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A diagnosis method of capsule surface damage based on convolutional neural network

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Abstract. In order to accurately identify whether there are damages and damage types on the surface of the aerostat capsule, combined with the powerful data processing capabilities and abnormal pattern recognition capabilities of deep learning, this paper proposes a continuous wavelet transform (CWT) and deep convolution. The diagnosis method of capsule surface damage combined with convolutional neural network (Convolutional Neural Networks, CNN). First, use CWT to convert the collected original stress and strain signals into time-frequency domain images, and then use CNN to classify and identify the time-frequency domain images to determine the damage category of the capsule surface. The CWT-CNN method is different from the traditional fault diagnosis method, it needs to go through the traditional feature extraction process, and the pros and cons of the extracted features often determine the final recognition accuracy. This method effectively overcomes the traditional fault diagnosis method that requires a large amount of signal processing technology. And rich engineering practice experience to extract the shortcomings of fault experience. The experimental results show that the CWT-CNN method can achieve an accuracy of more than 95% in the recognition of the surface damage of the capsule.

Keywords: Capsule material, Continuous wavelet transform, Convolutional neural network.

1 Introduction

The aerostat is one of the earliest applications and developments in human history. It relies on the lighter than air gas filled into the airbag to generate buoyancy, overcome its own weight to float in the air, and then perform tasks and perform functions in the high altitude. The working environment of the aerostat capsule in the air is very harsh, such as large temperature difference between day and night, strong ultraviolet radiation, changing wind load, etc., plus the long working time of the aerostat, there is bound to be a tendency of structural damage and strength degradation after long-term service. There may also be safety hazards such as cracks, skipping wires, tearing, and creeping. Therefore, comprehensive and

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continuous collection of key state data of the capsule and scientific assessment of the health of the capsule are of great practical significance for reducing the risk of aerostat operation.

At present, deep learning has become a hot research direction in machine learning, and it has very mature applications in fault diagnosis and damage identification. She[1]et al. proposed a multi-layer deep convolutional neural network, which can effectively identify the fault types of rolling bearings. Zhang[2] et al. proposed a WDCNN model, which has the characteristics of the first-layer large convolution kernel and the multi-layer small convolution kernel, and the recognition rate on the CWRU database can reach 100%. However, there is less research on damage identification on braided materials, mainly because these materials usually have a multi-layer structure, and the failure mechanism is more complicated than traditional structures. Wu[3] et al. proposed a Lamb wave-based damage detection method for composite structures, combined with convolutional neural networks for damage identification of braid materials. The advantage of this method is that the damage information of the composite structure can be identified efficiently and accurately, and there is no need for excessive feature extraction and reduction, and the operation is simple.

2 Principle of continuous wavelet transform (CWT)

Wavelet transform is a time-frequency analysis method with self-adaptive ability. It can automatically adjust the size of the time window according to the signal frequency, and can perform multi-resolution analysis. Similar to the short-time Fourier transform, the continuous wavelet transform is defined as follows:

$$W(s,\tau)=\langle x(t),\varphi_{s,t}(t)\rangle=\frac{1}{\sqrt{s}}\int x(t)\cdot\varphi^{*}(\frac{t-\tau}{s})\,dt$$

The wavelet basis function has two parameters, s,τ, called the scale factor and the translation factor, which control the center frequency of the wavelet transform and its translation along the signal on the time axis, respectively. Because these two parameter factors both take continuously changing values, they are also called continuous wavelet basis functions, which are a series of functions obtained by the same generating function through expansion and contraction, and the continuous wavelet transform is also named. It is precisely because the wavelet has two variables, scale and translation, that the time signal can be projected onto the time-scale phase plane, which is beneficial to extract the characteristics of certain time functions. Compared with short-time Fourier transform, continuous wavelet transform is more complicated, but it has advantages in solving certain problems.

The key to CWT lies in the selection of wavelet basis functions. Wavelet basis functions are divided into two types: orthogonal and non-orthogonal. Generally, orthogonal wavelet basis functions should be used for discrete wavelet transform and wavelet packet transform, while continuous wavelet transforms can be either orthogonal or non-orthogonal. Can choose non-orthogonal wavelet basis function. The size of the wavelet transform coefficient actually reflects the similarity between the signal part and each wavelet basis function. The larger the coefficient, the more similar the signal part and the corresponding wavelet basis function.

3 Convolutional neural network (CNN)

Convolutional Neural Network (CNN) is a feed-forward neural network, which is a supervised learning network and has excellent performance in computer vision and target recognition. Generally speaking, a convolutional neural network includes convolutional layer, activation layer, pooling layer, and fully connected layer.

The convolution layer uses the convolution kernel to perform convolution operations on the input signal or the local area of the feature, and extract the input feature. The most important feature of the convolutional layer is weight sharing, that is, the same convolution kernel traverses the input signal or feature once according to a fixed step. Weight sharing can reduce the network parameters of the convolutional layer, avoid over-fitting due to too many parameters, and can speed up the calculation. The basic formula of convolution operation is as follows:

$$y^{l(i,j)} = K_j^l * X^{l(r^j)} = \sum_{j'=0}^{W-1} K_i^{l(j')} X^{l(j+j')}$$

$K_i^{l(j')}$ is the j'th weight of the ith convolution kernel of the lth layer, and X^l(r^j) is the jth convolution in the lth layer In the local area, W is the width of the convolution kernel. It can be seen that the convolution operation is to multiply the convolution kernel and the coefficient corresponding to the neuron in the convolved area to obtain the first value, and then move the convolution kernel by the set step size, and repeat the previous convolution operation, until the convolution kernel traverses all areas of the input signal.

After the convolution operation of the convolution layer, it is necessary to use the activation function to perform a nonlinear transformation on each output obtained by the convolution. The purpose is to map the originally linear and inseparable multi-dimensional features to another space, so that the neural network can approximate any function. The neural network can be applied to many nonlinear models, and the neural network expression ability is better. Commonly used activation functions are Sigmoid function, hyperbolic tangent function Tanh and modified linear unit ReLU. Because the derivative value of the ReLU function when the input value is greater than 0 is always 1, which well overcomes the gradient dispersion object, ReLU is used as the activation function of the experimental network, and its expression is as follows:

$$a^{l(i,j)} = \max\{0, y^{l(i,j)}\}$$

$y^{l(i,j)}$ is the output of the convolutional layer, $a^{l(i,j)}$ is the activation value of the convolutional layer output $y^{l(i,j)}$.

The pooling layer mainly performs down-sampling operations, so the pooling layer is also called the down-sampling layer, mainly to reduce the parameters of the neural network. Commonly used pooling functions include average pooling and maximum pooling. Average pooling uses the mean value of the pooling area as the output value, and maximum pooling uses the maximum value of the pooling area as the output value.

The fully connected layer classifies the pooled features, arranges the pooled feature maps into a column to form a set of feature vectors, as the input of the fully connected layer, and finally fully connects the input and output. The activation function used by the fully connected layer is ReLU. When the neural network is used for classification, a classifier will be trained in the fully connected layer, and the number of nodes in the output layer is the same as the number of classifications.

4 Experiment preparation and data acquisition

4.1 Experiment preparation

Use a rope to hang the balloon in the air to maintain a free state, and inflate the balloon to 5kPa before collecting data. Use a constant 200Hz sound wave signal as the excitation signal for 100s. The signal acquisition uses a dynamic stress-strain test system, and the sampling frequency is set to 2K. The distance between the outer ring of the strain gauge is 10cm, and the distance between the inner ring is 8cm. Each ring is arranged with 4 strain gauges, and each strain gauge corresponds to a channel. Channels 5-8 are outer ring channels, and channels 9-12 are inner ring channels. Each time the balloon was inflated to the working pressure of 5kPa, it can be inflated to the experimental state in about half an hour. Due to the different degrees of air leakage in various parts of the balloon, it needs to be inflated repeatedly to 5kPa after each data collection and the inflation shall be stopped during the data acquisition process.

Figure 1 shows the arrangement of strain gauges and the location of defects.

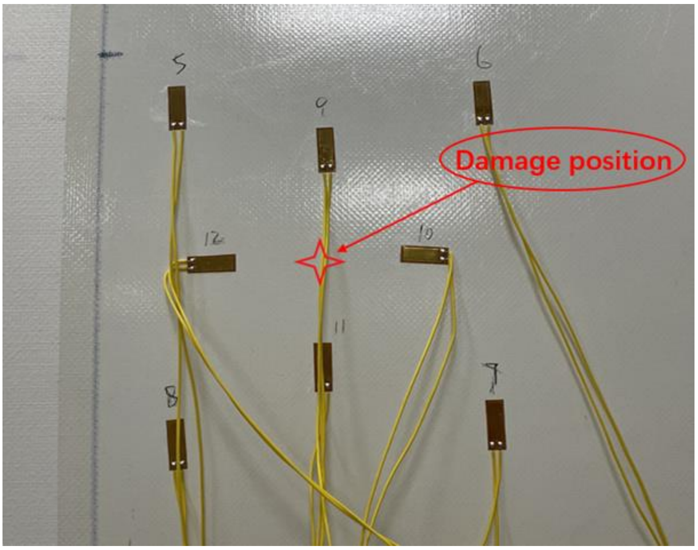

Fig. 1. Strain gauge layout and damage location.

4.2 Data acquisition

A total of three types of damage were set to the capsule during the experiment, namely a transverse 5mm slit, a 5mm×5mm cross slit, and a 5mm×5mm irregular wear. The data was collected in the non-damaged state and each damage state repeated ten times. The original data was exported to the mat file through the signal acquisition system. During the export process, the useless data at the beginning and the end of the experiment were cut off in advance.

5 Damage identification

In the process of data preprocessing, it is found that under 200Hz excitation, the vibration signals of different damaged capsules above 300Hz are quite different. Therefore, in the final CWT, the part above 300Hz is intercepted and the time-frequency diagram is drawn for training. Take random eight of the ten experiments for each state as the training sample, and the other two as the test sample. In the training sample, the ratio of the training set to the validation set is 7:3. The specific parameters of the convolutional neural network used in this article are as follows: the size of the three convolutional layer convolution kernels are 5, 3, 3, the convolution step size is 1, the learning rate is 0.0005, and Batch Normalization and Drop out are used. To prevent the model from overfitting, the batch size is set to 128, and the number of training generations is 10 generations. The following Table 1 is an introduction to the training samples and test samples. Table 2 is the recognition accuracy under different classification situations.

Table 1. Introduction to training samples and testing samples.

Damaged state	Air pressure state	Training /Test samples	Label
no damage	5.1KPa	5636/1372	0
5mm transverse slit	5.0KPa	5432/1372	1
5mm×5mm cross slit	5.0KPa	5308/1276	2
5mm×5mm irregular wear	4.9KPa	5358/1394	3

Table 2. Diagnosis accuracy under different classifications.

Damage classification	Verification accuracy	Test accuracy
no damage/single slit	100%	98.78%
no damage/cross slit	100%	99.48%
no damage/irregular wear	99.94%	98.89%
single slit /cross slit /irregular wear	98.59%	98.74%
no damage/single slit/cross slit/irregular wear	95.30%	95.72%

As shown in Table 2, the two-class recognition accuracy of normal and any kind of damage can reach 99%, the three-class recognition accuracy of three kinds of damage can reach 98%, and the four-class recognition accuracy of normal and three kinds of damage can reach 99%. 95%. The proposed method has high recognition accuracy, and the recognition results are in good agreement with the actual results.

6 Conclusion

Due to the complexity of the capsule material structure, the failure mechanism is more complicated than traditional models, and it is difficult to extract features. Combining the advantages of deep learning, this paper proposes a method of capsule surface damage recognition based on continuous wavelet transform and convolutional neural network. This method does not require the complicated process of extracting features in traditional recognition algorithms, and transforms the problem of damage recognition into a classification problem of signal time-frequency domain images. The CWT-CNN method proposed in this paper has high accuracy in the recognition of capsule surface damage, and provides a new idea for the fault diagnosis of capsule materials.

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