A Motion Estimation Method of High Speed Craft in Irregular Sea by using Onboard Monitoring Motion Time Series Data for Motion Control

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ABSTRACT

In order to establish a control method for automatic dangerous situations avoidance using an onboard monitoring ship motions data, a time series model for model predictive control is investigated. A radial basis function-based state-dependent autoregressive (RBF-AR) model is selected, since it is confirmed that the model is effective to predict nonlinear phenomena. As to the parameter estimation of RBF–AR coefficients and so on, the structured parameter optimization method is focused on, moreover it is improved that their method to an algorithm to realize on-line analysis. In order to verify the effectiveness of the proposed modeling procedure, off-line analysis using model experiment data is carried out. As the results, it is confirmed the effectiveness of the proposed procedure, although several future tasks exists.

Keywords: *RBF-AR model, AIC, Simplified structured parameter optimization method.*

1. INTRODUCTION

Planing crafts in irregular seas are subject to excessive acceleration due to the waves they encounter. In the worst case, marine accidents such as injuries of passengers and crew and hull damage occur (e.g. Japan Marine Accident Tribunal 2017). In order to prevent such the situation, it is necessary for ship's crews to understand the characteristics of encounter waves. This is called "sharp lookout" in maritime terms.

As to a way of the sharp lookout, there are visual observation and RADAR and so on. If a captain, officers and crews, namely, ship operators can handle the situation well, then basically it can prevent marine accidents caused by waves by the sharp lookout with these ways. If such a premise does not satisfy, then marine accidents occur as described above. Therefore, in order to prevent marine accidents under wave conditions beyond the capacity of ship operators, it is necessary to develop a system that supports decision making of ship operators and an automatic control system to avoid dangerous situations. To realize this purpose simply, it is necessary only to monitor the ship motions appropriately according to the knowledge of statistical science. In recent years, many inexpensive and highly reliable measuring devices have been developed, so the monitoring of ship motions has become relatively easy (Sasa et al., 2015). Thus, the idea as the mentioned here is feasible.

As to a general displacement type ship, a decision making support system using ship motions data had been already proposed by Iseki and Terada (2001). However, there are no studies on decision making support systems in planing crafts. With regard to the automatic dangerous situation avoidance system, neither research on displacement type nor research on planing crafts has been conducted. The reason for this is that because the motion of the planing craft is highly nonlinear, it is difficult to construct a mathematical model or a time series model.

In this research, a time series model for model predictive control is investigated for the purpose of establishing a control method for automatic dangerous situations avoidance using an onboard monitoring ship motions data. A radial basis function-based state-dependent autoregressive (RBF-AR) model (Vesin, 1993) as a time series model to predict nonlinear phenomena is focused on. As to the modeling procedure of it, the parameter estimation procedure proposed by Peng et al. (2002)

is focused on, because it can realize the stable computation for the parameter estimation. In order to verify the effectiveness of the model, off-line analysis using model experiment data is carried out. Obtained findings are reported in detail.

2. RADIAL BASIS FUNCTION-BASED STATE-DEPEND AUTOREGRESSIVE MODELING PROCEDURE

The RBF-AR model is expressed as

$$y_n = \phi_0(\mathbf{x}_{n-1}) + \sum_{i=1}^{L} \phi_i(\mathbf{x}_{n-1}) y_{n-i} + \varepsilon_n \tag{1}$$

where y_n is the measured time series and ε_n is the normally distributed white noise in the observed noise with mean 0 and variance σ^2, and

$$\mathbf{x}_{n-1} = \left[y_{n-1}, y_{n-2}, \cdots, y_{n-nx}\right]^T \tag{2}$$

$$\mathbf{z}_k = \left[z_{k,1}, z_{k,2}, \cdots, z_{k,nx}\right]^T \quad \left(k = 1, \cdots, M\right) \tag{3}$$

$$\phi_0(x_{n-1}) = c_0 + \sum_{k=1}^{M} c_k \exp\left(-\lambda_k \left\|x_{n-1} - z_k\right\|_2^2\right) \tag{4}$$

$$\phi_i(x_{n-1}) = c_{i,0} + \sum_{k=1}^{M} c_{i,k} \exp\left(-\lambda_k \left\|x_{n-1} - z_k\right\|_2^2\right) \tag{5}$$

where z_k denotes the center of the RBF network, and λ_k is the scaling parameter. c_k ($k = 0,\ldots, M$) and $c_{i,k}$ ($k = 0,\ldots, M$) are the weighting coefficients, L and M are the orders of regression, n_x is the dimension of vector $\mathbf{x}_{n-1}$, and $\|\cdot\|_2$ is the L2 norm, respectively.

The unknown parameters in equation (1) are estimated using a method introduced by Peng et al. (2002). In this method, by assigning suitably assumed values for z_k and λ_k, the problem changes into that of the least squares estimation of the linear parameters c_k and $c_{i,k}$. Subsequently, the estimated values to the linear parameters are assigned and z_k and λ_k are estimated by the Levenberg–Marquardt method, which is a nonlinear optimization method. Iterative calculations are then performed until the convergence condition is satisfied and the final estimates of each parameter are obtained. The best model is determined by using the Akaike information criterion (AIC) (Akaike, 1974) shown in equation (6).

$$\begin{aligned} &\mathrm{AIC} = N \log \hat{\sigma}^2 + 2(s+1) \\ &for\ N >> \max(L, M) \end{aligned} \tag{6}$$

where N is the data number for the fitting of the RBF-AR model, and $\hat{\sigma}^2$ is the variance of the residual of the fitting, and s is the total number of the parameters.

In order to evolve a process suitable for online analysis, the method adopted in the present study skips the iterative calculation of cases where the fitting in the initial calculation is poor. Thus, we were able to neglect the unnecessary calculations for model selection.

3. TECHNIQUE FOR FAST COMPUTATION OF PARAMETERS

In this study, as mentioned before, the planing craft which is high speed as the target ship is focused on. Thus, in order to perform the on-line analysis, it is needed to calculate at high speed for the parameter estimation. Then, in order to evolve a process suitable for on-line analysis, the method adopted in the present study skips the iterative calculation of cases where the fitting in the initial calculation is poor. That is, it is able to neglect the unnecessary calculations for model selection. By this processing, high speed calculation for the modeling is realized.

4. OFF-LINE ANALYSIS USING MODEL EXPERIMENT DATA

4.1 Outline of model experiments

To verify the effectiveness of the proposed procedure, an off-line analysis using model experiment data is conducted. In the model experiment, the object ship is toward at the constant speed in irregular waves, and the vertical acceleration of the bow is measured by an acceleration sensor made by Kyowa Electronic Instruments Co., Ltd. That is, the object ship is towed at 25 knots in actual scale, and the acceleration measurement is done at the sampling interval 200 Hz. Fig. 1 shows the experimental set up and the definition of coordinate system. As shown this figure, the acceleration upward is positive. Table 1 and Fig. 2 show principal particulars in the actual scale and the body plan of the object ship, respectively. Table 2 shows the wave condition in the actual scale. In this case, the mean period of waves is calculated by the Equation (7). Equation (8) shows the shape of spectrum proposed by the International Ship and Offshore Structures Congress (ISSC, 1964), and irregular waves are reproduced based on this equation.

$$T_1 = 3.86\sqrt{H_{1/3}} \tag{7}$$

$$\begin{aligned} S(\omega) &= \frac{0.11}{2\pi} H_{1/3}{}^2 T_1 \left(\frac{\omega T_1}{2\pi}\right)^{-5} \\ &\times \exp\left\{-0.44\left(\frac{T_1}{2\pi}\omega\right)^{-4}\right\} \end{aligned} \tag{8}$$

where, ω is an angular frequency of waves.

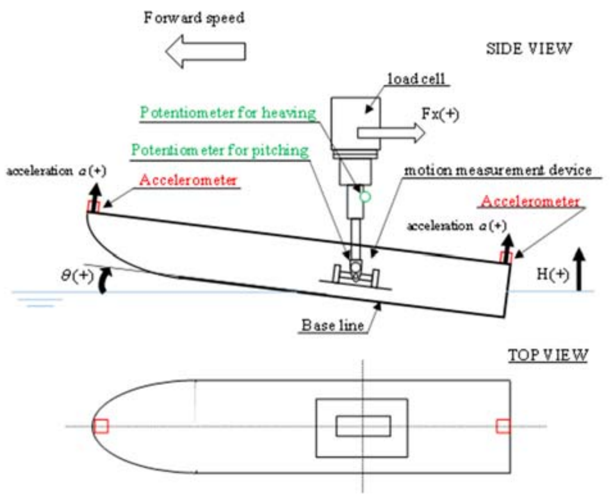

Figure 1: Schematic view of experimental set up and the definition of coordinate system.

Table 1: Principal particulars of the object ships in actual scale.

Scale of model: $1/s$	1/23.4
Water line length: L_{WL} [m]	21.46
Breath: B [m]	4.0
Deadrise angle at s.s. 5: β [deg]	16.0
Draft: d [m]	0.76
Displacement [ton]	37.0

Table 2 Wave condition in actual scale.

Significant wave height $H_{1/3}$[m]	2.0
Mean wave period T_1[s]	5.5

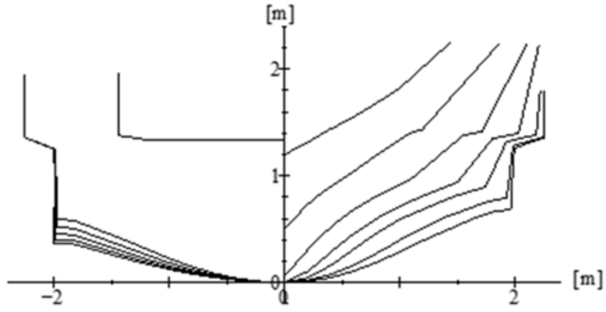

Figure 2: Body plan of the target ship.

4.2 *Example of prediction results*

In this subsection, the one example of prediction results is shown. As to the prediction based on the RBF-AR modeling, from the view point of computational time, it is decided that the maximum of model order L is 10, the maximum value of the number of center of the RBF network M is 3 and the maximum value of the dimension n_x of state vector is 3, respectively. Here, Fig. 3 shows the result of the 30th step ahead prediction, namely the prediction for 1.5 seconds, in which the number of data N for the fitting of the RBF-AR model, which is called "Batch data", is 300. In this figure, the horizontal axis indicates the time, and the vertical axis indicates the vertical acceleration. Moreover, the black line indicates the measured data in the experiment, and the dotted red line indicates the predicted one. As you can see, the predicted data captures the tendency of the measured one. Thus, it is consider that the proposed procedure has the possibility to predict the vertical acceleration such that the strong nonlinearity.

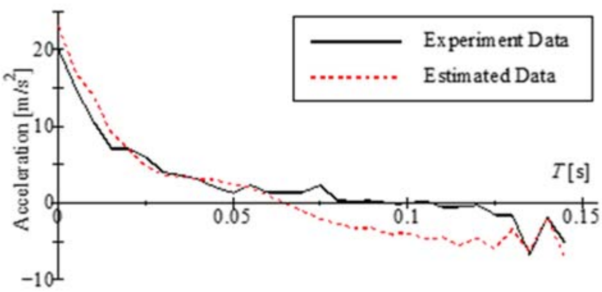

Figure 3: Comparison with the measured time history and predicted vertical acceleration. Note that this figure does not include the data set of the analysis.

4.3 *Verification of accuracy*

In the previous subsection, the usefulness of the proposed procedure is confirmed.

In this subsection, as to the recursive fitting of the RBF-AR model, the accuracy of the proposed procedure in detail more is verified. That is, the several off-line analysis in which the number of prediction step and the number of data N for the fitting of the RBF-AR model are changed is carried out. The conditions for the verification is summarized in Table 3. Here the measured data as a notation A_{Exp}, and the predicted one as a notation A_{Pre} are defined respectively. Firstly, the dispersion relationship between the A_{Exp} and the A_{Pre} based on a root mean squares (RMS) of them, which expresses the following equation, is investigated.

$$\mathrm{RMS} = \sqrt{\frac{1}{n_{(Pre)}} \sum_{i=1}^{n_{(Pre)}} \left(A_{Exp}(i) - A_{Pre}(i) \right)^2} \tag{9}$$

In this case, it is evaluated that "RMS > 500 (m/s^2)" is a failed prediction. Fig. 4 shows one of the example for the time series of RMS and measured vertical acceleration. In this figure, the horizontal axis indicates the time, the left side vertical axis indicates the measured vertical acceleration and the right side vertical axis indicates the RMS. Moreover, the upper figure shows the result of the condition in which N=400 and $n_{(Pre)}$=30, and the lower figure shows the result of the condition in which N=500 and $n_{(Pre)}$=5. From these figures, it can be seen that when an impact acceleration occurs, the value of RMS exceeds the threshould value 500 and the evaluation of the result is the failed prediction. This tendency regarding other cases is also confirmed, although the ratio of divergence varies depending on the combination of the N and $n_{(Pre)}$. This result is caused by calculating RMS using all values in the prediction period $n_{(Pre)}$. Basically, the phenomena dealt with here is strongly nonlinear. Therefore, even if the prediction of several steps ahead can be achieved successfully, there are many events in which the prediction result diverges in the subsequent prediction period. The results shown here express this fact well and it is necessary to decide the prediction period after making sufficient consideration. It should be noted that as to one ahead prediction the result can predict the mesured one well.

Table 3: Conditions for the verification.

Number of the Batch Data for the model fitting: N	50, 100, 200, 300, 400, 500
Number of the prediction period: $n_{(Pre)}$	5, 10, 20, 30

It is certain that there are cases where it can be predicted well, although there are the failed prediction in the several conditions. Thus, the all combinations of the N and the $n_{(Pre)}$ as shown in Fig. 5 are investigated secondly. In this figure, the horizontal axis indicates the N, and the vertical axis indicates the rate in which RMS diverges, respectively. As to each symbol, as shown in the figure, the circle indicates the results of $n_{(Pre)}$=5, the square indicates the results of $n_{(Pre)}$=10, the diamond indicates the results of $n_{(Pre)}$=20, and the triangle indicates the $n_{(Pre)}$=30, respectively. This figure shows the following.

(1) The more N and the less $n_{(Pre)}$, the rate in which RMS diverges is smaller.

(2) When the N exceeds 400 samples, the ratio of divergence is almost the same.

Therefore, it is considered that as to the data number N for the model fitting, it is desirable to use more than 400 samples, although the problem of the computational time for the model fitting exists.

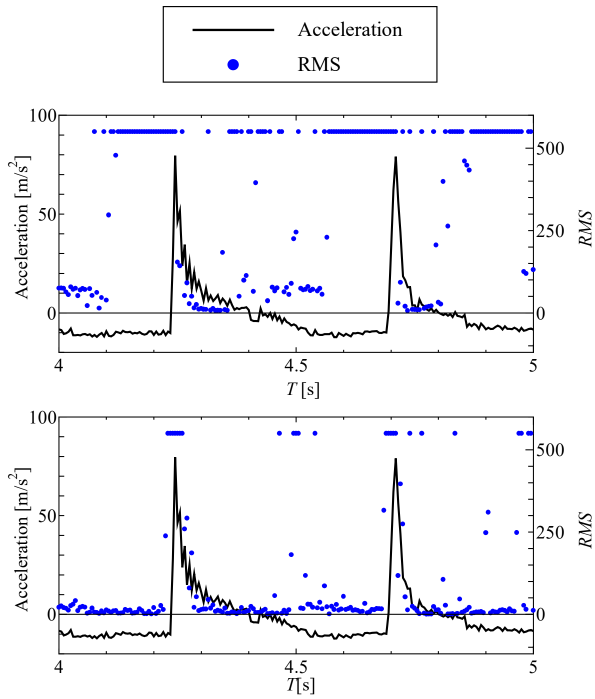

Figure 4: Time series of RMS and measured vertical acceleration; Upper figure: N=400, $n_{(Pre)}$=30, Lower figure: N=500, $n_{(Pre)}$=5.

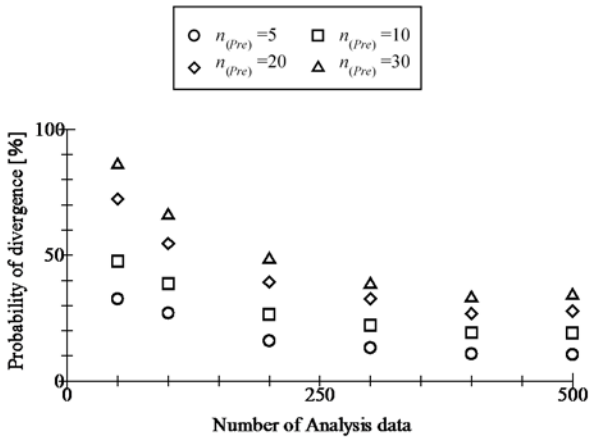

Figure 5: The ratio of divergence of RMS for each conditions for verification.

5. CONCLUSIONS

In this research, a time series model for model predictive control in order to establish a control method for automatic dangerous situations avoidance using an onboard monitoring ship motions data is investigated. Concretely, a radial basis function-based state-dependent autoregressive (RBF-AR) model as a time series model to predict nonlinear phenomena is focused on. As to the modeling procedure of it, the structured parameter optimization method as the parameter estimation procedure is focused on, their method to an algorithm for realizing on-line analysis is improved. In order to verify the effectiveness of the model, off-line analysis using model experiment data is carried out. Obtained findings are summarized as follows:

(1) As to the prediction used the Batch Data, it can be seen that the predicted results are good agreement with the measured data as shown in the subsection 4.2. Therefore, the proposed procedure is useful for the prediction of the vertical acceleration in the batch data analysis.
(2) As to the recursive fitting of the RBF-AR model, the predicted results diverge sometimes in meaning of the root mean square (RMS). This cause is the calculation of the RMS using all values in the prediction period.
(3) However, the more data for the model fitting and the less prediction period, the rate in which RMS diverges is smaller. Moreover, if the data for the model fitting exceeds 400 samples, then the ratio of divergence is almost the same.

As a future task, it is needed to investigate to improve the accuracy of prediction.

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REFERENCES

Akaike, H., 1974, “A new look at the statistical model identification”, IEEE Trans. Autom. Control vol. 19, pp. 716–723.

Iseki, T. Terada, D., 2002, “Bayesian estimation of directional wave spectra for ship guidance system”, International Journal of Offshore and Polar Engineering, Vol. 12, No. 1, pp.25–30.

ISSC, 1964, “Report of the Committee 1. Environmental Conditions”, Proceedings of 2nd ISSC.

Japan Marine Accident Tribunal, 2017/04/11(accessed), “http://www.mlit.go.jp/jmat/saiketsu/saiketsu.htm” (In Japanese).

Peng, H., Ozaki, T., Haggan-Ozaki, V. and Toyoda, Y., 2002, “Structured parameter optimization method for the radial basis function-based state-dependent autoregressive model”, Int. J. Systems Science, vol. 33(13), pp. 1087–1087.

Sasa, K., Terada, D., Shiotani, S., Wakabayashi, N., Ikebuchi, T., Chen, C., Takayama, A, Uchida, M, 2015, “Evaluation of ship performance in international transportation using an onboard measurement system – in case of a bulk carrier in international voyages”, Ocean Engineering, Vol. 104, pp.294–309.

Vesin, J., 1993, “An amplitude-dependent autoregressive signal model based on a radial basis function expansion”, in Proc. ICASSP, vol. 3, pp. 129–132.

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