

Implementation of Automatic Ship Berthing using Artificial Neural Network for Free Running Experiment

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Abstract: Ship berthing has always considered as a multiple input multiple output phenomenon. And such controlling action becomes even more sophisticated when the ship approaches to a pier especially in low speed. The current and presence of wind also make the task more complicated. But, if a human brain can be replicated by any artificial intelligence technique to perform the same necessary action that human brain does, then automatic operation during complete berthing process is believed to be possible by many researchers. For that purpose as an initial stage of this research, artificial neural network is chosen as one of AI techniques for automatic berthing and to increase its learnability, concentration is given on the consistency of the teaching data provided. To do that, nonlinear programming method is used where ship's actual behavior is predicted using famous manoeuvring mathematical group model. After successfully training, ANN controller is tested for various known and unknown condition including wind disturbances and found good results. Finally, to verify the simulated successful results, the current research is based on execution of free running experiment with the implementation of automatic ship berthing using the same trained ANN where adequate decisions for command rudder and propeller revolution taken are decided automatically depending on real time multiple input parameters.

Keywords: Free running experiment, Artificial Neural Network (ANN), Non Linear Programing, Manoeuvring Mathematical Group (MMG), Global Positioning System (GPS), Gyroscope.

1. INTRODUCTION

Ship handling during berthing has considered as one of the most sophisticated tasks that a ship handler has to face. Each ship's response is different during manoeuvring and presence of wind and other external disturbances make the task of berthing more complicated especially in low speed. As a result, since 1997 the annual cost of dock damage claims increase from \$3 million to \$12 million. And almost 70% of the these claims can be put down to bad handling, errors in ship control, tug error or pilot error. To reduce such accidents, the use of automation for ship berthing would be a great relief. To bring the automation in ship berthing different researchers tried different algorithms. Different types of controller such as feedback control, fuzzy theory, neural network, optimal control theory and expert system are tried to cope with such situation. The first research in automatic ship berthing using ANN was started by Yamato et al. (1990) but he then changed his approach and adapted expert system. Fujii et al. (1991) then used both supervised and non-supervised learning system to construct neural network based controller for AUVs and compared the results. Since then Hasegawa et al. (1993), IM et al. (2001, 2002) and many others have continued such research for berthing purpose. But their success was up to certain limit. Especially the maximum wind velocity consideration was limited to somewhat small value and the cross wind was

crucial. Moreover, for training the neural network the teaching data contained lack of consistency. As a result, even such data are used for training net, it often possesses confusion when using non-teaching data for berthing process. To eliminate such difficulties and to make the controller more robust, in this research the whole manoeuvring plan is divided into three basic elementary manoeuvres which are course changing, step deceleration and stopping. For course changing part, a new concept is used to ensure the consistency of the teaching data which is named as virtual window concept (Ahmed et al., 2012). Using this concept ships from any possible heading angle can make necessary course change to merge with the imaginary line well ahead from the berthing goal point. Imaginary line is another concept that most of the ship handlers follow during approaching the pier and it is usually imagined making a certain angle like $30^{\circ} \sim 45^{\circ}$ to the pier. For course changing manoeuvre, using NPL method (Sugita et al., 2012) four virtual windows are formed with rudder angles restricted within $\pm 10^\circ$, $\pm 15^\circ$, $\pm 20^\circ$ and $\pm 25^\circ$. If a ship passes through its desired position of any window, then by taking the calculated command rudder using NPL method, it is guaranteed to reach the imaginary line well ahead. After merging with imaginary line, ship commands to go straight by following sequential telegraph order which is constructed maintaining speed response equation. Finally the engine idling time is tuned in such a way that when engine idling followed by propeller revering, ship will stop as close to the berthing point as possible which is assumed to be at a distance of 1.5 m from the pier for further tug assistance. Therefore the term berthing is not appropriate here to use, but this can be considered as a part of berthing followed by automatic tug assistance which will be studied as future work.

For different initial headings of ship and for the four virtual windows, all complete berthing process are then combined to a make a single set of consistent teaching data. Here, teaching data not only include the variations of ship heading and position but also variations in command rudder angle. And this makes the trained network more robust. As it has already proved that using separate controller for rudder and propeller revolution command are more effective than using centralized controller by IM *et al.* (2001) thus in this research separate controller is also given preference.

While considering wind disturbances, for course changing part by adjusting the rudder the ANN itself can take adequate decision considering gust wind of different velocities and from different directions. But, when ship moves straight along with imaginary line and its velocity gradually reduces then the effect of such wind is very severe. So, PD controller is implemented instead of ANN to control the rudder action while the propeller revolution is wholly decided by ANN. As a result it will be a combined effort of PD and ANN controller during low speed straight forward motion.

Finally, after making several successful simulations for different wind velocities (maximum 1.5 m/s) from different directions (Ahmed *et al.*, 2012), the implementation of automatic ship berthing is planned and executed for the first time with virtual window concept and some results are included.

2. MATHEMATICAL MODEL AND ITS VALIDATION

2.1 Subject Ship and Coordinate System

In this research, the mathematical model is developed for 3 meter Esso Osaka model ship. Principal particulars of the corresponding model ship used for simulation and experiment are shown in Table 1.

 Table 1. Principal particulars and parameters of model ship

Hull		Propeller		Rudder	
<i>L</i> (m)	3	$D_{p}\left(\mathbf{m} ight)$	0.084	<i>b</i> (m)	0.083
<i>B</i> (m)	0.48	<i>P</i> (m)	0.06	<i>h</i> (m)	0.1279
<i>D</i> (m)	0.2	Pitch Ratio	0.7151	A_R (m ²)	0.0106
C_b	0.831	Ζ	5	Λ	1.539

The coordinate system used to formulate the equation of motion together with the wind direction consideration is shown in Fig. 1. Here ship heading is assumed as clockwise and wind direction as anti-clock wise positive. However such assumptions can be altered in program code.



Fig. 1. Coordinate system

A modified version of mathematical model based on MMG $(23^{rd}$ ITTC meeting) for describing the ship hydrodynamics in three degree of freedoms is used for this model ship. The equations of motion as well as measured hydrodynamic forces are considered at CG (centre of gravity) of the ship. The corresponding equations of motions are expressed in the following form:

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

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

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

 X_H, Y_H, N_H : Hydrodynamic forces and moment acting on hull X_p, Y_p, N_p : Hydrodynamic forces and moment due to propeller X_R, Y_R, N_R : Hydrodynamic forces and moment due to rudder X_W, Y_W, N_W : Hydrodynamic forces and moment due to wind

2.2 Validation of the Mathematical Model

To validate the mathematical model and to judge the predictability during course changing, turning simulations for four different rudder angles are compared with the free running experiment result for both port and starboard turning. The comparisons are shown in following figures.



Fig. 2(a). Turning circle compassion for $\pm 10^{\circ}$



Fig. 2(b). Turning circle compassion for $\pm 20^{\circ}$

All above figures confirm the validation of the MMG in most extent.

3. BERTHING SIMULATIONS WITH CONSTRUCTED ANN-PD CONTROLLER

3.1. Construction of ANN-PD Controller

The main objective of the controller in this research is to guide the ship from any position within the constructed virtual windows to the berthing goal point by providing adequate rudder command and propeller revolution considering wind disturbances. To attain that purpose, after creating consistent teaching data using NPL method, Neural Network is formed considering Lavenberg-Marquardt algorithm as training function. As transfer function log sigmoid is used for hidden layers and pure linear is used for output layer.

The resulting ANN can be demonstrated in following figure:



Fig. 3. Artificial Neural Network construction

For command rudder output, input parameters for the net are *u*: surge velocity; *v*: sway velocity; r: yaw rate; ψ : heading angle; (*x*, *y*): ship's position; δ : actual rudder angle; *d1*:distance to imaginary line; *d2*: distance to berthing point.

For propeller revolution, input parameters are u: surge velocity; ψ : heading angle; (x, y): ship's position; dl:distance to imaginary line; d2: distance to berthing point.

In case of gust wind condition, the propeller revolution order is fully controlled by ANN during whole berthing process but in case of command rudder angle, ANN controller is used only during course changing and PD controller is introduced during straight running when ship speed is very low, therefore more prone to deviate due to wind disturbances. In this research the following expression for PD controller is used to ensure earlier response during deviation.

$$\begin{split} \delta_{order} &= C_1 * (\psi_d - \psi) - C_2 * \psi - C_3 * d_1 \\ \Rightarrow if \begin{cases} \delta_{order} > 0^0, \delta_{order} = 10^0 \\ \delta_{order} = 0^0, \delta_{order} = 0^0 \\ \delta_{order} < 0^0, \delta_{order} = -10^0 \end{cases} \end{split}$$

 ψ_d : Desired heading angle; d_l : Deviation from imaginary line; C1=0.30; C2=0.08; C3=0.010

3.2. Berthing Simulations

Before doing the experiment, simulations are necessary to judge the controller's effectiveness for different situations. In this research berthing is assumed to be successful within 1.5 times of ship length area around the goal point. This goal point is again considered at a distance of 1.5 m from the pier for further tug assistance. In the previous stage of this research (Ahmed et al., 2012), simulations were done considering several teaching and non-teaching data. While considering the non-teaching data, simulations were done for the ship's initial position on a particular point of the virtual window corresponding to its heading, which are not used as teaching data. But in real situation, a ship may approach with an unexpected heading corresponding to any particular virtual window point. Moreover a ship may have its initial position in between two virtual windows. Such cases are investigated in current research to judge the robustness of the trained ANN. Figs. 4 and 5 demonstrate some of them where the dotted line shows the constructed virtual windows for different rudder angles and the green square represents the assumed successful zone for berthing.

Considering Fig. 4, in both cases ship initiated with heading 210° but from different initial positions. For left side figure, it starts from the corresponding point desired for 200° heading. On the other hand, in case of right side figure ship starts form the corresponding point desired for 220° heading. But, instead of approaching from certain different initial points in both cases ANN together with PD controller succeed to berth the ship.

Considering Fig. 5 for left side, ship approaches with 380° or 20° heading but passes through the point desired for 400° or 40°. Even in such case, the controller takes proper rudder and propeller revolution to guide the ship to berth successfully. For right side figure, ship starts from somewhat intermediate point between two virtual windows and controller is still found successful.



Fig. 4. Average wind velocity 1. 3 m/s, Wind angle 135° Ship's initial heading 210°



Fig. 5. Average wind velocity 1.0 m/s, Wind angle 180° Ship's initial heading 380° or 20°

However, such results may vary relative to ship's initial speed, position, wind direction and wind speed. For severe wind above 1.5 m/s, such simulation results may not valid. Figs. 6 demonstrate one of them.

In case of Fig. 6, for both left and right hand side ship starts from an arbitrary point with in virtual window area but due to different wind speed success of automatic berthing varies.



Fig. 6. Wind angle 315°, Ship's initial heading 180°

These above mentioned simulations are done by considering gust distribution of wind for any particular average velocity generated by program code using Davenport (1967) expression for wind power spectrum. Since the velocity distribution of wind in the simulation cases and actual cases may differ each other, therefore controlling action may also vary in real situation than shown in simulation results.

4. FREE RUNNING EXPERIMENT AND ARTIFICIAL NEURAL NETWORK

4.1 Plant to be Controlled and its Basic Equipments

Free running experiment is a unique type of experiment where the model ship is allowed to run freely, thus external disturbances are acting freely as in real cases. IM *et al.* (2010) describes elaborately about the free running experiment system. The controlling plant for such system is the same as for motion control of ship. The following shows the plant which is considered to be controlled during automatic berthing experiment.



Fig. 7. Plant to be controlled

Taking the advantages of such experiment system, different types of experiment including speed test, turning test, zigzag or spiral manoeuvring test can be done. As an initial step, speed test and turning test are conducted in this research to justify the prediction ability of MMG model. The results are already included in the previous section.

To understand the total configuration of the free running experiment equipment system, Fig. 8 is given.



Fig. 8. Experiment equipments system

Regarding the important equipments for free running experiment such as among the basic sensors, GPS system is used to calculate the real time ship's position and velocities. Gyroscope is used for measuring roll, pitch and yaw rate together with their corresponding angle. Anemometer is used for measuring wind direction and velocity. Stepping motor is used for rudder rotation and DC motor is used for propeller rotation.

In this research, Matlab 2009 is used for neural network creation using back propagation technique and after being successful each weight and bias matrices are saved as ascii format. Such files are then read in the free running experiment program and real time calculations are done for each set of new and updated input parameters depending on ship response.

Here, GPS serves the current ship's position and its surge and sway velocities at the same time. Gyroscope provides the yaw rate and ship's heading angle. Rudder driver pulse count gives the actual rudder angle and d1 and d2 are calculated depending on ship's position (x, y). Thus, a set of input parameter goes for the network calculation and results a particular command rudder angle and propeller revolution for the next step to execute. And the same procedure goes on until ship stops with in the assumed successful zone.

4.2 Experimental Validation for Trained Network

Considering the above mentioned methodology, the free running experiments are executed using ANN-PD controller to make automatic berthing. The following shows some experiment results recently done for automatic ship berthing. Here anemometer wind direction consideration during experiment is clock wise positive.



Fig. 9. Results for initial ship heading 99.4°



Fig. 10. Results for initial ship heading 406.9° or 46.9°

Figs. 9 and 10 demonstrate the experiment results conducted for virtual window 15° and 10° respectively. In case of Fig. 9, ship starts from the corresponding point desired for 100° ship heading. On the other side, in case of figure 10, ship starts from the corresponding point desired for 405° or 45° ship heading. Moreover the initial surge velocity, sway velocity and yaw moment are also different. In spite of that, in both cases controller is intelligent enough to guide the ship successfully towards assumed successful zone with speed drops beyond 0.05 m/s.

Sometimes ship may face unexpected initial condition than used during training net. Wind speed may also become severe. Such cases are also investigated to check the effectiveness of ANN-PD controller. Fig. 11 demonstrates one of them where wind speed is over 2 m/s during slow speed running.

Considering fig. 11, due to unfavourable initial conditions or current effect the ANN decides to rotate the ship first and then finally make it align with imaginary line and drop the propeller revolution. Due to strong wind presence, ANN also adjusts the propeller revolution by reversing and idling sequentially. Finally ship stops near the successful zone.



Fig. 11. Results for initial ship heading 124.2°

The following experiment is done for high ship speed than used during training net. The ship's initial position is also chosen arbitrarily. The wind is also severe. Fig. 12 demonstrates the experiment result.



Fig. 12. Experiment with high ship speed

Here, ship stops just near pear. Due to strong following wind ship is drifted towards its forward direction therefore it reaches closer than expected. During such experiments, in low speed ANN may take reversing and idling subsequently which results PD controller to take fluctuating rudder. But this can be smoothened by considering no change in rudder angle when making reversing by ANN.

5. CONCLUSIONS

In this research as a continuation of previous research work, berthing simulations are tested where ship approaches form any undesired position of the constructed virtual windows or in between of them. After finding successful results within certain wind limit, for the first time automatic ship berthing is implemented for free running experiment program together with the virtual window concept. Recent experiments are done for both left and right hand side approach of the ship towards the pier. Initial conditions are found playing vital role for different judgement by the controller during experiment. In severe wind condition, the controller is still found effective enough to guide the ship close to the pier.

As a next step, more experiments will be conducted to judge the capability of the trained ANN with PD in real world. After being successful, automatic tug assistance will also be studied for finally moving the ship towards pier.

ACKNOWLEDGEMENTS

We would like to acknowledge Z.I. Awal and K.G. Oh for their kind advice and necessary discussions for the experiment.

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