Fault Diagnosis of Gearbox based on Convolutional Neural Network and Infrared Thermal Imagining

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***Abstract*—Diagnosis of gearbox is crucial to prevent catastrophic failure and reduce financial losses. In this study, we introduce a novel fault diagnosis technique using the infrared thermography (IRT). The IRT-based techniques have merits of non-contact measurement and high-scalability. Since the convolutional neural network (CNN) is proven to be powerful in image processing, a fault diagnosis strategy is designed by combining the IRT and CNN. Then, the pattern identification is achieved by using softmax regression (SR) classifier. One experimental data is used to validate the effectiveness of the proposed method. Results demonstrate that this diagnosis strategy can recognize gearbox with various oil-level faults. Furthermore, some important distinguishable areas of IRT images are marked for further focused research field.**

Keywords—gearbox; fault diagnosis; infrared thermal imaging; convolutional neural networks; softmax

I. INTRODUCTION

Gearbox is one of the most important and common transmission components, which is widely used in modern industry. Once the fault occurs, it may cause the breakdown of machines and great financial losses [1-3]. Health condition monitoring of gearbox is crucial to guarantee safety operation and avoid unexpected accidents. Until now, there are many mature techniques for HCM of gearbox. Among these techniques, the vibration-based method is most widely applied in industrial applications. However, the vibration-based method is a contact measurement method, which is not allowed in many real applications. Moreover, prior knowledge is required when extracting the fault features. Therefore, it is essential to find a convenient and effective method to acquire effective information on machines. Currently, using temperature for fault diagnosis gives researchers a new horizon. When the localized damage occurred, a higher temperature will be generated by the frictions. Furthermore, different temperature distributions will be generated by different fault types of machines. Hence, the infrared thermography (IRT) is a viable technique to differentiate various faults of gearbox.

Nowadays, with the development of the computer technology, the deep learning (DL) are booming due to its features of accuracy and convenience [4]. Among these, a highly desirable approach is convolutional neural network (CNN). CNN has an outstanding performance for image identification due to its special network structure: convolution layer and pooling layer. Therefore, CNN can be used to obtain important fault features for the IRT images [4]. After the fault extraction, the softmax regression (SR) is adopted for pattern identification. Furthermore, we utilize CNN and SR method to discover the important region of the IRT images. These important areas contain main fault information, which can be further researched in future work.

Motivated by the IRT and CNN, an automatic method is developed to diagnose various oil-level faults of gearbox. It can be seen as a two-stage method. First, CNN is adopted to describe the fault characteristics from the measured IRT images. Second, the recognition of various fault types is achieved by using SR classifier. The rest of this paper is organized as follows. A detailed explanation of CNN method and the proposed diagnosis framework is presented in Section II. Section III introduces the detection process of important region of the IRT images. Section IV validates the effectiveness of the proposed method using the experimental data and the important area is also detected in this section. Finally, Section V represents a conclusion for this paper.

II. THE PROPOSED METHOD

A. Convolutional Neural Networks

CNN has been proven to be powerful tool in processing the images. A typical CNN commonly consists of one feature extraction stage and one classification stage. Four kinds of layers are contained in the feature extraction stage. More details of each layer will be introduced as follows. In the classification stage, softmax activation function is applied for pattern identification. In this paper, CNN is directly used to extract features from the raw IRT images, thereby, this is an end-to-end intelligent system.

1) Convolutional layer

The convolutional layer is a very key component of the feature extraction stage. It is mainly used to extract the abstract feature using a series of filters. Weight sharing is also utilized that the filter utilizes the same kernel, which much avoids the huge parameters of the traditional fully connected network.

2) Batch normalization layer

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For a deep neural network, a little change occurred on the input can cause the output changing greatly after multiple layers, which may bring instability to the network. Batch normalization layer (BNL) is proposed to deal with this problem. BNL takes a normalized operation for the input to keep the stability of the network and accelerate the training process further.

3) Activation layer

Activation layer is used to introduce nonlinear learning and processing ability in the neural networks. Recently, approximate activation of biological neurons has become a hot research spot, such as Rectified linear unit (ReLU). Compared with traditional Sigmoid function, ReLU has some obvious advantages: unilateral inhibition, a relatively wide exciting boundary, and sparse activation.

4) Pooling layer

Pooling layer is a very important component of CNN, which is often placed after the convolutional layer. Pooling layer aims to take a downsampling operation, which can reduce a large number of parameters for the network and avoid overfitting. Moreover, the operation can keep invariance of the local linear transformation. Common pooling operation consists of max pooling, average pooling, and weighted average pooling. In this paper, max pooling is applied to obtain the largest value for the local input region. The process can be expressed as Eq.(1):

$$x^{l} = \max_{(j-1)W+1 \le i \le jW} \{x^{l-1}(i)\} \tag{1}$$

where W represents the size of the max-pooling region.

B. *Steps of the proposed method.*

This section aims to propose a novel fault diagnosis framework of gearbox using IRT and CNN. The proposed method can be described into four steps:

Step 1: Using the thermal camera to obtain the infrared video;

Step 2: Intercepting the infrared images from the infrared video. Then, the obtained infrared images are divided into training dataset and testing dataset;

Step 3: CNN is adopted to describe the fault characteristics from the training dataset. After that, an intelligent classification model can be built by using CNN and SR;

Step 4: Validating the effectiveness of this model by using the testing samples.

III. IMPORTANT REGION DETECTION OF THE IRT IMAGES

In real industrial applications, it is crucial to find the fault related regions to monitor the health conditions of machines. In this paper, we apply CNN and SR can discover the important regions for a given machine condition. As we know, SR is a probability model. The output of SR is a one dimensional array and the position of the max value is the classification result. As well known, the distinguishing ability for one region will be low if the feature extracted from this region is indistinguishable. Thus, the output of SR can reflect the discriminating level for the extracted features from special regions. Based on this, some fault information will be removed if certain important regions of the thermal image are masked. Therefore, the important region of the thermal image will be detected. The process of important regions detection required three steps:

The flowchart of detecting important regions is as follows.

Step 1: Mask a part of the images by giving a constant value 0 for the masked part. In this paper, the size of the masked part is 10 × 10 pixels.

Step 2: Use the trained CNN to classify the modified incomplete images and apply the SR activation function to estimate the probability value in the output layer.

Step 3: The correct class probability will be saved in a matrix. For the masked area, there will be a probability value indicating whether the masked area is more important than others.

IV. EXPERIMENTAL VALIDATION

A. *Experimental settings*

In order to validate the proposed method for fault diagnosis of gearbox, a helical gearbox was established in the University of Huddersfield. Fig. 1 gives a sketch of the experiment device. The infrared data is obtained by the thermal camera settled on one side of gearbox 1(GB1). Table I describes the parameters for the thermal camera.

TABLE I. THE PARAMETERS OF THERMAL CAMERA

Specification		Setting	
Frame rate	25/1	Alg Type	PHE
Temperature measurement range	-25°~260°	Contrast	50
Environmental temperature	18.90°	Brightness	50
Thermal sensitivity	0.050°	Gain	2
Definition	384init	Palette	rainbow

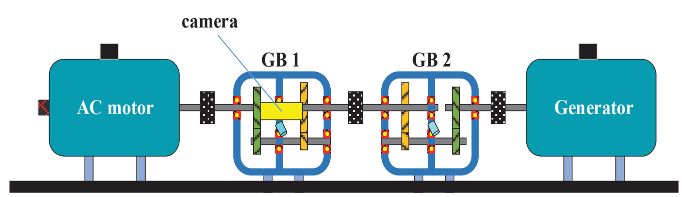

Figure. 1. The sketch of the test rig

In this case, four different specification loads (0%, 30%, 70%, and 100%) are added to this case to keep the dataset rich enough. Therefore, variability is introduced into the dataset by using different loads. Under each working condition, when the test rig is stabilized, which means the oil temperature is nearly constant, the data will be collected by using an infrared camera for 3 minutes.

In this study, a typical CNN is adopted to process the thermal images. The CNN consists of four convolutional layers. Pooling layer is placed after the convolutional layer to reduce the size of the data. After the last pooling, the extracted features will be converted to one-dimensional data as the input of the fully connected network. Finally, SR is used to classify different working conditions in the output layer. The structure of CNN is illustrated in Fig. 2.

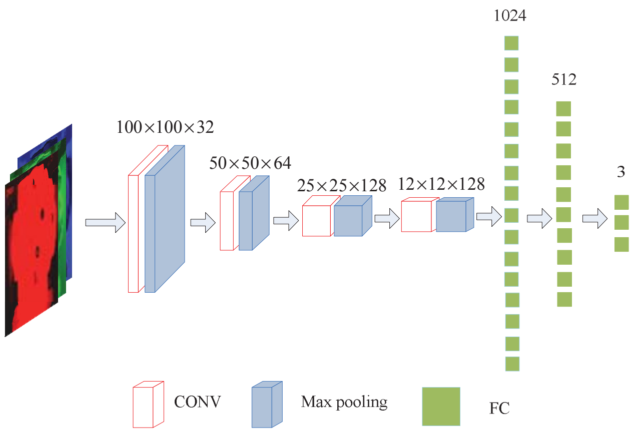

Figure. 2. The structure of CNN

B. *Validation of the proposed method*

In this experiment, three working conditions are designed. Condition 1 is the healthy condition with recommended oil 2600 ml (simplified into OS2600). Condition 2 is with decreasing oil 600 ml (simplified into OS2000). Condition 3 is with decreasing oil 1100 ml (simplified into OS1500). All three working conditions are operated under four different loads. In total, there are 960 samples for three working conditions and the training rate for the tests is 35%. Table II illustrates the size of training and testing data of gearbox with different oil-level faults.

TABLE II. THE DETAILED DATASET OF CASE 1

Oil-level	Label of condition	Size of training samples	Size of testing samples
OS1500	1	112	208
OS2000	2	112	208
OS2600	3	112	208

In order to validate its advantage in distinguishing various faults of helical gearbox, it is necessary to compare the performance of the proposed method with reported vibration-based method [5]. We use 25 features to describe its fault characteristics from the raw vibration signals of helical gearbox. which are given in Table III.

TABLE III. LIST OF THE EXTRACTED FEATURES OF HELICAL GEARBOX

Number	Feature	Number	Feature
F1	Mean	F14	M6A
F2	Standard deviation	F15	M6A*
F3	Root mean square	F16	NA4
F4	Peak	F17	NA4*
F5	Skewness	F18	NB4
F6	Kurtosis	F19	NB4*
F7	Crest factor	F20	Energy ratio
F8	Clearance factor	F21	Energy operator
F9	Shape factor	F22	Mean frequency
F10	Impulse factor	F23	Frequency centre
F11	FM0	F24	Root mean square frequency
F12	FM4	F25	Standard deviation frequency
F13	FM4*		

Notation: FM0 is a key indicator for gear mesh fault; FM4 is the kurtosis of the difference signal; NA4 is calculated by a residual signal of a time record; NB4 is designed on the envelope analysis of filtered signal; * represents an improvement.

For a fair comparison, SR is also selected to classify the various oil level of the helical gearbox for the vibration-based method. Meanwhile, the training rate and testing rate are the same as the proposed method. Note that 20 rails are conducted for each method to avoid the randomness. Table IV gives the classification results. It can be found that: 1) the mean accuracy of the vibration-based approach is 67.69% (422/624) while the proposed method has much higher accuracy than that of the vibration-based method. 2) The proposed method has a lower standard deviation compared with the vibration-based method. This indicates the IRT-CNN method is more stable.

TABLE IV. CLASSIFICATION RESULTS FOR OIL-LEVEL CLASSIFICATION.

Method	Conditions	Mean Accuracy	Standard deviation
The proposed method	OS1500,OS2000,OS2600	100%	0
Vibration-based method	OS1500,OS2000,OS2600	67.69%	6.33%

In addition, Fig. 3 gives the clustering maps of two methods, which are generated by PCA method. Seen from Fig.3, three conditions can be easily classified by using the IRT-CNN method. However, in vibration-based method, only the OS1500 fault can be distinguished. The OS2000 and OS2600 are mixed together. Therefore, we can draw the conclusion that the vibration signal is not sensitive for small range variation of lubricating oil, such as OS2000 and OS2600.

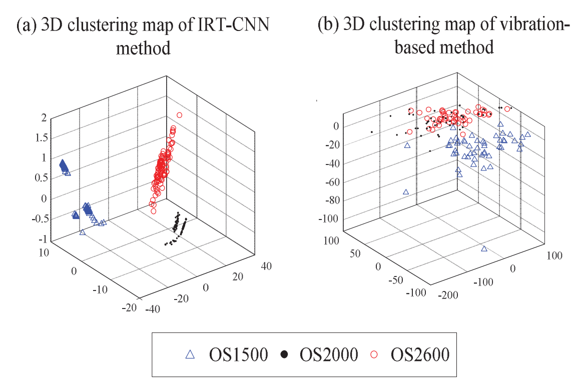

Figure. 3. The clustering maps of the proposed method and vibration-based method.

C. *Important region detection of the IRT images*

In order to discover the important regions of the IRT images, we mask each image separately for different area with the pixel size of 10×10. The obtained results are shown in Fig. 4. The part of the red circle shows the important regions in the IRT image for the specific conditions. In addition, we can see that different oil-level shows different important regions. For example, it can be seen that the important region focuses on the left bearing for OS1500. This phenomenon can be explained that the left bearing generates much more heat due to insufficient lubricant.

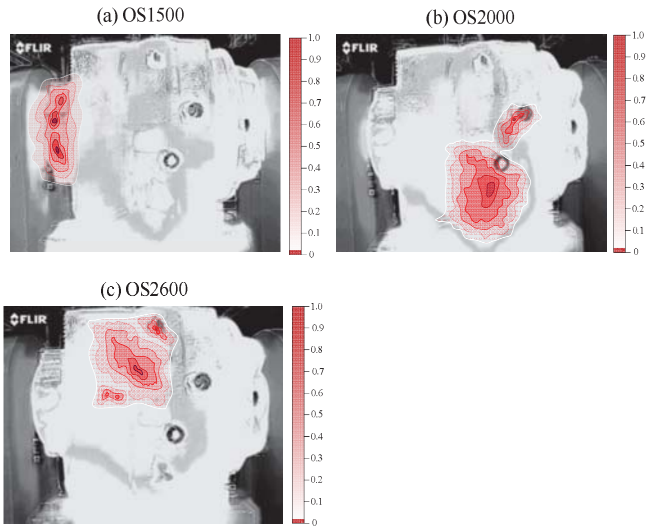

Figure. 4 The important region of the IRT images: (a) OS1500; (b) OS2000; (c) OS2600

CONCLUSION

The paper proposes a fault diagnosis strategy of gearbox using IRT and CNN. Compared with the vibration-based method, the superiority of the IRT-CNN method is validated by diagnosing various faults of gearbox. Results indicate the IRT-CNN method offers a promising tool for condition monitoring of gearbox. Meanwhile, this study gives a sight of discovering the important region of the IRT images for further discussion.

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