Detection of Spike-type Stall of Axial Compressors Based on Dilated Causal Convolutional Neural Networks

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Abstract. An aerodynamic instability inception and short-length-scale periodic anomaly prior to stall onset known as spike-type stall inception in axial compressors is observed in aero-engine. In this paper, a deep dilated causal convolutional neural network (CNN) named as WaveNet is applied to spike-type stall inception detection and prediction in time-series data of axial compressors. WaveNet can implement fast anomaly detection and spike-type stall prediction in long-time term series data. Furthermore, a single WaveNet can be trained to capture and learn the time-domain statistical characteristics of different spike-type stall inception training data with equal fidelity. The trained WaveNet model can rapidly detect the occurrence of anomaly point and predict the probability of rotating stall and surge in axial compressors as an early warning signal. By comparing with the time domain analysis, the calculation results are represented with experimental data to show the effectiveness and feasibility of spike-type stall detection approach based on WaveNet.

1. Introduction

The turbofan aero-engine is the main power plant used for military aircraft and large civilian aircraft in the world[1]. The axial compressor of aero-engines is one of the most important components deciding the overall performance of the turbofan engine[2]. Therefore, the reliability and stability of axial compressors are the key points for the security and performance of aero-engines. Rotating stall and surge are two aerodynamic instability phenomena observed commonly in the axial compressor[3]. In the event of surge or rotating stall, the efficiency and performance of axial compressors decreases with violent vibration and dynamic pressure signal fluctuation. Therefore, the research on the detection of stall inception has important significance for aero-engine industry.

There are two generally recognized stall-inception types, each with its own distinctive characteristics called modal-type stall inception and spike-type stall inception[4-7]. A typical spike-type stall inception is characterized by the formation of three-dimensional, finite-amplitude disturbances localized to the tip region in a multistage compressor[8]. Spike-type stall inception can be captured by dynamical pressure signals in rotor blade tip[7, 9-11].

The detection method of stall inception has been studied extensively since the spike-type stall was discovered[12]. Some stall detection methods were based on the amplitude difference of pressure and vibration signals in time or frequency domain, such as spatial Fourier transform[4, 12], traveling wave energy[13], correlation[14-16], wavelet method[10, 17]. These detection methods of stall can only be applied under certain conditions, because they can only extract the pre-stall features partly. To solve the part-features problem mentioned above, the deterministic learning(DL) combined with Moore-Greitzer(MG) model is presented to interpret the stall inception as small fault[1, 12]. However, the
excessive number of compressor sensors is demanded in this method, so the application of DL&MG method is limited in practical situations. To overcome the limit of the above detection methods, a dilated causal convolutional neural network method named as WaveNet is studied to detect and predict the spike-type stall in this paper.

2. Spike-type Stall Detection Based on WaveNet

2.1. Dilated Causal Convolutions: WaveNet

In this paper, WaveNet is a generative model operating directly on the time domain sensor signals in the axial compressors[18]. The joint probability of a sensor signal $x = \{x_1, ..., x_T\}$ is considered as a product of conditional probabilities as follows:

$$p(x) = \prod_{t=0}^{T} p(x_t | x_1, ..., x_{t-1})$$  \hspace{1cm} (1)

The main framework of WaveNet is dilated causal convolution, the stall prediction $p(x_t | x_1, ..., x_{t-1})$ emitted by the model at timestep $t$ is independent of any of the future timesteps. For 1-D data such as audio one can more easily implement this by shifting the output of a normal convolution by a few timesteps. Causal convolution can be calculated in parallel without recurrent connection, so the training speed is fast.

In order to increase the reception field of neuron to solve the long time step problem, the dilated convolution is added on the basis of causal convolution. A certain amount of timesteps are skipped in the calculation, so the information from the longer timesteps can be captured in the current timestep.

WaveNet model also has taken advantage of some key technique: gated activations, residual connections[19], skip connections[20]. Gated activation unit is as follows[21]:

$$z = \tanh(W_{g,k} * x) \odot \sigma(W_{f,k} * x)$$  \hspace{1cm} (2)

where $*$ denotes a convolution operator, $\tanh()$ denotes hyperbolic tangent activation function, $\odot$ denotes an element-wise multiplication operator, $\sigma()$ denotes sigmoid activation function, $k$ is the layer index, $f$ and $g$ denote filter and gate respectively, and $W$ is a learnable convolution filter. $W_f$ and $W_g$ are learnable convolution filters. The input data was compressed between (-1, 1) to adjust the network after passing through the $\tanh()$ function. Then the information demanded to extract has been verified.

Residual connection refers to the mapping of the input $x$ in the $l$-th layer to output through formula $x_{o,l} = f(x, w) + x$, instead of $x_{o,l} = f(x, w)$. Skip connections keep the outputs of every convolutional layer, then the sum of all the output in every convolutional layer is calculated as the final output feature. The entire architecture of WaveNet is shown in Fig.2. The classification probability of input data is calculated through the function $sigmoid$. 

[Fig.1 Dilated causal convolutional neural network[18]]
2.2. Spike-type Stall Detection Model Based on WaveNet
Spike-type detection model based on WaveNet can detect and predict the probability of spike-type stall in the axial compressor. The input data is the dynamic pressure signals from the sensor installed on the tip region of the blade in axial compressors. The probability of stall or surge can be calculated and predicted by extracting the features of spike-type stall inception in the dynamic pressure data. Fig.3 show the function and architecture of spike-type stall inception detection model. Based on this model, the spike-type stall inception can be detected and the classification probability of aerodynamic instability (stall and surge) in axial compressors is calculated and predicted.

3. Experiments
3.1. Data preprocessing
Fig.4 shows the dynamic pressure data at the tip of the stator collected from stall to surge. From 7.48s, a downward development tip appeared, and entered the initial disturbance period of stall. With the development of stall disturbance, violent fluctuations began to appear at 7.82s, and the stall completely developed into surge. It takes 340ms from the appearance of spike-type stall inception to surge, and the change is very fast.
Fig. 4 Dynamic pressure of the tip of the stator from stall to surge

The experimental data is filtered through a low-pass filter, and down-sampling is performed to reduce the amount of data. According to the observation of the experimental data, the period of the spike-type stall inception is between 10 measurement points and 200 measurement points. To ensure that the spike-type stall inception is included in each timestep, and to maximize the efficiency of the model calculation, the timestep is set to 256. The data is divided by sliding window method to generate training samples.

3.2. Model training

In order to ensure that the receptive field reaches 256, two identical dilated causal convolution modules are set. The maximum dilation is 64, that is, the dilation of the convolution layer are as follows:

\[1, 2, 4, \ldots, 64, 1, 2, 4, \ldots, 64\]

If we use the RMSProp (Root Mean Square Prop) algorithm to update the parameters, after 5 rounds of iterations, the training curves on the training set and validation set are shown in Fig. 5.

The recall and accuracy of the prediction model on the validation set are 0.98 and 0.97, and the confusion matrix is shown in Fig. 6.
3.3. Results
The traditional time domain analysis method is used to predict the spike-type stall, and compared with the stall prediction model based on WaveNet. The performance of the two models on the test set is shown in Table 1. As the stall threshold increases, the recall is significantly reduced, resulting in failing to respond in time during the initial disturbance period of the stall, which may cause a detection failure. By comparing the comprehensive evaluation index between the two models, the spike-type stall prediction model based on WaveNet has a better performance than the time domain analysis method.

| model                  | threshold | recall | precision | F2-score |
|------------------------|-----------|--------|-----------|----------|
| Time domain analysis   | 0.02      | 0.78   | 1.00      | 0.326    |
|                        | 0.01      | 0.97   | 0.87      | 0.379    |
|                        | 0.005     | 1.00   | 0.74      | 0.374    |
| WaveNet                | 0.37      | 0.99   | 1.00      | 0.397    |
|                        | 0.30      | 0.99   | 0.99      | 0.396    |
|                        | 0.17      | 1.00   | 0.85      | 0.386    |

A set of experimental data in the test set is taken for real-time prediction. When the stall probability exceeds the set threshold, a stall warning signal is given. The test data is shown in Fig.7, and the three curves are the pressure values measured at the three measuring points.

(a) The pressure at the tip of the first stator  
(b) The pressure at the tip of the third stator  
(c) The pressure at the wall of outlet

Fig.7 Test Data

The prediction results of the time domain analysis and the model based on WaveNet are shown in Fig.8 and Fig.9. For the time domain analysis method, the time-domain feature isn’t changed significantly during the initial disturbance period of stall, and the warning signal is given only after the occurrence of the surge. For the prediction model based on WaveNet, the stall prediction probability gradually rises during the initial disturbance period of stall, and the probability rises to 100% before the stall completely develops into a surge. Therefore, early warning signal given by the model based on WaveNet before the occurrence of the surge is regarded as a highly effective result.
4. Conclusion

Based on the results and discussions presented above, the conclusions are obtained as below:

(1) Experiments show that the spike-type stall prediction model based on WaveNet can detect and predict the emergence of spike-type stall inception in the time domain, and early warning signal at the initial disturbance stage of the stall can be calculated and the detection and prediction of stall and surge can be achieved effectively and precisely. The WaveNet method can present a better performance than the traditional time domain analysis method which can only calculate warning signals when the stall completely develops into a surge.

(2) Experiments show that WaveNet performs well in small fault and anomaly detection in time series data with tremendous potential application.
(3) The dilated causal convolution neural network may be applied to multi-dimensional data to process time series images or videos.

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