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Experiment Results for Automatic Ship Berthing using Artificial Neural Network Based Controller

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Abstract: Experiment results are often worthy and would be a great topic of discussion. Since many years, research on automatic ship berthing had already been going on to make it actually possible so that one can minimize the annual cost of dock damage as well to ensure safe operation for such sophisticated multi input-multi output phenomenon. But, success up to the extent to execute it in real cases not yet possible. Recently upon developing the unique concept named 'virtual window', the authors of this paper had already challenged the automatic ship berthing for Esso Osaka 3-m model even considering wind disturbances up to 1.5 m/s which is 15 m/s for full scale ship and considered as dead end for most ports in Japan. After getting success, for the first time using this concept, automatic ship berthing is planned and executed for free running experiment. This paper is aimed to publish some of valuable experiment results in categorised way depending on behavior of Artificial Neural Network which is used as a controller during the berthing manoeuvre.

Keywords: Artificial Neural Network (ANN), Nonlinear Programing Language (NPL), Ship Berthing Experiments, Consistent Teaching Data.

1. INTRODUCTION

Automation in most cases is objected to ensure better safety and provide assistance where decision making by human beings demands no scope for errors. Such a sophisticated phenomenon is ship berthing. In presence of environmental disturbances, captain with vast knowledge of experience even face difficulties in making successful berthing. Therefore during berthing manoeuver not only controlling speed and also to adjust course in low speed often draw the attention to bring automation in this sector. To achieve that purpose, different controlling aspect like fuzzy theory, expert system, feedback controller etc. were tried by researchers. But success was not up to the expecting limit due to having some limitations in each of mentioned cases. For an example, using expert system means to include all possible situations with their corresponding solutions in written words. So, this makes the controller more rigid and it may give good results in some limited situations. Moreover, in case of fuzzy theory, fuzzy rules need to be defined properly. But defining such rules are also very tough for berthing case since any unpredictable situation may arise include environmental disturbances which cannot be pre-implemented as a rule. At last, first success came when ANN was proposed to use for berthing by Yamato *et al.* (1990). Later on Fujii *et al.* (1991) confirmed the effectiveness of ANN as a controller using both supervised and non-supervised learning system for AUVs and compared the results. For automatic ship berthing, after Yamato *et al.*, Hasegawa *et al.* (1993) and IM *et al.* (2001, 2002) had continued the research. Hasegawa used neural network combined with expert system where expert system was tried to assist ANN to go for boosting or take appropriate rudder angle within some defined range of ship's velocity or yaw rate. On the other hand, Im proposed to use two separate networks for the command rudder angle and propeller revolution instead of previously used centralised controller. His proposed method worked quiet well especially in no wind condition. Later on he also proposed motion identification method with two rule based adjusters to improve the ANN's effectiveness in wind condition and was succeed up to certain limit. But for parallel wind, results were not that good enough. After him, his results were tried to improve by other researchers by putting weights on the creation of teaching data. Some used free running experiment data as teaching data to train ANN for berthing and some also used standard manoeuvring plan consist of some empirical equations to decide the correct timing of counter rudder angle change for any particular course change. But, doing experiments are time consuming and the trajectories for berthing may vary depending on user's choice. On the other hand, empirical formulas also need to be reconstructed for each ship and to do that there is no proper rule defined. So, in both cases consistency was not ensured. Later on, IM *et al.* (2007) proposed selective controller for berthing where he divided the approaching ship area into several zone and use separate neural network to guide the ship from one zone to other. The main intention of his research was to make ANN independent of particular port shape and predetermined approach pattern. Therefore, none of the mentioned researches put weights on creation of consistent teaching data. In the meanwhile, Ohtsu *et al.* (2007) proposed a new minimum time ship manoeuvring method using nonlinear programing method, where the user can set desired equality and non-equality constraints. Using his proposed method for course changing, for the first time an attempt was made to ensure the consistency of teaching data by Ahmed *et al.* (2012), the author of this paper. He introduced a unique concept named virtual window, inspired by aircraft landing. Therefore, same as aircraft, ship will make course change first from any possible initial heading to merge with the so called imaginary line which will act as a runway for ship for further decent. Then, by dropping propeller revolution followed by reversing ship will stop at the end of the imaginary line.

Couse keeping especially in low speed while also having environmental disturbances is extremely difficult. So, more sophisticated controller is demanded during straight running with gradually dropping propeller revolution. Ahmed *et al.* (Nov., 2013) then proposed a modified version of PD controller for such situation which can correct not only ship's heading but also minimize the distance from ship's CG to imaginary line. Such consistent teaching data were then used to train multilayer neural network and already confirmed the controller's effectiveness in wind condition up to 1.5 m/s for model ship of Esso Osaka 3-m model.

Finally, after being successful automatic ship berthing was implemented for free running experiment using the same trained ANN as used in simulation works. Ahmed *et al.* (Sept., 2013) already published some experiment result using the same model used for simulation and this paper will be the continuation of publishing more results in categorised way depending on ANN's behavior during berthing experiment.

2. CONSISTENT TEACHING DATA CREATION

2.1 Need for Consistency

The success of ANN as a controller in most extent depends on how it is trained, especially for supervised learning and it is judged by observing its evaluation function after learning. So, some similarities in teaching data often help ANN for better learning and vice versa. If there would be no similarities and some random data are used for training, then often it provides confusion for ANN when it needs to do some extrapolation or interpolation for any unexpected and unknown situation. In case of berthing, consideration of consistency during creating teaching data is very important. Fig. 1 shows some trajectories for successful berthing. If the corresponding particulars for these trajectories are used to train ANN, then for an example in case of tested condition 'a', it may choose the red line or purple line as its path as inspired by its nearest two trajectories used in teaching data. Therefore, it results confusion as well as fluctuating rudder and may guide the ship in a wrong way. Same will happen for case 'b' also.

Since any berthing process usually involves both course changing and course keeping, therefore mixing these two randomly while creating teaching data may results confusion for ANN as clearly seen in fig. 1.

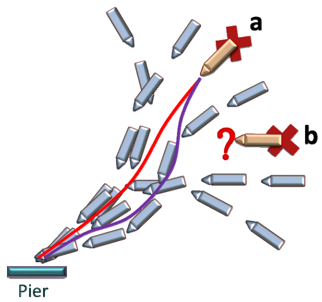

Fig. 1. Inconsistent teaching data results confusion

In case of propeller revolution determination, following some specific telegraph order also assist consistency. Following different rules like dropping propeller revolution while course changing in some cases and maintain specific one in other cases, may also provide some hidden inconsistency since in both cases the trajectories may look like same, only the difference will be in time taken for berthing.

Together with consistency, to make the controller more robust, involving all possible ship's heading as well as different rudder angle operations are also very important which are not yet done in previous researches.

2.2 Berthing Plan to Ensure Consistency

Knowing all possible facts which may results inconsistency in teaching data, in this research the authors are inspired by aircraft landing. Aircraft before landing always make its course change and align itself with the runway maintaining some specific speed. Then after touching down, the captain goes for further decent and provides reverse thrust to finally stop it. Similarly, in this research berthing plan is divided into two subsequent manoeuvring operations. First is for course changing and second is for course keeping along imaginary line. Here, imaginary line is the same as run way for aircraft and in case of berthing, most of the captains consider this line to align their ships first with it and then keep their course along in order to approach near pear. Fig. 2 explains the details of the co-ordinate system considered in this research together with defining other valuable parameters.

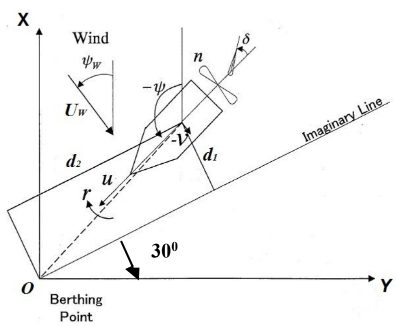

Fig. 2. Coordinate system

The imaginary line is assumed to be of length of 15L according to the IMO standard and the berthing goal point is considered at a distance of 1.5L from pier as proposed by

Kose *et al.* (1986) by analysing the manoeuvring procedure followed by the captain in case of real large ship to ensure safety.

2.2.1 Course Changing

In this research to ensure consistency as well as to make the controller robust, it had been tried to include all possible ship's initial heading as well as different rudder angle operation during teaching data creation. To attain that purpose, nonlinear programming method for minimum time course change was proposed and used by Ahmed *et al.* (2012). During such study, the authors of this paper developed a unique concept named virtual window. The following figure explains the creation of virtual windows using NPL method.

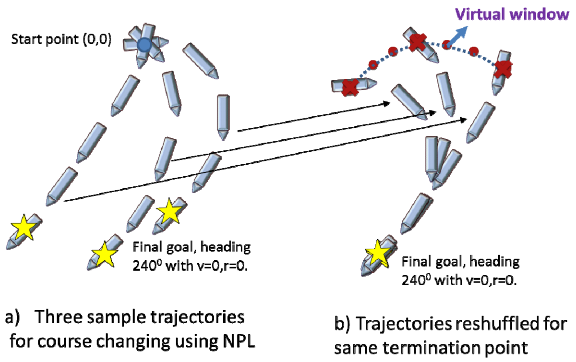

Fig. 3. Virtual Window Creation Using NPL method

Using repeated optimisation technique in NPL method, in this research trajectories are created for different ship's initial heading staring from (0, 0) point as indicated in fig. 3(a). The final goal is to make the ship heading 240° i.e. 30° with pier and ship will go straight with no sway and yaw rate. Such trajectories can be found for each different restricted rudder angle used as non-equality constraint in NPL. In this research, by considering four different rudders as ±10°, ±15°, ±20° and ±25°, different rudder angle operations are included in teaching data to make the controller robust. Here, it is usual that since staring from same initial point and different heading to satisfy the given termination conditions, the ending points will be different. But, if the trajectories are reshuffled as indicated in fig. 3(b) for same termination point, then it is possible to get several initial points from where ships may start and by taking the calculated rudder command by NPL method, it can reach the same destination point which will be the starting point of imaginary line. Thus by adopting such reshuffling process, it is possible to draw a 2D window for each restricted rudder angle operation, which the authors call virtual window. Therefore, if any ship passes through it corresponding point of any window, then by taking the calculated rudder it is guaranteed to reach the imaginary line well ahead so that it can go for further decent. Here, for prediction of manoeuvring motion while using NPL method, a modified version of MMG model was used. The effectiveness of adopted MMG was already verified by performing free running experiment for both port and starboard turning by Ahmed *et al.* (Nov., 2013).

2.2.2 Course Keeping Along Imaginary Line

In this research, course keeping along imaginary line is subjected to both deciding proper telegraph order and designing a sophisticated controller in low speed of ship for wind disturbances. In order to decide the telegraph order, only half ahead is considered during course change and then deceleration manoeuvring along imaginary line is performed by dropping ship speed from Half Ahead → Slow Ahead → Dead Slow Ahead → Stop Engine step by step and then finally go for reversing. The proper timing for propeller revolution change without making any damage for engine and shaft is decided by considering Tp concept from speed response equation as proposed by Endo *et al.* (2003).

Regarding controller for course keeping during straight running in low speed, famous PD controller is adopted here. The following expression is used to ensure earlier response during deviation for the controller.

$$\delta_{order} = C_1 * (\psi_d - \psi) - C_2 * \dot{\psi} - C_3 * d_1$$

$$\Rightarrow if \begin{cases} \delta_{order} > 0^0, \delta_{order} = 10^0 \\ \delta_{order} = 0^0, \delta_{order} = 0^0 \\ \delta_{order} < 0^0, \delta_{order} = -10^0 \end{cases}$$

ψ_d : Desired heading angle; d_1: Deviation from imaginary line; *C1, C2, C3:* Coefficients;

Here, the first part of the expression is for heading angle correction, second part is for yaw rate and third is for minimizing the distance of ship's CG from imaginary line in case of deviation occurs.

Finally, the completed teaching data for training net is given in fig. 4.

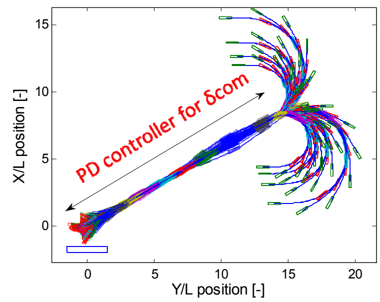

Fig. 4. Completed teaching data

3. IMPLEMENTATION OF ANN DURING BERTHING EXPERIMENT

Diving the total completed teaching data into two as left hand side (LHS) and right hand side (RHS) approach to ensure same direction of rudder operation during course changing, two separate multi layered neural networks are then created for command rudder and propeller revolution output respectively using Lavenberg-Marquardt algorithm as training function and MSE as evaluation function in each case i.e. for both LHS and RHS approach. As transfer function log sigmoid is used for hidden layers and pure linear is used for output layer.

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; $d1$:distance to imaginary line; $d2$: distance to berthing point.

To feed these necessary inputs, free running experiment system has three major sensors. One of them is GPS, which will give ship's position together with surge and sway velocity. The gyroscope will calculate all possible angular velocities and their corresponding rates. Therefore, heading angle and yaw rate are belong to this sensor. Actual rudder angle is determined by counting pulses sent to the stepping motor for desired rotation of rudder. One more sensor is anemometer for wind information, which can be used for analysis of experiment results.

The trained ANNs are then ready to be implemented for free running experiment code using virtual window concept by following the sequential steps as shown in fig. 6.

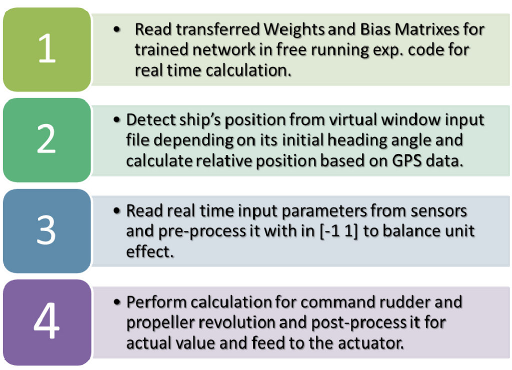

Fig. 5. Implementing ANN in Free Running Exp. code

During berthing experiment, ANN solely is used to determine the proper propeller revolution according to situation demand. On the other hand for command rudder, ANN is used for course change only and it is then followed by PD controller for straight running in low speed. So for rudder command, it would be combined effort of ANN-PD controller.

4. EXPEIMENT RESULTS

Experiment results for automatic ship berthing are precious. Not that many experiments have carried out for berthing by researchers yet. After being successful in simulation works, using the proposed controller, some experiments are recently conducted to judge the effectiveness of ANN-PD controller in real world where all environmental disturbances are acting freely as in real cases especially wind.

During training the neural network the initial conditions are considered as ship running straight with different heading angle. It means the initial rudder angle, sway velocity and yaw rate are set to zero. The surge velocity is also considered as half ahead. But, in real situation, i.e. during experiment due to the presence of wind and current disturbances as well as experiment field shape it becomes very difficult to attain such initial conditions. Inspite of that, due to using well trained ANN as controller, it is expected that the controller will take proper decision on situation demand which is not possible to show in simulation.

As seen when constructing the virtual windows, ship approaches both from left and right hand side of the imaginary line. So, two different types of experiment are conducted. One for LHS approach and other one for RHS approach of ship.

4.1 Ship Approaching from Left Hand Side (LHS)

Some experiments are done for ships approaching to the imaginary line from left hand side. Considering the pattern of ship trajectories during the experiments, the results can be categorised as following three types.

1) When ship reaches to the imaginary line as provided in teaching data and proceeds almost along to it by gradually dropping propeller revolution.

2) When ship makes one complete left turn to make it in a favourable situation and then proceeds for approaching the imaginary line.

3) When ship makes slight left or right turn to compensate any existing sway or yaw moment at initial state and then start approaching to the imaginary line.

These kinds of trajectories are found when ANN initiates with either starboard rudder or port rudder depending on ship's initial condition during experiment. As it is mentioned before that it would be difficult to maintain same initial condition as used during training network, therefore depending on situation demand ANN may take the starboard rudder or port rudder first then go for further approach. It actually depends on the combination of initial surge, sway and yaw rate or any unknown influencing factor.

Category 1: These kinds of trajectories result when ANN takes starboard rudder depending on the combination of v and r. Some unknown factors may also incorporate with such trajectories like presence of wind, current etc. Fig. 6 is a good illustration of such trajectories where the wind is under considerable limit and ANN behaves in a similar way as expected.

Category2: Such trajectories can be found when existing initial sway and yaw rate influence the ANN to take port rudder to compensate the initial yaw rate. Due to taking such port rudder if the ship exceeds the safest zone to make complete berthing, then ANN rotates the ship by taking max port (-25º) and followed by max starboard (25º) when it appears in suitable position. After that ship starts to approach the imaginary line. During that turning and approaching to imaginary line, ANN continuously maintain half ahead speed. Fig. 7 represents one of such results belong to this category.

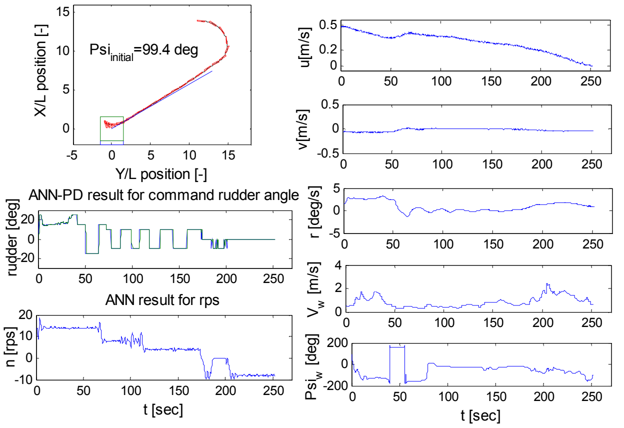

Fig. 6. Results for initial ship heading 99.4°

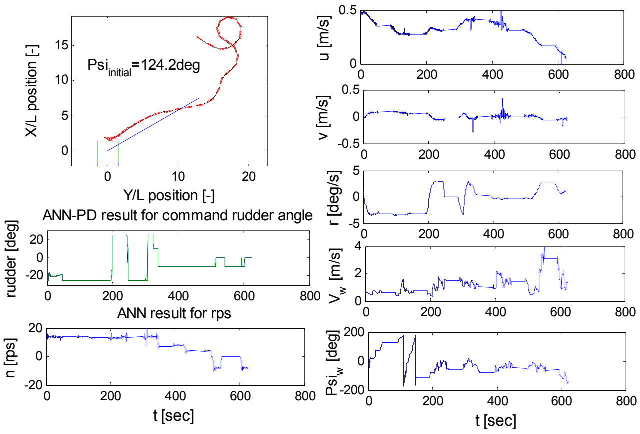

Fig.7. Results for initial ship heading 124.2°

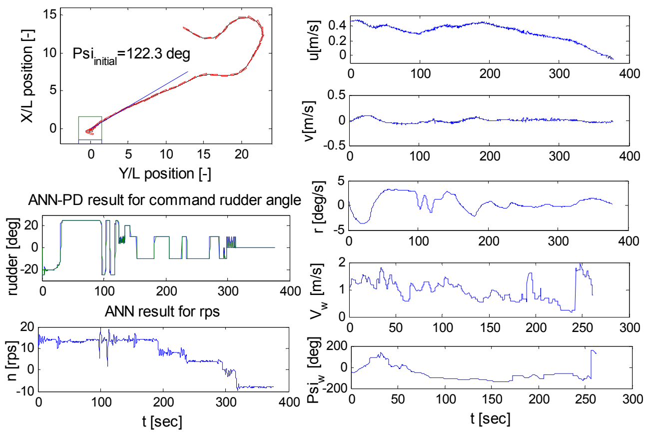

Fig. 8. Results for initial ship heading 122.3°

Category3: Such trajectories results due to the subsequent port to starboard or starboard to port rudder angle taken by ANN depending on existing sway velocity and yaw rate. In such cases, ANN prevents the complete turn by taking counter rudder as ship is believed to be in suitable position to reach the imaginary line by ANN. Fig. 8 represents the experiment result belongs to this category.

During carrying out the LHS experiments, the success rate was very good. Sometimes problem happened if wind blew beyond the expected limit. In such cases, sometimes ship exceeded the assumed berthing zone or stopped before entering it as shown in fig. 7.

4.2 Ship Approaching from Right Hand Side (RHS)

Due to having difficulties in finding good days for experiment, very limited numbers of experiments are done for ships approaching to the imaginary line from right hand side. Considering the pattern of ship trajectories during such experiments, the results may categorised as following types.

1) When ship reaches to the imaginary line as provided in teaching data and proceeds almost along to it by gradually dropping propeller revolution.

2) When ship makes 'S' shape trajectory maintaining the imaginary line passes through it and sometimes exceeds the successful berthing zone due to presence of high wind.

3) When ship fails to reach the imaginary line and the difference between the desired and actual heading is small. During such situation ship continues parallel to the imaginary line during step deceleration and may exceed the safety zone due to presence of high wind.

Category 1: These kinds of trajectories result when ship reaches to the imaginary line almost successfully and then proceeds along to it by gradually decreasing the propeller revolution. This usually happens if the wind is under considerable limit during course changing and step deceleration. Fig. 9 demonstrates such illustration.

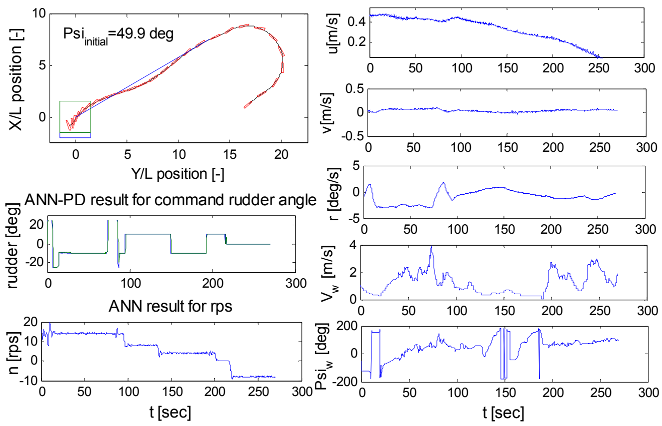

Fig.9. Results for initial ship heading 49.9°

Category 2: All trajectories belong to this category looks like S shape. Such trajectories also results when ship fails to merge with the imaginary line after course changing or there exists a large difference in desired and actual heading angle after course changing. As a result PD controller takes necessary action to compensate it. Within considerable wind limit it succeed and ship pass through the imaginary line during step deceleration stage and again return back to the pier. Such action results in total an S shape like trajectory. Fig. 10 illustrates such trajectory.

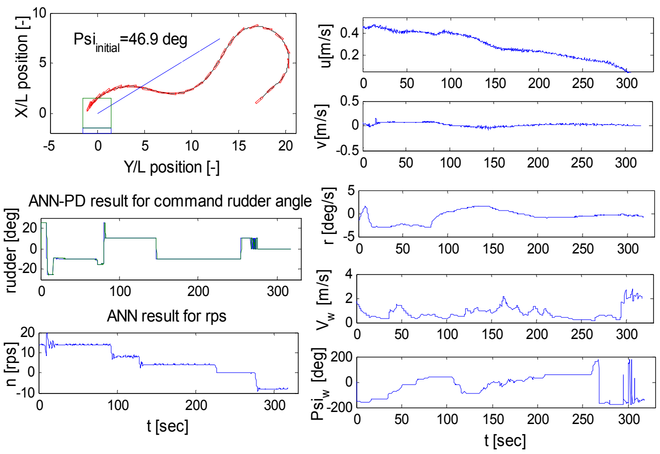

Fig. 10. Results for initial ship heading 46.9°

Category3: Such trajectories result when ship fails to reach the imaginary line after course changing but it can achieve the desired heading which is almost parallel to the imaginary line. This means the whole course changing trajectory is shifted little bit due to wind disturbances or any other unknown factor. In such situation PD controller continues to maintain the ship trajectory parallel to the imaginary line instead of merging during step deceleration. Fig. 11 represents such result.

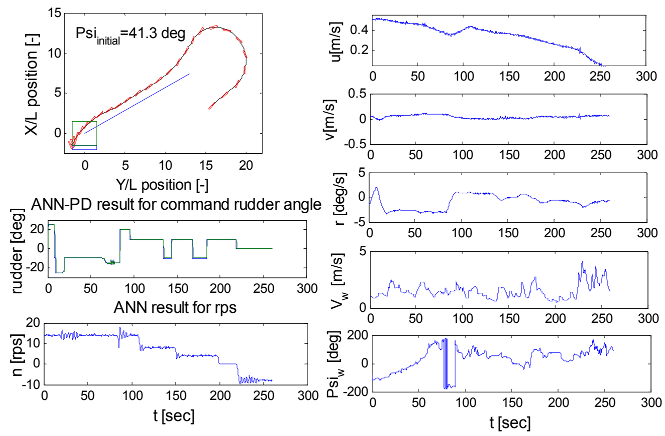

Fig.11. Results for initial ship heading 41.3°

During RHS experiments, the day was very windy. Therefore, success rate is not that much as for LHS approach.

5. CONCLUSIONS

This paper is objected to publish some useful results of automatic ship berthing experiment recently done in categorised way. Possible causes of ANN's behaviour during berthing experiments are tried to explain. At least one representative result in each mentioned category is tried to include. Since the categorised trajectories are based on current available results, therefore further experiments in near future are expected to assist more detail analysis of ANN's behaviour especially for RHS approach and provide some aspects for further improvement.

Moreover, during the experiment, ship is expected to stop within the assumed berthing zone around berthing goal point which is at a distance of 1.5L from pier. As a result, automatic tug assistance needs to be studied in order to shake hand with current controller to finally make the ship align with the pier by proving automated side thrust.

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