A multilayer transfer convolutional neural network for bearing fault diagnosis at variable speed

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***Abstract*—Intelligent algorithm is widely used in the field of device health monitoring because of its good feature extraction ability. However, the fault features for rotating parts of mechanical equipment often change with the change of rotating speed. Failure labels at various speeds are impossible to obtain. In this case, the traditional deep learning model often fails to achieve good diagnostic results. In this paper, a multilayer transfer network relied on the CNN module named MTCNN is proposed to overcome the above difficulties. The GAP layer is employed in the CNN architecture. The Maximum Mean Discrepancy (MMD) transfer function is applied to the second last layer and the deep coral transfer function is used on the last layer. Finally, a set of test data from the test bench is applied to verify the manifestation of the MTCNN architecture. The performance shows that it has good diagnostic capability and strong domain adaptive capability.**

Keywords—Intelligent algorithm; health monitoring; CNN; deep coral; domain adaptive

I. Introduction

With the arrival of the era of the Internet of everything, factories have higher and higher requirements on the reliability of equipment, and at the same time, more and more data of mechanical equipment are collected. Among them, vibration signal data of mechanical equipment is widely used in fault detection for the mechanical equipment. In the early days, experts used traditional signal processing methods to process vibration data to diagnose faults[1]. However, these methods are not only labor intensive, but also time consuming. With the advent of artificial intelligence era, various neural networks are gradually used to the field of device health monitoring [2]. For example, Sreejith et al.[3] presented a feedforward network architecture, which uses positive logarithmic likelihood and kurtosis values extracted from vibration datasets as input to realize fault diagnosis. Li et al.[4] made use of a new WPT method to build the energy feature vector, and then input the neural network for fault diagnosis. Yin et al.[5] proposed a new DBN network which could handle the state monitoring information at high speed..

From the above analysis, it can be seen that in the early stage of the researches, scholars mainly manually extract fault features based on their prior knowledge, and then use neural network for classification. These methods are very effective, and the fault features extracted based on the prior knowledge of experts are not prone to errors, and the diagnosis accuracy is high. However, on the one hand, it consumes a lot of labors of the relevant experts; on the other hand, it is impossible to complete real-time status monitoring the equipment by relying on these methods. Therefore, with the explosion of intelligent algorithms, real-time diagnosis module relied on data-driven emerges. The current deep learning models applied to fault diagnosis mainly include deep convolutional neural network[6], deep sparse encoders network[7] and deep transfer learning neural network.

Wu et al. [8] presented an improved Long Short-Term Memory network model, which used sampling policy (wLRCL-D) to handle the difficult point of sample imbalance in the field of health monitoring. Chen et al.[9] presented a multi-sensor data fusion architecture based on sparse encoder, which can learn fusion features from different sensors and then carry out automatic classification. Wang et al.[10] innovatively presented an improved DRNN architecture relied on deep CNN, which has self-adaptive ability. This method solves a difficult problem in the field of equipment condition monitoring. Zhang et al.[11] proposed a novel domain adaptive architecture relied on subspace alignment. This method can minimize the difference of feature distribution between two different data fields, and accurately classify the faults under various unlabeled rotating speeds.

It can be seen from the above analysis that various deep learning network models are applied to solve various difficulties in fault diagnosis. However, the domain adaptive problem under variable speed is still a hot topic of current scholars. Therefore a multilayer transfer convolutional neural network(MTCNN) is proposed. Using the convolutional neural network model as the basic architecture, MMD algorithm[12] is used in the full connection layer to carry out domain self-adaptation for the feature information from two different rotational speeds, and deep coral algorithm[13] is used in the global average pooling layer to carry out domain self-adaptation for the feature information from two different rotational speeds.

The main architecture of this paper is described below: section 1 is the introduction to CNN; next section is the detailed parameters of the MTCNN model and the main application algorithms; section 3 mainly describes the performance of the MTCNN architecture, and describes the visualization of features; section 4 is the conclusion.

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II. CONVOLUTIONAL NEURAL NETWORK

First, the MTCNN architecture based principal architecture is introduced.

A. *Characteristic training layer*

The characteristic extraction layer of CNN mainly includes convolutional layer and pooling layer. The purpose of the convolution layer is to learn the different characteristics from the original signal. It can be expressed as follows:

$$z^{l+1}(i) = W^l * v^l(i) + b^l \tag{1}$$

where W^l and b^l denote the weights and bias in layer l respectively. $v^l(i)$ denotes the input vibration signal. $z^{l+1}(i)$ represents the output.

The feature is immediately activated by the RELU function after being output through the convolutional layer. Hypothesis $a^{l+1}(i)$ represents the eigenvalue after activation, so the expression is as follows:

$$a^{l+1}(i) = \mathrm{Re}\,LU[z^{l+1}(i)] \tag{2}$$

The convolution layer is often followed by the pooling layer, which has the function of feature sampling. There are many different forms of nonlinear pooling functions, among which the most commonly used is maximum pooling. Then the maximum pooling layer is employed, and its simplified expression is shown:

$$p^{l+1}(i) = \max[a^{l+1}(i)] \tag{3}$$

In order to join the multi-layer transfer learning network, we use the full connection and the GAP layer[14] after the pooling layer. Finally, features are fed into the classification layer.

B. *Feature classification layer*

Cross entropy loss function is employed in various neural networks due to its excellent classification ability. Therefore, the softmax function is employed as the classifier for the MTCNN model. g_i represents the features of the global average pooling layer. The loss function L_1 is expressed as follows:

$$L_1 = q(g_i) = \frac{e^{g_i}}{\sum_i^{10} e^{g_i}} \tag{4}$$

The schematic diagram of CNN architecture is as follows:

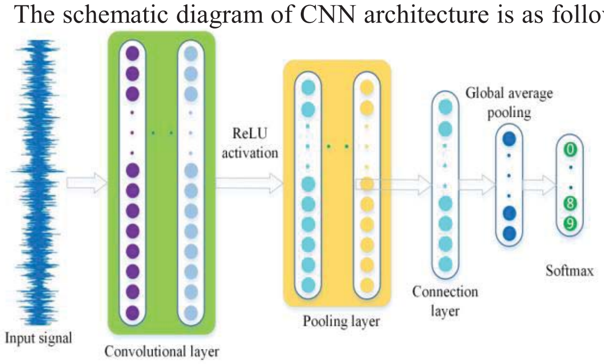

Figure 1. CNN Architecture.

TABLE I. MTCNN MODEL ARCHITECTURE PARAMETERS

No.	Layers	Kernel size/stride	Kernel channel size
1	Convolutional1	45*1/3*1	16
2	Pooling1	2*1/2*1	16
3	Convolutional2	5*1/3*1	32
4	Pooling2	2*1/2*1	32
5	Convolutional3	3*1/1*1	48
6	Pooling3	2*1/2*1	48
7	Convolutional4	3*1/1*1	64
8	Connection layer	100	1
9	Global average pooling	5*1/1*1	1
10	Softmax	10	1

III. PROPOSED FRAMEWORK

Aiming at the problem of fault diagnosis at variable speed, we propose a multilayer transfer CNN (MTCNN), whose overall architecture is shown in Figure 2 and detail parameters are shown in table I. And the input data are vibration data at any two speeds, the vibration data label of one speed is known (source domain), and the vibration data label of the other speed is unknown (target domain). MMD transfer learning function[19] is emploied in the full connection layer. Here is the mathematical expression:

$$\begin{aligned} L_2 = {} & \frac{1}{n_s^2}\sum_{i=1}^{n_s}\sum_{j=1}^{n_s} k(c_i^{(S)}, c_j^{(S)}) \\ & + \frac{1}{n_t^2}\sum_{i=1}^{n_t}\sum_{j=1}^{n_t} k(c_i^{(T)}, c_j^{(T)}) \\ & - \frac{2}{n_s n_t}\sum_{i=1}^{n_s}\sum_{j=1}^{n_t} k(c_i^{(S)}, c_j^{(T)}) \end{aligned} \tag{5}$$

where $c^{(S)}$ and $c^{(T)}$ are the features in connection layer for different domains. n_s and n_t denote the number of training samples for them, respectively. *k(•,•)* denotes the kernel function. L_2 represents loss function.

In GAP layer, we use the deep coral transfer learning function [20] to constrain the characteristics from two different rotational speeds.

$$\begin{aligned} L_3 = {} & \frac{1}{4d^2} \| \{\frac{1}{n_s - 1}[G_s^T G_s - \frac{1}{n_s}(1^T G_s)^T (1^T G_s)]\} \\ & - \{\frac{1}{n_t - 1}[G_t^T G_t - \frac{1}{n_t}(1^T G_t)^T (1^T G_t)]\} \|_F^2 \end{aligned} \tag{6}$$

where $\| \cdot \|_F^2$ represents the squared matrix Frobenius norm. G_s and G_t are the training samples from different domains, respectively.

Finally, model's back-propagation algorithm is the stochastic gradient descent algorithm. The total loss function of MTCNN model can be expressed as:

$$L_{total} = L_1 + L_2 + L_3 \tag{7}$$

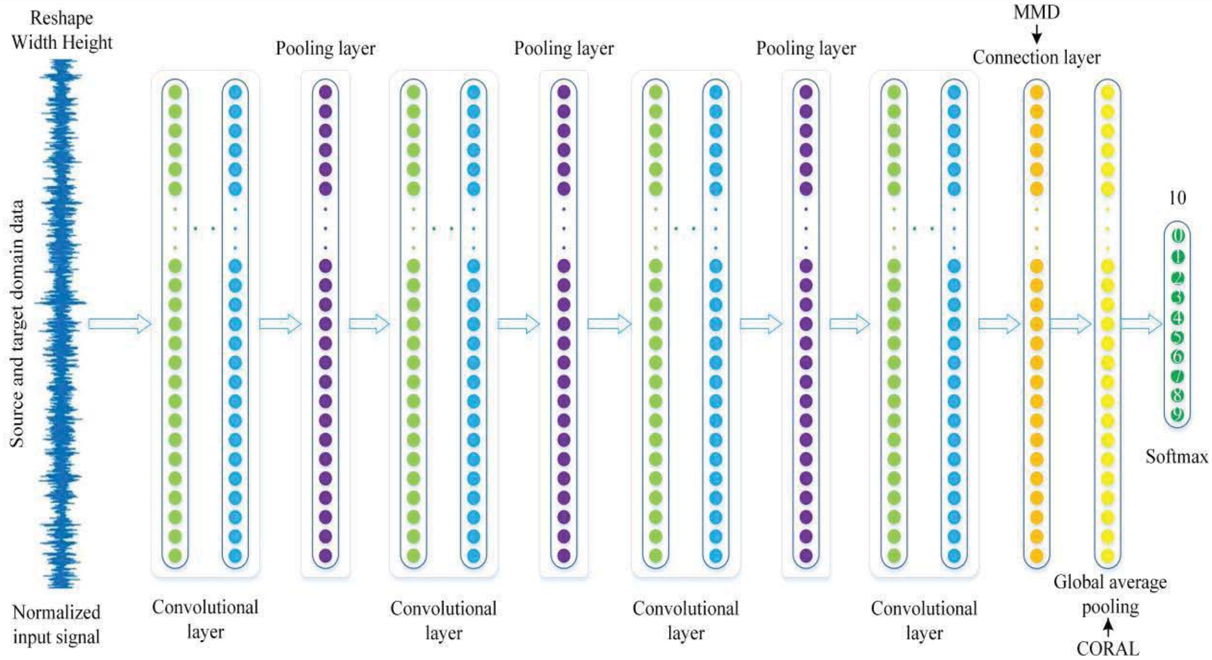

Figure 2. The overall structure of the MTCNN model.

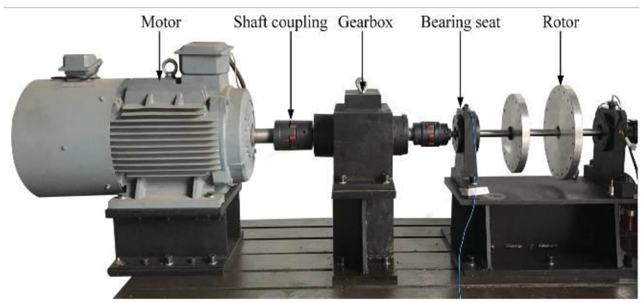

Figure 3. Test bench.

Figure 4. The fault components.

IV. Experimental verification

A. Data description

A test bench for integrated fault diagnosis of rotating components is used for vibration signal acquisition. The test bench is mainly include the motor, shaft coupling, gearbox, bearing seat and so on, as shown in Figure 3. The failure bearing is put on the output shaft, and the bearing speed of the test signal is 2100r/min(Load1), 2700r/min(Load2) and 3300r/min(Load3) respectively. The placement of the vibration sensor is shown in the figure, and its sampling frequency is 12.8 kHz. Bearing failure types are shown in Figure 4. Therefore, including the normal data sample, there are 10 health conditions, which are respectively recorded as C1 to C10. 2000 data points were collected for each sample, 500 samples were acquired for each health condition. So 15,000 samples were collected under 3 different load speeds.

B. Diagnosis result

The transfer learning results at three different speeds are listed in table II. It shows that the MTCNN model has better diagnosis results than the classical domain adaptive DAFD model[19]. The diagnostic accuracy of MTCNN model is 98.92% on the test data set, while that of DAFD model is only 94.82%. It can be seen that the performance of the proposed multilayer transfer convolutional neural network model is more excellent.

In order to show the diagnostic accuracy more clearly, we have drawn a confusion matrix for the diagnosis results of the conditions marked blue in table II. Specific results are shown in Figure 5. The diagnostic performance of the MTCNN architecture is up to 100.00% in most fault types, but low in only a few fault types. For example, the performance of the MTCNN is only 96.00% under the C4 category.

TABLE II. FULL TRANSFER ACCURACY TABLE

Source domain	Method	Target domain		
		Load 1	*Load 2*	*Load 3*
Load 1	DAFD[19]	-	96.54%	94.21%
	MTCNN		98.63%	98.92%
Load 2	DAFD[19]	93.22%	-	96.65%
	MTCNN	99.11%		98.86%
Load 3	DAFD[19]	93.77%	94.55%	-
	MTCNN	99.02%	98.97%	

Actual label \ Predict label	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C2	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C3	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C4	0.00	0.03	0.00	0.96	0.01	0.00	0.00	0.00	0.00	0.00
C5	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.00
C6	0.00	0.00	0.00	0.01	0.00	0.99	0.00	0.00	0.00	0.00
C7	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
C8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00
C9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00
C10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Figure 5. The confusion matrix.

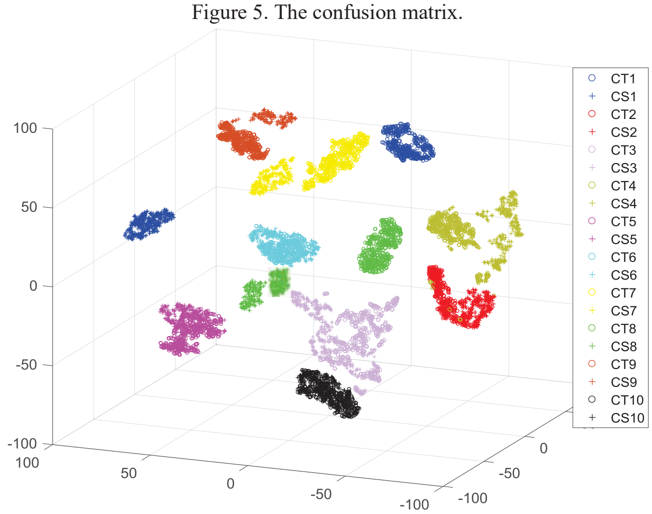

Figure 6. Features visualization in FC.

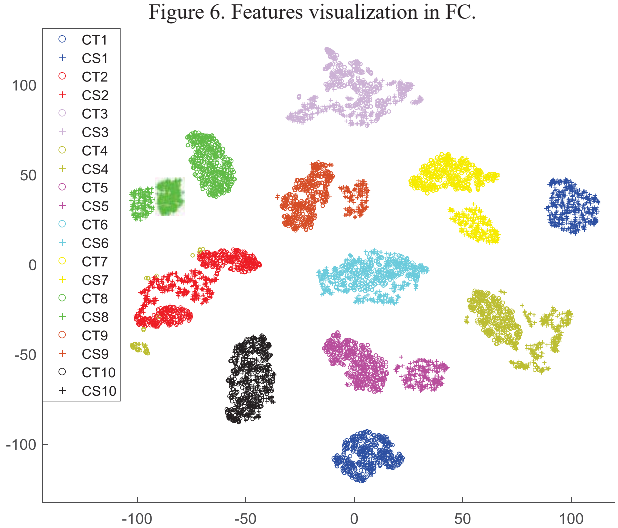

Figure 7. Features visualization in GAP layer.

C. Feature visualization

To better demonstrate the features extracted from the presentation architecture, we visualized the features of the full connection and the GAP layer, as shown in Figure 6 and Figure 7. CT1 and CT2 in the figure respectively represent the characteristics of the target domain and source domain under category 1. In Figure 6, the features from the different rotational speeds are clearly classified, and features belonging to the same type are clustered together. This proves that MMD algorithm plays a very good role. In Figure 7, the feature classification coming from the two rotation speeds is more obvious, which proves that the deep coral algorithm also plays a role. At the same time, the features of C4 category and C2 category overlap on the feature visualization to a certain extent. It can be seen that it is precisely because of this that the diagnostic accuracy under the C4 category is only 96.00%. However, we suspect that this may be caused by the relative inaccuracy of the experimental data, rather than by the MTCNN model itself.

V. Conclusion

Aiming at the equipment state detection under the condition of variable speed, this paper proposed a multilayer transfer convolutional neural network (MTCNN) model to learn domain invariant features. The main innovation in this paper is to propose a multi-level transfer learning method using different transfer learning functions. Based on the traditional CNN architecture, the GAP layer is added. Then, MMD and deep coral transfer learning are used to the model's full connection layer and global average pooling layer, respectively. The test results prove that MTCNN architecture has wonderful domain adaptability and can be applied to fault diagnosis at variable speed. Moreover, the visualization analysis results show that the same class characteristics are aggregated in two different migration learning layers. These have some reference value for the equipment state detection under the condition of variable speed. We will continue to study the application of multi-level and multi-type transfer learning in future.

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