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A Study on Automatic Ship Berthing Using Parallel Neural Controller *1

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In this paper a parallel neural controller for the automatic berthing will be discussed. This controller has separated hidden layer that outputs the engine and rudder respectively. A general neural network that used in berthing just has one set of hidden layer, but authors proposed parallel hidden layer. The effect of this parallel control produced good results in comparison with conventional neural controller. Furthermore many simulations conducted in this paper have different initial situations with the teaching data. In other words, starting parameters such as heading angle, ship ' s positions, are not same with the teaching data. But they produced successful results. Finally some simulations are conducted under slight disturbance conditions such as wind conditions and current conditions.

Keywords : *Parallel Artificial Neural Networks, Automatic Berthing, Hidden Layer, Expert System, Fuzzy Theory*

1. Introduction

Automatic berthing control is one of the unresolved problems in ship control. Many methods and theories were adopted to achieve the goal.A typical example is feedback control which has been used as a controller in some research[6] . Even though conventional feedback controller is great tool, ship ' s berthing is so complicated that a lot of limitations still are found. Therefore many studies[1−5,7] suggest other controllers such as fuzzy theory, neural network, and expert system. A neural network controller is one of them. Yamato[2] suggested automatic berthing by a neural network and produced excellent results, but he soon changed his field of research to others such as expert system[7] . Hasegawa[3,4] took over the study. Excellent results were produced even though many things should be overcome: general simulations have same initial value with teaching data and oscillation phenomenon occurred in controller. In other hands, when you look to the existing research that is done for the automatic berthing, it is found that main concept is based on the centralized controller. In other words, output units just come from one command line system. Some studies[5] mentioned that the concept of centralized control may make the problem more difficult. This paper is based on the same idea. Parallel order system in artificial neural networks(ANN) is suggested. Two feed forward networks are adopted to compose a parallel ANN.

2. Model of a Ship and ANN

2.1 Model Ship.

A 260,000 tons of tanker is adopted in this paper, of which dynamics and details are well explained in other research[8] . Particulars of the ship are presented in table 1 and the dynamics coordinate is given in Fig. 1.

2.2 ANN

A typical three-layer network is used. The main feature is the separated structure of hidden layer as shown in Fig. 2. As it is mentioned in introduction, parallel control is adopted in this neural network.

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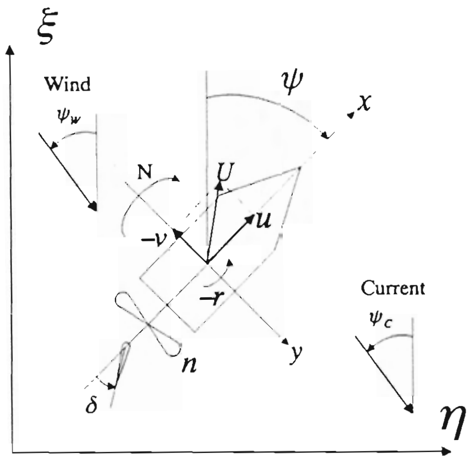

Fig. 1 Coordinate system for ship dynamics.

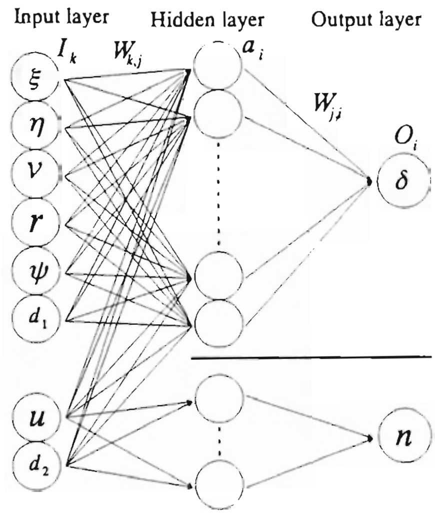

Fig. 2 Neural network with parallel hidden layer.

A conventional neural network used in ship berthing problem just has one of command line for output units. But a neural network in this paper has separated command line in hidden layer that controls the engine and rudder respectively.

For example, the engine control would not be effected by the heading angle, lateral speed , angular velocity and etc. when a ship is far away form a wharf. A navigator usually takes remaining distance to goal point or present ship's speed into consideration, when speed reduction is needed. These facts are reflected well in parallel neural controller.

Input units are composed of 8 factors and output units are two. The details are given in Fig.1,2 and 3.

The d1 is a beam distance to a imaginary line used by navigators to help safe berthing. The d2 is a remaining distance to the goal point. These factors can explain the fact that navigators usually make imaginary line to goal point when he is under berthing work. Even if ξ,η can explain the location information, they are not enough to explain the ship's location information.

Table 1 Particulars of ship.

Hull	Ship type	tanker
	Lenght	304(M)
	Beam	52.5(M)
	Draft	17.4(M)
	Cb	0.827
Propeller	Beam	52.5(M)
	Rudder Height	12.94(M)
	Propeller Diameter	8.5(M)
	Propeller Pitch	5.16
	Rudder area	98.0
	Pitch ration	1.709

3. Procedure for Learning and Making Teaching Data

3.1 Teaching data

This paper focuses mainly on how a parallel neural network will work effectively. So the authors didn'

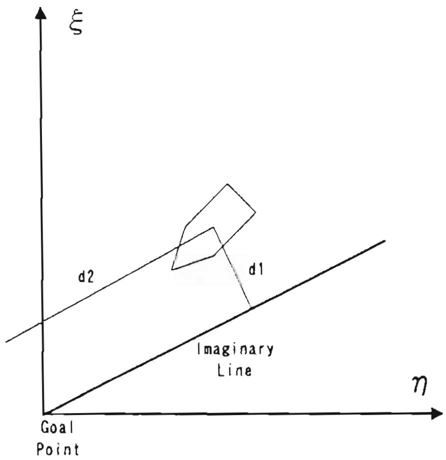

Fig. 3 Coordinate system for berthing.

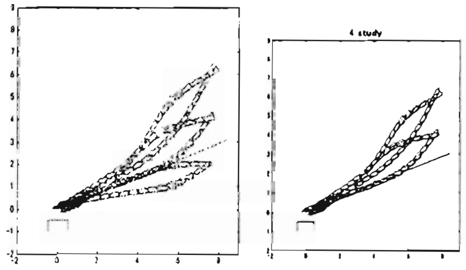

Fig. 4 6 sets of teaching data provided and 4 sets.

t try the automatic berthing problem using a tug or side thrusters. This problem will be a next challenge. Automatic berthing mentioned here means that a ship stops near the goal point within 0.2m/s of speed and between 250-270deg of heading angles. Basically 6 sets of teaching data provided were adopted where disturbances is not considered. 4 sets of teaching data provided are also adopted to compare their effectiveness with 6 sets of teaching data provided. Fig. 4 shows the details.

3.2 Learning

Back propagation learning is adopted. The Neural Network Toolbox from the MATLAB package has been used to train the model.

Variable learning rate method is used to minimize the taken time. Generally the learning rate is held constant throughout training. if the learning rate is set too high, the algorithm may oscillate and become unstable. If the learning rate is set too small, the algorithm will take too large to converge. So variable learning rate is adopted here.

The sum of the squared errors over the output values is used to evaluate efficiency of learning. This can be described by the follows equation:

$$E = 1/2 \sum_i \{T_i - g\{\sum_j W_{j,i} g\{\sum_k W_{k,j} I_k\}\}\}^2 \quad (1)$$

$$W_{j,i} = W_{j,i} + \alpha \frac{\partial E}{\partial W_{j,i}} \quad (2)$$

$$W_{k,j} = W_{k,j} + \alpha \frac{\partial E}{\partial W_{k,j}} \quad (3)$$

where E is the sum of the squared errors, g is sigmoid function, T_i is the target(desired) output, α is the learning rate, $W_{j,i}, W_{k,j}$ are weights on the link form unit j to unit i and k to j.

Since the neural network in this paper uses separated hidden layers, learning is needed twice to make two sets of weight and bias. Groups for rudder and for engine are trained separately.

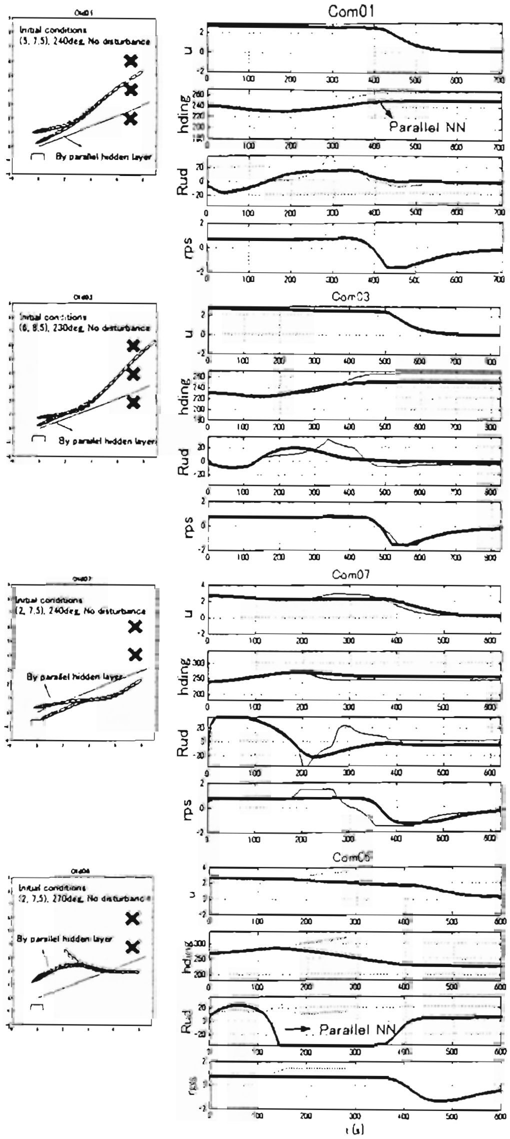

Fig. 5 Comparison of parallel ANN and normal ANN. (Cross marks indicate initial positions of teaching data used for controller).

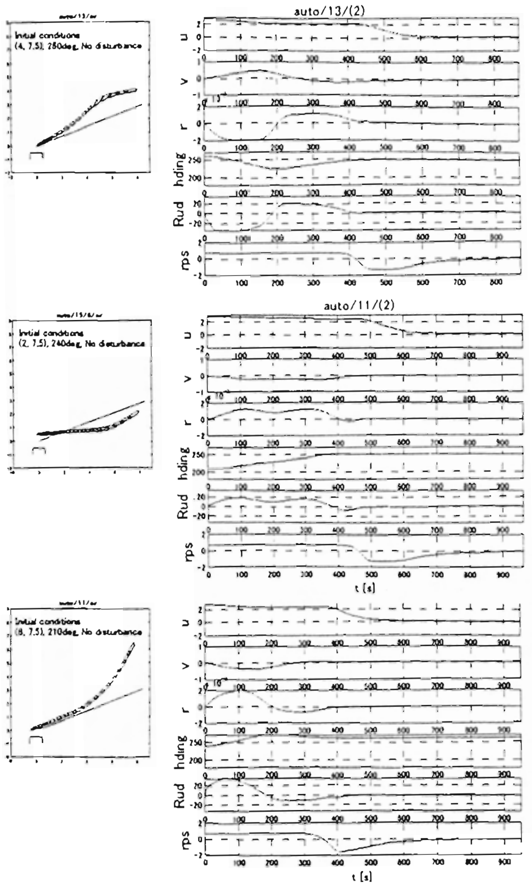

Fig. 6 Same initial conditions with teaching data provided.

4. Simulation Results

4.1 Effect of Parallel Neural Controller

Fig. 5 shows comparisons with the parallel hidden layer and conventional layer. The red line (heavy line) is the results of separated control. The thin line is the results of united hidden layer. Cross marks indicate initial positions of the teaching data used for controller. This figure shows that even if the ship ' s states of two models are same in the initial stage, the output of the rudder and the engine are different because of the different command line system.

It is easy to understand that the parallel neural controller has more stable and corrective control than the united hidden layer by these figures. Take a look at the last case of Fig. 5,even if both cases failed successful berthing, the parallel NN is showing its improvement in stopping ability and keeping track comparing with normal NN. Especially in the case of last two of Fig.5, even if weights and bias of four cases in teaching data are used, in other words, starting positions and state are different with training data, but the parallel neural controller ' s results is showing good ability comparing with that of normal hidden layer.

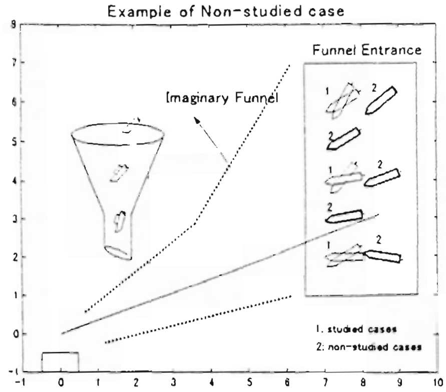

Fig. 7 Description of starting point in simulations.

4.2 Simulations Having the Same Initial Conditions as the training data

As it is shown in Fig. 6, the ability of stopping near the wharf and seeking a goal point is very good. Especially the stopping ability is good .It was possible to end within 0.2m/s at the wharf in all the cases. Also the final heading angles were within 250-270deg. The details are shown in Fig. 6.

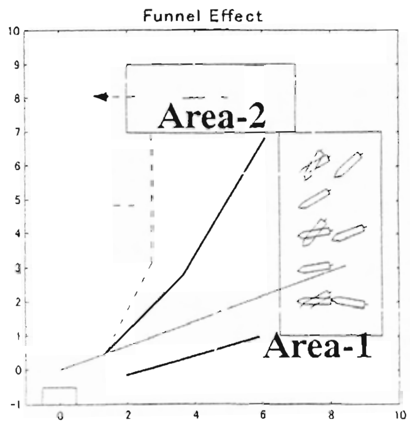

Fig. 8 Extension of 'Funnel-form' area.

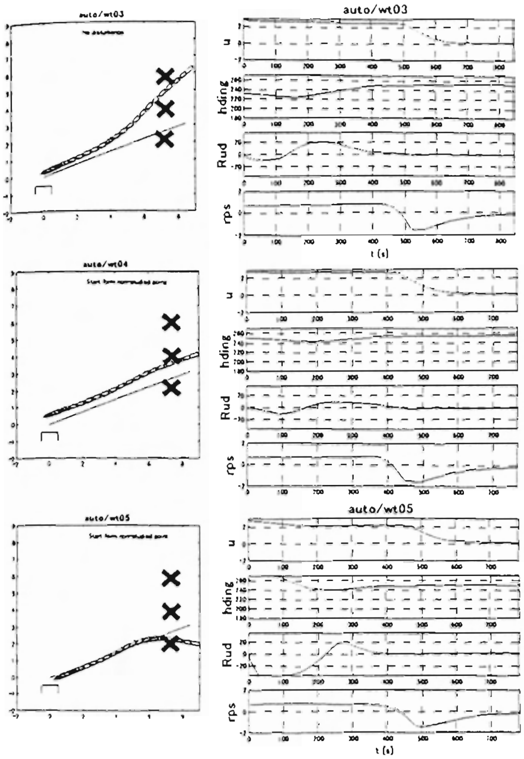

Fig. 9 Different conditions with teaching data provided.

4.3 Simulations Having Different Conditions with Teaching Data

A lot of simulations that have different initial conditions with teaching data are presented in this section. Fig. 7 shows the details. While the No. 1 represents simulation case that the same initial data as the teaching data are used, No.2 has different initial data with teaching data. Fig. 9 shows the results. It is easy to understand that successful automatic berthing has been accomplished even though they have different initia conditions and different starting point with the teaching data.

This is due to the interpolation ability of neural networks. ANN has great power of interpolation to solve a faced problem even though situations are different with teaching data. In Fig. 7 the square area is marked. It is an area, which guarantees safe automatic berthing to the wharf from that area. The authors would like to call it ' funnel-form area '. For example, an object comes into the entrance of a funnel, like Fig. 7, the object should reach the opposite side of the funnel without escaping from the funnel passage. In this paper all simulations which are started at the square area are finished with good automatic berthing like Fig. 6 and 9. This funnel- form area suggests the possibility that if more of these funnel-form areas are established like Fig. 8, automatic berthing can be realized form every direction.

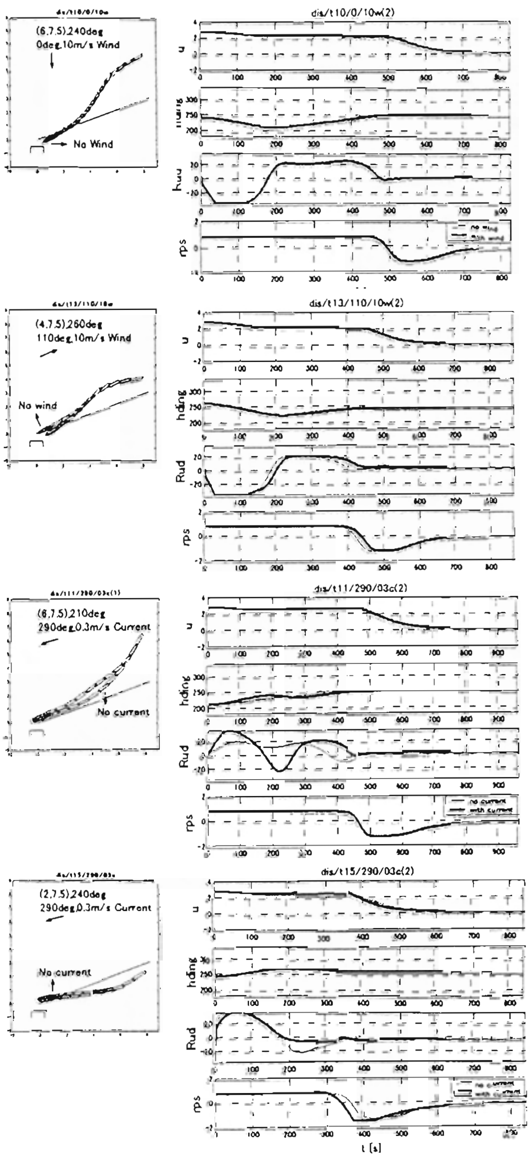

Fig. 10 Simulations under disturbance effects.

4.4 Simulations under Disturbance Effect

Simulations are presented that have disturbance effects. Fig. 10 shows the details. It is easy to understand that parallel ANN also can cope with slight disturbance effects. Wind equations are referred to Isherwood's study[9]. When you look at first two of simulations where 10m/s of wind is considered, it is found that appropriate control is taken to cope with wind. Especially when a ship is affected by a counter wind like in second case of Fig. 10, delayed control for engine is needed to reduce ship's speed. As shown in that figure, delayed control in rps can be seen under a counter wind.

In last of simulations in Fig. 10, current effect is added. It is found that big difference in rudder control can be seen due to current effect. Also it is found that faster control in rps is taken to reduce the ship's speed under a following tide.

5. Conclusions and Discussion

In this paper, A parallel ANN for ship berthing was discussed. Conclusions will be drawn as follows.

1) A parallel ANN was adopted in automatic berthing as a controller.

2) A parallel ANN has good control ability comparing with normal ANN of united hidden layer.

3) Successful berthing has been accomplished even though under different initial condition and different starting point with teaching data.

4) A parallel ANN has ability to cope with slight disturbance effects.

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