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INTERNAL MODEL CONTROL USING NEURAL NETWORK FOR SHIP ROLL STABILIZATION

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Short Paper

INTERNAL MODEL CONTROL USING NEURAL NETWORK FOR SHIP ROLL STABILIZATION

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Key words: ship roll stabilization, internal model control, and neural network.

ABSTRACT

In this paper, a neural network (NN) based on internal model control (IMC) is developed to adjust control parameters for roll motions of a container ship. Controller architecture, which combines neural network with internal model control, has been outlined and its effectiveness demonstrated on the container ship roll stabilizer. The control signal error is used with back-propagation algorithm to update the weights of the neural controller. In conclusion, the neural network based on internal model control systems are analyzed, and compared to classical PID control results. As can be seen from numerical results, the NN based on IMC is implemented successfully to reduce roll amplitude.

INTRODUCTION

The roll motion of ships in large amplitudes is very difficult to control due to nonlinear dynamics. For these reasons during the last decades many researchers have been making a study about roll motion control. The background to the problem of designing roll stabilization controls for ships was reviewed [10] and an overview has been presented [13]. Fin stabilizers are attractive for roll reduction since they are highly effective, work on a large number of ships, and are much easier to control, even for varying load conditions and actuator configurations. Therefore, fin stabilizers can be used in order to provide satisfactory roll damping performance.

Various control strategies have been presented for the roll motion control of ships. Proportional-Integrative-Derivative (PID), which is control classical control system, is proposed for roll motion control [6]. The performance of classical PID optimized PID given, and H-infinity controllers are compared in [2, 5, 9]. Because of the unpredictable operating environment of ships, conventional control methods such as the PID controller may not be able to give good damping performance. Hence, researchers developed internal model control (IMC) systems in order to provide satisfactory performances. IMC concept have found acceptance in industrial applications due to high performance and robustness [16, 17]. A detailed analysis has been given by [11].

For the implementation of IMC algorithm, neural network control method is able to adapt on order to improve the IMC performance. The idea of using neural network for IMC has been considered by [1]. As cited earlier as powerful computational tools neural network techniques have been utilized in many disciplines as well as in marine fields [4, 14, 19]. Efficiency of the proposed NN adaptive control is studied by back-propagation algorithm to update weights of the controller. The back-propagation algorithm introduced two main advantages in accelerating both the speed of the learning process and the speed of the evaluation [7, 8].

In this paper, neural network is adopted in IMC design and shows good advantages. Applicability of a neural network controller based on model reference adaptive control is investigated for designing roll stabilizer control for a container ship.

EQUATION OF MOTION

The equation of motions for a container ship has been obtained from Newton's second law. The dynamic model of the ship is shown Figure 1 [3].

In literature a ship's six degrees of freedom dynamic equations are expressed as:

$$M\dot{\upsilon} + B(\upsilon)\upsilon + C(\eta) = M_f + M_w \quad (1)$$

with

η: position and orientation of the ship

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υ: linear and angular velocity of the ship
M: inertia matrix including added mass
B: matrix consisting of damping terms
C: vector of restoring forces and moments due to gravity and buoyancy
M_f: vector of fin control inputs
M_w: vector of wave inputs

The mathematical model of a container ship used in this study is described in reference [3]. Three degrees of freedom model of the container ship was developed to design a roll controller that uses the fins as a control input.

$$
\begin{aligned}
(m - Y_{\dot v})\dot v &= Y_v + Y_\phi \phi + Y_p p + Y_r r + Y_\alpha \alpha + Y_w s \\
(I_x - K_{\dot p})\dot p &= K_p p + K_v v + K_r r - mgGM\phi + K_\alpha \alpha + K_w s \\
(I_z - N_{\dot r})\dot r &= N_r r + N_\phi \phi + N_p p + N_v v + N_\alpha \alpha + N_w s
\end{aligned} \quad (2)
$$

The above described mathematical model gives a good approximation of the maneuvering behavior of a container ship. Where v is the sway velocity; p, r respectively are the roll and yaw rates. Y_v, K_p and N_r indicates the hydrodynamic coefficients of sway, roll and yaw moments, respectively; m is the mass of the ship; g is the gravity constant; I_x and I_z respectively are the moment of inertia about the X-Z axis; and GM is the ship metacentric height, which indicates the restoring capability of a ship in roll motion. The fin angle is represented by α. The wave slope is s. The fin and wave forces and moments are represented by the terms Y_α, K_α, N_α and Y_w, K_w, N_w, respectively. The ship inertia matrix for 3 DOF,

$$
M = \begin{bmatrix} m - Y_{\dot v} & 0 & 0 \\ 0 & I_x - N_{\dot p} & 0 \\ 0 & 0 & I_z - N_{\dot r} \end{bmatrix} \quad (3)
$$

the Coriolis matrix,

$$
B = \begin{bmatrix} -Y_v & -Y_p & -Y_r \\ -K_v & -K_p & -K_r \\ -N_v & -N_p & -N_r \end{bmatrix} \quad (4)
$$

the restoring matrix,

$$
C = \begin{bmatrix} 0 & -Y_\phi & 0 \\ 0 & mgGM & 0 \\ 0 & -N_\phi & 0 \end{bmatrix} \quad (5)
$$

fin and wave forces and moments are given.

$$
M_f = \begin{bmatrix} Y_\alpha \\ K_\alpha \\ N_\alpha \end{bmatrix} \quad (6)
$$

$$
M_w = \begin{bmatrix} Y_w \\ K_w \\ N_w \end{bmatrix} \quad (7)
$$

1. Fin-wave forces and moments

The force and moments derivatives for the pair of fins are as follows:

$$
\begin{aligned}
Y_\alpha &= \rho V^2 S_f C_{l\alpha} \cos 38^\circ \\
K_\alpha &= \rho V^2 S_f C_{l\alpha} R_f \\
N_\alpha &= \rho V^2 S_f C_{l\alpha} L_f \cos 38^\circ
\end{aligned} \quad (8)
$$

The total ship's velocity is V and R_f is the vertical distance from the fin center of pressure to the roll center of the ship. Lever arm L_f is the distance from the fin center of pressure to midships. The fin angle which is expressed by cos38° shows the location of the fins from the roll center. The effects of the fins are added into the coefficient matrices depending on the location angle.

The wave disturbance was modeled by an input disturbance. The forces and moments generated by the wave acting upon the ship's hull have been established using the results of JONSWAP spectrum. The wave forces and moments are given by Y_w, K_w, N_w and they should be added to the right-hand side of the Eq. (2) as [15].

$$
\begin{aligned}
Y_w &= m\, \overline{a_1}\, S(t) \\
K_w &= mL\, \overline{a_2}\, S(t) \\
N_w &= mL\, \overline{a_3}\, S(t)
\end{aligned} \quad (9)
$$

where Y_w is the sway force, K_w is the roll moment and N_w is the yaw wave moment. $\overline{a_1}, \overline{a_2}$ and $\overline{a_3}$ are filter parameters. $S(t)$ is a spectrum for each exciting force

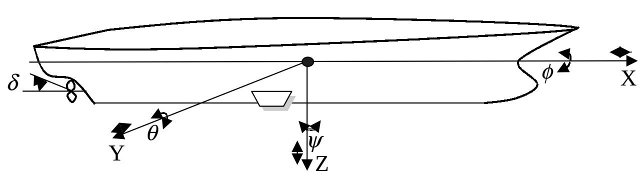

Fig. 1. Ship coordinate system.

and moments.

STRUCTURE OF ROLL STABILIZATION CONTROL SYSTEM

The previous section about mathematical models is described. In this section, the controller is designed to stabilize roll motion of the container ship. Figure 2 shows a block diagram of an actual roll stabilization system. In this diagram, ϕ is the ship rolling angle and is the angle of the fin. ϕ_d is represent and desired roll angle.

The stabilizing force will reduce the roll of the containership. The designed system has three degrees of freedom structure using a IMC and neural network control methods. In this study, it is considered neural network based on IMC system designed to make the output of the plant track a desired angle.

1. PID control for the container ship

In the following, the design of conventional controllers will be discussed. In general the PID control method is employed in the roll control. The control is made by proportioning the fin angle to the rolling angle. First PID controller is considered. The control signal of the PID controller is given by Eq. (10). The closed loop diagram of the feedback system is shown in Figure 3.

Here, $\alpha(t)$ is the control signal, ϕ_d, ϕ_e and ϕ are the desired roll angle, the rolling error and the actual rolling, respectively. PID control has been used in industry widely and successfully. The control input $\alpha(t)$ and the roll error are obtained as follows:

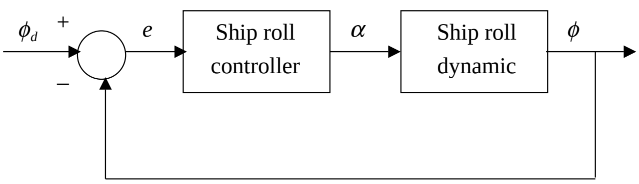

Fig. 2. Containership roll control system.

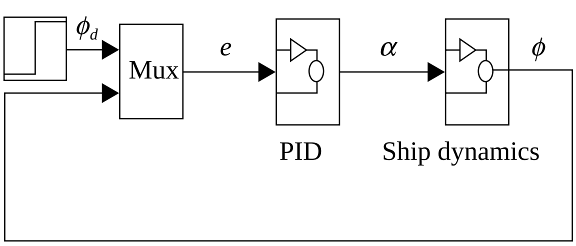

Fig. 3. Feedback control system with PD controller.

$$\alpha(t) = \left[k_p \phi_e(t) + k_d \frac{d\,\phi_e(t)}{dt} + k_i \int \phi_e(t)\, dt \right] \tag{10}$$

$$\phi_e(t) = \phi_d(t) - \phi(t) \tag{11}$$

k_p, k_i, k_d are proportional, integrative and derivative constants. For the PID controllers, parameters have to be tuned. These values are obtained by use of Ziegler-Nichols method [12].

2. The internal model controller design

In order to control the roll motion of the container ship, an internal model controller is considered. A basic internal model control is shown in Figure 4. Where $\hat{G}$ is the process model of the roll motion and $Q(s)$ is a regulator. $\alpha(s)$ denotes fin control input, ϕ_c represents commanded roll angle, $G(s)$ is the roll motion transfer function as follows.

$$G(s) = \frac{\phi(s)}{\alpha(s)} = \frac{2.4s + 13.5}{s^3 + 5.4s + 3085.5s + 12085} \tag{12}$$

The IMC and classical feedback structures are equivalent under the following transformations [16].

$$C = \frac{Q}{1 - C\hat{G}} \tag{12}$$

$$Q = \frac{C}{1 + C\hat{G}} \tag{13}$$

Where C represents the controller. The main feature of this control system is the way in which it checks difference between the outputs of the process and of the internal models. This difference is fed back into the controller to reject error effects. In order to obtain the internal stability, the mismatch effect between the roll motion and the model of the roll motion should be minimized. Hence, the controller can include a filter to increase robustness to model mismatch and disturbances.

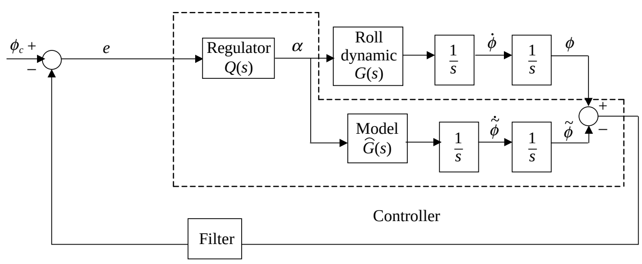

Fig. 4. Schematic of the IMC scheme.

$$Q = F\hat{G}_{inv} \tag{14}$$

Where $\hat{G}_{inv}$ is an approximation to the inverse of the vehicle model $\hat{G}$. $F(s)$ is a low pass function of appropriate order.

$$F(s) = \frac{1}{(1 + \tau_f s)^n} \tag{15}$$

Where τ_f is the filter parameter and n is the order of the filter. Orders of the filter are chosen in such away so that the controllers transfer functions are proper.

3. Back-propagation neural network

The back-propagation algorithm is the most important algorithm for the supervised training of NN it derives its name from the fact that error signals are propagated backward through the network on a layer-by-layer basis. The neural network is three layers in this study. The network consists of input, hidden and output layers. The network converts the inputs according to the connection weights. These weights are adjusted during the learning process. To minimize the sum of the squared errors between the desired output and the network output. A simple neural network represents in Figure 5.

The output layer is given by

$$net_j = \sum_j^i w_{ji} o_i + \theta_j \tag{16}$$

where w_{ji} represents the weight between hidden node j and input node i. The output of unit in the hidden and input layers are represented by o_i. The back-propagation algorithm adjusts the network parameters in order to minimize the mean square error.

$$E_p = \frac{1}{2} \sum_{j-output} (t_{pj} - o_{pj})^2 \tag{17}$$

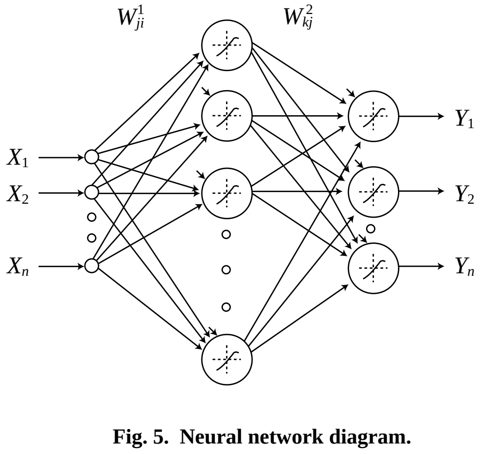

Fig. 5. Neural network diagram.

where t_{pj} is the desired output and o_{pj} actual output. If a sigmoid transfer function is used in the operation element

$$o_{pj} = \frac{1}{\sum_j 1 + e^{-w_{ji} o_{pj} + \theta_j}} \tag{18}$$

Using Eq. (16) and (18), the activity of each unit is propagated forward through each layer of the network. Error for each unit is calculated.

$$\delta_{pj} = o_{pj}(t_{pj} - o_{pj})(1 - o_{pj}) \tag{19}$$

A hidden layer error is back propagated as follow,

$$\delta_{pj} = o_{pj}(1 - o_{pj}) \sum_k \delta_{pk} w_{kj} \tag{20}$$

The change in each weight is calculated. This rule for the adaptation of the weights is known as the generalized delta rule.

$$\Delta_p w_{ji}(t + 1) = \alpha \delta_{pj} o_{pi} + \varepsilon \Delta_p w_{ji}(t) \tag{21}$$

where α is constant that determines the learning rate of the back propagation algorithm, ε determines the effect of previous weight changes on the current direction of movement in weight space. The learning rate has used between 0.01 to 10.

SIMULATIONS

The controller design objectives are to reduce roll amplitude and to evaluate any differences in performance between the PID and the NN based on IMC design. To demonstrate effectiveness of this proposed controllers a series of simulations are performed on the container vessel.

Using the process input α and previous output ϕ the neural network calculates ϕ_m which is used to calculate the error of the neural model $e = \phi - \phi_m$ used to adapt the neural mode with back propagation method and to produce feedback signal.

The Neural Network input and output functions for the container ship roll stabilizer system are given in Figure 6. The figure shows the NN plant model and the NN controller. The Neural Network is constituted by an input layer of two neurons, a hidden layer of thirteen neurons and an output layer one neuron. The controller inputs are the desired roll angle and the actual roll angle.

The output is the fin angle, which should drive the containership roll to the desired roll angle. In order to upgrade the NN based on IMC, the actual error is calculated by back propagation algorithm. A container ship and fin stabilizer whose main particulars are given

Table 1. Container ship main data

Container ship			Roll fins		
Length between perpendiculars	L	230.66 (m)	Profil area	s_f	3.6 m^2
Maximum beam	B	32 (m)	Lift coeff. slope	$C_{L\alpha}$	2.464 1/rad
Design draft	T	10.7 (m)	Mean span	s_p	3 m
Design displacement volume	∇	46070 (m^3)	Mean chord	$\overline{c}$	1.2 m
Metacenter height	GM	0.83 (m)	Section shape		NACA 0015

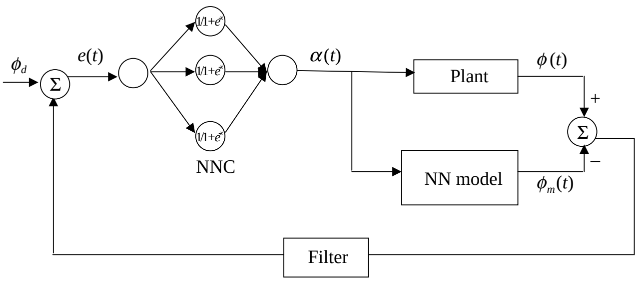

Fig. 6. Neural network as a controller in the IMC approach.

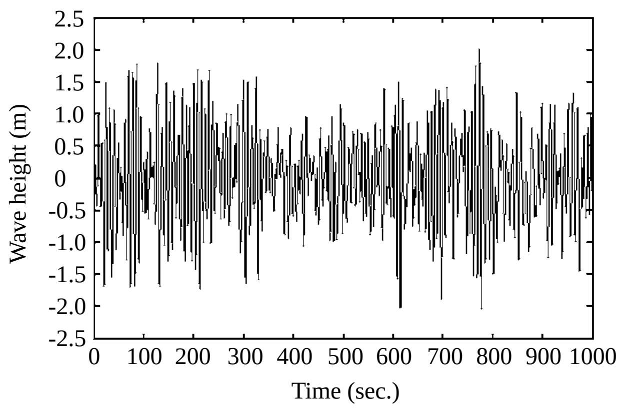

Fig. 7. Wave function.

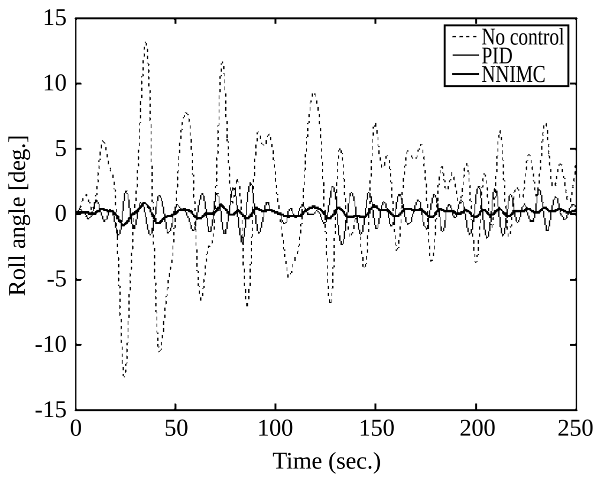

Fig. 8. Neural network based IMC of roll motion.

in Table 1. Due to safety reasons, the fin angle is limited in the range of ±30°.

The wave disturbance may be modeled as an input disturbance, which is generated by Fossen [3] in Figure 7. The damping ratio ζ is set to between from 0.05 to 0.1, the encounter frequency is set to between 0.3 to 1.3 rad/sec and the wave strength factor is K_ω set to 10.

In order to obtain damping ratio, the formula suggested by reference [18] can be used. Roll reduction ratio

$$\text{Roll reduction ratio}\,(\%) = 100 \cdot \frac{AP - RCS}{AP} \tag{22}$$

where AP is the standard deviation (RMS) of roll amplitude when the fin stabilizer off. RCS is the standard deviation of roll amplitude while the fin stabilizer is open.

Figures 8 and 9 show control performance for PID and neural network based on internal model controllers. The results in figures show that the scheme proposed in this paper has good response speediness and robustness. It is observed that the roll control system is capable of attaining the NN based on internal model controller result. The roll angle has been reduced from 8.6° to 0.5°, which corresponds to a 94% roll angle reduction with NN based on IMC. Table 2 summarizes the roll reduction results. Figure 10 shows the fin angle when the surge speed is set equal to 12.7 m/sec.

Very good roll reduction is achieved with minimal control effort required with NNIMC.

CONCLUSION

In this paper an internal model controller of a roll motion stabilizer system was designed. Controller architecture combines neural network based on internal model control. Simulation studies are included to illustrate the effectiveness of a neural network control algorithm. This leads to the conclusion that the NN

Table 2. Controller performance

	Roll angle (deg.)	Roll velocity (deg./sec.)	Roll reduction ratio (%)
No control	8.6	3	
PID	1.8	0.85	79
NNIMC	0.5	0.17	94

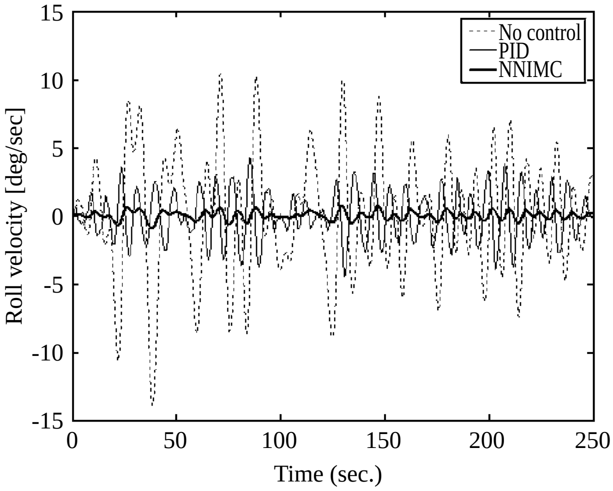

Fig. 9. Neural network based IMC of roll velocity.

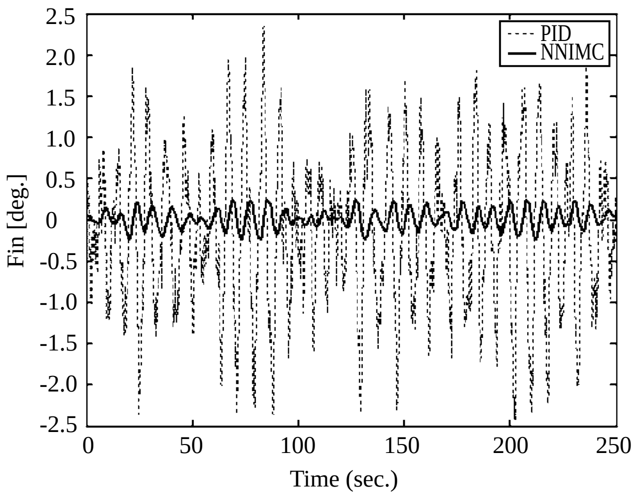

Fig. 10. The corresponding fin response.

based on internal model controller approach is a good alternative to classical controller design.

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