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Fault Diagnosis of Rotating Machinery under Variable Operating Conditions Based on Multi-Feature and Transfer Learning

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***Abstract*—The reliability of rolling bearings is one of the crucial guarantees for the continuity and safety of industrial production. However, due to the high temperature, high pressure, and long duration characteristics of their operating environment, the vibration signals often exhibit certain non-stationarity and non-linearity. Additionally, the lack of fault samples makes it challenging to apply data-driven diagnostic methods. This paper proposes a fault diagnosis method for rotating machinery under variable operating conditions based on multi-feature and transfer learning. Firstly, dimensionless features of bearing vibrations are extracted to address the non-linearity of bearing information. To tackle the issue of missing fault samples, an improved convolutional neural network transfer model is proposed to transfer large-scale data models to small-sample models. Validation on the bearing experiment platform of Case Western Reserve University shows that the proposed method achieves an average diagnostic accuracy of 95.9%, providing a theoretical basis for the fault diagnosis of rolling bearings.**

Keywords-Rotating Machinery; Dimensionless Features; Transfer Learning; Fault Diagnosis

I. INTRODUCTION

As one of the critical components in rotating mechanical systems, rolling bearings play a key role in various industrial applications. They bear the heavy loads and the challenges of variable operating conditions of mechanical devices, making it crucial to monitor and maintain their performance and reliability[1]. Significant research has been conducted by scholars domestically and internationally on rolling bearing fault diagnosis, resulting in numerous achievements that have advanced the technology. Currently, fault diagnosis techniques are mainly divided into traditional methods based on knowledge, model-based methods, and data-driven methods[2-4]. For example, reference[5] proposed a method based on Convolutional Neural Networks (CNN) for the diagnosis of bearing and gear faults. Some scholars have developed methods based on Recurrent Neural Networks (RNN)[6] for analyzing vibration signals in machinery.

In bearing fault diagnosis, the high temperature, high pressure, and long operation time characteristics of bearings result in nonlinear and non-stationary signal behaviors, making it difficult to capture fault features. Many scholars have conducted extensive research on sensitive feature extraction, which is mainly divided into time-domain[7], frequency-domain[8], and time-frequency domain methods[9]. In time-domain analysis, reference[10] compared dimensional and dimensionless features of vibration signals in petrochemical machinery and performed high-value feature selection. Shaowu Dai et al.[11] combined time-domain feature extraction with Support Vector Machines (SVM) to predict the lifespan of bearings. Qinghua Zhang's team constructed new mutual dimensionless features based on dimensionless features, overcoming the sensitivity and nonlinearity diagnostic issues of existing dimensionless indicators, thereby improving diagnostic accuracy and reliability[12-13].

To address the issue of imbalanced fault samples, extensive research has been conducted, including Generative Adversarial Networks (GANs) and transfer learning. For instance, reference [14] proposed a Conditional Generative Adversarial Network (CGAN) to generate data in different fault modes using conditional variables to constrain the generation process. Dong et al. applied transfer learning methods to neural networks, proposing a rolling bearing fault diagnosis model based on deep feature decomposition and class-level alignment[15].

In existing research on bearing fault diagnosis, although a series of important achievements have been made, some key issues and challenges still remain. For instance, as a core aspect of fault diagnosis, traditional time-domain feature extraction methods may not fully capture the complex nonlinear characteristics of bearings under variable operating conditions. Moreover, current data-driven methods require a large amount of fault data for training. When dealing with small sample sizes and imbalanced datasets, the generalization capability and accuracy of the models still need improvement. To address these issues, this paper proposes a fault diagnosis method for rolling bearings under variable operating conditions based on dimensionless features and transfer learning. By extracting dimensionless features, it is possible to effectively overcome the sensitivity and nonlinearity issues of traditional dimensionless features in bearing fault diagnosis, thereby enhancing the feature representation capability. At the same time, utilizing transfer learning technology, the knowledge learned from models trained on large datasets is transferred to the target domain with small samples, effectively mitigating the underfitting problem in small sample scenarios and improving the model's generalization capability and diagnostic accuracy. Finally, the diagnostic model is validated on a bearing data platform, which is expected to promote the advancement of bearing fault diagnosis technology and improve the operational reliability and safety of industrial equipment.

II. THEORETICAL BASIS OF FAULT DIAGNOSIS OF ROLLING BEARINGS UNDER VARIABLE OPERATING CONDITIONS BASED ON MULTI-FEATURE AND TRANSFER LEARNING

A. Theoretical Basis of Multi-Feature Extraction for Fault Diagnosis

Dimensionless features have been widely used in fault diagnosis feature extraction due to their high sensitivity to faults and their relative invariance to changes in operating conditions. The Mutual Dimensionless Feature (MDF) index, developed by Zhang Qinghua's team based on the concept of dimensionless features and the idea of signal separation, is a novel indicator. Compared to traditional dimensionless features, MDF is more sensitive to faults and has lower overlap, making it more advantageous for fault diagnosis and classification of bearings. The mathematical model of the vibration signal actually collected during the operation of faulty equipment can be defined as follows:

$$z(t) = y(t) + cs(t-\tau) \tag{1}$$

In the formula: y(t) represents the superposition of the fault signal and noise signal, s(t) represents the fault-free signal, τ represents the delay time, and represents the correlation coefficient between the vibration signal $z(t)$ and the delayed fault-free $s(t-\tau)$ signal. The relationships between these indicators are shown in Figure 1.

By separating the fault signals, a novel mutual dimensionless feature index can be constructed:

$$\zeta_{ys} = \frac{\left[\int_{-\infty}^{+\infty} |y|^{l} p(y)dy\right]^{\frac{1}{l}}}{\left[\left[\int_{-\infty}^{+\infty} |s|^{m} p(s)ds\right]^{\frac{1}{m}}\right]} = \frac{\sqrt[l]{E(|y(t)|^{l})}}{\sqrt[m]{E(|s(t)|^{m})}} \tag{2}$$

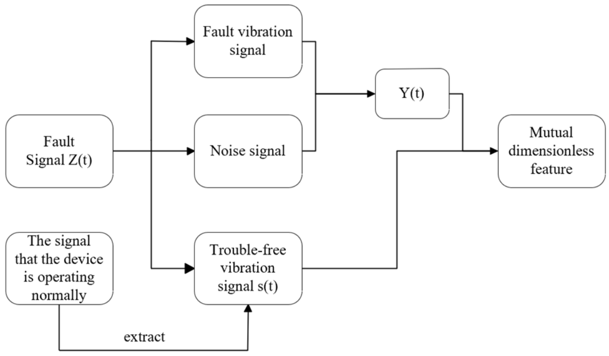


Figure 1. Mutual ondimensional characteristics and each signal

The five most representative mutual dimensionless feature indices are shown in Table 1.

TABLE I. FIVE NEW DIMENSIONLESS FEATURES

New dimensionless features	Formula;formulae；formulary
Mutual dimensional waveform features	$S_{ys} = \frac{\sqrt{E(\|y(t)\|^{2})}}{E(\|s(t)\|)}$
Mutual dimensionless peak characteristics	$C_{ys} = \frac{\lim_{l\to\infty}\sqrt[l]{E(\|y(t)\|^{l})}}{\sqrt{E(\|s(t)\|^{2})}}$
Mutual-dimensionless pulse characteristics	$I_{ys} = \frac{\lim_{l\to\infty}\sqrt[l]{E(\|y(t)\|^{l})}}{E(\|s(t)\|)}$
Mutual nondimensional cliff degree characteristics	$K_{ys} = \frac{E(\|y(t)\|^{4})}{[E(\|s(t)\|^{2})]^{2}}$
Mutual onless margin characteristics	$CL_{ys} = \frac{\lim_{l\to\infty}\sqrt[l]{E(\|y(t)\|^{l})}}{[E(\sqrt{\|s(t)\|})]^{2}}$

B. Theoretical Basis of Transfer Learning

Transfer learning can effectively enhance the recognition ability of minority classes and address the problem of sample imbalance by transferring the knowledge of pre-trained models on large-scale datasets to small sample problems. Scholars have conducted extensive research on transfer learning[16-17], improving the performance of the target task or domain by transferring existing knowledge from one task or domain to another. This paper proposes a variable operating condition fault diagnosis method based on transfer learning. It utilizes Convolutional Neural Networks (CNN) to apply the "knowledge" trained on one operating condition dataset to another operating condition, thereby improving the training speed and generalization ability of the model.

To achieve effective partitioning of different types of source domain data features in the deep feature space, supervised training of the convolutional neural network model with labeled data in the source domain can be conducted. According to the optimal transport theory, targeted adaptive adjustment of the local distribution of deep features is performed to reduce the feature distribution differences between the equipment data. Therefore, the guidance route of the target domain for the samples to be diagnosed can be set as follows:

$$d_{j,i}^{t\to s}=\begin{cases}2\arcsin(\left\|\widetilde{x}_i^{s}-\widetilde{x}_j^{t-a}\right\|/2) & a_{jk}b_{ik}=1\\ \varepsilon & a_{jk}b_{ik}=0\end{cases} \tag{3}$$

In the formula: ε is a constant. If the i-th source domain sample and the j-th sample to be diagnosed are in different targeted regions, the guidance route $\varepsilon \to +\infty$ will be shifted during the targeted adaptation. To minimize the cost of transferring the target domain samples to the targeted region, the transformation matrix $T^{t\to s}$ is searched using the optimal transport theory. Thus,

$$OT(P_t\|P_s)=\sum_{i}^{n_s}\sum_{j}^{n_a}T_{j,i}^{*t\to s}\cdot d_{j,i}^{t\to s} \tag{4}$$

CNN diagnostic model is trained for domain sharing using the following function:

$$\min_{\theta,\omega} L_c+\alpha\cdot(L_{clu}^{t-b}+L_{clu})+\beta\cdot OT(P_t\|P_s) \tag{5}$$

Where: α and β are the penalty coefficient of the regular term. L_{clu}^{t-b} is the distance between the guidance anchor point and the center of gravity of the similar source domain sample:

$$L_{clu}^{t-b}=\frac{1}{m}\sum_{i=1}^{m}\sum_{k=1}^{n_b}2b_{ik}\arcsin(\left\|\widetilde{x}_k^{t-b}-\widetilde{x}_i^{s}\right\|/2) \tag{6}$$

III. Fault Diagnosis Model Construction

This paper proposes a fault diagnosis method for rotating machinery under variable operating conditions based on multi-feature and transfer learning. The specific process is shown in Figure 2. The training process of the model is mainly divided into three parts: (1) Data preprocessing: Both source domain and target domain data are one-dimensional vibration acceleration data. To better utilize the data, this paper employs a sliding window sampling method to extract five types of mutual dimensionless features; (2) Pre-training of the large data model: The source domain data is input into the convolutional neural network model for training, obtaining the initial parameters such as weights and biases of the source domain network model; (3) Transfer training of the model: The convolution and pooling layers of the source domain classification model are fixed, while the fully connected layer and output layer remain unchanged. The target domain data is then input into the new classification model for training, resulting in the diagnostic classification model of the target domain.

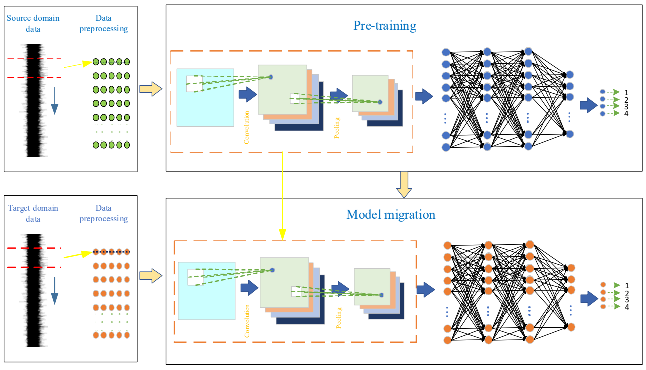


Figure 2. The diagnostic model flow

IV. Experimental Analysis and Validation

A. Experimental platform

The experimental data was validated using the bearing dataset from the Case Western Reserve University Bearing Data Center. The platform consists of a 1.5 KW motor, torque sensor, encoder, power meter, electronic controller, and test bearings. The bearing faults are single-point damages caused by electrical discharge machining, with damage diameters of 0.1778 mm, 0.3556 mm, and 0.5334 mm. Signal acquisition was performed at a sampling frequency of 12 kHz, with 9 rolling elements. This experiment used three rotational speeds as different operating conditions: 1797 rpm, 1772 rpm, and 1730 rpm. The damage diameter was 0.1778 mm, and the fault types were inner race fault, rolling element fault, and outer race fault. The dataset distribution is shown in Table 2.

TABLE II. Distribution of the Experimental Data Sets

operating mode	load (HP)	speed （r/min）	sample number	Data points	Number of states
A	0	1797	5000	1200	4
B	1	1772	5000	1200	4
C	2	1730	5000	1200	4

B. data preprocessing

Taking the operating condition with a rotational speed of 1797 rpm as an example, the time-domain data of the four bearing states are shown in Figure 3.

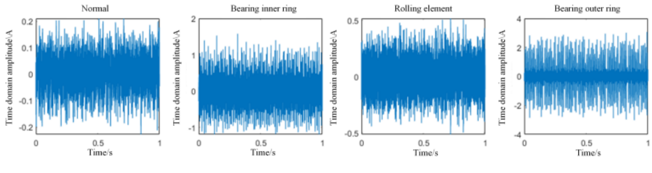
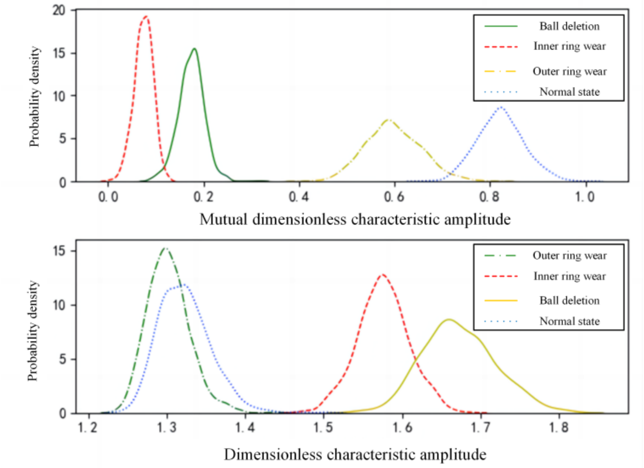
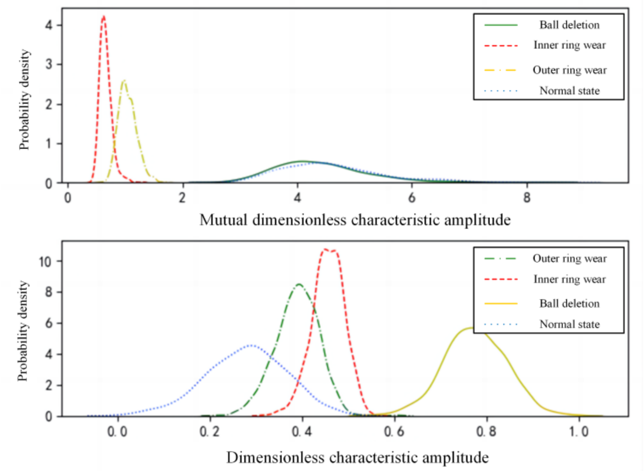


Figure 3. shows the time-domain plots of the four bearing states under the operating condition with a rotational speed of 1797 rpm.

Before inputting the data into the convolutional neural network, sensitive feature extraction is performed on the raw data. The extracted features are mutual dimensionless features, which are relatively more sensitive to faults compared to traditional dimensionless features. Two types of mutual dimensionless features data are selected and compared with traditional dimensionless feature data. The probability distribution comparison of different feature indices is shown in Figure 4.



a） Mutual waveform features



b） Each peak characteristics

Figure 4. shows the probability distribution of the Mutual Dimensionless Feature (MDF) indices.

As seen in Figure 4, the Mutual Dimensionless Features exhibit better clustering effects compared to traditional dimensionless feature indices. While the dimensionless waveform and peak features have some degree of differentiation, the dimensionless pulse and kurtosis features exhibit significant overlap. In contrast, all Mutual Dimensionless Features show good differentiation. The mutual waveform feature can effectively distinguish between different states; the mutual peak feature shows some overlap in the case of ball missing fault but can well distinguish the other three states; the mutual pulse feature has a clustering effect similar to that of the mutual peak feature; the mutual kurtosis feature index also shows some overlap in the case of ball missing fault but can well distinguish the other three states.

C. *Model pre-training*

Firstly, the mutual dimensionless feature data from the source domain is used to train the CNN model. After multiple tests, the final determined basic structure of the diagnostic classification model is as follows: (1) Two convolutional layers, with the first and second convolutional layers having 5 and 10 layers respectively, and both using convolution kernels of size 3×3, with the ReLU activation function and padding set to 1; (2) Three fully connected layers with lengths of 70, 20, and 4, respectively, using the sigmoid activation function, and the output layer uses the softmax activation function for data classification. The loss function for the CNN is the cross-entropy function, and the optimization function is the first-order SGD optimizer. The learning rate is set to 0.01, with 100 iterations and a batch size of 32.

D. *Model transfer training*

To validate the advantage of transfer learning with small samples, the number of feature samples in the source domain and target domain were set to 5000 and 500, respectively. The convolutional layers and pooling layers of the CNN model were fixed, and only the fully connected layers and output layers of the target domain were trained. Different operating conditions were used as the source domain and target domain for training. SVM and CNN transfer models were selected for comparative analysis with the transfer method proposed in this paper. The classification accuracy of the trained models is shown in Figure 5.

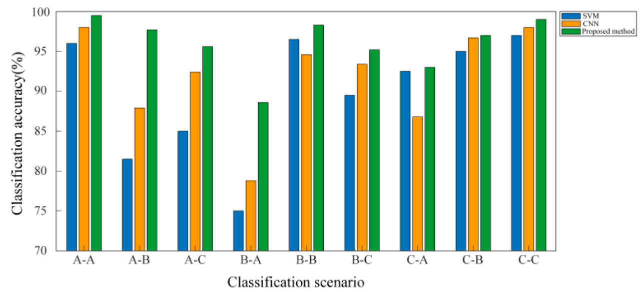


Figure 5. Classification and comparison

In the figure, A-B represents the classification scenario where A is the source domain condition and B is the target domain condition. As shown in Figure 5, the proposed transfer learning method achieves good classification accuracy even with a small number of target domain samples, with an average classification accuracy of 95.9%. Moreover, the transfer learning method proposed in this paper has higher diagnostic accuracy compared to SVM and CNN transfer learning models. Significant improvements in diagnostic accuracy were observed in scenarios A-B, A-C, and B-A. These results demonstrate the superiority of the proposed fault diagnosis method for rolling bearings under variable operating conditions based on mutual dimensionless features and transfer learning.

V. CONCLUSIONS

This paper proposes a fault diagnosis method for rolling bearings under variable operating conditions based on mutual dimensionless features and transfer learning. Firstly, mutual dimensionless features are used as representations of the four bearing states. Then, data from one operating condition is used as the source domain, and data from another operating condition is used as the target domain for model transfer training on the bearing data. Validation using the bearing dataset from the Case Western Reserve University Bearing Data Center shows that the proposed method achieves an average diagnostic accuracy of 95.9%. Additionally, compared to the original transfer learning methods using SVM and CNN, the proposed method shows significant improvement in accuracy, demonstrating the effectiveness of the proposed diagnosis method.

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