Fast prediction method of propeller hydrodynamic performance based on SPF-LSTM

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Abstract. In order to realize fast and accurate prediction of hydrodynamic performance of UUV propeller, a hydrodynamic performance prediction model based on SPF-LSTM neural network was proposed in this paper, which combined with real propeller flow test and CFD numerical simulation technology. The model comprehensively considered the test data of real paddle and the simulation data based on CFD numerical simulation, and adopted the Sample penalty factor (SPF) to optimize the initial weight of the model, adjust the sensitivity of the model to different samples, and further improve the prediction accuracy. The experimental results show that the prediction results of this model are in good agreement with the test data of real propeller, and the calculation period is very short and the efficiency is high, which meets the requirement of real-time and accurate prediction of the open water performance of propeller.

Keywords: CFD, Fluent, propeller, SPF-LSTM, UUV.

1. Introduction

At present, with the increasingly urgent demand for Marine resources exploration, the performance requirements of UUV are becoming higher and higher. How to rapidly design UUV propellers according to the actual needs has become a concern of scholars around the world. The open water performance of propeller is an important basis for checking and optimizing propeller design and verifying propeller performance. At present, there are three main methods to obtain propeller open water performance: real propeller open water test, prediction method based on potential flow theory and CFD method based on viscous fluid theory. The real paddle open water test is the most accurate method to obtain the performance of open water, but the preparation process of the real paddle open water test is complicated and requires relatively perfect external conditions, so the cost is high and the ability of rapid prediction is not available. The prediction method based on potential flow theory does not take into account the viscosity of water flow itself, so the calculation error is large. The CFD method based on the viscous fluid theory considers the viscosity of the fluid, and the calculation results are of high reliability, so it has become a conventional method for the optimization design of propeller performance. However, this method depends on the performance of the computer hardware, and the calculation time is long, so it still cannot meet the requirements of real-time prediction.

Therefore, it is of great significance to develop a fast and accurate method to predict the water flow performance of propeller based on its design parameters. At present, the development of deep learning provides a new idea for solving the prediction of propeller water flow performance. Deep learning can deduce basic rules from heavy and multi-data samples, so as to predict the development trend of data. Constantinos C. Neocleous has developed a neural network system that helps naval architects select the appropriate Marine propellers to meet the required propulsion requirements [1]. Jiamin T established a fast prediction method for ship resistance performance based on convolutional neural network, and systematically analyzed the effectiveness of the method and the correlation between ship half width and ship resistance [2]. The open water performance prediction model (IDRN) proposed by Nan G is combined with Inception structure on the basis of residual connection structure to predict the open water performance of different types of propellers [3]. Mohammad Mahdi Shora predicts hydrodynamic performance and cavitation volume of propeller under predetermined conditions based on BP neural network [4]. In short, the speed and accuracy of machine learning have been recognized and applied by more and more scholars in the aspect of rapid optimization of propeller design.

In this paper, three methods of real oar open water test, CFD numerical simulation and deep learning were combined, the results of real oar open water test and CFD numerical simulation were used as the input of deep learning, and SPF-LSTM neural network was used to optimize the initial weights of the two types of data, strengthen the sensitivity of the model to the data of real oar open water test, and improve the prediction accuracy of the model. It can provide reference for the rapid design of propeller.

2. Design the input data set

In order to ensure the validity of input for model design, two types of data, namely CFD numerical simulation and real paddle open water test, are used in this paper. Although the calculation time of CFD numerical simulation is long, a large number of experimental data of propeller water flow can be obtained. The real propeller open water test process is complicated and the data amount is small, but accurate propeller water flow test data can be obtained. Both types of data can be used as design input for SPF-LSTM.

2.1 CFD numerical simulation

The CFD method of propeller is mainly used in the performance optimization and design of propeller. The performance characteristics and flow field distribution of propellers with different shapes and working conditions can be obtained by CFD numerical simulation. The main scale parameters of the propeller in this paper are shown in Table 1.

Table 1. Main scale parameters of propeller.

Definition	Symbol	Characteristic
Diameter	D (m)	FS_1
Pitch ratio	P/D	FS_2
Disk area ratio	AE/A0	FS_3
Hub ratio	dh/D	FS_4
Number of blades	Z	FS_5
Side bevel	Skew (°)	FS_6
Trim Angle	Rake (°)	FS_7
Rotational speed	V	FS_8
Force	FN	WP_2
Torque	T	WP_3

In terms of watershed and grid division, this paper adopts the calculation method of multiple reference frames, takes propeller as the dividing line, and divides the whole watershed into static and dynamic regions. All basins adopt cylindrical regions, and the scale of the whole is shown in Figure 1. The mesh unit is divided into tetrahedral unit and hexahedral unit to encrypt the propeller area.

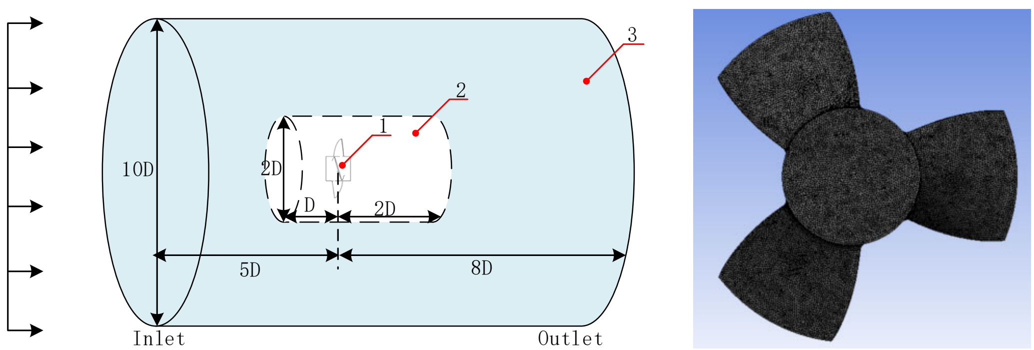

Figure 1. Watershed and grid division

Boundary conditions were set for the model. The state of fluid and water medium was pure, constant temperature and incompressible. Factors such as cavitation, impurities and heat transfer were ignored, and only the steady-state open water test of the propeller was considered. Among them, blade and propeller hub adopt smooth adiabatic wall condition without sliding. Turbulence model adopts SST k-ω model, which makes up for the shortcomings of model and model respectively. Its equation can be expressed as:

$$\frac{\partial}{\partial t}(\rho k)+\frac{\partial}{\partial x_i}(\rho k u i)=\frac{\partial}{\partial x_j}\left(\Gamma_k \frac{\partial k}{\partial x_j}\right)+G_k-Y_k \tag{1}$$

$$\frac{\partial}{\partial t}(\rho\omega)+\frac{\partial}{\partial x_j}(\rho\omega uj)=\frac{\partial}{\partial x_j}\left(\Gamma_\omega \frac{\partial \omega}{\partial x_j}\right)+G_\omega-Y_\omega+D_\omega \tag{2}$$

Where, G_K is the generation term of turbulent kinetic energy; k is turbulent kinetic energy; ρ is density; u_i is the average amount of turbulent velocity; x_j is the coordinate component; D_ω is the cross-diffusion term; ω is turbulence special dissipation.

2.2 Real propeller open water test

In order to obtain the water flow performance of the real propeller, 3D printing technology is used to manufacture the real propeller, and the real propeller test is carried out in the pool, and the measured data of part of the propeller is obtained. The test process is shown in Figure 2.

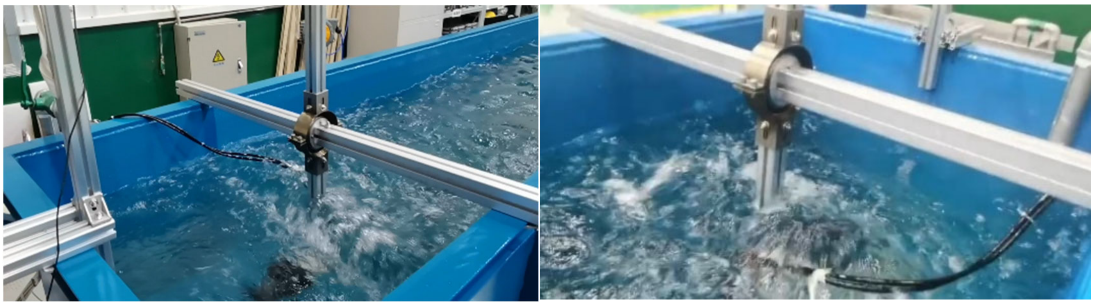

Figure 2. Real propeller open water test

Based on the above process, a large number of propeller CFD numerical simulation data and real propeller water flow test data can be obtained, providing sufficient data sets for subsequent neural network analysis.

3. Prediction model based on SPF-LSTM

LSTM is mainly used to predict and deal with long time series problems. Compared with widely used RNN, LSTM have a more complex chain structure, which ensures effective transmission of information in the sequence chain through cell state and "gate" structure. The addition and removal of information are mainly realized by forgetting gate, input gate and output gate [5]. The main structure of LSTM is shown in Figure 3.

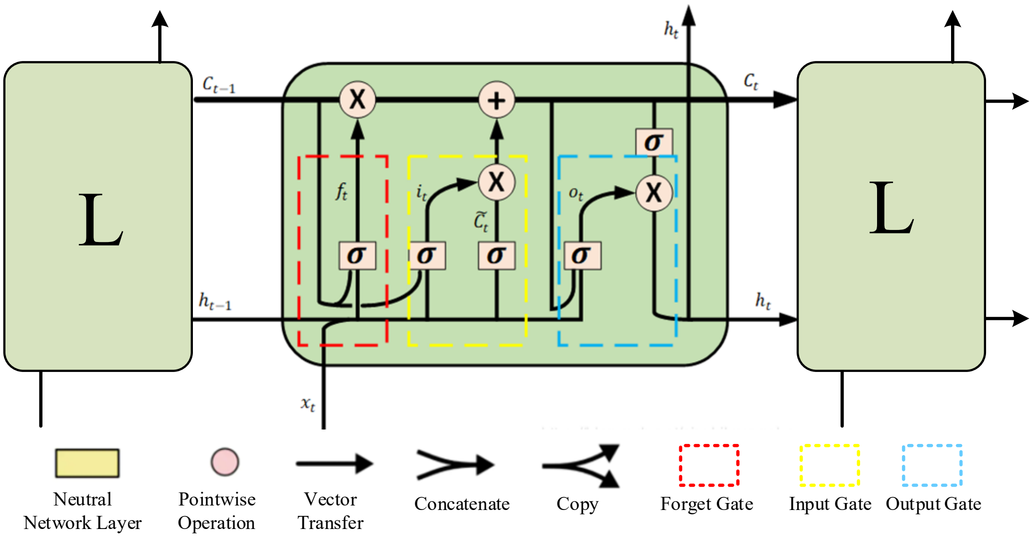

Figure 3. LSTM main structure.

3.1 Network construction

Based on the above description of the input data, feature extraction was carried out on the CFD numerical simulation and real propeller open water test data divided in the input layer using the double-layer SPF-LSTM algorithm model, and the extracted features were spliced through the feature splicing layer. Finally, the full-connection layer was used to reduce the dimension of the time sequence features. Thus, the fast prediction method of propeller dynamic performance is realized. Its network structure is shown in Figure 4.

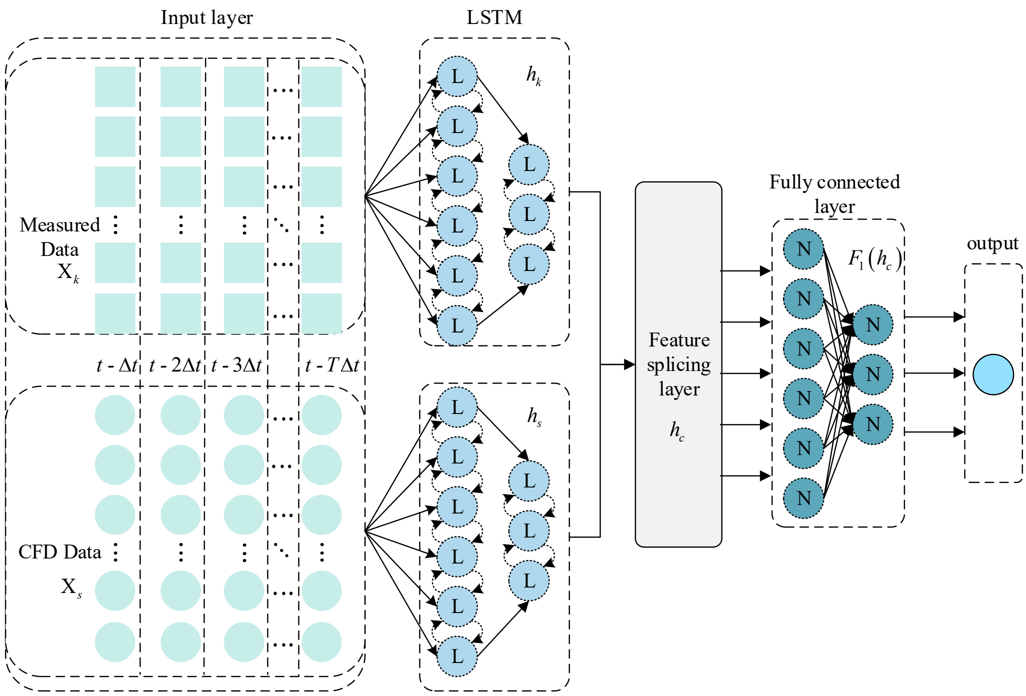

Figure 4. Dual layer SPF-LSTM model network structure

Output feature vectors h_k^t and h_s^t of LSTM are obtained by extracting real propeller open water test data X_k and CFD numerical simulation data X_s from LSTM, respectively. $L(\cdot)$ represents LSTM's mapping function to data, which can be described as:

$$\begin{cases} h_k^t = \mathrm{L}\left(x_k, h_k^{t-1}\right) \\ h_s^t = \mathrm{L}\left(x_s, h_s^{t-1}\right) \end{cases} \tag{3}$$

Feature splicing of parallel LSTM outputs is carried out through feature splicing layer:

$$h_c = \left\langle h_k^t, h_s^t \right\rangle \tag{4}$$

The concatenated feature vector $\lambda = F_1\left(h_c\right)$ can be used for further dimension reduction and lower dimension feature λ can be obtained through the full connection layer. The process can be described as follows:

$$\lambda = F_1\left(h_c\right) \tag{5}$$

In the training process of LSTM model, due to the small amount of real propeller open water test data and large amount of CFD numerical simulation data, CFD simulation data accounts for the main part of the data set, while the measured data is small, which belongs to the unbalanced data set. This study starts from the perspective of algorithm and combines the idea of cost-sensitive learning. In the process of model training, Sample penalty factor (SPF) was adopted to reduce the weight of CFD simulation data samples and increase the weight of measured data samples, so that the model would focus on the measured data samples and obtain more accurate prediction effect, which could be expressed as:

$$C_w = \frac{N_1}{N_2} \tag{6}$$

Where, C_w represents the sample penalty factor, N_1 and N_2 respectively represent the weights of CFD simulation data and real propeller test data.

Since the final output prediction is a regression prediction problem, the sample penalty factor is applied to the loss function of the two types of sample data respectively to adjust the sensitivity of the model to the two types of data. Finally, in the process of model training, 7:3 was used to divide the training data and test data, and the number of model iteration training was 50. Finally, the predicted value of the SPF-LSTM model showed good agreement with the real experimental data.

4. Conclusion

In this paper, a new model based on SPF-LSTM is proposed to predict the hydrodynamic performance of propeller rapidly by combining CFD numerical simulation technique with real propeller flow test. In the early stage of propeller design, the method proposed in this paper can replace CFD simulation to give rapid propeller design results, which can be used as reference for designers, improve the efficiency of designers, and is of great significance for propeller design.

Acknowledgments

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