# Automatic Berthing System Using Artificial Neural Network Based on Teaching Data Generated by Optimal Steering

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## 1. INTRODUCTION

Automatic ship berthing control is considered as one of the most difficult problems in the field of ship control. It quite depends on operator's experience and knowledge. So far, many methods and theories have been adopted to achieve the goal of performing automatic ship berthing. A typical example is using the feedback control, which has been used as a controller in some researches1). Even though conventional feedback controller is considered as a great tool, a lot of limitations are still found in this method to be used in such a complicated method like automatic ship berthing. Many methods and theories are adopted in automatic ship berthing control by researchers. Many studies also suggested a number of other controllers such as fuzzy theory, neural network, optimal control theory as well as expert system as part of their control system.

Artificial neural network (ANN) is considered as a convenient tool to deal with complicated nonlinear model such like ship automatic berthing control. So far, even several advancements have been achieved by using ANN, but there are still many obstacles to be overcome such as how to create teaching data consistently and the verification of ANN whether it has an ability to cope with wind disturbances.

Teaching data are used to train ANN, and the trained ANN can do tasks even under conditions different from teaching data. Consequently, the characteristics of teaching data determine the characteristics of neural network, how to get reliable teaching data is a very important work to train ANN. Then, at first, a safe and appropriate berthing maneuvering plan which is divided into three phases of minimum time course changing, step deceleration and stopping maneuvering is planned. Following this maneuvering plan, for teaching data creation, a minimum time course changing from a fixed start point to an ordered terminal point is solved consistently under some restrictions by using nonlinear programming optimization method.

Suitable ANN is constructed by trail-and-error and using mean squared error as the evaluation parameter along with the obtained teaching data. Then, effectiveness of ANN is verified by performing automatic berthing simulations even under different initial conditions with teaching data and wind disturbances.

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## 2. SHIP MODEL AND MATHEMATICAL MODEL

The subject ship used in numerical simulation is ESSO OSAKA's 3 meters model ship. Principal particulars of ESSO OSAKA are shown in Table 1.

Table 1 Principal particulars and parameters of model ship

| Hull | | Propeller | | Rudder | |
|---|---|---|---|---|---|
| L(m) | 3 | Dp(m) | 0.084 | b(m) | 0.083 |
| B(m) | 0.48 | P(m) | 0.06 | h(m) | 0.1279 |
| d(m) | 0.2 | Pitch Ratio | 0.7151 | Ar(m$^2$) | 0.0106 |
| Cb | 0.831 | Z | 5 | λ | 1.539 |

In order to formulate the equation of ship motion, a system of reference axes used in this research is shown in Fig 1.

The mathematical model based on MMG model for describing the ship hydrodynamics in three degree of freedoms are used for simulation. The equations can be expressed in the following form:

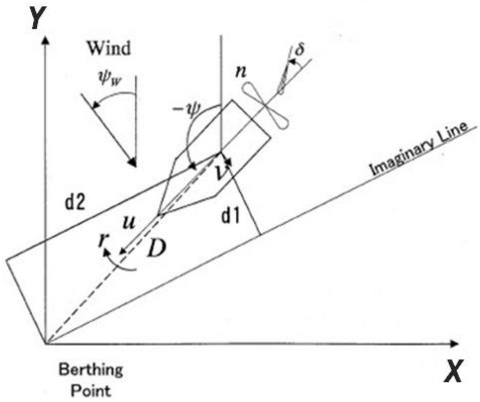


Fig 1 Coordinate system for simulation

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

$X_H, Y_H, N_H$: Hydrodynamic forces and moment acting on a hull
$X_P, Y_P, N_P$: Hydrodynamic forces due to propeller
$X_P, Y_P, N_P$: Hydrodynamic forces and moment due to rudder
$X_W, Y_W, N_W$: Hydrodynamic forces due to wind

## 3. TEACHING DATA

### 3. 1 Maneuvering Plan

For automatic berthing is one of the most difficult controls of ship during the navigation, it is very important to perform a safe and fast berthing maneuvering plan. In this research, berthing maneuvering is divided into three phases of elemental maneuvering such as minimum time course changing, step deceleration and stop maneuvering. For the sake of performing a safe and fast maneuvering, these three elemental maneuvering will not be repeated during operation in one berthing process.

K. Kose proposed two concepts by analyzing the maneuvering motions of pilots during performing berthing maneuvering plan of large ships considering a fast and safe request. One is that the goal of berthing maneuvering is a supposed goal which has an interval distance before pier instead of approaching the pier board to board. The second one is planning a maneuvering which considers a well-to-do operation which has an ample in order to modify the operation in case of miss operation or operation timing delay or wind and wave disturbances.

In this research, the following two rules are adopted. The supposed berthing goal is a place before the pier with a distance of 1 of ship length. However, the ship approaches the pier along with a imaginary line which is from the direction has a 30° degree angle with respect to the pier. Other one, considering the traffic in the harbor is very busy, it is important to plan a comfortable maneuvering which can modify the ship motion easily when un-expectation things occur during operation. The rudder angle is restricted within ±10° .

#### 3. 1. 1 Course Changing Maneuvering

In this research, course changing maneuvering is using optimal control of ship maneuvering to minimize course changing time based on nonlinear programming. Ship starts from a fixed position and goes to a fixed position which is on the imaginary line with optimal course changing in minimum time. The constraint conditions of nonlinear programming method are shown in Table 2.

Table 2 Constraints condition of optimal course changing

| Optimal object | Course changing time | |
|---|---|---|
| Optimal variable | Rudder angle: $\delta$ | |
| Initial conditions | Ship velocity<br>Heading angle<br>Position | Half Ahead<br>$\Psi$<br>(x, y) |
| | Others | $v=0; r=0; \delta=0$ |
| Termination conditions | Heading angle<br>Position<br>Ship velocity | 240[deg]<br>On the imaginary line<br>Free |
| | Others | $v=0; r=0; \delta=0$ |
| Other limitations | Rudder restriction | $\lvert\delta\rvert<=10$[deg] |

#### 3. 1. 2 Deceleration Maneuvering and Stop Maneuvering

In this research, deceleration maneuvering is performed by dropping ship speed from Half Ahead→Slow Ahead→Dead Slow Ahead→Stop Engine step by step in a straight course. The step change timing is as much as time constant $Tp$ of ship speed response equation which is shown in the following:

$$T_P\frac{dU(t)}{dt}+U(t)=K_P n(t)$$

$U(t)$ : ship velocity (m/s); $n(t)$ : propeller revolution (rps)
$Tp$ : time constant; $Kp$ : gain

Stop maneuvering is using slow astern of engine telegraph to stop the ship from a 1.5 ship length distance before the berthing goal.

The standard minimum stop distance is adopted as 15 ship length which coincides with the proposed distance of IMO standard. The termination position of minimum time course changing also is where places at 15 ship length before berthing goal on the imaginary line.

### 3. 2 Teaching Data Creation

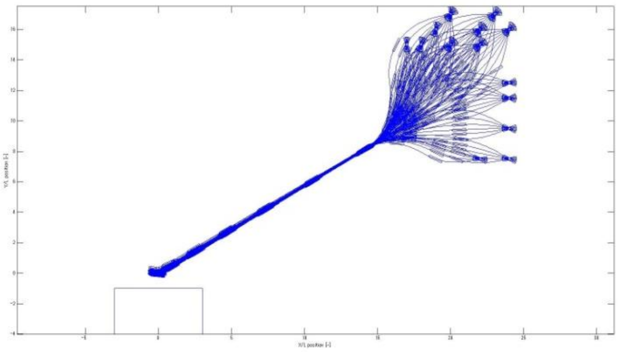

Fig 2 All the teaching data

Based on the above maneuvering plan, 14 different start positions are selected and 106 automatic berthing cases are created. Refer to Fig 2. There are 11 elements concluded in the teaching data to represent ship position and ship states. Correspond to the coordinate system shown in Fig 1, the elements are listed here:

X Position: x [m]; Y Position: y [m];Surge velocity: u [m/s];
Sway velocity: v [m/s]; Heading angle: $\Psi$ [deg];
Yaw rate: r [deg/s]; Rudder: $\delta$ [deg]; RPS: n [r/s];
Command rudder angle: $\delta_{order}$ [deg];
Distance to imaginary line: d1 [m];
Distance to berthing point: d2 [m].

## 4. ARTIFICIAL NEURAL NETWORK

### 4. 1 Accuracy of Artificial Neural Network

In order to train the best ANN, it is necessary to use a parameter to evaluate the accuracy of ANN. In this research, MSE (mean squared error) is used as the evaluation parameter.

Normalized teaching data is in the following form:

$$\{\ p_1,q_1\ \},\{\ p_2,q_2\ \},\cdots\cdots\ \{\ p_n,q_n\ \}$$

$p$: Input of network; $q$: Output target.

Consequently, MSE can be calculated as follows:

$$MSE=\frac{1}{n}\sum_{i=1}^{n}e(i)^2=\frac{1}{n}\sum_{i=1}^{n}(q(i)-O(i))^2$$

$O$: Output of network.

### 4.2 Construction of Artificial Neural Network

In this research, ANN is trained by trail-and-error method. The construction of ANN can be demonstrated in Fig 3:

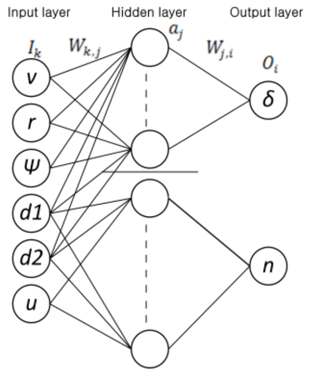


Fig 3 Artificial Neural Network System

### 4.3 Verification of Artificial Neural Network

The verifications of ANN are performed using the same initial ship position and ship states with teaching data. As what are shown in Fig 4 and Fig 5, the berthing results are satisfactory in the phase of course changing, but the trajectory deviation accumulates gradually in the phase of deceleration. This is because of the fact that it is difficult to control heading angle in low ship speed.

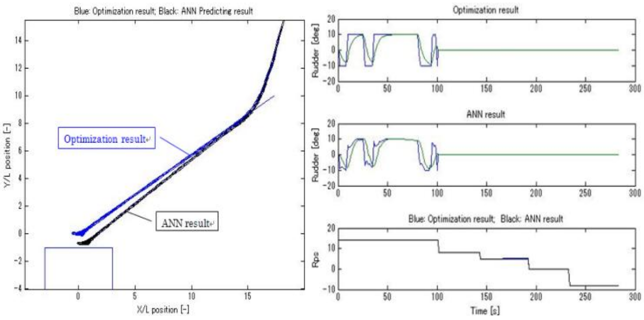


Fig 4 Comparison of trajectories using ANN controller

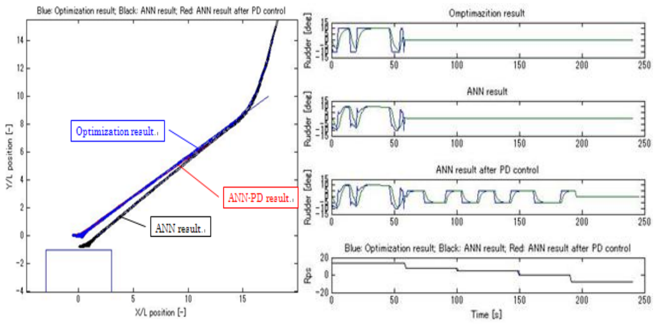


Fig 5 Comparison of Trajectories using ANN-PD controller

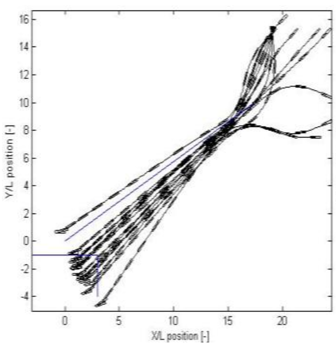


Fig 6(a) ANN Results

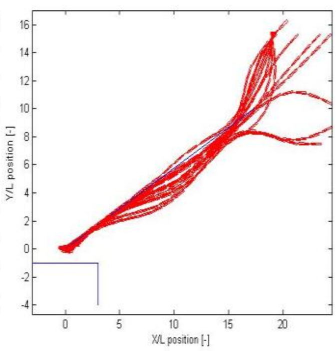


Fig 6(b) ANN-PD Results

### 4.4 Artificial Neural Network-PD Controller

From the verifications result in Fig 4, it seems that after ANN controller, to cope with the deviation reduced during the deceleration phases, a feedback control should be considered. In this research, the following PD controller is constructed. The coefficients of this formula are decided experientially.

$$\delta_{order} = C1 * (\psi_d - \psi) - C2 * \dot{\psi} - C3 * d1$$

$$\Rightarrow \begin{cases} if\ \delta_{order} > 0°, & \delta_{order} = 5° \\ if\ \delta_{order} = 0°, & \delta_{order} = 0° \\ if\ \delta_{order} < 0°, & \delta_{order} = -5° \end{cases}$$

$\psi_d$: Desired heading angle;

d1: Deviation from imaginary line;

C1 = 0.14; C2 = 0.07; C3=0.009.

The result using improved ANN-PD controller is shown in Fig 5. It is confirmed that the improved ANN-PD controller can work well on decreasing the deviation, and the rudder angle change during deceleration phase is between -5° and 5° which can be considered as appropriate rudder operation.

Consequently, simulation results having different initial ship position and ship states with teaching data are performed. However, comparisons of trajectories between ANN and ANN-PD controller are shown in Fig 6(a) (b).

## 5. WIND DISTURBANCES

### 5. 1 Wind Force Model

The influence of wind on ship behavior during ship berthing operation is significant. For wind model, Isherwood coefficients are adopted and wind is considered as steady wind. The wind forces model are expressed as follows.

$$X_W = \frac{1}{2} C_X \rho V_R^2 A_T$$

$$Y_W = \frac{1}{2} C_Y \rho V_R^2 A_L$$

$$N_W = \frac{1}{2} C_N \rho V_R^2 A_L L_{OA}$$

$X_W$ : Fore and aft component of wind force;

$Y_W$ : Lateral component of wind force;

$N_W$ : Yawing moment; $V_R$ : Wind speed relative to ship

### 5. 2 Verification of ANN-PD Controller under Steady Wind

In this section, ship automatic berthing under wind disturbances are performed by using ANN-PD controller. Wind is considered as steady wind and come from 30°, 120°, 210° and 300° direction $\psi_W$ at the speed $U_W$ of 0.2m/s, 0.5m/s, 0.8m/s and 1.0m/s (2m/s, 5m/s, 8m/s and 10m/s for actual ship cases). Results under wind comes from 30° direction are shown in Fig 7-10. It is confirmed that the ANN-PD controller can cope with above wind conditions and perform successful automatic berthing.

## 6. CONCLUSIONS

In this research, automatic berthing system using a parallel ANN based on teaching data generated by optimal steering was discussed. Conclusions are drawn as follows.

For teaching data creation, minimum time course changing from a fixed start point to an ordered terminal point can be solved under some restrictions by using nonlinear programming optimization method.

Teaching data which combining with optimal course changing, step deceleration and stopping maneuvering based on a maneuvering plan can be created automatically and consistently by ordering a start position and initial states.

Artificial neural network (ANN) controller trained by the teaching data based on the optimal steering works consistently. However, by combining the feedback PD control, it performs successful automatic berthing even in case of untrained initial conditions.

ANN-PD controller has an ability to cope with steady wind disturbances.

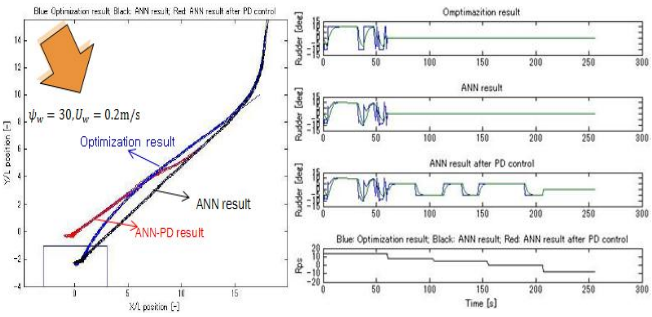


Fig 7 Results comparison ($\psi_w = 30, U_w = 0.2\text{m/s}$ )

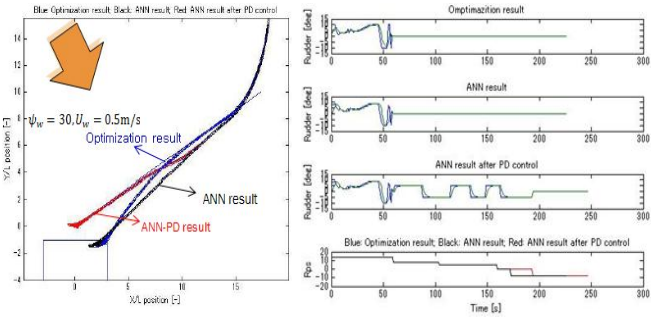


Fig 8 Results comparison ($\psi_w = 30, U_w = 0.5\text{m/s}$ )

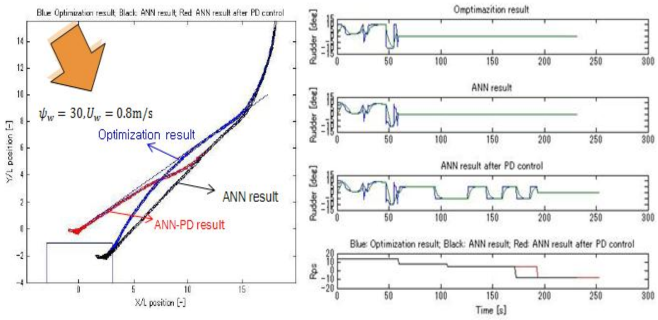


Fig 9 Results comparison ($\psi_w = 30, U_w = 0.8\text{m/s}$ )

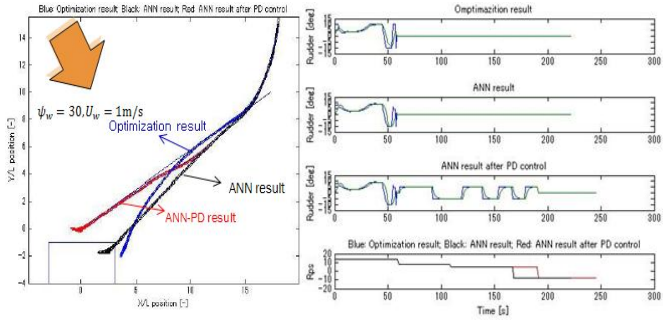


Fig 10 Results comparison ($\psi_w = 30, U_w = 1.0\text{m/s}$ )


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