TRANSNAV
http://www.transnav.eu
the International Journal on Marine Navigation and Safety of Sea Transportation
Volume 11
Number 1
March 2017
DOI: 10.12716/1001.11.01.01

Parameter Identification of Ship Maneuvering Models Using Recursive Least Square Method Based on Support Vector Machines

M. Zhu & A. Hahn
Carl-von-Ossietzky University of Oldenburg, Oldenburg, Germany

Y.Q. Wen
School of Navigation, Wuhan University of Technology, Hubei, China

A. Bolles
Institute of Information Technology, Oldenburg, Germany

ABSTRACT: Determination of ship maneuvering models is a tough task of ship maneuverability prediction. Among several prime approaches of estimating ship maneuvering models, system identification combined with the full-scale or free- running model test is preferred. In this contribution, real-time system identification programs using recursive identification method, such as the recursive least square method (RLS), are exerted for on-line identification of ship maneuvering models. However, this method seriously depends on the objects of study and initial values of identified parameters. To overcome this, an intelligent technology, i.e., support vector machines (SVM), is firstly used to estimate initial values of the identified parameters with finite samples. As real measured motion data of the Mariner class ship always involve noise from sensors and external disturbances, the zigzag simulation test data include a substantial quantity of Gaussian white noise. Wavelet method and empirical mode decomposition (EMD) are used to filter the data corrupted by noise, respectively. The choice of the sample number for SVM to decide initial values of identified parameters is extensively discussed and analyzed. With de-noised motion data as input-output training samples, parameters of ship maneuvering models are estimated using RLS and SVM-RLS, respectively. The comparison between identification results and true values of parameters demonstrates that both the identified ship maneuvering models from RLS and SVM-RLS have reasonable agreements with simulated motions of the ship, and the increment of the sample for SVM positively affects the identification results. Furthermore, SVM-RLS using data de-noised by EMD shows the highest accuracy and best convergence.

1 INTRODUCTION

Since International Maritime Organization (IMO) clearly presents standards for the ship maneuverability to ensure ship navigation safety, the prediction of ship maneuverability has become a vital and attractive issue. The system based maneuvering simulation has been proved as an effective and economic way to predict the ship maneuverability. One of the preconditions is the estimation of maneuvering models. To a high degree, the accuracy of the estimation guarantees the effectiveness of prediction of the maneuvering model.

The main methods for estimating the maneuvering model include towing-tank experiments, captive model experiments (Skjetne et al. 2004), computational fluid dynamics (CFD) and system identification combined with the full-scale or free-running model (Xu et al. 2014). The last is becoming an attractive and cost-effective tool for estimation of ship maneuvering models.

System identification is a very broad topic with different techniques that depend on the character of models to be estimated: linear, nonlinear, hybrid, nonparametric, etc. (Ljung 2010). Various conventional system identification methods, such as least squares method (LS), maximum likelihood method (ML) and extended Kalman filter (EKF), have been successfully applied to estimate the ship-maneuvering model. For instance, Xu et al. (Xu et al. 2014) incorporated LS with integral sample structure and Euler method to identify the linear hydrodynamic model in the horizontal plane of an underwater vehicle using simulated data. Åstrom and Kållstrom (Åstrom & Kållstrom 1976) applied ML to determine steering dynamics of a freighter and a tanker using free steering experiments on full-scale ships. Shi et al. (Shi et al. 2009) tackled identification of a non-linear ship maneuvering model based on EKF. This method was also used by Perera et al. (Perera et al. 2015) to identify the stochastic parameters of a nonlinear ocean vessel steering model. In recent years, a variety of novel methods based on the modern artificial intelligent technology, such as the artificial neural network (ANN), genetic algorithm (GA) and support vector machines (SVM), have been used successfully in the parameter identification of the ship maneuvering model. ANN was used by Rajesh and Bhattacharyya (Rajesh et al. 2008) to deal with system identification of a nonlinear maneuvering model for large tankers. Sutulo and Guedes Soares (Sutulo & Guedes Soares 2014) developed an identification method based on the classic genetic algorithm to estimate a mathematical model describing the ship maneuverability by using simulation data corrupted by the white noise of various levels. Comparatively, SVM directs at finite samples, which requires no initial estimation of parameters but has good generalization performances and global optimal (Luo & Cai 2014). In 2009, Luo and Zou (Luo & Zou 2009) firstly successively applied SVM to identify hydrodynamic derivatives of Abkowitz model from the free-running model test, and predicted zigzag tests using the regressive Abkowitz model. Other studies can be found from the research group guided by Zou (Zhang et al. 2013 & Zhang et al. 2011 & Xu et al. 2012 & Wang et al. 2013) and references therein.

In such a variety of identification methods, some are developed to on-line identify time-varying coefficients, for instance, recursive least square method (RLS) algorithm and least mean squares (LMS) algorithm (Ljung 2002). Since the change of current weather and ship loading conditions can cause parameter variations of ship maneuvering models, the well-known RLS with an advantage of simple construction is used in this paper to identify parameters of ship maneuvering models.

As well known, the identification results of RLS are sensitive to the initial values of parameters (Zhang et al. 2013). Hence, this contribution aims at conquering such drawback of RLS by benefiting from applying firstly SVM which is a kind of batch identification technique and requires no initial estimation of the parameters, to provide RLS initial values. Additionally, this paper makes an effort to analyze the choice of the training sample number applied for SVM to identify initial values of ship maneuvering models.

The data for learning and validation of identification procedure are obtained from simulation of ship maneuvering models combined with existing particulars. For consideration of real navigation situation influenced by different disturbances, such as wind, wave and currents, the simulation test data are corrupted by non-correlated white noise, i.e., Gaussian white noise. Then, two different filters, namely, Wavelet filters (Barford 1992) and Empirical Mode Decomposition (EMD) algorithm (Wang et al. 2014) are used to omit negative influence of external disturbances on identification results.

The paper is organized as follows. In section 2, the mathematical model of ship maneuvering is described. The identification methods including RLS and SVM are introduced in section 3. The implementation of ship maneuvering models' identification is conducted and the identification results are analyzed in section 4. Finally, the conclusion of the work is summarized in section 5.

2 THE MATHEMATICAL MODEL OF SHIP MANEUVERING

Ship dynamics are complex due to nonlinear and coupling characteristics. At present, three types of mathematical model of ship maneuvering are common. MMG model is modular model separately describing rudder effects and propeller effects. Abkowitz model is whole-ship model regarding influences on the ship as the whole using Taylor series expansion. The response model, particularly, is the Nomoto models (Fossen 2011). In this study, the problem of determining ship steering dynamics is focused from the point of view of parameter identification. Assuming that the ship forward speed is constant (u_0), the steering dynamics of a surface ship can be described as (Åstrom & Kållstrom 1976)

$$\begin{bmatrix} m'-Y_{\dot{v}}' & m'x_G'-Y_{\dot{r}}' & 0 \\ m'x_G'-N_{\dot{v}}' & I_z'-N_{\dot{r}}' & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \dot{v}' \\ \dot{r}' \\ \dot{\psi}' \end{bmatrix} = \begin{bmatrix} Y_v' & Y_r'-m' & 0 \\ N_v' & N_r'-m'x_G' & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v' \\ r' \\ \psi' \end{bmatrix} + \begin{bmatrix} Y_\delta' \\ N_\delta' \\ 0 \end{bmatrix} \delta \tag{1}$$

where m' is the non-dimensional mass of the ship; x_G' is the non-dimensional longitude coordinate of the ship's center of gravity; I_z' is the non-dimensional inertia moment about z -axis; $\dot{v}'$, $\dot{r}'$ are non-dimensional small perturbations respectively; v' is the non-dimensional sway linear velocity; $\dot{\psi}'$, r' are non-dimensional yaw rate; ψ' is the non-dimensional heading angle; δ is the rudder angle; $Y_{\dot{v}}'$, $Y_{\dot{r}}'$, Y_δ', Y_v', Y_r' are respective hydrodynamic coefficients of the sway motion; $N_{\dot{v}}'$, $N_{\dot{r}}'$, N_δ', N_v', N_r' are respective hydrodynamic coefficients of the yaw motion, and

$$\dot{v}' = \frac{\dot{v}L}{U^2}, \quad \dot{r}' = \frac{\dot{r}L^2}{U^2}, \quad \dot{\psi}' = \frac{\dot{\psi}L}{U}, \quad v' = \frac{v}{U}, \quad r' = \frac{rL}{U},$$

$$\delta' = \delta, \quad U = \sqrt{u_o^2 + v^2}.$$

The normalized equations of motion, i.e., Eq.(1), are easily converted to standard state space notation by solving for the derivatives $\dot{v}'$ and $\dot{r}'$, which is given as

$$\begin{bmatrix} \dot{v}' \\ \dot{r}' \\ \dot{\psi}' \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & 0 \\ a_{21} & a_{22} & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v' \\ r' \\ \psi' \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{21} \\ 0 \end{bmatrix} \delta' \quad (2)$$

where the parameters are expressed respectively by

$$a_{11} = \frac{(I_z' - N_{\dot{r}}')Y_v' - (m'x_G' - Y_{\dot{r}}')N_v'}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

$$a_{12} = \frac{(I_z' - N_{\dot{r}}')(Y_r' - m') - (m'x_G' - Y_{\dot{r}}')(N_r' - m'x_G')}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

$$a_{21} = \frac{(m' - Y_{\dot{v}}')N_v' - (m'x_G' - N_{\dot{v}}')Y_v'}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

$$a_{22} = \frac{(m' - Y_{\dot{v}}')(N_r' - m'x_G') - (m'x_G' - N_{\dot{v}}')(Y_r' - m')}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

$$b_{11} = \frac{(I_z' - N_{\dot{r}}')Y_\delta' - (m'x_G' - Y_{\dot{r}}')N_\delta'}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

$$b_{21} = \frac{(m' - Y_{\dot{v}}')N_\delta' - (m'x_G' - N_{\dot{v}}')Y_\delta'}{(m' - Y_{\dot{v}}')(I_z' - N_{\dot{r}}') - (m'x_G' - Y_{\dot{r}}')(m'x_G' - N_{\dot{v}}')}$$

Rewriting the state variables of Eq.(2) with dimensional format, it can be given as

$$\begin{bmatrix} \dot{v} \\ \dot{r} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} a_{11} v \frac{U}{L} + a_{12} r U + b_{11} \delta \frac{U^2}{L} \\ a_{21} v \frac{U}{L^2} + a_{22} r \frac{U}{L} + b_{21} \delta \frac{U^2}{L^2} \\ r \end{bmatrix} \quad (3)$$

3 IDENTIFICATION METHOD

3.1 *LS-SVM Method*

With several years' application of SVM, it has been proved that it can also be designed to deal with sparse data in the condition of many variables but few data (Vapnik 2000). LS-SVM is the one modified form of SVM, which has the ability to simultaneously minimize the estimation error in the training data (the empirical risk) and the model complexity (the structural risk) for both regression and classification. Consider a model in the primal weight space

$$y(x) = \omega^T \varphi(x) + b (x \in R^n, y \in R) \quad (4)$$

where x is the input data; y is the output data; b is a bias term for the regression model; ω is a matrix of weights; and $\varphi(.) : R \to R^{n_h}$ is the mapping to a high-dimensional Hilbert space, the n_h can be infinite. The optimization problem in the primal weight space for a given training set $\{x_i, y_i\}_{i=1}^{N_s}$ with N_s as the number of samples becomes

$$\min_{w,b,e} J(\omega, e) = \frac{1}{2}\omega^T \omega + C \frac{1}{2} \sum_{i=1}^{N_s} e_i^2 \quad (5)$$

subject to

$$y_i = \omega^T \varphi(x_i) + b + e_i \quad (6)$$

where e_i is regression error; C is the penalty factor with positive values.

In the case of ω becoming infinite dimensional, the problem in the primal weight space cannot be solved. The Lagrangian is computed to derive the dual problem

$$J(\omega, b, e, \alpha) = J(\omega, e) - \sum_{i=1}^{N_s} \alpha_i (\omega^T \varphi(x_i) + b + e_i - y_i) \quad (7)$$

where $\alpha_i (i = 1, \cdots, N_s)$ are the Lagrange multipliers. Now the derivatives with respect to ω, b, e_i, and α_i are computed and set to be zero, respectively

$$\begin{cases} \frac{\partial J(\omega,b,e,\alpha)}{\partial \omega} = 0 \to \omega = \sum_{i=1}^{N_s} \alpha_i \varphi(x_i) \\ \frac{\partial J(\omega,b,e,\alpha)}{\partial b} = 0 \to \sum_{i=1}^{N_s} \alpha_i = 0 \\ \frac{\partial J(\omega,b,e,\alpha)}{\partial e_i} = 0 \to \alpha_i = Ce_i \\ \frac{\partial J(\omega,b,e,\alpha)}{\partial \alpha_i} = 0 \to \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases} \quad (8)$$

After straightforward computations, variables ω and e are eliminated from Eq.(8). Then the kernel trick is applied. The kernel trick allows us to work in large dimensional feature spaces without explicit computations on them. Therefore, the problem formulation yields

$$y(x) = \sum_{i=1}^{N_s} \alpha_i K(x, x_i) + b \quad (9)$$

where $K(x, x_i)$ represents the kernel function. For the problem of parameter identification, the linear kernel function is usually adopted, i.e., $K(x, x_i) = (x \bullet x_i)$, because the identification equation of the steering model is linear with respect to identification parameters. So the identified parameters θ can be regressed by using linear kernel based on LS-SVM, the regression model is

$$\theta = \sum_{i=1}^{N_s} \alpha_i x_i \quad (10)$$

3.2 *RLS method*

Considering the limitation of space, RLS is briefly introduced. RLS is developed for on-line parametric identification based on off-line method, LS. Given a system organized with a linear regression form using a model parameter vector θ, a lagged input-output data vector $X(k)=[x^T(1)\ \ x^T(2)\ \ \ldots\ \ x^T(k)]^T$, and an unspecified noise process $v(k)$ as follows

$$y(k)=X^T(k)\theta+v(k) \tag{11}$$

Then, parameters θ are estimated using RLS as

$$\begin{cases}\hat{\theta}(k)=\hat{\theta}(k-1)+K(k)[y(k)-x^T(k)\hat{\theta}(k-1)] \\ K(k)=P(k-1)x(k)[I+x^T(k)P(k-1)x(k)]^{-1} \\ P(k)=[I-K(k)x^T(k)]P(k-1)\end{cases} \tag{12}$$

4 PARAMETRIC IDENTIFICATION BY SVM-RLS

4.1 *Construction of Samples*

The continuous Eq.(3) is discretized using Euler forward method. Its difference form can be expressed as

$$\begin{bmatrix} v(k+1) \\ r(k+1)\end{bmatrix}=\begin{bmatrix} v(k)+\frac{a_{11}\Delta t}{L}v(k)U(k)+a_{12}\Delta t r(k)U(k) \\ r(k)+\frac{a_{21}\Delta t}{L^2}v(k)U(k)+\frac{a_{22}\Delta t}{L}r(k)U(k)\end{bmatrix}$$
$$\begin{bmatrix} +\frac{b_{11}\Delta t}{L}\delta(k)U^2(k) \\ +\frac{b_{21}\Delta t}{L^2}\delta(k)U^2(k)\end{bmatrix} \tag{13}$$

where $k+1$ and k denote two successive sampling times, Δt is the sampling interval. Then the input-output pairs are used for SVM and RLS to identify the parameters in Eq.(13).

The inputs are expressed as

$$\boldsymbol{Y}=[v(k), v(k)U(k), r(k)U(k), \delta(k)U^2(k)]^T_{4\times 1} \tag{14a}$$

$$\boldsymbol{Z}=[r(k), v(k)U(k), r(k)U(k), \delta(k)U^2(k)]^T_{4\times 1} \tag{14b}$$

Let $\boldsymbol{B}=[1\ b_1\ b_2\ b_3]_{1\times 4}$, $\boldsymbol{C}=[1\ c_1\ c_2\ c_3]_{1\times 4}$, then the outputs are $v(k+1)=\boldsymbol{BY}$, $r(k+1)=\boldsymbol{CZ}$.

Once the parameters of $\boldsymbol{B}$ and $\boldsymbol{C}$ are obtained through identification algorithms, the parameters of the state space model (Eq.(2)) can be achieved immediately, namely,

$$a_{11}=\frac{b_1 L}{\Delta t},\quad a_{12}=\frac{b_2}{\Delta t},\quad a_{12}=\frac{b_2}{\Delta t},\quad b_{11}=\frac{b_3 L}{\Delta t},$$
$$a_{21}=\frac{c_1 L^2}{\Delta t},\quad a_{22}=\frac{c_2 L}{\Delta t},\quad b_{21}=\frac{c_3 L^2}{\Delta t}.$$

4.2 *Data Preprocessing*

The data used for learning and validation of parametric identification of the ship steering model are generated by synergistically employing forth-order Runge-Kutta algorithm and Eq.(3) with parameters extracted from the study in (Åstrom & Kållstrom 1976). The ship parameters are shown in Table 1.

Table 1. The parameters of Merchant ship Mariner class

Mariner			
Length L (m)	161	Speed $u_o(m/s)$	7.7
a_{11}	-0.693	a_{21}	-3.41
a_{12}	-0.304	a_{22}	-2.17
b_{11}	0.207	b_{21}	-1.63

The Runge-Kutta algorithm is represented as

$$\dot{x}=f(x,\delta) \tag{15}$$

$$\begin{cases}k_1=f(x_n,\delta_n) \\ k_2=f(x_n+\frac{h}{2}k_1,\delta_{n+1/2}) \\ k_3=f(x_n+\frac{h}{2}k_2,\delta_{n+1/2}) \\ k_4=f(x_n+hk_3,\delta_{n+1})\end{cases} \tag{16}$$

$$x_{n+1}=x_n+\frac{h}{6}(k_1+2k_2+2k_3+k_4) \tag{17}$$

where n donates time series; $k_i(i=1,2,3,4)$ represents the intermediate variable; h is the sampling interval; $x=[v,r,\psi]$ is the state vector; and $\delta_{n+1/2}=(\delta_n+\delta_{n+1})/2$.

Two groups of zigzag simulation tests, that are 20°/20° for identifying parameters and 10°/10° for validation, are derived with initial states including the forward speed of $7.7m/s$, the rudder angle of $0°$, the heading angle of $0°$, the yaw rate of $0°/s$, and the sway speed of $0m/s$. The sampling time is 1000s, and the interval is 0.5s. 2000 measurement pairs of v, r, δ, and resultant speed U are recorded for parameter identification of the steering model. The simulation results are illustrated in Fig.1.

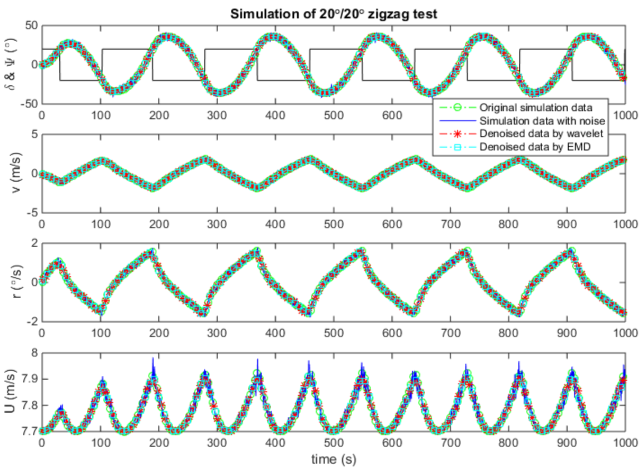

Figure 1. Comparison of training data of the 20°/20° zigzag test

As the real data of ship maneuvering will be inevitably corrupted by measurement noise and environmental disturbances which are generally considered as Gaussian white noise assumed to be independent one with zero means, the original simulation data are corrupted by Gaussian white noise. Then the data are de-noised by filters. In order to effectively analyze the influence from de-noised data by different filters on the accuracy of identification results, wavelet filters and EMD are resorted, respectively. The comparison between the original simulation data, the simulation data corrupted by Gaussian white noise, and de-noised data by respective wavelet and EMD are presented in Fig.1.

4.3 *Selection of Sample Number for SVM*

LS-SVM as a batch technique avoids lengthy iteration and needs no initial estimation of parameters. However, it can be seen that the problem of applying LS-SVM is the choice of the number of samples. The solution of such problem is proposed by analyzing the convergence of LS-SVM used with different numbers of samples. The samples are selected from original simulation test data, the number varies from 10 with the interval of 10 to 2000. The identification results of different numbers of samples are shown in Fig.2 where the upper-right one is identified parameters of the steering model and the down-right one is a partially enlarged view. Additionally, the upper-left one indicates the relative error of each parameter between identification results and true values, and the down-left one represents a partially enlarged view. Obviously, all parameters match well with true values while the sample number increases to around 80. Considering that the training data are corrupted by noise, the samples used for LS-SVM is 160 that means the 80s.

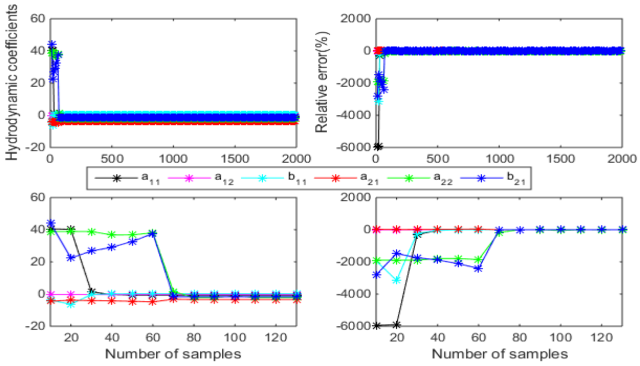

Figure 2. The identification results of different numbers of samples

Table 2. Identified values of steering model

Parameters	True value	RLS(Wavelet algorithm)		RLS(EMD)		LSSVM-RLS(EMD&160)	
		Identified value	Relative error	Identified value	Relative error	Identified value	Relative error
a_{11}	-0.693	-2.5808	2.2738	-0.7665	0.1061	-0.7140	0.0303
a_{12}	-0.304	-0.9821	2.2306	-0.2835	-0.0674	-0.2949	-0.0299
b_{11}	0.207	0.1972	-0.0473	0.1987	-0.0401	0.1904	-0.0802
a_{21}	-3.41	0.3409	-4.0691	-3.1485	-0.0767	-3.2232	-0.0548
a_{22}	-2.17	-3.5498	0.6359	-2.2424	0.0334	-2.1846	0.0067
b_{21}	-1.63	-1.4722	-0.0968	-1.4996	-0.08	-1.5159	-0.07

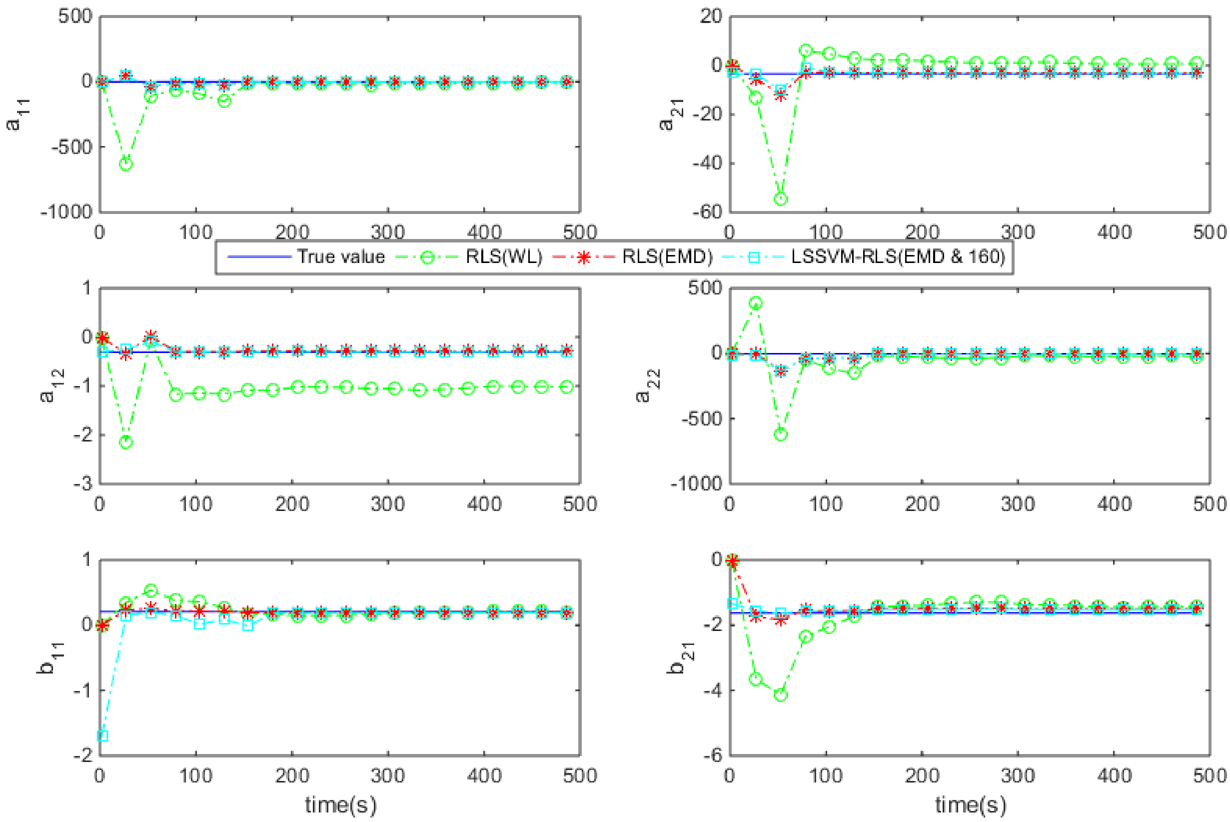

Figure 3. Comparison between true and identified parameters

4.4 *Identification Results*

For the purpose of clearly showing the identification results of the steering model, the former 500s results are selected and presented in Fig.3, because most parameters converge well after 150s except for b_{11}. The identified values of the steering model by different identification methods are listed in Table 2. It is obvious that the identification results from using de-noised data by EMD are more precise than the ones from Wavelet algorithm. Both the estimated values of the steering model by RLS and LSSVM-RLS converge well into the true values.

Comparatively, the identified values from LSSVM-RLS have higher accuracy, in particular a_{12}, a_{21}, b_{21}, because the initial values of those parameters provided by LSSVM are close to true values. Additionally, LSSVM-RLS shows better convergence performance. It is deserving to note that the identified value of b_{11} by LSSVM-RLS is worse than RLS. This may be attributed to two aspects. Firstly, under conditions of training data corrupted by noise even filtered, LSSVM still needs more data samples to achieve accurate values of parameters. Secondly, the difference between the initial value of b_{11} applied to identification algorithms and true value has an impact. The initial value of b_{11} set for RLS is closer to the true value than the one obtained from LSSVM.

4.5 *Prediction and Verification*

Verification of identification results is the essential procedure for parameter identification. Hence, a 10º/10º zigzag test is predicted by using the identified steering model. As presented in Fig.4, the comparison between predicted data and original simulation data indicates that the identified steering model has a satisfied agreement with the real model, which illustrates that the identification method preforms good generalization.

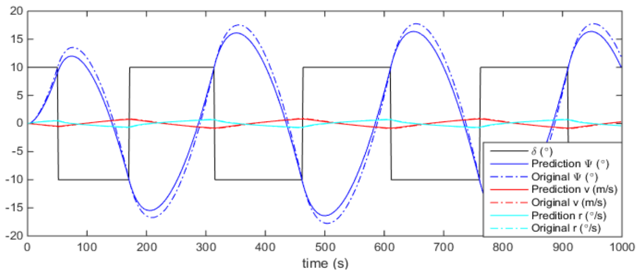

Figure 4. Prediction and comparison of the 10°/10° zigzag test

5 CONCLUSION

In this paper, we have developed a solution to overcome the problem of initial value definition for parameter identification in linear ship dynamic models using recursive least squares (RLS) approach. For the definition of the parameters, we combined LSSVM with an RLS algorithm. To show the benefit of this approach, we have executed a zig-zag simulation based evaluation, in which we added Gausssian noise calculated by signal ration proportional approach to generate realistic training and validation data. To filter the noise we used a wavelet algorithm and an empirical mode decomposition (EMD) for the RLS approach, and EMD for the LSSVM approach. We have shown that our LSSVM-RLS approach for parameter identification is suitable and for most parameters even better than the RLS-only approach with predefined initial values. We also have shown that EMD filtering provides better results for de-noising data.

Forthcoming work will focus on expanding the application of the proposed parameter identification method to the nonlinear identification algorithm, such as Extend Kalman filter algorithm, for the nonlinear ship maneuvering model. The further points worthy of attention will be data acquisition through extracting from real ship navigation motions recorded by navigation devices mounted in ship body, and the data filtering.

ACKNOWLEDGE

The paper is supported by the Ministry of Science and Culture of Lower Saxony for the Graduate School Safe Automation of Maritime Systems (SAMS).

REFERENCES

Skjetne, S., Smogeli, V., & Fossen, T. I. 2004. Modeling, identification, and adaptive maneuvering of Cybership II: A complete design with experiments. *IFAC Conference on Control & Application in Marine System (pp.203-208).* Ancona, Italy.

Xu, F., Xiao, T., et al. 2014. Identification of Nomoto models with integral sample structure for identification. *The 33rd Chinese Control Conference* (pp.6721-6725). Nanjing, China.

Åstrom, K., & Kållstrom, C. 1976. Identification of ship steering dynamics. *Automatica*, 9-22.

Barford, L. A., Fazzio, R. S., & Smith, D. R. 1992. An introduction to wavelets. *Hewlett-Packard Labs, Bristol*, UK, Tech. Rep. HPL-92-124, 1–29.

Fossen, T. I. 2011. *Handbook of Marine Craft Hydrodynamics and Motion Control*. Wiley.

Jiang, Z., Yan, W., Jin, X., & Gao, J. 2012. Identification of an Underactuated Unmanned Surface Vehicle. *JOURNAL OF NORTHWESTERN POLYTECHNICAL UNIVERSITY*, 699-705.

Ljung, L. 2002. Recursive identification algorithms. *Circuits, Systems, and Signal Processing*, 57-68.

Ljung, L. 2010. Perspectives on system identification. *Annual Reviews in Control*, 1-12.

Luo, W. L., & Zou, Z. J. 2009. Parametric Identification of Ship Maneuvering Models by Using Support Vector Machines. *Journal of Ship Research*, 19-30.

Luo, W., & Cai, W. 2014. Modeling of ship maneuvering motion using optimized support vector machines. *Intelligent Control and Information Processing (ICICIP), 2014 Fifth International Conference on* (pp. 476 - 478). Dalian: IEEE.

Perera, L. P., Oliveira, P., & Guedes Soares, C. 2015. System Identification of Nonlinear Vessel Steering. *Journal of Offshore Mechanics and Arctic Engineering*, 31302-31307.

Rajesh, G., & Bhattacharyya, S. K. 2008. System identification for nonlinear maneuvering of large tankers using artificial neural network. *Applied Ocean Research*, 256-263.

Sutulo, S., & Guedes, Soares, C. 2014. An algorithm for offline identification of ship manoeuvring mathematical models from free-running tests. *Ocean Engineering*, 10-25.
Shi, C., Zhao, D., Peng, J., & Shen, C. 2009. Identification of Ship Maneuvering Model Using Extended Kalman Filters. *TransNav, the International Journal on Marine Navigation and Safety of Sea Transportation*, 105-110.
Vapnik, V. 2000. *The nature of statistical learning theory*. New York: Springer.
Wang, X., Zou, Z. J., & Yin, J. 2013. Modular Parameter Identification for Ship Manoeuvring Prediction Based on Support Vector Machines. *The Twenty-third (2013) International Offshore and Polar Engineering* (pp. 834-839). Anchorage, Alaska, USA: the International Society of Offshore and Polar Engineers.
Wang, Y.-H., Yeh, C.-H., Young, H.-W. V., Hu, K., & Lo, M.-T. 2014.On the computational complexity of the empirical mode decomposition algorithm. *Physical A: Statistical Mechanics and its Applications*, 159-167.
XU, F., CHEN, Q., ZOU, Z.-J., & YIN, J.-C. 2014. Modeling of underwater vehicles' maneuvering motion by using integral sample structure for identification. *JOURNAL OF SHIP MECHANICS*, 211-220.
Xu, F., Zou, Z. J., Yin, J. C., & Cao, J. 2012. Parametric identification and sensitivity analysis for Autonomous Underwater Vehicles in diving plane. *Journal of Hydrodynamics*, 744-751.
Zhang, X. G., & Zou, Z. J. 2011. Identification of Abkowitz model for ship manoeuvring motion using ε-support vector regression. *Journal of Hydrodynamics*, 353-360.
Zhang, X.-G., & Zou, Z.-J. 2013. Estimation of the hydrodynamic coefficients from captive model test results by using support vector machines. *Ocean Engineering*, 25-31.