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An Adaptive Autopilot for Course-keeping and Track-keeping Control of Ships using Adaptive Neural Network (Part II: Simulation study)

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Abstract : *In Part I (theoretical study) of the paper, a new adaptive autopilot for ships based on Adaptive Neural Networks was proposed. The ANNAI autopilot was designed for course-keeping, turning and track-keeping control for ships. In this part of the paper, to show the effectiveness and feasibility of the ANNAI autopilot, computer simulations of course-keeping and track-keeping tasks with and without the effects of measurement noise and external disturbances are presented. Additionally, the results of the previous studies using Adaptive Neural Network by backpropagation algorithm are also showed for comparison.*

Key words : *Adaptive Neural Networks, Adaptive Interaction, Autopilot, Course-keeping and Turning Control, Track-keeping Control.*

1. Introduction

In this part of the paper, computer simulations for course-keeping and track-keeping control performance of the proposed NNC presented in Part I are undertaken. In these simulations, the effects of random measurement noise and wind disturbances are considered to test the reliability and the robustness of the NNC.

To compare with the proposed ANNAI autopilot, simulations of backpropagation neural network (hereinafter called BPNN) autopilot of previous studies are also shown with the same number of training iterations and the effects of measurement noise and wind disturbances. Additionally, the algorithm for automatic adapting NN parameters (see Part I) is applied to the ANNAI autopilot.

The NNC is designed under the assumption that an accurate measurement of the ship's state (heading, position, yaw rate) is available on board. With the availability of the general and additional navigational aids such as gyrocompass or satellite compass, rate gyro, and GPS/DGPS receiver, accurate measurement of the ship's state is possible. In this paper, a mathematical ship model is used to provide the ship's state and to verify the performance of the controllers. The ship model used in this study is a realistic model of a *Mariner Class Vessel*. The planar motion mechanism tests and full-scale steering and maneuvering predictions for this *Mariner Class Vessel* were performed by the hydro-aerodynamics laboratory in Lyngby, Denmark. To be able to do turning control and cope with large steps of set courses, a reference model that reflects the dynamics of the vessel is used to produce a feasible desired course (Fossen, 2002). The simulations are carried out using the MATLAB 7.0.

2. Simulations

2.1 Course-keeping and turning control simulations

In the previous study (Nguyen, 2005) we showed that the proposed ANNAI autopilot needs much less iterations for training than BPNN-based autopilot does. This significantly reduces calculation time of the NNC, which is important in digital controller design. Many simulations have been carried out to verify the ANNAI autopilot to select the proper n and γ to achieve the best performance. Also in the previous study, we selected the initial weights with opposite signs in the hidden neurons as suggested in Saikalis *et al.*(2001), and activation function of the output neuron was sigmoid and linear gain. But in the following simulations we select the initial weights as rather small random values and good adaptation does occur.

Firstly in this section, an ANNAI autopilot is simulated in the case when the activation function of the output neurons is tangent sigmoid without the adaptation of n and γ. And next, the adaptation strategy of n and γ is used in the proposed ANNAI autopilot to show its effectiveness and improvement. In order to test the

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robustness of the ANNAI autopilot, wind disturbance and measurement noise are used. The effect of pressing water against the rudder caused by wind disturbance against the body of the ship is defined as an additive sine disturbance to the rudder input with amplitude of 0.5 degree and period of 1000 sec. A random signal with a uniform distribution on [-0.02, +0.02] degree is used as the sensor noise in the heading sensor.

The constraints in the actuators is $\delta \in [-35^0, 35^0]$ and $\dot{\delta} = r \in [-2.5^0/s, 2.5^0/s]$. Firstly, the desired course is 20^0 from 0 to 300, then -20^0 from 300 to 600, and finally 20^0 from 600s to 900s. Next, the desired course is 30^0 from 0 to 300, then -30^0 from 300 to 600, and finally 30^0 from 600s to 900s. These rather large steps in course changing are for testing turning control performance. In all simulations, the initial speed is 15 knots (or 7.7175 m/s).

The design of the ANNAI autopilot was described in subsection 3.1 of Part I and the BPNN autopilot configuration is based on Zhang *et al.* (1997a,b). A set of performance indices is also defined to provide a numerical comparison

$$E_\psi = \sum_k (\psi_k^d - \psi_k)^2 \tag{1}$$

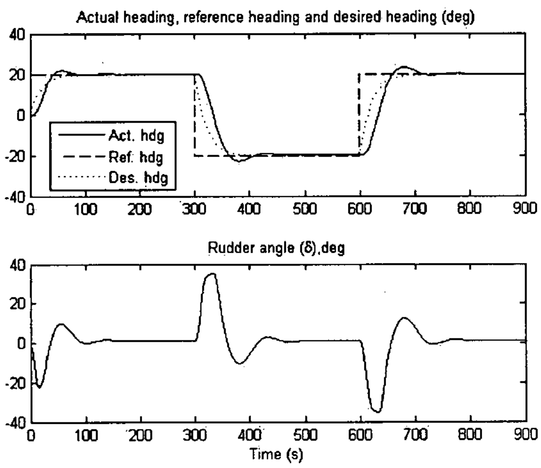
$$E_\delta = \sum_k (\delta_k - \delta_{k-1})^2 \tag{2}$$

where, E_ψ is the squared amplitude of the heading error, E_δ is the variation in rudder adjustment.

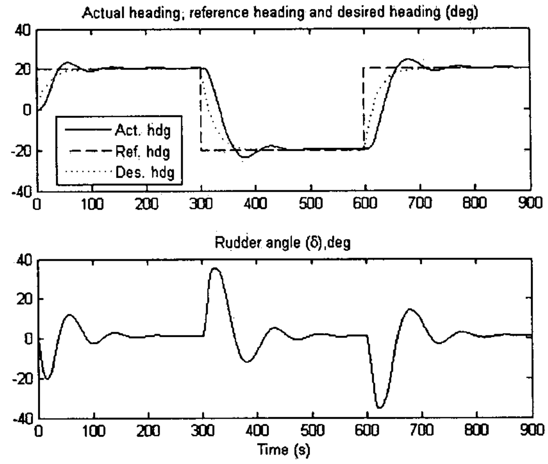
① Without adaptation of n and γ

(1) Course change from -20^0 to $+20^0$

In Fig. 1 and Fig. 2, the learning rate and number of training iterations are fixed (n = 50, γ = 1 for ANNAI and γ = 0.25 for BPNN). The ANNAI and BPNN autopilots have shown good performance with and without noise and disturbances.

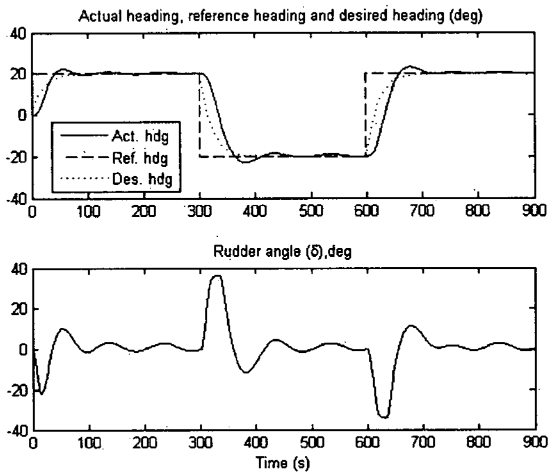


(a) ANNAI autopilot: n=50, γ=1, ρ=1, $\lambda=\sigma$=0.2

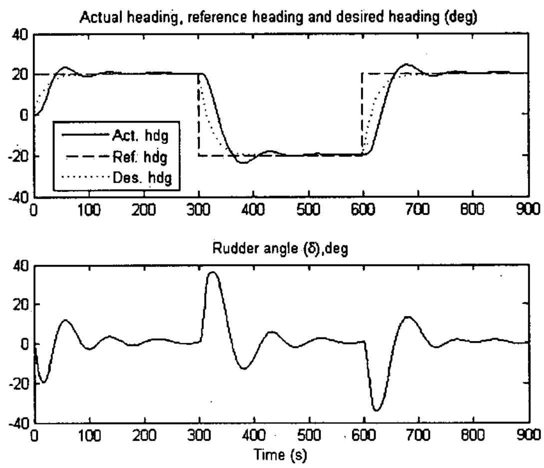


(b) BPNN autopilot: n=50, γ=0.25, ρ=1.5, $\lambda=\sigma$= 0.1

Fig. 1 Simulations of ANNAI and BPNN autopilot without wind and noise, course change from -20^o to $+20^o$



(a) ANNAI autopilot: n=50, γ=1, ρ=1, $\lambda=\sigma$=0.2



(b) BPNN autopilot: n=50, γ=0.25, ρ=1.5, $\lambda=\sigma$= 0.1

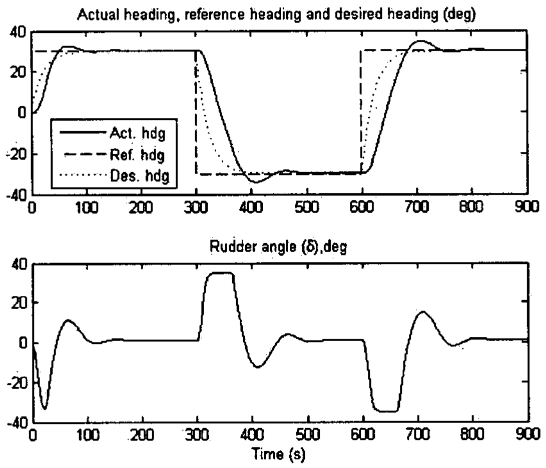
Fig. 2 Simulations of ANNAI and BPNN autopilot with wind and noise, course change from -20^o to $+20^o$

These simulations show the feasibility and effectiveness of the proposed ANNAI autopilot. However, as shown in Nguyen (2005), if n or/and is increased, the large overshoot in heading and oscillations in rudder will occur due to exceed of training. Thus, pre-tests are necessary here.

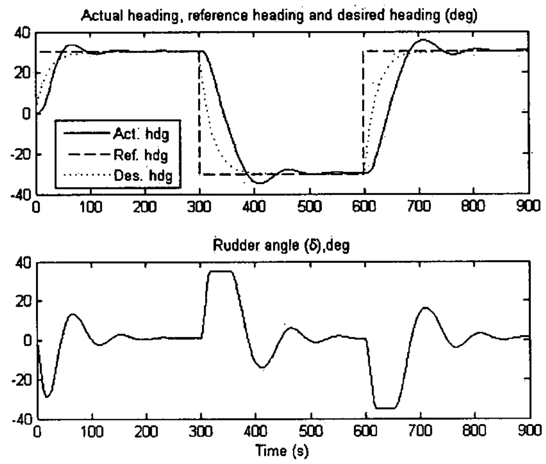
(2) Course change from -30^0 to +30^0

Simulations in Fig. 3 and Fig. 4 showed good performance of both autopilots in case the course change is from -30^0 to +30^0, with and without noise and disturbances. From Figs. 1 ~ 4, better course-keeping, smaller overshoot and less rudder efforts of ANNAI autopilot in comparison with BPNN autopilot are observed.

In Table 1, the numerical comparisons of the two autopilots in Figs. 1 ~ 4 are shown. These numerical results show that, E_ψ of ANNAI autopilot is smaller than that of BPNN autopilot with almost same E_δ.

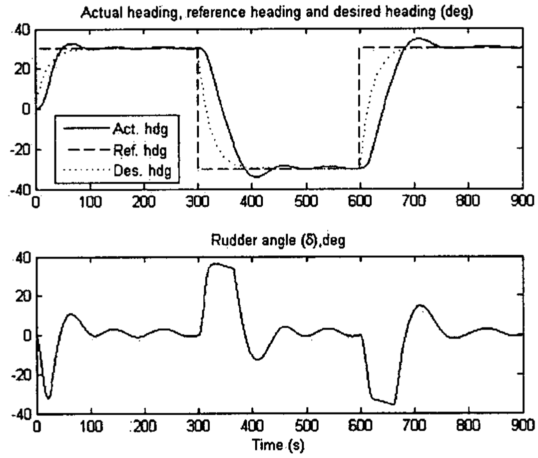


(a) ANNAI autopilot: n=50, γ=1, ρ=1, λ=σ=0.2

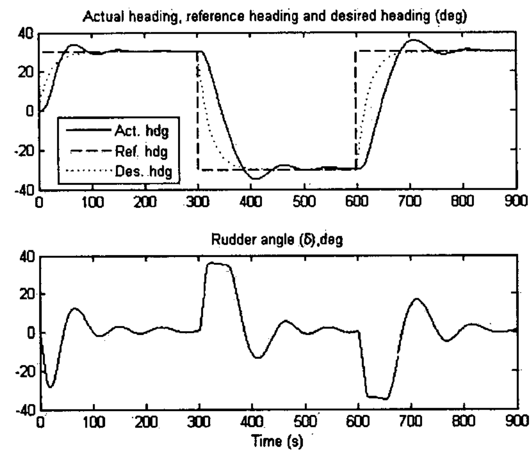


(b) BPNN autopilot: n=50, γ=0.25, ρ=1.5, λ=σ= 0.1

Fig. 3 Simulations of ANNAI and BPNN autopilot without wind and noise, course change from -30° to +30°



(a) ANNAI autopilot: n=50, γ=1, ρ=1, λ=σ=0.2



(b) BPNN autopilot: n=50, γ=0.25, ρ=1.5, λ=σ= 0.1

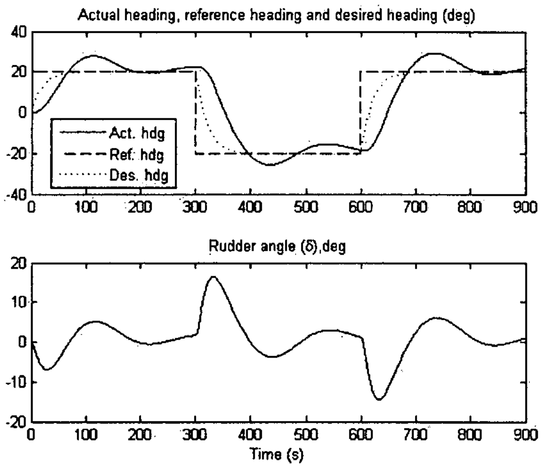
Fig. 4 Simulations of ANNAI and BPNN autopilot with wind and noise, course change from -30° to +30°

Table 1. Comparison performance indices

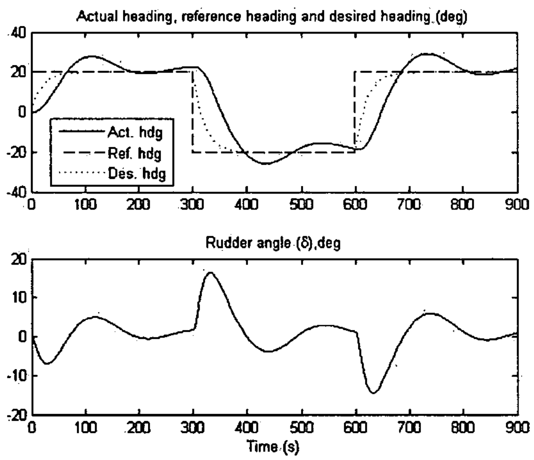
	Fig. 1		Fig. 2		Fig. 3		Fig. 4	
	(a)	(b)	(a)	(b)	(a)	(b)	(a)	(b)
E_ψ	18680	19759	18781	19758	73008	74290	73208	74328
E_δ	349	356	354	355	407	407	404	402

(3) ANNAI autopilot with improper initial parameters

In Fig. 5 the simulations have been carried out with the improper value of learning rate γ = 0.1 (Fig.5a) and improper number of training iterations n = 5 (Fig.5b) for the ANNAI autopilot. The adaptation is poor even no wind and noise applied and course change is from -20° to +20°. Actually, many pre-tests have been done to select proper value of learning rate and number of training iterations in order to achieve the good performance described in Figs. 1 ~ 4.

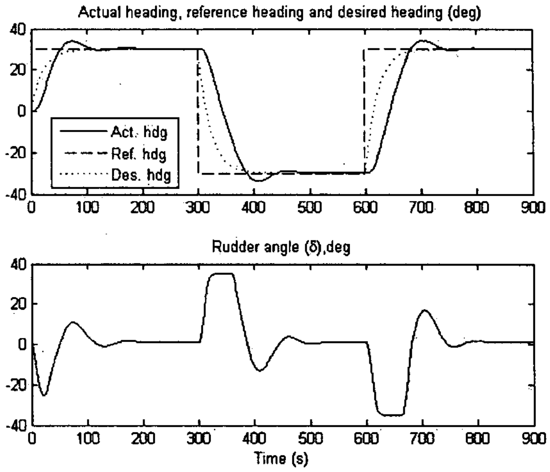


(a) Simulation with: n=50, γ=0.1, ρ=1, λ=σ=0.2

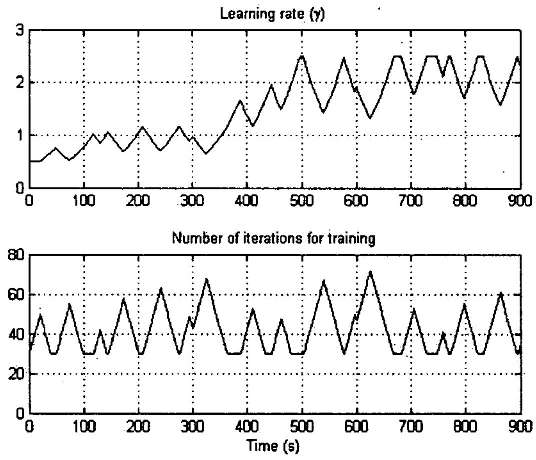


(b) Simulation with: n=5, γ=1, ρ=1, λ=σ=0.2

Fig. 5 Simulations of ANNAI autopilot with improper values of learning rate (5a); number of training iterations (5b)



(a) Heading and rudder angle



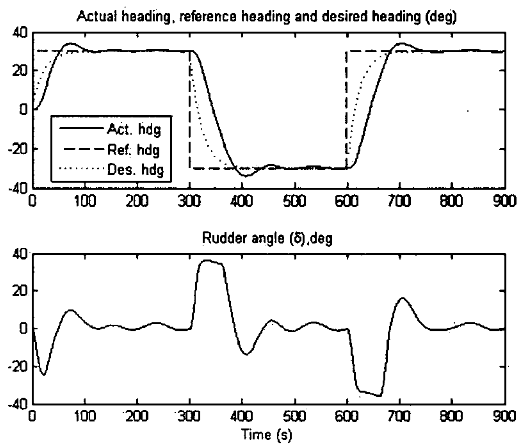
(b) Learning rate and number of training iterations

Fig. 6 Simulations of ANNAI autopilot with initial n=5, initial γ=0.01; ρ=1, λ=σ=0.2, no wind and noise, course change from -30° to +30°

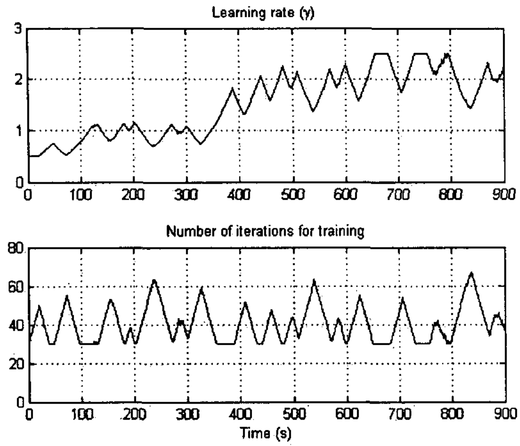
② With adaptation of n and γ

To improve the proposed ANNAI autopilot performance and remove the time-consuming manual selections of n and γ, an automatic adaptation algorithm for these parameters is adopted. Computer simulations are shown in Fig. 6 and Fig. 7. In these simulations, no pre-tests are necessary and we try to use improper initial values of n and γ (n = 5, γ = 0.01) but they do not degrade the adaptation and performance of the NNC. Because both n and γ are updated at every control cycle. The small average values of n are also observed. The poor performance shown in Fig. 5 has been overcome.

Fig. 6 is the simulation result of ANNAI in case of no noise and wind applied and course change from -30^0 to $+30^0$. In Fig. 7, the effects of measurement noise and wind disturbances are included.



(a) Heading and rudder angle



(b) Learning rate and number of training iterations

Fig. 7 Simulations of ANNAI autopilot with initial n=5, initial γ=0.01; ρ=1, $\lambda=\sigma$=0.2, with wind and noise, course change from -30° to +30°

These simulations show good adaptation ability of the autopilot when coping with large course change setting and the robustness are maintained through time. We do not need to adjust the NNC's learning rate and number of training iterations manually as they can be automatically selected.

2.2 Track-keeping control simulations

In this subsection, computer simulations results of track-keeping control system using ANNAI autopilot presented in section 4 (Part I) are shown. BPNN autopilot is also used for the same task and simulations result are presented for comparison purpose.

In Fig. 8 and Fig. 9, a simple path consists of straight segments connecting the following way-points: (0, 0), (2000, 1000), (2500, 3000), (5000, 5000), (5100, 7000). The unit is (m), simulation time is 1200s.

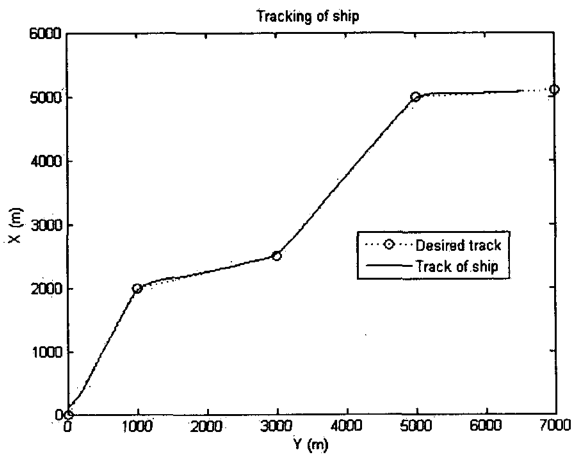


Fig. 8 Track by ANNAI autopilot with wind and noise

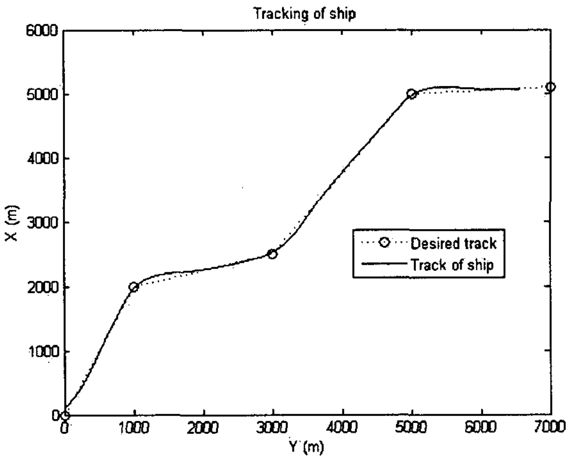


Fig. 9 Track by BPNN autopilot with wind and noise

In case no noise and wind applied, both autopilots perform well. Fig. 8 and Fig. 9 show the simulation results of ANNAI and BPNN autopilots under the effects of measurement noise and wind disturbances. The start point is (100, 0). The two autopilots can control the ship heading to follow LOS guidance heading and make the ship track the desired path. However, the proposed ANNAI autopilot performed better in comparison with the BPNN autopilot in terms of the difference between actual ship's track and desired path.

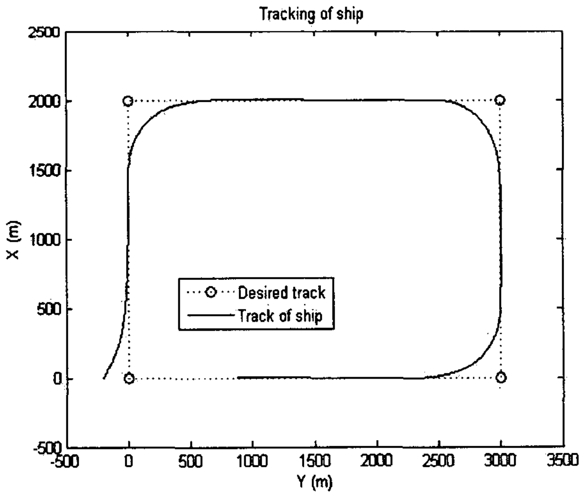


Fig. 10 Track by ANNAI autopilot with wind and noise

In Fig. 10 and Fig. 11, the selected path consists of straight segments connecting the following way-points: (0, 0), (2000, 0), (2000, 3000), (0, 3000), (0, 0). The start point is (0, -200). The ship's course change at intermediate waypoints is 90 degree. The ANNAI autopilot performed well while the BPNN autopilot failed to track the desired path. It is also observed that the proposed NNC has a good adaptation ability and the selection of n and γ has been automatically optimized so that, the ship heading can follow LOS guidance heading well.

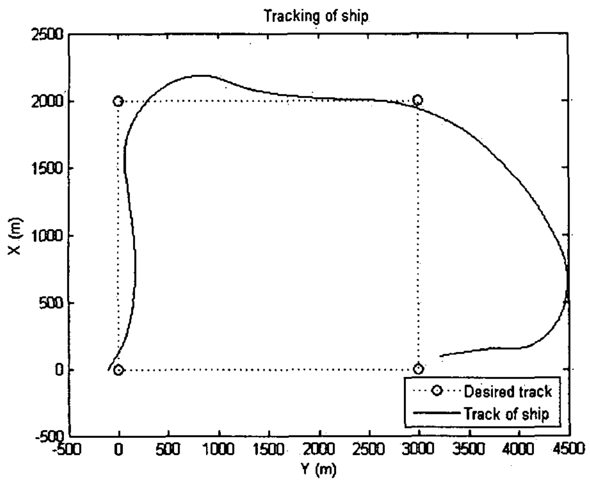


Fig. 11 Track by BPNN autopilot with wind and noise

3. Conclusions

This paper presented an application of neural network control to automatic course-keeping, turning and track-keeping control for ship. A new approach of neural network training using adaptive interaction theory was further developed and applied to automatic ship control. Various computer simulations were undertaken to validate the proposed ANNAI autopilot. The obtained results lead to the following conclusions which are the advantages of the proposed NNC:

(1) It can work well with good performance coping with non-linear and time-varying characteristics of the ship.

(2) It can remove the necessity of a mathematical model of the controlled ship, the error in ship model can be avoided.

(3) Its parameters can be dynamically updated to ensure the robustness through time and speed up adaptation process while maintaining sufficient training.

(4) The on-line training ability can help to cope with new situations, including different ships or environmental conditions.

(5) The proposed NNC is also stable as all its parameters are updated at every control cycle.

(6) It is not very sensitive to measurement noise of input signals.

The NNC can adapt directly without approximating the ship dynamics by a NN. This not only eliminates the error in approximation, but also significantly reduces the complexity of design. Furthermore, the proposed NNC can adapt faster than BPNN and its configuration is simpler (Nguyen, 2005). With the proposed algorithm for automatic adaptation of learning rate and number of training iteration, the adaptation of NNC can be improved and manual time-consuming selection of the NNC parameters is removed.

The proposed NNC can be applied to other types of ship and more complicated control problems because of its adaptation ability. To improve the performance, it might be used in combination with other techniques and theory such as fuzzy control. These will be further research topics of the authors.

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