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Parameter Identification of Ship Maneuvering Model Based on Support Vector Machines and Particle Swarm Optimization

Combined with the free-running model tests of KVLCC ship, the system identification (SI) based on support vector machines (SVM) is proposed for the prediction of ship maneuvering motion. The hydrodynamic derivatives in an Abkowitz model are determined by the Lagrangian factors and the support vectors in the SVM regression model. To obtain the optimized structural factors in SVM, particle swarm optimization (PSO) is incorporated into SVM. To diminish the drift of hydrodynamic derivatives after regression, a difference method is adopted to reconstruct the training samples before identification. The validity of the difference method is verified by correlation analysis. Based on the Abkowitz mathematical model, the simulation of ship maneuvering motion is conducted. Comparison between the predicted results and the test results demonstrates the validity of the proposed methods in this paper. [DOI: 10.1115/1.4032892]

Keywords: ship maneuverability, parameter identification, support vector machines, parameter drift, particle swarm optimization

1 Introduction

Ship maneuverability has been explicitly required in the Standards for Ship Maneuverability that was promulgated by the International Maritime Organization (IMO) in 2002 [1]. To obtain the maneuvering parameters, such as advance, transfer, and overshoots, three ways are available. The first one is the no-simulation, which refers to the database method, full-scale trial, or free-running model test. The second one is the system-based maneuvering simulation, in which the database method, empirical formulas, captive model test, computational methods, and SI combined with full-scale trials or free-running model tests can be adopted. The third way is the computational fluid dynamics (CFD) based maneuvering simulation, in which inviscid methods and Reynolds-Averaged Navier–Stokes methods are available [2].

System-based maneuvering simulation has been proved as an effective and practical way to predict the ship maneuverability at the ship design stage. To use this method, the mathematical model of ship maneuvering motion is required and accurately determining the hydrodynamic coefficients in the mathematical model is the key to the accuracy of prediction. Several methods can be used to derive the hydrodynamic coefficients, including captive model test method, database method, empirical formulas method, CFD calculation method, and SI method combined with model tests (mainly referred to free-running model tests). Generally, for a newly designed ship, the result from the database method is inaccurate if the ship particulars investigated cannot be found in the database even if the interpolation method can be used. By use of the captive model test or its induced empirical formulas, the results of hydrodynamic coefficients are considered to be the most creditable. However, the expense required for this method hinders its wide application because many institutes and universities cannot afford it actually. The CFD-based method can directly give the hydrodynamic coefficients. Nevertheless, it is known that the verification and validation of this method have a long way to go. Comparatively, SI combined with free-running model test provides a more practical method to determine the hydrodynamic coefficients. The requirement of free-running model test is lower than that of captive model test. Moreover, the so-called scale effects due to different Reynolds numbers between that of the ship model and full-scale can be avoided since this method can be applied directly to analyze the full-scale trials. With the development of modern measurement equipment and advanced SI techniques, SI will find its wider application in ship maneuverability prediction.

Classical SI techniques applied in the ship maneuvering include least squares (LSs) method [3,4], model reference method [5,6], extended Kalman Filter method [7,8], maximum likelihood method [9], and recursive prediction error method [10,11]. During the last decades, these methods have been continuously applied and developed. For example, the application of a nonlinear LS method was addressed for the identification of high-speed craft dynamics [12]. A recursive LS method and a recursive prediction error method were proposed for the identification of ship maneuvering dynamics and hydrodynamics [13]. An iterative prediction error method was applied to the identification of autopilot models [14]. The prediction error method combined with Kalman filter was proposed for the parameter estimation of linear ship maneuvering models [15]. A nonlinear prediction error method with the unscented Kalman filter was presented for the identification of nonlinear maneuvering models of a modern high-speed trimaran ferry [16]. The performance of extended Kalman filter on the parameter estimation of a nonlinear vessel steering model under dynamic navigation conditions was evaluated [17]. The ridge regression method incorporated by estimation-before-modeling was proposed for the identification of hydrodynamic derivatives [18]. The extended Kalman filter and constrained LS method were proposed to estimate the maneuvering parameters with the help of experimental fluid dynamics (EFD) and CFD techniques [19]. In addition to the traditional SI techniques, several new approaches have also been proposed for the modeling of ship maneuvering, including the frequency spectrum analysis [20,21], PSO [22], artificial neural networks (ANN), and SVM, among which many efforts were devoted to the application of ANN. For example, Haddara and Wang used the backpropagation neural network (BPNN) for the identification of an Abkowitz model [23]. Ebada and Abdel-Maksoud proposed the BPNN to predict the limits of ship turning maneuvers [24]. Moreira and Guedes Soares applied the recursive neural networks to the identification of the dynamic

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model of ship maneuverability [25]. Hess et al. made a lot of contribution to the online prediction of marine maneuvering by using dynamical recursive neural networks [26–29]. Rajesh and Bhattacharyya addressed the blind prediction of ship maneuvering by using multilayer feedforward neural networks [30], etc. In recent years, a novel artificial intelligent technique, i.e., the SVM, was proposed for the modeling of ship maneuvering. Like the NN, SVM is also applicable both in the parameter identification and blind prediction of ship maneuvering. Differently, for the parameter identification, the hydrodynamic coefficients or derivatives can be obtained directly by means of SVM whereas by using NN, another regressor (e.g., the LS method) is required to determine the hydrodynamic coefficients. For the blind prediction of ship maneuvering, it can be confirmed that SVM gains better generalization ability than NN. By using SVM, Luo and Zou performed the studies on parameter identification of the Abkowitz model combined with simulated data [31] and black-box modeling of ship maneuvering [32]. Luo et al. studied the SVM-based simulation of ship maneuvering in the proximity of a pier [33]. Zhang and Zou used ε-SVM to identify the Abkowitz model [34]. Xu et al. applied SVM to the identification of nonlinear dynamics of underwater vehicles [35]. Zhang and Zou estimated the hydrodynamic coefficients from captive model tests [36]. Wang et al. studied the SVM-based identification of ship maneuvering motion with four degrees-of-freedom [37]. Moreno-Salinas et al. identified the response model combined with real experiments [38].

As an extension of the work in Ref. [31], this paper investigates the application of SVM to the parameter identification of an Abkowitz model combined with free-running model tests, rather than simulation tests adopted in many studies, e.g., Refs. [31,34,35,37]. Combined with model tests, SVM has been successfully used to identify the parameters in the response model [33,38] or linearized hydrodynamic mathematical model [36]. However, SVM-based identification of a complicated hydrodynamic model such as the Abkowitz model and MMG model proposed by the Japanese Mathematical Modeling Group is not preferred much. In this paper, by analyzing the free-running model test data of the large tanker KVLCC2, the hydrodynamic coefficients in an Abkowitz model are identified, which can be expressed by the combination of the Lagrangian factors and the support vectors in the SVM regression model. To alleviate the simultaneous drift of hydrodynamic coefficients, the Abkowitz model is simplified and a difference method is adopted to reconstruct the training samples for SVM. Correlation analyses are conducted to verify the alleviation measure. To obtain the optimal structural parameters in SVM, PSO is incorporated into SVM. At last, ship maneuvering motions are predicted by using the Abkowitz model and comparisons between the predicted results and the experiments are performed to demonstrate the validity of the methods proposed.

2 Mathematical Model of Ship Maneuvering Motion

Usually, two kinds of hydrodynamic models are used to predict ship maneuverability. The first one is the Abkowitz model named after Professor Abkowitz, and second one is the MMG model proposed by the Japanese Maneuvering Modeling Group. In addition, in some cases, the response model or Nomoto model that is frequently applied in ship control is employed for simple research on ship maneuvering. In this paper, the Abkowitz model is made use of because it is considered to be more suitable for analysis of the free-running model test.

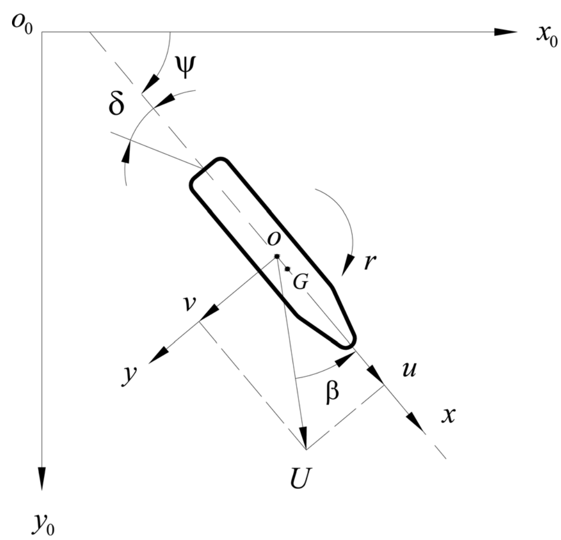

Fig. 1 Coordinate system of ship maneuvering motion

In the Abkowitz model, Taylor series expansion is applied to express the marine hydrodynamic forces and moments [39]. For a surface ship, this model can be described by a three degrees-of-freedom dynamical system. Figure 1 describes the coordinate system of surface ship maneuvering motion, where the inertial coordinate system is denoted by $x_0o_0y_0$, xoy is the attached coordinate system, G is the gravity center, u is the surge speed, v is the sway speed, r is the yaw rate, U is the total velocity, δ is the rudder angle, ψ is the heading angle, and β is the drift angle.

With the help of the prime nondimensional operation

$$\Delta u' = \frac{\Delta u}{U}, \quad \Delta v' = \frac{\Delta v}{U}, \quad \Delta r' = \frac{L\Delta r}{U}, \quad \Delta \dot{u}' = \frac{\Delta \dot{u}}{(U^2/L)},$$
$$\Delta \dot{v}' = \frac{\Delta \dot{v}}{(U^2/L)}, \quad \Delta \dot{r}' = \frac{\Delta \dot{r}}{(U^2/L^2)}$$

the equation of surface ship maneuvering motion can be given in the form

$$\begin{bmatrix} m' - X'_{\dot{u}} & 0 & 0 \\ 0 & m' - Y'_{\dot{v}} & m'x'_G - Y'_{\dot{r}} \\ 0 & m'x'_G - N'_{\dot{v}} & I'_z - N'_{\dot{r}} \end{bmatrix} \begin{bmatrix} \Delta \dot{u}' \\ \Delta \dot{v}' \\ \Delta \dot{r}' \end{bmatrix} = \begin{bmatrix} \Delta f'_1 \\ \Delta f'_2 \\ \Delta f'_3 \end{bmatrix} \tag{1}$$

where m' is the nondimensional mass of the ship; I'_z is the nondimensional inertia moment about the Z axis (vertically downward) in attached coordinate system; x'_G is the nondimensional longitude coordinate of the ship's center of gravity; $X'_{\dot{u}}$, $Y'_{\dot{v}}$, $Y'_{\dot{r}}$, $N'_{\dot{v}}$, and $N'_{\dot{r}}$ are the nondimensional acceleration derivatives; $\Delta u'$, $\Delta v'$, $\Delta r'$, and $\Delta\delta'$ are the nondimensional small perturbations from nominal surge speed u_0, sway speed v_0, yaw rate r_0, and rudder angle δ_0, respectively; $\Delta f'_1$, $\Delta f'_2$, and $\Delta f'_3$ are given by Taylor series expansion in which a number of hydrodynamic coefficients are contained, e.g., in Ref. [40], the three nonlinear functions give the forms as follows, under the assumption that the external forces and moment acting on the ship have appropriate port and starboard symmetry except for a constant force and moment caused by the propeller:

$$\begin{aligned} \Delta f'_1 = {} & X'_u\Delta u' + X'_{uu}\Delta u'^2 + X'_{uuu}\Delta u'^3 + X'_{vv}\Delta v'^2 + X'_{rr}\Delta r'^2 + X'_{\delta\delta}\Delta\delta'^2 + X'_{\delta\delta u}\Delta\delta'^2\Delta u' \\ & + X'_{vr}\Delta v'\Delta r' + X'_{v\delta}\Delta v'\Delta\delta' + X'_{v\delta u}\Delta v'\Delta\delta'\Delta u' + X'_{uvv}\Delta u'\Delta v'^2 + X'_{urr}\Delta u'\Delta r'^2 + X'_{uvr}\Delta u'\Delta v'\Delta r' \\ & + X'_{r\delta}\Delta r'\Delta\delta' + X'_{ur\delta}\Delta u'\Delta r'\Delta\delta' + X'_0 \end{aligned} \tag{2}$$

$$\Delta f_2' = Y_{0u}'\Delta u' + Y_{0uu}'\Delta u'^2 + Y_v'\Delta v' + Y_r'\Delta r' + Y_\delta'\Delta\delta + Y_{vvv}'\Delta v'^3 + Y_{\delta\delta\delta}'\Delta\delta'^3 + Y_{vvr}'\Delta v'^2\Delta r' + Y_{vv\delta}'\Delta v'^2\Delta\delta' + Y_{v\delta\delta}'\Delta v'\Delta\delta'^2 + Y_{\delta u}'\Delta\delta'\Delta u' + Y_{vu}'\Delta v'\Delta u' + Y_{ru}'\Delta r'\Delta u' + Y_{\delta uu}'\Delta\delta'\Delta u'^2 + Y_{rrr}'\Delta r'^3 + Y_{vrr}'\Delta v'\Delta r'^2 + Y_{vuu}'\Delta v'\Delta u'^2 + Y_{ruu}'\Delta r'\Delta u'^2 + Y_{r\delta\delta}'\Delta r'\Delta\delta'^2 + Y_{rr\delta}'\Delta r'^2\Delta\delta' + Y_{rv\delta}'\Delta r'\Delta v'\Delta\delta' + Y_0' \tag{3}$$

$$\Delta f_3' = N_{0u}'\Delta u' + N_{0uu}'\Delta u'^2 + N_v'\Delta v' + N_r'\Delta r' + N_\delta'\Delta\delta' + N_{vvv}'\Delta v'^3 + N_{\delta\delta\delta}'\Delta\delta'^3 + N_{vvr}'\Delta v'^2\Delta r' + N_{vv\delta}'\Delta v'^2\Delta\delta' + N_{v\delta\delta}'\Delta v'\Delta\delta'^2 + N_{\delta u}'\Delta\delta'\Delta u' + N_{vu}'\Delta v'\Delta u' + N_{ru}'\Delta r'\Delta u' + N_{\delta uu}'\Delta\delta'\Delta u'^2 + N_{rrr}'\Delta r'^3 + N_{vrr}'\Delta v'\Delta r'^2 + N_{vuu}'\Delta v'\Delta u'^2 + N_{ruu}'\Delta r'\Delta u'^2 + N_{r\delta\delta}'\Delta r'\Delta\delta'^2 + N_{rr\delta}'\Delta r'^2\Delta\delta' + N_{rv\delta}'\Delta r'\Delta v'\Delta\delta' + N_0' \tag{4}$$

As can be seen, 60 hydrodynamic coefficients are contained in the above expressions. In practical application, such a "large" parametric system makes it inconvenient to predict ship maneuvering. One important reason is that some derivatives are actually difficult to be determined accurately. This paper attempts to simplify the Abkowitz model. All the nonlinear terms related to the surge perturbation $\Delta u'$ are eliminated from Eqs. (2) to (4). Two considerations account for this simplification. First, by taking the ship total velocity U as the nondimensionalization factor, the effect of velocity loss has been taken into account in every velocity term. Second, the linear dependence between the linear and nonlinear terms relating to the surge perturbation is significant, which will result in the parameter drift in identification. Taking the first two terms in the right-hand side of Eq. (2) as examples, they can be, respectively, rewritten as $X_u'\Delta u(k)U(k)$ and $X_{uu}'\Delta u^2(k)$ in the form of discretization (k denotes the sampling time). For the total velocity, it can be calculated as

$$U(k) = (u_0 + \Delta u(k))\sqrt{1 + \left(\frac{\Delta v(k)}{u_0 + \Delta u(k)}\right)^2} \tag{5}$$

For moderate maneuvers, it holds that

$$U(k) \approx (u_0 + \Delta u(k)) \tag{6}$$

Then, $X_u'\Delta u(k)U(k)$ becomes $X_u'\Delta u^2(k) + X_u' u_0 \Delta u(k)$. Obviously, the term $X_u'\Delta u^2(k)$ is linearly dependent on the $X_{uu}'\Delta u^2(k)$. For the sake of avoidance of parameter drift in regression and in consideration of the importance of the linear derivative as well, the nonlinear terms are removed from the equations. Thus, Eqs. (2)–(4) are simplified as

$$\Delta f_1' = X_u'\Delta u' + X_{vv}'\Delta v'^2 + X_{rr}'\Delta r'^2 + X_{\delta\delta}'\Delta\delta'^2 + X_{vr}'\Delta v'\Delta r' + X_{v\delta}'\Delta v'\Delta\delta' + X_{r\delta}'\Delta r'\Delta\delta' + X_0' \tag{7}$$

$$\Delta f_2' = Y_v'\Delta v' + Y_r'\Delta r' + Y_\delta'\Delta\delta' + Y_{|v|v}'|\Delta v'|\Delta v' + Y_{|v|r}'|\Delta v'|\Delta r' + Y_{|r|r}'|\Delta r'|\Delta r' + Y_{v|r|}'\Delta v'|\Delta r'| + Y_{\delta\delta\delta}'\Delta\delta'^3 + Y_{vv\delta}'\Delta v'^2\Delta\delta' + Y_{v\delta\delta}'\Delta v'\Delta\delta'^2 + Y_{r\delta\delta}'\Delta r'\Delta\delta'^2 + Y_{rr\delta}'\Delta r'^2\Delta\delta' + Y_{rv\delta}'\Delta r'\Delta v'\Delta\delta' + Y_0' \tag{8}$$

$$\Delta f_3' = N_v'\Delta v' + N_r'\Delta r' + N_\delta'\Delta\delta' + N_{|v|v}'|\Delta v'|\Delta v' + N_{|v|r}'|\Delta v'|\Delta r' + N_{|r|r}'|\Delta r'|\Delta r' + N_{v|r|}'\Delta v'|\Delta r'| + N_{\delta\delta\delta}'\Delta\delta'^3 + N_{vv\delta}'\Delta v'^2\Delta\delta' + N_{v\delta\delta}'\Delta v'\Delta\delta'^2 + N_{r\delta\delta}'\Delta r'\Delta\delta'^2 + N_{rr\delta}'\Delta r'^2\Delta\delta' + N_{rv\delta}'\Delta r'\Delta v'\Delta\delta' + N_0' \tag{9}$$

in which the number of derivatives decreases from 60 to 36. Moreover, the cross flow model is adopted in the model to replace the third-order nonlinear terms $Y_{vvv}'\Delta v'^3 + Y_{vvr}'\Delta v'^2\Delta r' + Y_{rrr}'\Delta r'^3 + Y_{vrr}'\Delta v'\Delta r'^2$ and $N_{vvv}'\Delta v'^3 + N_{vvr}'\Delta v'^2\Delta r' + N_{rrr}'\Delta r'^3 + N_{vrr}'\Delta v'\Delta r'^2$, in consideration of the physical essence of ship maneuvering.

3 SVM-Based SI

Support vector machine learning strategy was formally put forward in 1990s [41]. During the last decade, it has found wide application in system engineering and presented to be a useful method in SI. As a batch technique, SVM-based identification avoids lengthy iteration and requires no initial estimation of hydrodynamic coefficients. The convergence and robustness of this algorithm are improved. Moreover, to compare with other traditional repressors, SVM has better generalization ability because the tradeoff between empirical error and complexity of the model is considered in the SVM algorithm. That is, the so-called structural risk minimization.

3.1 SVM Formulation. Generally, SVM can be used for classification and regression. For regression purposes, SVM gives a general approximation function form

$$y = \mathbf{w}^{\mathrm{T}} \cdot \Phi(\mathbf{x}) + b \tag{10}$$

for a multi-input single-output system

$$x \times y \in \mathbb{R}^n \times \mathbb{R}: (x_1, y_1), \ldots, (x_i, y_i), \ldots, (x_l, y_l), \; i = 1, 2, \ldots l$$

where $\mathbf{x}$ is the input vector of the system, y is the scalar output of the system, and l is the number of samples. In the expression (10), $\mathbf{w}$ is a weight matrix, b is a constant, and $\Phi(\cdot)$ is a nonlinear function. These three variables are introduced to construct a linear function in a so-called high-dimensional feature space to approximate the hidden mapping underlying in the original low-dimensional feature space. Theoretically, $\mathbf{w}$ and $\Phi(\cdot)$ can be infinite dimensional.

To satisfy the minimization of structural risk, a cost function is defined in a standard SVM algorithm

$$\min_{w,b,\xi} \left\{ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\left(\xi_i + \xi_i^*\right) \right\} \tag{11}$$

and subjected to

$$\left.\begin{aligned} y_i - [\mathbf{w}^T\Phi(\mathbf{x_i}) + b] \le \varepsilon + \xi_\mathbf{i} \\ \mathbf{w}^T\Phi(\mathbf{x_i}) + b - y_\mathbf{i} \le \varepsilon + \xi_\mathbf{i}^* \\ \xi_\mathbf{i}, \; \xi_\mathbf{i}^* \ge 0 \end{aligned}\right\} \tag{12}$$

where ε is the insensitivity factor, ξ and ξ^* are the slack variables, and C is the regularization factor.

Applying convex quadratic programing theory to the cost function (11) and its constraint condition (12), Eq. (10) can be deduced to a kernel expression

$$y = \sum_{\mathbf{i}=1}^{\lambda} \alpha_\mathbf{i} \mathrm{K}(\mathbf{x_i}, \mathbf{x}) + b, \tag{13}$$

where α_i is the Lagrange factor, $\mathrm{K}(\mathbf{x_i}, \mathbf{x})$ is the kernel function, and λ is the number of so-called support vectors. The principle of SVM is illustrated in Fig. 2.

To reduce the difficulty of selecting structural parameters in the standard SVM, several modified SVM were proposed, in which LS-SVM provides a simpler structure [42]. By adopting a quadratic form of slack variable in the cost function (11) and loosing the constraint condition (12), the following matrix equation can be obtained:

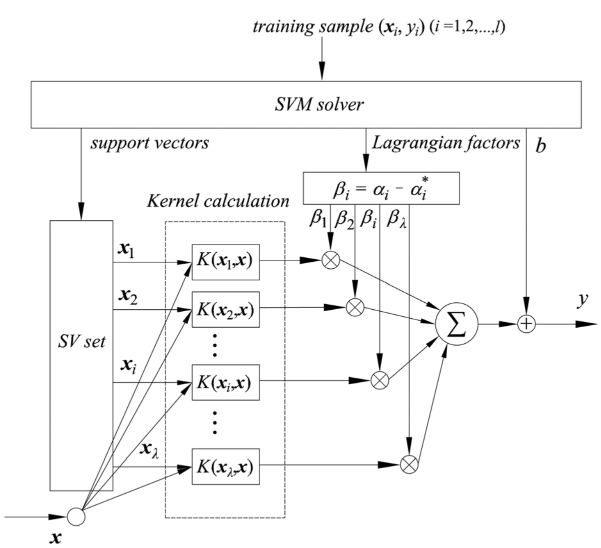

Fig. 2 Framework of SVM regression

$$\begin{bmatrix} 0 & \mathbf{1}^T \\ \mathbf{1} & \mathbf{Q} + C^{-1}\mathbf{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \tag{14}$$

where $\mathbf{1} = [1, \;\cdots,\; 1]_{1\times l}^{\mathrm{T}}$; $\mathbf{I}$ is a l-dimensional unit matrix; $\mathbf{Q} = (q_{ij})_{l\times l}$ is a kernel matrix, where $q_{ij} = \Phi^T(x_i)\Phi(x_j)$; $\boldsymbol{\alpha} = (\alpha_i)_{l\times 1}$; and $\mathbf{y} = (y_i)_{l\times 1}$.

Obviously, Eq. (14) provides a kind of batch identification for given training samples, and it simplifies the calculation of Lagrangian factors and the bias. In this paper, the LS-SVM is employed.

3.2 Parameter Identification Based on SVM. For the purpose of parametric identification, SVM regression can be written as

$$y_i = \left(\sum_{\mathbf{j}=1}^{\lambda} \alpha_\mathbf{j}\mathbf{x_j}\right) \cdot \mathbf{x_i} + b \tag{15}$$

by taking the linear kernel $\mathrm{K}(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j})$. The coefficients of x_i in Eq. (15) are equal to the parameters to be identified. The relationship between the coefficients in SVM and those in the Abkowitz model gives as follows.

Usually, the Abkowitz model is considered as a nonlinear hydrodynamic model. However, from the viewpoint of regression analysis, this model can be viewed as a linear model with respect to structural parameters. Hence, Eq. (1) can be rewritten as

$$\left.\begin{aligned} \Delta\dot{u}' &= \mathbf{A}\cdot\mathbf{X} \\ \Delta\dot{v}' &= \mathbf{B}\cdot\mathbf{Y} \\ \Delta\dot{r}' &= \mathbf{C}\cdot\mathbf{Z} \end{aligned}\right\} \tag{16}$$

where the variable vector and coefficient vector are, respectively, defined as

$$\mathbf{X} = [\Delta u', \Delta v'^2, \Delta r'^2, \Delta\delta'^2, \Delta v'\Delta r', \Delta v'\Delta\delta', \Delta r'\Delta\delta', 1]_{8\times 1}^{\mathrm{T}}$$

$$\mathbf{Y} = \mathbf{Z} = [\Delta v', \Delta r', \Delta\delta', |\Delta v'|\Delta v', \Delta\delta'^3, |\Delta v'|\Delta r', \Delta v'^2\Delta\delta',$$
$$\Delta v'\Delta\delta'^2, |\Delta r'|\Delta r', \Delta v'|\Delta r'|, \Delta r'\Delta\delta'^2, \Delta r'^2\Delta\delta', \Delta r'\Delta v'\Delta\delta', 1]_{14\times 1}^{\mathrm{T}}$$

$$\begin{aligned} \mathbf{A} &= [\,a_1 \quad a_2 \quad a_3 \quad \cdots \quad a_8\,]_{1\times 8} \\ \mathbf{B} &= [\,b_1 \quad b_2 \quad b_3 \quad \cdots \quad b_{14}\,]_{1\times 14} \\ \mathbf{C} &= [\,c_1 \quad c_2 \quad c_3 \quad \cdots \quad c_{14}\,]_{1\times 14} \end{aligned}$$

where a_i, b_i, and c_i can be expressed by the hydrodynamic coefficients. For details of their relationship, see Ref. [31]. Comparing Eq. (15) with Eq. (16), one can say that the coefficients in these two systems are identical if SVM approximates the actual outputs well.

In short, for given samples from experiments, if the coefficient vector in Eq. (16) can be identified, the hydrodynamic coefficients in the maneuvering model (1) can also be obtained. It should be noted that not all hydrodynamic coefficients of a state-space model such as Eq. (16) can be estimated by SI because of parameter identifiability [43]. Nevertheless, the theoretical calculation results of the five acceleration derivatives, i.e., $X'_{\dot{u}}$, $Y'_{\dot{v}}$, $Y'_{\dot{r}}$, $N'_{\dot{v}}$, $N'_{\dot{r}}$, usually have enough practical preciseness. Hence, they can be determined beforehand in SI.

4 Analyses of the Free-Running Model Tests Using PSO–SVM

Before identification, the training samples (i.e., the test data) are preprocessed so as to improve the identification accuracy. First of all, a zero-phase forward and reverse digital filter is used to deal with the outliers in the test data [44]. Second, to diminish the drift effect of hydrodynamic coefficients in identification, the samples are reconstructed by using a difference method.

4.1 Reconstruct the Samples for Identification. Drift effect of the hydrodynamic coefficients is inevitable in modeling of ship maneuvering motion by using SI techniques. To improve the accuracy of modeling and subsequent prediction of ship maneuverability, this effect should be minimized. Hwang applied the slender body theory to explain the mechanism of parametric drift effect and proposed some measurements to alleviate this effect [43]. However, only linear hydrodynamic coefficients were discussed and processed, versus nonlinear hydrodynamic coefficients.

From the viewpoint of regression analysis, the drifts of hydrodynamic coefficients result from the so-called multicollinearity. It can be explained that if the input variables of a regression model are strongly linearly dependent on each other, the regression results of their coefficients may be incorrect or worse, even if the predicted outputs agree well with the desired. The case is more possible and serious, especially when the system contains a large number of parameters to be identified. Multicollinearity cannot be eliminated but only moderated, because the input variables are always linearly dependent on each other, more or less. In this paper, samples are reconstructed to diminish the drift effect.

The drift effect is determined by the characteristics of the regression model and those of samples. Modification or reconstruction of the samples provides an effective way to moderate the multicollinearity and subsequent parameter drift. In literature, to obtain a new sample, pseudo random binary signal excitation was used to activate the ship maneuvering motion and the drift effect was moderated and verified by simulation results [18,45]. However, for given samples from maneuvering motion, such excitation is not consistent with the fact. In this paper, difference method is used to reconstruct the samples.

Without loss of generality, a system, linear with respect to parameters, is given as

$$y(k) = a_1 x_1(k) + a_2 x_2(k) + \cdots + a_n x_n(k) \tag{17}$$

where k is the sampling time, and $a_i\ (i = 1, 2, \ldots n)$ is the structural parameter. At a neighbor time, the following equation holds:

$$y(k-1) = a_1 x_1(k-1) + a_2 x_2(k-1) + \cdots + a_n x_n(k-1) \tag{18}$$

By introducing a constant μ and combining Eqs. (17) and (18), one has

$$\begin{aligned} y(k) - \mu y(k-1) = {} & a_1[x_1(k) - \mu x_1(k-1)] + a_2[x_2(k) - \mu x_2(k-1)] \\ & + \cdots + a_n[x_n(k) - \mu x_n(k-1)] \end{aligned} \tag{19}$$

Obviously, when $\mu = 1$, the above equation is a standard difference form. As can be seen from Eqs. (17) and (19), although the inputs and output are different, the parameters in the original system (17) remain unchanged. Usually, if the degree of linear dependence of input variables in the original system is serious, it can be moderated after difference of samples. This can be verified by correlation analysis. Take the system (17) as an example, the correlation coefficient between any two elements, e.g., x_1 and x_2, is calculated by

$$\rho_{x_1 x_2} = \frac{\mathrm{cov}(x_1, x_2)}{\sqrt{D(x_1) D(x_2)}} \tag{20}$$

where $D(x_1)$ and $D(x_2)$ denote the variance, and $\mathrm{cov}(x_1, x_2)$ denotes the covariance, calculated by expectations. By using the formula (20), degree of the linear independence between x_1 and x_2 can be confirmed, i.e., the nearer to one the absolute value of $\rho_{x_1 x_2}$ approximates, the more serious the linear dependence between x_1 and x_2 is.

4.2 Parameter Selection Based on PSO. As a learning machine, the performance of SVM depends on its structural parameters, such as insensitivity factor, regularization parameter, and kernel parameters. The coefficients of variables in the regression model are sensitive to the parameter in SVM. Unfortunately, how to calculate optimal parameters theoretically still has a long way to go because of the difficulty of determination of VC dimension [46]. Often, parameters in SVM are determined by trials. In this paper, PSO is introduced to obtain the parameter in LS-SVM. For LS-SVM, the object for parametric optimization is the regularization factor.

Particle swarm optimization was put forward in 1995 by Kennedy and Eberhart [47]. This method optimizes a problem from a population of candidate solutions, so-called dubbed particles, and moves these particles in the search-space according to iteration formulae about the particle's position and velocity. It is expected that particles move toward the best solutions. Generally, PSO makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. Also, it is not required that the optimization problem be differentiable as is required by classic optimization methods. Furthermore, compared

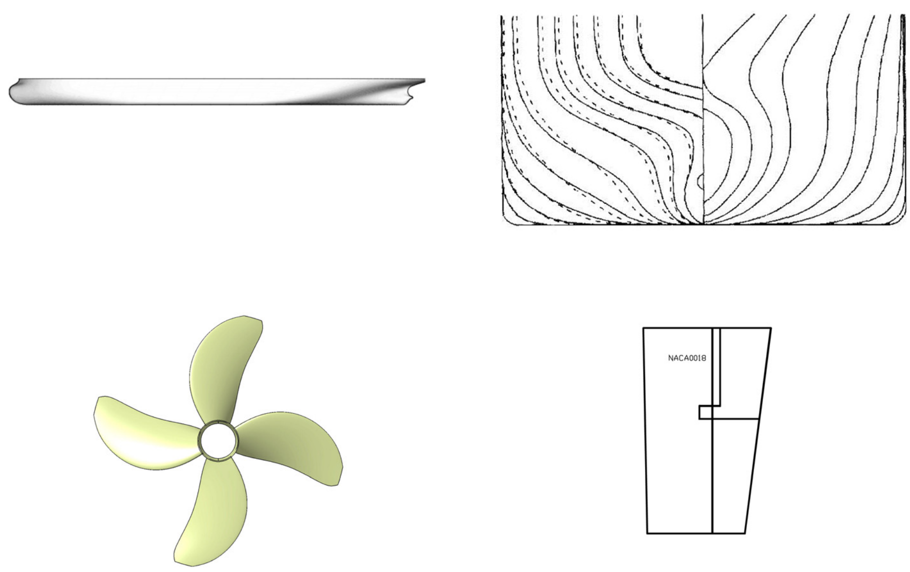

Fig. 3 Hull, propeller, and rudder profiles of KVLCC ships

Table 1 Principal particulars of KVLCC2

Description	Full-scale	KVLCC2
Scale ratio	1:1	1:45.714
Perpendicular length (L_{pp})	320.0 m	7 m
Length on water line (L_{wl})	325.5 m	7.1204 m
Breadth (B_{wl})	58 m	1.2688 m
Ship depth (D)	30.0 m	0.6563 m
Draft (d)	20.8 m	0.4550 m
Beam coefficient (C_B)	0.8098	0.8098
Displacement (∇)	312,622 m^3	3.2724 m^3

Table 2 Condition numbers of correlation coefficient matrix

	Surge	Sway	Yaw
Without difference	4.2×10^4	1.3×10^6	3.2×10^5
With difference	1.7×10^4	4.8×10^3	2.7×10^3

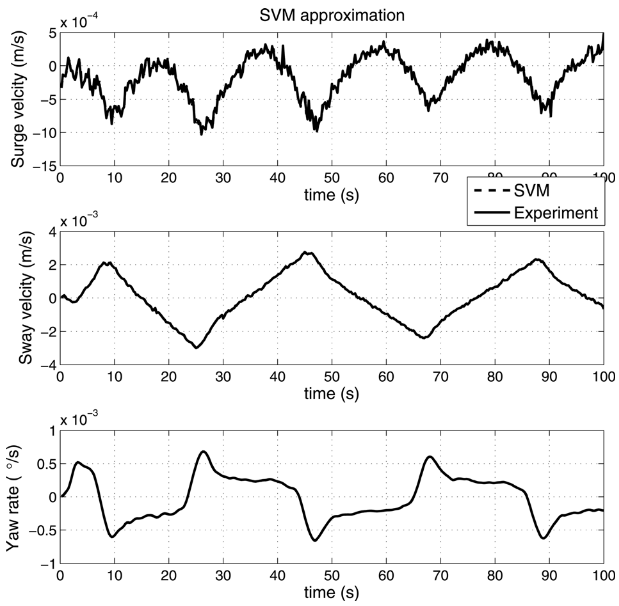

Fig. 4 SVM regression

Table 3 Identified coefficients ($\times 10^{-5}$)

Constant	Value	X coefficient	Value	Y coefficient	Value	N coefficient	Value
$X'_{\dot{u}}$	-95.4	X'_u	-128	Y'_v	-94	N'_v	-7
$Y'_{\dot{v}}$	-1283	X'_{vv}	175	Y'_r	2066	N'_r	-142
$Y'_{\dot{r}}$	0	X'_{rr}	-118	Y'_δ	486	N'_δ	-199
$N'_{\dot{v}}$	0	$X'_{\delta\delta}$	-116	$Y'_{\|v\|v}$	63	$N'_{\|v\|v}$	43
$N'_{\dot{r}}$	-107	X'_{vr}	-303	$Y'_{\|v\|r}$	67	$N'_{\|v\|r}$	49
x'_G	3486	$X'_{v\delta}$	196	$Y'_{\|r\|r}$	737	$N'_{\|r\|r}$	-26
m'	1908	$X'_{r\delta}$	-455	$Y'_{\|v\|r}$	177	$N'_{\|v\|r}$	-145
I'_z	119	X'_0	-85	$Y'_{\delta\delta\delta}$	-58	$N'_{\delta\delta\delta}$	65
				$Y'_{v\delta\delta}$	29	$N'_{v\delta\delta}$	27
				$Y'_{vv\delta}$	17	$N'_{vv\delta}$	23
				$Y'_{r\delta\delta}$	-50	$N'_{r\delta\delta}$	50
				$Y'_{rr\delta}$	99	$N'_{rr\delta}$	-141
				$Y'_{rv\delta}$	-40	$N'_{rv\delta}$	37
				Y'_0	-56	N'_0	18

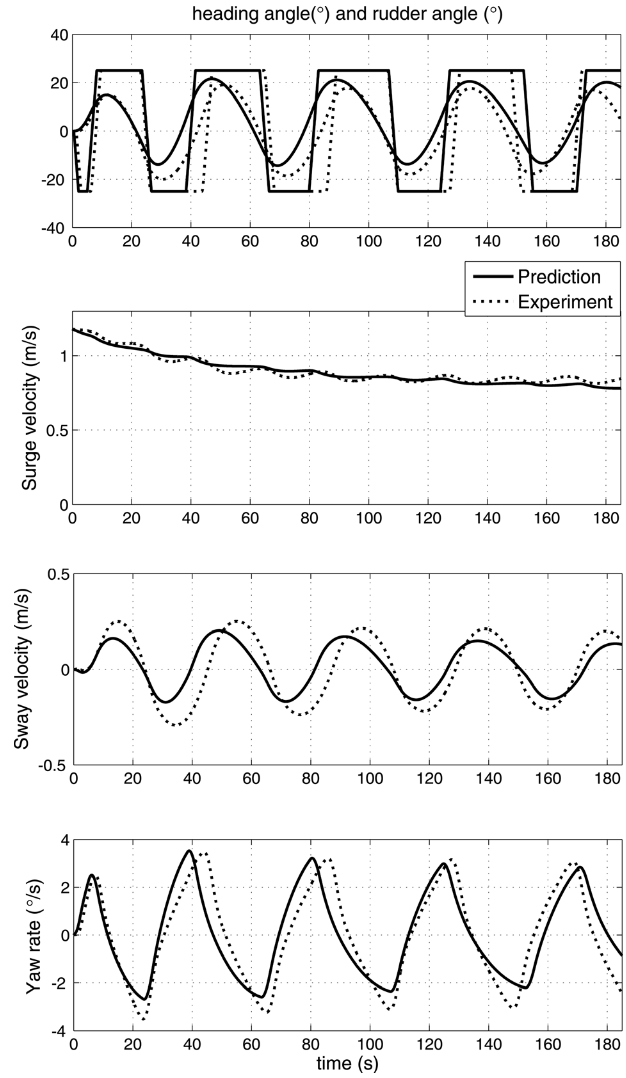

Fig. 5 Prediction of 25 deg/5 deg zigzag maneuver

to other optimization methods, the algorithm in PSO is simpler which is easy to implement. During the last ten years, this method has been increasingly paid attention to. It has found wide application in parameter optimization.

PSO algorithm has the general form as

$$V_{id}^{k+1} = W \cdot V_{id}^{k} + c_1 \xi (p_{id}^{k} - X_{id}^{k}) + c_2 \eta (p_{gd}^{k} - X_{id}^{k}) \tag{21}$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \tag{22}$$

where V_{id}^k is the velocity of a particle at the kth step; $i = 1, 2, \ldots n$, n is the number of particles; $d = 1, 2, \ldots q$, q is the dimension of particle; X_{id}^k is the position of a particle at the kth step; W is the inertia weight; c_1 and c_2 are the acceleration coefficients; p_{id}^k is the best position of a individual particle while p_{gd}^k is the swarm or social best position; and ξ and η are both random.

4.3 Identification Results. The samples for identification by SVM are taken from the zigzag maneuver tests of large tankers KVLCC2, one of the benchmark ships for verification and validation of ship maneuvering simulation methods [48], recommended by the International Towing Tank Conference Maneuvering Committee. The ship model and the steering apparatus are shown in Fig. 3, in which the dotted lines denote the stern profile of KVLCC1 while the solid lines are with KVLCC2. The principal particulars of the KVLCC2 ship are given in Table 1. Tests were

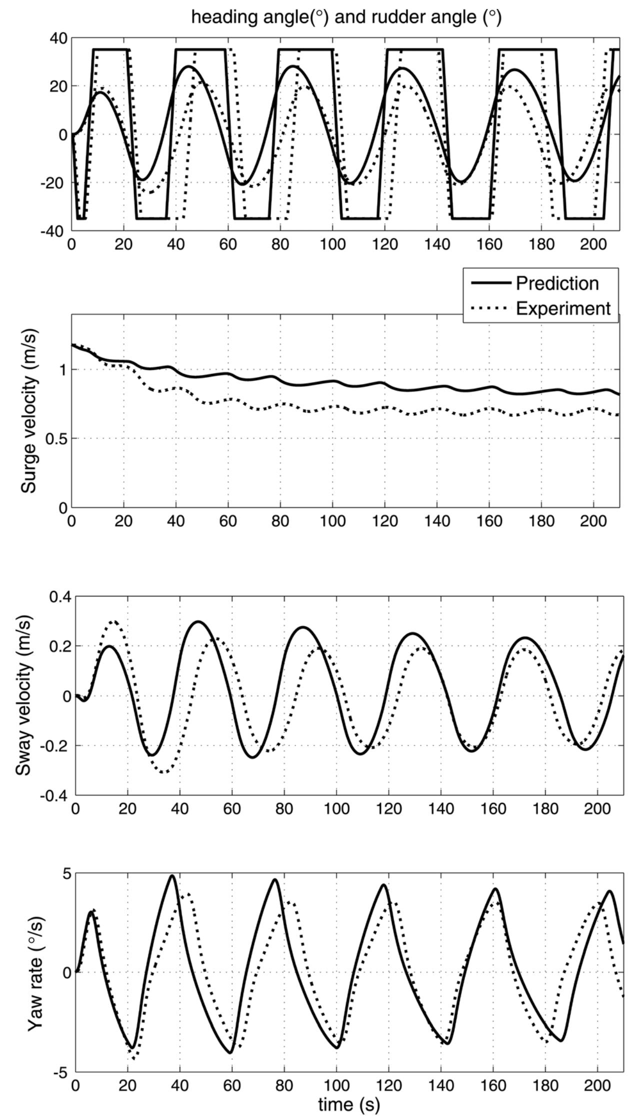

Fig. 6 Prediction of 35 deg/5 deg zigzag maneuver

carried out at an approach speed of $U_0 = 1.179$ (m/s) in deep water at the Hamburg Ship Model Basin. The rate of revolutions of the propeller was kept at $n = 10.23$ (1/s), and the average helm rate was $\dot{\delta}_R = 15.8$ deg/s.

In parameter identification, 400 training samples are taken from 25 deg/5 deg zigzag maneuver tests. The sampling interval is 0.05 s. The order of the zero-phase digital filter is set 10, and the desired cutoff frequency is 0.003. The training samples are dealt with by the difference method. Table 2 gives the condition numbers of correlation coefficient matrix of input variables with respect to surge, sway, and yaw motion. As seen, the linear dependence of the input variables is obviously decreased.

Support vector machine and PSO are then used to identify the hydrodynamic coefficients in the ship maneuvering model. In PSO, the number of particles is selected as 50. The initial positions of the particles are random numbers restricted in [2000, 3000]. The optimal regularization factor is obtained as $C = 2544$. The SVM regression results are shown in Fig. 4. As seen, the SVM approximations agree well with the experimental results. The identified hydrodynamic coefficients are given in Table 3, in which the added mass and moment are calculated by slender body theory. Based on the ship maneuvering model, 25 deg/5 deg and 35 deg/5 deg zigzag maneuvers are predicted, respectively, as shown in Figs. 5 and 6. It can be seen from the comparisons between predictions and experiments that prediction of the first overshoot angle is satisfying. Nevertheless, it should be noted that errors exist. In future works, more efforts will be devoted to the improvement of prediction accuracy.

As a comparison between SVM and other well-established regression techniques, Table 4 lists the coefficients identified by ridge regression, an improved LS approach. The sway and yaw motions are considered. In the algorithm, the damping factor ξ is selected as 0.01 and 100, respectively. Three different initial values of coefficients are given as −0.01, 0, and 20. The tolerance is set to 10^{-4}. The number of iterations is set to 500. As can be seen from the results, the identified results are sensitive to the damping factor and initial values of coefficients. In some cases, even erroneous results are obtained. For example, $Y'_v > 0$ and $N'_r > 0$ happen in the case of $\xi = 100$. Comparatively, for SVM, initial estimation of coefficients is not required since SVM is a kind of batch identification.

5 Conclusions

System-based maneuvering simulation is an effective and practical way to predict the ship maneuverability. To use this method, modeling of the ship maneuvering motion is the premier, which requires the determination of hydrodynamic coefficients therein. The accuracy of prediction depends on the accuracy of the hydrodynamic coefficients. Combined with free-running model tests, system identification provides an effective way of determining those coefficients. This paper presents a PSO–SVM based SI approach to obtain the hydrodynamic derivatives in an Abkowitz model, except for the inertia derivatives that are determined by

Table 4 Coefficients identified by ridge regression

	$\xi = 0.01$		$\xi = 100$			$\xi = 0.01$		$\xi = 100$	
Y coefficient	Initial value = 0	Initial value = 20	Initial value = −0.01	Initial value = 0	*N* coefficient	Initial value = 0	Initial value = 20	Initial value = −0.01	Initial value = 0
Y'_v	−0.015039	−0.012727	0.71868	0.73702	N'_v	0.00091452	0.002036	−0.010469	−0.00044597
Y'_r	0.024494	0.02457	−0.12788	−0.10101	N'_r	−0.0010634	−0.0010218	0.14817	0.15876
Y'_δ	0.0059788	0.0058675	1.1422	1.1332	N'_δ	−0.0023677	−0.0024211	−0.026624	−0.027958
$Y'_{\|v\|v}$	−0.37894	−0.41832	0.13161	0.17558	$N'_{\|v\|v}$	−0.0078725	−0.027164	−0.020258	1.1759×10^{-5}
$Y'_{\|v\|r}$	0.035478	0.037634	−0.13328	−0.082296	$N'_{\|v\|r}$	0.0040697	0.0051312	−0.0062564	0.016417
$Y'_{\|r\|r}$	0.018275	0.017902	−0.035595	0.0061843	$N'_{\|r\|r}$	−0.0013836	−0.0015651	0.037178	0.055604
$Y'_{\|v\|r}$	0.0026202	0.0027522	0.061519	0.10914	$N'_{\|v\|r}$	0.0020683	0.0021371	−0.029767	−0.0079528
$Y'_{\delta\delta\delta}$	−0.0024937	−0.0016866	0.18063	0.22055	$N'_{\delta\delta\delta}$	−0.00039411	-1.91×10^{-6}	−0.023898	−0.0053443
$Y'_{v\delta\delta}$	−0.023363	−0.036279	0.093415	0.13861	$N'_{v\delta\delta}$	−0.0054855	−0.011793	−0.021393	−0.00066045
$Y'_{vv\delta}$	0.84896	0.93995	0.028169	0.076248	$N'_{vv\delta}$	0.029206	0.073806	−0.02196	-7.4084×10^{-5}
$Y'_{r\delta\delta}$	0.0016539	0.0018665	−0.088962	−0.039901	$N'_{r\delta\delta}$	−0.0049482	−0.0048474	−0.0001097	0.021765
$Y'_{rr\delta}$	0.013144	0.012599	−0.030517	0.020903	$N'_{rr\delta}$	−0.0064604	−0.0067287	−0.036327	−0.012977
$Y'_{rv\delta}$	−0.066188	−0.071674	−0.08933	−0.038034	$N'_{rv\delta}$	0.016045	0.013356	−0.016403	0.0066022
Y'_0	-7.36×10^{-5}	-6.83×10^{-5}	0.056403	0.057116	N'_0	0.00014581	0.0001488	0.0031324	0.0035631

slender body theory. To diminish the multicollinearity in the regression, the data samples are reconstructed by a difference method. To obtain an optimal control parameter in SVM, the PSO method is incorporated into SVM. Based on the mathematical model of ship maneuvering motion, zigzag maneuvers are simulated. The comparison between the predicted results and the experimental results demonstrated the validity of the PSO–SVM based modeling method proposed.

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