_A$  : relative angle of encounter wind,  
 $C_{FX}, C_{FY}, C_{MZ}$  : wind force and moment coefficients.

The wind force and moment coefficients of the ship were estimated as the mean value of tankers conducted by Fujiwara (2003).

**CONSTRUCTION OF TEACHING DATA**

Manoeuvre of ship is classified into three patterns of elemental manoeuvres such as course alteration, deceleration and stopping. Endo (2003) has proposed simple formulas for path planning combining these fundamental manoeuvres. The formulas are tried to be implemented for berthing manoeuvre. They are confirmed by model experiments. Consequently, berthing manoeuvre is standardized without any human-oriented inconsistent operation.

**Standard Deceleration Manoeuvre**

The speed response of a telegraph order that is approximated to a first order differential equation is expressed by Eq. 4.

$$T_p \frac{dv(t)}{dt} + v(t) = K_p n(t)
 \tag{4}$$

where  
 $v(t)$  : ship speed (m/s),  
 $n(t)$  : propeller revolution,  
 $T_p = m/c$ ,  
 $K_p = k/c$ ,  
 $m$  : mass,  
 $c$  : resistance factor,  
 $k$  : thrust factor.

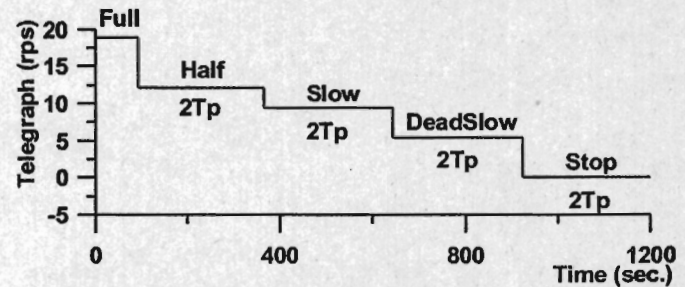


Fig. 2 Propeller revolution of each telegraphs order

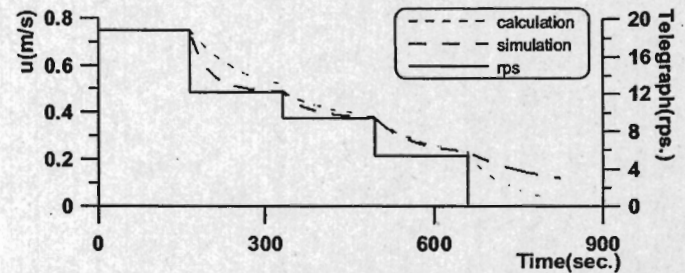


Fig. 3 Comparison of speed between the calculation by standard deceleration and simulation

Endo (2003) has proposed as follows; a series of telegraph orders for deceleration are executed during twice of constant  $T_p$  respectively. Propeller revolution for each telegraph order is set as shown in Fig. 2. The speed that is calculated by the equation for standard deceleration is compared with that of simulation in Fig. 3. It is verified that Endo's proposal is suitable for the deceleration of Esso Osaka, because both

are shown same tendency and similar values. The distance for each deceleration is decided by Eq. 5. Eq. 6 presents to the total distance of decelerations.

$$D_{F-H} = \int_0^{2T_p} v(t)dt = T_p K_p (0.865n_F + 1.135n_H) \quad (5)$$

$$D_{F-0} = T_p K_p (0.865n_F + 2n_H + 2n_S + 2n_D) \quad (6)$$

where

$n_a$  : Revolutions per second of telegraph at  $a$  .

#### Standard Course Alteration Manoeuvr

Parameters for the standard course alteration are presented in Fig. 4.

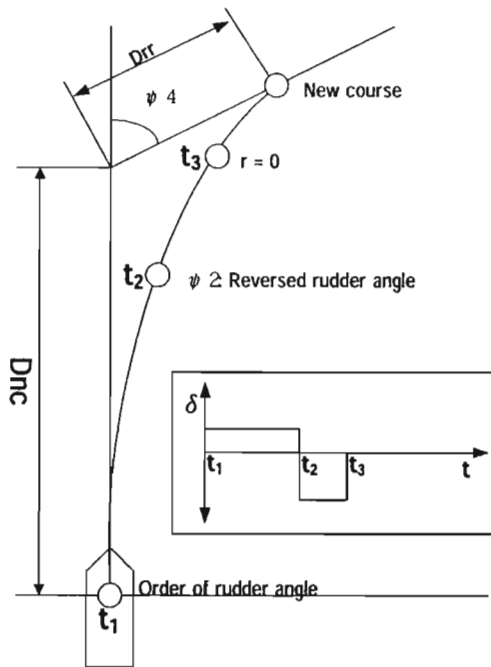


Fig. 4 Schematic definition of Parameters in the course alteration

The distance  $Dnc$  can be found by solving the following equations (Eq. 7). Reversed rudder angle is executed to reduce angular velocity at heading angle  $\psi 2$  . Reversed rudder angle is set twice of  $\delta$  . The relation between the final heading angle of the course alteration  $\psi 4$  and heading angle  $\psi 2$  is presented Eq. 8. Reversed rudder angle is kept when angular velocity is zero.

$$Dnc = \frac{T_d}{2} v + T'L \left( 1 - \frac{K_v \delta}{v} e^{D1} \right) + \frac{L}{0.7K'\delta} \tan\left(\frac{\psi 2}{2}\right) \quad (7)$$

$$D1 = - \frac{\frac{T_d}{2} + \frac{T'L}{v}}{\frac{T'L}{v}}$$

$$\psi 4 = \psi 2 + 0.3068K'T'\delta \quad (8)$$

The model tests are carried out to confirm the effectiveness of Eqs. 7-8. The condition of tests are  $\pm 10^\circ$  and  $20^\circ$  for rudder angles, SLOW, HALF and FULL for telegraph order, and  $\pm 10^\circ$ ,  $30^\circ$  and  $60^\circ$  for  $\psi 2$  . Total 36 sets of experiments are done. The results of experiments are shown in Figs. 5~6. The horizontal axis is presented the results of experiments, and the vertical axis is the value of calculation that is solved by equations in both graphs. The values of experiments almost coincide with those of the calculation.

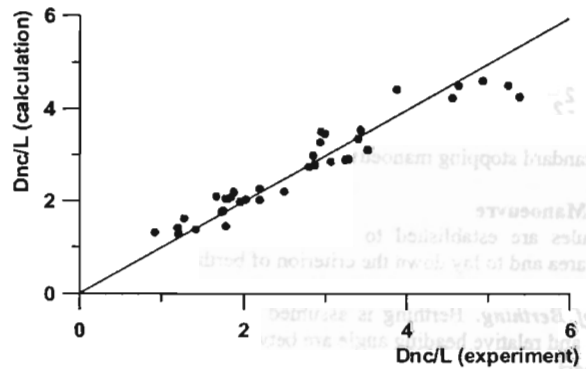


Fig. 5 Comparisons of  $Dnc$  between calculations and experiments with 3m model of Esso Osaka

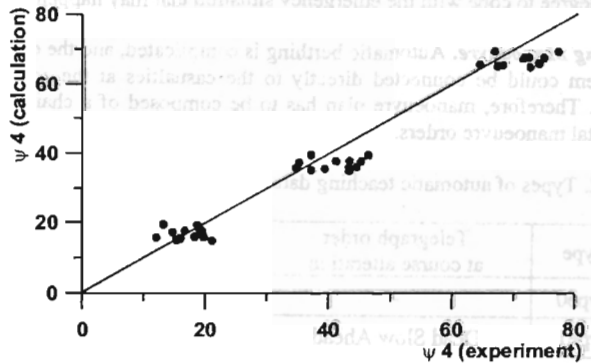


Fig. 6 Comparisons of  $\psi 4$  between calculations and experiments with 3m model of Esso Osaka

Simple PD Control system is adopted for course keeping to keep route in imaginary line as shown in Eq. 9. Coefficients are chosen as  $C1=1.5$ ,  $C2=1.2$  and  $C3=10$ .

$$\delta_{order} = C_1 \psi_e + C_2 r + C_3 d_e \quad (9)$$

where

$\psi_e$  : Angle of Deviation of heading angle from the imaginary line,

$r$  : Angular velocity,

$d_e$  : Perpendicular distance between the ship and imaginary line.

#### Standard Stopping Manoeuvr

Propeller is reversing for stopping. The telegraph order is set at Slow Astern. It is ordered at  $1.5L$  from goal point. The heading angle is affected by propeller revolution. Fig. 14 shows the simulation of standard stopping manoeuvre.

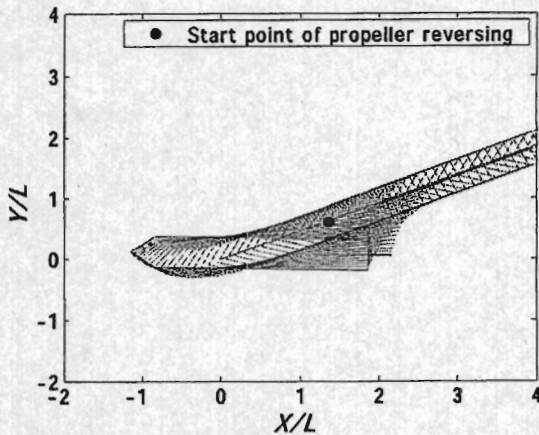


Fig. 7 Standard stopping manoeuvres

**Plan of Manoeuvre**

Three rules are established to achieve the effective manoeuvre in harbour area and to lay down the criterion of berthing.

**Judge of Berthing.** Berthing is assumed to be successful, when the distance and relative heading angle are between  $0.5L \sim 1L$  and  $0^\circ \sim 45^\circ$  from wharf.

**Maximum Rudder Angle.** The maximum rudder angle of the system is set 20 degree to cope with the emergency situation that may happen.

**Planning Manoeuvre.** Automatic berthing is complicated, and the error of system could be connected directly to the casualties at the actual voyage. Therefore, manoeuvre plan has to be composed of a chain of elemental manoeuvre orders.

Table 2. Types of automatic teaching data

Type	Telegraph order at course alteration	Direction of course alteration
Type0	-	-
Type1	Dead Slow Ahead	starboard
Type2	Slow Ahead	starboard
Type3	Half Ahead	starboard
Type4	Full Ahead	starboard
Type5	Dead Slow Ahead	port
Type6	Slow Ahead	port
Type7	Half Ahead	port
Type8	Full Ahead	port

9 types of teaching data are considered to create the teaching data for ANN. The maximum number of course alteration is set 1 to simplify the teaching data. Course alterations to port and starboard are considered. The telegraph orders at course alteration are decided by the distance from goal point automatically. The telegraph orders at starting point are set Full Ahead. The types of teaching data are shown in Table. 2 and Fig. 8. For example, Type 0 has no course alteration; it is a straight run to goal. Type 1 has a starboard side course alteration during Dead Slow Ahead.

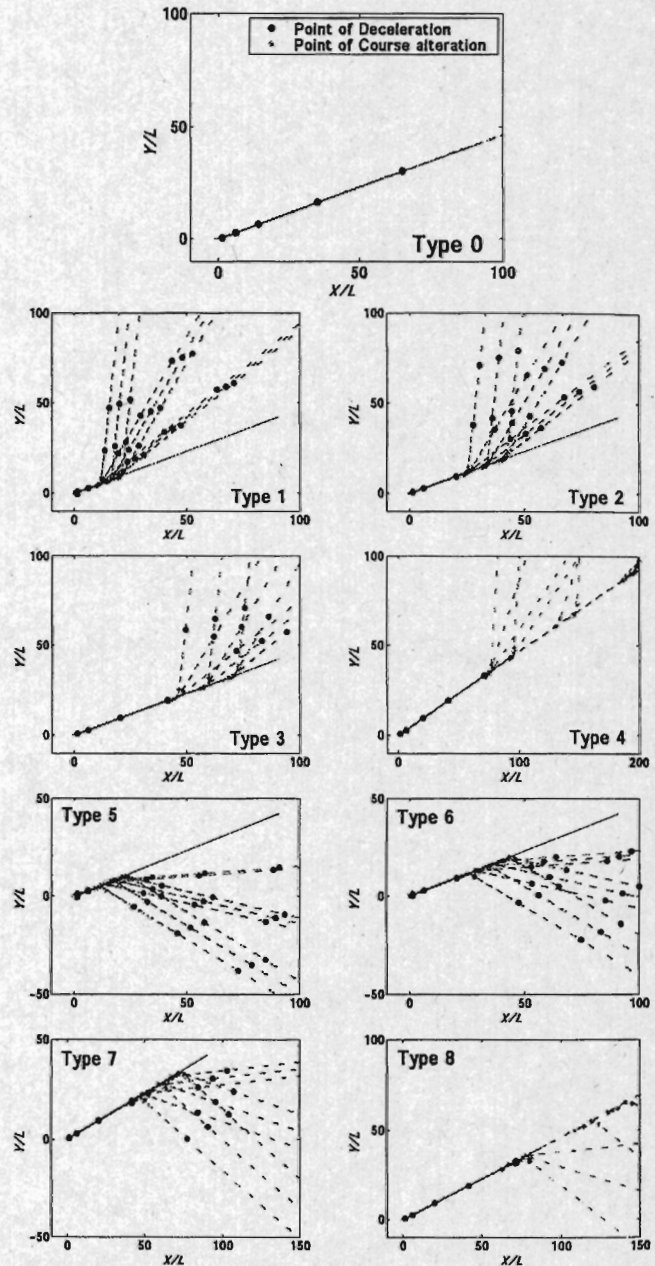


Fig. 8 Types of automatic teaching data

**CONSTRUCTION OF NEURAL NETWORK**

Back propagation learning is adopted. The parallel neural controller (Im, 2001) that is more effective than centralized controller is adopted for the control system.

The teaching data that were calculated at interval of 0.2 second, but using all of the data may take too much time to train ANN. The data are generated to emphasize the valuable data such as deceleration and course alteration, and are minimized to reduce the time of training. The data is picked out at intervals of 1 second during deceleration and course alteration manoeuvres, and at those of 10 seconds for orders. The sum of the squared errors over the output values is used to evaluate efficiency of learning. This can be described by the following equation.

$$E = \frac{1}{Q} \sum_{k=1}^Q e(k)^2 = \frac{1}{Q} \sum_{k=1}^Q (t(k) - a(k))^2 \quad (10)$$

where  
 $e$  : error,  
 $t$  : target of output,  
 $a$  : answer of output.

### Selection of Input Data

It is well known that the maneuvering system is governed rudder angle and propeller revolution. Those are set for the output of ANN. Selection of input parameter of ANN is important to improve the accuracy of the system. Therefore the sensitiveness of input parameters is examined. For example, the location can be expressed by either of  $[x, y]$ ,  $[d1, \theta]$  or  $[d1, d2]$ , but each of them does not yield same result. Input parameter that dose not affect output much may hurt the accuracy of the system.

Parameters for input layer are divided by their specific qualities, and contributions of input parameter to output are examined. The examinations for rudder angle and propeller revolution are performed respectively. Figs. 9~10 show both examinations.

According to the examination of parameter's contribution,  $[d1, d2]$  meets with good results comparing with other location parameters for the ANN ordering rudder angle.  $[u, v, r]$  and  $[dr]$  are selected for velocity and acceleration parameters for the ANN ordering rudder angle for input layer respectively. The same procedure is achieved for the ANN ordering propeller revolution. Table 3 shows the parameters that are chosen.

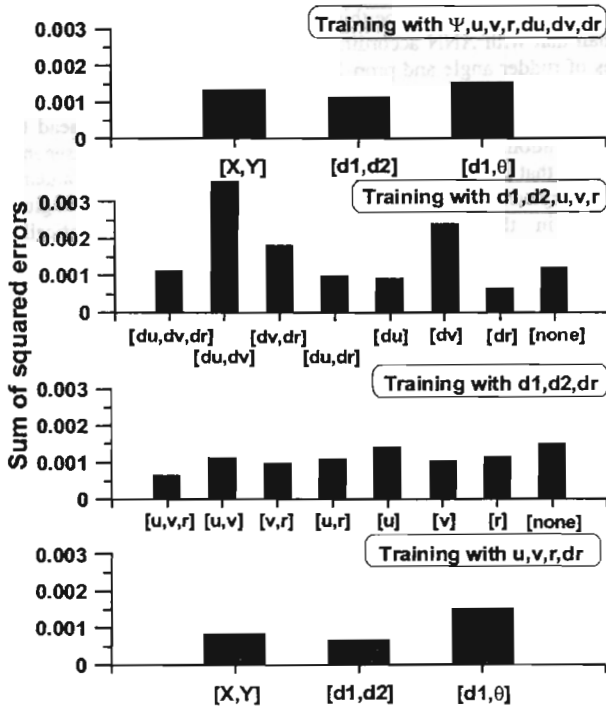


Fig. 9 Results of the examination of input parameters for rudder angle

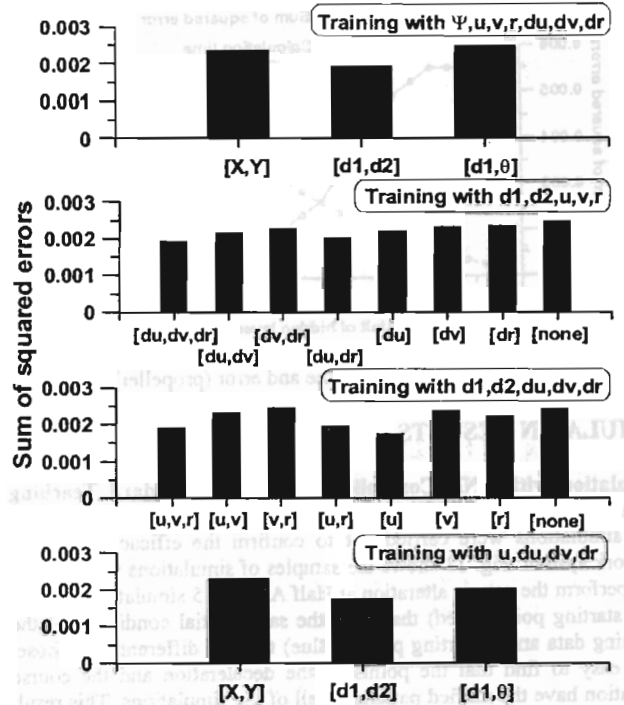


Fig. 10 Results of the examination of input parameters for propeller revolution

Table 3. Input parameters for neural network

Rudder angle	$d1, d2, \psi, u, v, r, dr$
RPS of propeller	$d1, d2, \psi, u, du, dv, dr$

### Hidden Layer

One of the solutions to increase learning capability of neural network is to add a suitable hidden layer during training process. The lack of hidden units may yield some deflection. On the contrary, excessive hidden units may put to train with unexpected noise. Therefore, the selection of suitable number of those is very important. The numbers of hidden units for rudder angle and propeller revolution were tested from 1 to 21 to find the appropriate numbers of them. The results are shown in Figs. 11~12 and found 15 units for hidden layer is suitable for each system. It is possible that the number of hidden units over 21 derives more accuracy result, but takes much more time to train. The numbers of units are decided at 15 units taking the calculation time into consideration, because the time of calculation increases as a quadratic curve.

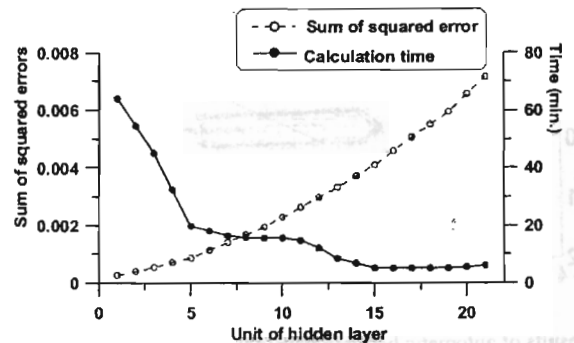


Fig. 11 Comparison of calculation time and error (rudder)

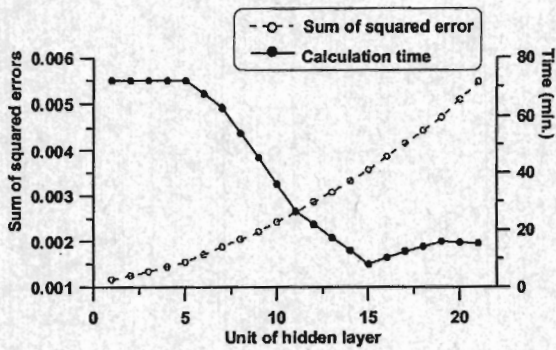


Fig. 12 Comparison of calculation time and error (propeller)

**SIMULATIN RESULTS**

**Simulation with ANN Controller Trained by Standard Teaching Data**

The simulations were carried out to confirm the efficacy of neural network system. Fig. 13 shows the samples of simulations with Type 3 that perform the course alteration at Half Ahead. 15 simulations consist of 9 starting points (Red) that have the same initial conditions of the teaching data and 6 starting points (Blue) that are different with those. It is easy to find that the points of the deceleration and the course alteration have the unified patterns at all of the simulations. This result implies that the ANN controller with the standardized teaching data is suitable for the deceleration and the course alteration. Fig. 14 magnifies with the destination of berthing. The figure shows that the ANN controller with those has stable and corrective control in the automatic berthing.

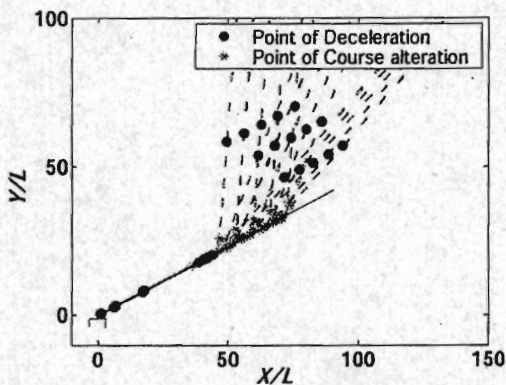


Fig. 13 Automatic berthing with ANN controller

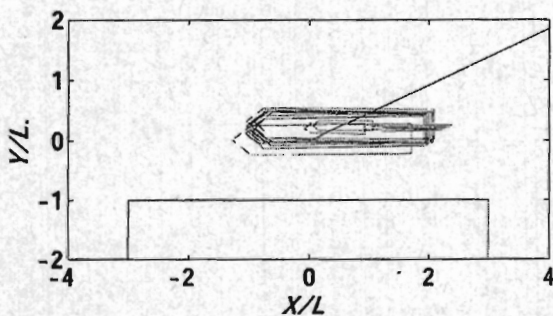


Fig. 14 Results of automatic berthing with ANN controller

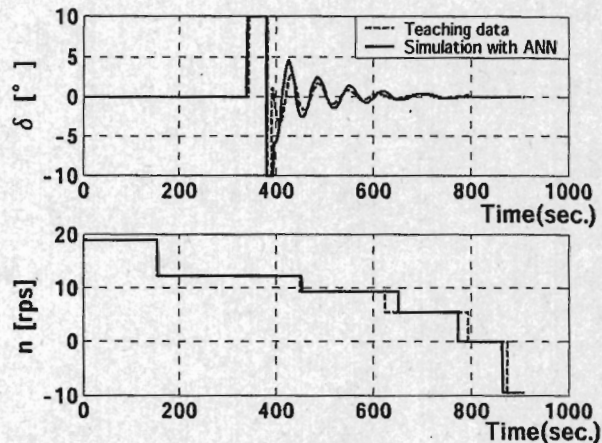


Fig. 15 Comparison of rudder angle and propeller revolution between teaching data and simulation with ANN controller

Fig. 15 shows a sample of the comparison of rudder angle and propeller revolution between teaching data and simulation with ANN controller starting from the same initial condition. The ANN system is suitable for the general berthing problem, because the results of simulation almost coincide with the teaching data.

**Simulation Having the Unexpected Initial Condition**

Location, heading angle, velocity and acceleration are considered at the stage of creating teaching data, but the initial telegraph order was fixed at Full Ahead. The unexpected initial condition that is started with Slow Ahead is set for both simulations with standard manoeuvre and with ANN. Fig. 16 shows the results of both simulations, which achieve the successful automatic berthing. In the view of berthing time, the total time of automatic berthing with standard manoeuvre takes more than that with ANN according to Fig. 17, which shows the time histories of rudder angle and propeller revolution. The ANN controller changed its telegraph order to Full Ahead after starting the simulation, but standard manoeuvre system kept ship's speed at Slow Ahead to next deceleration. The simulation with ANN finished 200 second earlier than that with the standard manoeuvre system. The standard manoeuvre system may overcome this problem easily by changing parameters in the program, but ANN controller automatically overcomes the unexpected problem itself.

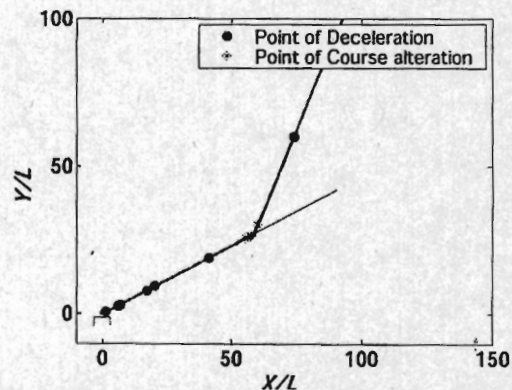


Fig. 16 Results of the simulations having the unexpected initial condition

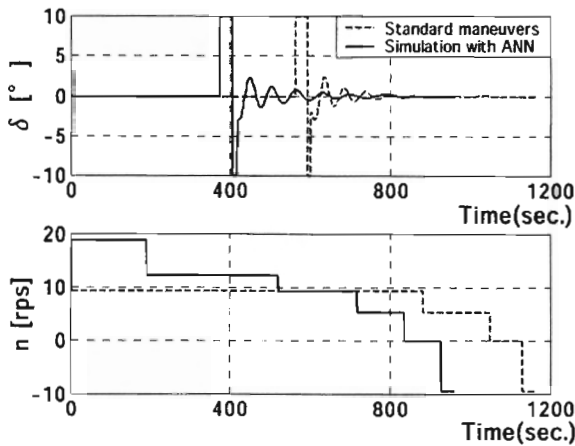


Fig. 17 Time histories of rudder angle and propeller revolution in the simulations having the unexpected initial condition

#### Simulation under Disturbance Effect

The wind is considered in the disturbance effect, because the ship which runs with low speed in the procedure of berthing is often affected by wind. Figs. 18-19 show the result of simulation under wind and the time histories of parameters in the same simulation, respectively. It is easy to understand that ANN controller trained by the standardized teaching data can cope with wind effect to some extent.

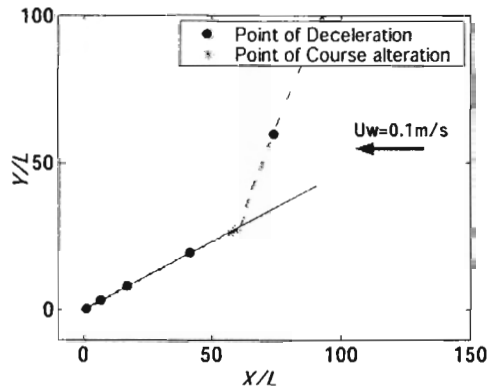


Fig. 18 Results of the simulation under wind effect

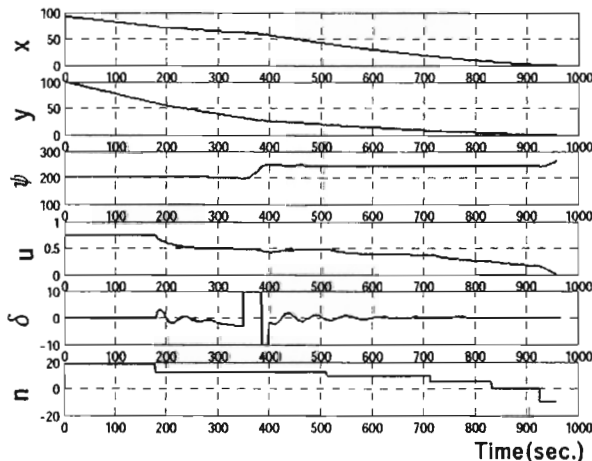


Fig. 19 Time histories of parameters in the simulation under wind effect

## CONCLUSIONS

In this paper, automatic teaching data creation for ANN is discussed. The teaching data were made by three patterns of standard manoeuvres such as deceleration, course alteration and stopping. The neural network controller trained by those data is tested to confirm its effectiveness. Conclusions are drawn as follows.

1. The equation of course alteration using constants K, T is suggested and confirmed by the model tests.
2. The teaching data is automatically created with the standard plan of manoeuvres consisting deceleration, course alteration and stopping to avoid human inconsistent operation.
3. Neural network controller trained by the teaching data automatically created works consistently even in the case of untrained initial conditions.
4. Successful automatic berthing is confirmed even with wind disturbance, but further study is required for more general conclusion.

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