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ORIGINAL ARTICLE

Prediction of the vertical vibration of ship hull based on grey relational analysis and SVM method

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Abstract There are certain limitations when empirical formulas are used to predict the ship hull vertical vibration. Natural frequency of ship's vertical vibration is predicted by support vector machine (SVM), which possesses many characteristics such as small sample learning, global optimization and strong generalization. Considering the parameters that influence the natural frequency of ship's vertical vibration are much more, a grey relation model between ship's main parameters and natural frequency of ship's vertical vibration is established by grey relational analysis theory to get the grey correlation degree of each parameter. The parameters with greater correlation degree are used as input data and the measured values of natural frequency of vertical vibration are used as output data in SVM to build the nonlinear regression model of the natural frequency of vertical vibration. Natural frequencies of eight ships' vertical vibration are predicted by the nonlinear regression model, and the results are coincident with the measured values. The proposed method in this paper is proved to be accurate and feasible, which provides a new idea to the prediction of natural frequency of ship's overall vertical vibration.

Keywords Ship hull vertical vibration · Natural frequency · Support vector machine · Grey relational analysis · Vibration prediction

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1 Introduction

Ship is a kind of complex elastic structure. During ship sailing operation, it will encounter the external exciting forces from main engine, propellers and wave loads. These excitation forces will cause the hull vibration issue and even ship structural damage. The excessive vibration may lead to structure fatigue failure; affect the shipping efficiency, the health of human-being and the service life of equipments [1]. So, to predict the natural frequency of ship hull accurately at design stage is very important for avoiding harmful vibration especially the overall vertical vibration.

In general, empirical formulas are widely and efficiently used to predict the ship hull vertical vibration on the scheme design stage. Whilst on the detail design stage, the 1D or 3D FEM method is used for the more accurate vibration analysis. Since the empirical formula method is more simple and practical, many professionals have done lots of works in the study of empirical formulas for prediction of the natural frequency of ship's overall vertical vibration [2–6]. The Schlick formula, the Todd formula, the Kumai formula recommended by Det Norske Veritas (DNV) [7], the formula recommended by Japanese shipbuilding design [8], and the formula specified in the ship industry standard of the People's Republic of China [9], etc. are widely used to predict the natural frequency of ships in the shipbuilding industry. However, all the aforementioned empirical formulas are obtained by statistical analysis of large amounts of measured natural frequency results based on the beam theory. Due to the discreteness of samples, the calculation error is relatively larger. Intelligent method possesses many characteristics such as strong ability of identification and generalization so that it can handle uncertainty and nonlinear problems well. Therefore intelligent method can be used to predict the natural frequency of ship's vertical vibration. Compared with 1D and 3D FEM methods, only some ship's main parameters are needed when intelligent methods are used to predict the natural frequency of vertical vibration. It is very suitable for the prediction at the beginning design stage of lacking detailed drawings data. After nonlinear regression model built by intelligent methods, only some main parameters are needed as input to predict the natural frequency of ship's vibration quickly, without complicated data calculation and modelling, so the method is very simple and convenient.

Support vector machine (SVM) is a machine learning theory which specially solves the small samples' problems based on statistical learning theory. The algorithm solves the practical problem in a high-dimensional feature space by nonlinear transformation and constructing linear decision function in the former space to realize nonlinear decision function in the original space [10]. Compared with neural network and other intelligent methods, SVM which has many characteristics such as small samples study, global optimization and better generalization can handle small samples, nonlinear and other practical problems well. At present, SVM is mainly used in the fields of identification and nonlinear regression [11], especially in the study of graph and image recognition [12], fault diagnosis [13, 14], model prediction [15] and time series prediction [16], etc. Since prediction of natural frequency of ship's vertical vibration is a complex nonlinear problem and the measured data of the natural frequency is limited, SVM is more suitable for prediction of the natural frequency. For the reason that there are many parameters that influence the natural frequency, and excessive input parameters will make an effect on training speed and complexity of regression model, prediction precision can be influenced if less effective parameters are taken as input. Therefore, grey relation theory is used to analyse the main ship's parameters and natural frequency in this paper. Through grey relational analysis, the correlation degree of the parameters is obtained and parameters with greater correlation degree are used as input data in SVM. Then SVM is utilized to build nonlinear regression model and predict the natural frequency of ship's vertical vibration.

2 Grey relational analysis of ship parameters

2.1 Grey relation theory

Grey system theory, founded by Prof. Deng in 1982 [17], becomes more and more widely applied in all areas at present [18, 19]. Grey relation is a mathematical model study on the correlation degree of the internal factors of a system. The basic principle is to determine the correlation degree by analysing and comparing the relationship between the set of sequences. Grey relational analysis theory is as follows:

(1) Select sequence $\boldsymbol{Y}_0$ and $\boldsymbol{X}_i$, then:

$$\begin{cases} \boldsymbol{Y}_0 = \{y_0(1),\ y_0(2), \ldots, y_0(n)\} \\ \boldsymbol{X}_i = \{x_i(1),\ x_i(2), \ldots, x_i(n)\} \end{cases} \quad (i = 1,\ 2, \ldots, m), \tag{1}$$

where $\boldsymbol{Y}_0$ is reference sequence, $\boldsymbol{X}_i$ is comparison sequence, n is the number of characteristic variables and m is the number of comparison sequence.

(2) Dimensionless process of original sequence. Since dimensionless method can simplify the modelling and analysis process and increase the comparability of data, dimensionless transformation on the original sequence is made in grey relational analysis. That is

$$\begin{cases} y_0^0(k) = y_0(k) - y_0(1) \\ x_i^0(k) = x_i(k) - x_i(1) \end{cases} \quad (k = 1,\ 2, \ldots, n). \tag{2}$$

Get:

$$\begin{cases} \boldsymbol{Y}_0^0 = \{y_0^0(1),\ y_0^0(2), \ldots, y_0^0(n)\} \\ \boldsymbol{X}_i^0 = \{x_i^0(1),\ x_i^0(2), \ldots, x_i^0(n)\} \end{cases} \quad (i = 1,\ 2, \ldots, m). \tag{3}$$

(3) Seek absolute correlation degree of sequence $\boldsymbol{X}_i$ and $\boldsymbol{Y}_0$

$$\begin{aligned} \varepsilon_i = {} & \left(1 + \left|\sum_{k=1}^{n-1} y_0^0(k) + \frac{1}{2} y_0^0(n)\right| + \left|\sum_{k=1}^{n-1} x_i^0(k) + \frac{1}{2} x_i^0(n)\right|\right) \Big/ \\ & \left(1 + \left|\sum_{k=1}^{n-1} y_0^0(k) + \frac{1}{2} y_0^0(n)\right| + \left|\sum_{k=1}^{n-1} x_i^0(k) + \frac{1}{2} x_i^0(n)\right| \right. \\ & \left. + \left|\sum_{k=1}^{n-1} \left(y_0^0(k) - x_i^0(k)\right) + \frac{1}{2}\left(y_0^0(n) - x_i^0(n)\right)\right|\right). \end{aligned} \tag{4}$$

2.2 Modelling grey relation of ship parameters

The natural frequency of vertical vibration usually depends on the mass and stiffness of the ship structure and their distributions in the ship. Approximate formulas used to calculate the natural frequency of the first-order vertical vibration are as follows:

(1) The Kumai formula recommended by DNV:

$$f_{\mathrm{V}} = 1.61 \times 10^6 \sqrt{\frac{I_{\mathrm{V}}}{\Delta_{\mathrm{V}} L^3}}, \tag{5}$$

where f_{V} is the natural frequency of first-order vibration, Hz; L is the length, m; I_{V} is the midship section moment of inertia for horizontal axis, m^4; Δ_V is the mass of ship structure including added mass, $\Delta_V = \left(1.2 + \frac{B}{3T}\right)\Delta$, Δ is the displacement of ship, kg; B is breadth, m; T is draft, m.

(2) Recommended formula in Japanese shipbuilding design handbook:

$$f_V = 27.1 \times 10^5 \sqrt{\frac{I_V}{\Delta_V L^3}} + 14.5, \tag{6}$$

where for cargo ship $\Delta_V = \left\{1 + 0.3\left(\frac{B}{T}\right) - 0.033\left(\frac{B}{T}\right)^2\right\} \times \Delta$, Δ is displacement of ship, t; for tankers $\Delta_V = \left\{1 + 0.4\left(\frac{B}{T}\right) - 0.035\left(\frac{B}{T}\right)^2\right\} \times \Delta$.

(3) The formula specified in the ship industry standard of the People's Republic of China:

$$f_V = K_{ib}\left(A_{iv} K_{iv} E_{iv} \sqrt{\frac{I_V}{\Delta_V L^3}} + B_{iv}\right), \tag{7}$$

where A_{iv} and B_{iv} is regression coefficient, K_{ib} is reduction coefficient of bending stiffness for vertical vibration of hull girder, K_{iv} is influence coefficient for natural frequency of vertical vibration caused by the change of moment of inertia of section along the ship length, E_{iv} is influence coefficient of the superstructure, the calculation method of each parameter can refer to references [9].

As can be seen from the above empirical formula, the length (L), the midship section moment of inertia (I_V), the mass of ship structure including added mass (Δ_V) and ship type are the main parameters affecting the natural frequency of ship's vertical vibration. The value of Δ_V depends on the displacement (Δ) and the ratio of breadth (B) and draft (T). Because empirical formula is based on the beam theory, the influence of breadth and depth is not considered. Based on the above analysis, the length, breadth, depth, midship section moment of inertia, displacement, draft and ship type are regarded as influence factors of natural frequency of ship's vertical vibration in this paper. In order to determine the influence of different parameters on the natural frequency of ship's vertical vibration, the relation degree between the parameters and the natural frequency of ship's vertical vibration is required to compare. Since grey relational analysis is effective to quantify the impact amongst different parameters, it can be used to get the correlation degree between each parameter and the natural frequency of ship's vertical vibration.

The process of grey relational analysis of ship's main parameters and natural frequency of vertical vibration is shown as follows:

(1) *Select reference sequence and comparison sequence* according to the empirical formula (5)–(7) of natural frequency of ship's vertical vibration, approximate relationships of the frequency related to length, breadth, depth, displacement, midship section moment of inertia and draft are as follows:

$$\begin{cases} f_V \propto \theta_1 L^{\gamma_1} & f_V \propto \theta_2 B^{\gamma_2} & f_V \propto \theta_3 D^{\gamma_3}, \\ f_V \propto \theta_4 I_V^{\gamma_4} & f_V \propto \theta_5 \Delta^{\gamma_5} & f_V \propto \theta_6 T^{\gamma_6}. \end{cases} \tag{8}$$

Least-squares fitting are used to obtain the coefficients θ and γ of the parameters in formula (8). Each ship's natural frequency of vertical vibration f_V is selected as the reference sequence $\boldsymbol{Y}_0$ and the parameters $\theta_1 L^{\gamma_1}$, $\theta_2 B^{\gamma_2}$, $\theta_3 D^{\gamma_3}$, $\theta_4 I_V^{\gamma_4}$, $\theta_5 \Delta^{\gamma_5}$, $\theta_6 T^{\gamma_6}$ are selected as the comparison sequence $\boldsymbol{X}_i$ in formula (1), where n refers to the number of ship, m refers to the number of parameters that influence the natural frequency of ship's vertical vibration.

(2) Make dimensionless transformation on the reference sequence and comparison sequence using formula (2).

(3) Seek absolute correlation degree of sequence $\boldsymbol{X}_i$ and $\boldsymbol{Y}_0$ using formula (4), that is seeking absolute correlation degree ε_i (i = 1, 2,…,m) of L, B, D, I_V, Δ, T and f_V.

(4) Present the correlation degree in descending order, and determine the influence of different parameters on the natural frequency of ship's vertical vibration.

3 Prediction of natural frequency of ship's vertical vibration based on SVM

By the grey relational analysis of parameters and natural frequency of vertical vibration, parameters with greater correlation degree are used as input data $\boldsymbol{x}$ in SVM and measured values of natural frequency are used as output data $\boldsymbol{y}$. Establishing the input and output data sets in SVM $\{\boldsymbol{x}_i, y_i\}_{i=1}^{q}$, $\boldsymbol{x}_i \in \boldsymbol{R}^d$, $y_i \in \boldsymbol{R}$, where q is the number of samples, then the nonlinear regression model of natural frequency of vertical vibration is fitted as follows:

$$f(\boldsymbol{x}) = \boldsymbol{w}^{\mathrm{T}} \boldsymbol{\varphi}(\boldsymbol{x}) + b, \tag{9}$$

where $\boldsymbol{w} \in \boldsymbol{R}^d$ is weight vector, $b \in \boldsymbol{R}$ is threshold, $\boldsymbol{\varphi}(\boldsymbol{x})$ is nonlinear transformation mapping the input data into a high-dimensional feature space.

In formula (9), fitting problem in high-dimensional feature space can be transformed into solving the following optimization problem [20]:

$$\begin{cases} \min J(\boldsymbol{w}, e) = \dfrac{1}{2}\boldsymbol{w}^{\mathrm{T}}\boldsymbol{w} + C\displaystyle\sum_{i=1}^{q} e_i^2, \\ \text{s.t. } y_i = \boldsymbol{w}^{\mathrm{T}}\boldsymbol{\varphi}(x_i) + b + e_i, \quad i = 1, 2, \ldots, q, \end{cases} \tag{10}$$

where C is penalty function, e_i is the error between actual values y_i and fitted values $f(\boldsymbol{x}_i)$, the loss of function in optimization goals is the two-norm of error e_i.

The Lagrange function defined according to formula (10) is shown as follows:

$$\tilde{L}(\boldsymbol{w}, b, e, \alpha) = J(\boldsymbol{w}, e) - \sum_{i=1}^{q} \alpha_i \left[\boldsymbol{w}^T \boldsymbol{\varphi}(\boldsymbol{x}_i) + b + e_i - y_i\right], \tag{11}$$

where α_i is Lagrange multiplier.

The formula has the optimal solution when the partial derivatives of $\tilde{L}$ to $\boldsymbol{w}$, b, e_i, α_i are equal to 0, that is:

$$\begin{cases} \boldsymbol{w} = \sum\limits_{i=1}^{q} \alpha_i \boldsymbol{\varphi}(\boldsymbol{x}_i), \\ \sum\limits_{i=1}^{q} \alpha_i = 0, \\ \alpha_i = Ce_i, \\ \boldsymbol{w}^T \boldsymbol{\varphi}(\boldsymbol{x}_i) + b + e_i - y_i = 0. \end{cases} \tag{12}$$

In other words, the optimization problem of formula (10) is transformed into solving following linear equations:

$$\begin{bmatrix} \boldsymbol{I} & 0 & 0 & -\boldsymbol{Z}^T \\ 0 & 0 & 0 & -\boldsymbol{1}^T \\ 0 & 0 & C\boldsymbol{I} & -\boldsymbol{I} \\ \boldsymbol{Z} & \boldsymbol{1} & \boldsymbol{I} & 0 \end{bmatrix} \begin{bmatrix} \boldsymbol{w} \\ b \\ \boldsymbol{e} \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \boldsymbol{y} \end{bmatrix}, \tag{13}$$

where $\boldsymbol{Z} = [\boldsymbol{\varphi}(\boldsymbol{x}_1), \boldsymbol{\varphi}(\boldsymbol{x}_2), \ldots, \boldsymbol{\varphi}(\boldsymbol{x}_q)]^T$, $\boldsymbol{1} = [1, 1, \ldots, 1]^T$, $\boldsymbol{e} = [e_1, e_2, \ldots, e_q]^T$, $\boldsymbol{y} = [y_1, y_2, \ldots, y_q]^T$, $\boldsymbol{\alpha} = [\alpha_1, \alpha_2, \ldots, \alpha_q]^T$. Eliminate $\boldsymbol{w}$ and $\boldsymbol{e}$, then get:

$$\begin{bmatrix} 0 & \boldsymbol{1}^T \\ \boldsymbol{1} & \boldsymbol{\Omega} + C^{-1}\boldsymbol{I} \end{bmatrix} \begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix}, \tag{14}$$

where $\boldsymbol{\Omega} = \{\Omega_{ij}\}_{q \times q}$, $\Omega_{ij} = \boldsymbol{\varphi}(\boldsymbol{x}_i)^T \boldsymbol{\varphi}(\boldsymbol{x}_j) = k(\boldsymbol{x}_i, \boldsymbol{x}_j)$, $i, j = 1, 2, \ldots, q$, $k(\cdot, \cdot)$ is kernel functions satisfying the Mercer condition. Radial basis function is selected as the kernel function in this paper, that is:

$$k(\boldsymbol{x}_i, \boldsymbol{x}_j) = \exp\left(-\frac{||\boldsymbol{x}_i - \boldsymbol{x}_j||^2}{2\sigma^2}\right), \tag{15}$$

where σ is variance of kernel determined by debugging.

Solve the linear equations (14) and get:

$$\begin{cases} b = \dfrac{\boldsymbol{1}^T \boldsymbol{A}^{-1} \boldsymbol{y}}{\boldsymbol{1}^T \boldsymbol{A}^{-1} \boldsymbol{1}}, \\ \boldsymbol{\alpha} = \boldsymbol{A}^{-1}(\boldsymbol{y} - b\boldsymbol{1}). \end{cases} \tag{16}$$

Combine formula (12) with formula (16) to get the nonlinear regression model of natural frequency of vertical vibration:

$$f(\boldsymbol{x}) = \sum_{i=1}^{q} \alpha_i k(\boldsymbol{x}_i, \boldsymbol{x}) + b. \tag{17}$$

4 Numerical analysis

4.1 Calculation of grey correlation degree of ship parameters

The measured data of vibration were collected from more than 70 ships of different types by the author for many years. The above established grey relational models are utilized to calculate the grey correlation degree of length, breadth, depth, moment of inertia, displacement, etc. and the natural frequency of vertical vibration, respectively. The calculation results are shown in Table 1.

It can be seen from the results in Table 1, for the three types of ship, the grey correlation degree of parameters and natural frequency of vertical vibration in descending order is approximately as follows: main dimensions of ship, displacement, moment of inertia, draft.

4.2 Regression model of natural frequency of ship's vertical vibration based on SVM

By means of the grey relational analysis in Sect. 4.1, grey correlation degree of parameters and natural frequency of vertical vibration is obtained, and the input data of SVM can be chosen by the size of the grey correlation degree. Since the grey correlation degree of draft and natural frequency of vertical vibration is minimal, the impact on natural frequency of vertical vibration of draft is investigated first. Two models are built as follows: length, breadth, depth, displacement, moment of inertia, types of ship, draft are used as input data in SVM in model 1;

Table 1 Grey correlation degree of ship parameters

Ship types	Numbers	Grey correlation degree					
		Length	Breadth	Depth	Displacement	Moment of inertia	Draft
Three types of ship	78	0.9181	0.6328	0.5862	0.6816	0.5256	0.5214
Tanker	30	0.9637	0.6928	0.6342	0.7866	0.6325	0.5478
Bulk carrier	44	0.9553	0.8368	0.7384	0.7088	0.5808	0.5545
Container ship	4	0.9998	0.9975	0.9953	0.9899	0.9175	0.8745

Table 2 Parameters of eight ships

Nos.	Length (m)	Breadth (m)	Depth (m)	Moment of inertia (m^4)	Displacement (t)	Ship types
1	162.00	22.30	13.20	66.00	28,000	Bulk carrier
2	192.00	27.50	16.10	152.00	21,652	Bulk carrier
3	153.00	21.00	13.50	66.70	9,660	Bulk carrier
4	144.77	20.42	12.19	50.23	19,720	Bulk carrier
5	192.00	27.20	13.75	115.00	45,190	Tanker
6	161.54	21.11	11.89	62.51	24,400	Tanker
7	219.00	32.20	18.50	207.39	75,014	Tanker
8	175.00	25.20	15.30	84.80	15,143	Container ship

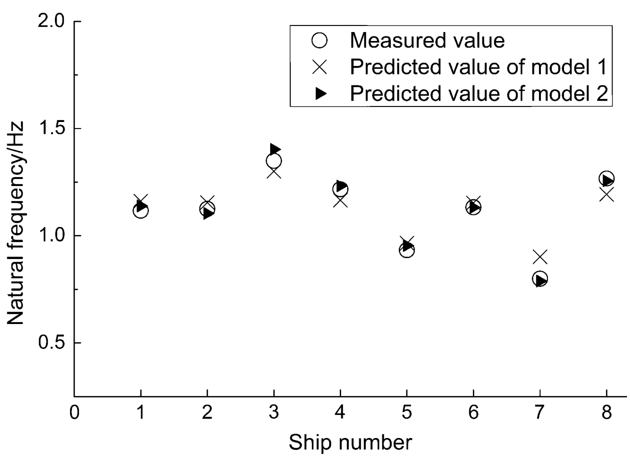

Fig. 1 Prediction results of models 1 and 2

length, breadth, depth, displacement, moment of inertia, types of ship are used as input data in SVM in model 2. 78 ships are used for training in both models. Two created regression models are used to predict the natural frequencies of vertical vibration of eight ships including four bulk carriers, three tankers and a container ship. The parameters of the eight ships are shown in Table 2. The results of prediction are shown in Fig. 1. The prediction results and errors of two models are listed in Table 3.

Referring to the calculated results in Table 3, a relatively large error of prediction is found in model 1. Due to the relatively small grey correlation degree of draft and natural frequency of vertical vibration, the draft used as input data influences the prediction precision of regression model in SVM. The prediction results of model 2 is better than that of model 1, which indicates that good prediction results can be obtained when length, breadth, depth, displacement, moment of inertia, types of ship are used as input data in SVM.

In order to investigate the influence of the moment of inertia with relatively small correlation degree and the length with relatively large correlation degree on the regression model, model 3 is created in which length, breadth, depth, displacement, types of ship are used as input data in SVM, and model 4 is created by using breadth, depth, displacement, moment of inertia and types of ship as input data in SVM. 78 ships are used for training in both models. Two created regression models are used to predict the natural frequencies of vertical vibration of the eight ships, and the results of models 3 and 4 are compared with model 2. The results of prediction are shown in Fig. 2. The prediction results and errors are shown in Table 4.

From the data in Tables 3 and 4, we can see that the moment of inertia has little effect on the prediction results of the natural frequency of vertical vibration by comparing model 3 with model 2. The prediction results of model 2 are relatively better than those of model 3. Due to the lack of moment of inertia at the very beginning design stage of ships, model 3 can be used to predict natural frequency of vertical vibration. Without considering the length with greater correlation degree, errors in the prediction results of model 4 have significantly increased compared to those of model 2.

From the above analysis, it can be seen that without considering the draft with smaller correlation degree, using the parameters with greater correlation degree as input data can reduce the dimension of the input data, increase training speed and improve the prediction precision in SVM.

In order to validate the correctness of the proposed method in this paper, formulas (5)–(7) are used to calculate the first-order natural frequencies of the eight ships including four bulk carriers, three tankers and a container ship. The prediction results of the model 2 are compared with the results calculated by empirical formula and measured values, which are shown in Table 5.

From the data in Table 5, it can be seen that the prediction results in SVM are close to the measured values, which indicates that the natural frequency of vertical

Table 3 Results and errors of natural frequency of vertical vibration

Nos.	Model 1		Model 2		Measured value (Hz)	Ship types
	Predictions (Hz)	Error (%)	Predictions (Hz)	Error (%)		
1	1.161	3.94	1.139	1.98	1.117	Bulk carrier
2	1.155	2.65	1.104	1.90	1.125	Bulk carrier
3	1.301	3.60	1.403	3.93	1.350	Bulk carrier
4	1.166	4.17	1.232	1.24	1.217	Bulk carrier
5	0.965	3.39	0.954	2.22	0.933	Tanker
6	1.153	1.74	1.132	0.12	1.133	Tanker
7	0.902	12.70	0.789	1.40	0.800	Tanker
8	1.193	5.86	1.256	0.87	1.267	Container ship

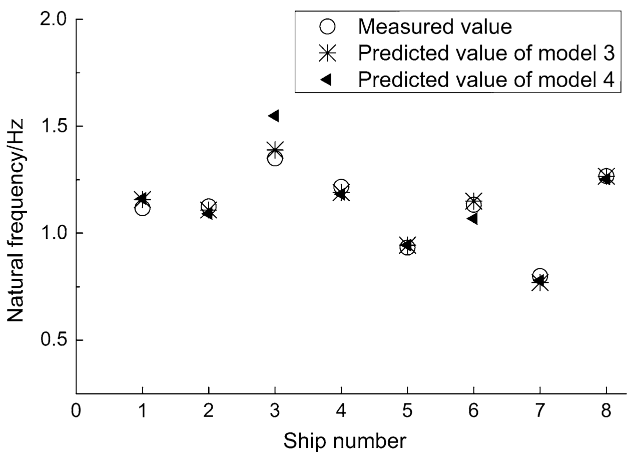

Fig. 2 Prediction results of models 3 and 4

vibration can be predicted through SVM method quickly and accurately. There are some errors between measured values and the results of the empirical formulas, and some big differences between the results calculated by different empirical formulas as well. Since the regression coefficients in empirical formulas depend on the statistical ships and the measured data of vibration are limited, which is difficult to cover all of the ships, and SVM is specialized in complex nonlinear problems with small samples, using SVM to predict the natural frequency of vertical vibration can give full play to its advantages and it is an effective tool to predict the ship vibration.

Due to the lack of measured data of natural frequency of vertical vibration, 44 ships (including 20 tankers, 20 bulk carriers, 4 container ships) and 30 ships (including 12 tankers, 14 bulk carriers, 4 container ships) are taken as the training samples respectively in models 2 and 3 to check the predictive effect under the condition of fewer samples. The created regression models are used to predict the natural frequency of vertical vibration of eight ships above and the results are compared with measured data. The prediction results and errors of two models are listed in Table 6.

Refer to the results in Table 6, using SVM to predict the natural frequency of vertical vibration, prediction precision under the condition of fewer samples can also be high whilst it will be better with more samples.

5 Conclusions

Since the prediction of natural frequency of vertical vibration is a complex nonlinear problem and the measured data of the frequency are limited, SVM is used to predict the natural frequency. For the reason that there are many parameters which can influence the natural frequency, grey relation theory is used to analyse the grey correlation degree of parameters and natural frequency. The parameters with greater correlation degree are used as input data and the measured values of natural frequency of vertical vibration are used as output data in SVM to build nonlinear regression model of natural frequency of vertical vibration. Then the regression model is utilized to predict natural frequency of vertical vibration of the eight ships. The prediction results are close to the measured values, which proves the feasibility of this method and it provides a new idea for frequency prediction. The regression model in this paper is mainly applicable to tanker, bulk carrier and container ship, the length of which is between 70 and

Table 4 Results and errors of natural frequency of vertical vibration

Nos.	Model 3		Model 4		Measured value (Hz)	Ship types
	Predictions (Hz)	Error (%)	Predictions (Hz)	Error (%)		
1	1.157	3.55	1.162	4.02	1.117	Bulk carrier
2	1.108	1.49	1.091	2.98	1.125	Bulk carrier
3	1.389	2.89	1.548	14.66	1.350	Bulk carrier
4	1.190	2.24	1.182	2.86	1.217	Bulk carrier
5	0.944	1.23	0.944	1.20	0.933	Tanker
6	1.150	1.53	1.068	5.75	1.133	Tanker
7	0.770	3.79	0.779	2.58	0.800	Tanker
8	1.266	0.09	1.253	1.09	1.267	Container ship

Table 5 Results and errors of natural frequency of vertical vibration

Nos.	Kumai formula recommended by DNV		Formulas in Japanese shipbuilding design handbook		Industry standard of China		Prediction of SVM		Measured value
	Frequency (Hz)	Error (%)	Frequency (Hz)	Error (%)	Frequency (Hz)	Error (%)	Frequency (Hz)	Error (%)	
1	0.850	23.90	1.103	1.25	0.998	10.65	1.139	1.98	1.117
2	0.943	16.18	1.341	19.20	1.107	1.60	1.104	1.90	1.125
3	1.307	3.19	1.777	31.63	1.497	10.89	1.403	3.93	1.350
4	1.045	14.13	1.301	6.90	1.181	2.96	1.232	1.24	1.217
5	0.673	27.87	0.881	5.57	0.894	4.18	0.954	2.22	0.933
6	0.893	21.18	1.086	4.15	1.194	5.38	1.132	0.12	1.133
7	0.583	27.13	0.794	0.75	0.783	2.13	0.789	1.40	0.800
8	1.034	18.39	1.371	8.21	1.301	2.68	1.256	0.87	1.267

Table 6 Results and errors of natural frequency of vertical vibration

Nos.	44 Training samples				30 Training samples				Measured value (Hz)	Ship types
	Model 2		Model 3		Model 2		Model 3			
	Predictions (Hz)	Error (%)	Predictions (Hz)	Error (%)	Predictions (Hz)	Error (%)	Predictions (Hz)	Error (%)		
1	1.150	2.95	1.154	3.31	1.151	3.04	1.152	3.13	1.117	Bulk carrier
2	1.102	2.04	1.099	2.31	1.100	2.22	1.098	2.40	1.125	Bulk carrier
3	1.449	7.33	1.450	7.41	1.455	7.78	1.455	7.78	1.350	Bulk carrier
4	1.276	4.85	1.270	4.35	1.313	7.89	1.312	7.81	1.217	Bulk carrier
5	0.951	1.93	0.942	0.96	0.955	2.36	0.940	0.75	0.933	Tanker
6	1.118	1.32	1.117	1.41	1.118	1.32	1.116	1.50	1.133	Tanker
7	0.771	3.63	0.751	6.13	0.758	5.25	0.742	7.50	0.800	Tanker
8	1.261	0.47	1.260	0.55	1.265	0.13	1.273	0.50	1.267	Container ship

330 m. Only three types of ship are calculated in this paper because of the limitation of the accumulated data. More data of different types of ships are needed to be collected and more influential factors are needed to be considered to make the prediction results more accurate and the range of application more wide in the following research.

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