Research Article

A Vortex Identification Method Based on Extreme Learning Machine

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Vortex identification and visualization are important means to understand the underlying physical mechanism of the flow field. Local vortex identification methods need to combine with the manual selection of the appropriate threshold, which leads to poor robustness. Global vortex identification methods are of high computational complexity and time-consuming. Machine learning methods are related to the size and shape of the flow field, which are weak in versatility and scalability. It cannot be extended and is suitable for flow fields of different sizes. Recently, proposed deep learning methods have long network training time and high computational complexity. Aiming at the above problems, we present a novel vortex identification method based on the Convolutional Neural Networks-Extreme Learning Machine (CNN-ELM). This method transforms the vortex identification problem into a binary classification problem, and can quickly, objectively, and robustly identify vortices from the flow field. A large number of experiments prove the effectiveness of our method, which can improve or supplement the shortcomings of existing methods.

1. Introduction

Vortex is one of the most important characteristics in the flow field, which is figuratively compared to “the tendon of fluid movement” [1], and it plays an important role in many engineering problems. Therefore, the accurate extraction of the vortex is of great significance for the study of the physical mechanism of the complex flow field. At present, conventional vortex feature extraction methods can be divided into three categories: local methods, global methods [2], and partial local-global hybrid methods [3–7].

The local methods obtain some characteristics based on the physical properties of the flow field. For example, the Q -criterion [8], the Ω -criterion [9], the Δ -criterion [10], and the λ_2 -criterion [11], which can get results quickly. However, in practical applications, local methods require careful selection of appropriate thresholds to obtain valid results. But there are still many false positives and false negatives in local methods [12].

The global methods are usually based on the global topological properties of the flow field, such as winding Angle method [13], Elliptic Object Eulerian Coherent Structures (Elliptic OECs) [14], and Instantaneous Vorticity Deviation (IVD) [15]. The method mentioned above requires global flow field information to identify vortex feature regions. With strong objectivity and robustness, global methods are used to verify the precision of identification results. However, these methods are based on global information and therefore require more time than local methods. And they require a lot of user intervention to get reliable results. So, global methods are difficult to be applied to vortex feature recognition of large data sets.

Combining the advantages of local methods and global methods, some machine learning methods are proposed, such as Boosting vortex enhancement algorithm [4] and Majority voting [5], which are proposed based on the advantages of the two methods. The generality and extensibility of these methods are poor. To solve these problems, several

FIGURE 1: Convolution ELM network. The input layer is a small data set that provides data input for the CNN network. The last layer of the CNN network's fully connected layer provides data input for the ELM network.

methods based on convolutional neural networks are proposed. Such as Eddy-Net [16], fluid R-CNN [17], Vortex-CNN [6], and Vortex-Seg-Net [7]. These network methods are targeted at local points rather than the entire flow field of different sizes and shapes. Therefore, these methods are independent of the size and shape of the flow field and have better universality and extensibility.

These methods obtain considerable precision and less time than global methods, but they consume more time than local methods. Through the research, we found two disadvantages of limiting their time performance. First, Vortex-CNN is data-driven and requires a lot of data to train the network, leading to a long time of network training. In addition, their complex network structure means that the network test time is long.

In order to solve these problems, we propose a fast vortex feature identification method for the Convolutional Neural Networks-Extreme Learning Machine (CNN-ELM), as shown in Figure 1. To be specific, we used a simple CNN network to extract the feature of flow field data and used the feature extracted from the CNN network to train the ELM network. In the CNN-ELM network, the network parameters of the CNN network are determined randomly, and will not change once determined, thus reducing the time for repeated training of network parameters. The parameters of the ELM network are few. Only the parameters of the output layer need to be trained, and the other parameters are determined randomly. A large number of experimental results show that the precision and recall rate of this method is similar to that of conventional methods. In addition, our proposed method consumes less time than other methods.

The main contributions of this paper are the following:

- (1) We propose a new CNN-ELM-based vortex identification method. This method combines the advantages of global and local vortex identification methods
- (2) The method proposed in this paper is designed for local small block data. The whole flow field is divided

into local small patches data, and local small block data is predicted at the same time, instead of point by point. By doing this, we will greatly improve the speed of vortex identification

- (3) We combine the characteristics of the ELM network and CNN network, extract the characteristics of the flow field by CNN network, improve the overall prediction precision of the flow field, and adopt the ELM network for vortex identification to realize rapid identification of vortex features
- (4) Through a large number of experiments, compared with the traditional method, our method can objectively and robustly detect vortices from the flow field.

The rest of this article is organized as follows. The second part introduces related work. The third part introduces the details of the proposed method. The fourth part gives the experimental results. The fifth part is the conclusion of this article.

2. Related Work

In this section, the existing vortex current identification methods are briefly introduced.

2.1. Local Vortex Identification Methods. Given n -dimensional velocity field μ , the Jacobian matrix J of the velocity is an $n \times n$ matrix, which can be used for analyzing the flow pattern characteristics in a small zone around a given point. Many local vortex identification methods are based on the Jacobian matrix J decomposition into $J = \Omega + S$, where the antisymmetric matrix is Ω called the spin tensor, and the symmetric matrix S is called the strain-rate tensor. The Q -criterion, the Ω -criterion, the Δ -criterion, and the λ_2 -criterion are the most important local methods that depend on the Jacobian matrix J . The Q -criterion treats the connected region as a vortex, when $Q > Q_{\text{thresh}}$. Similar to Q -criterion, Liu et al. [9] present the Ω -criterion that

defines a vortex region by $\Omega > \Omega_{\text{thresh}}$, where Ω is empirically set to 0.52. The Δ -criterion [10] defines a vortex region by $\Delta > \Delta_{\text{thresh}}$, where $\det J$ is the determinant of J . The above conditions indicate that the Jacobian matrix J has complex eigenvalues related to the vortex structure. Generally, the limit of Δ is less than Q , so the Δ -criterion will extract a larger vortex region [18]. The λ_2 -criterion proposed by Jeong and Hussain assumes that the region of Hessian matrix ($S^2 + \Omega^2$) with at least two negative eigenvalues is the vortex region, which is more reliable and effective than other local vortex identification methods.

All local vortex identification methods are related to a threshold. Choosing the appropriate threshold is the key to determine the effectiveness of the given vortex identification method. However, there is no suitable criterion to judge whether the threshold value of these local vortex identification methods are the best ones since the selection of threshold value requires domain knowledge of fluid mechanics and can rather be subjective [19].

2.2. Global Vortex Identification Methods. The global method treats the vortex as an ellipse and uses the closed contour method. Sadarjoen et al. [13] used the winding Angle method to extract vortices from the flow field based on the geometric characteristics of streamlines. The disadvantage of the winding Angle method is that it is computationally intensive and requires global tracking of streamlines in the whole region. Elliptic OECS [14] defined the vortex boundary as an outermost closed curve with a tangential strain rate constant at each point and proposed an automatic method to calculate such curves effectively based on geodesic geometry [20]. The scheme requires significant numerical effort to compute the null-geodesics of general Lorentzian metrics and is only used for 2D flow fields. Haller et al. [15] proposed an objective definition of vortices suitable for any translational rotating reference frame and a global vortices identification method (IVD) independent of a threshold.

2.3. Machine Learning Methods for Vortex Identification. Machine learning methods are receiving more and more attention to vortex feature identification and visualization problems. These methods utilize multiple local methods to construct more accurate and robust methods. Zhang et al. [4] used the adaptive boosting (AdaBoost) [21] method to assign different weights to four different local vortex detectors based on expert information, and obtain a reduced misclassification rate in two CFD data sets. Biswas et al. used the Majority voting [5] to assign equal weights to each local vortex region detector and introduced a fuzzy-based method to combine the uncertainty in the output of the four existing local vortex identification methods. Compared with the AdaBoost method, the Majority voting method can provide more robust and reliable identification results. In a word, these methods can improve the precision of vortex feature identification results to some extent by reducing false positives and false negatives, but they require the results of multiple local vortex area identification methods, thus increasing the calculation cost. In addition, these methods rely heavily on the labeled data from domain experts to optimize the

model. Worse, these methods depend on the size and shape of the flow field, so they are less universal and scalable.

Recently, two new vortex identification methods-based CNN Vortex-Net [6] and Vortex-Seg-Net [7] have been proposed. Vortex-CNN uses local patches around each point in the velocity field to train the CNN network through the labels obtained by the global method, thereby transforming the vortex feature identification task into a binary classification problem. Vortex-Seg-Net uses the mesh padding strategy to fill the boundary of the flow field data to ensure that the points near the boundary have enough neighbors to sufficiently obtain the local velocity patches. Both methods aim at local points rather than the whole flow field to improve the universality and expansibility. Although these two methods achieve the same precision and less time as the global method, they both take more time than the local method. And Vortex-CNN and Vortex-Seg-Net network training time is very long.

In order to solve the above problems, we introduce the method of convolution extreme learning machine and design a complete convolutional extreme learning machine network for vortex identification.

3. Proposed Method

3.1. Extreme Learning Machine. The extreme learning machine (ELM) was proposed by Huang et al. to improve the Backpropagation Algorithm (BP) to improve learning low efficiency and simplified setting of learning parameters [22]. In the subsequent research, the application scope of ELM has been promoted, including unsupervised learning problems represented by clustering [23], and there have been changes with representative learning capabilities and improved algorithms [24]. The extreme learning machine has a speed and generalization performance unmatched by other methods when processing big data [25], which can improve the efficiency of flow field data processing, so ELM is used to extract flow field vortex features.

In addition, the ELM network requires a few parameters. The parameter to be adjusted is the number of neurons in the hidden layer of the ELM network. The weights and offsets of the input layer are randomly generated, and no loop iteration is required, thereby reducing the complexity of algorithm operations.

The extreme learning machine (ELM) network has three layers: the input layer, hidden layer, and output layer. Suppose there are N sample sets, where

$$\begin{aligned} X_j &= [X_{j1}, X_{j2}, \dots, X_{jn}]^T \in R^n, \\ Y_j &= [Y_{j1}, Y_{j2}, \dots, Y_{jn}]^T \in R^m. \end{aligned} \quad (1)$$

For a single hidden layer neural network with L hidden layer nodes, it can be expressed as

$$\sum_{i=1}^L \beta_i g(\omega_i x_j + b_i) = o_j, j = 1, 2, 3, \dots, N. \quad (2)$$

FIGURE 2: The architecture of the method proposed in this paper, flow field data vortex feature identification process. The preprocessing part preprocesses the data and provides the required input for the network part. The network model part trains a network model for vortex feature recognition. The output of the network model part provides predicted small patches of data for the postprocessing part, and the postprocessing part performs flow field reconstruction on the small patches of data.

Among them, $g(x)$ is the activation function, $\omega_i = [\omega_{i1}, \omega_{i2}, \dots, \omega_{in}]^T$ is the input weight of the i th hidden layer unit, b_i is the cell offset of the i th hidden layer unit, and $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{in}]^T$ is the output weight of the i th hidden layer unit. After the input data is activated, H is the abovementioned $g(\omega_i x_j + b_i)$. The pseudoinverse of and the inner product of the sample set y_i are β_i .

The vortex feature identification method based on the convolution extreme learning machine proposed by us includes data pre-processing part, network model part, and postprocessing part, as shown in Figure 2. The preprocessing section provides the data input for the second section. The network part is called Vortex-ELM-Net, which is used to train a network model to identify the vortex characteristics in the flow field. The third part reconstructs the flow field data identified in the second part.

3.2. Preprocessing. In this section, we would introduce the preprocessing part of our method. This part includes four steps: vorticity calculation, grid transformation, data normalization, and data sampling.

The first step is to process the data and calculate the vorticity value by using the velocity in X and Y directions.

The second step is to transform the nonuniform mesh in the physical plane into a uniform mesh in the computational plane. The uniform mesh can be directly expressed as a rectangular array, and each mesh point has relevant position information and vorticity value in the Cartesian coordinate system. Thus, we can easily sample data of a fixed size on the computational plane without considering the original flow field.

The third step is to normalize the data of vorticity value in the flow field. The data normalization method we use is Z-score-sigmoid normalization, which first normalizes z -score and then normalizes sigmoid.

$$X = \frac{1}{1 + e^{-(x_0 - x/\sigma)}}. \quad (3)$$

We first identify local maxima of the IVD field, then extract nearby closed IVD level curves using the level set

TABLE 1: Flow field data used in the experiment.

Purpose	Data name	Grid size
Train data	Cylinder_0005000	101 × 761
	Cylinder_0050000	101 × 381
	Cylinder_0100000	101 × 381
	Plate_0005000	101 × 761
	Plate_0140000	101 × 381
	Plate_0180000	101 × 381
Test data	Triangle	101 × 381
	Square	101 × 761
	Airfoil	101 × 381

method. Finally, we consider the outermost convex IVD level curve around an IVD maximum as vortex boundary. The internal mark of the vortex boundary is 1, and the external mark of the vortex boundary is 0. In the fourth step, to mark all points in the flow field, instantaneous vorticity deviation (IVD) is used to identify global vortices. Based on integration measures, global information can be integrated into the approach presented in this article. After vorticity normalization is carried out on the four training data in Table 1, random sampling is conducted on the local small patches around each point of vorticity value in the four flow fields, and 10000 small patches of 32×32 size are collected in each flow field, and these small patches and labels were taken as the input of Vortex-ELM-Net, making the method applicable to different scales and shapes.

3.3. Vortex-ELM-Net. After the preprocessing part, a network model is trained using Vortex-ELM-Net to distinguish between vortex points and nonvortex points and classify the points in each small patches. In this section, we first introduce the structure of the Vortex-ELM-Net. The network has good permeability, and it is not necessary to design the network model and parameters for different simulation data while maintaining less training parameters and lower

computational costs. Then, we briefly introduce the training and testing process of Vortex-ELM-Net. During the Vortex-ELM-Net training phase, learn the parameters of the network through labeled data. In the Vortex-ELM-Net test phase, the vortex feature identification is performed on the flow field data through the trained network model, and the identification result of the vortex feature is obtained.

3.3.1. The Structure of Vortex-ELM-Net. The Vortex-ELM-Net we used is an improved network of a single-layer ELM network. A convolutional network is added before the single-layer ELM network. The convolutional neural network includes an input layer, three convolutional layers, and two fully connected layers. The second to the fourth layers are convolutional layers. All these convolutional layers use 3×3 convolution kernels. The number of feature maps is 16, 32, and 64, respectively. The data is downsampled after each convolutional layer. The number of the first fully connected layer neurons is 4096, and the number of the last fully connected layer neurons is 2048. The activation function used in the convolutional network is a rectified linear unit (ReLU). The output of the last fully connected layer of the convolutional neural network is used as the input layer of the ELM network. The convolutional ELM network is shown in Figure 1:

3.3.2. The Training and Testing. In the training phase, the training set was obtained by using the preprocessing phase; 80% of the training set was taken as the training data of the network. The Vortex-ELM-Net network is trained to obtain the features representing the vortex labeled data. Set a confidence threshold. The part that exceeds the threshold is marked as 1 (1 represents the position of the vortex). The part that does not exceed the threshold is marked as 0 (0 represents the position of the nonvortex). Thus, the position of the vortex in the test data is marked. 20% of the training set is used as the test data of the network. The test data tests the network model to obtain precision and recall. The performance of the network model is evaluated by these two parameters, the parameters of the network model are adjusted, and the network model is repeatedly trained and adjusted repeatedly.

$$\begin{aligned} \text{Precision} &= \frac{TP}{(TP + FP)}, \\ \text{Recall} &= \frac{TP}{(TP + FN)}. \end{aligned} \quad (4)$$

FP, FN, TP, and TN represent the number of false positives, false negatives, true positives, and true negatives, respectively. We compare the training time of network training with the training time of existing deep learning methods.

In the test phase, the test data is sequentially sampled. The size of the sample is the same as the size of the small patches randomly sampled when training the network. Then, we input these small patches data sets into the trained network to obtain the small patches data of the flow field prediction. Finally, all the small pieces of data output by the net-

FIGURE 3: In the test phase, the data is sequentially sampled according to the size of the data patches during the training phase, and the vorticity field is divided evenly into several local small patches.

FIGURE 4: In the postprocessing phase, the predicted patches coordinates are used to reconstruct the patches data back to the 2D space.

work of the flow field are allocated to the appropriate locations to obtain the visualization results of the entire output as shown in Figure 3.

3.3.3. Postprocessing. The postprocessing part only works during the test phase. The output of Vortex-ELM-Net is the prediction result of local small patches. In order to obtain the labeled of the entire flow field, all these local small pieces of data must be combined. In the postprocessing stage, all predicted chunks are reconstructed and reconstructed according to the coordinate points of the center point of each patch to obtain the predicted vortex structure in the whole flow field; the process of flow field reconstruction is shown in Figure 4.

4. Results and Discussion

In this section, we compare Vortex-ELM-Net networks with other methods, including four popular local vortex

FIGURE 5: Visualization results of 2D flow field training data. Colour map with green and blue denote the vortex region and the nonvortex region. (b, c) The vortical structures in the same cylinder flow field on the different time steps. (e, f) The vortical structures in the same plate flow field on the different time steps.

identification methods (Q -criterion, Ω -criterion, Δ -criterion, and λ_2 -criterion), two traditional machine learning methods (Random Forest and AdaBoost), three deep learning methods (Vortex-CNN, Vortex-Seg-Net, and Vortex-ELM-Net), and IVD method. Four classic metrics were used to measure the performance of each method, including precision, recall, network training time, and running time.

4.1. Data Sets. Several 2D flow fields that we use are described in detail in Table 1. The two-dimensional flow field includes cylindrical flow field, flat flow field, square flow field, triangle flow field, and flow field generated by different attack angles of the same airfoil. The proposed method was evaluated in several cases of a two-dimensional flow field. All cases are time-dependent simulation results under different flow conditions. We select the most representative time step for each

TABLE 2: The performance of different methods in the triangle flow field of 101×381 and the square flow field of 101×761 .

Cases	Methods	Precision (%)	Recall (%)	Training time	Execution time (s)
Triangle	Q-criterion	89.15	42.8	\	1.7
	Ω -criterion	87.7	38.4	\	2.1
	Δ -criterion	89.1	41.4	\	2.5
	λ_2 -criterion	88.9	41.35	\	4.3
	Random Forest	92.9	71.1	112 s	12.7
	AdaBoost	85.5	54.3	150 s	18.14
	Vortex-CNN	95.85	88.2	>24 h	19.45
	Vortex-Seg-Net	96.64	94.72	>24 h	0.81
	Vortex-ELM-Net	96.17	89.4	90.72 s	2.4
	IVD	100	100	\	227
Square	Q-criterion	93.22	61.6	\	3.6
	Ω -criterion	89.7	60.4	\	4.4
	Δ -criterion	93.1	56.7	\	5.3
	λ_2 -criterion	93.1	60.7	\	8.6
	Random Forest	87.35	90.1	112 s	24.6
	AdaBoost	88.2	83.44	150 s	33.2
	Vortex-CNN	84.4	95.7	>24 h	41.4
	Vortex-Seg-Net	86.65	90.98	>24 h	1.24
	Vortex-ELM-Net	92.6	91.5	90.72 s	3.9
	IVD	100	100	\	433

simulated flow field for vortex identification and visualization. Test data in Table 1 describes the detailed flow field.

The test of the local method and IVD method is realized in MATLAB. The traditional machine learning algorithms and our method are implemented in Python. All methods are run on the same desktop computer, which has an Intel (R) Xeon (R) Gold 6144 CPU @ 3.50 GHz, 64 GB of memory.

4.2. Two-Dimensional Flow Field. This section involves identifying the vortex in 2D flow cases. The Vortex-ELM-Net is trained using six flow fields: the cylinder flow fields with grid sizes of 101×761 , the cylinder flow fields with grid sizes of 101×381 , the cylinder flow fields with grid sizes of 101×381 on different time steps, the plate flow field with a grid size of 101×761 , the plate flow field with a grid size of 101×381 , and the plate flow field with a grid size of 101×381 on different time steps. 10000 small blocks of data were collected for each flow field data, 60000 small pieces of data in total to train the network model, and the vortex regions marked by each training data are shown in Figure 5.

In order to prove the generality and expansibility of our method, the flow fields of different sizes and shapes were used for testing. Here are proposed approach is tested on three different flows, including the square flow field with grid size 101×381 , the triangular flow field with grid size 101×761 , and the airfoil flow field with grid size 101×381 .

Table 2 shows the precision, recall, and execution time of different methods for the prediction of the triangle and square flow fields. And the time required for three deep learning methods to train the network. Our network (Vortex-ELM-Net) training time is 90.72 s, which is 1/960 of

Vortex-CNN and Vortex-Seg-Net. Compared with Vortex-CNN, the implementation time of our network and Vortex-Seg-Net will be less than 5 seconds.

For the precision, the precision of Vortex-ELM-Net in the triangle flow field is 7.46% higher than the local method on average, and 10.67% higher than the traditional machine learning method. 0.32% higher than Vortex-CNN. The precision of Vortex-ELM-Net is similar to Vortex-Seg-Net. In the square flow field, the precision of Vortex-ELM-Net is 0.32% higher than the local method on average, 4.4% higher than the traditional machine learning method, 8.2% higher than the Vortex-CNN, and 5.95% higher than the Vortex-Seg-Net.

For the recall rate, Vortex-ELM-Net has a recall rate of 89.4% and 91.5% in the triangle flow field and the square flow field, respectively. Compared with the local method, the average recall of Vortex-ELM-Net in these two cases Increased by 48.41% and 31.65%, respectively. Compared with traditional machine learning methods, the recall rate of the proposed method is improved by triangles and 8.06% in the case of squares.

From the comparison of precision and recall, it is difficult for local methods to obtain higher precision and recall on test data at the same time. For example, in the square data, the Δ -criterion method has a precision of 93.1%, whereas the recall rate is only 56.7%, which means there are a lot of false negatives in the Δ -criterion. By contrast, Vortex-CNN, Vortex-Seg-Net, and Vortex-ELM-Net can achieve high precision and recall rates simultaneously.

In terms of network training time, because the four local methods and the global methods are physical methods, all have no network training time. Comparing the three deep

FIGURE 6: Visualization results of different methods in 101×761 square flow field. We use vorticity to colour the flow field. The vorticity used here is the dot product of the original vorticity value of the flow field data and the predicted label.

learning methods and machine learning methods, Vortex-ELM-Net has the least training time, the training only takes about 90 seconds, compared to more than 24 hours for the Vortex-CNN and Vortex-Seg-Net. Vortex-ELM-Net saves a lot of network training time. The short train-

ing time of Vortex-ELM-Net is caused by the following two factors:

- (i) The network has few parameters to be determined by training

- (ii) The network is similar to a simple feedforward neural network and does not require repeated training to adjust parameters

In terms of execution time, Vortex-ELM-Net is about the same as the local method execution time. However, all these local methods are an iterative process and require careful selection of thresholds. Therefore, the overall execution time of these local methods cannot be measured accurately. Comparing the three deep learning methods, the execution time of the Vortex-CNN flow field prediction in the triangle flow field is 19.45 seconds, while the execution time of the Vortex-ELM-Net network only takes 2.4 seconds. In the square flow field, the execution time of the Vortex-CNN for flow field prediction is 41.4 seconds, while the execution time of the Vortex-ELM-Net network only takes 3.9 seconds. Compared with Vortex-CNN, Vortex-ELM-Net is shorter in both network training time and program execution time. Compared with the Vortex-Seg-Net, the Vortex-ELM-Net takes less network training time and the equivalent execution time to achieve better forecast results. Compared with the IVD method, Vortex-ELM-Net has an acceleration ratio of 94.58 in the triangle flow field and 111.03 in the square flow field. There are two reasons for the short execution time of Vortex-ELM-Net:

- (i) The network model is simple
- (ii) Vortex-ELM-Net makes predictions for each small patches of data instead of predicting each point in the small patches

In the CFD visualization, the precision and recall cannot reflect the flow phenomenon in detail, so we visualize the identified results, as shown in Figure 6. In the local method, there are a large number of missed or false detection of vortical structures. Although traditional machine learning methods have higher precision and recall, they cannot reflect the vortex separation in the flow field. The visual vortex structure obtained by the Vortex-ELM-Net method is consistent with the IVD method. At the same time, Vortex-ELM-Net can accurately reflect the vortex shedding phenomenon in the flow field.

In order to further compare the three deep learning methods, we predict the flow field data generated by 5 different attack angles of the same airfoil, and the results are shown in Tables 3–5. The figure shows the precision, recall, and execution time of the Vortex-CNN, Vortex-Seg-Net, Vortex-ELM-Net, and IVD methods. It can be seen from the figure that the Vortex-ELM-Net method has better performance than Vortex-CNN and Vortex-Seg-Net, which indicates that the method has better generalization performance than Vortex-CNN and Vortex-Seg-Net. In addition, our proposed method has shorter network training and execution time.

5. Discussion

The purpose of this study is to solve the problems of local and global vortex detection methods and the training time and running time of the existing CNN network through the con-

TABLE 3: The precision of Vortex-CNN, Vortex-Seg-Net, Vortex-ELM-Net, and IVD in airfoil flow field with different attack angles.

Airfoil	Precision (%)				
	2	4	6	8	10
Vortex-CNN	31.4	39.5	41	38.1	33.1
Vortex-Seg-Net	74.6	69.1	70.5	70.3	60.7
Vortex-ELM-Net	64.93	57.06	59.4	62.78	54.32
IVD	100	100	100	100	100

TABLE 4: Recall rate of Vortex-CNN, Vortex-Seg-Net, Vortex-ELM-Net, and IVD in airfoil flow field with different attack angles.

Airfoil	Recall (%)				
	2	4	6	8	10
Vortex-CNN	66.3	78.2	74.8	77.7	77.9
Vortex-Seg-Net	87.86	82.9	83.3	85.4	84.9
Vortex-ELM-Net	94.97	94.24	94.2	93.48	95.77
IVD	100	100	100	100	100

TABLE 5: Vortex-CNN execution time, Vortex-Seg-Net execution time, Vortex-ELM-Net execution time, and IVD execution time.

Airfoil	Time (s)				
	2	4	6	8	10
Vortex-CNN	21.5	21.6	22.2	21.7	21.4
Vortex-Seg-Net	1.01	0.94	1.04	1	0.98
Vortex-ELM-Net	3.71	3.68	3.72	3.69	3.68
IVD	238	239	241	228	255

volution extreme learning machine (Vortex-ELM-Net). The results of the two-dimensional flow field analysis show that the Vortex-ELM-Net method has higher recognition precision, higher recall rate, and faster speed than the local method. At the same time, the method is independent of threshold and can provide vortex recognition results objectively and robustly. Compared with the traditional machine learning algorithm, Vortex-ELM-Net can accurately detect the vortex structure and reveal the flow phenomena in the flow field. Once trained, the Vortex-ELM-Net network model proposed by us can be directly applied to other cases, avoiding long training, and having good universality and expansibility.

6. Conclusion

In this paper, a rapid method to detect vortices in a flow field, called Vortex-ELM-Net is proposed. Different from the existing vortex identification methods, this method can combine the advantages of the global method and the local method. Similar results can be obtained with only local information as with the global approach. Compared with the local method, this method has higher precision and recall rate and requires less time than the global method. Compared with the recently proposed Vortex-CNN and Vortex-Seg-

Net, the proposed method has a shorter time for network training under the same conditions. More importantly, our method is independent of threshold and has good universality and expansibility.

In addition, our proposed method also has limitations. The method fails in the following situations, such as the Reynolds number changes too much, or in the case of unstructured grids. The method in this paper did not consider unstructured grids for the time being and did not consider vortex identification in constant IVD fields. We leave these questions for future work and focus on exploring a simpler and faster network model for processing flow field data and applying this method to 3D flow field data.

Data Availability

The data used to support the findings of this study have not been made available because the National Natural Science Foundation of China.

Conflicts of Interest

We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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