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A hybrid AR-EMD-SVR model for the short-term prediction of nonlinear and non-stationary ship motion*

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Abstract: Accurate and reliable short-term prediction of ship motions offers improvements in both safety and control quality in ship motion sensitive maritime operations. Inspired by the satisfactory nonlinear learning capability of a support vector regression (SVR) model and the strong non-stationary processing ability of empirical mode decomposition (EMD), this paper develops a hybrid autoregressive (AR)-EMD-SVR model for the short-term forecast of nonlinear and non-stationary ship motion. The proposed hybrid model is designed by coupling the SVR model with an AR-EMD technique, which employs an AR model in ends extension. In addition to the AR-EMD-SVR model, the linear AR model, non-linear SVR model, and hybrid EMD-AR model are also studied for comparison by using ship motion time series obtained from model testing in a towing tank. Prediction results suggest that the non-stationary difficulty in the SVR model is overcome by using the AR-EMD technique, and better predictions are obtained by the proposed AR-EMD-SVR model than other models.

Key words: Nonlinear and non-stationary ship motion, Short-term prediction, Empirical mode decomposition (EMD), Support vector regression (SVR) model, Autoregressive (AR) model
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1 Introduction

Ship motions occur due to ocean environmental disturbances, such as sea waves, wind, and ocean current. They are dangerous to ship related maritime operations like ship-borne helicopter recovery, float over, launch and recovery of submarines, and cargo transfer between ships, especially in harsh sea conditions. The short-term forecast of the ship motions 5 to 10 s ahead of time may be very useful for such offshore operations for both operational safety and efficiency. Prediction information can help to provide motion compensation, which may prevent the crash of cargo in cargo transfer, improve the firing accuracy of ship-borne weapon systems (Khan *et al*., 2006; Ra and Whang, 2006) and performance of the motion control systems. In addition, motion predictions are employed to extend operational limits by forecasting quiescent periods where the ship motions are within acceptable limits for performing a desired maritime task. Conventional prediction approaches employ statistical data to assess whether a task can be executed. This may result in an outcome where an operation is never executed, whereas quiescent periods do exist (Riola *et al*., 2011).

Short-term prediction of ship motion has been widely explored for its application values in practical engineering over past decades. A large number of forecast models have been developed. According to the theoretical differences among various methods, short-term prediction models may be classified into

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three types: hydrodynamic-based, classic time series, and nonlinear and intelligent learning related prediction models (Huang *et al*., 2014). Essentially, classic time series prediction and nonlinear and intelligent learning related prediction models are both statistical approaches.

Early efforts in short-term prediction were derived from ship hydrodynamics. Hydrodynamic-based prediction consists of a convolution-based approach and a state-space-based Kalman filter approach.

The convolution-based predictor (Kaplan and Sargent, 1965) is developed using wave height measurements at the bow serving as input data. The measured wave heights are then convoluted with the ship response kernel function to obtain the motion estimation in the coming seconds. Accurate response functions and wave inputs are required. However, the ship response kernel functions are derived under the consumption of linear hydrodynamic theory while wave excitation (Chakrabarti, 1989) and loads are nonlinear (Hirdaris *et al*., 2014). Furthermore, uncertainties modeling should also be considered in convolution-based predictor due to their significant influences on ship response. Effects that the uncertainties in wave spectra and ship response kernel functions have on the short-term ship motions and loads were examined by Guedes Soares (1990; 1991) and Chakrabarti (1989). Papanikolaou *et al.* (2014) addressed the importance of understanding and integrating uncertainties in assessing ship wave-induced loads and operations. Hirdaris (2014) summarized the uncertainty modeling for ships as well as offshore structures.

The Kalman filter is another hydrodynamic-based prediction method. Triantafyllou and Athans (1981), Triantafyllou and Bodson (1982), and Triantafyllou *et al.* (1983) presented a Kalman filtering technique for predicting ship motions based on a precise state-space model. Numerical results on a DD-963 destroyer suggested the feasibility of applying the Kalman filter in short-term prediction. In addition, its prediction precision greatly depended on the ocean wave frequency and the noise. For example, 5 s predictions of pitch can be reached without a noise condition, while for a noise condition, the prediction horizon is then reduced to 2–3 s. Apart from being noise sensitive, the Kalman filter is difficult to apply because of two further shortcomings. One is that accurate state-space equations and noise statistics are necessary in implementing the Kalman filter. These are hard to obtain in practical engineering situations. The other is the very large computational effort required (Yang, 2013) to derive the ship hydrodynamic coefficients from the state-space equations, resulting in difficulty in real time implementation.

Hydrodynamic-based prediction models are in essence linear methods and hence applicable for small amplitude wave-induced ship motions. Their performance depends on how exactly the linear hydrodynamic coefficients are worked out. Modeling uncertainties should be taken into consideration. These models fail to model ship motions where fluid structure interactions are strong, e.g., the influence of hydro-elasticity is significant (Hirdaris and Temarel, 2009), as nonlinear hydrodynamic coefficients are required in such a case.

Hydrodynamic-based prediction models have introduced linear assumptions, boundary conditions, simplification of nonlinear wave-wave interaction, etc. Whereas, there are no such prior restrictions in statistical prediction models as they do not explain physical processes taking place for generating ship motions. Comparatively, statistical models show advantages including relatively simple modeling and a small requirement of computer memory and time. If exact input-output values are continuously known, time series models can be identified using known input-output values based on learning processes. In the present work, statistical time series models that are usually applied in ship motion forecasting are divided into two categories. They are the classic time series and nonlinear and intelligent learning related models.

Time series analysis provides a possible solution only requiring the time history of the ship motions or the ocean waves while modeling (Yumori, 1981). Classic time series prediction models that are frequently used include autoregressive (AR) and autoregressive moving average (ARMA) models. In addition to short-term prediction, classic time series models (AR, ARMA) have also been extensively applied in other disciplines of engineering (Sakellariou and Fassois, 2006; Lee and Jun, 2010). Practical limitations of requiring accurate state-space and noise estimation in the Kalman filter and precise response kernel function in the convolution predictor are avoided. The linear and stationary AR prediction model is mostly employed for advantages such as less computational complexity and memory demands, and being convenient for real-time realization (Zhang and Chu, 2005). Order determination and parameters estimation for AR model have been widely studied. However, predictions of a single AR model in harsh condition and large forecast lead times fail to satisfy expectations. To further improve the prediction performance, Yumori (1981) developed a novel ARMA model based on a leading indicator method using a statistical way that finds a time domain model which best fits an input wave sensor time history to the ship response time history. It showed good predictions of phase and amplitude for 2 to 4 s in advance. When the prediction lead time reaches 8 s, predictions fail to capture the amplitude of the target. Moreover, satisfactory prediction is only obtained if it could sense waves at a distance from the ship, which is not always available in a practical situation. Despite its high efficiency and adaptive nature, prediction results produced by the classic time series models (AR, ARMA) are far from the expected in harsh sea conditions. As the ship motions and ocean waves are always non-stationary, it conflicts with the stationary assumption of classic time series models.

To overcome the nonlinearity hidden in real-life ship motions, nonlinear and intelligent learning related prediction models have been extensively studied. Zhou and Zhao (1996) proposed a nonlinear autoregressive (NAR) model by applying orthogonalization technique. Results indicated that the NAR model gave better prediction accuracy than the AR model. But it is still limited in nonlinear ship motion forecasting, as explicit relationships for the data sets at hand have to be hypothesized with little knowledge of the underlying law to construct the NAR model.

In contrast to model-based nonlinear methods (e.g., NAR), intelligent learning related prediction models like artificial neural networks (ANN), back-propagation (BP) networks, and wavelet neural networks (WNN) are more capable of performing nonlinear modeling without a priori knowledge of the relationships between input and output variables. Hence, they are more general and flexible modeling tools in this context. Investigations into this application of ANN methods were conducted by Khan *et al.* (2004; 2005; 2006) where it was seen that ANN models produced excellent predictions and were able to predict ship motions satisfactorily for up to 7 s. To deal with chaos characteristic in the ship motion, a prediction method based on the chaotic time series theory and radial basis function (RBF) ANN model was implemented by Gu *et al.* (2013). Simulation results revealed that the proposed model was able to predict ship motion acceptably for up to 10 s. Recently, Zhang and Liu (2014) constructed WNN with delayed system information for on-line ship dynamics prediction. Sensitivity analysis is employed to determine the inputs to the WNN and improve the generalization ability. Simulation results of ship motion prediction using measured data demonstrate the feasibility. However, prediction results of pitch, roll, and heave motions were not given.

Though the above nonlinear and intelligent models perform better in data fitting, their applications in real engineering problem are still constrained because of disadvantages, such as high computational cost, the need for substantial samples, being non-adaptive in model identification, and so forth. Furthermore, the existence of non-stationarity in ship motions also limits the prediction models in practical implementation. Although intelligent learning related prediction models may perform well in handling nonlinearity, they may not be capable in modeling non-stationary data if pre-processing of the input is not performed (Cannas *et al.*, 2006; Deka and Chandra, 2012), especially for a long forecast horizon. In fact, modeling a nonlinear and non-stationary data set using a single nonlinear model is very difficult since there are too many possible patterns hidden in the data. A single nonlinear model may not be general enough to capture all important features.

As a result, enhanced approaches are necessary. Hybrid models that combine pre-techniques with single prediction models become variable alternatives for more effective modeling. Wavelet-based models were presented for non-stationary time series forecasting as a wavelet technique is effective in handling non-stationarity (Ozger, 2010; Deka and Chandra, 2012). However, wavelet-based hybrid models still have limitations in nonlinear and non-stationary time series forecasting because of the linearity restriction of the wavelet transform. As a consequence, it may not be suitable for nonlinear data

(Huang and Wu, 2008). However, empirical mode decomposition (EMD) technique is capable of processing nonlinear and non-stationary time series. Therefore, it has been popularly employed in developing hybrid models for various time series predictions (Castro-Neto *et al.*, 2009; Fan and Tang, 2013; Cheng and Wei, 2014; Wang *et al.*, 2015). Hou and Qi (2011) developed an EMD based on a radial basis function neural network (EMD-RBFNN) model to handle the nonlinearity and non-stationarity in ship motions. However, a sufficiently large sample is still required for training the RBFNN model. However, a support vector regression (SVR) model requires a relatively small sample size with strong ability in learning nonlinear time series. Zhou and Shi (2013) presented an EMD based least mean square support vector machines (EMD-LSSVM) for prediction. But the performance of the EMD-LSSVM in forecasting nonlinear and non-stationary ship motions was not further studied or compared with other models. Also, the end effects in EMD processing which greatly affect the prediction results (Xiong *et al.*, 2014) had not been addressed. In this paper, an improved AR-EMD-SVR model is proposed, where the AR model is employed in ends processing to eliminate the influences of end effects on prediction accuracy. Performance of the enhanced model is further examined by comparative studies with AR, SVR, and EMD-AR models using experimental ship motion data.

This paper first introduces the theoretical background of the AR model, EMD technique, and the SVR model and its enhanced model. Then numerical results and comparisons are presented and discussed.

2 Theoretical formulations for the AR model and AR-EMD technique

2.1 AR prediction model

Time series analysis theory assumes that relations exist among the variables of the time sequence. As a result, the present variable is able to be represented by the previous in time. Of which, the AR model is the most used in time series forecasting because of its convenience in real-time model identification, high adaptive nature, and better frequency resolution (Zhang and Chu, 2005). For a given time series $\{x(t), t=1, 2, \ldots, n\}$, the AR model is formulated as

$$x(t)=\varphi_1 x(t-1)+\varphi_2 x(t-2)+\ldots+\varphi_p x(t-p)+a(t),\quad t=1, 2, \ldots, n, \tag{1}$$

where p is the model order, $\{\varphi_1, \varphi_2, \ldots, \varphi_p\}$ are parameters of the AR model, which are unknown. $\{a(t), t=1, 2, \ldots, n\}$ is zero-mean white noise. Identification of the AR model as shown in Eq. (1) concerns the selection of model order p and corresponding parameters $\{\varphi_1, \varphi_2, \ldots, \varphi_p\}$, which can be found in many papers (Yang, 2013).

Various algorithms have been developed for the estimation of model parameters. In this study, the Levinson-Durbin (L-D) algorithm is employed in parameter estimation. With the given ship motion sequence x_i ($i=1, 2, \ldots, n$) and model order p, L-D algorithm can be summarized in Table 1 (Huang *et al.*, 2015). The least mean square algorithm suffers from convergence speed and an eigenvalue spread problem (Myllylä, 2001), and the use of the recursive least square algorithm introduces memory intensive and numerically-unstable problems (Douglas, 1996). In addition, the determination of the forgetting factor is not always adaptive.

Table 1 Summary of Levinson-Durbin algorithm

Compute: Autocorrelation function r_k ($k=0, 1, \ldots, p$);
Initialization: $\rho_k=r_1/r_0$; $\varphi_{1,1}=\rho_1$; $\sigma_k^2=r_0(1-\rho_1^2)$;
Main iteration: Do for $k=2, 3, \ldots, p$,
$\rho_k=\left(r_k-\sum_{i=1}^{k}\varphi_{i,k-1}r_{k-i}\right)\Big/\sigma_{k-1}^2$;
$\varphi_{k,k}=\rho_k$; $\varphi_{i,k}=\varphi_{i,k}-\varphi_{k-i,k-1}\rho_k$ ($i=1, 2, \ldots, k-1$);
$\sigma_k^2=\sigma_k^2(1-\rho_k^2)$;

ρ_k: reflection coefficient; r_k: autocorrelation function for a lag k; $\varphi_{i,k}$: the kth order model parameter; σ_k: covariance with respect to order p

There are several available methods to specify model orders, such as Akaike information criterion (AIC), Bayesian information criterion (BIC), and final prediction error criterion (FPE). The BIC criterion is applied for model order selection in this study. The BIC value of general AR(p) is defined as

$$\mathrm{BIC}(p)=\lg\sigma^2+(p+1)(\lg N)/N, \tag{2}$$

where σ^2 is the covariance. Model order p_0 that leads to the minimum BIC value is chosen as the optimal order.

Once the prediction model as presented in Eq. (1) is determined, a k-step-ahead adaptive predictor can be presented as

$$\hat{x}(t+k)=\begin{cases}\sum_{i=1}^{p}\varphi_i x(t+k-i), & k=1,\\ \sum_{i=1}^{k-1}\varphi_i \hat{x}(t+i)_{N+i}+\sum_{i=k}^{p}\varphi_i x(t+k-i), & k=2,3,\cdots,p,\\ \sum_{i=1}^{p}\varphi_i \hat{x}(t+k-i), & k>p,\end{cases} \quad (3)$$

where $\hat{x}(t+k)$ is the prediction value of k steps advancing.

2.2 EMD technique using AR model in ends processing

Decomposition is critical in signal processing. Complex signals are frequently decomposed into several simple components. Then, information contained in each component would be analyzed to reduce the complexity and enhance interpretability. Conventionally, Fourier transform and wavelet analysis are the approaches adopted most often. However, it is well known that Fourier transform fails to extract the frequency information from non-stationary signals. Although effective in handling non-stationarity, wavelet analysis suffers from its non-adaptive nature as it applies the same type of basis functions to the entire range of data. Similarly, wavelet analysis also represents a signal by a linear combination of wavelet basis functions. Its decomposition results for nonlinear data can be misleading (Huang and Wu, 2008; Kim *et al.*, 2012). Therefore, a set of basis functions that reflects the time-varying property of a signal is required.

A data-driven technique known as EMD has been proposed by Huang *et al.* (1998), which is powerful and adaptive in analyzing nonlinear and non-stationary data sets. It provides an effective approach for decomposing a signal into a collection of so-called intrinsic mode functions (IMFs), which can be treated as empirical basis functions. An IMF resulting from the EMD procedure should satisfy two conditions: (1) the number of extremas and the number of zero-crossings should be equal or differ by one, and (2) the local average should be zero, i.e., the mean of the upper envelope defined by the local maxima and the lower envelope defined by the local minima is zero (Huang *et al.*, 1998).

Algorithms of EMD for decomposing a given sequence $x(t)$ are summarized as follows:

(1) Identify the local extrema.

(2) Generate the upper envelope $u(t)$ and the lower envelope $l(t)$ via the spline interpolation among all local maxima and local minima, respectively. Then, the mean envelope is obtained: $m(t)=[l(t)+u(t)]/2$.

(3) Subtract $m(t)$ from the signal $x(t)$ to obtain the IMF candidate: $h(t)=x(t)-m(t)$.

(4) Verify whether $h(t)$ satisfies the conditions for IMFs, do step (1) to step (4) until $h(t)$ is an IMF.

(5) Get the nth IMF component $\text{imf}_n(t)=h(t)$ (after n shifting processes) and the corresponding residue $r(t)=x(t)-h(t)$.

(6) Repeat the whole algorithm with $r(t)$ obtained in step (5) until the residue is a monotonic function.

By implementing these algorithms, the decomposition procedure of a signal is expressed as

$$x(t)=\sum_{i=1}^{n}\text{imf}_i(t)+r(t). \quad (4)$$

In practice, one of the essential questions in EMD is boundary effects processing. Researchers have proposed techniques for processing the boundary effects, such as the characteristic wave extending method (Huang *et al.*, 1998), a ratio extension method (Wu and Riemenschneider, 2010), and the mirror image extending method (Zhao and Huang, 2001). Among the various approaches, the symmetric extending method is the most popular when implementing EMD processing. However, extended results by using symmetric extension method and non-predictive methods are far from satisfactory as great differences always exist between the extended and real extrema. Despite the fact that EMD-based prediction models have already been extensively researched in substantial papers and generally proved to be an effective way for improving prediction performance of various models (Yu *et al.*, 2008; Fan *et al.*, 2013), the influence of end effects on prediction results (Xiong *et al.*, 2014; Huang *et al.*, 2015) is rarely properly established.

In this study, the AR model as presented in Section 2.1 is applied in boundary effects processing. An analytical signal comprised of three sine functions in Eq. (5) is studied as an example to compare the performance of EMD-SVR models using the symmetric extension method and AR-based extension method.

$$y = 1.5\sin(0.628t) + \sin t + 5\sin(1.5t). \quad (5)$$

Fig. 1 presents the extension results of the AR prediction model and the symmetric extension method, from which it is seen that the AR prediction model provides reasonable and satisfactory extension results, while the exterma produced by the symmetric extension method fail to match the true ones.

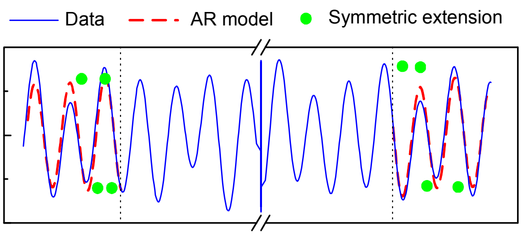

Fig. 1 Boundary extension results using AR prediction model and symmetric extension approach

Results presented in Fig. 2 further highlight that considerable reduction of the end effects on prediction accuracy has been made by employing the AR model in boundary processing instead of the symmetric extension method.

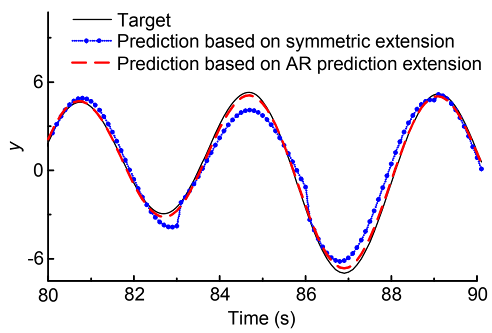

Fig. 2 Prediction results of EMD-SVR models using symmetric extension and AR prediction extension methods

3 SVR and AR-EMD-SVR prediction models

3.1 Formulation descriptions of SVR model

Support vector machine (SVM) theory is a statistical learning theory-based method with a strong capacity to handle nonlinear problems. Its basic idea is to map the nonlinear data into high dimension feature space using a nonlinear mapping function, where linear techniques are available (Zhou and Shi, 2013). SVR is a nonlinear prediction model that is based on SVM theory. It has been widely applied in short-term prediction problems, such as traffic flow forecasting (Castro-Neto *et al.*, 2009) and electric load forecasting (Fan *et al.*, 2013). Descriptions of identification algorithms for the SVR model can be found in (Castro-Neto *et al.*, 2009; Fan and Tang, 2013; Huo *et al.*, 2014).

Given a training data set of N points $\{(\boldsymbol{x}_i, y_i), i=1, 2, \ldots, N\}$ with input data $\boldsymbol{x}_i \in \boldsymbol{R}^N$ and output data $y_i \in \boldsymbol{R}$, then, according to SVM theory, a linear regression function can be presented as

$$y(\boldsymbol{x}) = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\Phi}(\boldsymbol{x}) + b, \quad \boldsymbol{w} \in \boldsymbol{Z}, b \in \boldsymbol{R} \quad (6)$$

in a feature space $\boldsymbol{Z}$, where $\boldsymbol{w}$ is a vector in $\boldsymbol{Z}$, and the input space $\boldsymbol{R}^N$ is mapped into feature space $\boldsymbol{Z}$ through the corresponding mapping function $\boldsymbol{\Phi}(\boldsymbol{x})$. Eq. (6) in the feature space is usually designated as an SVR model and applied to estimate the unknown nonlinear function, where the parameters $\boldsymbol{w}$ and b need to be selected.

As is well known, the SVM method aims to minimize the empirical risk and overall fitting errors. The regression problem is equivalent to the optimization problem as

$$\begin{aligned} &\min J(w, \boldsymbol{e}) = \frac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + \frac{C}{2}\sum_{i=1}^{N} e_i^2, \\ &\text{s.t. } \ y_i = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\Phi}(\boldsymbol{x}_i) + b + e_i, \ \ i = 1, 2, \cdots, N, \end{aligned} \quad (7)$$

where C is a regularization constant and e_i is the estimation error.

To solve the optimization problem, the Lagrangian function L can be given as

$$L(\boldsymbol{w}, b, \boldsymbol{e}, \boldsymbol{a}) = J(\boldsymbol{w}, \boldsymbol{e}) - \sum_{i=1}^{N} a_i(\boldsymbol{w}\boldsymbol{\Phi}(\boldsymbol{x}_i) + b + e_i - y_i), \quad (8)$$

where $\boldsymbol{a}$=[a_1, a_2, …, a_N] represents the Lagrangian multipliers.

Then, Karush-Kuhn-Tucker (KKT) conditions for identifying the SVR model can be summarized as

$$\begin{cases} \dfrac{\partial L}{\partial a_i} = 0, \rightarrow \boldsymbol{w}\boldsymbol{\Phi}(\boldsymbol{x}_i) + b + e_i - y_i = 0, \\ \dfrac{\partial L}{\partial b} = 0, \rightarrow \sum_{i=1}^{N} a_i = 0, \\ \dfrac{\partial L}{\partial e_i} = 0, \rightarrow a_i = Ce_i, \\ \dfrac{\partial L}{\partial w} = 0, \rightarrow \boldsymbol{w} = \sum_{i=1}^{N} a_i \boldsymbol{\Phi}(\boldsymbol{x}_i). \end{cases} \tag{9}$$

The linear equation system (9) can be further written as

$$\begin{bmatrix} \boldsymbol{Q}_N + C^{-1}\boldsymbol{I} & \boldsymbol{e}_1 \\ \boldsymbol{e}_1 & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{a}_N \\ b \end{bmatrix} = \begin{bmatrix} \boldsymbol{y}_N \\ 0 \end{bmatrix}, \tag{10}$$

where $\boldsymbol{y}_N$=[y_1, y_2, …, y_N]$^{\mathrm{T}}$, $\boldsymbol{e}_1$=[1, 1, …, 1]$^{\mathrm{T}}$, $\boldsymbol{a}_N$=[a_1, a_2, …, a_N]$^{\mathrm{T}}$, $\boldsymbol{I}$ is an identity matrix, $\boldsymbol{Q}_N$=($\boldsymbol{\Phi}(\boldsymbol{x}_i)$, $\boldsymbol{\Phi}(\boldsymbol{x}_j)$)=$k(\boldsymbol{x}_i, \boldsymbol{x}_j)$, i, j=1, 2, …, N, and $k(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is a kernel function that satisfies the Mercer theorem. In the present study, the RBF with a width of β is chosen:

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp(-\| \boldsymbol{x}_i - \boldsymbol{x}_j \|_2^2 / \beta^2), \quad \beta > 0. \tag{11}$$

The parameters of b and $\boldsymbol{a}$ for SVR model can be reached by solving linear equation system in Eq. (10), and the regression is rewritten as

$$y(\boldsymbol{x}) = \sum_{i=1}^{N} a_i k(\boldsymbol{x}_i, \boldsymbol{x}_j) + b. \tag{12}$$

3.2 Hybridization process of AR-EMD-SVR prediction model

Time series of ship motions are kinds of complicated nonlinear and non-stationary signals, which consist of components with different characteristics. Despite being capable of handling nonlinearity, the SVR model fails to handle non-stationarity for short-term problems (Fan and Tang, 2013). A combination of AR-EMD and the SVR model provides an effective way to improve the prediction accuracy for nonlinear and non-stationary time series.

The implementation procedure for ship motion prediction using hybrid AR-EMD-SVR model comprises three steps, which are illustrated by a flowchart as shown in Fig. 3. In the first step, ship motion time series is decomposed into two simple and meaningful IMFs and a residual through EMD processing. In the second step, prediction of decomposed components is preformed individually with the SVR model. In the final step, the predictions are aggregated to attain the final forecast.

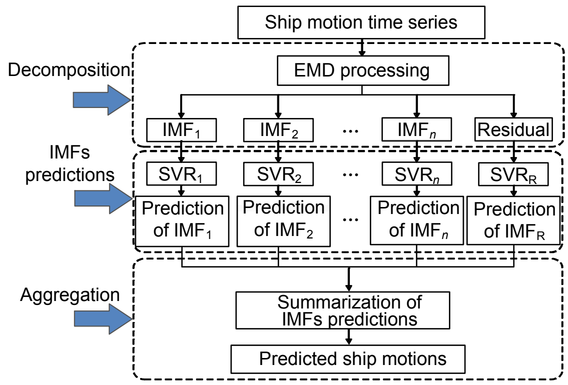

Fig. 3 Flowchart of the hybrid AR-EMD-SVR prediction model

4 Results and discussion

This section focuses on the prediction performance of the proposed AR-EMD-SVR model. Comparison studies among the AR-EMD-SVR model, AR model, SVR model, and EMD-AR model have been conducted using ship motion time series from model testing in a towing tank.

4.1 Brief description of ship motion data from model testing

4.1.1 Heave and pitch motion of a large container ship

Model testing based ship motion time series of a large container ship moving at a speed of 24 knots in heading waves with the condition of sea state 5 are used in the simulation (Fig. 4). The length, beam, and draft are 304 m, 35 m, and 10 m, respectively.

Ship motion status (heave, pitch) was sampled at 50 Hz in model testing and down-sampled to two points per second when the simulation was implemented.

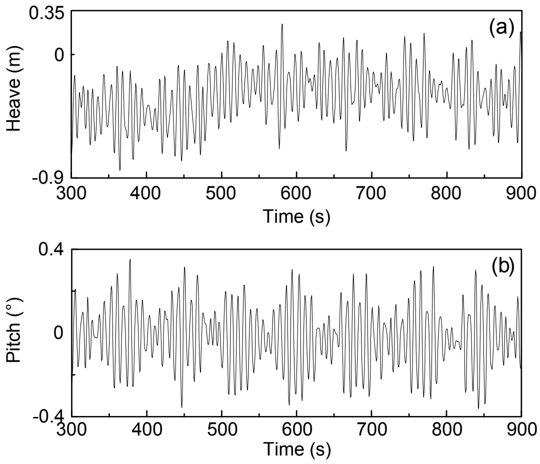

Fig. 4 Heave (a) and pitch (b) time history of a large container ship from model testing

4.1.2 Brief analysis of the non-stationary and nonlinear nature in ship motion

Conventionally, a time series, $\{x(t)\}$, is stationary in the board sense, if, for all t,

$$\begin{aligned} &E[x(t)] = \text{constant} < \infty, \\ &E[x^2(t)] < \infty, \\ &E[x(t_1)x(t_2)] = R_{xx}(t_2 - t_1), \end{aligned} \tag{13}$$

where $E[\ ]$ is the expected value defined as the ensemble average of the quantity, and R_{xx} is the covariance function (Brockwell and Davis, 1991).

In brief, for stationary time series, the expected values and covariance corresponding to specified time delay should not vary with time. As shown in Fig. 5, it can be seen that the expected value $E[x(t)]$ and covariance with time delay of 10 steps $E[x(t)x(t+10)]$ are approximately equal to zero.

Based on the definition of a stationary process, quantitative methods of consecutive statistics are used to analyze the stationarity of the ship motions in Fig. 4. Moreover, a recurrence plot, a direct and effective graphical approach for reflecting the evolution tendency and potential periodicity of a dynamic system (Eckmann *et al.*, 1987), is also applied in stationarity analysis. Recurrence plot lattices of stationary time series should subject to uniform distribution. However, the plot lattices of the non-stationary time series must be non-uniform.

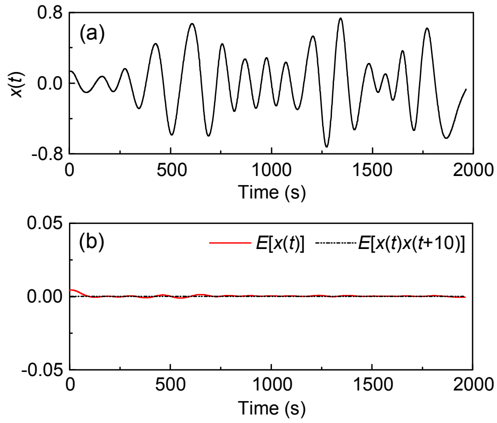

Fig. 5 Covariance functions and expected values of stationary time series: (a) a case of stationary time series; (b) covariance functions and expected values

Fig. 6 gives the covariance function and the expected values of heave and pitch motions. Obvious time dependent variations of the statistic for heave and pitch motions are suggested, indicating the existence of non-stationarity in the experimental ship motion data.

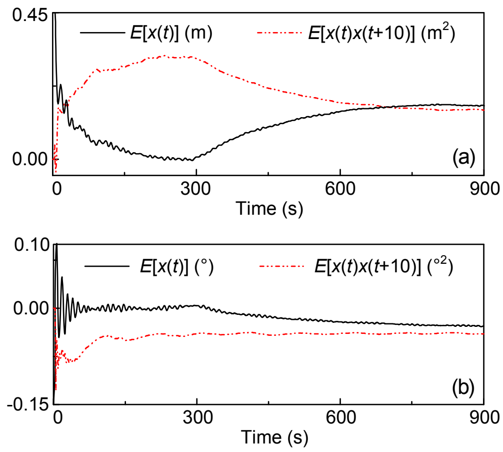

Fig. 6 Covariance functions and expected values of heave motion (*a*) and pitch motion (*b*)

This observation is further demonstrated by the recurrence plots in Fig. 7. The non-uniform distribution nature is easily found. This indicates that the given ship motions for prediction simulation study are non-stationary. Due to the non-stationarity, the intra-wave frequency modulation, designated as an indicator for nonlinearity (Huang *et al*., 1998; 2009), also exists in the motion data. Therefore, the heave and pitch motions in Fig. 4 are non-stationary and nonlinear.

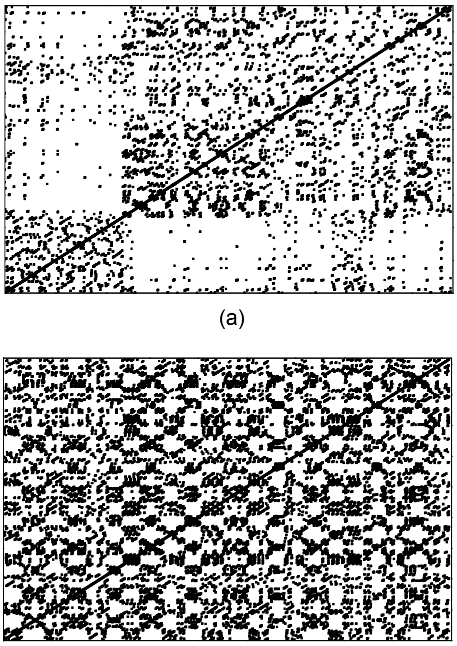

Fig. 7 Recurrence plots of the model testing ship motions: (a) heave motion; (b) pitch motion

4.2 Evaluation of prediction accuracy

For forecasting accuracy evaluation, prediction results are studied by (1) comparing time histories of the above models' forecasts with actual ship motions, (2) computing the correlation coefficient (r) and the root mean square error (RMSE) as shown in Eqs. (14) and (15), and (3) drawing scatter diagrams of prediction results and corresponding measured ship motions.

$$r=\frac{\sum_{t=1}^{n}(\hat{x}_t-\hat{x}_{\mathrm{m}})(x_t-x_{\mathrm{m}})}{\sqrt{\sum_{t=1}^{n}(\hat{x}_t-\hat{x}_{\mathrm{m}})^2\sum_{t=1}^{n}(x_t-x_{\mathrm{m}})^2}}, \tag{14}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{x}_t-x_t)^2}, \tag{15}$$

where $\hat{x}_t$ is the forecast results with a mean value of $\hat{x}_{\mathrm{m}}$, x_t is the measured ship motions, x_{m} is the mean value of x_t, and n represents the testing times.

4.3 Prediction results, comparison, and analysis

A sliding data window with the size of 500 points is used to construct the prediction models, and 1000 points are employed for testing.

Figs. 8 and 9 present the 10-lead-step predicted time histories of heave and pitch motions by models of SVR, AR, EMD-AR, and AR-EMD-SVR. It is immediately obvious that predictions of the nonlinear SVR model provide the lowest level of agreement with both the measured heave and the pitch motions. Spatial and temporal offsets generally exist relative to the targets, especially the spatial offsets, which are rather large in the troughs and peaks. Comparatively,

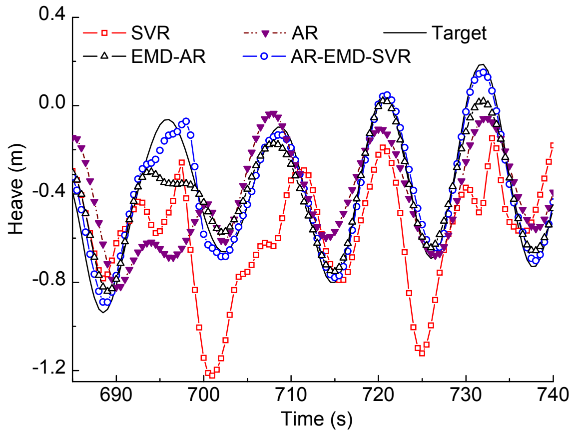

Fig. 8 Prediction of heave (10 lead steps)

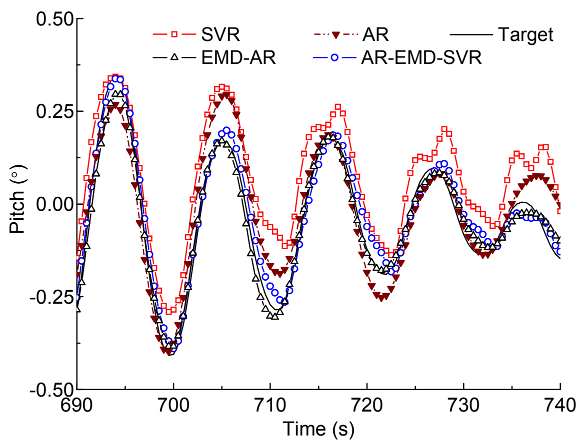

Fig. 9 Prediction of pitch (10 lead steps)

predictions of the linear AR model show smaller spatial and temporal deviations relative to the target. Nevertheless, deviations between the predictions and observations are still out of the expected range. Neither the single AR nor the SVR model produces reasonable predictions, as spatial offsets and temporal shifts generally exist and are seen to become larger as the non-stationarity increases from a comparison between Figs. 8 and 9.

In contrast, as the 10-lead-step forecasts suggested, EMD hybrid models predict far better than the single AR and SVR models. Not only are, for the most part, the peaks and troughs reasonably captured, but the short-term fluctuations in the ship motions are also reproduced remarkably well. Predictions in Figs. 8 and 9, in spite of minor spatial offset in local positions, display a fidelity to the measurements that is certainly acceptable for most practical applications. The AR-EMD-SVR model is superior to the EMD-AR model in that it captures the ship motions more precisely in the troughs and peaks.

The observations are further confirmed by the corresponding scatter diagrams given in Figs. 10 and 11, which are related to the heave and pitch motions, respectively. The relevant correlation coefficient *r*, a widely accepted measure of the degree of linear association between the target and the realized outcome of a prediction model, of each diagram is also provided. Note that in Fig. 10 the magnitudes of the correlation coefficients respect to scatter diagrams of AR, EMD-AR, SVR, and AR-EMD-SVR models are 0.75, 0.93, 0.80, and 0.97, and in Fig. 11 they are 0.91, 0.93, 0.90, and 0.95, respectively. Which are highly consistent with the observations from Figs. 8 and 9.

The poor performance of AR model in predicting non-stationary and nonlinear ship motions essentially results from its stationary and linear theoretical assumptions. On the other side, the unexpected predictions by SVR model provide evidence that the method is non-stationary limited, which agrees with the conclusion given by Fan *et al.* (2012).

Further comparison between the predictions given by Figs. 8–11 shows that the SVR model results in large prediction errors, indicating that the stationary nonlinear model is more sensitive to the non-stationarity than the linear model. This is probably because the prediction errors resulting from the nonlinear model are themselves nonlinear.

As shown in Figs. 8–11, substantial improvements in short-term predictions of nonlinear and non-stationary ship motions are obtained by using the AR-EMD coupled models. This demonstrates that non-stationarity brings obvious negative effects into the predictions. It is also clear that the AR-EMD technique is an effective way to improve the prediction performance of single AR and SVR models, as it is capable of handling nonlinear and non-stationary data. From Figs. 8–11 we can see that, the AR-EMD-SVR model matches the target better and produces higher prediction accuracy. The comparison of the EMD-AR and AR-EMD-SVR models highlights the difficulty of the former model. Even though AR-EMD can help handle the non-stationarity, EMD-AR model still suffers a "nonlinear" difficulty stemming from the linear assumption of the AR model. The AR-EMD-SVR model shows a superior performance in forecasting non-stationary and non-linear ship motion, where the non-stationarity and nonlinearity processing capabilities are inherited from the AR-EMD technique and the SVR model, respectively.

To learn the ensemble prediction behaviors of the above mentioned four models, short-term forecasts were made of ship motions with lead times varying from 1 s to 10 s. For comparison among the above prediction models and to understand the evolutionary process of error measures with respect to lead times, forecast errors of RMSE and *r* are represented graphically in Figs. 12 and 13 (p.573).

It appears from Figs. 12 and 13 that the forecasting accuracy of each model decreases as the predicted lead time increases. Taking AR-EMD-SVR as an example, in heave prediction, as the lead time varies from 1 s to 10 s, the value of RMSE increases from 0.01 m to 0.13 m while the corresponding correlation coefficient decreasing from 1.00 to 0.90. Comparison among prediction errors of AR, SVR, EMD-AR, and AR-EMD-SVR models lead to a more comprehensive validation that AR-EMD is effective in improving the accuracy of the AR and SVR models, and that the proposed AR-EMD-SVR model performs best in both heave and pitch predictions.

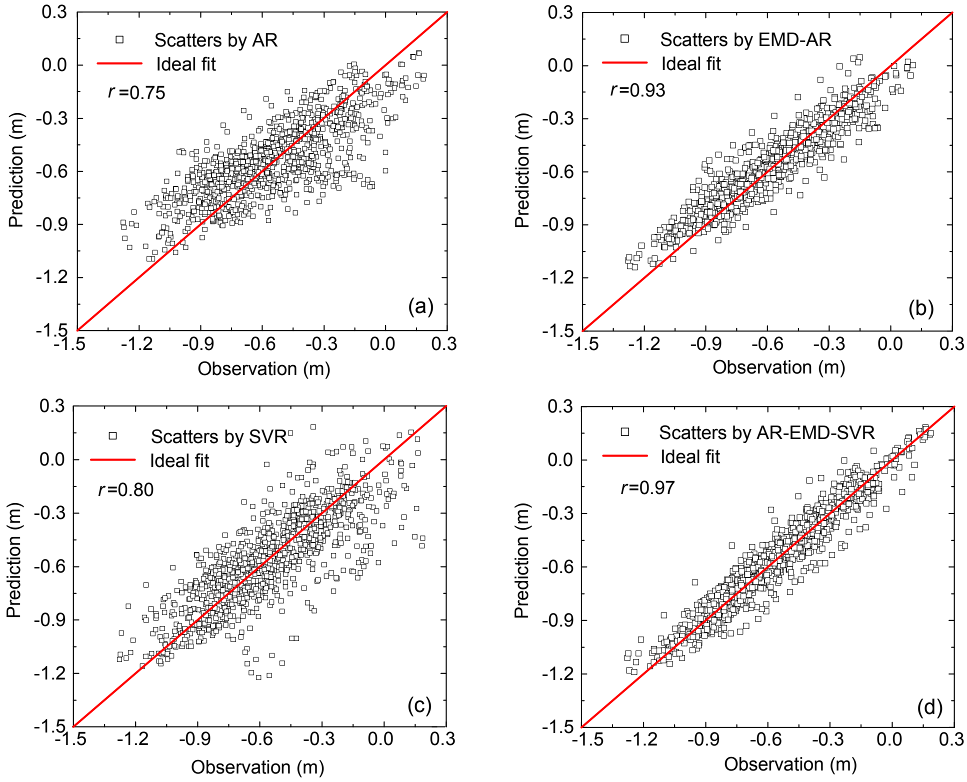

Fig. 10 Scatter diagram of predicted and corresponding measured heave motion (10 lead steps)
(a) AR model; (b) EMD-AR model; (c) SVR model; (d) AR-EMD-SVR model

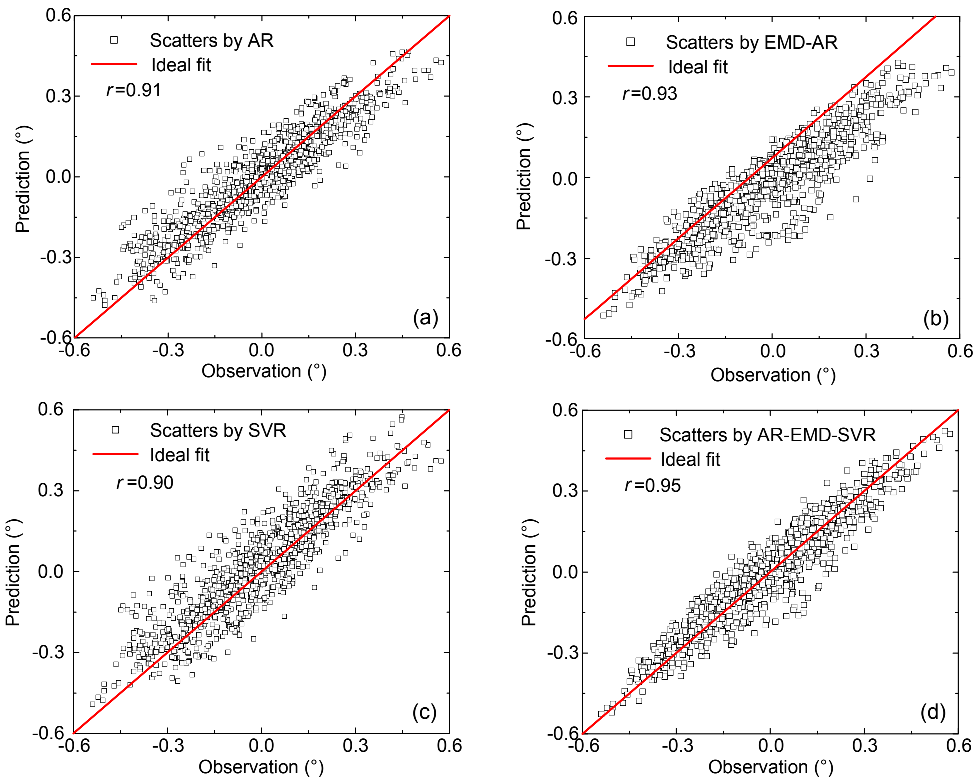

Fig. 11 Scatter diagram of predicted and corresponding measured pitch motion (10 lead steps)
(a) AR model; (b) EMD-AR model; (c) SVR model; (d) AR-EMD-SVR model

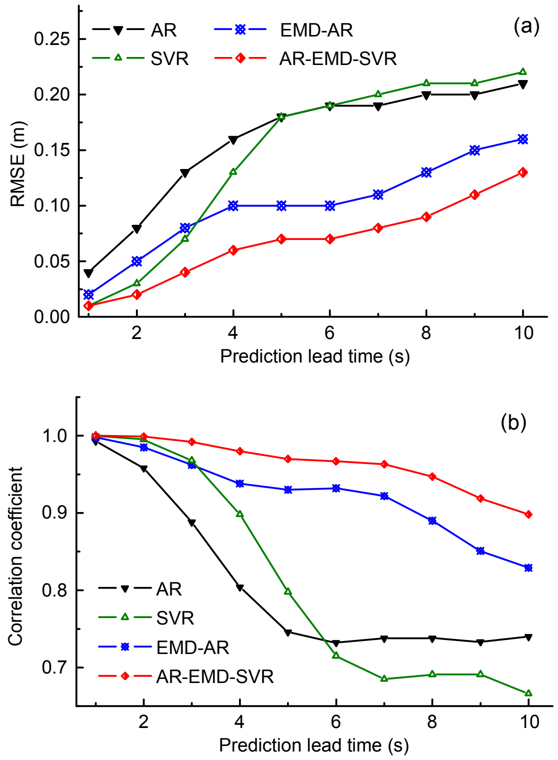

Fig. 12 Accuracy comparison of heave prediction
(a) RMSE; (b) Correlation coefficient

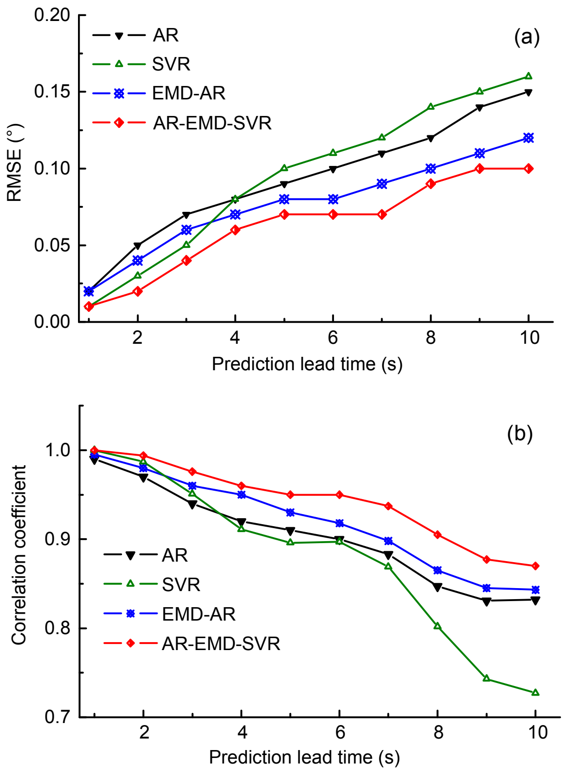

Fig. 13 Accuracy comparison of pitch prediction
(a) RMSE; (b) Correlation coefficient

Further comparison of the prediction errors of AR, EMD-AR, and SVR models reveals how the nonlinearity and non-stationarity impact on predictions as the lead time increases. It may be seen from the RMSE as shown in Figs. 12 and 13 that the SVR model is likely to produce better predictions than both AR and its EMD hybridized model when the prediction lead time is smaller than a certain bound. In the present case, the bound is 5 s for heave motion and 4 s for pitch motion. However, once the lead times exceed the bounds, the SVR model leads to overall higher prediction errors than the AR and EMD-AR models. The two observations indicate that the nonlinearity results in dominant effects on the predictions if the lead time less than a certain bound, whereas the non-stationarity shows a weak impact on the predictions. When the lead time surpasses the above mentioned bounds, the non-stationarity produces a stronger negative effect on the short-term predictions than the nonlinearity. Therefore, neither the nonlinear SVR nor the enhanced AR model shows limitation in predicting non-linear and non-stationary ship motions. As the results given in Figs 12 and 13, this difficulty has been well overcome by the proposed AR-EMD-SVR model.

5 Conclusions

In this paper, a hybrid AR-EMD-SVR model has been developed for short-term prediction of non-linear and non-stationary ship motions. The SVR model is coupled with an EMD technique using the AR model in boundary processing. An analytical signal is employed to examine the improvement of the AR model in boundary extension compared to the conventional symmetric extension method. Comparisons show that AR model-based boundary extension method leads to more reasonable extension results for EMD and provides better prediction accuracy. Research on performance of the proposed AR-EMD-SVR model compared to AR, SVR, and EMD-AR models was conducted applying ship motion data from model testing. Results suggest that AR-EMD is able to handle the non-stationarity in ship motions whereas conventional AR and SVR suffer difficulty. Comparative analysis of AR, SVR, EMD-AR, and

AR-EMD-SVR models highlights the superiority of the proposed method providing forecasts.

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中文概要

题　目： 用于非线性非平稳船舶运动极短期预报的一种复合自回归经验模态分解支持向量机回归模型

目　的： 基于支持向量机回归（SVR）模型在非线时间序列的预测能力及经验模态分解（EMD）方法在处理非线性非平稳性的优势，提出一种复合自回归经验模态分解支持向量机回归（AR-EMD-SVR）模型，提高非线性非平稳船舶运动极短期预报精度。

创新点： 1. 研究非线性非平稳船舶运动的极短期预报问题，提出一种复合的预报方法；2. 基于不同层次的预报模型和模型试验数据，分析非线性非平稳性对极短期预报精度的影响。

方　法： 1. 在 SVR 模型中引入基于自回归（AR）预报端点延拓的 EMD 方法，形成复合的 AR-EMD-SVR 预报模型；2. 基于集装箱船模水池试验运动数据将 AR-EMD-SVR 模型与 AR、SVR 和 EMD-AR 三种模型进行比较，分析非线性非平稳性对极短期预报的影响以及不同模型的预报性能。

结　论： 1. AR-EMD 方法能够有效的克服非平稳对极短期预报模型（AR 和 SVR）在精度上所带来的不良影响；2. 基于船模试验数据的预报结果表明：相较于 AR、SVR 和 EMD-AR 三种预报模型，基于 AR-EMD-SVR 模型的非线性非平稳船舶运动极短期预报结果具有更高的精度。

关键词： 非线性非平稳船舶运动；极短期预报；经验模态分解；支持向量机回归模型；自回归模型