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A Novel Adaptive Weighted Least Square Support Vector Regression Algorithm-Based Identification of the Ship Dynamic Model

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ABSTRACT This study contributes to developing a novel hybrid identification method based on intelligent algorithms, i.e. the least support vector regression algorithm (LS-SVR) and the artificial bee colony algorithm (ABC), to deal with the identification of the simplified ship dynamic model while the outliers exist in the measurements. The ship dynamic model is directly derived from our previous work which has been well verified and validated. The outliers are detected by introducing the robust estimation method namely the 3σ principle and then deleted from the training data. The weighted version of LS-SVR (WLS-SVR) with spareness and robustness ability is used as the fundamental identification approach. To improve the performance of the WLS-SVR, the structural parameters involved in it are optimized by utilizing the artificial bee colony algorithm (ABC), and the weights of it are adaptively set with the use of the adaptive weight method. Two case studies including the simulation study on a container ship and the experimental study on an Unmanned Surface Vessel (USV) are carried out to test the proposed hybrid intelligent identification method. The simulation study demonstrates the effectiveness and the acceptable time complexity in terms of the engineering application of the proposed identification method through the comparison with the cross-validation method and particle swarm optimization algorithm optimized LS-SVR. In the experimental study, ABC-LSSVR, ABC-LSSVR with the 3σ principle (D-ABC-LSSVR), ABC-LSSVR with the adaptive weight (ABC-AWLSSVR), and ABC-LSSVR with both the 3σ principle and the adaptive weight (D-ABC-AWLSSVR) are applied to identify the steering model for the USV. The results indicate that the influence of the outliers on model identification is effectively diminished by the robust 3σ principle and the adaptive weight method and that the D-ABC-AWLSSVR outperforms over the other three identification methods in terms of the mean squared error (MSE) of the model predictions.

INDEX TERMS Ship dynamics modeling, outlier detection, robust 3σ principle, adaptive weight, artificial bee colony algorithm, least square support vector regression algorithm, a hybrid intelligent identification method.

I. INTRODUCTION

With the shipping industry showing increasing interest in developing autonomous ships, International Maritime Organization (IMO) plans to review regulations pertaining to Maritime Autonomous Surface Ships (MASS) on September 2019 and furthermore to complete the regulatory scoping exercise by 2020 [1]. Compared with traditional manned ships, the safety of MASS is increased and the emission is reduced. The motivations of the application of MASS are diverse, for instance, which can be utilized widely in the marine sector from research and environmental monitoring programs to naval and defense applications. Besides, it has a relatively long lifespan and can be deployed in a wide range of challenging environments without risk to humans and could be used to take large and potentially hazardous loads.

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Although the MASS is defined as the ship which to a varying degree can operate independent of human interaction, it still relies on humans working on an onshore control center for its operation [2]. Until now, the technical aspects of MASS operation such as detection sensors, controller design and collision avoidance involving detection, path planning and anti-collision algorithms and adaptation of COLREGs (International Regulations for Preventing Collisions at Sea) have achieved great advances [3]. For controller design and collision avoidance, a suitable ship dynamic model is required and critical [4].

In general, the task of modeling ship dynamics envelops two sub-tasks, including the determination of model structure, and the estimation of parameters involved in the model.

A. DETERMINATION OF MODEL STRUCTURE

To establish the model structure, Newton's second motion law is the baseline and has been used to drive several typical ship dynamic models, such as Abkowitz model [5], MMG (Mathematical Modeling Group) model [6], vectorial representation model [7], and response model [8]. Abkowitz model expresses the hydrodynamic forces and moments acting on the ship hull, propeller and rudder by using the function of state variables and actuator variable, which is expended with a 3rd-order truncated Taylor-series at the steady-state status. This kind model has a good ability to capture ship dynamics in high precision but has high complexity and nonlinearity. Differently, MMG model just includes the hydrodynamic items with physical interpretation and excludes the meaningless coefficients indicated by the captive model test, the complexity of which to some degrees decreased. Vectorial representation model proposed by Fossen uses the vector-matrix form to express the forces and moments acting on the ship, which is straightforward to analyze the characteristics such as the passivity and stability of the ship to feed into especially the controller design. Response model describes the ship head reactions to the commanded rudder, which can be categorized into two core kinds, i.e. the first-order linear/nonlinear Nomoto model and the second-order linear/nonlinear Nomoto model. This kind model is of acceptable simplicity to be widely used for the autopilot design in marine engineering.

In Abkowitz model, the hull, propeller, and rudder of the ship are assumed as a holistic system, for which the relatively induced forces and moments are completely expressed by the Taylor series. But its application is restricted due to three facts. The local variation in the design of ship hull, propeller or rudder and the analysis of their interactions are impossible. Some coefficients have no clear physical interpretation. Too many coefficients involved in the model make the multicollinearity highly happen, which meanwhile challenges the estimation of coefficients. In MMG model, external forces and moments generated by ship hull, propeller and rudder are represented separately by modulus functions but completely captured, which makes each term have manifest physical interpretation at the same time makes changes on hull, propeller or rudder possible. The coefficients can be estimated through a suitable method necessarily incorporated with optimal experiments, but it is cumbersome and high finance-consuming to estimate so many coefficients. What's more, it is not to ensure convenient and fast model simulations. In the vectorial representation model, the equations of motion are completely expressed in the form of vector-matrix where each term can be interpreted physically and adjusted according to the property variations of hull, propeller or rudder. Applying the model for simulation is easy to be conducted in either MATLAB or C++. The irreplaceable advantage of this model is that the nonlinear system properties such as symmetry, skew-symmetry, and positiveness of matrices can be exploited in the passivity or stability analysis. Unavoidably, it must stand the pressure on demand for cumbersome processes and high financial consumption in estimating all coefficients. In response model, only 1 degree of freedom (DOF) dynamic concerning the yaw mode is considered, which is applicable for the course-keeping controller design but not satisfying the requirement of the path following, trajectory tracking, and highly realistic motion simulation.

Considering the above situation of each typical dynamic model, some researchers are committed to developing ship dynamic models by modifying and simplifying the typical model, aiming at matching their specific requirements of studies. An instance is a 3 DOF dynamic model modified and simplified based on the vectorial representation model, which is used for maneuvering simulation for different types of vessels [9], [10]. Even though the model is simplified with low complexity, the precision of it in describing ship dynamics is acceptable, which is evaluated through case studies.

B. ESTIMATION OF PARAMETERS INVOLVED IN THE MODEL

Among the estimation methods, these deserve particular attention, which are captive model test with planar motion mechanism (PMM) [11], estimation with empirical formulas [12], numerical calculation based on computational fluid dynamics (CFD) [13], and system identification with the use of full-scale trails or free-running model tests [14], [15]. The captive model test with PMM is applicable to obtain most parameters, but it has a remaining problem of scaling effect aroused by the difference of Reynold number between the real ship and the scaled model ship which makes the measured value of parameters not wholly reliable [16]. The estimation with empirical formulas is practical and straightforward. The formulas are built based on a statistical analysis of a set of ships, so the estimation results are not precise for the latest type of ships which are not included in the database. The rest two estimation methods are both powerful methods, but the numerical calculation based on CFD always requires extreme computing power, and its validation dramatically depends on the quality and amount of the experimental data. Comparatively, system identification in combination with a free-running model test or full-scale trial avoids the scaling effect and is easy to be undertook, but parameter drift unpredictably existing among parameters if there were too many parameters in a model would compromise the accuracy of identification results. Compared with the scaling effects, the demand of extreme computational power and uninvolved empirical calculation, the influence of parameter drift on estimation exactness of ship dynamic model is relatively easy to be weakened by adopting some measures, e.g. parallel processing [17] and additional excitation [18] to reconstruct the samples and improve the condition number, and truncated singular values decomposition and Tikhonov regularization [19] to diminish the uncertainty due to the noises in measurements.

According to the above analysis of estimation methods, we can find that the last method is a sufficient and high cost-effective selection in estimating parameters of a reduced-parameter ship dynamic model. When combined with full-scale trails, the scale effect due to the difference of Reynolds number between the full-scale ship and its model can be avoided. Besides, when combined with free-running model tests, the system identification technique is a cost-effective solution due to many maneuvers can be easily generated once the first set of free-running model tests is carried out.

Up to date, a variety of identification methods, e.g. maximum likelihood method (ML) [20], extended Kalman filtering algorithm (EKF) [21], least square method (LS) [22], neural network method (NN) [23], genetic algorithm (GA) [24], simulated annealing algorithm (SA) [25], SVM [26], [27], have been studied in parameter estimation of ship dynamic model. Nevertheless, the deficiencies existing in these methods require attention which can be explained as follows. ML and EKF are sensitive to the predetermined parameters. NN and GA cannot always ensure the global optimum for the model. Comparatively, SVM avoids these deficiencies when used as the identifier benefiting from its merits which are explained from two aspects. (1) It can work beyond the limitations of the data acquisition of the vessel maneuvers due to it requires only a finite set of data. In fact, the experiment of the vessel carried out to stem data is expensive and restricted to various factors such as the weather condition, equipment, mobility of the vessel. So usually a limited number of measurements can be obtained for the identification. (2) SVM can guarantee global optimal solutions because the optimization problem defined by it is a convex one typically quadratic programs (QP). This property makes a positive impact on the exactness of the identification results.

One point concerning SVM deserving particular attention is that the coefficients of variables in the regression model are sensitive to the structural parameters of SVM, such as the insensitivity factor, the regularization parameter, and kernel parameters, which implies that it is of high significance to assign these structural parameters with particular settings to guarantee good fitting of measurements. To determine these structural parameters particularly, methods such as cross-validation method (CV) [28], particle swarm optimization (PSO) [29], [30], jaya optimizer and salp swarm algorithms [31], ant colony algorithm (ACA) [32], ABC [14] have been successfully studied by scholars. CV is simple but time-consuming and at average accuracy. PSO and ACA present the unavoidable problem of the local optimum. ABC as one of the most recent nature-inspired algorithms has been proven to be a robust and efficient algorithm for solving global optimization problems over continuous space. It is also validated by some studies that the performance of ABC is better than or similar to PSO and ACA with the advantage of employing fewer control parameters [33].

C. WORK OF THIS STUDY

Least square support vector regression algorithm (LS-SVR) proposed by Suykens and Vandewalle [34] is one modified version of SVM, working with equality constraints instead of inequality constraints and the quadratic deviation. Such changes happening on LS-SVR reduces its complexity at the same the merits like working with finite samples to find a function for nonlinear system estimation are still inherited. Nonetheless, LS-SVR has a deficiency, which is sensitive to the noises or outliers corrupted in the measurements [35].

In this paper, a hybrid identification method named D-ABC-AWLSSVR method consisting of the robust 3σ principle (D), the ABC optimization algorithm and adaptive weight method (AW) is developed for the identification of the simplified 3 DOF ship dynamic models studied in [9] and [10]. The outliers from equipped sensors and environmental disturbances contaminated in the measurements are firstly detected and filtered from the training samples. Afterward, the ABC is employed to optimize the structural parameters of the LS-SVR and the weighted LS-SVR. The weighted LS-SVR method is then designed to adaptively adjust the weights by combining the adaptive weight method. In the end, the data extracted from relatively informative maneuvers containing the zigzag maneuvers and straight-line maneuvers of vessels are used to verify and validate the proposed hybrid method in identifying the simplified ship dynamic model for different type vessels. Compared with CV and PSO optimized LS-SVR based identification methods, ABC-LSSVR exhibits out-performance with the requirement of low computational cost, which is validated through the simulation study on a container ship. Additionally, the superior identification performance of the D-ABC-AWLSSVR method is demonstrated through the comprehensive comparison of the ABC-LSSVR method, ABC-AWLSSVR method, D-ABC-LSSVR method in the experimental study on a USV.

The main work and contributions of this study can be summarized as follows:

1) The performance especially the spareness and robustness of the LS-SVR based identification method is improved by introducing the outliers detector, i.e. the robust 3σ principle to pre-filter the potential noises, and the adaptive weight method to highlight the effect

of the efficient samples at the same time weaken the influence of the outliers.

2) The ABC with the advantage of fewer control parameters compared with the others bionic algorithms is applied for the optimization of the structural parameters of the LS-SVR based identification methods, which is optimal to control the trade-off between the empirical risk and the confidence interval for the LS-SVR.
3) Informative maneuvers such as zigzag maneuvers carried out on different type vessels are used to analyze the complexity and the performance of the proposed hybrid method.

The remainder of this paper is organized as follows: Section II briefly elaborates the procedure of modeling ship dynamics based on our previous work published in a peer-reviewed journal. In Section III, the methods further used to construct the hybrid identification method, i.e. the robust 3σ principle method, the ABC, the (weighted) LS-SVR, and the adaptive weight method are introduced in detail. Afterward, the hybrid identification method named D-ABC-AWLSSVR method is developed in Section IV where the procedure with a flowchart and the time complexity of this method are also explained. To verify and validate the effectiveness of the proposed method, two case studies including the simulation study of a container ship and the experimental study of a USV are undertaken in Section V. Finally, the work of this paper is concluded in Section VI.

II. MODELING OF SHIP DYNAMICS

A. REFERENCE FRAMES AND NOTATIONS

To describe the motion of ships, reference frames are necessary to specify what the motion is relative to. In this study, the North-East-Down (NED) frame and body-fixed frame are selected to describe the motion of ships. The NED frame is also regarded as the earth-fixed frame in the flat earth navigation, which is defined relative to the Earth's reference ellipsoid (WGS-84). For the earth-fixed coordinate system, the axes x, y and z are usually defined as the x axis directs to true north, the y axis directs to the east, and z axis directs downwards normal to earth's surface. In the earth-fixed frame, the first three coordinates and their time derivatives correspond to the position and translational motion along the x-axis, y-axis, and z-axis, while the last three coordinates and their time derivatives are used to describe the orientation and rotational motion [4]. The body-fixed frame is a coordinate system moving along with the body. The origin center is always defined to coincide with a point midship in the waterline. The axes x_b, y_b and z_b are usually set as the x_b axis is towards the fore of ships, the y_b axis directs to starboard of ships, and z_b axis directs towards the bottom of ships. Finally, the two reference frames consisted of a body-fixed frame and an earth-fixed frame (regarded as the inertial frame for the use of Newton's law) are shown in Fig. 1.

For some research issues of ships, f.i., control system designs, the surge, sway and yaw modes are mostly emphasized but the roll, heave and pitch modes are ignored. The corresponding planar coordinate system presented in Fig. 2 is needed to describe the horizontal motions and obtained by removing the z axis from the earth-fixed frame and the z_b axis from the body-fixed frame.

The notations commonly-used to describe motions of ships are listed in Table. 1. More information can be found in [36].

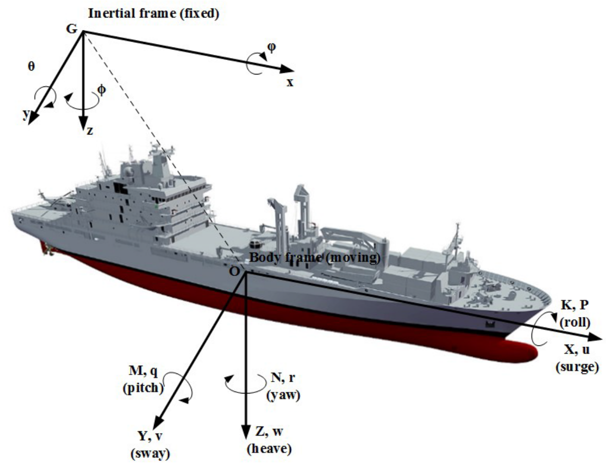

FIGURE 1. Illustration of reference frames.

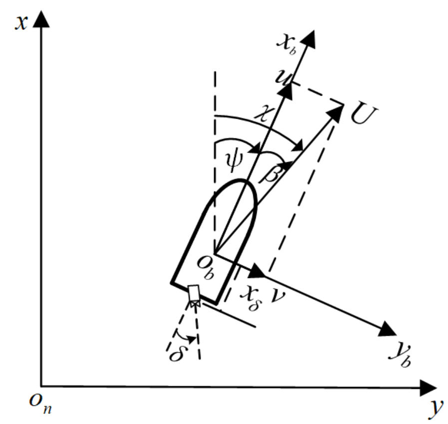

FIGURE 2. Description of planar motion variables. x_δ is the longitudinal moment arm from the center of rotation to the pivot point of the thruster/propulsion.

TABLE 1. Notations from SNAME.

DOF	Motions	Forces	Linear velocity	Positions
1	surge	X	u	x
2	sway	Y	v	y
3	heave	Z	w	z
	Rotations	Moments	Angular velocity	Rotation angles
4	roll	K	p	φ
5	pitch	M	q	θ
6	yaw	N	r	ψ

B. A SIMPLIFIED 3 DOF DYNAMIC MODEL

A full DOF ship dynamic model expressed in the vector-matrix form [7] is selected and simplified to a 3 DOF dynamic model where only the surge, sway and yaw motions are considered, and the forces and moments acting on the ship are calculated with the use of the function of the rudder deflections and the propeller revolutions. The 3 DOF dynamic model is written as (1) [9].

$$\begin{cases} T_{|n|n}\,|n|\,n = (m - X_{\dot u})\,\dot u + (Y_{\dot v} - m)\,vr - X_{|u|u}\,|u|\,u \\ \qquad + \left(Y_{\dot r} - mx_g\right) r^2 - X_u u \\ Y_\delta \delta = (m - Y_{\dot v})\,\dot v + \left(mx_g - Y_{\dot r}\right)\dot r + (m - X_{\dot u})\,ur \\ \qquad - Y_v v - Y_{|v|v}\,|v|\,v - Y_{|r|v}\,|r|\,v - Y_r r \\ \qquad - Y_{|v|r}\,|v|\,r - Y_{|r|r}\,|r|\,r \\ N_\delta \delta = \left(mx_g - N_{\dot v}\right)\dot v + (I_z - N_{\dot r})\,\dot r - (Y_{\dot v} - m)\,uv \\ \qquad - \left(N_{\dot v} - mx_g\right) ur - (m - X_{\dot u})\,uv - N_v v \\ \qquad - N_{|v|v}\,|v|\,v - N_{|r|v}\,|r|\,v - N_r r \\ \qquad - N_{|v|r}\,|v|\,r - N_{|r|r}\,|r|\,r \end{cases} \tag{1}$$

where n is the revolutions per second of the propeller, δ is the rudder actual angle, $T_{|n|n}$ is the coefficient of the propeller power, Y_δ and N_δ are the coefficients of the steering force and moment respectively, m means the masses of the ship, the remaining notations except for the ones depicted in Table. 1 are the hydrodynamic derivatives.

Through the simulation study on a large container ship and the experimental study on a small USV, the 3 DOF dynamic model (1) is verified and validated to be a further reduced-terms form [9]. Taking the research goal of this study aiming at testing the effectiveness of the hybrid LSSVR-based intelligent identification approach, and attempting to diminish parameter drift effect into consideration, this work decides to use the further reduced-terms 3 DOF dynamic model given in (2).

$$\begin{cases} \dot u = X_u^m u + X_{|u|u}^m |u|u + X_{uuu}^m u^3 + T_{|n|n}^m |n|n \\ \dot v = Y_v^m v + Y_r^m r + Y_{|v|r}^m |v|r + Y_\delta^m \delta \\ \dot r = N_v^m v + N_r^m r + N_{|v|r}^m |v|r + N_\delta^m \delta \end{cases} \tag{2}$$

in which the parameters are different from the hydrodynamic derivatives. For the sake of mathematical convenience, they are the consolidation of hydrodynamic derivatives such as $X_u^m = \frac{X_u}{m - X_{\dot u}}$. For more detail, see [9].

III. METHODOLOGY

A. OUTLIER DETECTION USING ROBUST 3σ PRINCIPLE

Given a dataset $x_k (k = 1, 2, \ldots, n)$, calculating the mean of the variable $\bar x$ and the standard deviation s yields

$$\bar x = \frac{1}{n}\sum_{k=1}^{n} x_k \tag{3}$$

$$s^2 = \frac{1}{n-1}\sum_{k=1}^{n}(x_k - \bar x)^2 \tag{4}$$

Generally, if the dataset does not contain any outliers, the mean and variance of the sample would present a good estimation for data location and scatter. However, the sample mean and variance would drift seriously when the dataset was contaminated with outliers even a single out-of-scale measurement [37]. To diminish the impacts of outliers on the dataset mean and standard deviation, the robust estimation method is employed, which is extremely effective in practice [38]. In this method, the median and the median absolute deviation instead of the mean and standard deviation are respectively calculated as follows:

$$x_{med} = median(x_1, x_2, \ldots, x_n) = \frac{x_{[\frac{(n+1)}{2}]:n} + x_{[\frac{n}{2}]+1:n}}{2} \tag{5}$$

$$S_{MAD} = 1.4826 median(|x_1 - x_{med}|, \ldots, |x_n - x_{med}|) \tag{6}$$

where x_{med} is the median of the dataset, S_{MAD} is the median absolute deviation of the dataset, $[\cdot]$ is the function of round-down, the 1.4826 is a constant set to ensure S_{MAD} an unbiased calculation of the standard deviation for Gaussian data.

Additionally, in order to propose the outlier detection algorithm, the absolute error e_{absk} of the kth variable x_k is given as follows:

$$e_{absk} = |x_k - x_{med}|, \quad k = 1, 2, \ldots, n \tag{7}$$

Consequently, the procedure of the robust 3σ principle based on the robust estimation method for outliers detection can be described in detail as follows:

1) Use (5) and (4) to calculate the median absolute deviation S_{MAD} of the dataset.
2) Calculate the absolute error e_{absk} for each variable via (7).
3) Compare e_{absk} with $3S_{MAD}$: if $e_{absk} \geq 3S_{MAD}$, then the variable x_k is defined as the outlier and removed from the dataset, otherwise, step to $k = k + 1$ to do the previous comparison until $k = n$.

B. LEAST SQUARE SUPPORT VECTOR REGRESSION ALGORITHM

Suppose the given training data $T = \{(\mathbf{X}_1, y_1), \cdots, (\mathbf{X}_l, y_l)\} \in (\chi \times y)^l$, in which $\mathbf{X}_i \in \chi = \mathbb{R}^d (i = 1, \cdots, l)$ are patterns, and each pattern is a p-dimensional real vector, and $y_i (i = 1, \cdots, l)$ are outputs, then to find a hyperplane fitting all patterns with adequate margins. Suppose the decision function expressed as.

$$f(\mathbf{X}) = \mathbf{W}\cdot\Phi(\mathbf{X}_i) + b \ \ with \ \ \mathbf{W} \in \chi, \quad b \in \mathbb{R} \tag{8}$$

where $\mathbf{W}$ is a parameter vector, normal to the hyperplane, b is the intercept, $\Phi(\cdot)$ is a nonlinear function used to map the patterns to a high-dimensional feature space. Then the optimization problem with equality constraints becomes like

$$\min \frac{1}{2}||\mathbf{W}||^2 + \frac{C}{2}\sum_{i=1}^{l} e_i^2, \quad s.t., \ y_i = \mathbf{W}\cdot\Phi(\mathbf{X}_i) + b + e_i \tag{9}$$

where $e_i (i = 1, \cdots, l)$ are regression errors, C is the regularization parameter. The Lagrange formulation of the

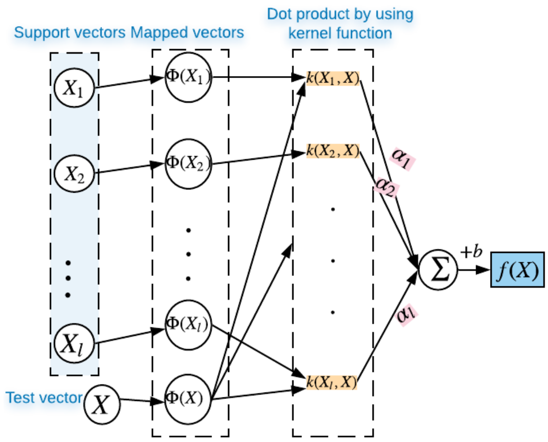

FIGURE 3. Graphical illustration of LS-SVR.

optimization problem is given as

$$L(\mathbf{W}, b, \alpha, e) = \frac{1}{2}||\mathbf{W}||^2 + \frac{C}{2}\sum_{i=1}^{l} e_i^2 - \sum_{i=1}^{l} \alpha_i(\mathbf{W} \cdot \Phi(\mathbf{X}_i) + b + e_i - y_i) \quad (10)$$

Now the derivatives with respect to $\mathbf{W}$, b, e_i, and α_i are computed and set to be zero, respectively.

$$\begin{cases} \frac{\partial L(\mathbf{W}, b, \alpha, e)}{\partial \mathbf{W}} = 0 \Longrightarrow \mathbf{W} = \sum_{i=1}^{l} \alpha_i \Phi(\mathbf{X}_i) \\ \frac{\partial L(\mathbf{W}, b, \alpha, e)}{\partial b} = 0 \Longrightarrow \sum_{i=1}^{l} \alpha_i = 0 \\ \frac{\partial L(\mathbf{W}, b, \alpha, e)}{\partial e_i} = 0 \Longrightarrow \alpha_i = Ce_i \\ \frac{\partial L(\mathbf{W}, b, \alpha, e)}{\partial \alpha_i} = 0 \Longrightarrow \mathbf{W} \cdot \Phi(\mathbf{X}_i) + b + e_i - y_i = 0 \end{cases} \quad (11)$$

After straightforward computations to eliminate variables $\mathbf{W}$ and e_i from (11), one obtains the solution

$$\begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 & 1_{l\times 1}^T \\ 1_{l\times 1} & \Omega + \frac{1}{C} \end{bmatrix}^{-1} \times \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \quad (12)$$

where $\boldsymbol{\alpha} = [\alpha_1, \ldots, \alpha_l]^T$, $1_{l\times 1}$ is the $l \times 1$ unit vector, Ω is the $l \times l$ Hessian vector of which the expression is $\Omega_{ij} = \Phi(\mathbf{X}_i)^T \cdot \Phi(\mathbf{X}_j) = k(\mathbf{X_i}, \mathbf{X_j})$, $\mathbf{y} = [y_1, \ldots, y_l]^T$. In application of the trick kernel, the decision function yields

$$f(\mathbf{X}) = \sum_{i=1}^{l} \alpha_i K(\mathbf{X}_i, \mathbf{X}) + b \quad (13)$$

Fig. 3 graphically illustrates the framework of LS-SVR according to the above description.

C. ARTIFICIAL BEE COLONY ALGORITHM

The performance of LS-SVR strongly depends on the regularization parameter. This is due to that the regularization parameter controls the trade-off between empirical risk and confidence interval, or in other words, the trade-off between the achievement of a low error on the training data and the minimization of the norm of the weights. Thus, the selection of the regularization parameter for LS-SVR is one of the most important steps when using it as an identifier.

ABC has been proven to be a robust and efficient algorithm for solving global optimization problems over continuous space [39], which consists of three groups of bees, i.e., employed bees, onlooker bees and scout bees, who play essential roles in completing the optimization procedure of ABC. The employed bees are responsible for exploring new food source positions in their neighborhoods, evaluating the food quality (fitness value) of the new food sources, updating the current food sources, and sharing this information with onlooker bees waiting in hives. Onlooker bees choose a food source for exploration based on the information obtained from employed bees and update food sources using the same way as employed bees. If an employed bee cannot improve its food source quality within a predefined number of iterations (*Limit*), it will become a scout bee. The scout bees will randomly find food sources within the search space. The details are explained as follows.

1) INITIALIZATION

The initial food sources randomly distributed within the search space are assigned to the employed bees. Every food source is an optimal solution, which includes information about the food position and food quality (fitness value). The food position is calculated by the following equation

$$x_{ij} = x_j^{min} + a\left(x_j^{max} - x_j^{min}\right), \quad (i = 1, \cdots, S,\ j = 1, \cdots, D) \quad (14)$$

where x_j^{max} and x_j^{min} are the lower and upper bounds of the jth parameter respectively which decide the search space, a is random number in range of [0, 1], S is the number of food sources which is usually equal to the number of the employed bees donated by NP or the onlooker bees donated by NP, and D is the dimension confirmed by the number of optimization parameter (here is 1 due to the optimized parameter is the regularization parameter of LS-SVR). The fitness value ($fitness_i$) is calculated by

$$fitness_i = \frac{1}{1 + Obj.f._i} \quad (15)$$

where $Obj.f._i$ is the objective function of the ith solution, which can be expressed by

$$Obj.f._i = \frac{1}{N}\sum_{n=1}^{N}(y_{act}(n) - y_{pre}(n))^2 \quad (16)$$

where y_{act} are actual outputs, y_{pre} are predicted outputs of the identified model, N is the number of samples.

2) THE EMPLOYED BEES STAGE

After initialization, employed bees start finding new food sources in their neighborhoods according to the following equation

$$x_{ij}^{new} = x_{ij} + a\left(x_{ij} - x_{kj}\right), \quad (i, k = 1, \cdots, S,\ j = 1, \cdots, D) \tag{17}$$

where x_{ij}^{new} is the jth dimension of the new food source, x_{kj} is the jth dimension of kth employed bee, a is a random number restricted in $[-1, 1]$, jth and kth are randomly selected among initial solutions and are not equal to each other. The information of the ith new food source then is updated via (15) and (16). The selection of new food source is decided by the greedy selection mechanism, i.e., if the fitness value of the new food source is better than the previous one, the new food source will replace the previous one, and *Limit* is set to zero, otherwise, the new food source will be ignored and *Limit* is added by one.

3) THE ONLOOKER BEES STAGE

The onlooker bees take food information from all employed bees. Every onlooker bee chooses a food source with a probability related to its fitness value. The probability is calculated by

$$P_i = \frac{fitness_i}{\sum_{i=1}^{S} fitness_i} \tag{18}$$

Obviously, the higher the fitness value the food source is, the better the food source is. In other words, the food source with high fitness value is much possible to be selected by onlooker bees. Then, the procedure of updating food sources used by employed bees is also applied to onlooker bees. If the fitness value of the new food source calculated for onlooker bees is better than employed bees, the employed bee is replaced by the onlooker bee.

4) THE SCOUT BEES STAGE

If an employed bee cannot improve its food source quality within a predefined number *Limit*, it will become a scout bee. The scout bees will randomly find food sources within the search space using (14).

D. ADAPTIVE WEIGHTED LEAST SQUARE SUPPORT VECTOR REGRESSION ALGORITHM

1) WEIGHTED LEAST SQUARE SUPPORT VECTOR REGRESSION ALGORITHM

In order to improve the performance of the LSSVR-based model parameter estimation, the error variables e_i of the previous LS-SVR can be weighted with weighting factors υ_i, which leads to the following optimization problem [35]:

$$\min \frac{1}{2}||\mathbf{W}||^2 + \frac{C}{2}\sum_{i=1}^{l} \upsilon_i e_i^2, \quad s.t.,\ y_i = \mathbf{W}\cdot\Phi(\mathbf{X}_i) + b + e_i \tag{19}$$

Then the Lagrangian becomes

$$L\left(\mathbf{W}, b, \alpha^*, e\right) = \frac{1}{2}||\mathbf{W}||^2 + \frac{C}{2}\sum_{i=1}^{l}\upsilon_i e_i^2 - \sum_{i=1}^{l}\alpha_i^*(\mathbf{W}\cdot\Phi(\mathbf{X}_i) + b + e_i - y_i) \tag{20}$$

By optimizing (20) and eliminating $\mathbf{W}$, e, one acquires the Karush-Khun-Tucker(KKT) system

$$\begin{bmatrix} b \\ \boldsymbol{\alpha}^* \end{bmatrix} = \begin{bmatrix} 0 & 1_{l\times 1}^T \\ 1_{l\times 1} & \Omega + V_C \end{bmatrix}^{-1} \times \begin{bmatrix} 0 \\ \mathbf{y} \end{bmatrix} \tag{21}$$

where $\boldsymbol{\alpha}^* = [\alpha_1^*, \ldots, \alpha_l^*]^T$, the diagonal martrix V_C is presented as $V_C = diag\left\{\frac{1}{C\upsilon_1}, \ldots, \frac{1}{C\upsilon_l}\right\}$, $\upsilon^* = [\upsilon_1^*, \ldots, \upsilon_l^*]^T$. Consequently, the decision function for the system is

$$f\left(\mathbf{X}\right) = \sum_{i=1}^{l}\alpha_i^* K\left(\mathbf{X}_i, \mathbf{X}\right) + b \tag{22}$$

2) ADAPTIVE WEIGHT

The outliers contaminated in the dataset can be detected through the robust 3σ principle which can effectively decrease the computation, but there are still some potential outliers unmarked existing in the dataset. Besides, the performance of the above introduced weighted LS-SVR highly depends on the distribution of data noises. Comprehensively considering, the adaptive weight method is proposed to dynamically adjust the weight of each error variable. The concrete adaptive weight process is defined as follows:

$$\upsilon_i = \frac{2}{1 + e^{\frac{e_i}{T'}}}, \quad i = 1, \ldots, l \tag{23}$$

with

$$\begin{cases} T' = mean(t1, t2) \\ t1 = median(e'_{\frac{1}{4}l+1}, e'_{\frac{1}{4}l+2}, \ldots, e'_{\frac{1}{2}l}) \\ t2 = median(e'_{\frac{1}{2}l+1}, e'_{\frac{1}{2}l+2}, \ldots, e'_{\frac{3}{4}l}) \\ e'_i = sort(e_i)(i = 1, 2, \ldots, l) \end{cases} \tag{24}$$

in which e_i is the ith sample error, e'_i is the error sorted according to the ascending order of the sample error series, $t1$, $t2$ are the partial robust estimation, and T' is the pseudo-median of the sample errors. One can see that the bigger error of the sample datum is, the smaller the weight is.

IV. THE HYBRID D-ABC-AWLSSVR APPROACH

A. PROCEDURE OF D-ABC-AWLSSVR FOR PARAMETERS ESTIMATION

In order to improve the identification results, and overcome the drawbacks, a combination identification approach (named as D-ABC-AWLSSVR) with the robust 3σ principle (named as D), ABC, adaptive weight (named as AW), and LS-SVR for parameters estimation of ship dynamic model is designed. Note that the linear kernel function is determined for the

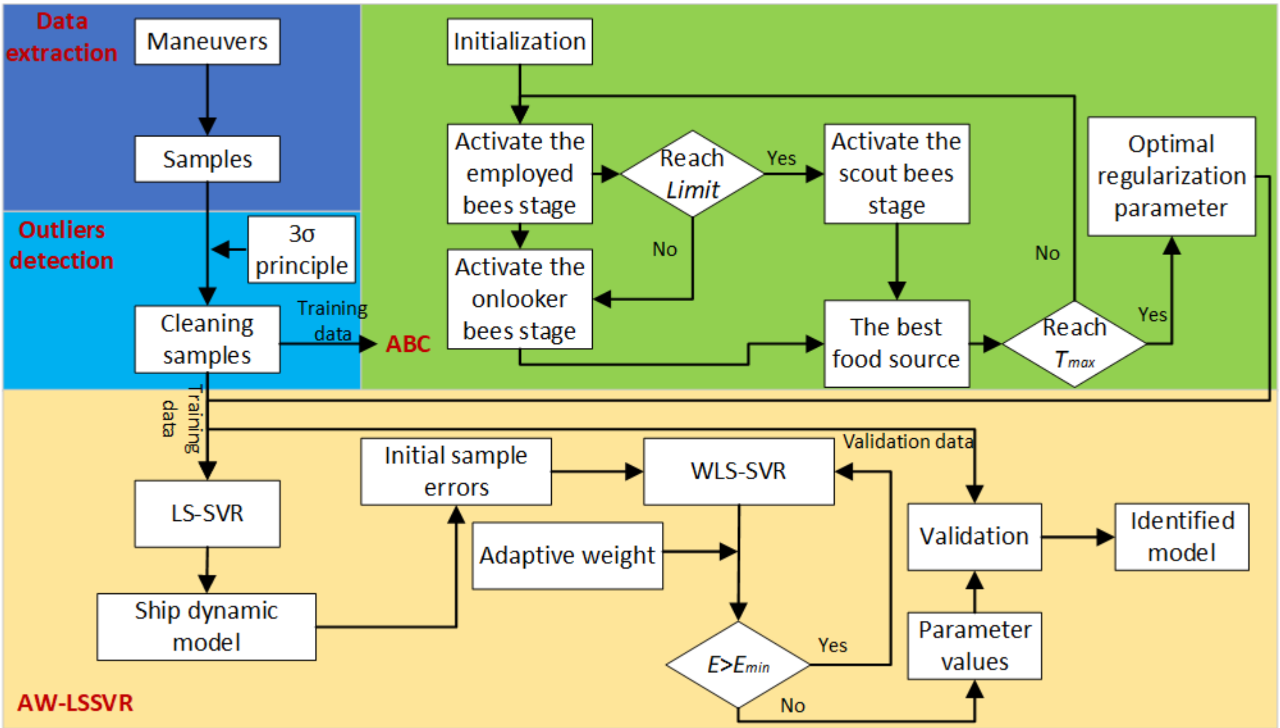

FIGURE 4. Flowchart of the D-ABC-AWLSSVR approach for parameters estimation.

LS-SVR due to the ship dynamic model is linear with respect to the parameters required to be estimated finally. The holistic flowchart is presented in Fig. 4.

The procedure of the D-ABC-AWLSSVR approach used to estimate parameters of ship dynamic models can be described from four steps as follows:

1) Data extraction. A series of specific ship maneuvers such as the standard zigzag maneuver is carried out under expected environmental conditions. Some training and validation samples are extracted from the maneuvering data.
2) Outliers detection. The robust 3σ principle is utilized to detect outliers corrupted in the samples. The outliers are deleted from the initial samples to get the cleaning data.
3) Regularization parameter optimization using the ABC algorithm. The parameters of ABC are firstly initialized, including the number of food sources S, the number of employed bees or onlooker bees NP, the maximum iteration T_{max}, and the special number $Limit$. The employed bees stage is activated to search and update food sources for the employed bees. After getting the food information from the employed bees, the onlooker bees stage is executed. If the food source quality of the employed bee is not improved or replaced by the onlooker bees within $Limit$, the scout bees stage will start. The above steps are repeated until reaching the T_{max}. The finally stored best food source is the tuned value for the regularization parameter.
4) Parameter estimation through the AW-LSSVR. LS-SVR is utilized to estimated parameters of the ship dynamic model with the use of the cleaning data. The initial sample errors or fitting errors are obtained. The initial weights υ_i $(i = 1, 2, \ldots, l)$ are calculated via 23. By applying the weighted LS-SVR with υ_i $(i = 1, 2, \ldots, l)$ the parameters of the ship dynamic model are estimated. The weights are updated according to the sample errors of the model identified by the weighted LS-SVR and the adaptive weight method and expressed as $\bar{\upsilon}_i$. The $E = \sum_{i=1}^{l} |\upsilon_i - \bar{\upsilon}_i|$ is compared with the summation of the required minimum deviation of the weights E_{min}. If the $E > E_{min}$, then $\upsilon_i = \bar{\upsilon}_i$ and return back to undertake the previous steps, otherwise, the weights are converged. Finally, the values of parameters of ship dynamic models are obtained by applying the weighted LS-SVR with the converged weights.

The indicator, namely the mean square error (MSE), is adopted to assess the accuracy of the model identified by the D-ABC-AWLSSVR approach. The calculation of the MSE is written as

$$MSE = \frac{1}{l}\sum_{i=1}^{l} |\hat{y}_i - y_i|^2 \tag{25}$$

B. COMPLEXITY ANALYSIS

In this subsection, the complexity mainly concerning the time complexity of the proposed D-ABC-AWLSSVR approach is discussed. According to the previous procedure of the D-ABC-AWLSSVR approach for model identification, its computational cost is the summation of the time complexity of ABC and the time complexity of AW-LSSVR.

The time complexity of ABC is major defined by five parts including the initialization, the search operation of employed bees, the calculation of the probability of food sources, the search operation of onlooker bees, and the search operation of scout bees. According to the prementioned optimization procedure of ABC, the computational cost of these five parts are $O(SN)$, $O(S(N+N^2))$, $O(S)$, $O(S(S+(N+N^2)+N))$, and $O(SN)$, respectively. Therefore, the overall time complexity of ABC is $O(SN+T_{it}(SN+S(S+N+N^2)))$ where S is the number of food sources, N is the number of samples selected for optimization, T_{it} is the number of iterations. Furthermore, the generic expression of the time complexity of ABC is $O(N^2)$.

For SVM, the time complexity depends on solving the convex quadratic programming problem and the dual optimization, which is $O(ln_{sv}^2+n_{sv}^3)$. Here l is the number of patterns, n_{sv} is the number of support vectors. Since LS-SVR is developed by Suykens and Vandewalle, [34] on the basis of the discussion of *How much can the SVM formulation be simplified without losing any of its advantages?* in which the equality constraints replace the inequality constraints of SVM, the convex quadratic programming problem of it is converted into the linear equations. However, all patterns are treated as the support vectors in LS-SVR, which implies that $l=n_{sv}$. Therefore, the overall time complexity of LS-SVR is given as $O(l^3)$. For the adaptive weighted LS-SVR, the time complexity is $O(dl^3)$ where d is the iteration number of the adaptive weighting procedure. Compared with l, d is generally too small to be accounted for. Consequently, the time complexity of the AW-LSSVR is $O(l^3)$. As seen, the overall time complexity of AW-LSSVR might increase drastically with the increase of the patterns adopted for identification. In the worst case, the pattern dataset should be not more than a couple of 10000 samples.

Consequently, one can conclude that the overall time complexity of the proposed identification method is $O(N^2+l^3)$.

C. CONSTRUCTION OF SAMPLES FOR MODEL IDENTIFICATION

According to the characteristics of the identification approach, the structure of the dynamic model is ought to be adjusted to construct suitable input-output pairs for the model identification. In this study, the forward-difference approximation of Eulers stepping method is adopted to discrete the perturbation dynamic model as shown in (26) which is generated under the initial condition of $u=u_0$, $v=0\ m/s$, $r=0\ rad/s$, $\delta=0\ rad$, and $n=n_0$.

$$\triangle\dot{u}=(X_u^m+2X_{|u|u}^m|u_0|)\triangle u+X_{uuu}^m\triangle u^3+2T_{|n|n}^m|n_0|\triangle n \quad (26)$$

where $\triangle u=u-u_0$, $\triangle n=n-n_0$. Then one can get the forms of the 3 DOF dynamic model presented in (27) to construct sample pairs according to the sampling interval.

$$\begin{cases}\triangle\dot{u}=[a_1,\ a_2,\ a_3]\times[\triangle u,\ \triangle u^3,\ \triangle n]^T\\ \dot{v}=[b_v,\ b_r,\ b_{|v|r},\ b_\delta]\times[v,\ r,\ |v|r,\ \delta]^T\\ \dot{r}=[c_v,\ c_r,\ c_{|v|r},\ c_\delta]\times[v,\ r,\ |v|r,\ \delta]^T\end{cases} \quad (27)$$

with $a_1=X_u^m+2X_{|u|u}^m|u_0|$, $a_2=X_{uuu}$, $a_3=2T_{|n|n}^m|n_0|$, $b_v=Y_v^m$, $b_r=Y_r^m$, $b_{|v|r}=Y_{|v|r}^m$, $b_\delta=Y_\delta^m$, $c_v=N_v^m$, $c_r=N_r^m$, $b_{|v|r}=N_{|v|r}^m$, $b_\delta=N_\delta^m$.

V. CASE STUDY

Two case studies are carried out for their respective purposes in this part. The first one using simulation maneuvers of the large container ship mainly focuses on investigating the computational cost of the proposed identification method from the engineering application perspective. The other study on a USV aims at testing the proposed D-ABC-AW-LSSVR approach in a realistic context. It is noticeable that in both cases the properties of the ABC are set as the same, i.e. $NP=20$, $S=20$, $D=1$, $Limit=30$, $T=30$, $x_j^{min}=10^{-2}$ and $x_j^{max}=10^{10}$ which define the search range of LS-SVR regularization parameter.

A. SIMULATION STUDY ON A CONTAINER SHIP

1) DATA PROCESSING

A nonlinear 4 DOF dynamic model with predetermined parameter values is found in the study [40]. The model has been well proved with relatively high exactness in describing maneuvers of a large container ship. Thus, in application of this 4 DOF model, four groups of specific maneuvers are undertook under the same initial conditions, i.e. $U_0=u_0=8\ m/s$, $v_0=0\ m/s$, $r_0=0\ rad/s$, $\delta=0\ rad$, $\psi=0\ rad$, $n_0=80\ rpm$. The simulation interval is 0.5 s. In the end, 1800 samples of each state variable are obtained. The first straight line maneuver is simulated by varying propeller speed in-between [120, 160] at the same time keeping the commanded rudder angle in 0°, from which data are extracted to identify the surge model. To verify the identified surge model, the study uses the data stemmed from the second straight line maneuver which is generated with the propeller speed varied in-between [100, 160] and the zero commanded rudder angle. The 10°/10° and 20°/20° zigzag maneuvers are generated to provide training data and validation data respectively for the identification of the steering model. The maneuvers simulated to feed into the identification procedure are shown in Fig. 5.

2) IDENTIFICATION RESULTS AND DISCUSSIONS

To comprehensively present and analyze the optimization performance of the ABC on tuning the regularization parameter of the LS-SVR, the commonly-used 5 fold CV and PSO are utilized for the comparison. To investigate the time complexity of the proposed identification method, a series of numerical simulations in identifying surge and steering models are carried out under the condition of the varying number of training samples with the steps of 10. In the

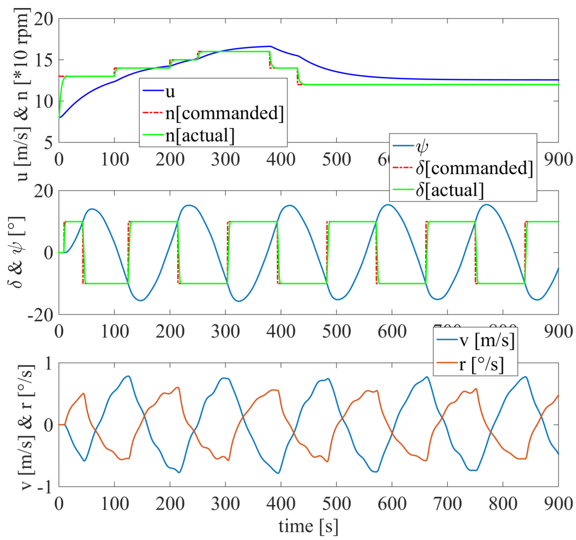

FIGURE 5. Simulation data of the first straight line and the 10°/10° zigzag maneuvers.

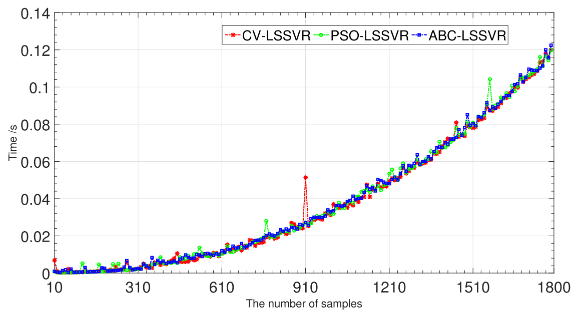

FIGURE 6. The time consumed by the three estimation methods on identifying the surge model.

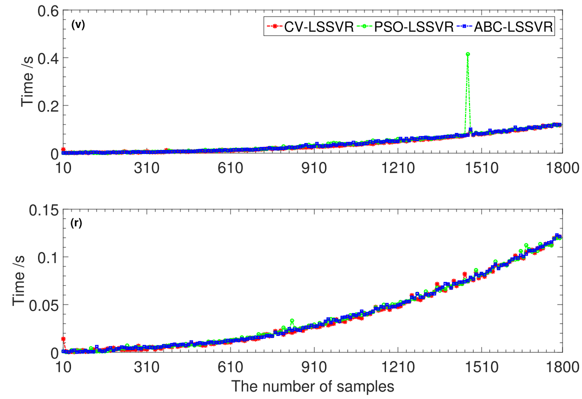

FIGURE 7. The time consumed by the three estimation methods on identifying the steering model. The top sub-figure presents the cost time of the sway model, the bottom sub-figure means the cost time of the yaw model.

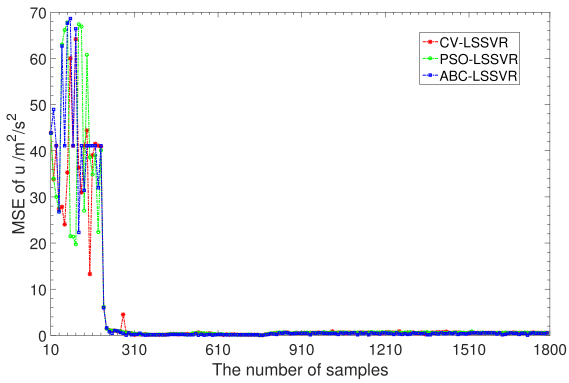

FIGURE 8. The MSE of the three identified surge models.

simulation of each group with the use of a specified number of samples, three indexes including the total cost time, MSE of the identified model, and estimated parameters are analyzed.

Figs. 6-7 present the comparison of the identification results of ABC-LSSVR, CV-LSSVR, and PSO-LSSVR on the simplified surge model and further simplified steering model in terms of the consumed time, respectively. From these figures, one can see that the cost time of the three identification methods increases with the increase of the number of samples. This implies that the number of samples has a direct effect on the time complexity of the proposed identification method, which is consistent with the analysis of time complexity in the complexity analysis section. Compared with CV-LSSVR and PSO-LSSVR, ABC-LSSVR takes approximately equivalent time to execute the identification.

The MSE and the estimated parameters of the models identified by the three estimation methods are summarized in Figs. 8-12. It can be observed that the fluctuation of MSEs and estimated parameters of all identified surge models is obvious within the first 350 samples but becomes stable soon after. Compared with CV-LSSVR and PSO-LSSVR, ABC-LSSVR mostly provides the identified surge model with the lowest MSE. For the identification of the steering model, the performance of PSO-LSSVR is not so desirable as that of CV-LSSVR and ABC-LSSVR. This is due to PSO-LSSVR is prone to fall into local optima. Through the identified steering models of CV-LSSVR and ABC-LSSVR, one can notice that MSE of the identified sway models and the identified yaw models have no apparent variations after the first 630 samples and the first 230 samples. Recall that the time complexity of ABC-LSSVR increases along with the increasing of the number of samples. Therefore, the suitable selection of samples for efficient identification of the surge model, the sway model, and the yaw model is 350, 630 and 230, respectively. Correspondingly, the optimized regularization parameter of LS-SVR decided by CV, PSO, and ABC are presented in Table. 2.

B. EXPERIMENTAL STUDY ON A UNMANNED SURFACE VESSEL

1) DATA ACQUISITION AND PROCESSING

A USV shown in Fig. 13 was carried out a series of maneuvering experiments in the East Lake in Wuhan China under

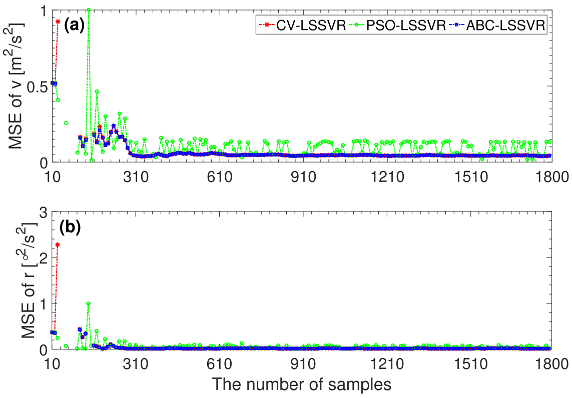

FIGURE 9. The MSE of the three identified further simplified steering model.(a) the MSE of the identified sway models. (b) the MSE of the identified yaw models.

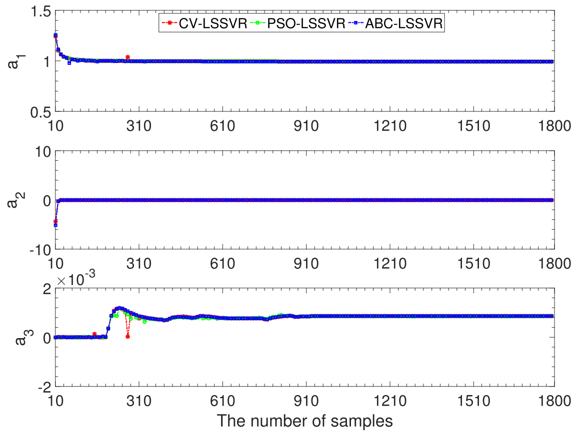

FIGURE 10. The estimated parameters of the three identified surge models. The top sub-figure is the parameter a_1, the middle sub-figure donates the parameter a_2, the bottom sub-figure means the parameter a_3.

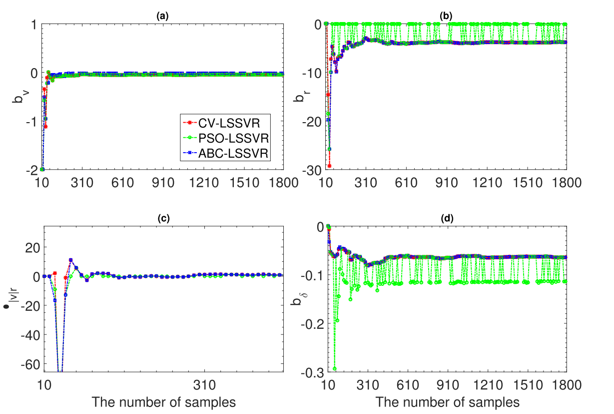

FIGURE 11. The estimated parameters of the three identified further simplified sway models. (a) parameter b_v, (b) parameter b_r, (c) parameter $b_{|v|r}$, (d) parameter b_δ.

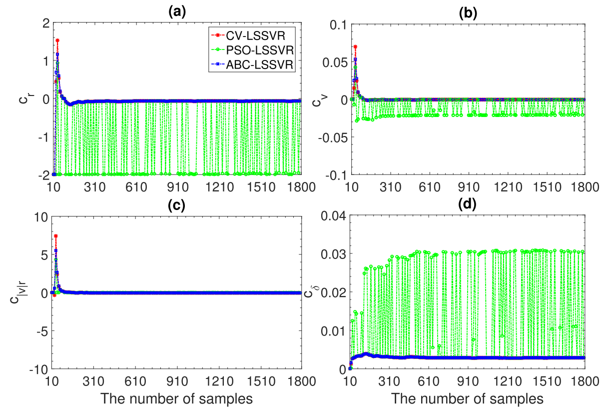

FIGURE 12. The estimated parameters of the three identified further simplified yaw models. (a) parameter c_r, (b) parameter c_v, (c) parameter $c_{|v|r}$, (d) parameter c_δ.

TABLE 2. Best regularization parameters optimized by the three optimization methods.

Method	Surge model(10^7)	Sway model(10^9)	Yaw model
CV	0.2318	0.8968	14.7966
PSO	1.7492	6.0000	19.7130
ABC	4.3313	9.9067	0.1289

FIGURE 13. The USV.

TABLE 3. Particulars of the USV.

Items	Description
length	4.15 m
breath	1.6 m
draught	0.3 $\sim$ 0.5 m
rudder deflection	$\pm 25^\circ$
engine	two batteries, max 48 V

a relatively calm water condition. Table. 3 illustrates the particulars of the USV. Some sensors such as a R93T GPS, a Mit-G-700 Inertial Measurement Unit, a HCM356B Compass, and a rudder indicator are equipped with the USV. Due to the lack of the *rpm* indicator, only the position, yaw rate, heading angle, and actual rudder angle are measured and collected to process the identification of the steering model for the USV. Compared to the turning circle maneuver, the zigzag maneuver is more informative. Hence, the data extracted from a number of zigzag maneuvers undertook under the condition of a steady forward speed at around 3 m/s are used in identifying the steering model. As the surge speed and sway speed

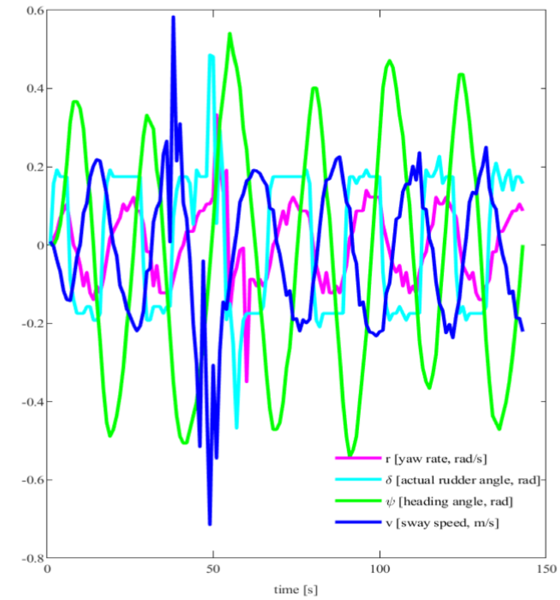

FIGURE 14. **The training data extracted from the 10°/10° zigzag maneuver.**

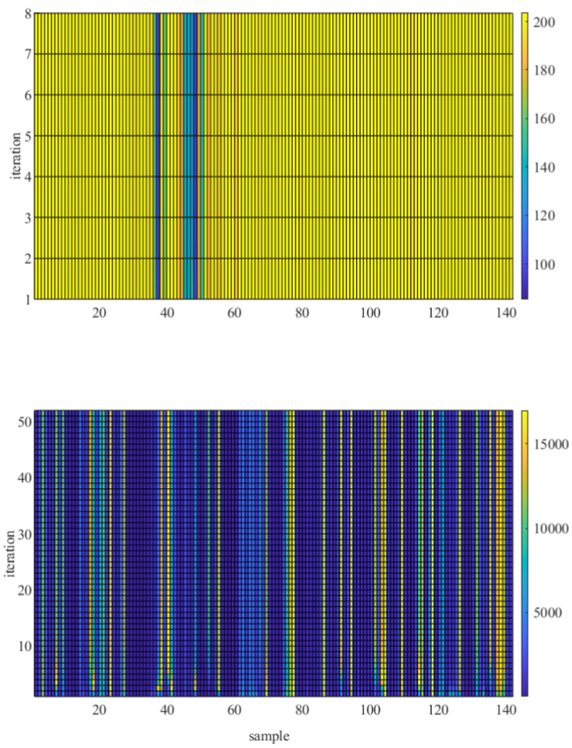

FIGURE 15. **Weights of the training sample for the ABC-AWLSSVR method. The upper subfigure is for the sway model. The lower subfigure is for the yaw model.**

can not be measured directly in this experiment, we obtain them by calculating the derivatives of the measured positions with a sampling interval of 1*s*. Finally, a set of samples of each state involving yaw rate, actual rudder angle, heading angle and sway speed are collected during the zigzag maneuverings. The 10°/10° zigzag maneuver provides the training data, meanwhile, the 25°/25° zigzag maneuver offers the validation data. The training data are visualized as Fig. 14 shown.

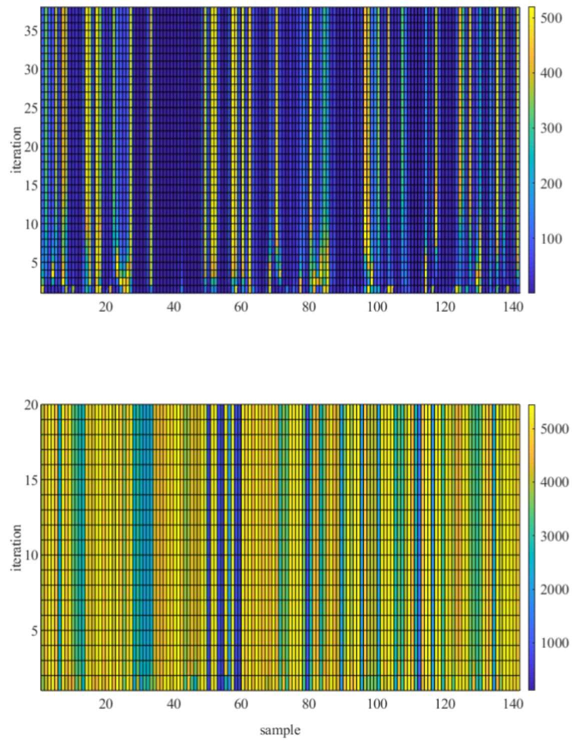

FIGURE 16. **Weights of the training sample for the D-ABC-AWLSSVR method. The upper subfigure is for the sway model. The lower subfigure is for the yaw model.**

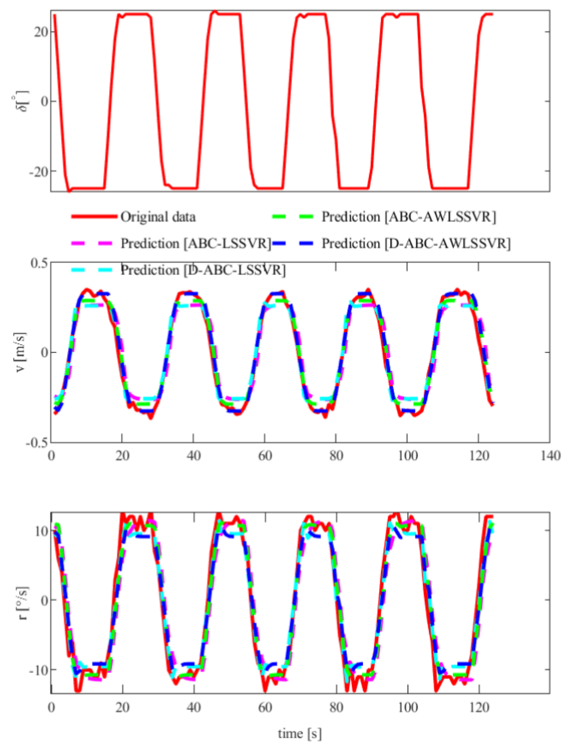

FIGURE 17. **Predictions of the 25°/25° zigzag maneuver.**

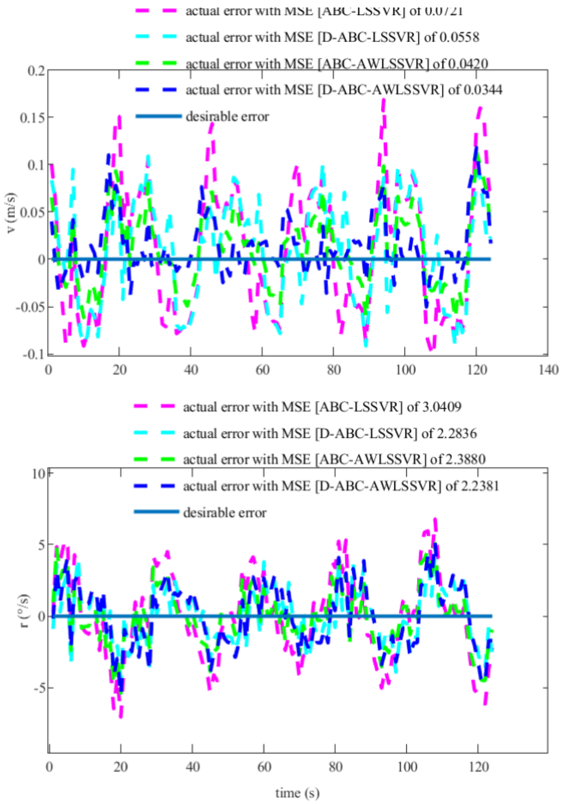

FIGURE 18. The prediction errors of the 25°/25° zigzag maneuver.

2) IDENTIFICATION RESULTS AND DISCUSSIONS

In the study, the iteration number is set as 500. In the process of identification, it is observed that the weights of training sample for the ABC-AWLSSVR method are converged in the 8th iteration for the sway model and the 52nd iteration for the yaw model, while for the D-ABC-AWLSSVR method these are respective the 38th iteration for the sway model and the 20th iteration for the yaw model. To well and obviously present the fluctuation of these weights, Fig. 15 and Fig. 16 just show the iterative weights of the training sample for the ABC-AWLSSVR method and the D-ABC-AWLSSVR method from the start iteration time to the converged iteration time, respectively. It can be seen that the maximum weight of the training sample for the D-ABC-AWLSSVR method is much bigger than that of the ABC-AWLSSVR method. This reveals that the outliers corrupted in the training sample are undetected but regarded as the efficient samples in the process of identification using the ABC-AWLSSVR method, while the D-ABC-AWLSSVR method can mostly detect the outliers and assign the other efficient samples with pretty large weights. Thus, it can be concluded that the effect of outliers on the identification results can be weakened when using the D-ABC-AWLSSVR method.

The prediction results of the 25°/25° zigzag maneuver of four identified steering models are shown in Fig. 17 where the predictions are compared with the original measurements. It can be seen from Fig. 17 that the trend of each group of predictions is very similar and close to that

TABLE 4. Comparison of the MSE of predictions of four identified steering model.

method	MSE	
	sway model $[m^2/s^2]$	yaw model $[\circ^2/s^2]$
ABC-LSSVR	0.0721	3.0409
ABC-AWLSSVR	0.0420	2.3880
D-ABC-LSSVR	0.0558	2.2836
D-ABC-AWLSSVR	0.0344	2.2381

of the original measurements which in other words means these four identification methods, i.e. ABC-LSSVR method, ABC-AWLSSVR method, D-ABC-LSSVR method, and D-ABC-AWLSSVR method are effective for the identification of the steering model for the USV. Comparatively speaking, the performance of the D-ABC-AWLSSVR method is superior to the other three methods due to the fact that the predictions of the model identified by the D-ABC-AWLSSVR method are the best ones close to the original measurements. For this point, the errors of predictions presented in Fig. 18 and the corresponding MSEs listed in Table. 4 can prove. It can be seen from the error results that the MSE from the steering model identified by the D-ABC-AWLSSVR method is the smallest, which to a large extent demonstrates the best performance of the D-ABC-AWLSSVR method. While studying these identification methods, one can find that the computation cost of them are nearly the same.

VI. CONCLUSION

In this work, a novel hybrid identification method named D-ABC-AWLSSVR method taking advantages of the robust 3σ principle method, the good optimization ability of the ABC and the adaptive weight method is proposed and studied for the identification of ship dynamic model. By introducing the adaptive weight method, the drawback of the LS-SVR based identification method, i.e. high sensitivity to the noises or outliers contaminated in the samples can be effectively overcome. Through the simulation study on a container ship, the computation cost of the proposed method has been proved to be low enough to satisfy the engineering application requirement. In addition, it has been demonstrated that the performance of the proposed method is superior to the ABC-LSSVR method, the D-ABC-LSSVR method and the ABC-AWLSSVR method in the experimental study on a USV.

In reality, the noises or outliers from sensors and environmental disturbances contaminated in the measurements can not be avoided completely. The proposed identification method is applicable to such a case where the contaminated measurements are used to identify models of systems like the ship dynamic model. The D-ABC-AWLSSVR is a hybrid method consisting of four components, and every component has an impact on its identification performance. Therefore, it is noticeable to pay full attention to the property of each component while doing model identification, e.g. the setting of *Limit* for the ABC due to the fact that the optimization performance of the ABC is severely sensitive to the setting of *Limit*.

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