Gated Neural Network-Based Unsteady Aerodynamic Modeling for Large Angles of Attack

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Abstract: Modeling of unsteady aerodynamic loads at high angles of attack using a small amount of experimental or simulation data to construct predictive models for unknown states can greatly improve the efficiency of aircraft unsteady aerodynamic design and flight dynamics analysis. In this paper, aiming at the problems of poor generalization of traditional aerodynamic models and intelligent models, an intelligent aerodynamic modeling method based on gated neural units is proposed. The time memory characteristics of the gated neural unit is fully utilized, thus the nonlinear flow field characterization ability of the learning and training process is enhanced, and the generalization ability of the whole prediction model is improved. The prediction and verification of the model are carried out under the maneuvering flight condition of NACA0015 airfoil. The results show that the model has good adaptability. In the interpolation prediction, the maximum prediction error of the lift and drag coefficients and the moment coefficient does not exceed 10%, which can basically represent the variation characteristics of the entire flow field. In the construction of extrapolation models, the training model based on the strong nonlinear data has good accuracy for weak nonlinear prediction. Furthermore, the error is larger, even exceeding 20%, which indicates that the extrapolation and generalization capabilities need to be further optimized by integrating physical models. Compared with the conventional state space equation model, the proposed method can improve the extrapolation accuracy and efficiency by 78% and 60%, respectively, which demonstrates the applied potential of this method in aerodynamic modeling.

Key words: large angle of attack; unsteady aerodynamic modeling; gated neural networks; generalization ability

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0 Introduction

The unsteady aerodynamic characteristics of the new generation of advanced fighters with large angles of attack represent their maneuverability, so accurate simulation or experimental prediction of the unsteady aerodynamic forces under various operating conditions becomes an important part of the aircraft design. The method of obtaining aerodynamic forces based on computational fluid dynamics (CFD) or wind tunnel tests is significantly expensive due to the high coupling between motion and aerodynamics, and the unsteady aerodynamic characteristics at high angles of attack exhibit extremely complex non-linear characteristics[1-3]. Therefore, researchers have developed a new idea of modeling large-angle-of-attack unsteady aerodynamic forces to predict time-varying aerodynamic forces under different operating conditions[4-6].

Current unsteady aerodynamic modeling methods are divided into two categories. One is the traditional modeling methods based on the physical properties of the flow field[7-9], including the integral model and the differential model. The integral model takes the maneuver as the sum of multiple order

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of motion and derives a strict mathematical model, but it is difficult to analyze or discrete it because of its high dimensios. The differential model starts from the concept of flow field separation point and uses the concept of differential equations or differential-difference to express the decomposition of the aerodynamic force, which is easy to understand. But this has poor applicability in highly complex scenarios, where it even loses its own physical meaning. The other class of models ignores the physical meaning of the flow field and trains the model using known sample data by intelligent algorithms[10-13], which are called intelligent modeling methods, such as neural network modeling and fuzzy logic modeling. Although these methods do not consider the variation of flow field properties, they have been widely developed because their modeling ideas are clear and can be extended to the case of longitudinal and transverse heading coupling modeling and cross-speed domain. Li et al.[14-15] carried out a work on unsteady aerodynamic modeling using machine learning algorithms to verify the feasibility of intelligent modeling based on multiple airfoil data. However, this modeling technique only considered inter-airfoil interpolation and cannot verify its outward extension modeling capability. Alkhedher et al.[11] studied and compared the accuracy of various intelligent modeling methods such as artificial neural network (ANN), adaptive neuro fuzzy inference system (ANFIS), and point completion network (PCN) in the representation of aerodynamic properties of flat plates with large angle of attack. The results showed that the prediction accuracy of the deep neural network algorithm-based model was always high under wide operating conditions, which demonstrated the prediction effect of multi-layer networks. Zhang et al.[16] applied machine learning algorithms to aerodynamic modeling of fan blades to model and predict the unsteady aerodynamic characteristics of the blades with high speed rotation. The results showed that the deep neural network was able to learn the aerodynamic variation pattern generated by the unsteady motion of the blade effectively, and the prediction results performed well. The study did not explain the extension capability of the intelligent model. It was trained only using existing data, and the prediction data was also derived from the modeling sample data. In general, intelligent modeling has been developed rapidly, but there is less research on its generalization capability, which seriously restricts the expansion of the application of intelligent modeling methods.

To address the above issues, this paper proposes a novel aerodynamic modeling method for recurrent networks. A high angle of attack gated recurrent network aerodynamic model is constructed based on gated neural units. It fully utilizes the time memory ability of gated neural units to learn and predict flow field information in unknown states. The model is validated with a typical high angle of attack pitching motion airfoil. The aerodynamic modeling process is enhanced to update and invert the flow field characteristics to further improve the applicability of the model by introducing the memory unit.

1 Aerodynamic Modeling Methods for Large Angles of Attack

1.1 Unsteady aerodynamic modeling with large angles of attack

During large angle-of-attack maneuvering flight, the motion and aerodynamic characteristics of the aircraft exhibit highly coupled and delayed effects. The coupling effect is mainly manifested by the fact that when the vehicle moves around the center of gravity position, the corresponding aerodynamic characteristics also show similar unsteady characteristics, and the dynamic motion may also lead to mutual coupling aerodynamic forces/moments between the longitudinal and transverse directions. For example, during the longitudinal large maneuver motion, the coupled roll moment appears due to the asymmetric rupture of the vortex system, which induces the lateral motion. The delay effect is manifested as the problem of asynchronous start of motion and corresponding aerodynamic changes, which is caused by the inertia of the airflow itself. The aerodynamic forces accompanying the motion usually exhibit a hysteresis loop shape because of the delay effect. Due to the complexity of high angle of attack maneuvering flight, neither conventional experiments nor simulation calculations can obtain a large amount of accurate data. Therefore, a method has been gradually developed to use less aerodynamic data as sample points and adopt physical or large-scale training techniques to build aerodynamic models.

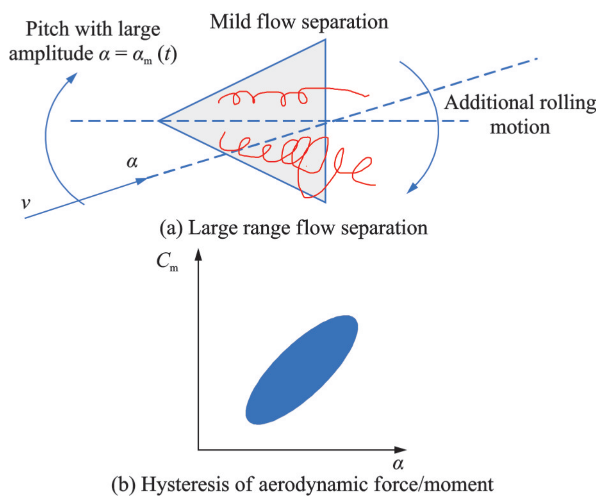

Fig.1 Unsteady aerodynamic characteristics at large angles of attack

The physical aerodynamic models include integral equation models, differential equation models and algebraic models, which are derived by rigorous mathematical laws. However, because of different understanding of physical phenomena and the laws of flow field features, the intelligent aerodynamic modeling technology with artificial intelligence algorithms as the core ignores the physical meaning and equates the internal modeling process to the "black box" process of training models with data, which greatly expands the accuracy and applicability of aerodynamic modeling. Certainly, because of the lack of physical meaning, the discription of the flow field characteristics is weak. Fig.2 shows a typical

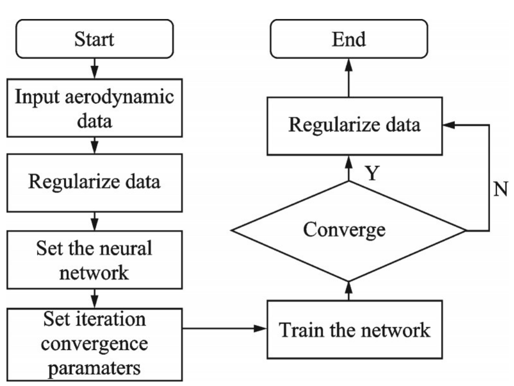

Fig.2 Multi-layer neural network modeling process

aerodynamic intelligent modeling process based on a neural network algorithm. The steps are as follows.

Step 1 Regularize the representation of the sample points, i. e., the aerodynamic data corresponding to the form of motion, given by the numerical simulation or the experiment.

Step 2 Construct the neural network model parameters for model training, including the number of network layers, the setting of hyperparameters, etc.

Step 3 Perform neural network training on the sample data.

Step 4 Obtain the "black box" aerodynamic model after the training process.

Step 5 Given the known motion law, output the aerodynamic prediction results, and compare them with the known results to verify the reliability of the model.

Step 6 Given an unknown motion law, the model is used to predict the corresponding aerodynamic values.

1.2 Gated neural networks

For the large angle unsteady aerodynamic modeling, the most important capability is the generalization ability of the model, which is the ability to predict state parameters based on known working conditions. Traditional neural network models, such as back propagation (BP) neural network and radial basis function (RBF) neural network, are basically forward static networks, which cannot reflect the dynamic characteristics of the system well. This is very different from the characterization of the unsteady dynamic characteristics of large-angle maneuvering flight, so the generalization ability of these models is relatively weak.

The recurrent neural network (RNN)[17] inputs are sequential data. In the forward recursion of the sequence, all internal nodes (recursive units) are connected into a chain. Based on this special structure, RNNs can reflect the dynamic characteristics of the system over time with memorable, parameter sharing, and turing completeness. Therefore, they have strong non-linear feature learning ability for sequence data. RNNs have been used in nonlinear system identification and are able to model most nonlinear systems, and thus have the potential to improve the weak generalization properties of aerodynamic modeling. However, RNNs have some drawbacks: It cannot remember what is too far ahead or too far behind due to gradient explosion or vanishing. In order to solve the problem of long-term dependence in general RNNs, the gate recurrent unit (GRU) model was developed[18], which features the ability to process and predict important events with relatively long intervals and delays in time series. The simple internal structure of GRU can largely improve the learning efficiency and save computational resources and time costs.

In this paper, we establish an unsteady aerodynamic intelligence modeling method based on GRU to balance the training efficiency and generalization ability of intelligent models. The GRU model is a special example of the RNN model. The idea of the RNN model can be graphically described as follows: The human brain does not start from a blank space every time when thinking. For example, instead of discarding all the previous information and using a blank brain, when reading an article, the brain will determine the meaning of the current word and predict the next content based on the previously read and learned information. The structure of GRU is similar to the internal self-loop structure (nodes) of the RNN model, but the repeating modules have a different structure, as shown in Fig.3.

The GRU network removes or adds information to the cell state through a structure called a gate, which selectively decides which information is allowed to pass through. Basically, these two gating vectors determine which messages end up as the output of the gated loop unit. The special feature of these two gating mechanisms is that they preserve the information in a long sequence and do not clear or delete it over time because the information is not related to prediction.

(1) Update gate

The update gate selectively passes past and current information to the future, helping the model decide which part of the information and how much in-

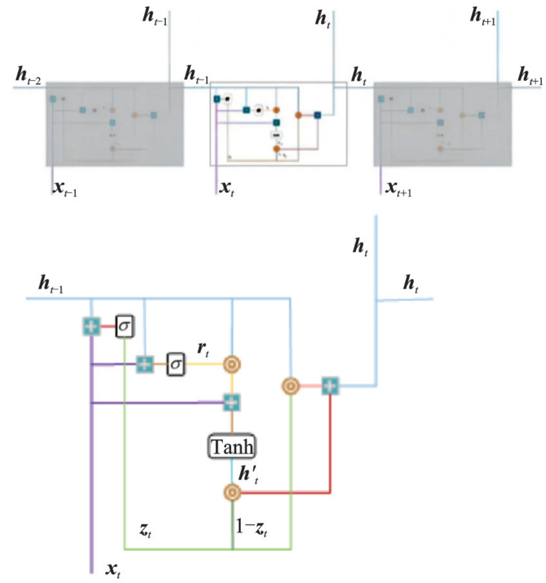

Fig.3 GRU structure

formation should be passed through, as shown in Fig.4. At time step t, the update gate z_t is calculated as

$$z_t = \sigma(W^{(z)} x_t + U^{(z)} h_{t-1}) \tag{1}$$

where x_t is the input vector at time step t, and it completes a linear transformation by multiplying with the weight matrix $W^{(z)}$; h_{t-1} the previous information passed through, which also undergoes a linear transformation. The update gate adds these two parts of information together. After the sigmoid function transformation, the result is normalized to [0,1].

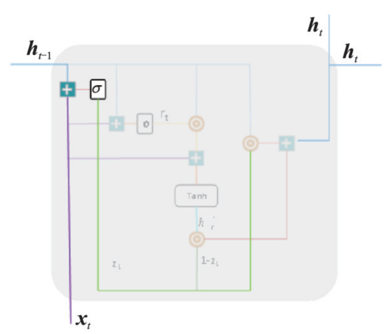

Fig.4 GRU update gate diagram

(2) Reset gate

In essence, the reset gate determines which past information to be forgotten. Its expression is

$$r_t = \sigma(W^{(r)} x_t + U^{(r)} h_{t-1}) \tag{2}$$

The expression of the reset gate is similar to that of the update gate, and the parameter meanings are also the same. The process is shown in Fig.5.

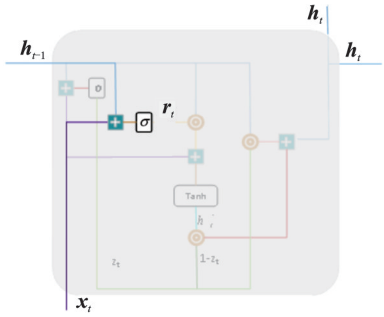

Fig.5 GRU reset gate diagram

(3) Memory content at the current time step

The current input information is obtained through the reset gate to obtain relevant past information and storeit. Its calculation expression is

$$h'_t = \tanh(\boldsymbol{W}\boldsymbol{x}_t + \boldsymbol{r}_t \odot \boldsymbol{h}^{U}_{t-1}) \tag{3}$$

where $\odot$ represents the exclusive NOR mathematical operation, that is, when two input variables have the same value, $F=1$. The current input content $\boldsymbol{x}_t$ and the information passed from the previous step $\boldsymbol{h}_{t-1}$ are first subjected to the linear transformation. Then, the hadamard product of the reset gate $\boldsymbol{r}_t$ and the update gate $\boldsymbol{h}^{U}_{t-1}$ is calculated. Since the reset gate calculated earlier is a vector consisting of numbers from 0 to 1, it measures the size of the gate opening. If the gate control value corresponding to an element is 0, it represents that all the information of that element is forgotten. Finally, the results of these two parts of calculations are added together and transformed using the hyperbolic tangent function. The calculation process is shown in Fig.6.

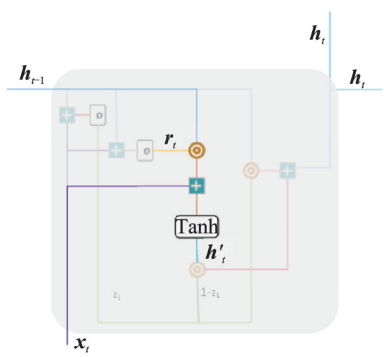

Fig.6 Illustration of current input content

(4) Output at the current time step

In the last step, the network needs to calculate the output $\boldsymbol{h}_t$ at the current time step. This vector will preserve the information of the current unit and then pass it on to the next unit. In this process, the update gate is required, which determines the information that needs to be collected in the current memory content $\boldsymbol{h}_t$ and the previous time steps $\boldsymbol{h}_{t-1}$. The expression for this process is

$$\boldsymbol{h}_t = \boldsymbol{z}_t \odot \boldsymbol{h}_{t-1} + (1 - \boldsymbol{z}_t) \odot \boldsymbol{h}'_t \tag{4}$$

where $\boldsymbol{z}_t$ is the activation result of the update gate, and it also controls the information transmission in a gated form. The Hadamard product of $\boldsymbol{z}_t$ and $\boldsymbol{h}_{t-1}$ represents the information preserved from the previous time step to the final memory. When it is added to the information saved from the current memory to the final memory, it becomes the output of the final gating loop unit. The process is shown in Fig.7.

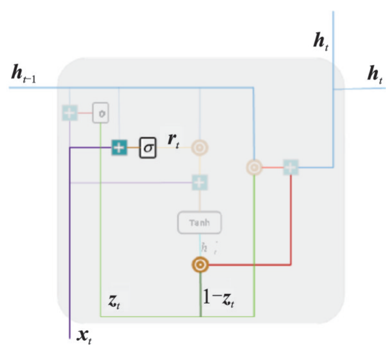

Fig.7 Illustration of current output

1.3 Aerodynamic modeling based on gated networks

In this paper, the gated neural unit is combined with unsteady aerodynamic data, and the sample data points required for network training are obtained by CFD simulation[19-20]. The parameters include two types: The motion parameters (initial angle of attack, motion amplitude, frequency) and the aerodynamic parameters (Mach number, lift, drag and pitch moment coefficients). The calculated data are used as sample points for network training to optimize the hyperparameters and construct a gated neural unit-based training model. The existing sample data are used to continuously verify the validity and accuracy of the training process in real time. Finally, the aerodynamic parameters of the unknown motion state are predicted by the model. The whole process is shown in Fig.8.

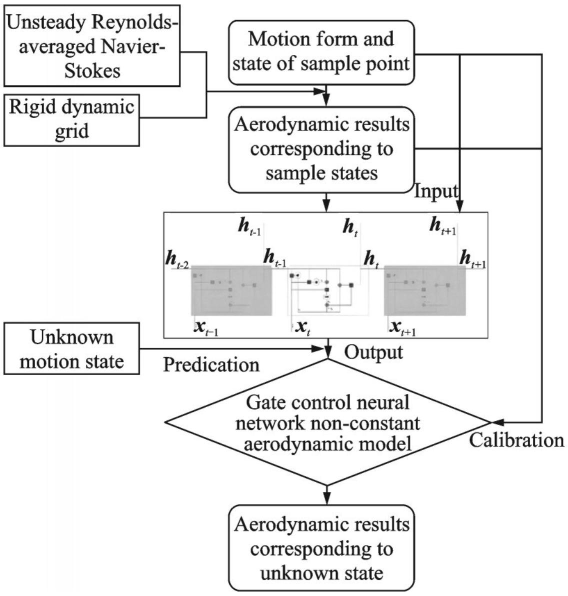

Fig.8 Process of unsteady aerodynamic modeling based on gated neural units

2 Validation of Intelligent Neural Network Modeling Methods

2.1 Interpolation modeling

Interpolation refers to modeling and predicting unknown states within the state boundary using known aerodynamic data. In this paper, two sets of training data and one set of test data are used for modeling prediction. The aerodynamic models are tested under different amplitude and deceleration frequency. The root mean square error e_{RMS} and the relative error e are used to evaluate the test results

$$e_{\mathrm{RMS}}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i-y_i)^2} \tag{5}$$

$$e=\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i-y_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2}}=\frac{e_{\mathrm{RMS}}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}y_i^2}} \tag{6}$$

The states predicted by the interpolation modeling are shown in Table 1.

When the aircraft performs high angle of attack maneuvers, the gating neural network constructed in this paper is used to model and predict the aerodynamics of the interpolation state, and the results are shown in Figs.9,10. The relative error of the entire forecast journey is shown in Table 2.

Table 1 Interpolation aerodynamic modeling data

Setting	Prediction under different amplitudes	Prediction under different contraction frequencies
Serial number	1	2
Training data	$\alpha_1=30^\circ+12^\circ\sin(4\pi t)$	$\alpha_1=30^\circ+10^\circ\sin(4\pi t)$
	$\alpha_2=30^\circ+8^\circ\sin(4\pi t)$	$\alpha_1=30^\circ+10^\circ\sin(2\pi t)$
Test data	$\alpha_1=30^\circ+11^\circ\sin(4\pi t)$	$\alpha_1=30^\circ+10^\circ\sin(3.5\pi t)$
Predicted data	$\alpha_4=30^\circ+10^\circ\sin(4\pi t)$	$\alpha_4=30^\circ+10^\circ\sin(3\pi t)$

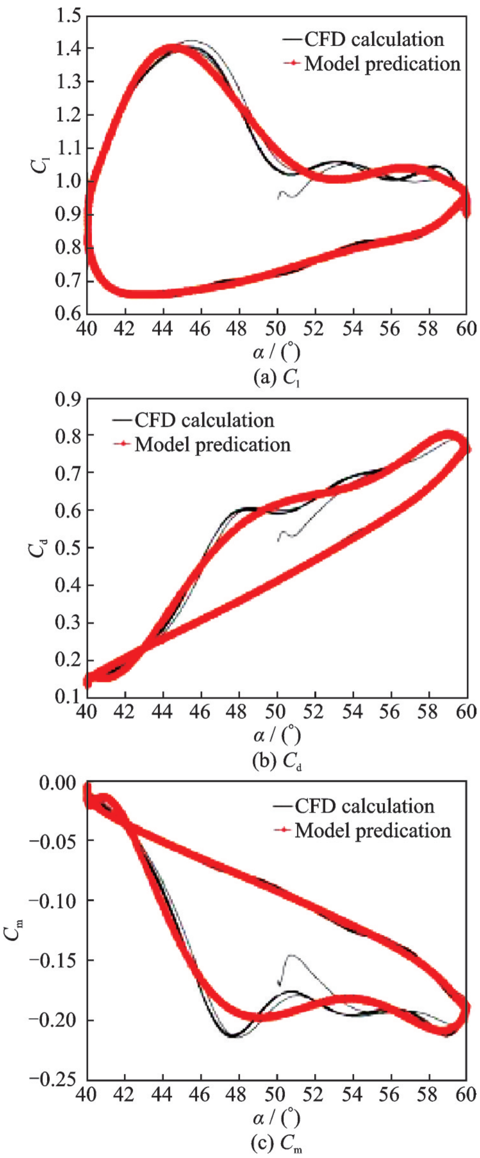

Fig.9 Comparison of aerodynamic predication data between CFD values and model predication at $\alpha_4=30^\circ+10^\circ\sin(4\pi t)$

According to the prediction results, it can be seen that the amplitude interpolation prediction results are slightly worse than the frequency prediction results. The error range of the lift drag coeffi-

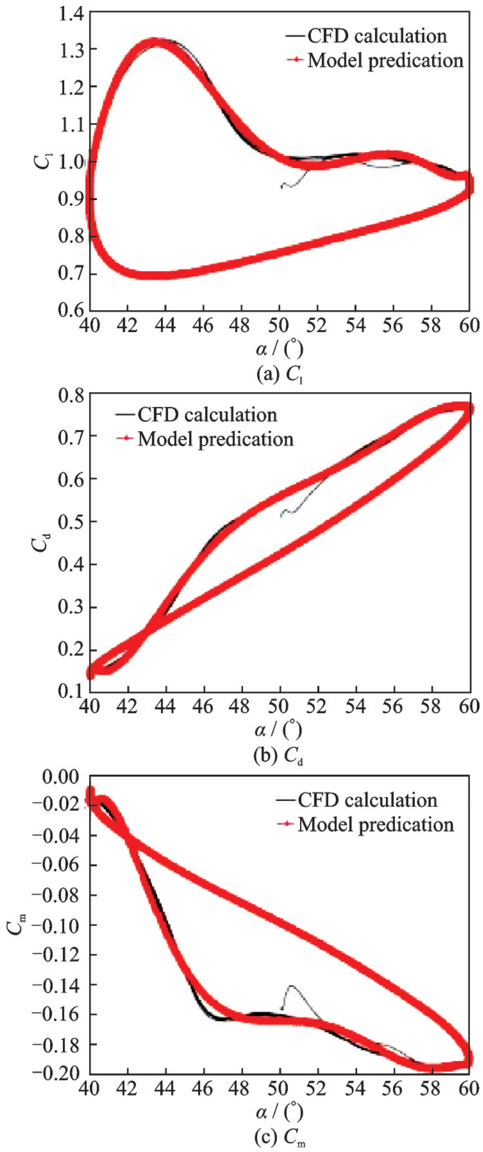

Fig.10 Comparison of aerodynamic predication data between CFD values and model predication at $\alpha_4 = 30^\circ + 10^\circ \sin(3\pi t)$

Table 2 Error in aerodynamic interpolation modeling of NACA0015 airfoil high angle of attack maneuvering motion

Case	C_l		C_d		C_m	
	e_{RMS}	$e/\%$	e_{RMS}	$e/\%$	e_{RMS}	$e/\%$
1	0.0173 0	1.99	0.017 7	2.35	0.009 1	8.18
2	0.0102 0	1.24	0.014 9	1.37	0.006 5	3.72

cient is below 5%, but the prediction error of the moment coefficient has reached 10%. In terms of physical phenomena, an increase in amplitude represents a further increase in the intensity of nonlinearity, because the range of instantaneous angle-of-attack courses may span more flow regimes. Therefore, the region of expression of nonlinear characteristics is larger, and the difference in flow field characteristics between the interpolated training data and the predicted data is relatively large at this time. Figs.9, 10 also illustrate that the predicted hysteresis loop of aerodynamic changes is basically consistent with CFD calculations, which also reflects the ability of RNN to memorize time-dependent histories and thus characterizing the corresponding nonlinear features. High deceleration frequency implies a larger instantaneous angular velocity. Therefore, at the same instantaneous angle of attack, a larger rate of change in the approach angle will enhance the nonlinearity of the instantaneous flow field. The lift, the drag and the pitch moment coefficients can be predicted well.

The interpolation modeling results show that the intelligent model of gated network, constructed for the prediction within the boundary of the training state in this paper, can learn to obtain the basic flow field characteristics better and provide more accurate prediction results. The accuracy of the model will also be further improved if the sample points and test points can be added in the training.

2.2 Extrapolation extension modeling

The nonlinear flow field characteristics of the predicted data in interpolation modeling are included in the training data, so that better prediction results can be obtained. However, it is obvious that the learning extension capability of the modeling process needs to be considered if the prediction is modeled for unknown states outside the boundary of the training data. In this section, the extrapolation modeling validation is carried out based on the NACA0015 large motorized aerodynamic data, and the data states of the prediction process are shown in Table 3.

Figs.11—14 show the results of extrapolation extension modeling predictions using known aerodynamic data, and the errors are shown in Table 4. From the results, it can be seen that extrapolation modeling will cause the original nonlinear flow field characteristics to change, either by changing the amplitude or decreasing the frequency. Because the

Table 3 NACA0015 wing extrapolation modeling at high angle of attack maneuvering motion

Case	Train test	Prediction data	Remark
1	$k=0.092\ 32$ $\alpha_m=12°, \alpha_m=10°$	$\alpha_m=8°$	Constant frequency
2	$k=0.092\ 32$ $\alpha_m=6°, \alpha_m=9°$	$\alpha_m=13°$	Constant frequency
3	$\alpha_m=10°$ $k=0.092\ 32, k=0.069\ 241$	$k=0.046\ 16$	Constant amplitude
4	$\alpha_m=10°$ $k=0.023\ 08, k=0.046\ 160$	$k=0.080\ 78$	Constant amplitude

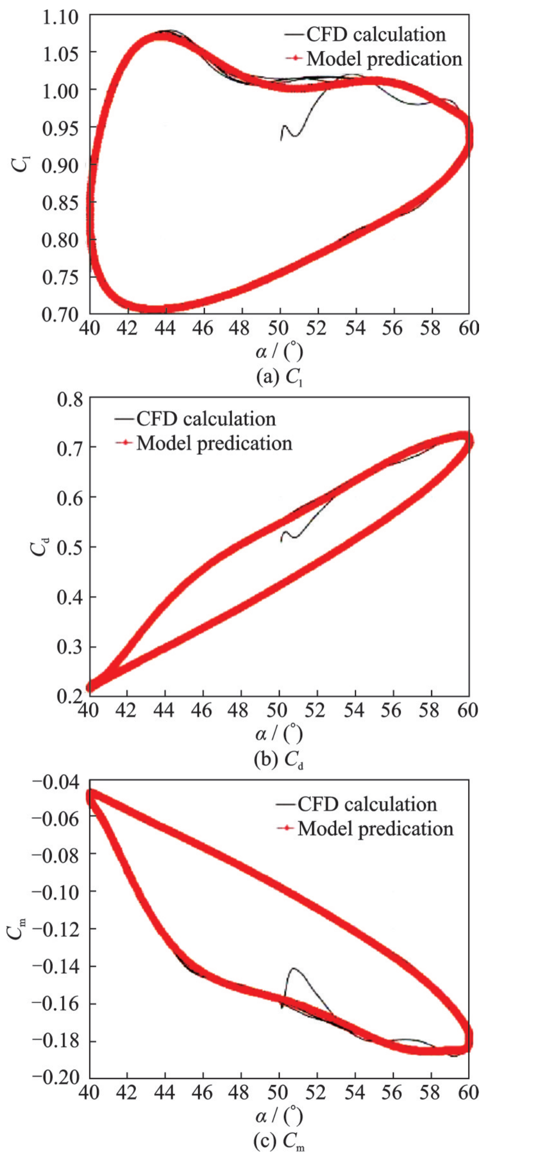

Fig.11 Comparison is extrapolation prediction results between CFD values and model predication at state $\alpha=30°+8°\sin(4\pi t)$

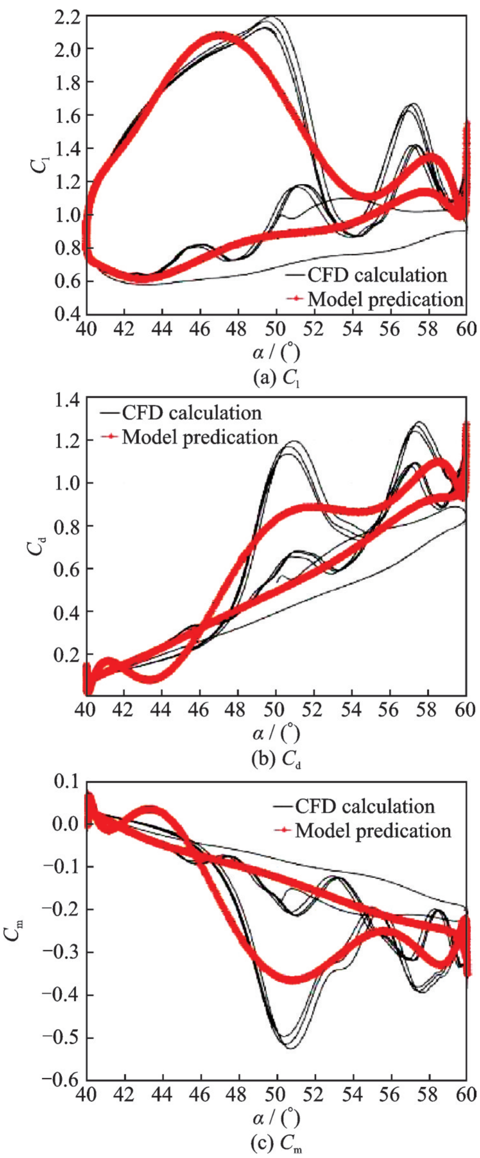

Fig.12 Comparison is extrapolation prediction results between CFD values and model predication at state $\alpha=30°+13°\sin(4\pi t)$

flow field itself is already in a large angle-of-attack nonlinear state. For the prediction case 1, the large amplitude data is used to predict the small amplitude case. Although the training data does not contain the data of the prediction case, the nonlinear characteristics of the training data are developed from the small amplitude data. The lift resistance and moment coefficients of the prediction case can be predicted more accurately. In contrast to the prediction of case 2, predicting large amplitude conditions by training with small amplitude data has a large difference in its nonlinear characteristics. The main reason for this result is that the training data with linear and weak nonlinear characteristic cannot be strongly non-

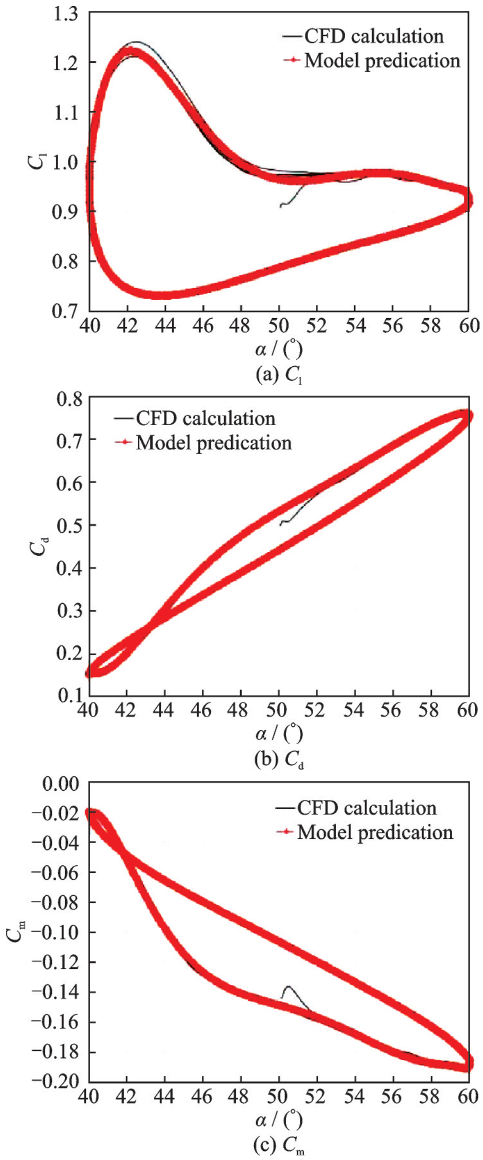

Fig.13 Comparison is extrapolation prediction results between CFD values and model predication at state $\alpha = 30^\circ + 10^\circ \sin(2\pi t)$

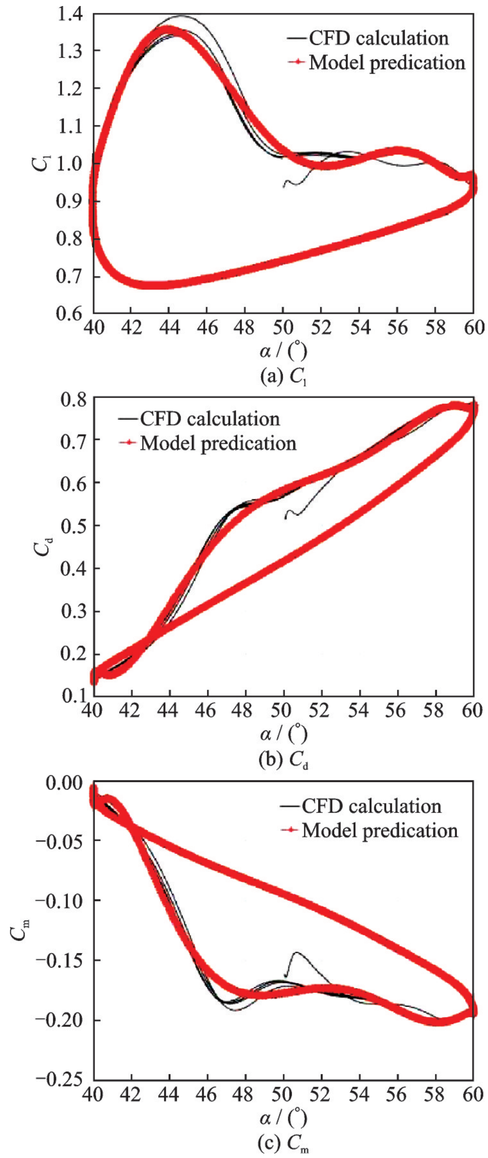

Fig.14 Comparison is extrapolation prediction results between CFD values and model predication at state $\alpha = 30^\circ + 10^\circ \sin(3.5\pi t)$

linear at large angles. In other words, the strong separation law of the flow field under large amplitude cannot be trained and learned through the small separation phenomenon, so the error of prediction case 2 is large. It also shows that the change in amplitude strongly affects the development of flow field properties, which changes dramatically with time course, and that the development of nonlinear characteristics of the flow field (especially from weakly nonlinear to strongly nonlinear flow field) predicted by interpolation needs to be supported by more physical models.

The predicted cases 3 and 4 are cases where

Table 4 Error in aerodynamic extrapolation modeling of NACA0015 airfoil high angle of attack maneuver motion

Case	C_l		C_d		C_m	
	e_{RMS}	e/%	e_{RMS}	e/%	e_{RMS}	e/%
1	0.009 2	1.14	0.008 3	1.21	0.006 1	2.39
2	0.187 0	20.71	0.169 7	29.81	0.018 9	26.65
3	0.006 7	1.01	0.006 7	1.00	0.003 9	2.03
4	0.012 3	1.99	0.014 8	1.73	0.012 9	4.55

the frequency and amplitude are changed respectively with the large non-linear properties of the flow field largely unchanged, but the construction time of the flow field varies, showing that the aerodynamic hysteresis is a change in local slope. The prediction network in this paper is more accurate for the extrapolation of frequency characteristics, but the prediction of working case 4 is obviously slightly higher error, which is similar to the law of amplitude prediction. In general, the gated-loop network aerodynamic prediction method constructed in this paper has certain extrapolation modeling capability, and its extrapolation accuracy can be further improved if the physical model characterizing the nonlinear flow field is integrated in the subsequent model.

2.3 Comparative analysis of gate control intelligent modeling method and other methods

An intelligent aerodynamic model based on gate controlled neural network is established in this paper. By training the aerodynamic data, it is possible to predict other states aerodynamic forces by better interpolation. By learning and storing the time-varying characteristics of the aerodynamic data, the intelligent model can better reveal the internal law of the unsteady aerodynamic performance, so it has a better generalization ability in principle.

In order to further verify the efficiency and accuracy of the methods constructed in this paper, the prediction capabilities of conventional state space equation models and conventional intelligent models based on BP neural networks are compared. The selected object remains the NACA0015 airfoil, with the same computing hardware configuration used for a comprehensive comparison of its extrapolation and extrapolation generalized capabilities, as shown in Fig.15. In terms of prediction efficiency, conventional state space equation models have the lowest

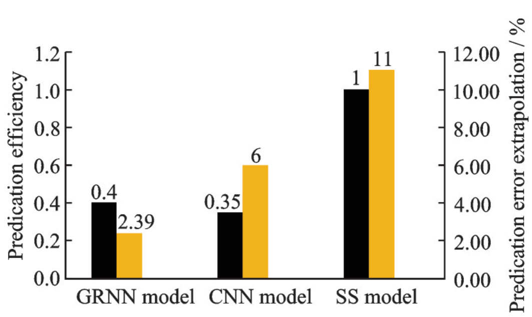

Fig.15 Predication efficiency and error of different aerodynamic models(GRNN—Gated recurrent neural network; TNN—Traditional neural network; SS—State-space)

prediction efficiency due to the large number of equations solved and complex logical relationships. Although the intelligent model is based on data training, the prediction efficiency can be improved by more than 60% compared to the state space model. Since the mechanism of the gated neural network model is more complex, its efficiency is slightly lower than the classical conventional neural network model. In terms of the generalized performance, the state space equations have the worst extrapolation accuracy, and the gated network has the best extrapolation accuracy, which reflects the effectiveness of historical data learning.

3 Conclusions

An intelligent aerodynamic model based on gated recurrent neural network is constructed to address the generalization problem of unsteady aerodynamic modeling at large angle of attack. Taking the NACA0015 airfoil high angle of attack maneuver as an example, the time memory of the gated neurons is used to verify the effectiveness of the model and improve the model's ability of generalization, and the main conclusions are as follows.

(1) Although ignoring the physical characteristics of the flow field, the intelligent model based on neural networks has good universality and can be applied to aerodynamic modeling and prediction in various states.

(2) The accuracy of the gated neural unit interpolating model based intelligent model is high. The training data represent flow field characteristics that already cover the predicted working conditions, so accurate predictions can be made for nonlinear flow fields of different frequencies and amplitudes.

(3) The accuracy of the extrapolation prediction varies with the development of nonlinear characteristics, and the prediction accuracy of the model trained with strong nonlinear data to predict the weak nonlinear flow field is better. However, when using weak linear data to extrapolate the nonlinear cases, the prediction error is large. At the same time, the prediction error of the model with variable amplitude is larger relative to that of the frequency-

varying case, because the effect of amplitude variation on the flow field characteristics is more dramatic.

(4) The gated network prediction model has a greater improvement than other models in terms of both generalization ability and prediction efficiency. Compared with the state space equation model and the traditional neural network model, the extrapolation ability is improved by 78% and 45%, respectively. The prediction efficiency is 60% higher than that of the state space equation model.

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基于门控神经网络的大迎角非定常气动力建模

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摘要： 基于少量实验或仿真数据构建未知状态下的大迎角非定常气动力模型，能够极大地提高飞机非定常空气动力学设计和飞行动力学分析的效率。针对传统气动模型通用性差以及智能模型泛化能力差的问题，提出了一种基于门控神经单元的智能气动力建模方法。充分利用门控神经单元的时间记忆特性，增强了学习和训练过程对非线性流场的表征能力，提高了整个预测模型的泛化能力。以NACA0015翼型为研究对象，在机动飞行条件下对其非定常气动力进行了预测和验证，结果表明本文构建的模型具有良好的适应性。在内插预测中，升阻系数和力矩系数的最大预测误差不超过10%，基本可以表征整个流场的变化特征；在外推建模预测中，基于强非线性数据的训练模型对弱非线性预测具有良好的准确性，而反过来预测则误差较大，甚至超过20%，这也表明外推和泛化能力需要通过与物理模型融合来进一步优化。与传统的状态空间方程模型相比，本文提出的方法可以将外推精度和效率分别提高78%和60%，充分说明了该方法在气动力建模中的应用潜力。

关键词： 大迎角；非定常气动力建模；门控神经网络；泛化能力