# A Short-time Prediction Method of Ship Motion Attitude Based on EEMD-LSSVM

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## Abstract

**For the study of ship motion attitude short-term prediction method has high precision, to solve the single forecast model of ship motion attitude of nonlinear and non-stationary time series modeling forecasting difficulties and support vector machine forecasting method of off-line training lead to poor real-time performance problems, put forward a set based on empirical mode decomposition and least squares support vector machine (SVM) the ship motion posture of short-term forecasting method. In this method, the ship motion attitude timing sequence is decomposed by EEMD. Then the IMF component was reconstructed into high, medium and low frequency components by the run-distance discrimination method. Finally, the least square support vector machine (LSVM) prediction model is established for each component, and the final prediction value is obtained by summing up the prediction results of each component. The method is used to predict the time series of a ship's swing Angle. The results show that the model can effectively improve the prediction accuracy and efficiency.**

## Keywords

**Ship Attitude, Ensemble Empirical Mode Decomposition, Least Squares Support Veotor, Short-term Prediction.**

## 1. Introduction

When a ship is sailing at sea, due to the influence of uncertain sea conditions such as sea wind, waves and ocean currents, there will inevitably be a six-degree-of-freedom oscillating motion that interacts with each other which makes the ship operating at sea a great safety hazard [1]. The research of ship motion attitude prediction method has always been a hot research issue in the field of ship and ocean engineering [2]. Short-term prediction is of great significance and practical application value for the study of ship motion at sea.

In recent years, with the rapid development of support vector machine (SVM) algorithm[3] has injected new vitality to ship motion prediction field. However, the current forecast method based on support vector machine [4] mostly adopts the off-line training method, without considering the dynamic characteristics of the sample led to the decrease of the prediction accuracy of overheated, and its learning speed is slow, so high real-time requirements of ship motion posture prediction of applicability of the problem [5]. Therefore, it is a new idea to study the on-line prediction of support vector machine (SVM). In addition, the existing prediction methods use a single prediction model for time series modeling [6]. But for nonlinear time series with extremely complex changes and multivariate dynamic evolution behavior, it is difficult for a single prediction model to directly express its nonlinearity and achieve better prediction effect [7]. Therefore, to have strong randomness and contains abundant characteristic information of time series, the research based on ensemble empirical mode decomposition technique [8] the complex of ship motion time series prediction problem into a number of strong regularity of component forecast problems, by combining forecast result to get accurate forecast value, so as to decrease the difficulty of modeling to improve forecast accuracy [9].Based on the above ideas, this paper proposes a hybrid intelligent prediction method of ship roll motion attitude using EEMD and online least square support vector machine.The method consists of four parts: time series empirical mode decomposition, component reconstruction, component prediction based on LSSVM and result superposition [10]. The results show that this method has obvious advantages, which not only reduces the difficulty of modeling and forecasting, but also improves the accuracy and efficiency of forecasting.

## 2. Fundamental

### 2.1 EEMD

Ensemble Empirical Mode Decomposition (EEMD) is an adaptive signal processing method based on the improvement of Empirical Mode Decomposition (Empirical Mode Decomposition,EMD). By adding the white noise of the set value to the original signal for many times, the distribution of the extreme point of the signal is more uniform and the Mode confusion is eliminated [11]. At the same time, using the characteristics of white noise with mean 0 to add multiple sets of different [12] white noise on the EMD decomposition, get more groups again after the IMF component to carry on the overall average, eliminate noise effects inherited the EMD can be realized according to the signal of local features the advantages of the corresponding time-frequency decomposition, and effectively solve the modal aliasing phenomenon, make the decomposed IMF component has more concentrated frequency information [13] and is especially suitable for the study of nonlinear nonstationary signal EEMD algorithm core is to make use of the zero mean gaussian white noise statistical characteristics. The core of EEMD algorithm is to make use of the statistical characteristics of zero mean value of gaussian white noise. The specific steps of the algorithm are as follows:

(1)Determine the analysis signal, add Gaussian white noise with an amplitude coefficient of, and set the number of iterations to, that is:

$$x_j(t) = x(t) + \varepsilon w_j(t) \quad j = 1, 2, \cdots\cdots, \ N_o \tag{1}$$

Among them, $w_j(t)$ represents the white noise sequence added for the $j$ first time, and $x_j(t)$ represents the noise-stained signal.

(2) Perform EMD decomposition to obtain the IMF component;

(3) Repeat steps (1) and (2) $N_o$ times, each time using a different white noise sequence;

(4) Average all IMF components by layer. which is:

$$\overline{IMF_i} = \frac{1}{N_0}\sum_{j=1}^{N_0} IMF_i^{\,j} \tag{2}$$

Among them, $IMF_i^j$ is the$j$layer IMF component of the$j$ decomposition.

(5) The decomposition result of EEMD is:

$$\mathrm{x}_j(\mathrm{t}) = \sum_{i=1}^{l} \overline{IMF_i} + r \tag{3}$$

Among them, $\vec{r}$ is the mean value of the $N_o$ decomposition trend term.

### 2.2 Run-length Discriminant Reconstruction

According to the EEMD decomposition principle, EEMD finally decomposes n IMF components and a $\mathrm{R}_n(t)$. Where $\mathrm{R}_n(t)$ represents the long-term trend of the original series. For n IMF components, run-length[14] determination method is used for reconstruction. The run length determination method completely relies on the characteristics of data fluctuation and data length to reconstruct the data, which is objective. The run-length determination method is used to reconstruct the IMF decomposed by EEMD. The idea is as follows:

First, calculate the number of runs for each IMF component obtained by the EEMD. Let the time series corresponding to an IMF component be the average value of $\{\mathrm{T}_j(t)\}$ as $\overline{\mathrm{T}}_j$, and the observations less than $\overline{\mathrm{T}}_j$ are recorded as "-", and the observations greater than$\overline{\mathrm{T}}_j$ are recorded as "+" , Which gives a symbol sequence. Among them, [15] each continuous sequence of the same symbol sequence is called a run, so that the number of runs of each IMF component can be obtained. The number of runs can reflect the degree of fluctuation of the sequence. The greater the number of runs of the IMF component, the more severe its fluctuation.

Then, according to the maximum possible number of runs N (this value is equal to the total number of samples), the number of runs is equally divided into n intervals, [16] and the IMF component with the number of runs falling in the same interval is reconstructed into one term. Those that fall in the larger interval are the high-frequency terms, followed by the intermediate-frequency terms, again the low-frequency terms, and the remainder. For each component after reconstruction, different forecasting methods can[17] be adopted according to their respective characteristics, and then the results of the forecast can be recombined, or a certain forecasting method can be used. For different components, only the corresponding parameters of the forecasting model must be adjusted This can effectively reduce forecasting costs.

### 2.3 Least Squares Support Veotor Maohine Literature References

LSSVM is an improved form of traditional SVM model. It replaces inequality constraints with equality constraints, and uses the sum of squared error and loss functions as the empirical loss of the training set. It turns the solution of the quadratic programming problem into a solution of linear equations. Compared with the[18] traditional support vector machine model, the LSSVM model can predict multiple output variables with better prediction accuracy and higher prediction speed.

Introducing least squares linear theory into SVM, replacing SVM with quadratic programming to solve function estimation problems, turning SVM inequality constraints into equality constraints, transforming solving quadratic programming problems into solving a set of linear equations, greatly improving the solution The convergence speed and accuracy of the problem. The basic principle of LSSVM is: First, use a non-linear mapping φ( )to map the samples from the original space to the feature space $\phi(x_i)$, so that the nonlinear regression problem in the original space is transformed into a linear regression in the high-dimensional feature space. problem. Then, in the feature space (xi), an optimal decision function is constructed. Finally, the original space is unmapped to complete the linear regression. [19]

The given training set is as follows:

$$T = \{(x_i, y_i)\}, i = 1,2,3 \dots \dots, n \tag{5}$$

Where n is the size of the training set; $x_i \in R^n$is thei input vector, and$y_i \in R^n$ is thei output value.

The core principle of LSSVM is to map training samples to high-dimensional feature space through non-linear mapping, and then perform linear regression in high-dimensional space. The regression function can be described as:

$$y = f(x) = \omega \cdot \phi(x) + b \tag{6}$$

Among them, ω is a weight vector; b is an offset; ϕ(x) represents a mapping relationship from a low-dimensional feature space to a high-dimensional feature space. Therefore, the optimization problem of LSSVM can be described as:

$$J(\omega, b, e)_{min} = \frac{1}{2}\|\omega\|^2 + \frac{1}{2}C\sum_{i=1}^{l} e_i^2 \tag{7}$$

$$s.t.\, \omega^T\phi(x_i) + b + e_i = y_i, i = 1, \dots \dots, l \tag{8}$$

Among them, $e_i$is the error; $e \in R^{l\times l}$ is the error vector; $C(C > 0)$ is the regularization parameter that controls the degree of error. [20] Equation (2) can be transformed into Lagrangian form

$$L(\omega, b, e, \lambda) = J(\omega, b, e) - \sum_{i=1}^{l}\lambda_i(\omega^T\phi(x_i) + b + e_i - y_i) \tag{9}$$

Among them, $\lambda_i > 0$ represents a Lagrangian multiplier.

According to Karush-Kuhn-Tucker (KKT) conditions, we can get:

$$\begin{cases} \frac{\partial J}{\partial \omega} = 0 \rightarrow \sum_{i=1}^{l} \lambda_i \varphi(x_i) \\ \frac{\partial J}{\partial b} = 0 \rightarrow \sum_{i=1}^{l} \lambda_i = 0 \\ \frac{\partial J}{\partial e_i} = 0 \rightarrow \lambda_i = \gamma e_i \\ \frac{\partial J}{\partial \lambda_i} = 0 \rightarrow \omega^T \varphi(x_i) + b + e_i - y_i = 0 \end{cases} \tag{10}$$

Eliminating ω and e, the solution of equation (4) is as follows:

$$\binom{b}{\lambda} = \begin{pmatrix} 0 & E^T \\ E & K+I/\gamma \end{pmatrix}^{-1} \binom{0}{\gamma} \tag{11}$$

Where $\lambda = [\lambda_1, \lambda_{2,} \dots \dots \lambda_l]^T, E = [1,1, \dots \dots 1]^T$ dimensional column vector; $y = [y_1, y_{2,} \dots \dots y_l]^T$ represents the identity matrix; K is a suitable kernel function that meets the Mercer condition,

$$K(x_i, y_i) = \varphi(x_i)^T \varphi(y_i) \tag{12}$$

In summary, the final regression function is:

$$y(x) = \sum_{i=1}^{l} \lambda_i K(x, x_i) + b \tag{13}$$

In regression problems, radial basis functions (RBF) are commonly used:

$$K(x, x_i) = \exp(\frac{-\|x - x_i\|^2}{2\sigma^2}) \tag{14}$$

$\sigma$is the kernel function width factor. [21] Both the penalty factor C and the kernel parameter$\sigma^2$ will affect the performance of LSSVM. Before using the LSSVM model to predict, these two parameters need to be determined first.

## 3. EEMD-LSSVM prediction algorithm

When EEMD is used to process the ship's motion attitude data, the number of IMF components obtained cannot be determined. If each component is modeled and predicted one by one, it may lead to high algorithm complexity and real-time performance Since several IMF components after EEMD decomposition will show similar regularity, you can reconstruct the IMF components to obtain a fixed number of components, and then model and predict them separately, which can effectively improve the calculation efficiency of the model.

In summary, the forecasting model proposed in this paper mainly includes four modules: EEMD decomposition, IMF reconstruction, LSSVM component forecasting and result superposition.. Specific steps are as follows:

(1) The EEMD algorithm is used to decompose the time series $\{T_j(t)\}$, $t = 1,2,3, \dots \dots n$ to obtain several independent IMFs and residuals $R_n(t)$with different amplitudes and frequencies. In order of low frequency.

(2) Run-length discrimination method is used to test the degree of fluctuation of the IMF and the residual term $R_n(t)$ obtained from the decomposition, and then classify and reconstruct them into three components:high frequency, intermediate frequency, and low frequency.

(3) Aiming at the three components of high frequency, intermediate frequency and low frequency with different changes, a least square support vector machine with different structures is established.

(4) Superimpose the predicted values of the three components of high frequency, intermediate frequency and low frequency to obtain the predicted value $x(t+1)$of the original sequence $x(t)$.

## 4. Ship Motion Attitude Prediction Simulation

When using the EEMD-LSSVM combined prediction method to predict the ship's motion attitude, sample data of different lengths are used as training windows for simulation experiments, and different data are used as training samples to establish prediction models to predict the ship in small, medium, and large waves. Swing angle. The paper carried out nearly 100 simulation experiments for different training lengths and prediction lengths. Because the prediction accuracy and simulation time of ship motion attitude data under the same conditions are approximately the same, this article only gives the results of one simulation experiment shown . This section does not analyze the simulation time in detail, but only analyzes and compares the prediction accuracy.

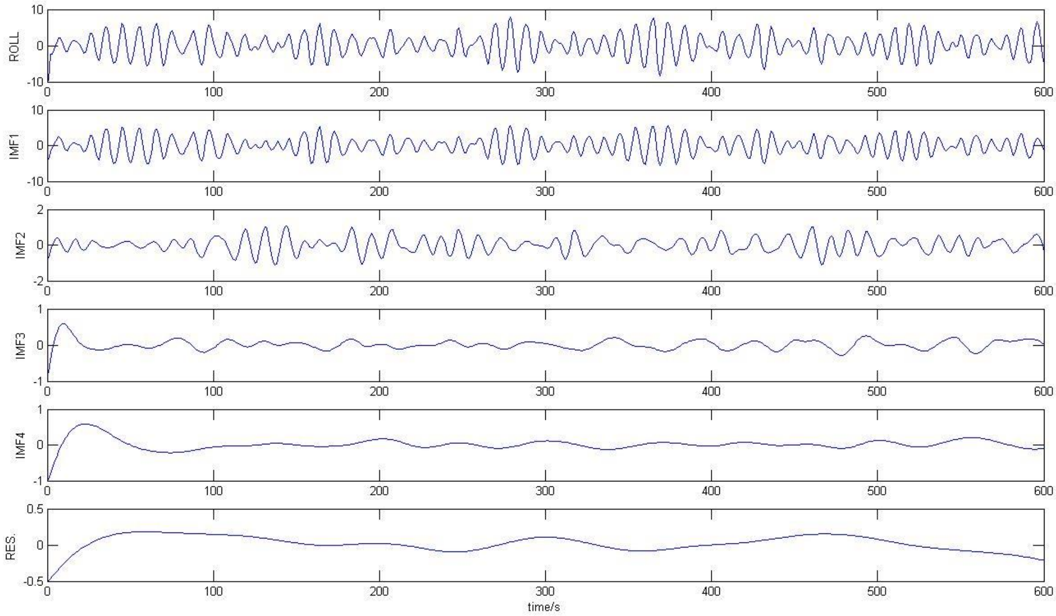


Fig. 1 EEMD decomposition results

Taking the actual roll Angle timing sequence of a large ship as an example, the prediction method proposed in this paper is tested.First, EMD decomposition was performed on the rolling timing sequence training samples to obtain each basic mode component.

Secondly, due to the length of 1 000 s respectively each roll after decomposition of time series model number uncertainty component is not the same, in order to make the number of single forecasting model is fixed and forecast, the feature information of the component concentration, each roll is obtained by using the criterion of run respectively time series after the EMD decomposition of the number of each component of the run.

Then, the threshold value n1=50 for the high-frequency component was set, namely, the threshold value n2=10 for the low-frequency component, namely, the low-frequency component was defined as less than n2, and the rest was defined as the intermediate frequency component in the interval 10≤n1≤50.Therefore, for small waves, IMF1 is taken as the high frequency component, IMF2~IMF3 is superimposed as the intermediate frequency component, IMF4~IMF5 and RES are taken as the low frequency component.In the case of medium waves, IMF1 is taken as the high frequency component, IMF2~IMF3 is superimposed as the intermediate frequency component, IMF4~IMF7 and res. as the low frequency component.For large waves, IMF1 is taken as the high frequency component, IMF2~IMF4 as the medium frequency component, IMF5~IMF6 and res. as the low frequency component.It can be seen that after reconstruction, the original roll Angle time series has been transformed into three components with frequency ranging from high to low and in the feature information set, so the prediction models with different structures can be designed for different components.

According to the high frequency, middle frequency and low frequency components of each roll Angle time series, the prediction method in this paper is applied to model the prediction respectively, and then the prediction results of each frequency are added up adaptively as the final prediction results.

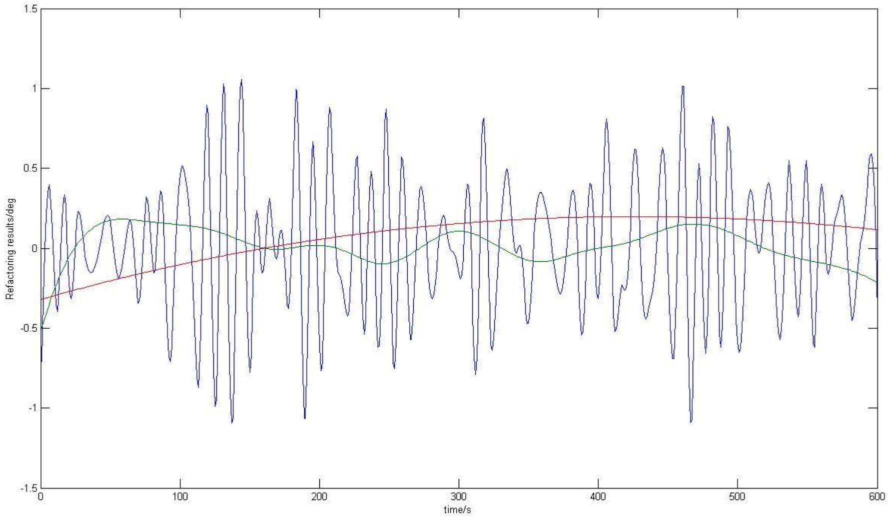


Fig.2 Results of high, medium and low frequency reconstruction of small waves

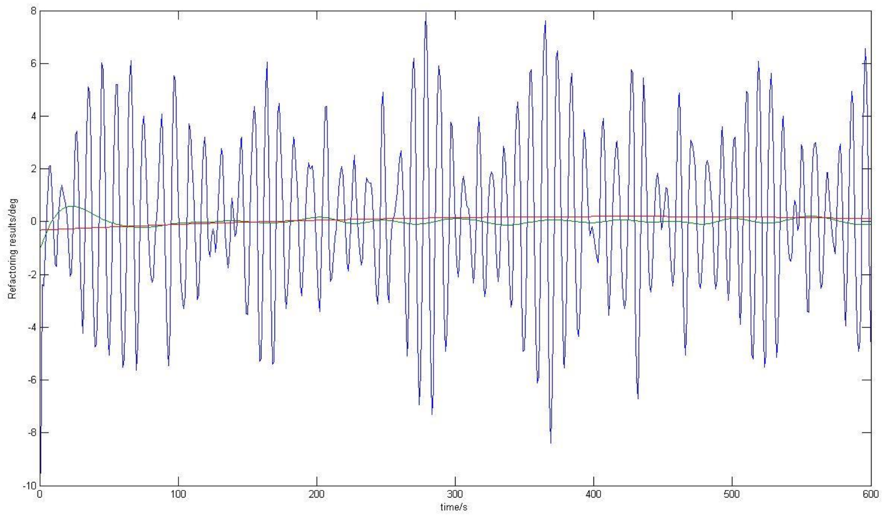


Fig. 3 Results of high, medium and low frequency reconstruction of moderate sea

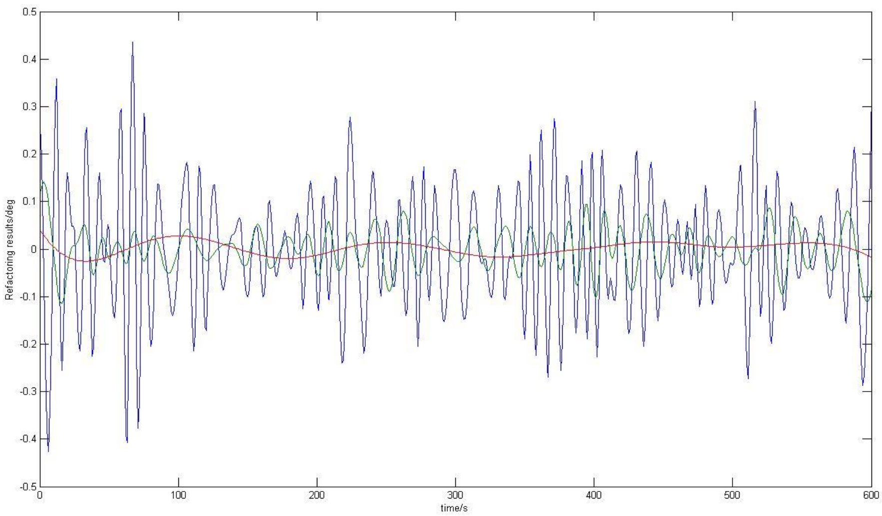


Fig. 4 Results of high, medium and low frequency reconstruction of rough sea

Table 1 Statistical results of forecast error based on least square support vector machine

| Sea level | Statistical error | Forecast time | | |
|---|---|---|---|---|
| | | 5s | 10s | 20s |
| small waves | MSE(deg) | 0.0742 | 0.0923 | 0.1732 |
| | RME | 0.0231 | 0.0308 | 0.0958 |
| moderate sea | MSE(deg) | 0.0410 | 0.0514 | 0.1246 |
| | RME | 0.0115 | 0.0142 | 0.0427 |
| rough sea | MSE(deg) | 0.1374 | 0.1413 | 0.1719 |
| | RME | 0.1231 | 0.1256 | 0.1654 |

Analyzing and comparing the error statistics table, we can get the following rules:

(1) In the EEMD-LSSVM-based intelligent forecasting model, the roll angle forecast values that are 10 s ahead of each time series agree well with the actual values, indicating that the multi-step forecast models established are consistent with the roll angle change law.

(2) From the perspective of forecasting statistical errors of each rolling time series, with the increase of forecasting time, the root mean square error and relative root mean square error are generally increasing, and the forecast accuracy is showing a downward trend.

(3) From the figure, the roll angle prediction value of the intelligent prediction model is closer to the actual value than that of the least squares support vector machine based prediction method at most forecast points. The statistical error values based on the combined forecasting method are basically smaller than the corresponding support vector machine-based forecasting methods, indicating that the forecast accuracy of the EEMD-LSSVM model is generally higher. This shows that the forecast model not only improves the overall accuracy of the forecast, but also ensures that the deviation between most forecast points and the actual roll angle is small, and can improve the accuracy of the roll angle forecast to a certain extent. In addition, online training is used. The forecasting model more accurately explains the variability existing in the sample and improves forecasting efficiency under conditions of poor information and uncertainty.

## 5. Conclusion

This paper proposes a short-term prediction method of ship motion attitude based on EEMD-LSSVM. This method is based on the ensemble empirical mode decomposition algorithm and component reconstruction strategy, which reduces the difficulty of accurate prediction of complex nonlinear time series by the prediction model. At the same time, the online least squares support vector machine with forgetting mechanism is used to learn the sample set. Features of updating sample set online and learning forecast online. It can be seen from the example simulation that the root mean square error and relative root mean square error of the prediction results of this method are smaller than the prediction model based on support vector machine, and the prediction accuracy does not decrease too quickly with time, indicating that the ship's rolling motion attitude The online forecasting model has good performance, and it can also be applied to forecasting in other fields.

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## References

[1] Marcelo A.S. Neves, Claudio A. Rodriguez. On Unstable Ship Motions Resulting From Strong Non-linear Coupling[J]. Ocean Engineering, 2006, 33(14): 1853-1883.

[2] Wei D, Ye J, Wu X, et al. Time Series Prediction for Generalized Heave Displacement of a Shipborne Helicopter Platform[C]. Isces International Colloquium on Computing, Communication, Control, &Management. IEEE, 2008.

[3] Bian Dejun, Qin Shiqiao, Wu Weo. A Hybrid AR-DWT-EMD Model for the Short-term Prediction of Nonlinear and Non-stationary Ship Motion[C]. Chinese Control and Decision Conference, 2016.

[4] Chao Wang,Lin Jia,Shuai Zhang,Yadong Li. Electrostatic induced charge signal extraction based on waveform characteristic in time domain[J]. Powder Technology,2020,362.

[5] Wu Zhaohua, Norden E. Huang, "Ensemble empirical mode decomposition: a noise-assisted data analysis method", Advances in adaptive data analysis, vol. 1, no. 01, pp. 1-41, 2009.

[6] J.Y. Zhou, K.W. Zhang, "Improvement of the Cuckoo Algorithm to Optimize Cigarette Sales Forecast of Mixed Core LSSVM", Computer Engineering and Applications, vol. 19, pp. 250-254, 2015.

[7] H. Liu, X.W. Mi, Y.F. Li, Wind speed forecasting method based on deep learning strategy using empirical wavelet transform long short term memory neural network and Elman neural network, vol. 156, pp. 498-514, 2018.

[8] Wu Zhaohua Huang N E. Ensemble empirical mode decomposition: a noise assisted data analysis method. Center for Ocean land Atmosphere Studies Technical Report 2005 (193):51.

[9] Dag Myrhaug, Lars Erik Holmedal. Bottom Friction and Erosion Beneath Long-crested and Short-crested Nonlinear Random Waves[J]. Ocean Engineering, 2011, 10(1016):2015-2022.

[10] Huang, L.M., Duan, W.Y., Chen, YS. A Review of Short-time Prediction Techniques for Ship Motions in Seaway[J]. Journal of Ship Mechanics, 2014, 18(12): 1534-1542.

[11] Lore Dirick, Gerda Claeskens, Vart Baesens. An Akaike Information Criterion for Multiple Event Mixture Cure Models[J]. European Journal of Operational Research, 2015, 241(2): 449-457.

[12] Chen, J.D., Pan, F. Online Support Vector Regresion-based Nonlinear Model Predictive Control[J]. Control and Decision, 2014, 29(3): 460-464.

[13] Ding W.P., Wang J,D., Guan Z.J. Cooperative Extended Rough Attribute Reduction Algorithm Based on Improved PSO[J]. Journal of Systems Engineering and Electronics, 2012, 23(1): 160-166.

[14] Khorshidi, Sh., Karimi, M. Modified AIC and FPE Criteria for Autoregressive(AR) Model Order Selection by Using LSFB Estimation Method[C]. Advances in Computational Tools for Engineering Applications, 2009.

[15] CHI Ennan, LI Chunxiang. Forecasting fluctuating wind velocity using optimized combination kernel and morlet wavelet kernel based LSSVM[J]. Journal of Vibration and Shock,2016,35(18): 52-57.

[16] LI Chunxiang, CHI Ennan, HE Lian, et al. Prediction of nonstationary downburst wind velocity based on time-varying ARMA and EMD-PSO-LSSVM algorithms[J]. Journal of Vibration and Shock, 2016, 35(17): 33-38.

[17] LI Chunxiang, DING Xiaoda, YE Jihong. Fluctuating wind velocity forecasting of hybridizing ant colony and particle swarm optimization based LSSVM[J]. Journal of Vibration and Shock, 2016,35(21): 131-136.

[18] LI Jinhua, WU Chunpeng, CHEN Shuisheng. Characteristics of non-Gaussian wind pressures on rectangular structure[J]. Journal of Vibration, Measurement & Diagnosis, 2014, 34(5): 951-959.

[19] H Mosskull, J Galic, B Wahlberg. Stabilization of Induction Motor Drives With Poorly Damped Input Filters[C]. Industrial Electronics, IEEE Transactions,Aug. 2007, 54(5):2724-2734.

[20] Zhao Shengkui, Man Zhihong, Suiyang Khoo, Wu Hong Ren. Variable step - size LMS algorithm with a quotient form[J]. Signal Processing, 2009, 89(1): 67-76.

[21] Zhou yanzhen, wu junyong, ji luyu, yu zhihong, hao liangliang. Chinese journal of electrical engineering. 2018(01).