iopscience.iop.org

Home Search Collections Journals About Contact us My IOPscience

Self-Organizing Neural-Net Control of Ship's Horizontal Motion

This article has been downloaded from IOPscience. Please scroll down to see the full text article.

2006 J. Phys.: Conf. Ser. 48 1284

(http://iopscience.iop.org/1742-6596/48/1/239)

View the table of contents for this issue, or go to the journal homepage for more

Download details:
IP Address: 38.107.179.213
The article was downloaded on 16/02/2012 at 01:34

Please note that terms and conditions apply.

Institute of Physics Publishing Journal of Physics: Conference Series **48** (2006) 1284–1288
doi:10.1088/1742-6596/48/1/239 International Symposium on Instrumentation Science and Technology

Self-Organizing Neural-Net Control of Ship's Horizontal Motion

X J Yang and X R Zhao

Automation College of Harbin Engineering University, Harbin 150001, China

E-mail: yangxuejing@hrbeu.edu.cn

Abstract. This paper describes the concept and an example of an adaptive neural-net controller system for ship's horizontal motion. The system consists of two parts, a real-world part and an imaginary-world part. The real-world part is a feedback control system for the actual ship. In the imaginary-world part, the model of ship and the controller are adjusted continuously in order to deal with changes of dynamic properties caused by disturbances and so on. In this paper, the adaptability of the controller system is investigated by controlling ship's horizontal motion including roll, yaw and sway. The results of simulation indicate that with self-organizing neural-net control, the mean square error of roll angle and yaw angle reduce to 0.92°, and 0.74° respectively. The control effect of SONC is better than conventional LQG controller.

1. Introduction

In recent years, interest in the safe navigation of ship has experienced a substantial increase. However, ship's dynamic character is influenced by unpredictable environment disturbances such as waves, winds and currents, and all these disturbances cause ship's horizontal motion which is unsafe for navigation and carrier planes' takeoff and landing [1]. Therefore, it is crucial to give an effective control of ship's horizontal motion.

A large number of researches on this direction have been conducted. Holzhuter has tested the LQG optimal control scheme [2]. Unar and Murray-Smith have studied the neural networks by simulation tests [3]. Jia has also presented the sea trial results of a prototype of a tracking autopilot for a fully scale ship based on the artificial neural network [4]. Roberts and Sutton have developed fuzzy controllers for integrated ship motion control [5,6]. Fossen has developed a nonlinear passive observer for marine vessel contro1 [7]. It may be seen that whenever a new control algorithm is introduced, it must be adapted to ship control.

In this paper, a controller called SONCS for self-organizing neural-net control system [8,9], which uses a so-called real-world and imaginary-world system, is proposed to control ship's pose of horizontal motion. In this control system, the error signals for the controller adjustment are calculated as the difference between the target values of the control and sampled motion data from the actual ship, there should, therefore, be idling time in the control system and in the operation of the controller's adaptation mechanism. In order to solve these problems, a new adaptation mechanism in which the controller is adjusted independent of time-dependent processes, such as control operations, data sampling should be introduced. Based on the experimental data of HD702, a ship, the detail control algorithm is presented. The results of simulation indicate that with self-organizing neural-net control,

© 2006 IOP Publishing Ltd

the mean square error of roll angle and yaw angle reduce to 0.92°, and 0.74° respectively. The control effect of SONC is better than conventional LQG [10] controller.

2. Ship's horizontal motion model

Ship dynamics is obtained by applying Newton's laws. The marine vehicle has 6 degrees-of-freedom. The spatial position and orientation of a rigid body are determined by the six coordinates. The six different motion components are called: sway, surge, heave, roll, yaw and pitch. Using earth-fixed reference frame, the linear displacements (heave, surge and sway) are described. The revolving movements (roll, yaw and pitch) are determined in the body-fixed reference frame. Accordingly, the most generally used notation for these quantities are: x, y, z, φ, θ, and Ψ.

Based the coupling of ship motion, the six different motion components are divided into vertical motion, including pitch, heave, surge, and horizontal motion, including roll, yaw, sway. This paper only focuses on the horizontal motion.

Assumed that the disturbance of different frequency waves can be linear superposed and the ship is lathy, we can slice the ship along its longness. On the cross-section of each slice, ignored the interactive interference, the three-dimensional current can be regard as two-dimensional current. Then, the integral of all the slices is the whole hydrodynamic force and moment. Based the experimental data in tank, the equation of horizontal motion is established [11]:

$$\begin{aligned}
&(\mathrm{m}+\mathrm{a}_{22})\ddot{y}+\mathrm{b}_{22}\dot{y}+\mathrm{a}_{24}\ddot{\varphi}+\mathrm{b}_{24}\dot{\varphi}+\mathrm{a}_{26}\ddot{\psi}+\mathrm{b}_{26}\dot{\psi}=\mathrm{nL_R}+F_{2W}\\
&\mathrm{a}_{42}\ddot{y}+\mathrm{b}_{42}\dot{y}+(\mathrm{I}_4+\mathrm{a}_{44})\ddot{\varphi}+\mathrm{b}_{44}\dot{\varphi}+\mathrm{c}_{44}\varphi+\mathrm{a}_{46}\ddot{\psi}+\mathrm{b}_{46}\dot{\psi}=\mathrm{nL_R Z_R}+F_{4W}\\
&\mathrm{a}_{62}\ddot{y}+\mathrm{b}_{62}\dot{y}+\mathrm{a}_{64}\ddot{\varphi}+\mathrm{b}_{64}\dot{\varphi}+(\mathrm{I}_6+\mathrm{a}_{66})\ddot{\psi}+\mathrm{b}_{66}\dot{\psi}=\mathrm{nL_R X_R}+F_{6W}
\end{aligned} \tag{1}$$

Herein, y is sway, φ is roll, Ψ is yaw. m= 442000(kg), is the ship's mass. F_{2W} is the disturbance force of roll, F_{4W} is the disturbance moment of roll and F_{6W} is the disturbance moment of yaw. L_R is force of rudder, L_RX_R and L_RZ_R are moment of rudder. X_R=25.8m, Z_R=1.32m. C_{44}=3370000, is the restoring force factors. a_{ij} (i,j=2,4,6) is the extra mass, b_{ij} (i,j=2,4,6) is the damping moment factors. I_4=3136828(kg.m2), I_6=99450000(kg.m2) are the inertial torque of roll and sway.

3. Self-organizing neural-net control

3.1. System structure

The self-organizing neural-net control system, SONCS, uses a so-called real-world and imaginary-world system [12]. In the imaginary-world system, which is a copy of the real-world system (including the ship's dynamics), a controller is constantly trained using an online updated recurrent forward model of the ship dynamics. This model, in turn, is regularly updated using inputs and outputs from the actual ship. At specified intervals the real-world controller updates its weights with the learned imaginary-world controller weights. Learning is thus performed in a loop totally independent from the control loop. Figure 1 shows the architecture with the real-world and imaginary-world controllers.

The time-dependent processes, such as data sampling, control of the actual ship with a feedback controller N1, are executed in the real-word part. The inputs to the N1 are the differences between the reference signals r(t) and state variables $\Psi_e(t)$, which are sampled data from the actual ship, and the control signals u(t-Δt) from the previous time step. The imaginary-world part includes a controller N2, and forward model networks which represent the dynamic properties of the ship. The controller adaptation process with the N1 and N3, and the modelling process for N3 are carried out simultaneously in the imaginary-world part. The inputs to N1 are therefore, the same as those of N2, but state variables denoted by Ψ(k) are calculated using the forward model instead of the actual ship.

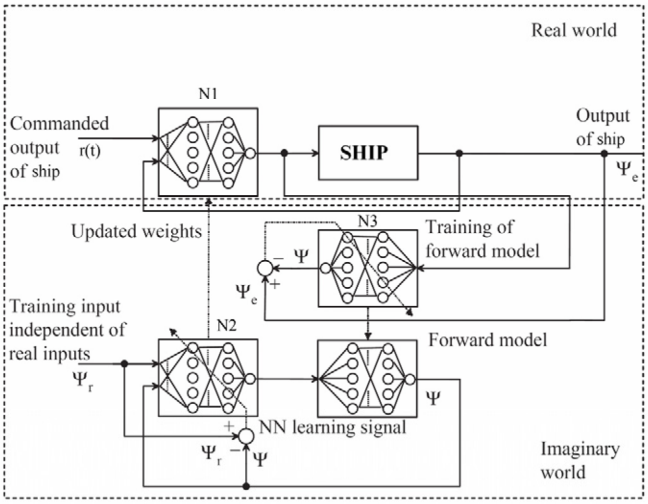

Figure 1. Block figure of SONC.

3.2. Forward model network

The FWD consists of three layers of neurons, time-integration layers and two kinds of recurrent connections as shown in Figure 2. Let the neural-network's mapping function be f, the state variable for evaluation $\Psi(k+\Delta k)$ (which means the roll, yaw or sway) and the outputs from the third layer $\Delta^2\Psi(k+\Delta k)$ (which means roll acceleration, yaw acceleration or sway acceleration).

$$\Delta^2\psi(k+\Delta k) = f(\Delta\psi(k), \Delta\psi(k-\Delta k), \ldots, u(k), u(k-1), \ldots) \tag{2}$$

$\Psi(k+\Delta k)$ can be calculated as a result of the following summation in the integration layers:

$$\Delta\psi(k+\Delta k) = \sum \Delta^2\psi(k) \tag{3}$$

$$\psi(k+\Delta k) = \sum \Delta\psi(k) \tag{4}$$

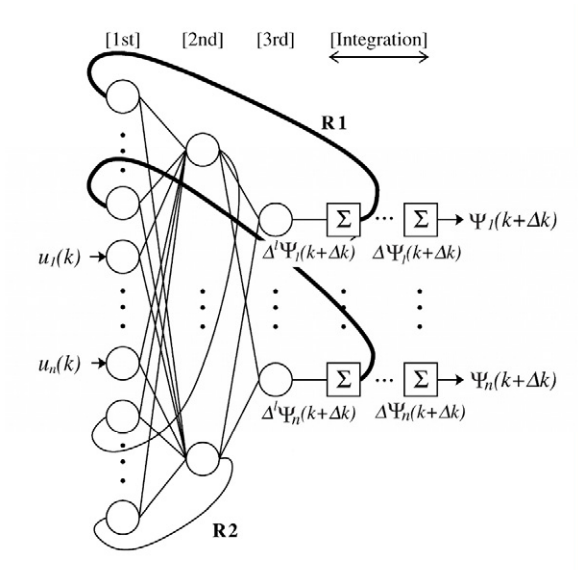

Figure 2. Structure of FMN.

In order to simulate the motion by giving initial values $\Psi(0)$ and u(k), the outputs of the first integration layer $\Delta\Psi(k)$ (which means roll rate, yaw rate or sway rate) are used as the inputs at the next time step. For this purpose, the state variables $\Delta\Psi(k+\Delta k)$ in (3) are passed to the first layer via the recurrent connections (indicated by R1). The recurrent connections from the second layer to the first layer (indicated by R2) allow the network to keep the influence of past data and to express the dynamic behavior with a reduced number of input state variables.

3.3. Controller Network

The network structure of the controller adaptation process of the ship is designed as in Figure 3. The inputs of the FWD are $\Delta\Psi(k)$ and the control moment u(k). Consequently, the output in the third layer is the heading acceleration $\Delta^2\Psi(k+\Delta k)$ at the next time step. The inputs of the N2 are the differences between the reference signals ($\Psi_r(k)$ and $\Delta\Psi_r(k)$) and the state variables ($\Psi(k)$ and $\Delta\Psi_r(k)$) given by the FWD and the control moment u(k-Δk) at the previous time step. The initial FWD has been constructed by learning from the sampled data of the indicial response. And the controller network is initialized by the imaginary training process using this constructed FWD.

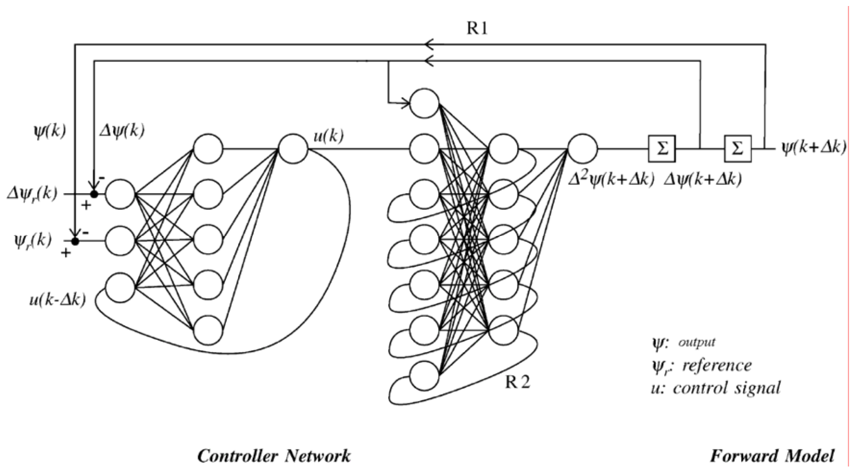

Figure 3. Structure of controller network.

3.4. Simulation

Figure 4 shows the control effect on roll angle. Herein, the thin line denotes the control effect of conventional LQG controller, and the thick line denotes the control effect of SONC. Table1 is the comparison of the two control methods in yaw and roll.

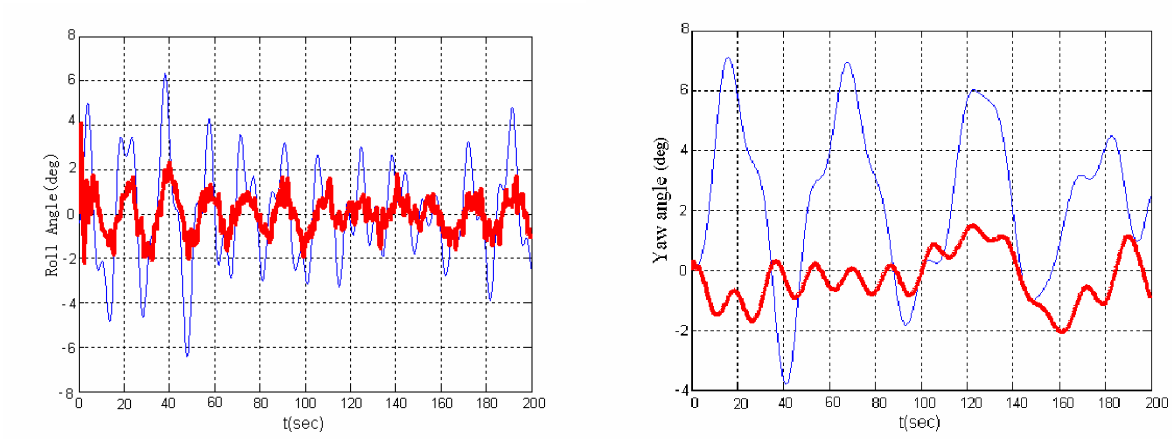

Figure 4. Comparison of roll angle and yaw angle between SONC and conventional LQG control.

Table 1. Mean square error of SONC and LQG.

Control Method	Roll(deg)	Yaw(deg)
SONC	0.92	0.74
LQG	1.42	1.68

4. Conclusion

In this paper, SONCS is used to control ship's horizontal motion. The simulation based on HD702 reveals that with SONC, the mean square error of roll angle reduces to 0.92°, and the mean square error of yaw angle reduces to 0.74°. With the conventional controller, these two numbers are 1.42° and 1.68° respectively. The control effect of SONC is better than conventional LQG controller. In SONC, the forward model and controller can be trained till desired performance is abstained, which makes it demand less computation, but makes the controller be trained with model of the past.

Acknowledgements

The experimental data of this research is provided by the Ship Research Center of China. This work is funded by the National Science and Industrial Council for Defense.

References

[1] Naoya Umeda and Hirotada Hashimoto 2002 Qualitative aspects of nonlinear ship motions in following and quartering seas with high forword velocity *Science and technology* **6** 111-121

[2] Holzhuter T 1997 LQG Approach for the High-precision Track Control of Ship *IEE Proc Control Theory Application* **44** 121-127

[3] Unar M A and Murray-Smith D J 1999 Automatic Steering of Ship Using Neural Networks *Int J of Adaptive Control and Signal Process* **13** 203-218

[4] Jia X 1999 Design and Sea Trials of a New Autopilot Based on Neural Network Controller *Proceedings of the 14th IFAC(Beijing, China)* pp 377-382

[5] Roberts G N 1999 A Fuzzy Controller for Integrated Ship Motion Control *Proceedings of the 14th World Congress of IFAC(Beijing, China)* pp 7-12

[6] Sutton R 1997 Tuning Fuzzy Ship Autopilots Using Artificial Neural Networks *Transactions of the Institute of Measurement and Control* **19** 94-106

[7] Fossen T I and Strand J P 1999 Passive Nonlinear Observer Design for Ships Using Lyapunov Methods: Full-scale Experiments with a Supply Vessel *Automatic* **35** 3-16

[8] Ishii, K. and Ura, T. 2000 An adaptive neural-net controller system for an underwater vehicle *Control engineering practice* **8** 177-184

[9] Labonte, G. 2002 Fast adaptive control of a non-linear system by an adaline: motion in a fluid *Proceedings of the 2002 International Joint Conference on Neural Networks* **2** pp 1837-41

[10] Chen Hongli, Zhao Xiren, Ye Kui and Peng Xiuyan 2004 Using LQG control method for pitch stabilization of ships *Editorial Board of Journal of Harbin Engineering* **25** pp 407-411

[11] Zhao Xi-ren 2003 *Application of Stochastic Processes* (Harbin Engineer University) pp 93-104

[12] Li, J.-H., Lee, P.-M. and Lee, S.-J. 2002 Neural net based nonlinear adaptive control for autonomous underwater vehicles *Proceedings of the 2002 IEEE International Conference on Robotics and Automation* **2** pp 1075-80