RIRCNN: A Fault Diagnosis Method for Aviation Turboprop Engine

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Abstract

Aero-engine is the 'heart' of the aviation aircraft. Practical failure prediction of aero-engines is difficult due to the performance degradation covered by the continuous switching between various operating conditions. In order to solve the above problem, we propose a new type of aero-engine fault diagnosis model–RIRCNN (Residual Independently Reccurent and Convolutional Neural Network). It can process long sequences, and has superior feature extraction effect. We gather flight data sets through ground bench experiment of the aviation turboprop engine, and intensively conduct comparative experiments to evaluate the effectiveness of our model. The verification results demonstrate that our model can achieve excellent performance compared with other available baseline models.

Key words- Air Circuit Fault Diagnosis; Aviation Turboprop Engine; Neural Networks

1 Introduction

The safety of the aircraft is very important to ensure the military and people's livelihood. Aviation turboprop engines are mainly used in military transport aircraft. Compared with other types such as gas turbine engines, turboprop engines have a harsher working environment. The air circuit is the most prone to failure, so it is important to detect its failure. The traditional model-based, data-driven, and knowledge-based diagnostic methods are not accurate and economical. Thus, it is necessary to carry out research on key technologies such as feature data extraction, intelligent fault diagnosis and turboprop engine health state prediction. The artificial intelligence algorithm has strong reasoning ability and generalization ability, and has inherent advantages for complex engine fault diagnosis. Some intelligent algorithms have been applied in advanced Aero-engine health management systems, such as Deep Belief Network [1], LSTM (Long Short-Term Memory) [2] and Data Mining Techniques [3]. Although effective in different ways, these methods all have certain drawbacks.

Our purpose is to perform diagnostics on air path fault data from aero-turboprop engines. Considering that the essence of engine flight data is a kind of regular time series data, the model used for processing time series data in machine learning is given priority. RNN (Recurrent Neural Network) has been proposed as a solution to process time series and widely used and improved. LSTM [4] is a variant of RNN, proposed for solving the gradient disappearance and explosion problems. However, for data dealing with long time steps LSTM still has the limitation, it can only discriminate tokens in a small range and have difficulty capturing long-term dependencies. The flight conditions are constantly changing, and the flight duration is not invariable, it may cause the amount of series data be very long. So a more suitable model is needed.

In this paper, after investigating a lot of methods we propose a new model named RIRCNN. It is a new model based on the residual combination of IndRNN (Independently Recurrent Neural Network) [5] and CNN (Convolutional Neural Networks) [6]. Our main contributions are shown below:

(1) In the aviation turboprop engine bench experiment, we simulate flight states of normal and component failures under different working conditions, and obtain the data sets.

(2) We propose a novel model called RIRCNN that can process for long-series time series data and extract global feature fast.

(3) We conduct extensive experiments and verify that

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our model outperforms other available methods in air circuit fault diagnosis of aero-turboprop engines.

2 Related Work

Since the aviation turboprop engine is mostly used in the military transportation bureau, its technology and data involve secrecy. Only few public information and research are publicly available. Almost of the existing more cutting-edge artificial intelligence method resea are based on some public civil aviation turbine engine data. For example, a study [7] utilized a DFC and LSTM to established an offline health flight state estimation model and a degradation trend prediction model. Another group studied out a transfer learning method based on CNN and SVM for gas turbine fault diagnosis [8]. Zhou [9] employed a Res-BPNN and introduced the method of maximizing the domain confusion loss based on the adversarial mechanism in the experiment, so that the features learned from different domains are as close as possible and reduce the distribution difference of each aero-engine model.

Therefore, in order to conduct research based on turboprop engine failure data, it is necessary to obtain the corresponding data of the relevant model engines first. For example, the Australian Aviation and Navigation Research Laboratory took the F404 turbofan engine as the object, injected corresponding faults into several components such as the variable geometric angle and nozzle area of the compressor. And in this way, they finally obtained the simulated fault flight data.

In this paper, we obtain the data set through the ground simulation experiment of aviation turboprop engine, which made up for the shortcoming of insufficient data of this type of engine failure. Then we design a neural network named RIRCNN which can classify the data and detect faults by extracting the time series features and global features of the data.

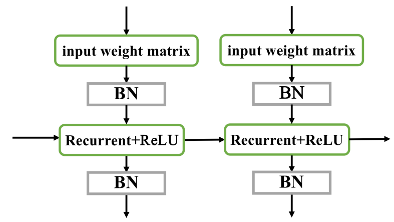
3 Approach

How IndRNN implements a neuron-independent architecture within a layer and solves the gradient problem are described in Subsection 3.1; the newly proposed model RIRCNN in the paper is introduced in Subsection 3.2.

3.1 Principle of IndRNN

Traditional RNNs models map the hidden states to outputs via the following recursive equation, it shares a weight $\mathbf{W}$ at each stage and its final output can be represented by $f[\mathbf{W}...[\mathbf{W}f[\mathbf{W}f_i]]]$. Obviously seen from the cumulative formula: when the gradient to be solved in reverse, if the derivative of f is not 1 or 0, it is easy to cause a gradient problem. Therefore, IndRNN is trying to introduce non-saturating activation functions ReLU to stack multiple layers of IndRNN to build very deep networks. The basic IndRNN structure is shown in Figure 1. Every neuron of IndRNN only receives information from the input and its own hidden state at the previous time step, which enables each neuron in the same layer can independently process a spatial-temporal pattern. Different neurons can be cross-correlated by stacking two or more layers, in which case each neuron in the next layer processes the output of all neurons in the previous layer. The hidden state calculation formula specific to a single neuron in the hidden layer of IndRNN is as follows:

Figure 1. IndRNN basic model.



$$\mathbf{h}_t = f(\mathbf{w}_{n,\mathbf{x}_t}\mathbf{x}_t + \mathbf{w}_{n,\mathbf{h}_t} \odot \mathbf{h}_{n,t-1} + \mathbf{b}) \tag{1}$$

where $\odot$ represent the Hadamard product, $\mathbf{w}_{n,\mathbf{x}_t}$ is the n^{th} row of the input weight matrix, and $\mathbf{w}_{n,\mathbf{h}_t}$ is the recurrent weight matrix in hidden layer, respectively. For the back-propagation of the temporal gradient of each layer, since there is no interaction between neurons in the layer, the gradient of each neuron can be calculated independently. For the nth neuron $\mathbf{h}_t$, assuming the output at time step T is $\mathbf{J}_n$, the gradient back-propagated to time step t is

$$\begin{aligned}\frac{\partial \mathbf{J}_n}{\partial \mathbf{h}_{n,t}} &= \frac{\partial \mathbf{J}_n}{\partial \mathbf{h}_{n,T}} \prod_{k=t}^{T-1} \frac{\partial \mathbf{h}_{n,k+1}}{\partial \mathbf{h}_{n,k}} \\ &= \frac{\partial \mathbf{J}_n}{\partial \mathbf{h}_{n,T}} \prod_{k=t}^{T-1} f_{n,k+1}(\mathbf{w}_{n,k+1} \odot \mathbf{h}_{t-1} + \mathbf{b}_n) \\ &= \frac{\partial \mathbf{J}_n}{\partial \mathbf{h}_{n,T}} \mathbf{w}_{n,\mathbf{h}_t}^{T-t} \prod_{k=t}^{T-1} f_{n,k+1}\end{aligned} \tag{2}$$

where $f_{n,k}$is the derivative of the activation function such as ReLU and Tanh, which shows its gradient $\mathbf{w}_{n,\mathbf{h}_t}^{T-t} \prod_{k=t}^{T-1} f_{n,k+1}$ is directly depends on the value of the recursive weight matrix $\mathbf{w}_{n,h_t}$. When using ReLU as activation function(the result is the constant 0 or 1). Assuming the maximum gradient value to ensure that the gradient doesn't explode is γ. So the range of $|\mathbf{w}_{n,\mathbf{h}_t}|$ can be represented as $[0, \sqrt[T-t]{\gamma}]$. In the case of $|\mathbf{w}_{n,\mathbf{h}_t}| = 0$, the neuron only regards the information from the current input and does not retain any past memory. This method basically maintains the gradient within an appropriate range and does not affect the gradient backtracked through the neuron. It avoids the errors caused by the commonly used gradient clipping method. By stacking the basic IndRNN structures, it is possible to build a deep network that can even handle sequences over 5000 time steps.

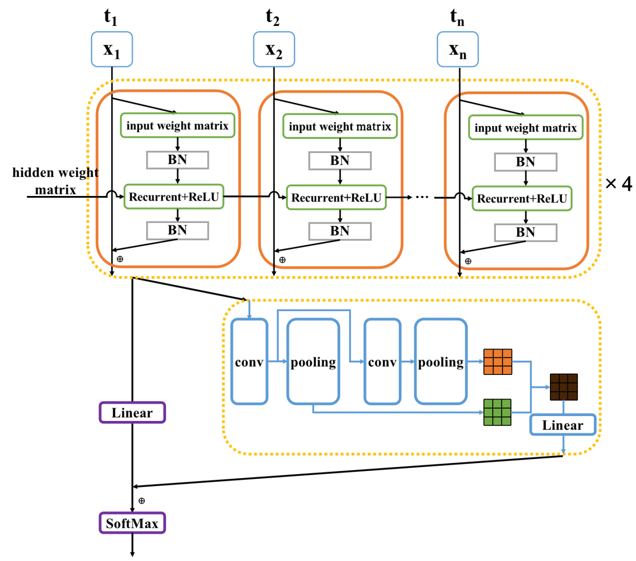
3.2 Structure of RIRCNN

As inferred by Li [5], neurons in first layer of IndRNN mainly sequence position information, one neuron in second layer aggregates input into long-term memory, while other neurons usually retain their state or process short-term memory. Therefore, in order to extract time series characteristics and state parameter characteristics of the aviation turboprop engine air circuit time series fault data as accurately as possible, we need to design a model with more than two layers. When a multi-layer IndRNN network stacked, the neurons in each layer contain the parameter characteristics of all neurons in the previous layer, and the output of the network contains the feature extraction results of all neurons in the hidden layer. We finally superimpose 4-layer IndRNN with 512 neurons in each layer. After the IndRNN model, if simply stacking the fully connected layer and the dropout layer to extract the classification results, although the probability distribution of the desired format can be obtained, the randomly discarded neuron information may cause the loss of some important information. It makes the classification precision exist a certain bottlenecks.

Therefore, in order to eliminate defects, this paper uses IndRNN as a general design for processing time series data to extract time series features. Then a convolutional neural network structure is introduced as a classifier, and the output tensor of IndRNN is used as the input of CNN. The probability distribution of the fault category can be obtained after the output of the convolution calculation. CNN adapts to data extraction features by combining convolutional layers and pooling layers. As the number of network layers increases, the corresponding extracted features are more complex, also, the receptive field is larger. When CNN calculates, the weight information of neurons in different positions is shared, and the global features of the input data can be extracted by integrating the information. These features make CNN as a classifier in the line with the purpose of digital data classification in this paper. IRCNN is a simple serial combination structure of 4-layer IndRNN and 2-layer CNN. However, simply superimposing CNN may cause overfitting of the model and reduce the diagnostic precision. Therefore, further research is needed.

Residual network proposed by He [10] is to address the degradation problem of Deep networks. The structure of residual learning is somewhat similar to a "short circuit" in

Figure 2. RIRCNN structure.



a circuit. It is to directly transfer concepts captured by previous layer to next layer. Our proposed RIRCNN residual connect 4-layer IndRNN and 2-layer CNN shown as Figure 2. We introduce residual connections between all network layers, and add the output data of the previous layers and the output data of the latter layers by weight directly. Explaining in principle, the stacked layers only do the identity mapping without increasing the parameters and computational complexity. It don't need to be re-learned every time, which improves reusability and reduces redundancy. In order to speed up the training, Batch Normalization is inserted after each layer. The output of residual connection is adjusted by fully connected linear layer, and then output to softmax activation function layer to calculate probability distribution of the fault category.

4 Experiment

4.1 Data Introduction

The existing aero-engine air circuit parameter baselines calculation model is not disclosed by the engine manufacturer as a commercial secret. And there are only a handful of fault data obtained during actual flight. In order to increase the reliability of data, we plan to obtain the data of changes in air circuit components sensed by sensors from the actual aviation flight and the ground experiments. In addition to collecting the history field data, simulating operation of the military aero-turboprop engine "WJ-XX"[1] under different

[1]The details of the aircraft cannot be disclosed due to non-disclosure agreements

working conditions in bench experiments is needed to obtain stable and long-term data.

We adjust performance parameters (such as pressure compressor Delta flow HPC/LPC-DW etc.), then we obtain the corresponding aviation turboprop engine air circuit measurement parameter changes. Aero-engines have hundreds of air circuit components, according to expert prior knowledge and historical experience, we extract the key attributes below: T1, torque, ITT, PCNF, PCNC, PCNP, P3, WFB and the working condition. We sample the data at interval (every 0.1s) according to the equipment situation and took out the data with same flight time. The data step size is maintained at about 800. Then, 8 main fault and 1 healthy states of the aviation turboprop engine air circuit are summarized: blade corrosion, blade tip wear, foreign object damage, blade fouling, insufficient opening of high-pressure/low-pressure turbine valve, improperly open/close of the turbine valve. Finally, a data set with sample size of 6149 is obtained. Training dataset and testing dataset are divided by the ratio of 8:2.

Considering the degradation trend of sensor measurement variables and some outliers are usually exist. We use the classic isolated forest algorithm to clean the data has achieved good results. Moreover, in order to make the distribution of the data more concentrated and accelerate the convergence of the model, we normalize the data. The cleaned effective data can also reduce unnecessary abnormal parameter troubleshooting.

4.2 RIRCNN Fault Classification Experiment

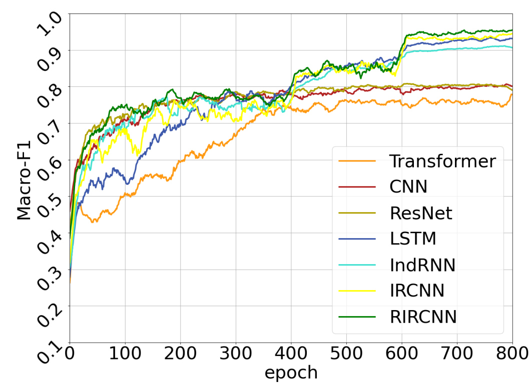
Affected by weight initialization, neural network outputs have correlated randomness. To counteract the effects of randomness, we repeat each experiment 10 times and take average of the fault classifications for comparison. We use a variety of models to compare the performance of the RIRCNN model on 6419 flight data including 9 states. Each model uses random 5.1k pieces data to train and another 1.4k pieces data to test.

The performance comparison experiments with RIRCNN include Transformer, CNN, ResNet, LSTM, IndRNN and IRCNN. During the designing of each neural network fault diagnosis model, we first use fully connected neural network to non-linearly map features extracted by each model. Then, we use function to normalize the output value of fully connected neural network to convert the probability of different categories predicted by the model. On this basis, in the training process of classifier model, the Categorical Cross Entropy Loss is used as evaluation function, Adam is used as optimization algorithm and Dropout technique is adopt to prevent the overfitting of model. In view of different structures of each model and different types of applicable data, we select the optimal configuration for each

Table 1. Memory-Usage(MemoUsg) and performance.

model	MemoUsg	Precision	Macro-F1
Transformer	2011Mib	76.82%	0.7710
CNN	1693Mib	82.38%	0.8258
ResNet	1689Mib	83.03%	0.8332
LSTM	2249Mib	92.50%	0.9277
IndRNN	1745Mib	92.53%	0.9291
IRCNN	1945Mib	94.44%	0.9466
RIRCNN	**1991Mib**	**95.73%**	**0.9610**

Figure 3. Macro-F1 of all models



in terms of number of layers and hidden units, so these parameters are not included in the assessment. We evaluate the model by calculating the failure classification precision and the multi-classification problem scoring metric Macro-F1. Table 1 records the memory required at runtime and the Precision and Macro-F1 score of fault diagnosis. Figure 3 visualizes Macro-F1 of each model.

It can be seen that the LSTM model has high precision in the task of air circuit fault data diagnosis of aero-turboprop engines, but with the highest memory consumption during model training. Compared to LSTM, RIRCNN has better performance with less memory consumption. The optimal average classification precision of LSTM and IndRNN can only reach 92.50% and 92.53%, while RIRCNN can exceed 95%, and also RIRCNN is better than other models in the Macro-F1 score. It proved that our proposed model is effective.

5 Conclusion

In this paper, we propose a novel model RIRCNN which can extract spatial information independently and extract global features and fast convergence. RIRCNN solves the limitation of RNN and its variants in terms of network depth, it can process long sequences without a large increase in memory consumption. Multiple comparison experiments were conducted with existing baseline models. The result verifies that the proposed RIRCNN model is superior to the existing neural network models in the problem of air-circuit fault data diagnosis of areo-turboprop engines.

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