Research on Dynamic Coefficient of Lift Feedback Fin Stabilizer and Its PIDNN Controller

Zhang Haipeng, Yao Xuliang, Chen Fang, Jin Hongzhang

***Abstract*--This only looks like the abstract. Dynamic lift coefficient is an important parameter in the calculation of lift in fin stabilizer system, but there exists great error in the formula. Lift feedback fin stabilizer is a new kind of fin stabilizer, which is the most effective ship roll reducing equipment. In this paper the defects of fin angle feedback fin stabilizer caused by the dynamic coefficient are discussed, the control principle of lift feedback fin stabilizer is given, and finally a PID neural network controller is proposed.**

***Keywords*--dynamic coefficient, lift, fin stabilizer, roll, PID controller, neural network,**

I. INTRODUCTION

Fin stabilizer has been used for more than seventy years as one of the most effective ship roll reducing equipments[1]. But it still has some defects. There are many uncertain factors in the conventional formula to calculate the lift which is gotten by the static hydrodynamic experiment because there exist errors in the static hydrodynamic experiment. People then designed a new kind of fin stabilizer—lift feedback fin stabilizer in which the lift of the fin is gotten not by calculated but measured directly. So the lift can be gotten more accurately and the fin stabilizer can work more efficiently.

PID controller is the most popular control strategy in industrial processes due to its versatility and tuning capabilities. Most fin stabilizers are controlled by PID controller now. But the conditions on the ship are uncertain and often change greatly, and the conventional PID controller can't modulate its parameters according to the system requirement as the conditions changing. Neural network can perform adaptive control through learning process. As the microprocessors providing powerful computation capabilities, neural networks can be used for controller. But there are some problems, which should be solved in practice. The main problems are the slow learning process, the long weight convergence time and uncertain property. PID neural network (PIDNN) controller utilizes the advantages of both PID control and neural structure. It can control the systems through quick learning process and has perfect performances. Because of the merits of the neural networks and the PID controller, the PIDNN controller can improve the effect of the fin stabilizer greatly.

The lift feedback fin stabilizer controlled by PIDNN controller shows perfect performance because it is improved on control structure and control theory based on the old one.

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II. LIFT FEEDBACK FIN STABILIZER

A. *The Roll Model of Ship*

There are so much uncertain factors when a ship navigates the sea, so the roll model of ship is nonlinear. But we can analyze the movement of roll using a linear model when the angle of roll is small. As the Conolly theory the linear roll model of ship is showed:

$$(I_x+\Delta I_x)\ddot{\phi}+2N_u\dot{\phi}+Dh\phi=-(\Delta I_x\ddot{\alpha}_2+2N_u\dot{\alpha}_2+Dh\alpha_1) \qquad (1)$$

Where

I_x ——inertia moment of roll, kg • m^2/s

ΔI_x ——added inertia moment, kg • m^2/s

$2N_u$ ——damping coefficient of roll

D ——displacement of ship, kg

h ——metacentric height of ship, m

ϕ ——angle of roll, rad

$$\alpha_1=\alpha_{01}\sin\omega_e t\text{ ,} \qquad (2)$$

$$\alpha_2=\alpha_{02}\sin\omega_e t\text{ ,} \qquad (3)$$

Where

α_{01} is the largest significant angle of wave slope corresponding to angle of wave slope;

α_{02} is the largest significant angle of wave slope corresponding to velocity and acceleration of wave slope;

ω_e is the encounter frequency of ship.

$\Delta I_x \ddot{\alpha}_2$ and $2N_u \dot{\alpha}_2$ are much smaller than $Dh\alpha_1$ in equation (1), because of which we can only consider the effect of $Dh\alpha_1$. The Eq. (1) becomes:

$$(I_x + \Delta I_x)\ddot{\phi} + 2N_u\dot{\phi} + Dh\phi = -Dh\alpha_1 \tag{4}$$

Assuming the initial condition is $\phi(0) = \dot{\phi}(0) = \ddot{\phi}(0) = 0$, the Laplace transform of Eq. (1) is written as:

$$W_c(s) = \frac{\phi(s)}{\alpha_1(s)} = \frac{1}{T_c^2 s^2 + 2T_c\zeta_c s + 1} \tag{5}$$

Where

$$T_c = \sqrt{\frac{I_x + \Delta I_x}{Dh}} \tag{6}$$

$$\zeta_c = \frac{N_u}{Dh(I_x + \Delta I_x)} \tag{7}$$

the natural roll period of ship is:

$$T_0 = 2\pi\sqrt{\frac{I_x + \Delta I_x}{Dh}} \tag{8}$$

A ship model is used in the paper, where $T_c = 1.4324$, $\zeta_c = 0.1325$. Eq. (5) becomes:

$$W_c(s) = \frac{\phi(s)}{\alpha_1(s)} = \frac{1}{2.0518s^2 + 0.3796s + 1} \tag{9}$$

B. *The Roll-reducing Principle of Lift Feedback Fin Stabilizer*

The roll reducing principle of lift feedback fin stabilizer is similar to that of the classical fin stabilizer[3]. But the lift is measured by lift sensors in the lift feedback fin stabilizer system. The ship will roll because of a disturbing moment when the wave acts on it. Then the fins will be driven to contrary angles so that they can produce a hydrodynamic righting moment, which is produced by the lift *L*, to reduce the ship roll. See Figure 1.

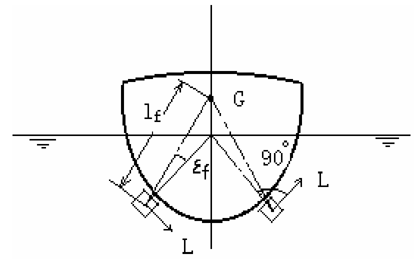

Figure 1. Lift and righting moment

The linear roll model of ship is expressed by Eq. (1) in which the right of the Eq. is the wave disturbing moment. If there existss a control moment K_c produced by the fin stabilizer, Eq. (1) becomes:

$$(I_x + \Delta I_x)\ddot{\phi} + 2N_u\dot{\phi} + Dh\phi = -Dh\alpha_1 - K_c \tag{10}$$

If $K_c = -Dh\alpha_1$, the right of Eq. (10) becomes zero and the ship will stop rolling. There exist three moments, which are the inertia moment $(I_x + \Delta I_x)\ddot{\phi}$, the damping moment $2N_u\dot{\phi}$ and the restoring moment $Dh\phi$. They balance with the disturbing moment $Dh\alpha_1$ and control moment K_c. If the control moment counteracts the disturbing moment, K_c should include three moment components of $A\phi$, $B\dot{\phi}$ and $C\ddot{\phi}$ where *A*, *B*, and *C* are proportionality coefficients. Thus the control moment K_c produced by the lift fin stabilizer should be:

$$K_c = A\phi + B\dot{\phi} + C\ddot{\phi} \tag{11}$$

Eq. (10) becomes:

$$(I_x + \Delta I_x + C)\ddot{\phi} + (2N_u + B)\dot{\phi} + (Dh + A)\phi = -Dh\alpha_1 \tag{12}$$

If *A*, *B* and *C* satisfy Eq.(13)

$$\frac{A}{Dh} = \frac{B}{2N_u} = \frac{C}{I_x + \Delta I_x} = F \tag{13}$$

where *F* is a constant, Eq.(12) becomes:

$$(I_x + \Delta I_x)(1+F)\ddot{\phi} + 2N_u(1+F)\dot{\phi} + Dh(1+F)\phi = -Dh\alpha_1 \tag{14}$$

and Eq(14) can be written as:

$$(I_x + \Delta I_x)\ddot{\phi} + 2N_u\dot{\phi} + Dh\phi = -Dh\alpha_1(1+F)^{-1} \tag{15}$$

Eq.(15) shows that the disturbing moment $Dh\alpha_1$ is reduced (1+F) times. The ship roll will be compensated completely if we choose the proportionality coefficients correctly.

C. Dynamic Coefficient of Lift Feedback Fin Stabilizer

The excellent roll stable effect of fin stabilizer has been recognized for many years. Figure 2 illustrates the control principle of classical fin angle feedback stabilizer[4].

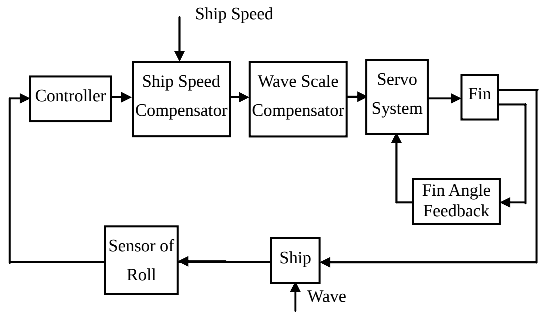

Figure.2 Fin angle feedback stabilizer

But the system showed in Figure 2 still has some defects. In Figure 2 we get the lift by calculating Eq. (16) that is

$$L = \frac{1}{2}\rho V^2 A_F C_L \tag{16}$$

Where
A_F : projected area of fins, m^2
C_L : lift coefficient of fin
ρ : density of sea water, kg/m^3
V : ship speed, m/s
α_f : fin angle, deg

There existss a great error in Eq. (16). The lift coefficient C_L we usually use in Eq. (16) is static lift coefficient and is linearized approximatively. The relationship between static lift coefficient C_L and fin angle α_f is expressed in Figure 3, which shows C_L and α_f are direct ratio.

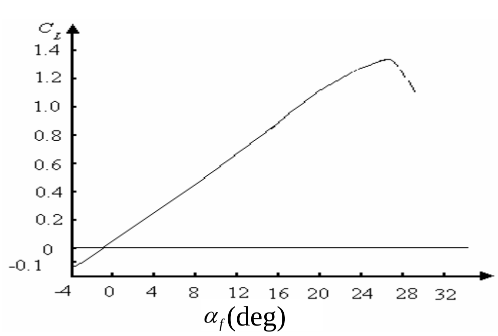

Figure.3 Relationship between static lift coefficient and fin angle

But in fact the lift coefficient C_L is dynamic and nonlinear that is very difficult to obtain. We got it via a fin model experiment in a towing tank[2] from which we can see that there exists great difference between the static lift coefficient and dynamic lift coefficient. Figure 4 shows a set of coefficients, which were obtained by us in the towing tank laboratory.

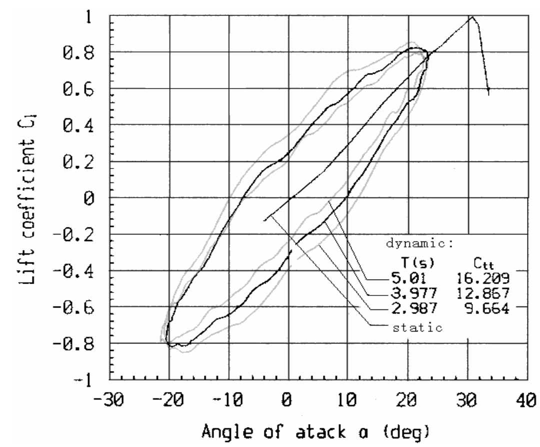

Figure.4 Compare of static and dynamic lift coefficient

In Fig.4 the dynamic coefficients are measured at three different periods: 5.01s, 3.977s and 2.987s, and the corresponding period coefficients C_{tt} obtained in Eq(17) are 16.209, 12.867 and 9.664.

$$C_{tt} = \frac{VT}{C} \tag{17}$$

Where
V: speed of tow truck, m/s
T: period of fin, s
C: average chord length, m

And the ship speed V is 1.2m/s in the experiment. From Fig.4 we can see the variation of static lift coefficient is linear and the slope can be regarded as a constant when the angle is less than the angle of stall. But the curves of the dynamic lift coefficients at different periods are three ellipses approximatively and nonlinear. There existss so much error between them that the L in Eq.(16) is different from the value of real lift.

In Eq.(16) V should be the inflow velocity in theory which will bring more uncertainties, but we substitute it for the ship speed in practice.

Usually in the design of the controller we take into account not all the factors that can produce the lift but only the ship speed, thus there is an evident hydrodynamic lift error; there are errors between the lift produced by the fin angle feedback stabilizer and what the ship needs to counterwork the sea factually.

All the above-mentioned errors influence the roll-reducing effect of fin angle feedback stabilizer greatly.

To overcome the errors, lift fin stabilizer is researched in which the lift of fins is not calculated but measured by lift sensor directly. The principle of lift fin stabilizer can be expressed in Figure 5.

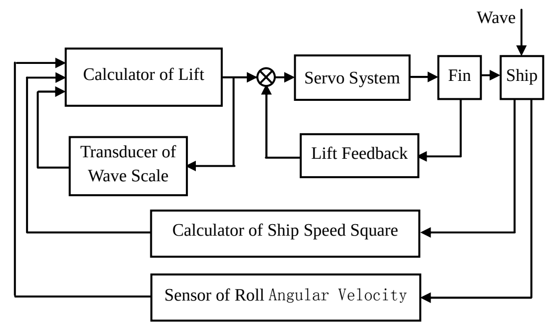

Figure 5. Lift fin stabilizer theory

In the system, because the lift is measured directly and fed back to produce the righting moment command, the lift errors produced as we use Eq. (16) can be avoided, and disturbing moment of roll produced by the wave can also be counteracted effectively. As the influence of the ship speed, fin angle and angular velocity on the lift is reflected by the lift directly, we can get the stability moment more precisely via ship speed and fin angle. The lift feedback fin stabilizer can avoid the problem that the fin angle feedback can't reflect the hydrodynamic lift error and influence on lift brought by ship pitching, rolling, heaving as well as ship hull and bilge keel.

III. PID NEURAL NETWORK CONTROLLER

Figure 6 illustrates the structure of the PID Neural Network controller[6].

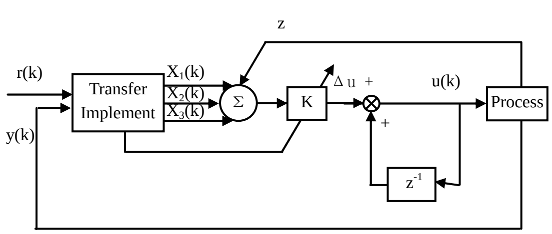

Figure 6 Structure of PID neural network controller

The input of the transfer implement is r(k) and output y(k); the output of the transfer implement is states x_1, x_2 and x_3 which are required in neuron learning control.

Where

$$\left.\begin{aligned} x_1(k) &= r(k) - y(k) = e(k) \\ x_2(k) &= \Delta e(k) \\ x_3(k) &= e(k) - 2e(k-1) + e(k-2) \end{aligned}\right\} \tag{18}$$

$z(k) = x_1(k) = r(k) - y(k) = e(k)$ is the performance index. K is the proportion coefficient of the neuron, $K > 0$. The control signal is obtained via Eq. (19)

$$u(k) = u(k-1) + K\sum_{i=1}^{3} w_i(k)x_i(k) \tag{19}$$

Where $w_i(k)$ is the weight coefficient of corresponding to $x_i(k)$. The function of self-learning and self-adaptation of PID neuron controller is realized by adjusting the weight coefficient. There are different learning rules to adjust the weight coefficient. We adopt the $Pe^2(k+d) + Q\Delta u^2(k)$ as the performance index. The function of performance index is written

$$J_2 = \frac{1}{2}\left|P[r(k+d) - y(k+d)]^2 + Q\Delta u^2(k)\right| \tag{20}$$

Where

$y(k+d)$——output of process when $t = k+d$;

$r(k+d)$——referential input of process when $t = k+d$;

d——total lag of process;

P,Q——weight coefficients of output error and control increment.

The amendment of weight coefficient $w_i(k)$ is towards the reduction direction of J_2 that is the direction of nonpositive gradient of $w_i(k)$. Thus the adjustive quantity of $w_i(k)$ is

$$\begin{aligned} &\Delta w_i(k) = w_i(k+1) - w_i(k) = -\eta_i \frac{\partial J_2}{\partial w_i(k)} = \\ &\eta_i K\left\{Pb_0 e(k+d)x_i(k) - QK\left[\sum_{i=1}^{3} w_i(k)x_i(k)\right]x_i(k)\right\} \end{aligned} \tag{21}$$

Where

$\eta_i (i = P, I, D)$——learning velocity;

b_0——the first value when an indicial response is input into the process, which can be gotten by experiment.

We use the unstandardized Eq. (19) in the deduction of Eq.

(20). If the output of neuron is standardized and induced, the learning algorithm becomes:

$$\left.\begin{aligned}
&u(k)=u(k-1)+K\sum_{i=1}^{3}\overline{w_i}(k)x_i(k)\\
&\overline{w_i}(k)=\frac{w_i(k)}{\sum_{i=1}^{3}\left|w_i(k)\right|}\\
&w_1(k+1)=w_1(k)+\eta_I K\left\{Pb_0 e(k+d)x_1(k)-QK\left[\sum_{i=1}^{3}w_i(k)x_i(k)\right]x_1(k)\right\}\\
&w_2(k+1)=w_2(k)+\eta_P K\left\{Pb_0 e(k+d)x_2(k)-QK\left[\sum_{i=1}^{3}w_i(k)x_i(k)\right]x_2(k)\right\}\\
&w_3(k+1)=w_3(k)+\eta_D K\left\{Pb_0 e(k+d)x_3(k)-QK\left[\sum_{i=1}^{3}w_i(k)x_i(k)\right]x_3(k)\right\}
\end{aligned}\right\} \tag{22}$$

In Eq. (22), $x_1(k)$, $x_2(k)$ and $x_3(k)$ are the same as those in Eq. (18). We replace $e(k+d)$ by $e(k)$ because it can't be measured.

The controller used in lift fin stabilizer system is designed by $K=0.06$, $\eta_P=80$, $\eta_I=160$, $\eta_D=15$, $w_1(0)=0.8$, $w_2(0)=0.7$, and $w_3(0)=0.6$.

Figures 7-9 illustrate the behavior of the system that is gotten from simulations. The significant wave height $h=3.8m$ and encounter angle $\beta=90^\circ$. The angle of roll with lift fin stabilizer is smaller than that with the angle feedback fin stabilizer obviously.

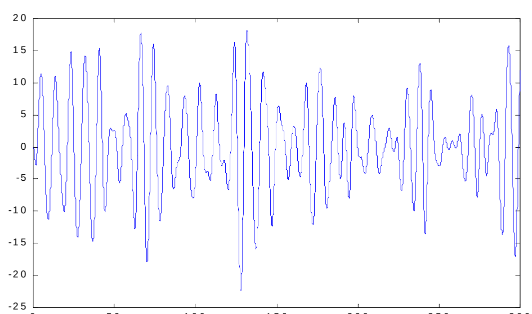

Figure 7. Roll angle of unstabilized ship

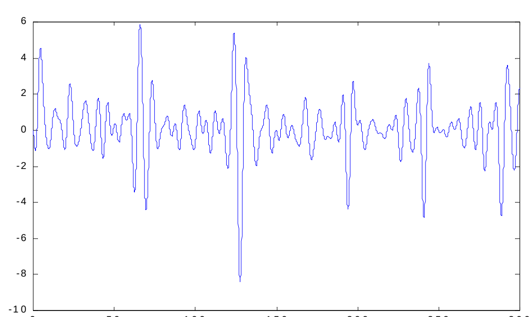

Figure 8. Roll angle of ship with angle feedback fin stabilizer

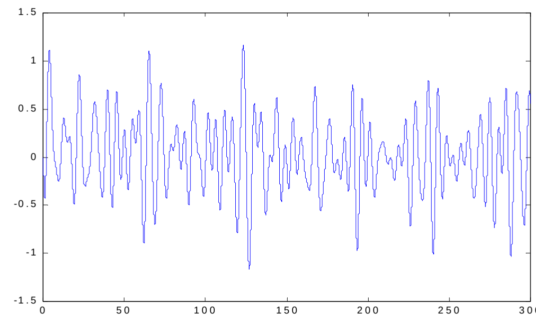

Figure 9. Roll angle of ship with lift feedback fin stabilizer

The standard deviations of Figures 7-9 are:

$\sigma[\phi(t)]=7.3150^\circ$, standard deviation of roll angle of unstabilized ship

$\sigma[\phi(t)]=1.6447^\circ$, standard deviation of roll angle of ship with angle feedback fin stabilizer

$\sigma[\phi(t)]=0.3991^\circ$, standard deviation of roll angle of ship with lift fin stabilizer.

IV. CONCLUDING REMARKS

In this paper we analyse defects of angle feedback stabilizer caused by the dynamic coefficient and show the control principle and composition of the lift feedback fin stabilizer system that is controlled by a neural network controller. Because the lift is measured directly for the lift feedback fin stabilizer, the error caused by the dynamic coefficient can be avoided, and the roll reducing effect is much better than the fin angle feedback stabilizer. The application of PID neural network controller in fin stabilizer can adapt the uncertainty of the ship model and assume to get better performance.

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