A ship-motion prediction algorithm based on modified covariance method and neural networks

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ABSTRACT

In order to provide accurate ship-motion prediction for safe seaboard operations, this paper presents a new ship-motion prediction algorithm based on modified covariance (MCOV) method and neural networks. This algorithm firstly uses the MCOV method to analysis spectrums of the ship motion. And then, major spectrums of the ship motion are used to find the ship motion model by using the Neural Network (NN). Simulation results show that this method can present a confidence performs on ship-motion prediction.

Keywords: Ship motion prediction, modified covariance method, neural network.

1. INTRODUCTION

While sailing in the sea, the ship will be affected by wind, waves and other sea conditions, and produce a six-degree-of-freedom swaying motion. These motions can lead a bad influence on the seaboard operations, like the safe navigation of the ship, the take-off and landing of carrier-based aircraft, the ship replenishment activities, etc.[1-3]. In that case, using the inertial measurement to measure ship motion and achieve 5 to 10 seconds of ship-motion prediction, has great significance for enhancing seaboard operational safety, improving ship motion control effects and ship combat effectiveness[4].

The researching ship-motion prediction methods conclude the spectral estimation method, the time series method, the Kalman filter method, etc. Those methods can obtain motion prediction results, but have different shortcomings. For example, the spectral estimation method can analyse and forecast the ship motion by using the perspective of energy superposition[5], which is too complex and abstract for using. The time-series method forecasts the ship motion by using the linear autoregressive sequence (AR) or autoregressive moving average model (ARMA)[6-8], which needs complex models and the forecasting results are not very good. The Kalman filter method considers the wave excitation as white noise, and the accuracy of the prediction results will be reduced with time growing[9, 10].

In order to solve the problem of ship-motion prediction, this paper presents a new ship-motion prediction algorithm based on modified covariance method and neural networks. This method considers the ship motion as a non-stationary random process, and uses the modified covariance method to analyse and decompose the ship motion into different frequencies periodic motions based on the power spectral density. After that, the BP neural network is used to simulate the ship motion model. The simulation experiment results show that this method can provide effective ship-motion prediction results, which are better than autoregressive sequence (AR), neural network (NN) and Wiener filter (Wiener).

2. SHIP-MOTION MODEL

The ship-motion affected by sea waves mainly includes roll, pitch, yaw, sway, surge and heave. It is a typical stable random process and has strong correlation and periodicity, which can be analysed and descripted by limited sine signal and white noise[11].

$$y_{(t)} = \sum_{i=0}^{k} A_i \sin(\omega_i t + \varphi_i) + w(t) \tag{1}$$

Among them, y is one kind of the ship motion (roll, pitch, yaw, sway, surge and heave), $\omega_i (i = 1, \cdots, k)$ is the periodic motion frequency, A_i and φ_i are the periodic motion amplitude and phase respectively.

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3. SHIP-MOTION PREDICTION ALGORITHM

The process of the ship-motion prediction method based on the modified covariance method and neural network is shown in Figure 1. Firstly, the ship-motion inertial sensors are used to obtain the ship motion data; secondly, the modified covariance method is used to analysis the main periodic frequency of the ship motion; finally, the BP neural network is used to form the ship-motion prediction model, and provide ship-motion prediction data.

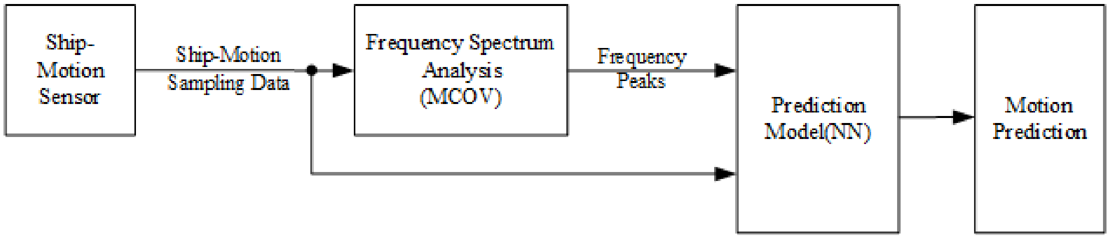

Figure 1. The process of the ship-motion prediction method base on MCOV and NN.

3.1. Power spectrum analysis

This paper uses the modified covariance method (MCOV) to analyse the power spectrum of the ship motion, and decomposes it into several periodic motions with different frequencies.

As a typical stationary random process, the ship-motion has same statistical characteristics in forward measurement sequences and reverse measurement sequences. The MCOV method uses the total energy of the prediction error, which is the minimum squares sum of the forward prediction error and the backward prediction error[12], to estimate the power spectral density of the ship motion.

The total energy of the prediction error is,

$$\varepsilon = \sum_{n=p}^{N-1}\left[e_p^f(n)^2 + e_p^b(n)^2 \right] \tag{2}$$

where, $e_p^f(n)$ and $e_p^b(n)$ are the forward prediction error and the backward prediction error respectively, which can be calculated by

$$\sum_{n=p}^{N-1}\left[e_p^f(n)^2 \right] = \sum_{n=p}^{N-1}\left[\sum_{i=0}^{p} a_{pi} x(n-i) \right]\left[\sum_{j=0}^{p} a_{pj} x^*(n-j) \right] \tag{3}$$

$$\sum_{n=p}^{N-1}\left[e_p^b(n)^2 \right] = \sum_{n=p}^{N-1}\left[\sum_{i=0}^{p} a_{pi} x^*(n-p+i) \right]\left[\sum_{j=0}^{p} a_{pj} x(n-p+j) \right] \tag{4}$$

Obviously when

$$\frac{\partial \varepsilon}{\partial a_{pj}} = \sum_{n=p}^{N-1}\left[\sum_{i=0}^{p} a_{pi} x(n-i) x^*(n-j) + \sum_{i=0}^{p} a_{pi} x^*(n-p+i) x(n-p+j) \right] = 0 \quad (j = 1,2,\cdots,p) \tag{5}$$

The total energy of the prediction error ε is the smallest, and the prediction accuracy of the model is highest.

From equation (5), we can obtain:

$$\begin{aligned} &\sum_{i=0}^{p} a_{pi}\left[\sum_{n=p}^{N-1} x(n-i) x^*(n-j) + \sum_{n=p}^{N-1} x^*(n-p+i) x(n-p+j) \right] \\ &= -\left(\sum_{n=p}^{N-1} x(n) x^*(n-j) + \sum_{n=p}^{N-1} x^*(n-p) x(n-p+j) \right) \end{aligned} \tag{6}$$

By introducing of the vector $C(i,j)=(\left[\sum_{n=p}^{N-1}x(n-i)x^{*}(n-j)+\sum_{n=p}^{N-1}x^{*}(n-p+i)x(n-p+j)\right])$, the linear equation (6) can be expressed in the matrix form

$$C_p \cdot A_p = E_p \tag{7}$$

where

$$C_p=\begin{bmatrix} C(0,0) & C(0,1) & \cdots & C(0,p) \\ C(1,0) & C(1,1) & \cdots & C(1,p) \\ \vdots & \vdots & \ddots & \vdots \\ C(p,0) & C(p,1) & \cdots & C(p,p) \end{bmatrix}$$

is p+1 order square matrix, and

$$A_p=\begin{bmatrix} 1 & a_{p,1} & \cdots & a_{p,p} \end{bmatrix}^T,\ E_p=\begin{bmatrix} \sigma^2 & 0 & \cdots & 0 \end{bmatrix}^T$$

After solving the equations (7), we can get $A_p = C_p^{-1} \cdot E_p$, where A_p is the optimal prediction coefficient under the minimum error criterion.

In order to solve equation (7), Marple proposed an efficient recursive algorithm. The algorithm introduces additional error energy $\varepsilon' = \sum_{n=p}^{N-2}\left[e_p^f(n+1)^2 + e_p^b(n)^2\right]$ and $\varepsilon'' = \sum_{n=p}^{N-2}\left[e_p^f(n)^2 + e_p^b(n+1)^2\right]$, to calculate the autoregressive coefficient $a_k(i=1,2,\cdots,p)$ and white noise σ^2 [13].

After obtaining $a_k(i=1,2,\cdots,p)$ and σ^2, the power spectrum of the ship motion can be obtained by the power spectrum density calculation formula, which is:

$$P_{(e^{j\omega})}=\frac{\sigma^2}{\left|1+\sum_{k=0}^{p}a_k e^{-j\omega}\right|^2} \tag{8}$$

Taking the calculated power spectrum peak as the main periodic frequency of the ship motion, we can obtain several main periodic motion frequencies in the ship motion.

3.2. Ship-motion prediction model

Based on the main periodic frequency of the ship motion $\tilde{\omega}_i(\mathrm{i}=1,\cdots,\mathrm{k})$ estimated by the MCOV method, the ship-motion prediction model can be established as follows:

$$\tilde{y}_{(t)}=\sum_{i=0}^{k}\tilde{A}_i\sin(\tilde{\omega}_i t+\tilde{\varphi}_i)=\tilde{\alpha}_0\sin(\tilde{\omega}_0 t)+\tilde{\beta}_0\cos(\tilde{\omega}_0 t)+\cdots+\tilde{\alpha}_k\sin(\tilde{\omega}_k t)+\tilde{\beta}_k\cos(\tilde{\omega}_k t) \tag{9}$$

where, $\tilde{y}$ is the estimated ship motion, $\tilde{\omega}_i(i=1,\cdots,k)$ is the periodic motion frequency obtained by the modified covariance method, $\tilde{A}_i$ and $\tilde{\varphi}_i$ are the amplitude and phase of the periodic motion, respectively.

By introducing $\tilde{x}_{(t)}=\begin{bmatrix}\sin(\tilde{\omega}_0 t) & \cos(\tilde{\omega}_0 t) & \cdots & \sin(\tilde{\omega}_k t) & \cos(\tilde{\omega}_k t)\end{bmatrix}^T$, we can use the BP neural network (NN) method[14, 15] to obtain the ship-motion prediction model parameters $\tilde{\alpha}_i$ and $\tilde{\beta}_i$.

The BP neural network adopts a three-layer neural network structure. The input layer is the ship motion data, which takes one node. The output layer is the non-linear ship-motion prediction model, which also take one node. The hidden layer takes three nodes, to estimate the non-linear mapping from input to output:

$$\tilde{y} = G(x) = \sum_{m=1}^{M} W_m f\left[\sum_{j=1}^{N} w_{mj} x_j\right] \tag{10}$$

where $x_j = \tilde{x}_{(j)}$ is the input of the BP neural network; $G(x)$ is the unknown nonlinear mapping; $f(x)$ is the activation function; N and M is the number of the input layer nodes and the hidden layer nodes, respectively. In the training of the BP neural networks, W_m and w_{mj}, the weights of the neural network, will be continuously adj usted to minimize.

$$E = \frac{1}{2}\sum_{p=1}^{l}(y_p - \tilde{y}_p)^2 \tag{11}$$

where l is the number of the training data.

When the neural network training is completed, the ship-motion prediction model $\tilde{y}_{(t)}$ can be obtained.

4. EXPERIMENT ANALYSIS

4.1. Ship-motion prediction experiment

This paper uses real ship roll motion data to predicate ship roll motion in advance 5 seconds and 10 seconds, respectively. The ship roll motion data is obtained by shipboard inertial navigation measurement (as shown in Figure 2), and the data's sampling frequency is 10 Hz.

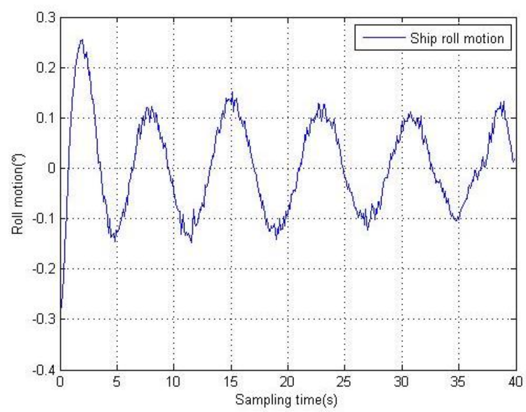

Figure 2. 40 seconds ship roll motion data.

A ship-motion prediction model is established based on 40 seconds ship roll motion data, and predict the ship's roll angle in advance 5 seconds and 10 seconds. The prediction results are shown in Figures 3 and 4, respectively.

The experimental results show that, the ship-motion prediction method, which is based on the modified covariance method and neural network, can obtain effective prediction results in the given sea conditions. The deviation between the predicted roll angle and the real roll angle is less than 0.02 degrees.

4.2. Comparative experiment

In order to better analyse the accuracy of the prediction method, we design four different experiments, by using 20-second and 40-second motion data to predict the ship motion in advance 5 seconds and 10 seconds, respectively. Every experiment will be carried out 50 times. After that, the average error and standard deviation of each experiment's results will be calculated, and compared with the autoregressive sequence (AR), the neural network (NN) and the Wiener filter (Wiener). The comparison experiments' results are shown in Tables 1 and 2.

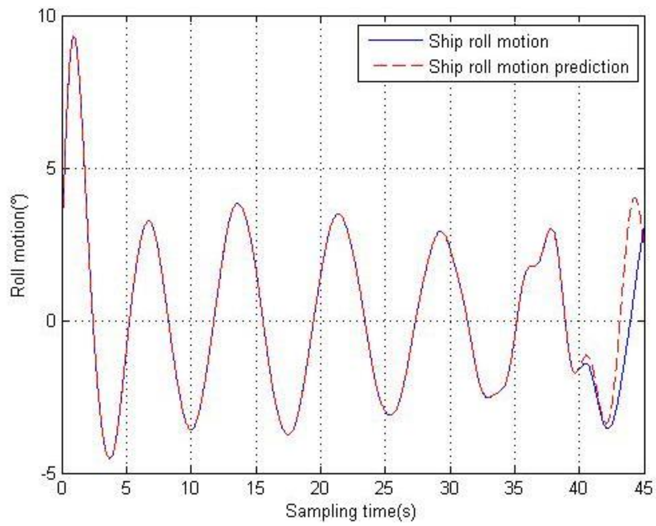

Figure 3. Roll motion prediction in advance 5 seconds.

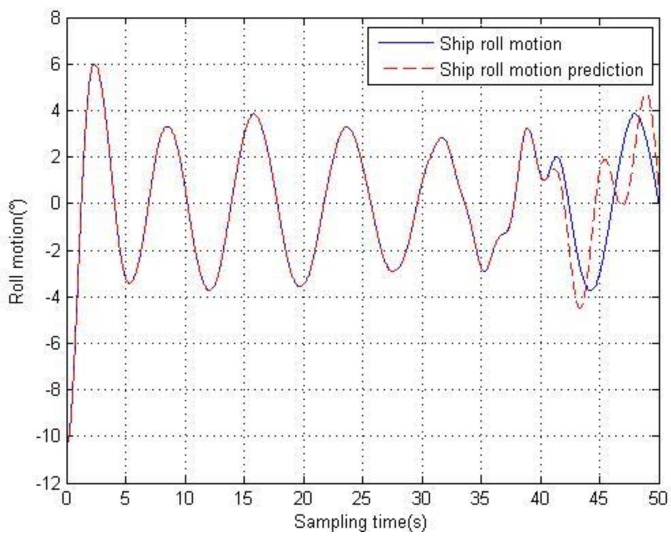

Figure 4. Roll motion prediction in advance 10 seconds.

Table 1. Performance for four prediction methods in advance 5 seconds.

Data sampling time	Parameter	MCOV+NN	AR	NN	Wiener
20 seconds	The average error (degree)	0.0018	0.1505	0.0043	0.0086
	Standard deviation (degree)	0.0171	0.1089	0.0542	0.0427
	Execution Time (second)	0.2369	0.3205	0.1799	1.0837
40 seconds	The average error (degree)	0.0030	0.1578	0.0035	0.0166
	Standard deviation (degree)	0.0241	0.1086	0.0405	0.0481
	Execution time (second)	0.2969	0.3215	0.3580	1.0786

Table 2. Performance for four prediction methods in advance 10 seconds.

Data sampling time	Parameter	MCOV+NN	AR	NN	Wiener
20 seconds	The average error (degree)	0.0059	0.1838	0.0076	0.0160
	Standard deviation (degree)	0.0647	0.1349	0.0944	0.1103
	Execution time (second)	0.2327	0.3360	0.3370	0.9940
40 seconds	The average error (degree)	0.0060	0.1729	0.0256	0.0182
	Standard deviation (degree)	0.0735	0.1358	0.1345	0.0820
	Execution time (second)	0.2688	0.3409	0.4337	1.0263

The comparison results show that, when using 40-second motion data, the average error of the 5-second prediction results is 0.0030°, and the standard deviation is 0.0241°; the average error of the 10-second prediction results is 0.0060°, and the standard deviation is 0.0735°. Meanwhile, this method can obtain better prediction effect when the motion data is less than 40 seconds. The average error of the 5-second prediction results is 0.0018°, the average error of the 10-second prediction results is 0.0059°, and the standard deviations are 0.0171° and 0.0647°, respectively. Except for special indicator (20-second motion data, 5-second execution time), the average error, standard deviation and algorithm execution time of this method are better than AR, NN and Wiener. In that case, this ship-motion prediction method can obtain an effective prediction result in different and complicated sea conditions.

5. CONCLUSION

The research of the ship-motion prediction has significant effect for the ship's safe navigation, the take-off and landing of carrier-based aircraft, the ship replenishment activities, and other seaboard operations. In that case, this paper proposes a new ship-motion prediction method based on the modified covariance method and neural network. The method uses the MCOV method to analysis spectrums of the ship motion, and then uses major spectrums of the ship motion to found the ship motion model through the Neural Network (NN). Simulation results show that this method can present a confidence performs on ship-motion prediction, and better adapt to different and complicated sea conditions.

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