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Parameter estimation for a ship's roll response model in shallow water using an intelligent machine learning method



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ABSTRACT

In order to accurately identify the ship's roll model parameters in shallow water, and solve the problems of difficult estimating nonlinear damping coefficients by traditional methods, a novel Nonlinear Least Squares - Support Vector Machine (NLS-SVM) is introduced. To illustrate the validity and applicability of the proposed method, simulation and decay tests data are combined and utilized to estimate unknown parameters and predict the roll motions. Firstly, simulation data is applied in the NLS-SVM model to obtain estimated damping parameters, compared with pre-defined parameters to verify the validity of the proposed method. Subsequently, decay tests data are used in identifying unknown parameters by utilizing traditional models and the new NLS-SVM model, the results illustrate that the intelligent method can improve the accuracy of parametric estimation, and overcome the conventional algorithms' weakness of difficult identification of the nonlinear damping parameter in the roll model. Finally, to show the wide applicability of the proposed model in shallow water, experimental data from various speeds and Under Keel Clearances (UKCs) are applied to identify the damping coefficients. Results reveal the potential of using the NLS-SVM for the problem of the roll motion in shallow water, and the effectiveness and accuracy are verified as well.

1. Introduction

Roll motion is one of the most critical responses the ship experiences in her lifespan. An accurate prediction of roll motion in real scenarios is then deemed necessary so to understand better the ship behavior and to avoid any hazardous condition (Jiang et al., 2016; Yin et al., 2018). The damping components of a roll model play a key role in properly predicting the ship's roll response. The estimation of these parameters is, however, difficult because of their nonlinear characteristics as a result of their viscous and fiction dependency (Oliva Remola et al., 2018). An efficient approach to obtain accurately the damping terms is still absent, especially in the estimation of the nonlinear term (Hou and Zou, 2016) and to avoid parameter drifting. For this purpose, the identification of the roll damping terms is of critical interest (Jiang et al., 2017).

Roll damping parameters have been investigated in numerous studies in literature (Oliveira and Fernandes, 2013; Lee et al., 2018; Falzarano et al., 2015). Generally, three main research directions are presented in literature to determine the damping coefficients, namely,

semi-empirical approaches (Ikeda et al., 1978; Kawahara et al., 2012), model tests (Atsavapranee et al., 2007; Oliva Remola et al., 2018; Jang et al., 2010; Avalos et al., 2014), and numerical simulations (Gokce and Kinaci, 2018; Yang et al., 2012). By comparison, the most common approach to obtain this component is by means of free roll decay tests and fitting the measured response by conventional methods such as Least Squares (LS) approach. This method, however, when applied in shallow water has some difficulties to provide a clear distinction of the viscous parameters (Tello Ruiz, 2018), especially in the nonlinear term. One may argue that other alternatives, available nowadays, can provide better results.

In recent years, the majority of efforts are devoted to developing advanced system identification techniques, so to obtain optimal roll damping parameters combined with numerical simulations or model tests. Mahfouz (2004) proposed a new robust method to obtain linear and nonlinear damping and restoring coefficients in ship roll motion equation. Sun and Sun (2013) combined the Partial Least-Squares regression algorithm with the Bass Energy and Roberts approaches for

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estimating nonlinear roll damping coefficients. Kim and Park (2015) employed the Hilbert transform method to study a FPSO's nonlinear damping and restoring moment. A wavelet approach was introduced to identify the nonlinear damping parameters in Sathyaseelan et al. (2017). Wassermann et al. (2016) compared the harmonic excited roll motion technique with the decay motion technique for establishing an efficient method to estimate the roll damping. A Radial Basis Function (RBF), neural network algorithm, was investigated for online prediction of the ship's roll motion based on full scale trials (Yin et al., 2013). Somayajula and Falzarano (2017) applied an advanced system identification approach to study the roll damping terms using model tests.

In spite of the acceptable results obtained for the roll damping parameters by several identification methods, the major disadvantages are: parameters drift, requiring a large sample data, dependency on the initial state, and an ill-conditioned solution. Additionally, to the authors' best knowledge, the studies mentioned above, among others, are all focused on deep water. No particular attention has been made to the shallow water problem (Tello Ruiz et al., 2019). In such condition the limited water depths reduces the Under Keel Clearance (UKC) hence increasing the risk of bottom touching which consequently makes the prediction of roll motion even more critical.

Motivated by the research opportunities mentioned above, the paper aims to investigate novel intelligent identification approaches which can be compared and tested against conventional methods. In the present work, the NLS-SVM (Nonlinear Least Squares - Support Vector Machine) algorithm will be investigated, which is a new generation machine learning method and can accurately identify model parameters by means of the RBF kernel function. Compared with other intelligent approaches, using large samples of data to estimate unknown parameters, the NLS-SVM only depends on limited support vectors based on small samples. Besides, the structure risk minimization theory instead of empirical risk minimization is adopted by the NLS-SVM to solve optimisation problems. A global optimisation result is obtained, and local optimisation issues are avoided. Moreover, high accuracy, time saving and wide applicability performances of the NLS-SVM are especially suitable for the identification of damping parameters in shallow water.

To verify the effectiveness, accuracy and applicability of the NLS-SVM parametric estimation model in shallow water, free roll decay tests for a scale model of an Ultra Large Container Vessel (ULCV) at different forward speeds and different UKCs were carried out. Then, numerical simulation and experiment data are used to identify and predict the ship's roll motions. Comparisons between predicted data and measured data illustrate the potential of employing the proposed method for the problem of ship roll motion in shallow water.

2. Ship roll hydrodynamic model

In a sense, an accurate definition and prediction of damping parameters (especially nonlinear damping coefficients) in the ship roll model is a very necessary task (Hou and Zou, 2016). On the basis of the rigid body theory (Hou and Zou, 2015), the 1DOF ship roll motion model can be written as (Xing and McCue, 2010):

$$(I_{xx} + A_{44}^{\infty})\ddot{\varphi} + B(\dot{\varphi}) + C_{44}\varphi = 0 \quad (1)$$

where I_{xx} is the mass moment of inertia, A_{44}^{∞} is the added mass moment of inertia (at infinite frequency), B is the moment due to the damping phenomena, C_{44} is the roll restoring coefficient, and φ is the roll angle. The single dotted and double dotted variables represent the first and second order derivatives.

The total damping coefficients are divided into a linear (b_{φ}), a nonlinear ($b_{\varphi|\dot{\varphi}}$) (Ikeda et al., 1977; Himeno, 1981), and a potential contribution components in the following form:

$$B(\dot{\varphi}) = b_{\varphi}\dot{\varphi} + b_{\varphi|\dot{\varphi}}|\dot{\varphi}| + \int_{-\infty}^{+\infty} h_{44}(t-\tau)\dot{\varphi}(\tau)d\tau \quad (2)$$

where $\dot{\varphi}$ is the roll rate and h_{44} is the Impulse Response Function (IRF). Substituting $B(\dot{\varphi})$ into Eq. (1), the final model in the time domain is expressed as follows:

$$(I_{xx} + A_{44}^{\infty})\ddot{\varphi} + b_{\varphi}\dot{\varphi} + b_{\varphi|\dot{\varphi}}|\dot{\varphi}| + \int_{-\infty}^{+\infty} h_{44}(t-\tau)\dot{\varphi}(\tau)d\tau + C_{44}\varphi = 0 \quad (3)$$

3. Parameters estimation approaches

3.1. Problem statement

Assuming that a parametric system in state-form is available in the form of:

$$\frac{dX}{dt} = g(X, T, \theta) \quad (4)$$

where $X = [x_1; x_2; \dots; x_n]$ is the state variable, $\frac{dX}{dt} = \left[\frac{dx_1}{dt}, \frac{dx_2}{dt}, \dots, \frac{dx_n}{dt} \right]^T$ is the derivative of each state variable, $T = [t_1, t_2, \dots, t_i]^T$ is the time variable, $\theta = [\theta_1, \theta_2, \dots, \theta_i]^T$ is an unknown set of parameters (Mehrkanon et al., 2012).

For the parametric system, the main goal is to identify the unknown parameters θ from observed data $Y = [y_1, y_2, \dots, y_i]^T$ at time variable $T = [t_1, t_2, \dots, t_i]^T$.

$$e_i = Y(t_i) - X(t_i), i = 1, 2, \dots, n \quad (5)$$

where $e_i = [e_1, e_2, \dots, e_n]^T$ is the error between observed data Y and output of the estimate state variable X . The final goal is shifted to get the set of unknown parameters by minimizing the error e_i .

3.2. Identification procedure

Step 1 Obtain sample data

Obtain training samples data $\{(t_i, y_i), i = 1, 2, \dots, n\}$, where t_i is the time series, and y_i is the numerical simulation data or experimental data.

Step 2 Approximate the state variable

Estimate the state variable $\hat{X} = [\hat{x}_1, \hat{x}_2, \dots, \hat{x}_i]^T$ based on simulation or experimental data $\{(t_i, y_i), i = 1, 2, \dots, n\}$. In the present study, the NLS-SVM approach is adopted to approximate the state variable \hat{X} . x_k or the k -th state variable can be obtained by an approximation function of the following form:

$$\hat{x}_k(t) = w_k^T \phi(t) + b_k \quad (6)$$

where t is the input data (time), \hat{x}_k is the output data, w_k is the weight value, $\phi(\cdot)$ is the nonlinear function, which maps the input data t to the Euclidean space, b_k is the bias (David et al., 2013; Xu and Guedes Soares, 2016).

To solve the convex optimisation issue according to the minimization of structure risk theory, construct and solve the following cost function:

$$\min_{w, b, e} f(w, e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \|e_i\|_2^2 \quad (7)$$

Subject to:

$$y_i = w^T \phi(t_i) + b + e_i \quad (8)$$

where $i = 1, 2, \dots, n$, γ is penalty factor, e_i is the error.

A Lagrangian function is introduced to solve the optimisation problem as follows:

$$L(w, b, e, a) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \|e_i\|_2^2 - \sum_{i=1}^n a_i [w^T \phi(t_i) + b + e_i - y_i] \quad (9)$$

where the coefficients a_i are the Lagrange multipliers. The derivative matrix is obtained by partially differentiating Eq. (9) with respect to w, b, e, a :

$$\begin{bmatrix} K + \gamma^{-1}I_N & 1_N \\ 1_N^T & 0 \end{bmatrix} \begin{bmatrix} a^k \\ b^k \end{bmatrix} = \begin{bmatrix} y^k \\ 0 \end{bmatrix} \quad (10)$$

where $K(t_i, t) = \phi(t_i)\phi(t)$ is the kernel function, I_N is the identity matrix, $1_N = [1; 1; \dots; 1]$, $\alpha^k = [\alpha_1^k; \alpha_2^k; \dots; \alpha_n^k]$.

The regression model is expressed as:

$$\hat{x}_k(t) = w_k^T \phi(t) + b_k = \sum_{i=1}^n \alpha_i^k K(t_i, t) + b_k \quad (11)$$

Step 3 Derivatives of the state variable approximation

Approximate the derivatives of the state variable $\frac{d}{dt}\hat{X} = \left[\frac{d}{dt}\hat{x}_1, \frac{d}{dt}\hat{x}_2, \dots, \frac{d}{dt}\hat{x}_n \right]$ by differentiating the approximated model with time.

Differentiation of $\hat{x}_k(t)$ with time, yields:

$$\frac{d}{dt}\hat{x}_k(t) = w_k^T \dot{\phi}(t) = \sum_{i=1}^n \alpha_i^k \phi(t_i)^T \dot{\phi}(t) \quad (12)$$

According to the Mercer Theorem (Steinwart and Scovel, 2012), the derivatives of the kernel are equal to the derivatives of the feature map. Therefore, the derivatives of the kernel can be obtained in the form of:

$$K_1(t_i, t) = \frac{\partial K(t_i, t)}{\partial t} = \phi(t_i)^T \dot{\phi}(t) \quad (13)$$

$$\frac{d}{dt}\hat{x}_k(t) = \sum_{i=1}^n \alpha_i^k K_1(t_i, t) \quad (14)$$

Step 4 Identification of unknown parameters, and model's prediction

$\hat{x}_k(t)$ and $\frac{d}{dt}\hat{x}_k(t)$ in Eq. (11) and Eq. (14) are the approximated values of the k -th state variable and its derivative. All the state variables \hat{X} and their derivatives $\frac{d}{dt}\hat{X}$ can be obtained by using the above same procedure based on the NLS-SVM model. After substituting \hat{X} and $\frac{d}{dt}\hat{X}$ in Eq. (4), the linear or nonlinear algebraic equation with unknown parameters is constructed.

Finally, the unknown parameters can be obtained by solving the optimisation problem as:

$$\min_{\theta} \frac{1}{2} \sum_i \|e_i\|_2^2 \quad (15)$$

Subject to:

$$e_i = \frac{d}{dt}\hat{X}(t_i) - g(\hat{X}(t_i), T, \theta), i = 1, 2, \dots, n \quad (16)$$

4. Experimental program

4.1. Towing tank

Free decay tests were carried out at the Towing Tank for Manoeuvres in Confined Water (co-operation Flanders Hydraulics Research and Ghent University) in Antwerp, Belgium. The main dimensions of the towing tank are listed in Table 1, and more detailed information about towing tank can be obtained in Delefortrie et al. (2016).

Table 1

The main dimensions of the Towing Tank for Manoeuvres in Confined Water.

Items	Value	Units
Total length	87.5	m
Useful length	68.0	m
Width	7.0	m
Maximum water depth	0.50	m
Length of the ship models	3.5–4.5	m

4.2. Ship model

A 1/90 scale model of Ultra Large Container Vessel (ULCV) was chosen to carry out free roll decay tests (Tello Ruiz, 2018). The main particulars and cross sectional view of the ship model are shown in the Table 2 and Fig. 1.

4.3. Free decay tests

The free decay tests were performed by providing an initial roll angle for the ship model. Then, the ship model was held at this initial position until the towing carriage reached its desired speed and immediately released by pulling the cord attached to a wooden stick (Tello Ruiz, 2018). A illustration of the model test setup and mechanism is displayed in Fig. 2.

The free decay tests were carried out at different UKCs (from 10% to 190% UKCs) and speeds (from 0 to 12 knots). For the present study, the UKCs of 10%, 20%, 35%, 190% and the speeds at 0, 3, 6, 9, 12 knots are selected as study cases. The initial roll angles at the chosen conditions are presented in Table 3 and Fig. 3.

5. Parameter identification

Taking into consideration of the parameters estimation method in the section 3, the novel NLS-SVM approach is introduced to estimate the linear and nonlinear viscous damping parameters in the nonlinear roll model (Eq. (3)). The identification processes are, in more detail, described in Table 4 and Fig. 4.

In order to verify the effectiveness, accuracy as well as applicability of the NLS-SVM model in shallow water, three case studies are conducted by using the novel identification method, they are:

Case 1. Validate the effectiveness of the NLS-SVM (5.1.)

Case 2. Illustrate the advantages of the NLS-SVM (5.2.)

Case 3. Verify the applicability of the NLS-SVM in shallow water (5.3.)

These cases are described in detail in the following subsections.

5.1. Effectiveness of NLS-SVM model

In this case study, the roll motions with known linear (b_ϕ) and nonlinear ($b_{\phi|\phi}$) viscous damping coefficients (Table 5) are selected to

Table 2

Main particulars of model scale and full scale for the Ultra Large Container Vessel (ULCV).

Items	Model scale (1/90)		Full scale	
	Value	Units	Value	Units
L_{OA}	4.418	m	397.6	m
L_{PP}	4.191	m	377.2	m
B	0.627	m	56.4	m
D	0.330	m	29.7	m
T_M	0.145	m	13.1	m
m	226.4	kg	165046	ton
C_b	0.6	–	0.6	–

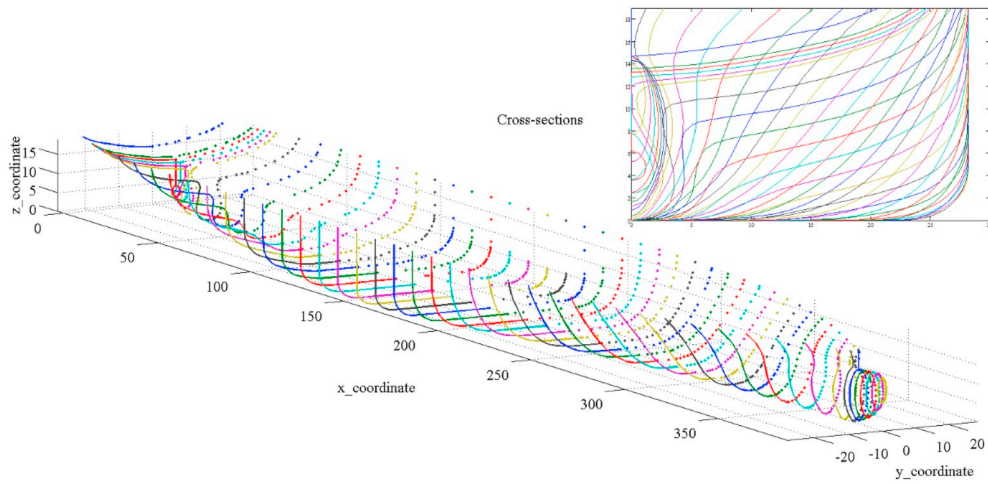


Fig. 1. The cross sectional view of the Ultra Large Container Vessel (ULCV).

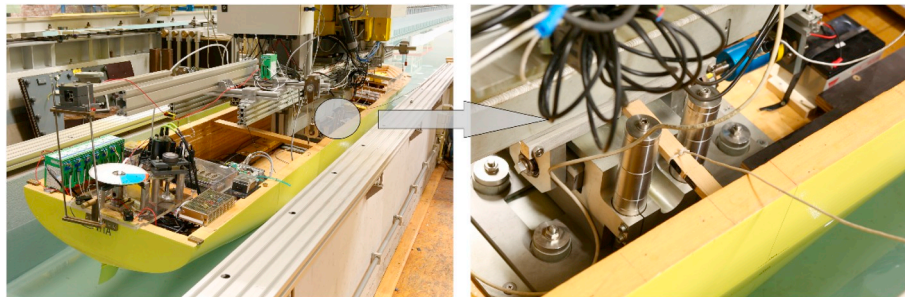


Fig. 2. The model test setup and mechanism of free decay tests.

Table 3
The initial roll angles at different speeds and UKCs.

UKCs	Speeds				
	0 kn	3 kn	6 kn	9 kn	12 kn
10% UKC (deg)	2.21	1.60	1.89	1.54	1.77
20% UKC (deg)	2.70	3.04	2.71	3.51	2.74
35% UKC (deg)	3.11	3.32	3.27	2.68	1.95
190% UKC (deg)	6.96	6.66	6.45	5.69	6.23

simulate a free roll decay test. The known linear and nonlinear damping parameters are substituted into the roll model, Eq. (3). It is worth noting that other parameters in Eq. (3) are regarded as known values, which can be found in Tello Ruiz (2018). Using a fourth-order Runge-Kutta approach to solve the differential equation, the simulated roll angles (samples data) are obtained.

Subsequently, simulated samples data are divided into two sets, the first set as a training sample (blue circles) is used to train the NLS-SVM model and the second set as a test sample (green circles) is selected to test the model. The results are displayed in Fig. 5 (a).

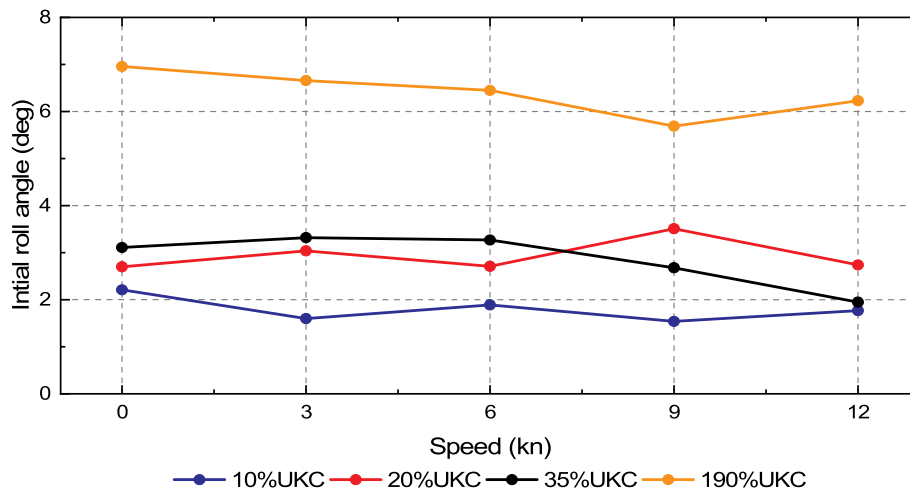


Fig. 3. The initial roll angles at different speeds for 10%UKC (blue line), 20%UKC (red line), 35%UKC (black line), 190%UKC (orange line). (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 4
Identification processes of the NLS-SVM model.

Parameter identification using the NLS-SVM model
1 Obtain the sample data $\{(t_i, \varphi_i), i = 1, 2, \dots, n\}$ based on numerical simulation tests or free decay tests. Where t_i is the time series and φ_i is the roll angles.
2 Estimate the trajectory of the roll angle φ (the state variable) by using the NLS-SVM model, Eq. (11).
3 Differentiate the NLS-SVM predicting model with respect to time, Eq. (14); And the closed-form approximation for the first ($\dot{\varphi}$) and second ($\ddot{\varphi}$) derivatives of the state variable are obtained respectively.
4 Identify the linear (b_φ) and nonlinear ($b_{\varphi \varphi}$) viscous damping coefficients by solving the optimisation problem in Eq. (15).
5 Substitute the identified linear and nonlinear viscous damping coefficients in the roll model, Eq. (3). After applying a fourth-order Runge-Kutta approach to solve the ship's roll response equation (Eq. (3)), the ship roll motions are predicted.

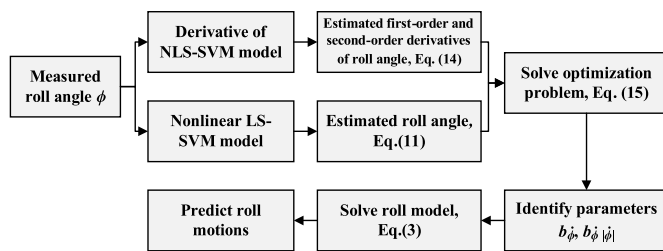


Fig. 4. Identification process of NLS-SVM.

Table 5
Known parameters and identified parameters using the NLS-SVM approach.

Parameters	Known	Identified	Error (%)
b_φ ($\text{kgm}^2/\text{s}, 10^8$)	6.0	6.02	0.33
$b_{\varphi \varphi}$ ($\text{kgm}^2, 10^7$)	4.0	4.04	1.00

After the NLS-SVM model being trained, unknown damping coefficients are identified by the proposed model and are shown in Table 5. Comparing the identified parameters with the known parameters, the results show that the relative errors of the linear (b_φ) and nonlinear ($b_{\varphi|\varphi}$) viscous damping coefficients are about 0.33% and 1.00%, respectively. These very small errors reveal that the NLS-SVM approach can accurately identify unknown parameters and can be well applied in identifying the roll model.

Furthermore, for a better idea of the importance of the method, the identified damping parameters are used to predict the roll motions and are compared against the sample data. Satisfactory agreement between predicted values and original values can be found in Fig. 5(b), with maximum errors between predicted values and original values of around 0.001 deg. This illustrates the potential of the NLS-SVM as it performs well with high prediction accuracy. Therefore, the novel NLS-SVM algorithm can be applied in identifying the ship roll model.

5.2. Comparison with different identification methods

In order to illustrate the characteristics of the NLS-SVM algorithm, traditional methods, such as Nonlinear Least Square (NLS) and Fitting Least Square (FLS) algorithms are selected for comparing and analyzing.

The NLS algorithm has been one of the most common approaches used to identify unknown parameters before intelligent algorithms appeared (Zhu et al., 2017a). The method is described in Fig. 6.

Apart from the NLS, the FLS algorithm has also been successfully applied for system identification. The main difference is that in the FLS approach the curve fitting is firstly applied to the initial data, then a basic LS algorithm is applied to identify the unknown parameters. This

process is relatively simpler than the direct application displayed Figs. 6 and 7 sketches the process for better illustration purposes.

Aiming at comparing and analyzing the performance of the three identification approaches, three evaluation indexes are selected, they are the Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) (Zhu et al., 2017b), and the Computational time (CPU time) (Huang et al., 2018). In machine learning theory, the MAE is employed to assess the performance of the model; the RMSE is utilized to measure the accuracy of the model; the CPU time is represented as calculation time (Zhang et al., 2018). The MAE and the RMSE are, respectively given by:

$$\text{MAE} = \frac{\sum_{i=1}^n |\varphi_i - \hat{\varphi}_i|}{n} \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\varphi_i - \hat{\varphi}_i)^2}{n}} \quad (18)$$

In this case study, the free decay tests data at the speed of 12 knot and the UKC of 20% are selected to compare and analyze. The parameters identified by the methods described above and their respective comparison can be found in Table 6. From the results, it can be seen that the linear damping coefficient (b_φ) can be identified by all methods within the same magnitude (10^9). The nonlinear term, however, has some discrepancies, the traditional NLS method estimates a magnitude of $b_{\varphi|\varphi}$ which is around 100 times smaller than other two approaches. The latter, draws the main attention to consider the use of intelligent method, the NLS-SVM, for improving the performance in practice.

Moreover, the MAE is around 0.0405 deg for the NLS-SVM model, which decreased by 27.9% from 0.0562 deg for the NLS model and by 17.2% from 0.0489 deg for the FLS model respectively. For accuracy analysis, the RMSE (0.0502 deg) of the NLS-SVM is reduced by 20.6% (0.0632 deg) compared to the NLS model and by 17.4% (0.0608 deg) compared to the FLS model, which demonstrates that the NLS-SVM model's errors are smaller, and the accuracy is higher than traditional methods. Moreover, comparing the CPU times, less time is taken by the proposed model.

Subsequently, the identified linear and nonlinear damping coefficients are employed to predict the ship's roll motions separately. The predicted results and errors (Eq. (19)) are presented in Fig. 8(a) and (b), respectively. From Fig. 8(a), there are small but not significant deviations between the original data and predicted data for the three identification approaches. It is noted that the predicted values by the NLS-SVM method are closer to the original values than the other two approaches. Furthermore, the overall errors of the NLS-SVM model in Fig. 8(b) are smaller than that of NLS and FLS methods.

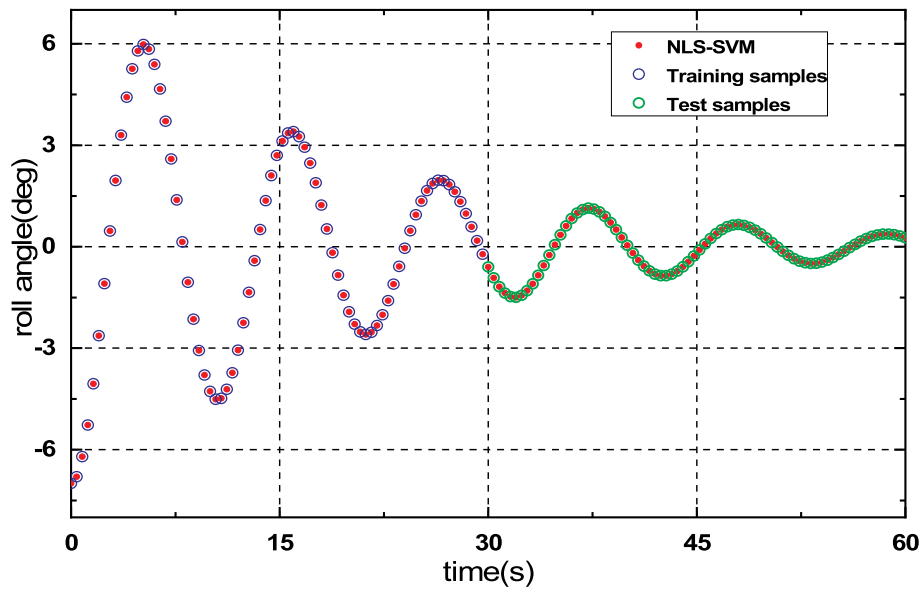
In conclusion, the analyzed results demonstrate that the new NLS-SVM model has better identification performance and time saving ability as well as higher accuracy compared to traditional algorithms. The advantages of the NLS-SVM are validated.

5.3. Applicability analysis of NLS-SVM

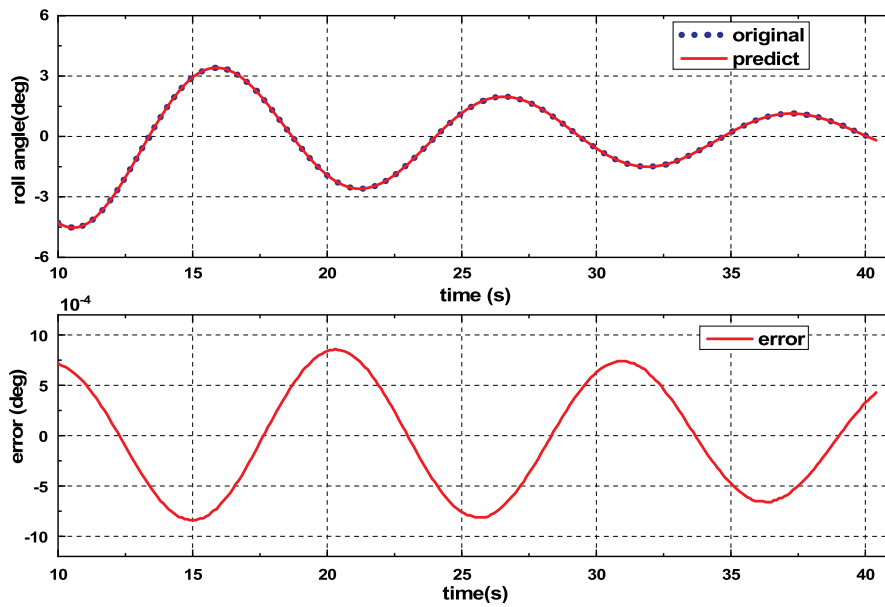
In this subsection, the free roll decay tests from various UKCs and speeds are studied. The applicability in shallow water of the NLS-SVM model is illustrated.

5.3.1. Applicability analysis for different UKCs

Considering the effect of water depth on the damping coefficients, the different UKCs (10%, 20%, 35% and 190% UKCs) at a speed of 6 knot are selected as case studies. After the NLS-SVM model being trained by the decay tests data in different UKCs, Table 7 presents a quantitative comparison of the identified results. It is noted that the MAE (around 0.01–0.05 deg) and the RMSE (the values around 0.02–0.07 deg) are pretty small, and computational time are very short (10–20 s), which reveal furtherly good generality and applicability of the NLS-SVM model both in shallow water and deep water.



(a) Train and test results



(b) Predicted results and errors

Fig. 5. Train, test and predict results with known damping coefficients using NLS-SVM method.

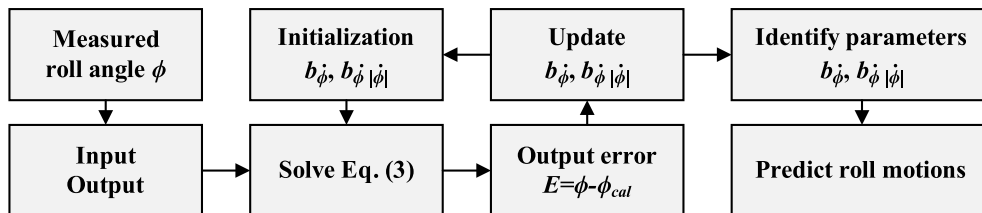


Fig. 6. Nonlinear Least Square (NLS) identification method.



Fig. 7. Fitting Least Square (FLS) identification method.

Table 6

Comparisons of identification results among NLS, FLS and NLS-SVM identification methods.

$$\text{error} = \phi_{\text{known}} - \phi_{\text{pred}} \quad (19)$$

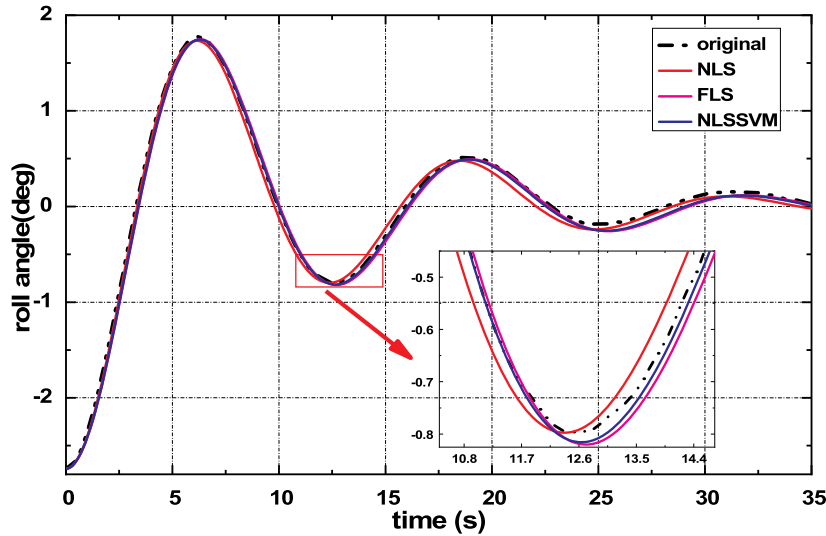
Parameters	Methods		
	NLS	FLS	NLS-SVM
$b_{\dot{\phi}}$ ($\text{kgm}^2/\text{s}, 10^9$)	3.30	3.43	3.38
$b_{\phi \dot{\phi}}$ ($\text{kgm}^2, 10^7$)	0.0493	5.14	3.55
MAE (deg, 10^{-2})	5.62	4.89	4.05
RMSE (deg, 10^{-2})	6.32	6.08	5.02
CPU time (s)	97	13	12

To have a better idea of the effect of the UKCs, substituting the identified parameters in the roll model, Eq. (3), the ship's roll motion for different UKCs are predicted. The results are displayed in Fig. 9(a) to 9(d), for 10%, 20%, 35% and 190% UKC, respectively. In Fig. 9(a) to 9(d)

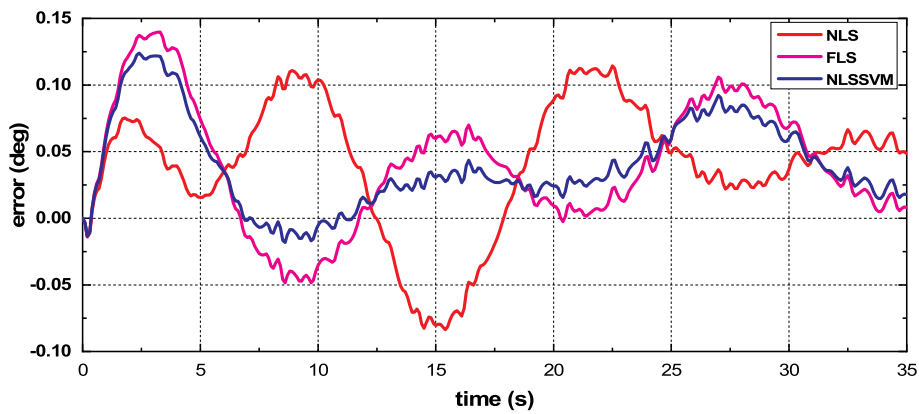
Table 7

Comparisons identification results for different UKCs at a speed of 6 knot.

Parameters	UKC (6 knot)			
	10% UKC	20% UKC	35% UKC	190% UKC
$b_{\dot{\phi}}$ ($\text{kgm}^2/\text{s}, 10^9$)	2.56	1.97	1.70	0.95
$b_{\phi \dot{\phi}}$ ($\text{kgm}^2, 10^7$)	2.58	3.01	3.26	4.03
MAE (deg, 10^{-2})	1.51	1.77	1.24	5.10
RMSE (deg, 10^{-2})	1.70	2.23	1.43	7.29
CPU time (s)	15	15	11	18



(a) Predicted results using NLS, FLS, NLS-SVM approaches



(b) Predicted errors using NLS, FLS, NLS-SVM approaches

Fig. 8. Predicted results and errors using NLS, FLS, NLS-SVM approaches.

it can be observed that the predicted roll angles agree well with the experiments for all tests and that the maximum errors for all UKCs are about 0.30 (at 10% UKC), 0.06 (at 20% UKC), 0.02 (at 35% UKC) and 0.20 (at 190% UKC) deg. Note that the larger error is obtained when a smaller initial roll angle is chosen (see 10% UKC). The latter can be associated to the model formulation needed to satisfy such magnitudes and not of the identification method itself. In spite of the relative larger errors obtained for the lower UKC the overall results show that the NLS-SVM method can successfully be used to identify parameters of the roll model in the shallow and deep water with small errors.

5.3.2. Applicability analysis for different speeds

Similarly, the applicability in shallow water (20% UKC) at different speeds are investigated. The experimental data at 0 to 12 knots are taken as examples to train the NLS-SVM model and to identify the unknown linear and nonlinear damping coefficients at different speeds. The identified results are shown in Table 8. The RMSE is around 0.0185–0.0891 deg, whose values are speed dependent. Moreover, the MAE at different speeds are with small values about 0.0185–0.0739 deg. For the CPU time, they are around 15–17 s. It can be seen that the three evolution indexes are very small. After quantitative comparison, it can be concluded that the NLS-SVM model has good applicability in shallow water at different speeds.

Furthermore, the predicted results in shallow water at speeds of 0, 6, 12 knots are obtained in Fig. 10(a) and (b) and 10(c). It can be observed that the predicted values have satisfactory agreement with the original data at different speeds. The predicted roll angles at a speed of 12kn are a little bit higher than the original ones, but the predicted results are still valid, because the overall errors are very small and the effect on the ship is not significant.

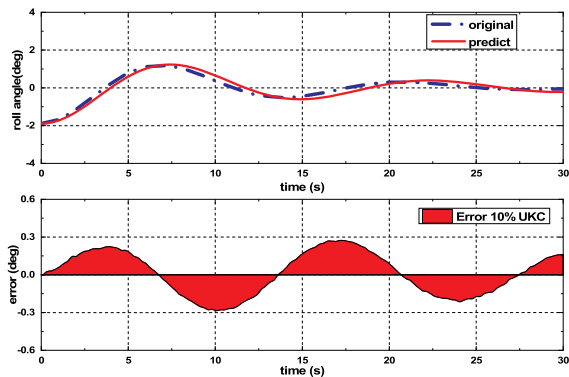
Table 8
Comparisons identification results for different speeds (20% UKC).

Parameters	Speed (20% UKC)				
	0kn	3kn	6kn	9kn	12kn
b_{ϕ} (kgm ² /s, 10 ⁹)	1.93	1.94	1.97	2.84	3.38
$b_{\phi \phi }$ (kgm ² , 10 ⁷)	2.66	2.93	3.01	3.45	3.55
MAE (deg, 10 ⁻²)	1.85	1.92	1.77	7.39	4.05
RMSE (deg, 10 ⁻²)	1.85	2.20	2.23	8.91	5.02
CPU time (s)	15	17	15	17	15

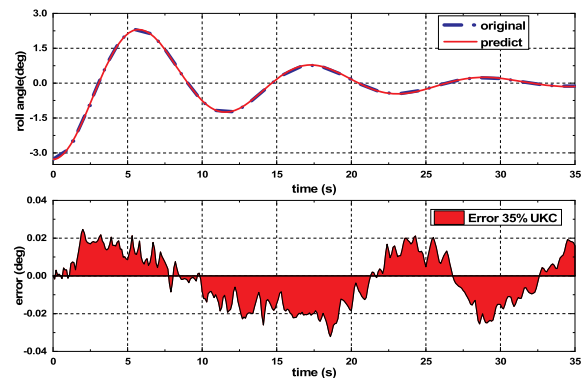
To summarize, the effectiveness and applicability of the NLS-SVM approach applied in shallow water at different speeds are verified.

6. Conclusions

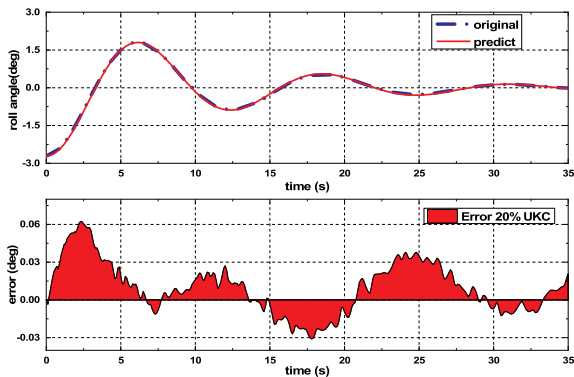
In this paper, the novel NLS-SVM parametric identification approach for estimating unknown damping coefficients in shallow water is investigated. Firstly, comparisons between numerical simulation roll angles based on the known damping coefficients and predicted roll angles using estimated damping coefficients presents satisfactory agreement, which illustrate the proposed identification algorithm can be effectively applied in identifying the roll model. Subsequently, comparing traditional identification approaches (NLS and FLS) with intelligent method, the NLS-SVM algorithm can perform better with higher accuracy, and overcome the weakness of conventional methods for identifying nonlinear damping coefficients. Moreover, free decay tests data in different UKCs and speeds were prepared for the purpose of demonstrating the shallow water effect in parametric identification based on the NLS-SVM method. The good agreement between decay



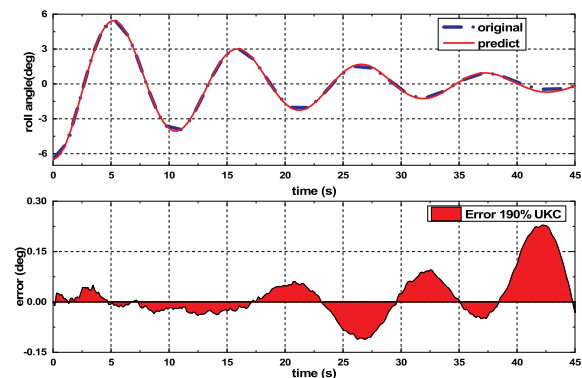
(a) Predicted results and errors for 10% UKC



(c) Predicted results and errors for 35% UKC



(b) Predicted results and errors for 20% UKC



(d) Predicted results and errors for 190% UKC

Fig. 9. Predicted results and errors for 10%, 20%, 35%, 190% UKCs.

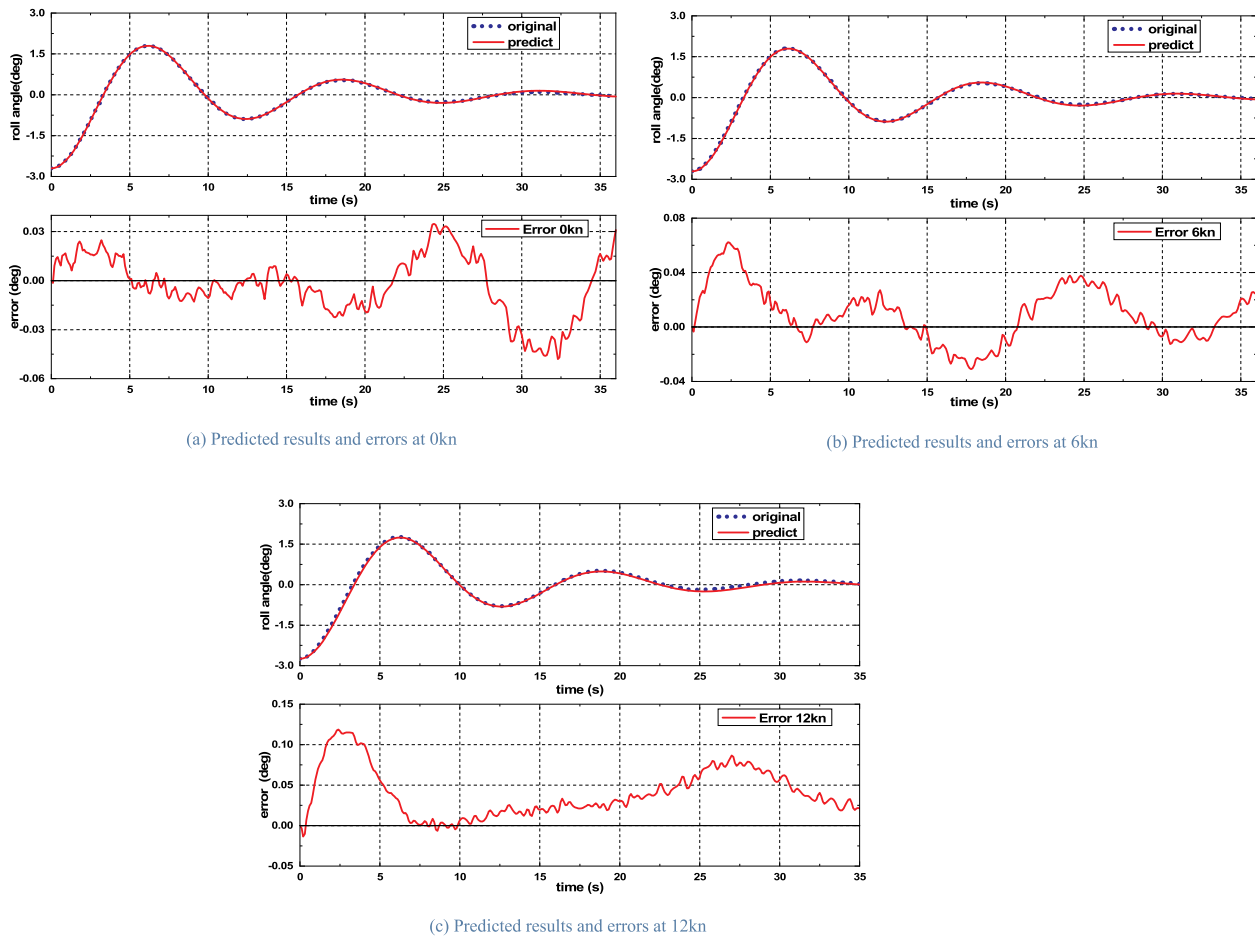


Fig. 10. Predicted results and errors at speed of 0, 6, 12 kn.

tests results and predicted results suggests the satisfactory applicability of the proposed algorithm in shallow water. Therefore, the effectiveness, accuracy and applicability of the NLS-SVM model applied in identifying the nonlinear roll model in shallow water, have been verified by qualitative and quantitative analysis.

Future work includes two main tasks: first, all coefficients of the roll model will be identified and analyzed (e.g. the roll damping and restoring moment coefficients) while the effect of the impulse response function “h” will be investigated; second, intelligent optimised algorithms (e.g. beetle antennae search and particle swarm optimization methods) will be considered as well as to obtain the best penalty factors and kernel factors of the NLS-SVM model.

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