Simulation and Model Experiments of Rudder Roll Stabilization System

Tetsunori Yamashita, Kazuhiko Hasegawa and Namkyun Im
Department of Naval Architecture and Ocean Engineering, Osaka University.
2-1, Yamada-oka, Suita, Osaka, 565-0871,JAPAN

ABSTRACT

In this paper, the authors discuss the rudder roll stabilization system (RRSS) to control not only yawing but also rolling simultaneously, using the modern optimal control theory. In this system, a multivariate auto regressive model of the rudder, roll and yaw motion are fitted to the actual data which are obtained by model experiments and the optimal control gain are chosen using appropriate evaluating function. Based on the theory, simulation and experiments were carried out. Through the simulation and the experiment, RRSS is discussed for its effectiveness.

Keywords: ship, roll reduction, rudder, optimal control, model experiment

1.INTRODUCTION

Roll stabilization or reduction is one of themes widely studied for the purpose of the better living condition onboard, secure of cargo safety, improvement of safety in the sea and giving proper working circumstance to onboard equipment. There are equipment regarded as a roll stabilization system such as a fin stabilizer, an anti-rolling tank and a weight stabilizer. But these equipment have many restraint factors such as the weight, the arrangement and the price in order to be used in common ship. For example though the fin stabilizer is one of the most effective equipment in the roll stabilization system, the restraints and practical are the cost and the difficulty of its arrangement. It is hard to equip it in relatively smaller ships. The rudder roll stabilization system (RRSS) is thus converted and various control theories are applied to realize it[1][2][3]. Rudder roll stabilization system is utilizing the lifting force to reduce the roll motion like a fin stabilizer. However, contrary to a fin stabilizer, it needs neither additional space nor cost.

The purpose of this paper is to verify the effectiveness of rudder roll stabilization system in simulation and in model experiments.

2.DESIGN OF RUDDER ROLL STABILIZATION SYSTEM

2.1 System identification

System modeling is essential in designing control system. In general, there are two kinds of modeling methods for dynamic system. One is a physical model, which analyzes inside mechanism with physical theory approach. The problem will be the approximation during the modeling and its validation. Besides, as the physical dynamics is sophisticated, it is actually difficult to model it with sufficient agreement. Therefore in such a case it had better model the system the statistically on the basis of input and output relation which explain the movement of the real world. One of them is time series model. This section discusses the modeling method for ship dynamic characteristics and external disturbance by using multivariate auto regressive model (AR model). In general, a time series variable vector $X(t)$ can be expressed as follows using this method:

$$X(t) = \sum_{m=1}^{M} A(m)X(t-m) + U_0(t) \tag{1}$$

where $X(t)$ is a stationary state vector composed of the relating ship motion, $U_0(t)$ is white noise variable and $A(m)$ is [3x3] coefficient array. In eq. (1) $A(m)$ can be derived Levinson-Dervin's method using the estimated value of cross covariance in the time series system.

Eq. (1) is inconvenient to design the optimum control system, so we can modify it so as that $X(t)$ is divided into two parts as:

$$X(t) = \sum_{m=1}^{M} a(m)X(t-m) + \sum_{m=1}^{M} b(m)Y(t-m) + U(t) \tag{2}$$

where $X(t)$ is 2-dimensional state vector composed of yaw angle and roll rate, $Y(t)$, 1-dimensional control vector of rudder angle, $a(m)$, coefficient matrix of [2x2] and $b(m)$, coefficient matrix of [1x1]. The relationship between coefficients of eqs. (1) and (2) is as follows.

$$A(m) = \begin{bmatrix} a(m) & b(m) \\ * & * \end{bmatrix}, \quad U_0(t) = \begin{bmatrix} U(t) \\ * \end{bmatrix}$$

By the way, M in eq. (1), a degree of model is determined by MAICE method, to minimize the value of AIC (Akaike's Information Criterion)[4] defined by

$$AIC(M) = N \log\{det(\Sigma_M)\} + 2r(r+s)M \tag{3}$$

where N is the number of data, r is that of state vector, s is that of control vector and Σ_M is matrix of $[r \times r]$ in the part of the covariance of $U(t)$.

2.2 State space representation

The state space representation is obtained as

$$\begin{aligned} Z(t) &= \Phi Z(t-1) + \Gamma Y(t-1) + W(t) \\ X(t) &= HZ(t) \end{aligned} \tag{4}$$

$$\Phi = \begin{bmatrix} a(1) & I & 0 & \cdots & 0 \\ a(2) & 0 & I & \cdots & 0 \\ \vdots & \vdots & \vdots & & \vdots \\ a(M-1) & 0 & 0 & \cdots & I \\ a(M) & 0 & 0 & \cdots & 0 \end{bmatrix}, \quad \Gamma = \begin{bmatrix} b(1) \\ b(2) \\ \vdots \\ b(M-1) \\ b(M) \end{bmatrix}, \quad W(t) = \begin{bmatrix} U(t) \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

$$H = \begin{bmatrix} I & 0 & \cdots & 0 & 0 \end{bmatrix},$$

where $Z(t)$ is state variable, $Y(t)$ is control variable, Φ is transition matrix, Γ is control vector, H is measurement vector and $W(t)$ is noise vector.

Even there are many methods to translate eq. (2) to eq. (4), we adopted the method proposed by Ohtsu[5].

2.3 Design of optimal control system under a quadratic performance function

To obtain the optimal control gain, we need to define certain performance function. Here we take the variation of the state vector and the amount of variable's change as the performance function.

$$J = E\left[\sum_{t=1}^{I} Z(t)^T Q\, Z(t) + Y(t-1)^T R\, Y(t-1)\right] \tag{5}$$

where Q and R are weighting matrices to the state vector and to the control one respectively and E is average operator.

$G(t)$, a control gain is obtained to minimize the value of performance function by dynamic programming method.

$$Y(t) = G(t)Z(t) \tag{6}$$

In eq. (6) $G(t)$ is converged to a constant value in the infinite evaluation period I. So it is possible to rewrite it as follows.

$$Y(t) = GZ(t) \tag{7}$$

3.EXPERIMENT WITH SHIP MODEL

3.1 System of experiment

To obtain matrix $A(m)$ in eq. (1) and to confirm the theory described above, experiments were carried out. Container ship model[6] was used for the experiments. The principal particulars of the ship model are shown in Table 1. Body plan and experimental setup and measurement / control system are shown Figs. 1 and 2. A rotating disk was equipped on the deck to excite the ship model for periodical rolling. In the experiment, the forced rolling period is 4 seconds, and sampling interval is 0.2 second.

Table 1 The principal particular of ship model

Items			Ship	Model
Hull	Length	L(m)	150	2.5
	Breadth	B(m)	27.2	0.455
	Depth	D(m)	13.5	0.225
	Draught	df(m)	8.5	0.142
		da(m)	8.5	0.142
	Block Coefficient	Cb	0.667	0.667
Rudder	Area	AR(m²)	28.52	0.007941
	Aspect ratio	Λ	1.6827	1.6827
	Model Scale			1/60

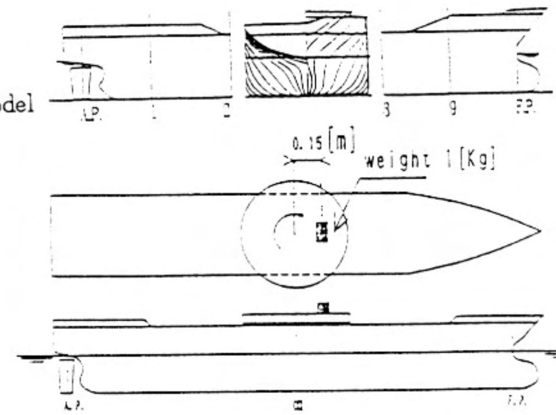

Fig.1 Body plan and experiment setup

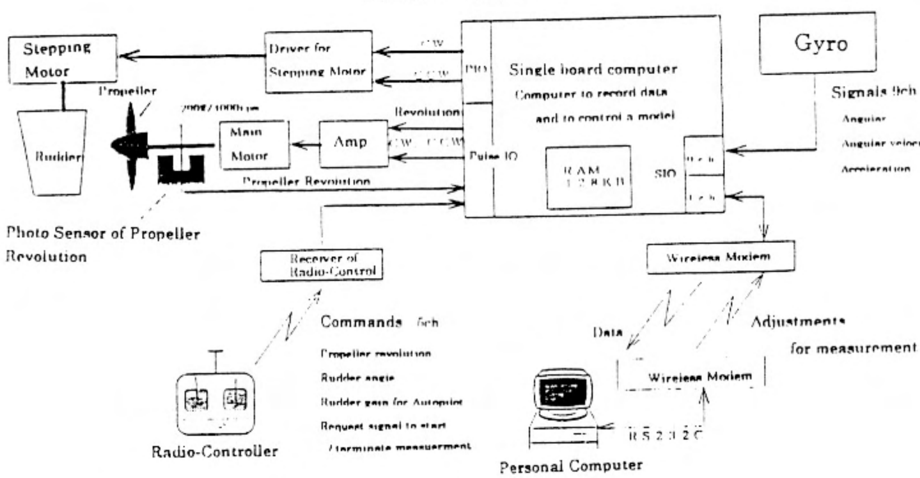

Fig.2 Ship model measurement / control system

3.2 Simulation

The random steering test was conducted to obtain coefficients of AR model. From the recorded data of roll rate, yaw angle and rudder angle, AR model was obtained. The order of the model was 9, using MAICE method. According to Oda *et al.*[3], roll rate is selected to be controlled. The data used in identification are shown in Fig.3.

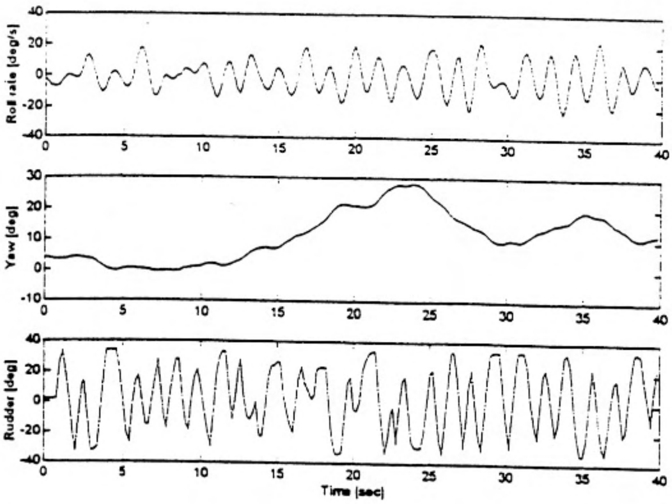

Fig.3 Data for identification of AR-model

The controlled gains are determined from the AR model thus obtained taking account of the weighting factors Q, R in eq. (5). Simulation is carried out to evaluate the effect of weighting factors. In simulation $Y(t\text{-}1)$ in eq. (4) is converted to $GZ(t\text{-}1)$ using eq. (7). Then eq. (4) becomes

$$\begin{aligned} Z(t) &= \Phi Z(t-1) + \Gamma Y(t-1) + W(t) \\ &= (\Phi + \Gamma G)Z(t-1) + W(t) \end{aligned} \tag{8}$$

where $W(t)$ is a white noise which have same value with deviation of $U(t)$ in eq. (2).

Fig. 4 shows time histories of one of simulation results. In the figure the solid line in time histories until 20 seconds denotes the result by autopilot control (with weight zero for roll rate), and the solid line over 20 seconds does that of by roll stabilization control system. The dotted line over 20 seconds is that of autopilot system.

There can be seen any significant improvement from the figure, but 23 % reduction is obtained from this result when we define roll reduction as

$$Roll\ reduction\ (\%) = \{(\sigma_{AP} - \sigma_{RRSS})/\sigma_{AP}\} \times 100 \tag{9}$$

where σ_{AP} denotes the standard deviation of roll rate in autopilot system and σ_{RRSS} that in RRSS respectively.

The result of simulation with different weighting factors is summarized in Table 2. From this simulation it is clear that around 20 % of reduction of roll motion can be achieved.

3.3 Result of experiment

Experiments were conducted by using ship model with weighting factors in Table 2. The result of the experiment with the weighting factors of roll rate: yaw: rudder = 0: 50: 1 is shown in Fig. 5. In the figure, AP (weighting factor to roll rate zero) is applied until

20 seconds after then the mode was switched to roll stabilization control system. In the experiment it includes less disturbances and lower frequency motion around 0.1 Hz is dominant than the simulation. Apart from the discussion on the performance, effectiveness of RRSS is analyzed by noise contribution[4]. Noise Contribution to roll rate, for example, means the contribution of roll rate in the power spectrum such as yaw, rudder angles and roll rate itself. We illustrate it by the normalized relative ratio in frequency domain in Figs. 6 and 7. Fig. 6 shows that of autopilot and Fig. 7 does that of RRSS. We can observe how RRSS contributes to roll motion differently from autopilot. However, it can be seen that rudder angle also contributes to rudder angle itself and self-exciting oscillation was observed. We need further consideration on the tuning of weighting factors.

4. CONCLUSIONS

The summaries of this paper are as follows.

- Rudder roll stabilization system was designed and certified its effectiveness by simulation and model experiment.
- We can get around 20% reduction in roll motion in the simulation, but the expected result can not be verified in the experiment.

5. ACKNOWLEDGEMENT

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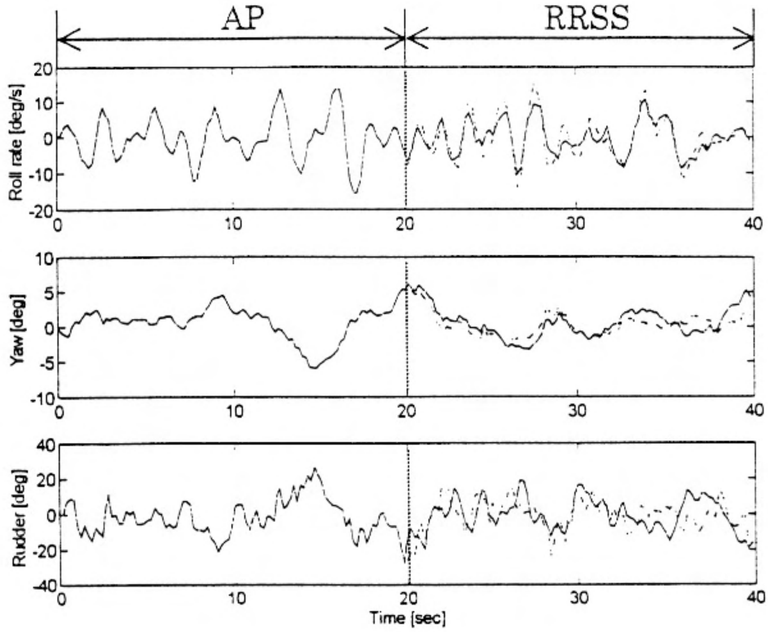

Fig.4 Time histories of simulation
(Roll rate : Yaw : Rudder = 50 : 50 : 1)

Table 2 Results of simulation

Weighting Matrix			Reduction (%)
Q		R	
roll rate	yaw angle	rudder angle	
10	50	1	13.80
50	10	1	23.07
100	10	1	25.41
50	30	1	21.64
50	10	3	19.79
10	100	1	10.88
50	50	1	20.71

$$\textit{Roll reduction}\ (\%) = \left\{\left(\sigma_{AP} - \sigma_{RRSS}\right)/\sigma_{AP}\right\} \times 100$$

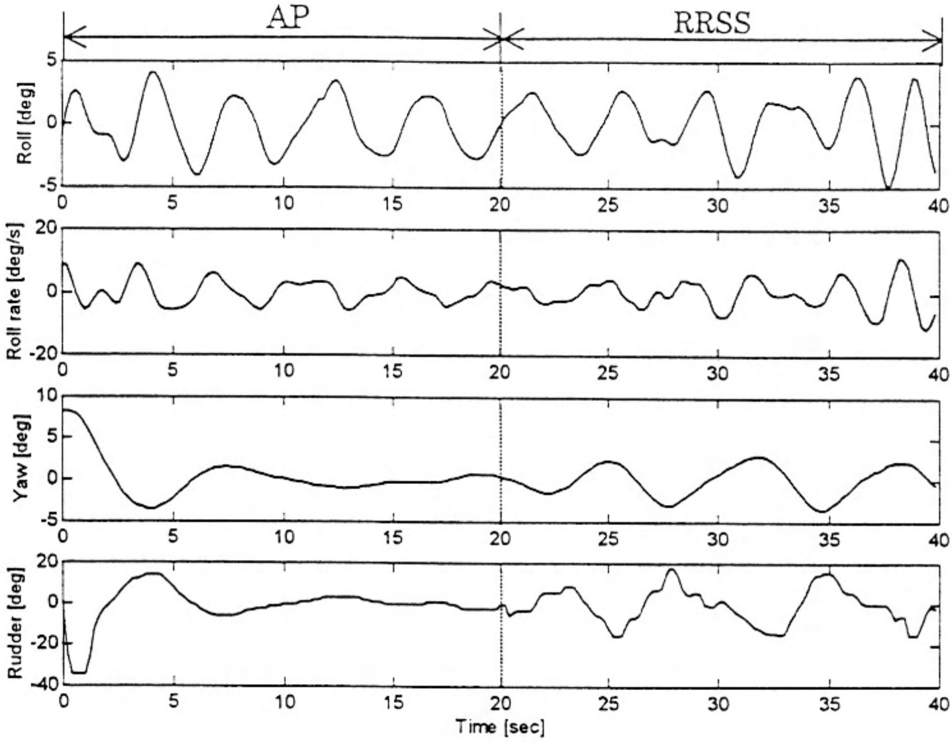

Fig.5 Time histories of experiment
(Roll rate : Yaw : Rudder = 50 : 50 : 1)

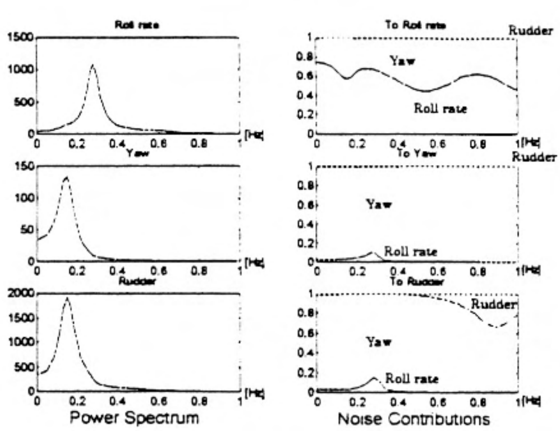

Fig. 6 Power Spectrum and Noise Contributions in autopilot

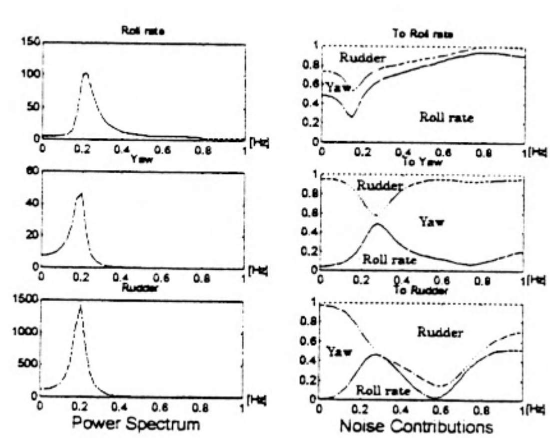

Fig. 7 Power Spectrum and Noise Contributions (Roll rate : Yaw : Rudder = 50 : 50 : 1)