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System identification modelling of ship manoeuvring motion based on ε-support vector regression*

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Abstract: Based on the ε- support vector regression, three modelling methods for the ship manoeuvring motion, i.e., the white-box modelling, the grey-box modelling and the black-box modelling, are investigated. The $10^{o}/10^{o}$, $20^{o}/20^{o}$ zigzag tests and the 35^{o} turning circle manoeuvre are simulated. Part of the simulation data for the $20^{o}/20^{o}$ zigzag test are used to train the support vectors, and the trained support vector machine is used to predict the whole $20^{o}/20^{o}$ zigzag test. Comparison between the simulated and predicted $20^{o}/20^{o}$ zigzag test shows a good predictive ability of the three modelling methods. Then all mathematical models obtained by the modelling methods are used to predict the $10^{o}/10^{o}$ zigzag test and 35^{o} turning circle manoeuvre, and the predicted results are compared with those of simulation tests to demonstrate the good generalization performance of the mathematical models. Finally, the modelling methods are analyzed and compared with each other in terms of the application conditions, the prediction accuracy and the computation speed. An appropriate modelling method can be chosen according to the intended use of the mathematical models and the available data for the system identification.

Key words: ship manoeuvring, hydrodynamic coefficients, mathematical model, system identification, ε- support vector regression

Introduction

The ship manoeuvrability is explicitly required in the Standards for Ship Manoeuvrability promulgated by the International Maritime Organization[1]. To predict the ship manoeuvrability at the ship design stage, some methods are available, including the database and/or empirical formula method, the free-running model test method, the numerical method and the computer simulation method based on mathematical models. The last one is popular and effective to predict the ship manoeuvrability. To use this method, constructing accurately the mathematical model is a necessary precondition. The application of the system identification (SI) based on the free-running model tests or the full-scale trials plays an important role in modelling the ship manoeuvring motion.

Various classical SI methods, e.g., the extended Kalman filter method[2,3], the maximum likelihood method[4], the recursive prediction error method[5] and the least squares method[6], were applied in modelling the ship manoeuvring motion and identifying the hydrodynamic coefficients. However, they have some inherent defects, such as the sensitivity to the initial values, the ill-conditioned solutions and the simultaneous drift. To eliminate these defects, some modern SI methods were proposed for estimating the hydrodynamic coefficients, including the frequency domain identification method[7,8], the neural network[9], the su-

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pport vector machines (SVM)[10-13] and the genetic algorithm[14]. Among them, the neural network and the support vector machines, as two kinds of artificial intelligence algorithms, can not only be used for the parametric identification, but also, even more suitably, for the nonlinear regression. Rajesh and Bhattacharyya[15] adopted the artificial neural network to regress the nonlinear dynamic model of a large tanker. Moreira and Guedes Soares[16] applied the recursive neural network to simulate the ship manoeuvring motion. Compared with the neural network, the SVM is direct at finite samples and has better generalization performances and a global optimal extremum[17]. It is mainly used for pattern recognition and parameter identification. It is known as the support vector regression (SVR) when it is used for parameter identification. Luo and Zou[10, 11], Zhang and Zou[12] identified the hydrodynamic coefficients in the Abkowitz model of the ship manoeuvring motion by using the least squares support vector regression (LS-SVR) and the ε - support vector regression (ε - SVR), respectively. The modelling method used in these two papers is only the white-box modelling, and to reduce the extent of parameter drift, a series of random signals is added into the training samples. However, the introduced random signal brings about another problem: the amplitude of the random signals is difficult to determine. Moreover, in order to obtain the hydrodynamic coefficients in the sway and yaw equations, it is necessary to solve a series of combined equations.

In the present paper, three modelling methods for the ship manoeuvring motion using the ε - SVR, i.e., the white-box modelling, the grey-box modelling and the black-box modelling, are investigated. The white-box modelling method is improved by reconstructing the identification formulas to avoid adding the random signals into the training samples and solving a series of combined equations. The grey-box modelling and the black-box modelling are clearly defined. The $10^{\circ}/10^{\circ}$, $20^{\circ}/20^{\circ}$ zigzag tests and the 35° turning circle manoeuvre are simulated by using the hydrodynamic coefficients obtained from the PMM test[18]. 5% of the simulation data of the $20^{\circ}/20^{\circ}$ zigzag test are used to train the support vectors, and the trained support vector machines are used to predict the whole $20^{\circ}/20^{\circ}$ zigzag test. The predicted results are compared with those of simulation tests to demonstrate the good predictive ability of the mathematical models obtained by the modelling methods. Then, the mathematical models are used to predict the $10^{\circ}/10^{\circ}$ zigzag test and the 35° turning circle manoeuvre, and the predicted results are compared with those of simulation tests to demonstrate the generalization performance of the mathematical models. The modelling methods are analyzed and compared with each other in terms of the application conditions, the prediction accuracy and the computation speed. An appropriate modelling method can be chosen according to the intended use of the mathematical models and the available data for the system identification.

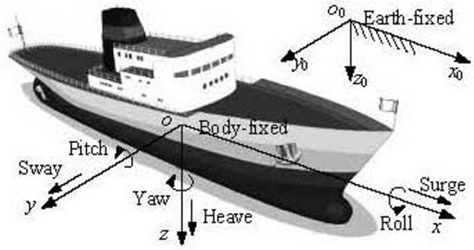

Fig.1 Coordinate systems

1. Mathematical model of ship manoeuvring motion

As shown in Fig.1, two right-handed coordinate systems, the earth-fixed inertial frame (the global coordinate system) o_0 - $x_0y_0z_0$ and the body-fixed moving frame (the local coordinate system) o - xyz , are adopted, with the plane o_0 - $x_0y_0z_0$ on the undisturbed free surface and z_0 - axis pointing downwards. At the initial instant, these two coordinate systems coincide with each other.

Generally, the manoeuvring motion of a surface ship can be described by the equations of the surge, sway and yaw motions in the following form[18]

$$\begin{bmatrix} m - X_{\dot{u}} & 0 & 0 \\ 0 & m - Y_{\dot{v}} & mx_G - Y_{\dot{r}} \\ 0 & mx_G - N_{\dot{v}} & I_z - N_{\dot{r}} \end{bmatrix} \begin{bmatrix} \dot{u} \\ \dot{v} \\ \dot{r} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ f_3 \end{bmatrix} \tag{1}$$

where

$$f_1 = X_u \Delta u + X_{uu} \Delta u^2 + X_{uuu} \Delta u^3 + X_{vv} v^2 + X_{rr} r^2 + X_{rv} rv + X_{\delta\delta} \delta^2 + X_{u\delta\delta} \Delta u \delta^2 + X_{v\delta} v\delta + X_{uv\delta} \Delta u v \delta \ ,$$

$$f_2 = Y_0 + Y_u \Delta u + Y_{uu} \Delta u^2 + Y_v v + Y_r r + Y_{vvv} v^3 + Y_{vvr} v^2 r + Y_{vu} v \Delta u + Y_{ru} r \Delta u + Y_\delta \delta + Y_{\delta\delta\delta} \delta^3 + Y_{u\delta} \Delta u \delta + Y_{uu\delta} \Delta u^2 \delta + Y_{v\delta\delta} v \delta^2 + Y_{vv\delta} v^2 \delta \ ,$$

$$f_3 = N_0 + N_u \Delta u + N_{uu} \Delta u^2 + N_v v + N_r r + N_{vvv} v^3 + N_{vvr} v^2 r + N_{vu} v \Delta u + N_{ru} r \Delta u + N_\delta \delta + N_{\delta\delta\delta} \delta^3 + N_{u\delta} \Delta u \delta + N_{uu\delta} \Delta u^2 \delta + N_{v\delta\delta} v \delta^2 + N_{vv\delta} v^2 \delta \ ,$$