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Research on Hovercraft Motion Prediction Based on Compound prediction*

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***Abstract* – Due to the strong coupling characteristic of the hovercraft during the movement and its own structural specificity, the hovercraft has poor maneuverability and is prone to danger during the navigation. In order to predict the attitude of the hovercraft and improve the hovercraft safety, this paper proposes a novel compound prediction model based on grey theory and improved Elman neural network. Grey prediction has the structural advantages of low number of original data and less effective information, but its processing ability to non-linear systems is weak. Elman neural network has the function of self-learning and self-organizing to solve the non-linear system. By combining the two models, a non-linear system with less raw data can be processed. The model prediction results are determined by the individual prediction results and the weighted weight values of the model. Different weight coefficient ratios are assigned to different models to jointly obtain the results of the final compound prediction model. The simulation results show that this kind of compound prediction method has higher prediction accuracy with smaller predictive error in the hovercraft motion prediction application.**

Index Terms - Hovercraft; Motion prediction; Compound prediction; Grey prediction; Elman prediction.

I. Introduction

As a kind of most typical high-speed ship, the air cushion vehicle (ACV), also called hovercraft, has received the attention of all countries with its unique advantages. The maneuverability of hovercraft is quite poor during its motion control process because of its nonlinear strong coupling characteristic and the uncertainty of environment and system [1]. Besides, the hovercraft floating on the surface of the water make the hull lack of underwater rotating parts due to its own structural specificity, so it is easy to produce side slip and tail flick during maneuvering process, which may cause the risk of overturning [2]. The above problems highly increase the difficulty of manipulate and control of the hovercraft. Therefore, the hovercraft motion prediction becomes an important solution for safe navigation of high-speed hovercraft.

In order to realize the prediction of hovercraft motion parameters, many scholars have done research in this field. The statistical prediction method uses the integral equation as a calculation tool to obtain the prediction results by judging the minimum mean square error [2]. Jianjun Hun et al used statistical prediction methods and proved that the theory can predict the ship's pitch state effectively in a very short time, but when the prediction duration is larger, the prediction bias also becomes larger. P.Kaplan proposed a convolution method for motion prediction. This theory uses convolution processing for ship motion state prediction using shipboard position wave height and ship response kernel function [2]. However, this theory requires accurate response kernel functions and wave height values, which are limited by maritime experiments. M.Traintayfllou et al. first used Kalman filter for motion prediction of ships and discussed the applicability of the method [3]. The ship's equation of state is needed in the calculation process, but the parameters of the ship that change in the marine environment lead to uncertainty of the state equation, so the method is not widely used in ship prediction. The grey theory was first proposed by Julong Deng [3]. The advantages of this theory are that the requirements for the amount of predicted data are low, the calculation is simple, and it is suitable for systems with strong periodicity. Jihong Shen and Lihong Sun first used the grey prediction method in the prediction of the motion state of the ship. However, the larger pitch angle the hovercraft is, the larger prediction deviation is. Many scholars used neural network to study ship motion prediction. The advantage of the neural network is that if the data volume of the training data set is large enough, the regularity of the data can be automatically analyzed through the continuous training of the neural network, and the well trained neural network model can effectively obtain the desired results [4].

Inspired by references [6-8], this paper proposes a compound prediction model for hovercraft motion based on grey theory and Elman neural network. Elman neural network not only has additional memory neurons and local feedback, but also has certain dynamic advantages [8-10]. The grey model can be built with only a few data, and can be used for prediction with high accuracy [9]. The compound prediction model connects two models in parallel, and assigns different weight values to the prediction results of each prediction model to obtain the final prediction results. This compound prediction model can make up the shortcomings of single prediction model and reduce the situation in which single model can easily miss valid information. The combined model

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can effectively improve prediction accuracy and reduce bias in prediction results. The simulation results show that this compound prediction model can improve the prediction accuracy in hovercraft motion prediction as an effective motion prediction method.

II. Predictive Model

A. Grey prediction model

Grey system theory is a way that deals with the uncertainty of a few data. Grey denotes the uncertainty of the data [11]. It theoretically holds that all grey sequences of the system can weaken its randomness through some kinds of generation and show its regularity. GM(1,1) is the basic grey model. It has the characteristics of differential and exponential compatibility [12]. The model parameters are adjustable and the structures can change with time, which break the limitations of general modeling requires a large amount of data.

Assuming that $X^{(0)}$ is an initial non-negative data sequence with n samples as following

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)) \quad (1)$$

Taking an accumulative calculation on the original sequence $X^{(0)}$, a first-order accumulated sequence is calculated $X^{(1)}$.
where $X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n))$ is derived by

$$x^{(1)}(k) = \sum_{i=0}^{k} x^{(0)}(i) \quad (2)$$

From $X^{(1)}$, we can form the first-order differential equation with

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = u \quad (3)$$

The Equation (3) is original form of GM(1,1) prediction model. The basic form of GM(1,1) is to analyze time-delay sequence with average idea. Where the parameters a and u in GM(1,1) are called the development coefficient and grey action quantity, respectively.

Constructing a series of sequence $Z^{(0)}$,

$$Z^{(0)} = (z^{(0)}(1), z^{(0)}(2), \dots, z^{(0)}(n)) \quad (5)$$

where

$$\begin{aligned} &Z^{(1)}(k) = \beta x^{(1)}(k-1) + (1-\beta) x^{(1)}(k), \\ &k = 2,3,\dots n, \beta = 0.5, \end{aligned} \quad (6)$$

Change the differential formula to the differential formula to get the result

$$x^{(1)}(k) + az^{(1)}(k) = u \quad (7)$$

The development coefficient a and u are calculated by the least squares method

$$\begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T Y_n \quad (8)$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \cdots \\ -z^{(1)}(4) & 1 \end{bmatrix} \qquad Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ x^{(0)}(4) \end{bmatrix} \quad (9)$$

The solutions of a and u in formula (8) are introduced into the differential equation of GM(1,1) model.

Therefore, GM(1,1) prediction model can be obtained

$$\begin{aligned} &\hat{x}^{(1)}(k) = \left[x^{(0)}(1) - \frac{u}{a} \right] e^{-a(k-1)} + \frac{u}{a} \\ &k = 2,3,\dots n \end{aligned} \quad (10)$$

Then the prediction result of the initial sequence can be calculated by the cumulative sequence

$$\begin{aligned} &\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1) \\ &k = 2,3,\dots n \end{aligned} \quad (11)$$

B. Elman neural network prediction model

Elman neural network model is a typical dynamic regression neural network. Dynamic attributes are mapped by storing internal states. Compared with the traditional feedforward network, the model has a receiving layer in its hidden layer, also known as the delay operator, which can realize the dynamic memory function, make the neural network system adapt to the time-varying characteristics, and can directly identify and analyze the characteristics of the dynamic process system [13]. The structure of Elman neural network is shown in Fig 1, which includes input layer, hidden layer, output layer and receive layer.

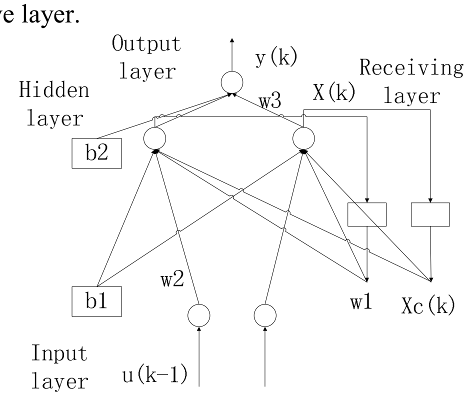


Fig. 1 Elman neural network structure

According to the analysis of the Elman neural network model, the formulas for calculating the non-linear state space are arranged as follows

$$\begin{aligned} &y(k) = g(w^3 x(k) + b_2) \\ &x(k) = f(w^1 x_c(k) + w^2 u(k-1) + b_1) \\ &x_c(k) = x(k-1) + a x_c(k-1) \end{aligned} \quad (12)$$

Where $y(k)$, $x(k)$ and $u(k)$ are the m-dimensional unit vector of the output layer neurons, the n-dimensional unit vector of the hidden layer neuron and the r-dimensional unit vector of the input layer neurons at time k, respectively. $x_c(k)$ is the n-dimensional unit vector of the receiving layer neurons at time k. Where $w^1 \in R^{n*n}$, $w^2 \in R^{n*r}$ and $w^3 \in R^{m*n}$ are the connection weight between receiving layer and hidden layer, the connection weight between input layer and hidden layer and the connection weight between hidden layer and output layer, respectively [14]. b_1 and b_2 represent the thresholds of the input and hidden layers, respectively. a is the self-joining feedback gain factor and takes a value of $[0,1]$. The function $g(x)$ is the transfer function of the output layer. The function $f(x)$ is the receiving layer unit transfer function, and taken as a sigmoid function

$$f(x) = \frac{1}{1+e^x} \tag{13}$$

The detailed learning algorithm is as follows

$$\begin{aligned}
&\Delta w_{ij}^3 = \eta_3 \delta_i^0 x_j(k), \\
&\Delta w_{jq}^2 = \eta_2 \delta_j^h x_q(k-1), \\
&\Delta w_{ij}^3 = \eta_1 \sum_{i=1}^{m} (\delta_i^0 w_{ij}^3) \frac{\partial x_j(k)}{\partial w_{jl}^1} \delta_i^0 x_j(k), \\
&\delta_i^0 = (y_{d,i}(k) - y(k)) g_i^{'}(\cdot), \\
&\delta_j^h = \sum (\delta_i^0 w_{ij}^3) f_j^{'}(\cdot), \\
&i = 1, 2, \ldots n \qquad j = 1, 2, \ldots n \\
&q = 1, 2, \ldots n
\end{aligned} \tag{14}$$

where η_1, η_2, η_3 is learning step of w^1, w^2, w^3.

C. *Elman neural network prediction model based on information entropy*

When traditional Elman neural network performs data prediction, the weight values of the input data are the same. This means that each individual data in input sample has the same effect on output. However, in practice, the closer to value of prediction time, the greater impact on prediction results. Therefore, this paper uses the information entropy weighting algorithm to calculate the input data weights and establish the information entropy weighted Elman neural network. Adding an information entropy data weighting layer between input layer and hidden layer of the Elman network, convert the Elman network into a five-layer network. An improved Elman neural network structure is shown as Fig 2.

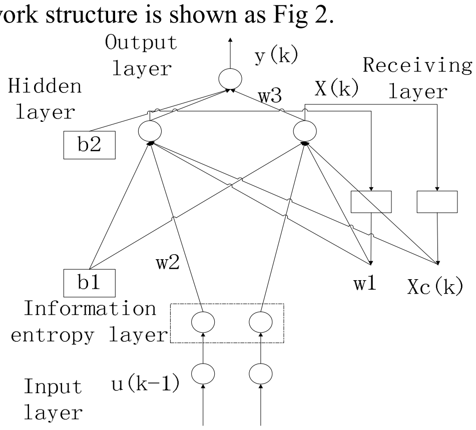


Fig. 2 Improved Elman neural network structure

The n data input by the system is denoted by the discrete random variable $X = \{x_1, x_2, \ldots x_n\}$, and the probability of each information data is denoted by $p_1, p_2, \ldots p_n$

$$p_i = x_i / \sum_{i=1}^{n} x_i \qquad i = 1, 2, \ldots n \tag{15}$$

Setting the information structure of the system as follows

$$S = \begin{pmatrix} X \\ P \end{pmatrix} = \begin{pmatrix} x_1 & x_2 & \cdots & x_n \\ p_1 & p_2 & \cdots & p_n \end{pmatrix} \tag{16}$$

Then, the information entropy of each input data in the system is defined as

$$\begin{aligned}
&E_i = -kp_i \ln p_i \qquad i = 1, 2, \ldots n \\
&k = \log_2 e
\end{aligned} \tag{17}$$

The prediction method uses information entropy weighting on the input information of the system, and the weighting coefficient w_i is defined as

$$w_i = E_i / \sum_{i=1}^{n} E_i \qquad i = 1, 2, \ldots n \tag{18}$$

The information entropy weighting layer can determine the degree of influence on the output results, through the amount of data information of the input layer.

III. High-Precision Prediction Model Based On Grey Elman Neural Network

Grey prediction can predict raw data with less quantity and effective information. However, because its basic model is a first-order differential equation, its ability to deal with non-linear systems is relatively weak. Elman neural network has the function of self-learning and self-organizing to solve the non-linear system. Based on the above considerations, a compound prediction model is proposed in this paper.

The compound prediction model is shown in Fig 3.

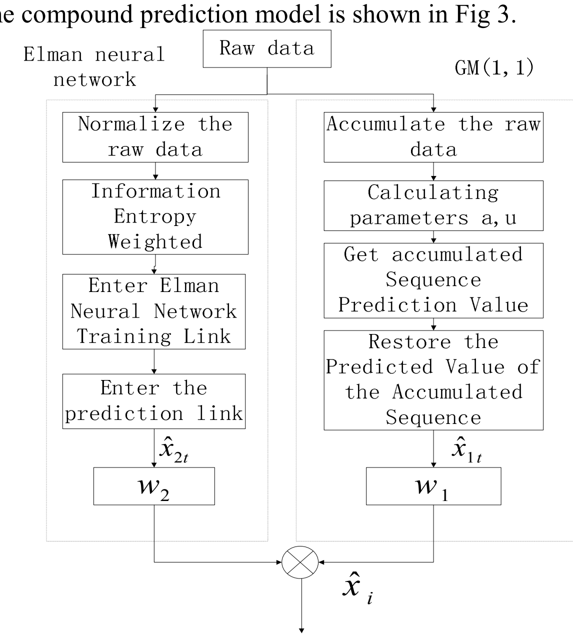


Fig. 3 Compound prediction flow chart

Let x_i be the input data set and $\hat{x}_{it}$ be the prediction results of the $i\text{-}th$ separate model at time t. Then, $e_{it} = x_i - \hat{x}_{it}$ is the deviation of the predicted results of the $i\text{-}th$ separate model at time t from the true results. w_i is the weight coefficient of the $i\text{-}th$ separate prediction model. The final data forecast results are as follows

$$\hat{x}_i = w_1\hat{x}_{1t} + w_2\hat{x}_{2t} + \cdots + w_m\hat{x}_{mt} = \sum_{i=1}^{m} w_i\hat{x}_{it} \tag{19}$$

where $i = 1,2,\ldots m$, $t = 1,2,\ldots n$. Here, just considering $i = 2$, the weight value w_i should satisfy

$$\sum_{i=1}^{m} w_i = 1 \qquad w_i \ge 0 \tag{20}$$

The prediction error of the combined model at time t is

$$e_i = x_i - \hat{x}_i = \sum_{i=1}^{m} w_i e_{it} Peu \tag{21}$$

In the previous section, the discrete random variable $X = \{x_1, x_2, \ldots x_n\}$ in the compound prediction should be the deviation of the prediction results $\{e_1, e_2, \ldots e_n\}$ of the single prediction model. In the process of calculating the weight, the relative error of the $i\text{-}th$ single prediction model at time t is calculated at first

$$p_{it} = \frac{e_{it}}{\sum_{t=1}^{n} e_{it}}, \qquad t = 1,2,\ldots n \tag{22}$$

Calculating the relative deviation of the population of a single prediction model, $k = \log_2 e$

$$E_i = -k\sum_{t=1}^{n} p_{it} \ln p_{it} \tag{23}$$

The deviation coefficient d_i is used to represent the degree of error of the prediction model

$$d_i = 1 - E_i, \qquad i = 1,2,\ldots m \tag{24}$$

The weight coefficient w_i of the prediction model is

$$w_i = \frac{1}{m-1}\left(1 - \frac{d_i}{\sum_{i=1}^{m} d_i}\right) \tag{25}$$

The predicted output value $\hat{x}_i$ of the final combined predictive model is as follows

$$\hat{x}_i = \sum_{i=1}^{m} w_i\hat{x}_{it}, \quad t = 1,2,\ldots n \tag{26}$$

Combined with a group of measured data of a medium-sized hovercraft, the compound prediction model forecasts the data of pitch angle, roll angle, yaw angular velocity and latitude and longitude respectively.

In the combined forecasting model, two kinds of forecasting models are used to measure the data of hovercraft and different weighted values are assigned to the two measuring results. The grey prediction model can deal with the original data directly. But in the improved Elman neural network prediction model, the original data are normalized first

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \tag{27}$$

A set of data entered is denoted by $\tilde{x}_i$, $x_{\max}$ and $x_{\min}$ are the maximum and minimum values in the data, respectively.

This paper uses mean square error as an error indicator.

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \hat{x}_i)}{n}} \tag{28}$$

IV. Simulation Results

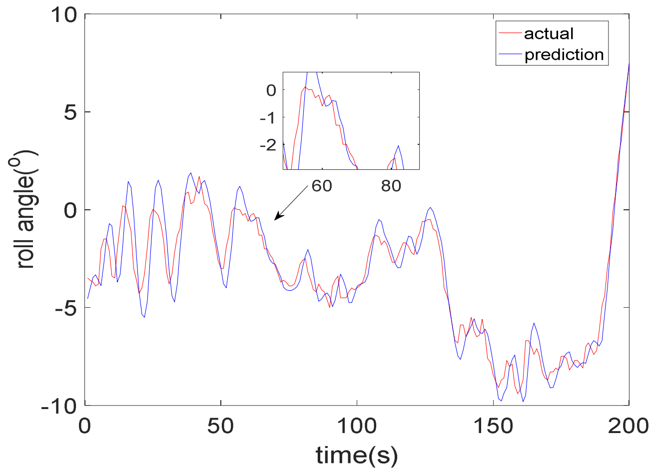
In order to verify the effectiveness of the integrated prediction model, this paper will use a group of actual navigation motion data of hovercraft for data prediction. In this paper, the pitching angle, pitching angle, yaw rate and latitude and longitude of the hovercraft will be used for data prediction. The frequency of each motion data is 200Hz, which is set to 1Hz when sampling and recording. The simulation duration is 200s. The lately 10 data values are used to predict the data in the next 2 steps. In the process of neural network training, a total of 1000 groups of measured hovercraft motion data are also used. The number of neurons in the input layer of Elman neural network is 10. The input layer is composed of two neurons. In the process of Elman neural network solution and grey prediction calculation, if there is a negative number in the data, it may lead to a virtual number in the calculation results. Therefore, before the data prediction, it is necessary to improve the calculation data.

In the simulation process, the mean square error is used as the judgment parameter of the prediction accuracy of the prediction model. The calculation results are as follows:

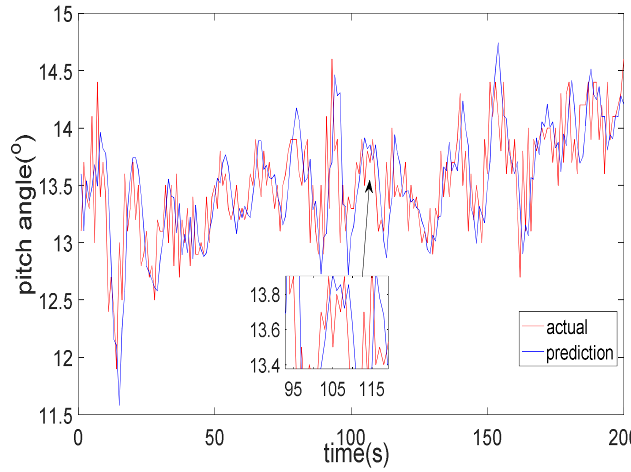
TABLE I
Mean Square Error Of Each Prediction Model Results

	Grey prediction	Improve Elman prediction	Combined prediction
Roll angle	0.9710	0.3588	0.1146
Pitch angle	0.2663	0.1670	0.0540
yaw angular velocity	3.5754	1.5188	1.4577

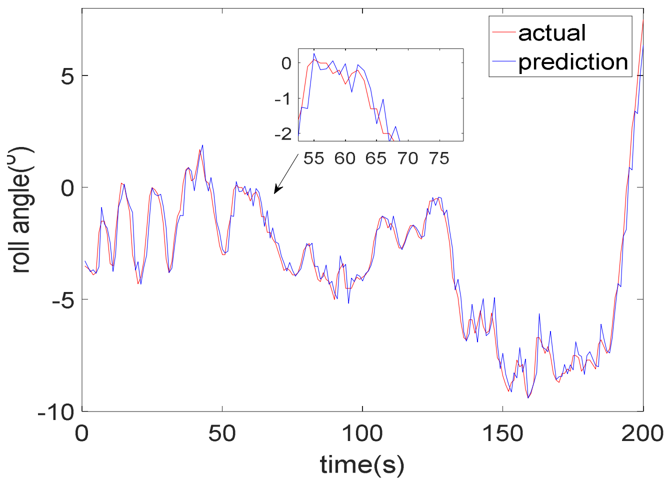
On the basis of simulation conditions, combined with a group of actual motion data of hovercraft, the compound model is simulated and verified. The simulation results are as follows:



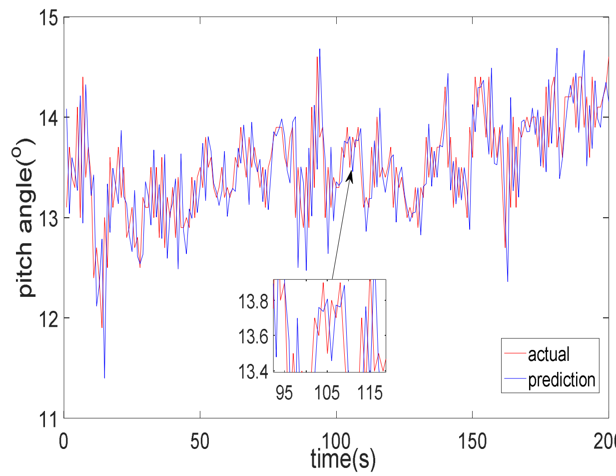
(1) GM(1,1) prediction results for roll angle



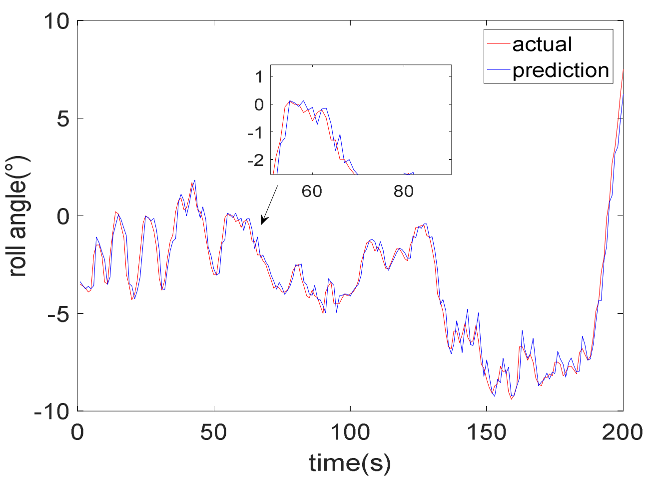
(1) GM(1,1) prediction results for pitch angle



(2) Elman model prediction results for roll angle

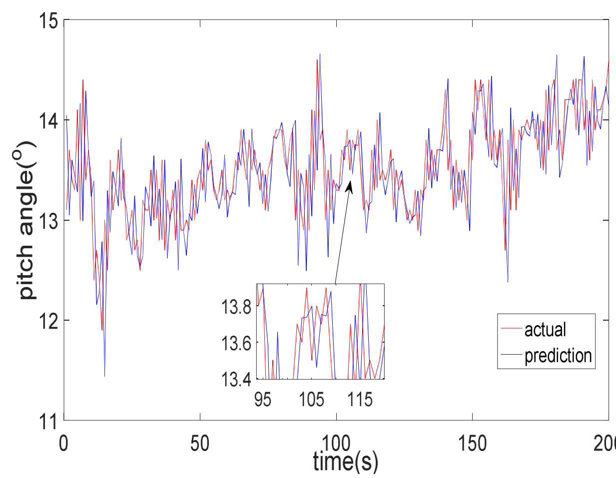


(2) Elman model prediction results for pitch angle



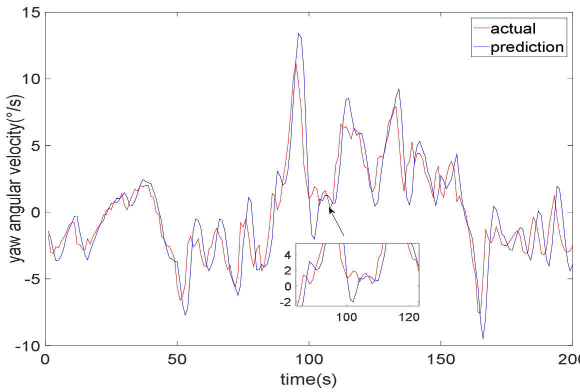
(3) Grey Elman model prediction results for roll angle

Fig. 4 Different prediction methods for roll angle

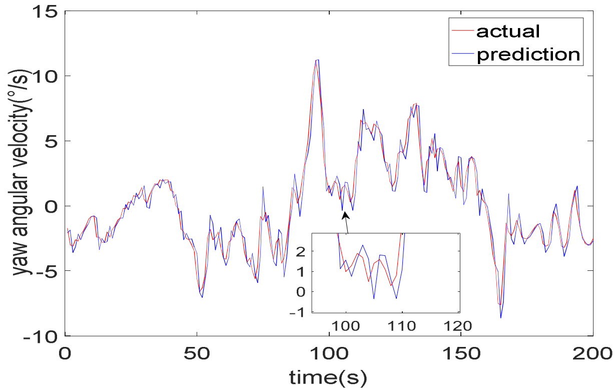


(3) Grey Elman model prediction results for pitch angle

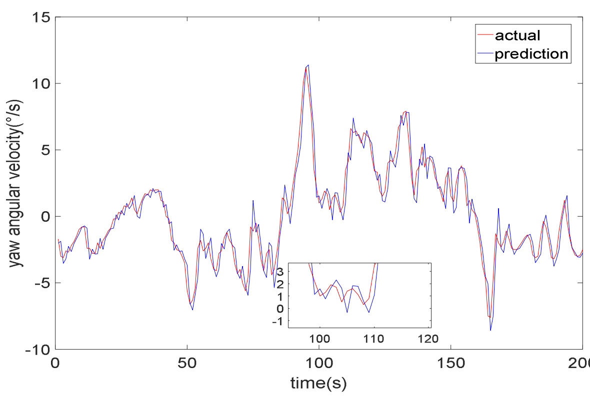
Fig. 5 Different prediction methods for pitch angle



(1) GM(1,1) prediction results for yaw angular velocity



(2) Elman model prediction results for yaw angular velocity



(3) Grey Elman model prediction results for yaw angular velocity

Fig. 6 Different prediction methods for yaw angular velocity

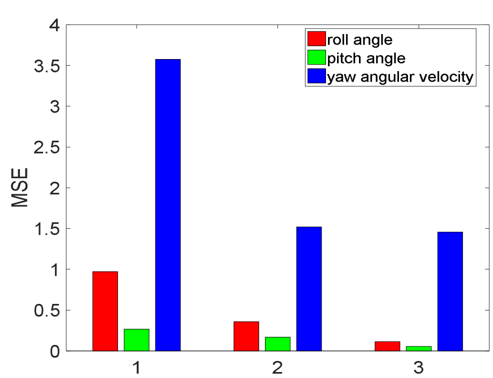


Fig. 7 Mean Square Error of Prediction Results of Various Prediction Models

It can be seen from table 1 and Figure 7 that the control effect of grey prediction model in hovercraft system is not ideal because grey prediction is applicable to linear system and hovercraft belongs to nonlinear system. The improved Elman neural network can predict the motion of the hovercraft for the nonlinear and complex hovercraft system, but there is a certain error between the actual data and the predicted data from the simulation diagram. Combined with the advantages of the two models, the simulation results show that the compound prediction model can achieve the prediction goal and the prediction error is reduced compared with the single model. Experimental results show that ensemble prediction can realize the complementary advantages of the two models and improve the accuracy of motion prediction of hovercraft.

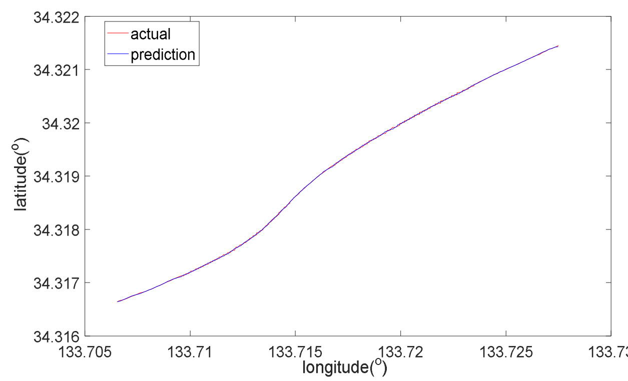


Fig. 8 Ship latitude and longitude compound prediction results map

As can be seen in Fig 8, the compound prediction can predict the latitude and longitude position information of the hovercraft. The predicted mean square error is 1.992e-9. From the mean square error, it can be found that the prediction model can effectively predict the position information of hovercraft. It can be seen that the compound prediction combines the advantages of grey prediction and improved Elman neural network prediction, and can effectively predict the hovercraft motion data.

V. CONCLUSION

Aiming at the problem of hovercraft motion prediction, a compound prediction model based on Grey Elman neural network is proposed. Combining grey theory with Elman neural network model, the multi-motion parameters of hovercraft are predicted. Grey forecasting model can weaken the randomness of original data, and Elman neural network has good forecasting ability for non-linear series. Moreover, grey forecasting model can forecast with less training data, which avoids the situation that Elman forecasting model needs a lot of data. The two models are combined in parallel, and the prediction results of the final hovercraft motion data are obtained by allocating different weight ratios and taking the mean square error as a measure. The experimental results show that among the three forecasting models, the grey forecasting model has the worst forecasting effect. The grey Elman neural network model is superior to the improved

Elman model and can predict the hovercraft very well. And the grey Elman combined forecasting model synthesizes the advantages of the two models. Compared with the existing forecasting models, it can not only deal with non-linear systems, but also use a small amount of forecasting data to predict parameters. Although the grey Elman prediction model can predict the motion of hovercraft, there are still some errors. In the future research, we can consider how to reduce the prediction error of the grey Elman model, or establish a new connection to verify the validity and accuracy.

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