A New Bearing Fault Diagnosis Framework With Deep Adaptation Networks For Industrial Application

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Abstract—**In the past decades, a host of fault diagnosis methodologies have been designed and successfully used for bearings. However, most of them still have two deficiencies. (1) Traditional methods extract and select features manually according to a specific issue, but these features may be not appropriate for other tasks, leading to performance degradation of fault diagnosis. (2) Many studies assume that the dataset for model learning obey the uniform distribution as the testing dataset do, which seldom accords with the practice. To remedy these problems, we devise a novel framework for bearing fault diagnosis. First, the raw condition monitoring data are converted to 2D images with continuous wavelet transform. Then the classification model is learned with these 2D images, during which the transfer learning scheme, deep adaptation networks, is introduced for adapting the deep model trained with source data for use in new but related target domain. The presented approach is demonstrated with bearing condition monitoring information, and the results indicate it can identify bearing faults effectively under different operational conditions and has a higher accuracy than conventional approaches.**

Keywords-transfer learning; fault diagnosis; continuous wavelet transform; deep adaptation network

I. INTRODUCTION

Since bearings play an essential role in rotating machinery, their failure can directly influence the entire performance of the equipment, leading to machine breakdown [1]. Hence, an army of investigations have been triggered for identifying bearing faults in the last few decades. Intelligent condition monitoring methods has been an effective tool for increasing equipment reliability and reducing maintenance costs [2]. Generally, there are three modules in the intelligent system: signal collecting, feature extracting, and fault recognizing.

To implement the task, a host of efforts have to be made for obtaining suitable features. Most of existing investigations extracted and selected features manually from different aspects with signal processing techniques [3, 4]. However, the sensitivity of the features obtained in this way can be easily influenced by working conditions, location of sensors, data collection system and so on. Consequently, the selected sensitive features under a certain scenario may be inadequate for other circumstances, which will lead to poor diagnosis performance.

In the third stage of intelligent diagnosis framework, machine learning techniques are usually utilized to detect and categorize faults. Artificial neural networks (ANN) is a widely used traditional algorithm, and it can nonlinearly map the signal features to equipment states. Also, support vector machine was employed for fault identification due to its superiority in addressing small samples. Moreover, introducing deep learning models, i.e., deep belief networks and convolutional neural networks (CNN), to tackle big data issues has become a research hotpot in condition-based maintenance (CBM) in recent years [5, 6]. Although these schemes work well, most of previous studies assume that the dataset for model learning obey the uniform distribution as the testing dataset do. However, in practice, differences may exist because of the variation of operational conditions, which restricts the use of the aforementioned methodologies. Transfer learning (TL) holds the potential to remedy this shortcoming. With TL, the pattern recognition model constructed in a source domain can be adapted to solve tasks in a new but related target domain. This technique has been successfully applied in text processing [7], image recognition [8], audio classification [9], and so on. One of the major strategies to implement the TL is learning domain-independent models to project data of two different domains to a feature space where high classification performance can be achieved. Previous investigations have shown that knowledge transfer on the basis of deep neural networks (DNN) are more powerful than some existing approaches on domain adaptation datasets.

Therefore, based on the deep model, this paper devises a novel fault diagnosis framework with a domain adaptation scheme for DNN, deep adaptation networks (DAN). First, time-frequency techniques are utilized to transform the original data to 2D images. Since we do not have to determine which features to use and how many features should be extract, this procedure can be implemented automatically. Then the images are utilized as input of the DNN, and the model is adapted with the DAN. Through this process, the learned DNN can be utilized to identify the health condition of samples in the target domain.

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II. Related Works

A. Continuous Wavelet Transform

The wavelet analysis is a widely used feature extraction strategy for mechanical CBM. Continuous wavelet transform (CWT) is an effective tool for representing signal information from time-frequency domain, and therefore we use it to convert raw sensor data to images in this study.

With a mother wavelet $\psi(t)$, a group of son wavelets can be generated by [10]

$$\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right), \tag{1}$$

where a denotes the scale parameter, corresponding to the frequency, b represents the translation parameter, corresponding to time.

The CWT of sequence (x) can be expressed as

$$W(a,b) = \left\langle x(t), \psi_{a,b}(t) \right\rangle = |a|^{-1/2} \int_R x(t) \psi^* \left(\frac{t-b}{a}\right) dt, \tag{2}$$

where $\psi^*(\cdot)$ stands for complex conjugate of $\psi(\cdot)$.

In Fourier transform, the frequency amplitude represents the similarity between the signal and each frequency. Similarly, in CWT, wavelet coefficients measure how the signal resemble each son wavelet. Hence, it is of great significance to select a suitable mother wavelet. In this work, we choose Morlet wavelet, because its shape is similar to the periodic impulses in the vibration signal caused by bearing faults.

According to (2), there are two variables for the CWT: a and b, so the CWT results can be mapped to two-dimension images.

B. Deep Adaptation Networks

A crucial issue in deep transfer learning (DTL) is the way of adjusting the learned deep model to solve new data different from the training data. In this investigation, we focus on the adaptation of the CNN. For the deep convolutional architecture, the features learned by the lower layers are general, and the features become more specific as the layer increases [11]. Accordingly, the performance of transferring is directly affected by the adaptation of high-level layers. Deep Adaptation Networks (DAN) [12] is an effective strategy to address this problem, which can adapt multiple layers of the network. Therefore, we utilize the DAN to adapt the deep convolutional network for fault diagnosis.

Multiple kernel variant of maximum mean discrepancies (MK-MMD) [13] is leveraged to measure the discrepancy between two different distributions in the DAN. Let $\boldsymbol{X}_s$, $\boldsymbol{X}_t$, $P_s(\boldsymbol{X}_s) \neq P_t(\boldsymbol{X}_t)$ be two different dataset, and Λ_k denote the reproducing kernel Hilbert space (RKHS) characterized with the kernel k. The MK-MMD between the two distributions $P_s(\boldsymbol{X}_s)$, $P_t(\boldsymbol{X}_t)$ is considered as the distance between the mean embeddings of $P_s(\boldsymbol{X}_s)$ and $P_t(\boldsymbol{X}_t)$ in RKHS space, which can be described as

$$d_k^2(P_s(\boldsymbol{X}_s), P_t(\boldsymbol{X}_t)) \triangleq \left\| \mathrm{E}_{P_s}\left[\phi(\boldsymbol{X}_s)\right] - \mathrm{E}_{P_t}\left[\phi(\boldsymbol{X}_t)\right] \right\|_{\Lambda_k}^2, \tag{3}$$

where ϕ denotes a nonlinear mapping function, and the characteristic kernel is related to ϕ, $k(\boldsymbol{X}_s, \boldsymbol{X}_t) = \langle \phi(\boldsymbol{X}_s), \phi(\boldsymbol{X}_t) \rangle$.

With the MK-MMD, the higher layers of the CNN can be adapted, and the optimization objective of the DAN is

$$\min_{\Theta} \frac{1}{n_a} \sum_{i=1}^{n_a} J(\theta(x_i^a), y_i^a) + \lambda \sum_{l=l_1}^{l_2} d_k^2(\boldsymbol{X}_s^l, \boldsymbol{X}_t^l), \tag{4}$$

where Θ represents CNN parameters, J stands for cross-entropy loss function, $\theta(x_i^a)$ represents conditional probability of classifying x_i^a as y_i^a, λ denotes the penalty parameter, l_1 and l_2 indicates two adjacent layers with the effective regularizer between them. The former term in (4) is the empirical risk of CNN, whereas the latter term is the MK-MMD between two datasets based on the representation of lth layer. On the basis of this, the model can achieve high accuracy for source samples through the learning process, and the divergence between training distribution and testing distribution can be minimized simultaneously.

III. Fault Identification with Deep Adaptation Networks

The proposed frame of bearing fault diagnosis is show in Figure 1, and there are two major modules: feature extracting and deep model construction. During the first part, the original condition monitoring data under different working conditions are converted to 2D images by the CWT, and the images can be employed to train the subsequent model without any further processing. In the second module, the DAN scheme is utilized to perform domain adaptation for the deep model, i.e., the CNN. The DAN is implemented on a pretrained model, the AlexNet architecture trained with ImageNet dataset [14], and the source data (or training data) and target data (a small amount of data obey the same distribution with the testing data) are used to learn the deep model, as depicted in Figure 2. The weights of convolutional layers *conv*1–*conv*3 are frozen (keep the parameters constant), because the features learned by them are general. As the layer becomes higher, the representation generated tends to be less transferable. Therefore, *conv*4–*conv*5 are finetuned (adjusting the parameters), and the fully connected layers *fc*6–*fc*8 are adapted with MK-MMD to for tackling new tasks in the target domain.

IV. Experimental Verification

During this segment, the presented framework is demonstrated with bearing fault dataset for verifying its validity and superiority.

A. Data depiction

The dataset used for experiment was obtained in the bearing testing center of Case Western Reserve University [15]. The data used in this work are vibration signals acquired from the drive end of the motor under three different working conditions. For each condition, monitoring data were collected under four health states, i.e., health status (HS), inner race fault (IF), ball fault (BF), and outer race fault (OF). The diameter of the fault injected to the bearing is 0.014 in. The sampling frequency is 12000 Hz. Each fault contains 100 samples, and the total number of samples under each operational state is 400. The length of each sequence is 1024. More details about the dataset is illustrated in TABLE I.

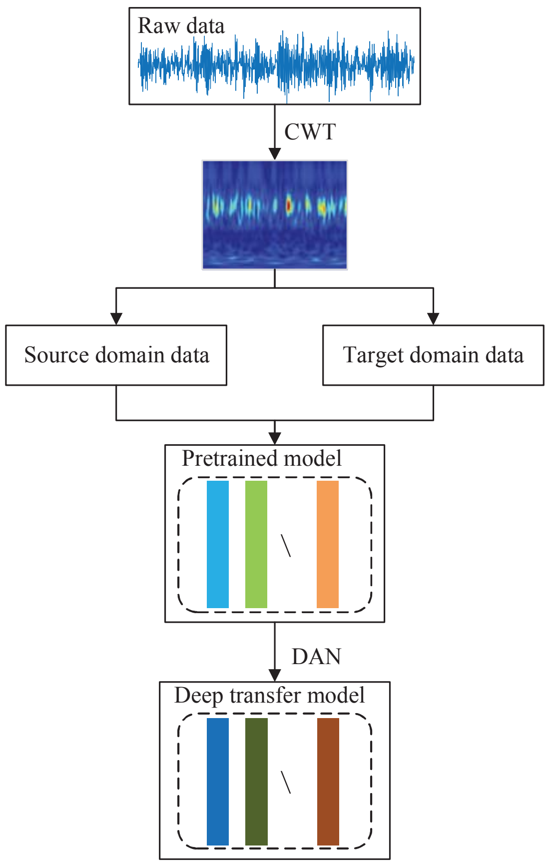

Figure 1. Fault diagnosis of bearings with Deep Adaptation Networks.

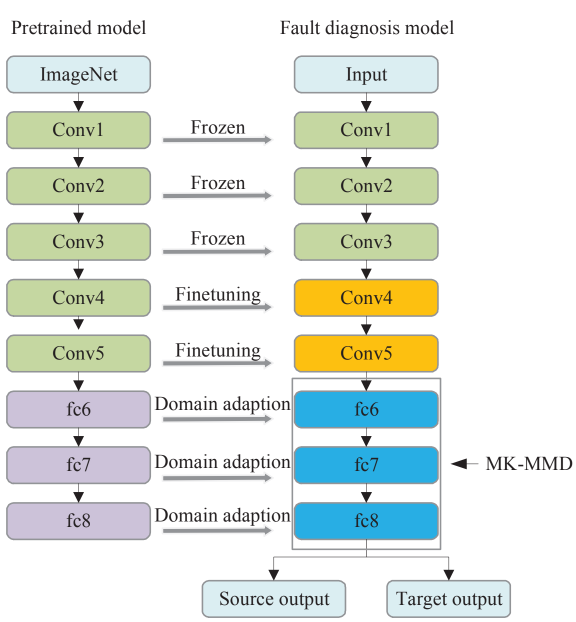

Figure 2. The DAN strategy for deep model learning.

TABLE I. BEARING FAULT DATASET

Name	Fault type	Load (HP)	Speed (r/min)
WC1	HC	1	1772
	IF	1	1772
	BA	1	1772
	OF	1	1772
WC2	HC	2	1750
	IF	2	1750
	BA	2	1750
	OF	2	1750
WC3	HC	3	1730
	IF	3	1730
	BA	3	1730
	OF	3	1730

B. *Discussion of Diagnosis performance*

According to Figure 1, all segmented data are processed with the CWT. In this way, the time series are converted to 2D images, which can be used directly for the subsequent model learning. Figure 3 shows time-frequency pictures of signals collected from bearings with ball fault under various speed and load, from which we can see that the images of signals with diverse working conditions are similar, indicating that there is some common information buried in the image and they can be learned by the deep model.

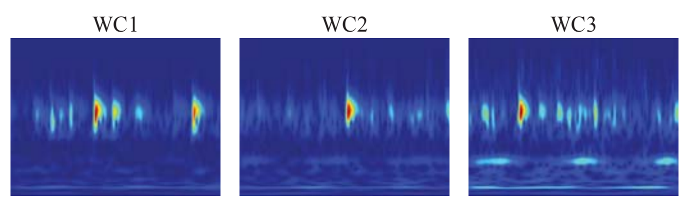

Figure 3. Time-frequency images of BF for different working conditions.

To further classify the advantage of selecting CWT for time-frequency image generating, the short-time Fourier transform (STFT) is introduced for comparison. First, the raw data are processed with CWT and STFT, respectively. Then the CWT images and STFT results are separately used to train the deep transfer model with the scheme illustrated in Figure 1. The testing results of three tasks using these two techniques are depicted in TABLE II, it can be observed that the model learned with CWT pictures has higher classification accuracy than that with STFT input. Hence, the CWT can provide more information for deep learning than the STFT.

To validate the classification rates of the presented framework, we conduct six transfer tasks, i.e., WC1→WC2 (The data collected in WC1 are used as training data, and the information of WC2 are regarded as testing samples. The same hereinafter), WC1→WC3, WC2→WC1, WC2→WC3, WC3→WC1, WC3→WC2. TABLE III gives the recognition rates, and the proposed approach can achieve accuracy of 100%

for most experiments except WC1→WC3 and WC2→WC3, but the recognition rates of them are acceptable in industrial engineering.

TABLE II. RECOGNITION RATES OF MODELS LEARNED WITH DIFFERENT IMAGES

Methods	Tasks		
	WC1→WC2	**WC2→WC3**	**WC3→WC1**
CWT + DAN	100.00%	98.75%	100.00%
STFT + DAN	97.50%	93.00%	92.75%

To further demonstrate the superiority of our method, the ANN, Transfer Component Analysis (TCA) [16], and Deep Domain Confusion (DDC) [17] are employed for comparison. When conducting the ANN experiment, time features (TF) are used. The origin data are used for TCA, and then the SVM is involved for classification. As for the DDC, the 2D images are utilized as the input, and then the DDC is employed to adapt the pretrained model. TABLE III illustrates the results of the aforementioned schemes. We can see that ANN with TF can achieve relatively good results for easy tasks WC1→WC2 and WC2→WC1 but has poor performance for difficult issues WC3→WC1 and WC3→WC1. Additionally, the performance of the TCA method without feature extraction are also not satisfactory, but the recognition rates for hard situations (WC2→WC1, WC3→WC1) can be slightly improved by TCA. The combination of CWT and deep transfer learning can significantly improve the recognition performance, because the DTL can effectively learn transferable features from the time-frequency image with the CWT. Moreover, the DAN scheme performs better than the DDC strategy, which verifies its superiority in mechanical diagnosis tasks.

TABLE III. COMPARISON OF DIFFERENT METHODS

Tasks	Methods			
	Our method	**TF + ANN**	**TCA + SVM**	**CWT + DDC**
WC1→WC2	100.00%	97.25%	79.75%	99.75%
WC1→WC3	98.50%	85.25%	85.50%	97.50%
WC2→WC1	100.00%	96.25%	80.75%	99.50%
WC2→WC3	98.75%	88.25%	82.25%	98.75%
WC3→WC1	100.00%	75.50%	81.50%	100.00%
WC3→WC2	100.00%	74.00%	79.25%	99.25%

V. CONCLUSIONS

In this work, we propose a new bearing fault diagnosis framework by integrating time-frequency technique and transfer learning. The validity and advantage of the presented methodology is illustrated with experimental bearing condition monitoring data, and two major conclusions are summarized as follows.

1) The CWT can be used to mine the essential characteristics buried in the bearing signal, which can be execute automatically without choosing and selecting features and are more adaptive than traditional methods. Moreover, the 2D images transformed from the raw data by the CWT can be directly used as input of the deep model.

2) The DAN scheme can effectively solve fault diagnosis problems under various working conditions, and it can give a higher accuracy than traditional approaches.

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