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Identification of ship manoeuvring motion based on nu-support vector machine

Zihao Wang [a,b], Zaojian Zou [a,c], C. Guedes Soares [b,*]

[a] School of Naval Architecture, Ocean and Civil Engineering, Shanghai Jiao Tong University, Shanghai, China
[b] Centre for Marine Technology and Ocean Engineering (CENTEC), Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal
[c] State Key Laboratory of Ocean Engineering, Shanghai Jiao Tong University, Shanghai, China

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ABSTRACT

A practical and robust system identification modelling method for ship manoeuvring motion is presented, to alleviate the impact of noise-induced problems, such as parameter drift or over-fitting, on the model reliability. The method is based on ν("nu")-Support Vector Machine (ν-SVM) algorithm, which can automatically control the number of support vectors to ensure the sparsity of the solution. Multiple standard manoeuvring datasets are simultaneously used as training data to cope with the parameter drift issues. The proposed method is validated by using polluted simulated data of three different levels. The results demonstrate that the identified model has good generalisation, verifying the robustness and efficiency of the algorithm.

1. Introduction

Accurate ship manoeuvring mathematical model is an essential foundation for the study of ship manoeuvring and control. In the study of ship manoeuvrability, simulation based on the mathematical model is the primary method of ship manoeuvrability prediction (e.g. Sutulo et al., 2002). In addition, designing modern control systems often requires model-based controller whose performance is closely related to the mathematical model. Therefore, establishing reliable mathematical models to meet the application requirement has a high practical value (Sutulo and Guedes Soares, 2011). Among the modelling method, the system identification (SI) based approach provides a practical and efficient way that requires low experiment time and cost. Only the state information and inertia terms are needed for this method, and it is not required to measure the forces. Furthermore, this method can be applied to a full-scale vessel to avoid the scale effects.

In the application of an identification modelling method, the identification algorithm extracts the characteristics of ship dynamics from the training data. However, the training data often contain noise, which is the main reason to cause problems such as parameter drift and overfitting in the identification. To improve the reliability of identification modelling, researchers have proposed different methods in the past two decades.

The improvement of some identification methods is mainly from the perspective of processing training data. Hwang (1980) discovered the problem of parameter drift and applied "parallel processing" to process the training data, while the results show that parameter drift still occurs. Yoon and Rhee (2003) proposed the Estimation-Before-Modelling technique to filter the training data and to estimate the forces and state information first. Besides, the modification of the input scenario was suggested to provide more information as the alternative. Araki et al. (2012) used CFD free-running trial data to obtain the training data, which can avoid the measurement noise in the free-running tests. Data pre-processing method was also proposed, by Luo and Li (2017), such as the difference method and the method of additional excitation. The results show that the collinearity can be diminished significantly but cannot be eliminated.

Some studies (Perera et al., 2016; Revestido Herrero and Velasco González, 2012) pointed out that the zigzag test may not have enough excitation for a large number of parameters. Revestido Herrero and Velasco González (2012) applied the stepwise method to select the parameters for a new model. However, the chosen model structure has limitations, because it may not be suitable for predicting other manoeuvres that have different dynamic characteristics than the manoeuvres in the training data. Gavrilin and Steen (2018) applied sensitivity analysis and repeated identification to the passenger ferry "Landegode" and concluded that the true parameters in the MMG model cannot be identified from full-scale tests. Wang and Zou (2018) argued that one

* Corresponding author.
E-mail address: c.guedes.soares@centec.tecnico.ulisboa.pt (C. Guedes Soares).

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should be cautious to use a single standard manoeuvre as the training data, because the zigzag test datasets of different rudder angle range may contain different dynamic characteristics. In this study, the goal is set to get a predictive model that focuses on the prediction performance instead of on the identified parameters. Multiple standard manoeuvring datasets are applied simultaneously as the training data to cope with the parameter drift problem, including datasets from 10°/10°, 20°/20° zigzag tests and 35° turning test, ensuring the ability to predict manoeuvring motion under more extensive range of rudder angles.

Identification modelling methods are also studied from the perspective of the identification algorithm. In addition to the traditional SI techniques, some new identification techniques have been applied in the past two decades, such as Neural Network (NN), Support Vector Machine (SVM), genetic algorithms and optimisation method. NN has been applied widely in the modelling of ship manoeuvring (Mahfouz and Haddara, 2003; Moreira and Guedes Soares, 2003; Rajesh and Bhattacharyya, 2008), such as recursive neural networks and feedforward neural networks. However, the neural networks methods have some defects, such as poor generalisation and the local extremum. A classic genetic algorithm using Hausdorff metric was used as an offline identification algorithm in Sutulo and Guedes Soares (2014). The method was validated using simulated responses polluted with the white noise. Xu et al. (2018a) applied the genetic algorithm to identify the parameters in a modified version of the Abkowitz model. The zigzag manoeuvre tests of a chemical tanker ship model were carried out, and the datasets were used to validate the method. Tran Khanh et al. (2013) proposed a method based on Mathematical Programming techniques to estimate the optimal ship hydrodynamic parameters. Perera et al. (2015) developed a nonlinear parameter estimation method under dynamic data handling conditions by using an Extended Kalman Filter but concluded that the estimation of the parameters of nonlinear vessel steering model can only be achieved when violent manoeuvres are performed. Du et al. (2017) proposed the multi-objective optimisation to identify the optimal hydrodynamic coefficients, and the model for ship manoeuvring in a confined waterway has been considered.

In recent years, SVM has been applied in the modelling of ship manoeuvring motions. SVM has three advantages: high generalisation performance, a globally optimal solution and overcoming the Curse of Dimensionality. Luo and Zou (2009) performed the studies on parameter identification of the Abkowitz model by using Least Squares Support Vector Machine (LSSVM). The hyper-parameter in LSSVM algorithm was optimised by particle swarm optimisation (PSO) (Luo et al., 2016) and the artificial bee colony algorithm (Zhu et al., 2017). Xu et al. (2018b) developed an online version of a sequential least square support vector machine to estimate the parameters of vessel steering in real-time, which compared well with a LSSVM run offline. The sequential LS-SVM was trained by different zigzag manoeuvres and was shown to be able of dynamic estimation of the nonlinear parameters. However, a drawback of LSSVM is the lack of sparsity as all the data points become support vectors (SVs). Zhang and Zou (2011) applied ε-SVM to identify the Abkowitz model, using the simulation data without noise as training data. ε-SVM can control the number of SVs by parameter ε, and then solves the quadratic problem to obtain the global optimal solution. However, there is still the problem of choosing an appropriate parameter ε, which is related to the degree of disturbance in the training data. In this paper, ν("nu")-SVM is applied to solve this problem. By constructing the cost function to adjust the parameter ε optimally, controlling the number of SVs, ν-SVM can tune the insensitivity tube automatically by a constant parameter ν. This makes the identification method to be robust under training data at different levels of disturbance.

The present study proposes a robust identification modelling method for a nonlinear model of ship manoeuvring motion, where ν-SVM is used for the first time for identification modelling of ship manoeuvring motion. Multiple standard manoeuvring datasets are used as training data simultaneously to obtain more information. The final aim is to get a predictive model of the manoeuvring motion at normal speed. Polluted training data is used to test the method, and process noise is considered by using different model structures for identification and training data simulation. The generalisation performance is verified by predicting manoeuvring motions not included in the training data. The rest of the paper is organised as follows: Section 2 describes the mathematical basis of the ν-SVM algorithm. Section 3 derives the regression model for identification from the mathematical model of 3DOF ship manoeuvring motion, where a Mariner class vessel is used as the study object. Section 4 describes the procedure of identification modelling by using ν-SVM. In Section 5, the identification modelling results are illustrated and analysed. Finally, Section 6 summarises with conclusions.

2. ν-Support vector machine regression

Support Vector Machines (SVM) for regression (also known as ε-SVM in Cortes and Vapnik, 1995) aims to solve a quadratic programming problem. Based on the principle of structural risk minimisation, ε-SVM has good generalisation performance and the ability to avoid parameter over-fitting. The parameter ε in ε-SVM controls the sparseness property, which directly affects the performance of the algorithm. Therefore, the prior determination of the desired accuracy ε is a crucial issue. In order to better solve this problem, a new algorithm is applied, called ν("nu")-SVM, which can automatically adjust ε and predetermine the fraction of training sample as support vectors (Schölkopf et al., 2000). It is not necessary to re-determine the parameter ε if the training dataset is polluted by different levels of noise, which makes the algorithm more intelligent and robust.

Suppose the training dataset are given as $\{(x_1,y_1),\ldots,(x_i,y_i),\ldots,(x_N,y_N)\}, x_k \in R^n, y_k \in R$. The regression problem is to find a function $f(x)$ to approximate the training dataset, taking the form:

$$f(x) = w^T\varphi(x) + b \tag{1}$$

where w is the weight vector; $\varphi(\cdot)$ is the nonlinear function; b is the bias term. For ε-SVM algorithm, according to the structural risk minimisation principle, the risk bound is minimised by the following optimisation problem:

$$\min_{w,\xi_k} \frac{1}{2}w^T w + C\cdot\frac{1}{l}\sum_{i=1}^{l}(\xi_i + \xi_i^*) \tag{2}$$

Subject to:

$$((w\cdot x_i) + b) - y_i \le \varepsilon + \xi_i \tag{3-a}$$

$$y_i - ((w\cdot x_i) + b) \le \varepsilon + \xi_i^* \tag{3-b}$$

$$\xi_i^{(*)} \ge 0 \tag{3-c}$$

Equation (2) is also called the ε-insensitive cost function, where $|\xi|_\varepsilon$ is called ε-insensitive training error, described by $|\xi|_\varepsilon = \max\{0, |\xi| - \varepsilon\}$. Only the errors above some $\varepsilon > 0$ will be penalised, the subset of these data is also called support vectors (SVs). The regularisation constant C determines the trade-off between model complexity and ε-insensitive training error. l is the dimension of the corresponding variables. The notation $^{(*)}$ is a shorthand for variables with and without an asterisk, i.e. ξ_i and are both satisfied the inequality.

In υ-SVM algorithm the ε-insensitive cost function is used but ε serves as a variable of the optimisation problem, becoming an additional term in the cost function that attempts to minimize ε. Hence, the optimisation problem becomes:

$$\min_{w,\xi_k} \frac{1}{2}w^T w + C\cdot\left(\nu\varepsilon + \frac{1}{l}\sum_{i=1}^{l}(\xi_i + \xi_i^*)\right) \tag{4}$$

Subject to:

$$y_i - \left(w^T\varphi(x_i) + b\right) \le \varepsilon + \xi_i \tag{5-a}$$

$$\left(w^T\varphi(x_i) + b\right) - y_i \le \varepsilon + \xi_i^* \tag{5-b}$$

$$\xi_i^{(*)} \ge 0, \quad \varepsilon \ge 0 \tag{5-c}$$

In the cost function, ε is a variable optimised by the constant υ. The Lagrange formulation of this optimisation problem is:

$$\begin{aligned} & L\left(w, b, \alpha^{(*)}, \beta, \xi^{(*)}, \varepsilon, \eta^{(*)}\right) \\ & = \frac{1}{2}w^T w + C\upsilon\varepsilon + \frac{C}{l}\sum_{i=1}^{l}\left(\xi_i + \xi_i^*\right) - \beta\varepsilon - \sum_{i=1}^{l}\left(\eta_i\xi_i + \eta_i^*\xi_i^*\right) \\ & - \sum_{i=1}^{l}\alpha_i\left(\xi_i + y_i - w^T\varphi(x_i) - b + \varepsilon\right) \\ & - \sum_{i=1}^{l}\alpha_i^*\left(\xi_i^* + w^T\varphi(x_i) + b - y_i + \varepsilon\right) \end{aligned} \tag{6}$$

where $\alpha_i^{(*)}, \beta, \eta_i^{(*)}$ are Lagrange multipliers. The optimal solution is given by the saddle point of the Lagrangian. Therefore, the conditions for optimality are:

$$\frac{\partial L}{\partial w} = 0 \quad \rightarrow \quad w = \sum_i\left(\alpha_i^* - \alpha_i\right)\varphi(x_i) \tag{7-a}$$

$$\frac{\partial L}{\partial b} = 0 \quad \rightarrow \quad \sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right) = 0 \tag{7-b}$$

$$\frac{\partial L}{\partial \xi_i^{(*)}} = 0 \quad \rightarrow \quad C\cdot\upsilon - \sum_i\left(\alpha_i^* - \alpha_i\right) - \beta = 0 \tag{7-c}$$

$$\frac{\partial L}{\partial \varepsilon} = 0 \quad \rightarrow \quad \frac{C}{l} - \alpha_i^{(*)} - \eta_i^{(*)} = 0 \tag{7-d}$$

Substituting Eq. (7) into Eq. (6), the υ-SVM optimisation formula is obtained in a quadratic programming form:

$$\min_{\alpha_i}\frac{1}{2}\sum_{i,j=1}^{l}\left(\alpha_i^* - \alpha_i\right)\left(\alpha_j^* - \alpha_j\right)\varphi(x_i)^T\varphi(x_j) - \sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right)y_i \tag{8}$$

Subject to:

$$\sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right) = 0 \tag{9-a}$$

$$\alpha_i^{(*)} \in \left[0, \frac{C}{l}\right] \tag{9-b}$$

$$\sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right) \le C\cdot\upsilon \tag{9-c}$$

The dot product of $\varphi(x)$ can be substituted by kernel functions, which can avoid the dimensionality curse. In this study, the linear kernel is used:

$$k\left(x_i, x_j\right) = \left(\varphi(x_i)^T\varphi(x_j)\right), \quad i \in \{1, ..., N\}, j \in \{1, ..., N\} \tag{10}$$

Then the regression function Eq. (1) can be rewritten as follows:

$$f(x) = \sum_{i=1}^{l}\left(\alpha_i^* - \alpha_i\right)\varphi(x_i)\varphi(x) + b \tag{11}$$

where the weight vector w is formulated as $\sum_{i=1}^{l}(\alpha_i^* - \alpha_i)\varphi(x_i)$ represented by SVs. Therefore, only the training data belonging to the SVs will affect the regression results. If the resulting ε is nonzero, the hyper-parameter υ is an upper bound on the relative number of training points lying outside the insensitivity tube and a lower bound on the number of SVs relative to the total number of training data, which belongs to $[0, 1]$.

By using the υ-SVM algorithm, the insensitivity tube width is automatically adjusted by automatically determining the hyper-parameter ε. The relative number of SVs is determined in advance by the constant υ. For the free-running test of ship manoeuvring, the data always contains noise such as measurement error and environmental disturbance. In this case, the υ-SVM method is more suitable for the dynamic identification of ocean vehicles, which can ensure generalisation performance and stability while taking into account the modelling efficiency.

3. Mathematical model for identification

To identify the model, a regression model in Eq. (1) format is deduced from the 3DOF model of ship manoeuvring motion. The model structure of ship manoeuvring motion is assumed to be known in advance. The final model is obtained by identifying the unknown parameters in the model.

There are different ways to express the hydrodynamic forces and moments in the mathematical model of the ship manoeuvring motion, which leads to different model structures. The selection of model structure is a trade-off between model complexity and model capacity. To improve the stability of the identified model, the model structure should be simplified appropriately while ensuring meeting the requirements. In the present study, the 3DOF Abkowtiz model of a Mariner class vessel is taken as a case study. This model structure is modified based on the mathematical model in (Chislett and Strom-Tejsen, 1965; Fossen, 1994), which ignore the influence of port-starboard asymmetry by removing three small value coefficients. The hydrodynamic forces and moments are expressed as moderately complex 3rd-order polynomial expressions, with 10 coefficients in surge equation and 12 coefficients in sway and yaw equation, respectively.

3.1. Dynamic model

To describe the 3DOF ship manoeuvring motion, two right-handed reference frames are adopted: (a) an earth-fixed reference frame $o_0 - x_0y_0z_0$ and (b) a body-fixed reference frame $o - xyz$. In the body-fixed coordinate system, the $x-$axis is pointing to the bow, the $y-$axis to starboard. The rigid-body kinetics in surge, sway and yaw motions can be expressed as:

$$m\left(\dot{u} - rv - x_G r^2\right) = X \tag{12-a}$$

$$m(\dot{v} + ur + x_G\dot{r}) = Y \tag{12-b}$$

$$I_z\dot{r} + mx_G(\dot{v} + ur) = N \tag{12-c}$$

where m is the ship mass; I_z is the moment of inertia about the z-axis; x_G is the position of the centre of gravity in the longitudinal direction of the body-fixed coordinate system; u, v, r are the surge speed, sway speed and yaw rate, X, Y, N are hydrodynamic force/moment.

The forces on the right-hand side of Eq. (12) are expressed as:

$$X = \frac{1}{2}\rho L^2U^2X', \qquad Y = \frac{1}{2}\rho L^2U^2Y', \qquad N = \frac{1}{2}\rho L^3U^2N' \tag{13}$$

where X', Y' and N' are the non-dimensional form of the hydrodynamic force/moment, ρ is the water density, L is the ship length, $U = \sqrt{(u_0 + \triangle u)^2 + v^2}$ is the instantaneous ship speed, $\triangle u$ is a small perturbation from the nominal surge speed u_0.

Using δ to indicate the rudder angle, the non-dimensional forms of hydrodynamic force/moment are represented as Eq. (14). To better test the property of the identification algorithm, it is assumed that a good model structure has been chosen as prior knowledge.

$$X' = X'_{\dot{u}}\triangle\dot{u}' + X'_{u}\triangle u' + X'_{uu}\triangle u'^2 + X'_{uuu}\triangle u'^3 + X'_{vv}v'^2 + X'_{rr}r'^2 + X'_{rv}r'v' + X'_{\delta\delta}\delta^2 + X'_{u\delta\delta}\triangle u'\delta^2 + X'_{v\delta}v'\delta + X'_{uv\delta}\triangle u'v'\delta \tag{14-a}$$

$$Y' = Y'_{\dot{v}}\dot{v}' + Y'_{\dot{r}}\dot{r}' + Y'_{v}v' + Y'_{r}r' + Y'_{vvv}v'^3 + Y'_{vvr}v'^2r' + Y'_{vu}v'\triangle u' + Y'_{ru}r'\triangle u' + Y'_{\delta}\delta + Y'_{\delta\delta\delta}\delta^3 + Y'_{u\delta}\triangle u'\delta + Y'_{uu\delta}\triangle u'^2\delta + Y'_{v\delta\delta}v'\delta^2 + Y'_{vv\delta}v'^2\delta \tag{14-b}$$

$$N' = N'_{\dot{v}}\dot{v}' + N'_{\dot{r}}\dot{r}' + N'_{v}v' + N'_{r}r' + N'_{vvv}v'^3 + N'_{vvr}v'^2r' + N'_{vu}v'\triangle u' + N'_{ru}r'\triangle u' + N'_{\delta}\delta + N'_{\delta\delta\delta}\delta^3 + N'_{u\delta}\triangle u'\delta + N'_{uu\delta}\triangle u'^2\delta + N'_{v\delta\delta}v'\delta^2 + N'_{vv\delta}v'^2\delta \tag{14-c}$$

Rewriting Eq. (12) in a non-dimensional form and substituting Eq. (14) into it. Then, placing the acceleration terms on the left side of the equation, the velocity terms and the rudder angle terms on the right side, the mathematical model of ship manoeuvring motion is obtained in non-dimensional form as follows

$$(m' - X'_{\dot{u}})\dot{u}' = f_1(u,v,r,\delta)' \tag{15-a}$$

$$(m' - Y'_{\dot{v}})\dot{v}' + (m'x'_G - Y'_{\dot{r}})\dot{r}' = f_2(u,v,r,\delta)' \tag{15-b}$$

$$(m'x'_G - N'_{\dot{v}})\dot{v}' + (I'_z - N'_{\dot{r}})\dot{r}' = f_3(u,v,r,\delta)' \tag{15-c}$$

where f_1, f_2 and f_3 are the polynomials related to the state information, as shown in Eq. (16). The coefficients of the same speed terms can be combined into new coefficients, such as $(m' + X'_{rv})r'v' \to X'_{rv\_new}r'v'$.

$$f_1(u,v,r,\delta)' = X'_{u}\triangle u' + X'_{uu}\triangle u'^2 + X'_{uuu}\triangle u'^3 + X'_{vv}v'^2 + X'_{rr\_new}r'^2 + X'_{rv\_new}r'v' + X'_{\delta\delta}\delta^2 + X'_{u\delta\delta}\triangle u'\delta^2 + X'_{v\delta}v'\delta + X'_{uv\delta}\triangle u'v'\delta \tag{16-a}$$

$$f_2(u,v,r,\delta)' = Y'_{v}v' + Y'_{r}r' + Y'_{vvv}v'^3 + Y'_{vvr}v'^2r' + Y'_{vu}v'\triangle u' + Y'_{ru\_new}r'\triangle u' + Y'_{\delta}\delta + Y'_{\delta\delta\delta}\delta^3 + Y'_{u\delta}\triangle u'\delta + Y'_{uu\delta}\triangle u'^2\delta + Y'_{v\delta\delta}v'\delta^2 + Y'_{vv\delta}v'^2\delta \tag{16-b}$$

$$f_3(u,v,r,\delta)' = N'_{v}v' + N'_{r}r' + N'_{vvv}v'^3 + N'_{vvr}v'^2r' + N'_{vu}v'\triangle u' + N'_{ru\_new}r'\triangle u' + N'_{\delta}\delta + N'_{\delta\delta\delta}\delta^3 + N'_{u\delta}\triangle u'\delta + N'_{uu\delta}\triangle u'^2\delta + N'_{v\delta\delta}v'\delta^2 + N'_{vv\delta}v'^2\delta \tag{16-c}$$

By deriving as the expressions for the acceleration terms, Eq. (15) can be rewritten as

$$\dot{u}' = f'_1 \big/ (m' - X'_{\dot{u}}) \tag{17-a}$$

$$\dot{v}' = \left[(I'_z - N'_{\dot{r}})f'_2 - (m'x'_G - Y'_{\dot{r}})f'_3\right]/S \tag{17-b}$$

$$\dot{r}' = \left[(m' - Y'_{\dot{v}})f'_3 - (m'x'_G - N'_{\dot{v}})f'_2\right]/S \tag{17-c}$$

where $S = (I'_z - N'_{\dot{r}})(m' - Y'_{\dot{v}}) - (m'x'_G - Y'_{\dot{r}})(m'x'_G - N'_{\dot{v}})$.

3.2. Regression model for identification

To be convenient for computer simulation, the dimensionless variables $\triangle u', \triangle v', \triangle r'$ are restored to the original dimensional forms by multiplying the first two equations of Eq. (17) by U^2/L and multiplying the last equation by U^2/L^2. In this way, the velocity terms and acceleration terms can be expressed in their dimensional forms, while the other terms are still expressed in non-dimensional forms. Then, the equations are discretised by using Euler's Stepping method and get the multiple linear regression model. The regression model can be written as a matrix form:

$$\triangle u(t+1) - \triangle u(t) = AX(t) \tag{18-a}$$

$$\triangle v(t+1) - \triangle v(t) = BY(t) \tag{18-b}$$

$$\triangle r(t+1) - \triangle r(t) = CZ(t) \tag{18-c}$$

where the left-hand side terms of Eq. (18) are the outputs at time $(t+1)$. A, B, C are unknown constant parameter vectors to be identified, corresponding to the weight vector w in Eq. (1). $X(t)$, $Y(t)$, $Z(t)$ are the input vectors at time t, corresponding to the $\varphi(\cdot)$ in Eq. (1). As can be seen from Eq. (17), the parameters in vectors B and C are the combinations of hydrodynamic coefficients in equations of sway and yaw motion. The input vectors and parameter vectors can be written as

$$X(t) = \left[\triangle u(t)U(t)/L, \triangle u^2(t)/L, \triangle u^3(t)/(U(t)L), \triangle v^2(t)/L, \triangle r^2(t)L, \triangle\delta^2(t)U^2(t)/L, \triangle u(t)\triangle\delta^2(t)U(t)/L, \triangle r(t)\triangle v(t), \triangle v(t)\triangle\delta(t)U(t)/L, \triangle u(t)\triangle v(t)\triangle\delta(t)/L\right]^T \cdot h/(m - X_{\dot{u}}) \tag{19-a}$$

$$Y(t) = \left[\triangle v(t)U(t)/L, \triangle r(t)U(t), \triangle v^3(t)/U(t)L, \triangle v^2(t)\triangle r(t)/U(t), \triangle v(t)\triangle u(t)/L, \triangle r(t)\triangle u(t), \triangle\delta(t)U^2(t)/L, \triangle\delta^3(t)U^2(t)/L, \triangle u(t)\triangle\delta(t)U(t)/L, \triangle u^2(t)\triangle\delta(t)/L, \triangle v(k)\triangle\delta^2(k)U(k)/L, \triangle v^2(k)\triangle\delta(k)/L\right]^T \cdot h/S \tag{19-b}$$

$$Z(t) = \left[\triangle v(t)U(t)/L, \triangle r(t)U(t), \triangle v^3(t)/U(t)L, \triangle v^2(t)\triangle r(t)/U(t), \triangle v(t)\triangle u(t)/L, \triangle r(t)\triangle u(t), \triangle\delta(t)U^2(t)/L, \triangle\delta^3(t)U^2(t)/L, \triangle u(t)\triangle\delta(t)U(t)/L, \triangle u^2(t)\triangle\delta(t)/L, \triangle v(k)\triangle\delta^2(k)U(k)/L, \triangle v^2(k)\triangle\delta(k)/L\right]^T \cdot hL/S \tag{19-c}$$

$$A = [a_1, a_2 \cdots a_{10}] \tag{19-d}$$

$$B = [b_1, b_2 \cdots b_{12}] \tag{19-e}$$

$$C = [c_1, c_2 \cdots c_{12}] \tag{19-f}$$

After deriving the regression model, the ν-SVM algorithm can be applied to identify the constant parameter vectors in Eq. (18). The input and output information need to be acquired in advance, where the speed terms and the rudder angle can be obtained by common sensors. The acceleration derivatives can be obtained by some mature calculation method, such as the slender-body theory.

4. Identification modelling via ν-SVM

4.1. Goal definition

In the actual data acquisition process, the data is inevitably polluted by measurement noise and environmental disturbance. In this case, the estimated parameters are prone to drift from the actual values due to the collinearity between the parameters, which is called parameter drift. After the parameter drift occurs, the identified model is still generally able to accurately predict the motion in the training data, but it cannot guarantee the prediction accuracy of other motions, especially when the collinearity structure of the parameters corresponding to the test datasets is different or unknown. Although many methods have been studied to diminish parameter drift, it cannot be eliminated without adding more training data. Therefore, if the target is to identify the hydrodynamic coefficients, it will be difficult to achieve under noise interference.

In this study, the ultimate goal is set to establish an accurate forecasting model instead of obtaining correct hydrodynamic coefficients. The forecasting model is expected to be able to predict the normal manoeuvres under design speed with rudder angle range from zero to full rudder, and then can be applied to simulators, controller simulations, and planning algorithms in the future. If the identified model can meet the forecasting requirements, the parameter drift within a reasonable range can be tolerated. To achieve this target, the training data is required to contain as many dynamics as possible.

4.2. Training data preparation

The selection and processing of training data are critical to the generalisation performance of the identification model. To improve the stability and generalisation performance of the model, the most straightforward solution is to add more training data that characterises different dynamics. Most previous studies typically applied a single standard manoeuvring data as training data, such as 20°/20° zigzag manoeuvres (Luo and Zou, 2009; Sutulo and Guedes Soares, 2014; Zhu et al., 2017). However, it has been argued that the zigzag test with varying angles of rudder contains different dynamic features (Wang and Zou, 2018), which means adding more manoeuvring datasets is reasonable.

In the present work, multiple manoeuvring datasets are simultaneously used as training data, including the standard 10°/10°, 20°/20° zigzag manoeuvres and 35° turning manoeuvre. These datasets are relatively easy to obtain because they are the tests required by the Standards for Ship Maneuverability (IMO, 2002). These manoeuvring datasets are sequentially combined in end-to-end form, and the length of each dataset is optimised by the D-optimality criterion. Then, the difference method is used to improve the data structure. More details about the length optimisation and difference method can be found in (Wang and Zou, 2018). Then, the dataset is divided into a large and a small group for training and evaluation, called training set and holdout set respectively. According to the derived regression model Eq. (18), the input of training data for each time step contains surge speed, sway speed, yaw rate and rudder angle.

To avoid characteristics of the larger range of values dominating characteristics of the smaller range of values, the variables in the training set are standardised and centralised. Suppose a linear regression model is given as Eq. (20). The scaling will be in the form of Eq. (21). Each characteristic is scaled to the range [-1, +1].

$$Y = \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n \tag{20}$$

$$\frac{Y - \overline{Y}}{\sigma(Y)} = \beta'_1 \frac{x_1 - \overline{x}_1}{\sigma(x_1)} + \beta'_2 \frac{x_2 - \overline{x}_2}{\sigma(x_2)} + \ldots + \beta'_n \frac{x_n - \overline{x}_n}{\sigma(x_n)} \tag{21}$$

where Y are the response variables, $x_1, \cdots, x_n$ are predictor variables and $\beta_1, \cdots, \beta_n$ are the parameters to be identified. $\overline{Y}$, $\overline{x}_n$ are the mean values of the variables and $\sigma()$ is the variance of the variable. $\beta'_1, \cdots, \beta'_n$ are the estimated parameter of the scaled regression model.

4.3. Modelling and validation

The corresponding item in Eq. (18) is brought into the optimisation problem Eq. (8) to solve the quadratic programming problem. The hyper-parameter C is set by the method of grid search and cross-validation, and the hyper-parameter ν is set manually considering the computing efficient and sample data structure. The smaller the ν, the fewer the support vectors and the faster the calculation will be. After the optimal solution is obtained, the identified model is derived from Eq. (11).

The validation of the modelling method is focused on the generalisation performance, which is the ability to predict other manoeuvring motion not included in the training dataset.

Before verifying the generalisation performance, the first step is to evaluate the degree of overfitting, which has a significant impact on the generalisation performance. Comparing the prediction on the training and holdout sets, if the performance on the training set is significantly better, it suggests overfitting. Then, the hyper-parameter C needs to be fine-tuned and to repeat the process to get the best performance.

In evaluating the generalisation performance of the identified model, other manoeuvring motions are used, including 10°/5°, 15°/5°, 20°/5°, 20°/10°, 25°/5° zigzag tests. Predicting the above manoeuvres by the identified model, the state information is compared with the actual sequence.

5. Verification and validation

5.1. Selection of samples

A Mariner class vessel is taken as the object of research. In order to test the adaptive ability and the generalisation performance of the algorithm, the polluted data from computer simulation programs are used as the training data. Moreover, the uncertainty of model structure during the identification process is considered: a model with different hydrodynamic force/moment expressions is selected as the simulator. The hydrodynamic coefficients are obtained from the PMM tests, and more details can be found in the literature (Strom-Tejsen, 1965).

The training data has a total of 2100 data points, including the three standard manoeuvres, namely 10°/10°, 20°/20° zigzag and 35° turning circle manoeuvres each with 700 data points with a time interval of 0.5 s. The training data is polluted artificially by varying degrees of white noise to simulate the effects of disturbance such as measurement noise. The method of noise generation refers to the literature (Sutulo and Guedes Soares, 2014), using the formula as:

$$\zeta_i = \zeta_{0i} + \zeta^{\max} k_0 k_\zeta \xi_i \tag{22}$$

where ζ_{0i} is the original clean response, and $\zeta^{\max} k_0 k_\zeta \xi_i$ is the disturbance part. Concretely, $\zeta^{\max}$ is the maximum absolute value of the clean response, k_ζ is the reduction factor for the different DOFs response, which is set to 0.05 for the rudder angle, 0.2 for the surge velocity and 1.0 for the other responses. ξ_i is the Gaussian white noise process. k_0 is the general reduction factor used to characterise the degree of noise, which is selected as 1%, 5%, 10%. The three cases will be referred as Noise Level 1 (Nlv1), Noise Level 2 (Nlv2) and Noise Level 3 (Nlv3), respectively. These levels simulate different degrees of measurement noise, which are related to the type of sensors and the way of data collection. For instance, Noise Level 1 corresponds to the data from precision sensors or pre-processed. Noise Level 2 and 3 can be the data collected by a normal navigation unit or other conventional sensors.

5.2. Identification results

The proposed method is used to model the ship manoeuvring motion from the free-running test dataset. The hyper-parameter υ is selected as 0.3. Table 1 shows the ε values and the number of SVs during the identification modelling under three noise cases. As the degree of noise increases, the ε value is adaptively adjusted. For example, the value of ε in Noise Level 3 is adjusted to be nearly 10 times the value of ε in Noise Level 1, thereby ensuring the stability of the number of SVs. The number of SVs remains almost the same, around 634. In this situation, the insensitivity tube with radius ε is tuned automatically. For an intuitive illustration, Fig. 1 shows the change of insensitivity tube in the sway motion under different noise cases. The black circle represents the training data point, the blue triangle symbol represents the regression value, and the two red lines are the boundary of the tube. The insensitivity tube controls the number of the SVs; only they affect the regression results.

The above results indicate that the adaptive adjustment of the method is active so that the algorithm ensures the sparsity of the solutions under different training data. This can improve the efficiency and robustness of the identification.

Table 2 presents a comparison of the identification coefficients with the original coefficients (Chislett and Strom-Tejsen, 1965). These coefficients are identified under the excitation of clean dataset and three noise levels datasets. For the clean datasets, most coefficients can be accurately identified, but some identified coefficients have a sign error. One possible reason is that the training data does not have enough information for each coefficient. Another reason may be the process noise caused by the uncertainty of the model structure. The parameter drift occurs when using datasets of three noise levels. The higher the noise

Table 1
Automatic adjustment information of SVs quantity and ε value during modelling by nu-SVM under different noise interference (with $\upsilon = 0.3$).

Noise level	Number of SVs for the surge motion	ε value for the surge motion	Number of SVs for the sway motion	ε value for the sway motion	Number of SVs for the yaw motion	ε value for the yaw motion
$k_0 = 1\%$	634	0.00113	636	0.00809	633	0.000146
$k_0 = 5\%$	633	0.00514	633	0.0372	634	0.000554
$k_0 = 10\%$	637	0.00935	634	0.0625	635	0.00107

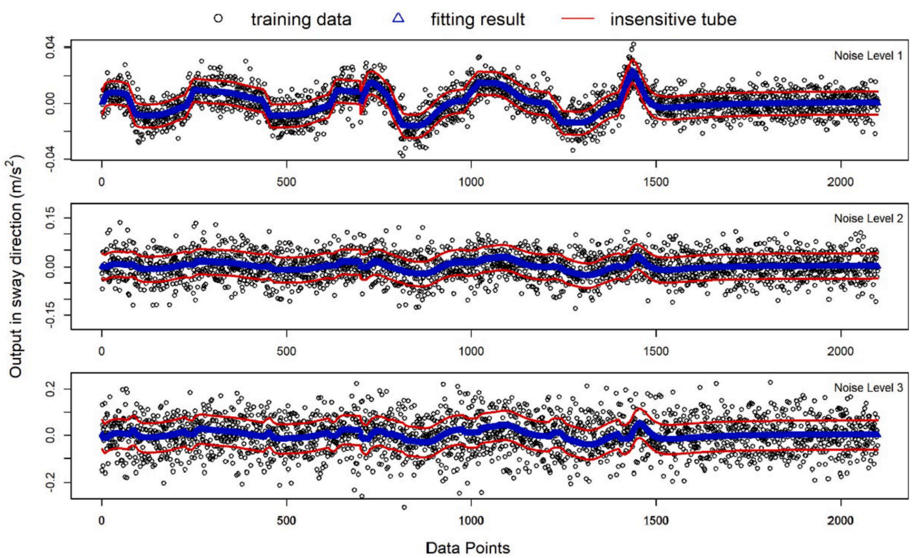

Fig. 1. Automatic adjustment of insensitive tubes under different noise interference (in the sway motion).

Table 2
Comparison of identification coefficients in yaw equation.

Coefficients	Original	Clean	Noise Level 1	Noise Level 2	Noise level 3
N'_v	−0.00264	−0.00235	−0.00062	−0.00907	−0.02424
N'_r	−0.00166	−0.00159	−0.00084	−0.00475	−0.01143
N'_{vvv}	0.01636	0.02256	0.00506	−0.41103	−0.71385
N'_{vvr}	−0.05483	−0.06544	−0.05862	−0.21516	−0.32591
N'_{vu}	−0.00264	0.00285	0.00645	0.01512	0.02089
N'_{ru}	−0.00166	0.00122	0.00297	0.01812	0.03312
N'_{δ}	−0.00139	−0.00149	−0.00113	−0.00275	−0.00501
$N'_{\delta\delta\delta}$	0.00045	0.00049	0.00020	0.00099	−0.00006
$N'_{u\delta}$	−0.00278	0.00041	−0.00072	0.00171	0.00777
$N'_{uu\delta}$	−0.00139	−0.00036	−0.00139	−0.00684	−0.00954
$N'_{v\delta\delta}$	0.00013	0.00049	−0.00111	−0.00442	−0.00450
$N'_{vv\delta}$	−0.00489	−0.00973	−0.01016	0.01048	0.09538

level, the more severe the parameter drifts. This problem arises when identifying under noise interference, but it is actually caused by multicollinearity. Therefore, it is difficult to eliminate parameter drift without adding more training data. As described in Section 4.1, the proposed identification scheme aims to establish an accurate forecasting model rather than obtaining correct hydrodynamic coefficients. Thereby the validation of the model will be focused on the generalisation ability.

5.3. Validation of the generalisation performance

The primary evaluation criteria of the forecasting model are the generalisation performance. In the present work, the generalisation performance of the identified model is verified by forecasting the manoeuvres including 10°/5°, 15°/5°, 20°/5°, 25°/5°, 30°/5°, 20°/10° zigzag manoeuvres. Root-mean-square error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE) are used to measure the prediction accuracy of the forecasting method. SMAPE is defined by the formula:

$$SMAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|F_t - A_t|}{(|A_t| + |F_t|)/2} \tag{23}$$

where A_t is the actual value and F_t is the predictive value. The result provides a percentage error between 0% and 200%, which is smaller when the forecast is more accurate.

The predictions of the speeds in the 3DOF motions and the heading angle are compared with the original data. The cases of 10°/5°, 15°/5°, 20°/10° and 30°/5° zigzag manoeuvres are shown in Figs. 2–5. The forecasts results of 20°/5° and 25°/5° zigzag manoeuvres are similar to those of 20°/10°, 30°/5° zigzag manoeuvres, respectively. Figs. 6 and 7 show the evaluation index for manoeuvring motion prediction. The effect of noise on forecast results is still somewhat noticeable, the accuracy of the forecast under Noise Level 1 is better than that under Noise Level 3, especially for the surge motion prediction. But overall, the prediction results agree well with the actual data. The time series of velocities can be well fitted under different degree of noise interference, which means an accurate prediction of trajectory.

From the perspective of RMSE index, the predictions of the manoeuvres are accurate under noise disturbance. There is still room for improvement in the prediction of large rudder angle manoeuvres. The forecasts of sway speed and yaw rate are accurate in the first 100s, but then a cumulative deviation occurs. The analysis results obtained from the SMAPE index are approximate. The prediction accuracy of most cases is satisfactory, that having a SMAPE index of less than 20%, except

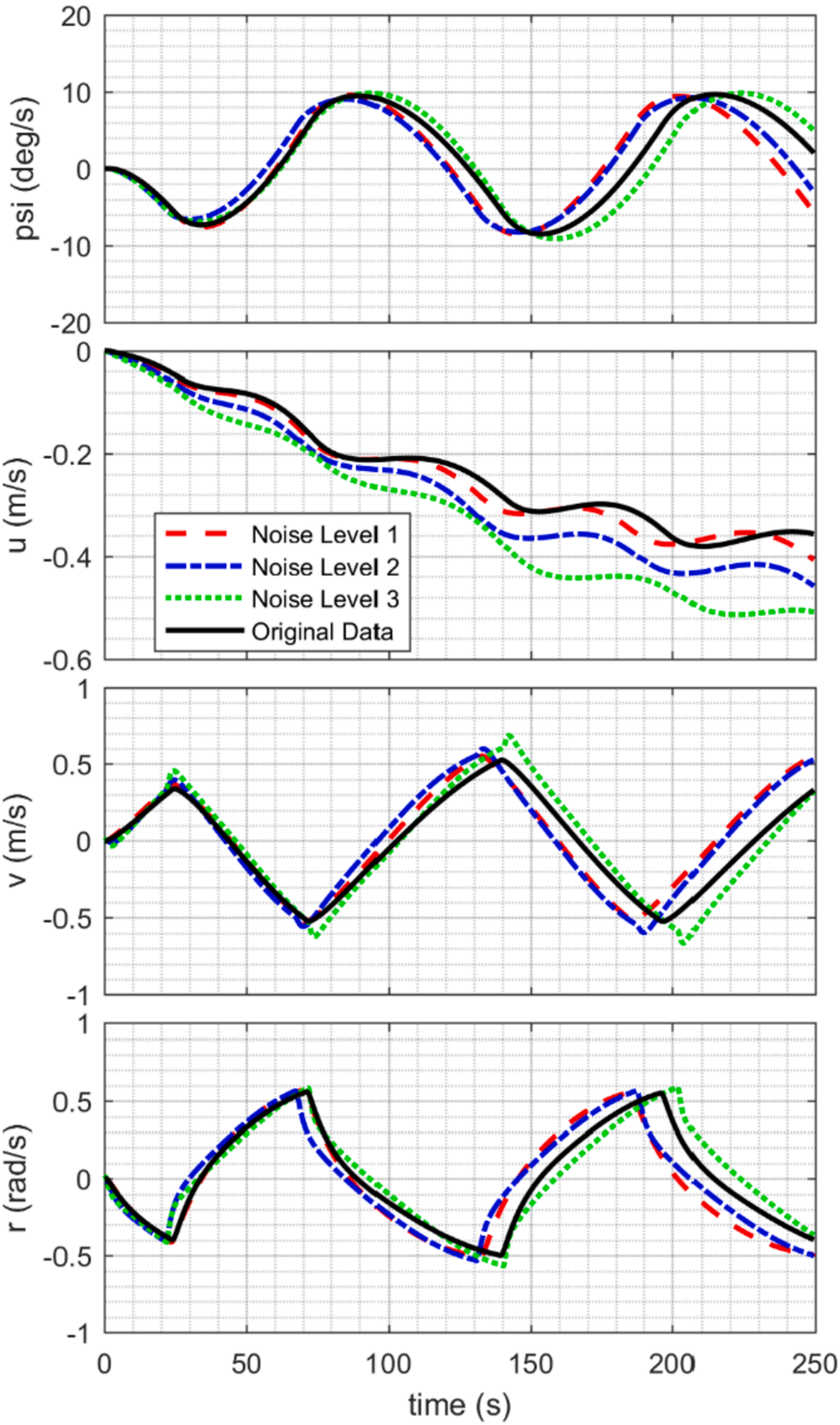

Fig. 2. Prediction of 10°/5° zigzag manoeuvre by model identified under different training data.

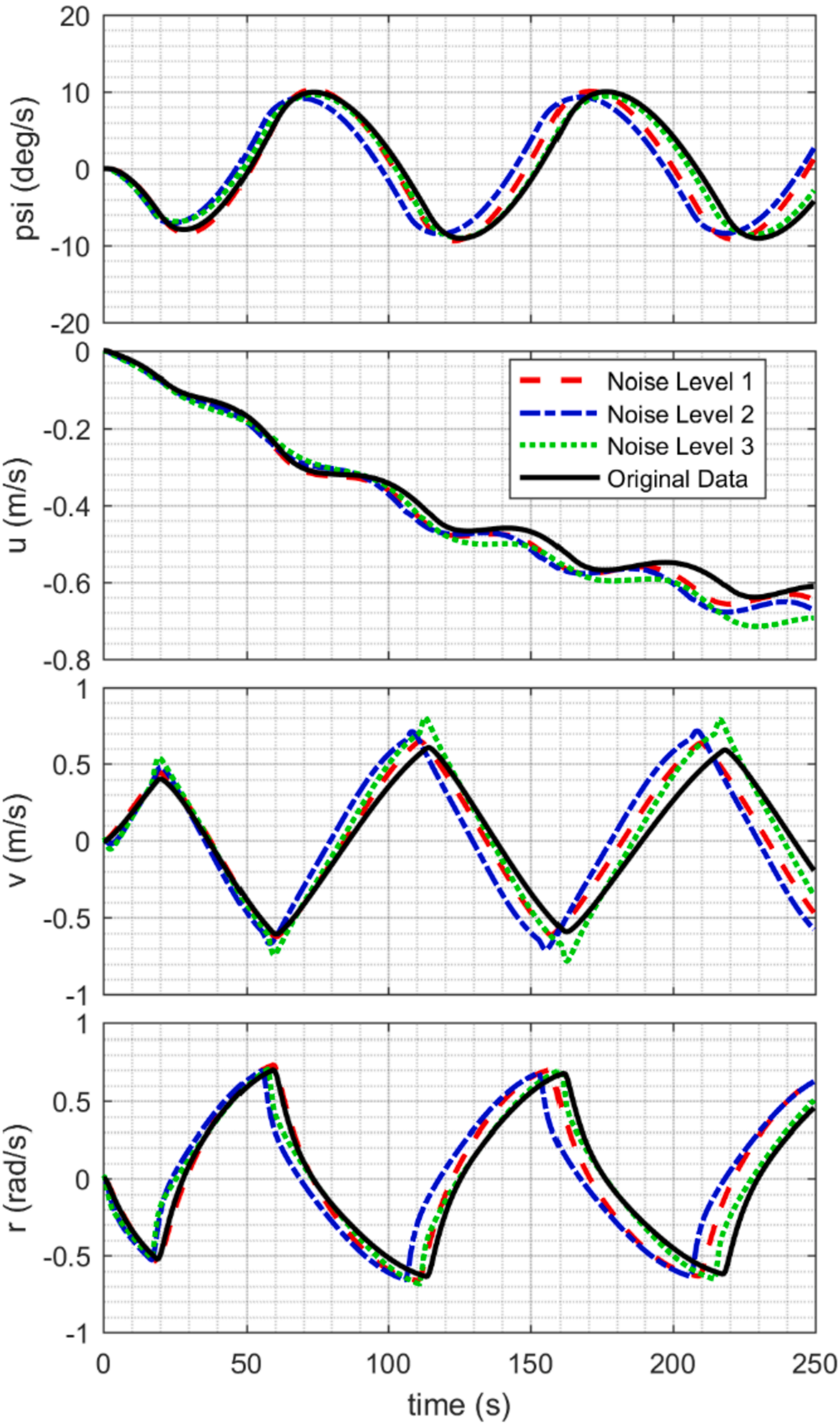

Fig. 3. Prediction of 15°/5° zigzag manoeuvre by model identified under different training data.

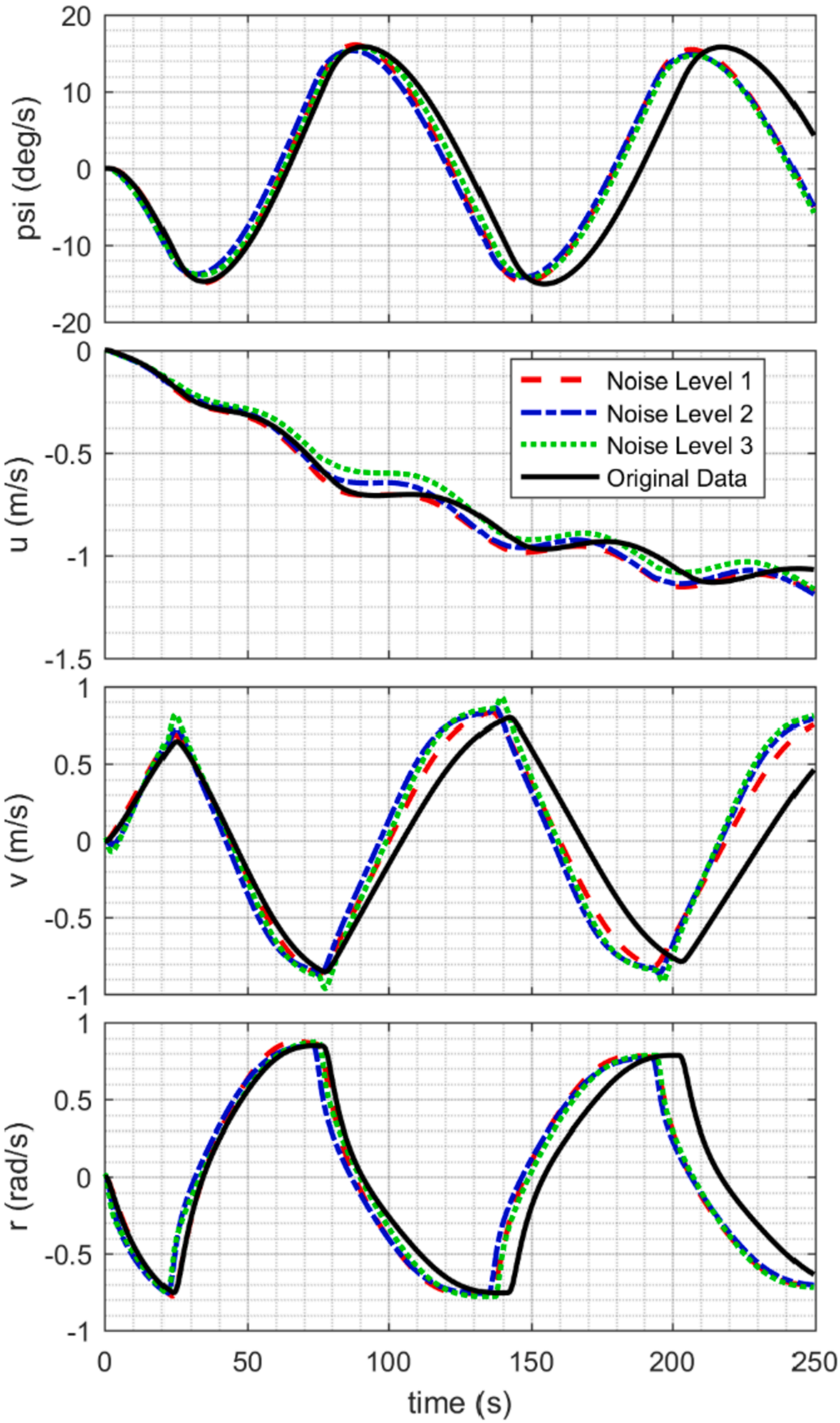

Fig. 4. Prediction of 20°/10° zigzag manoeuvre by model identified under different training data.

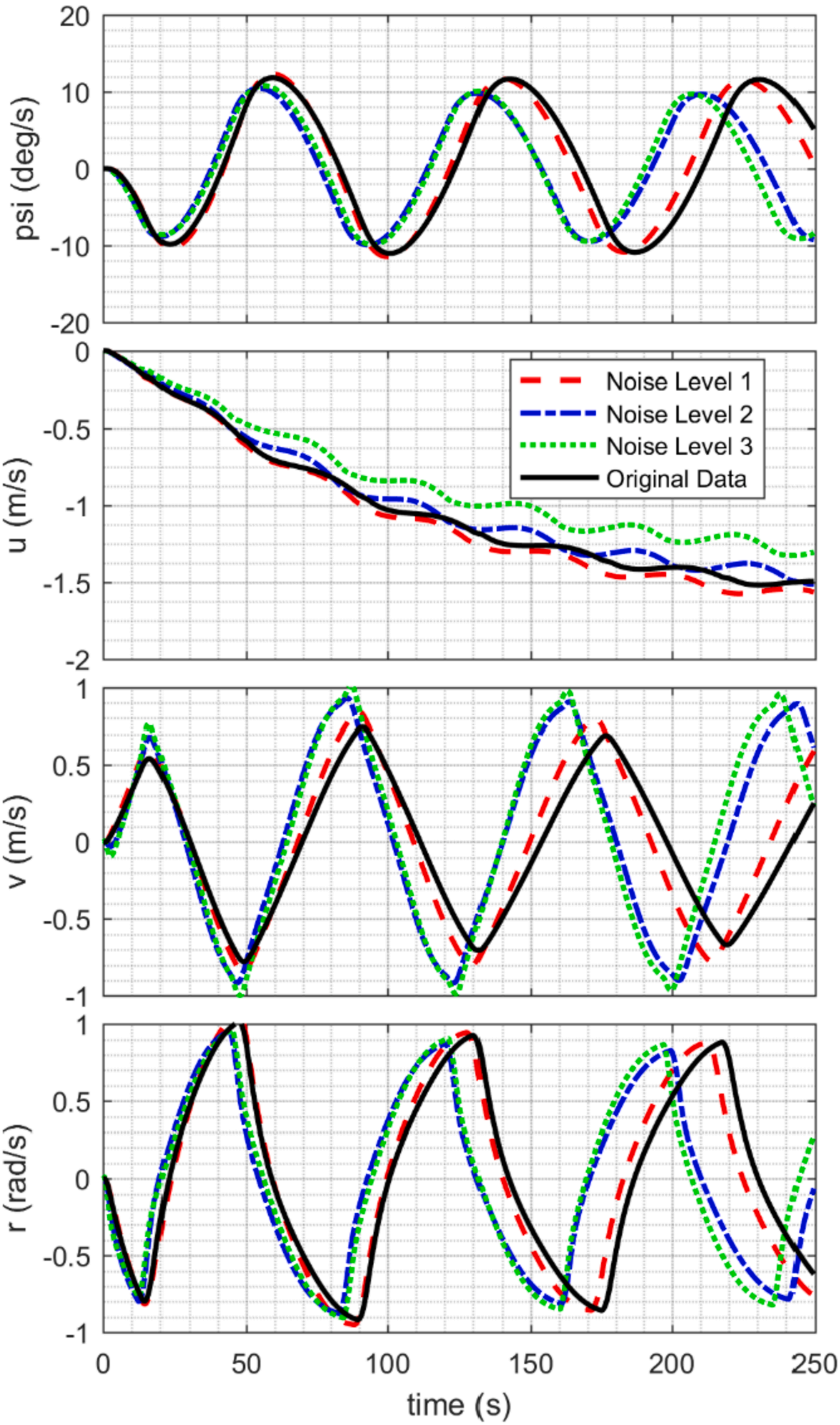

Fig. 5. Prediction of 30°/5° zigzag manoeuvre by model identified under different training data.

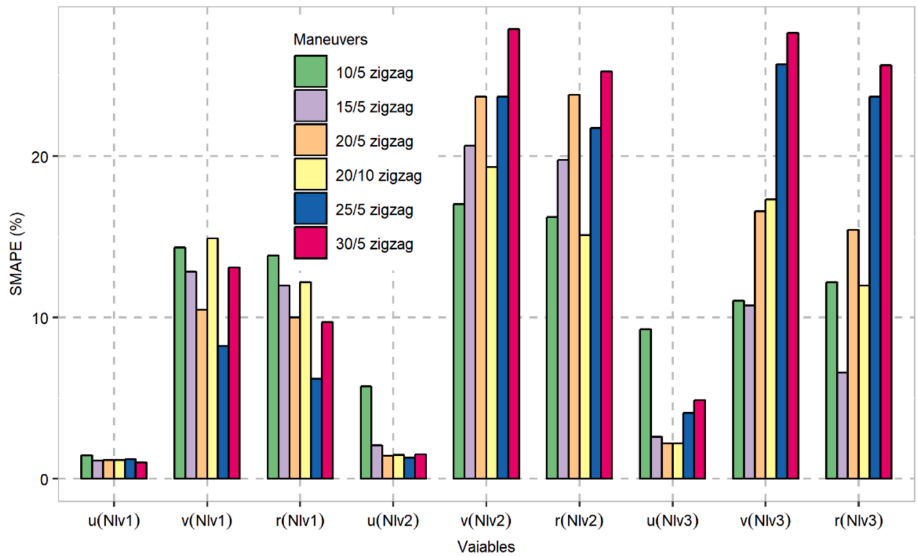

Fig. 6. Estimation of forecast accuracy by SMAPE for generalisation performance verification.

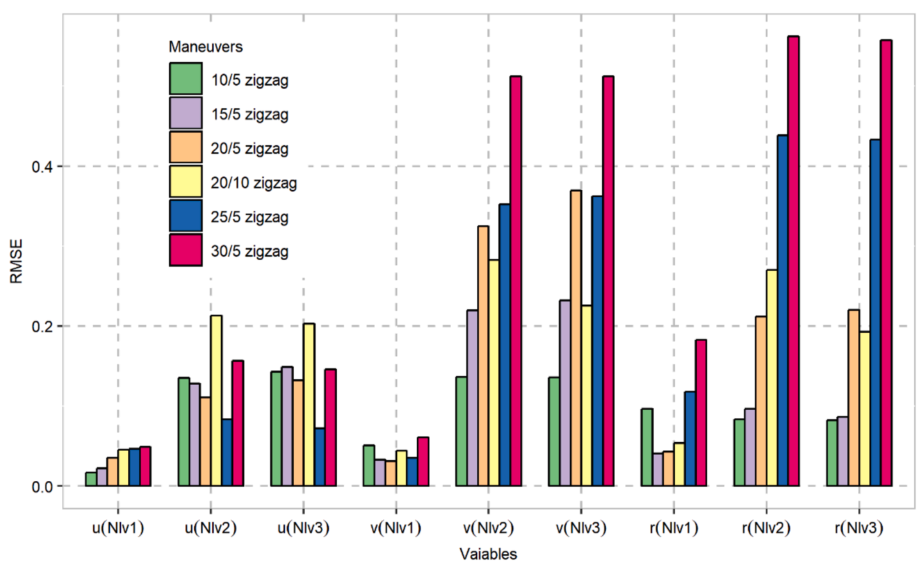

Fig. 7. Estimation of forecast accuracy by RMSE for generalization performance verification.

for the prediction of sway velocity and yaw rate in large-rudder-angle cases. In the design of training data, 35° turning circle manoeuvre is selected to cover the dynamic characteristics for large rudder angle motion. But the results indicate that the excitation for this region may not be sufficient, since turning circle motion involves much steady motion.

In the prediction of the 10°/5° zigzag manoeuvres under Noise Level 3, there is a deviation in the prediction of the surge speed. There may be two reasons for the deviation. First, the variation range of the surge speed is relatively small under small rudder angle. When the large noise pollution makes it difficult to distinguish the dynamic characteristics, the over-fitting is generated. Second, since the state variables in small rudder angle motion are less fluctuating relative to those in the large rudder angle motion, the weighting of the regression accuracy of the large rudder angle motion becomes larger when performing the grid search of the parameters. It suggests that the configuration of training data needs to be further improved in future work. In summary, identification modelling can meet the requirements of accurately predicting the normal manoeuvres of stable propeller revolution. It is also relatively stable under noise interference. The results demonstrate the effectiveness and good generalization performance of the proposed method.

6. Conclusion

This paper proposes a ν-SVM based identification method to establish a predictive model of ship manoeuvring motion. The advantages of ν-SVM are able to automatically determine parameter ε and predetermine the number of SVs. When the collected data is polluted, ν-SVM can ensure the sparsity of the solution through adaptive adjustment. This will reduce the time required for tuning and better leverage the advantages of the SVM algorithm to maintain efficiency and accuracy.

The modelling purpose is set to forecasting, rather than identifying parameters. Multiple manoeuvring motions are simultaneously used as training data to provide more dynamic features. Parameter drift still occurs, but by acquiring more information from the training data, the impact of parameter drift is minimised. The effects of parameter drift can be tolerated under the premise of ensuring generalisation performance. As a result, the proposed method can model manoeuvring motion efficiently under different levels of noise pollution. The prediction of other manoeuvres proves that the model has a good generalisation performance, verifying the robustness of the algorithm.

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