Research on Application of Transfer Learning in Equipment Fault Diagnosis

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Abstract: In view of the complex and changeable operating conditions of equipment, and the different distribution of measured data, it is difficult to promote the application of fault diagnosis technology. Many scholars have introduced transfer learning to overcome the lack of training data for deep learning by transferring existing data and models in similar domains into the target domain, it has expanded the application of fault diagnosis technology. This paper introduces the related concepts of transfer learning, summarizes the current applications and existing problems of transfer learning in the field of fault diagnosis, and finally puts forward further research directions and suggestions in general detection, real-time detection, etc. The purpose is to better improve equipment support capabilities.

1. Introduction

In the operation process of mechanical equipment, the overall or local state will change with the environment and working conditions. Small changes are easy to cause equipment failure after accumulation, and even cause huge loss of personnel and property [1]. Therefore, mechanical fault diagnosis technology arises at the historic moment. With the application of new technologies such as the Internet of Things, technicians can acquire status data by installing various sensor parts on mechanical equipment, so as to master all information of the equipment from the beginning of service to the stage of failure and abandonment. The acquisition of massive data makes mechanical fault diagnosis enter the era of "big data" [2].

Currently, the data-driven diagnosis method provides a new bottom-up solution for system fault diagnosis, prediction and health management through the use of increasing data volume [3], and has made great achievements. The most representative one is the application of deep learning in the field of fault diagnosis. At present, the commonly used deep learning models in the field of fault diagnosis are: Convolutional Neural Network (CNN), Deep Belief Network (DBN), Sparse Autoencoder (SAE), and Recurrent Neural Network (RNN) [4][5][6]. A lot of research results have been achieved by using deep learning to solve the problem of fault diagnosis. For example, Li Heng [7] et al. combined short-time Fourier transform with convolutional neural network to realize partial end-to-end bearing
fault diagnosis. Zhao Guangquan [8] et al. applied DBN in the field of fault diagnosis, and verified that DBN has the ability of directly extracting features layer by layer from original time-domain signals, independent of signal processing technology and expert knowledge, and not limited to signal periodicity. Cui Jiang [9] et al. used the optimized SAE network to extract the fault features of the aeroengine by adding feature layers to RNN. Zhang Jian [10] et al. increased the network's ability to constrain long-distance information by adding a feature layer to the RNN, and solved the traditional data sparseness and dimensionality explosion problems.

Although intelligent fault diagnosis technologies such as deep learning have been widely used to automatically extract fault features to identify the health status of equipment due to their powerful performance, and have become an important guarantee means for the safe operation of equipment under big data, and relevant theoretical research is booming [3][11], but the success of these machine fault diagnosis depends on two prerequisites: The training and test data meet the independent identical distribution and the target diagnosis data is sufficient and available [12]. However, in the actual engineering equipment monitoring, the data obtained has two characteristics : (1) Low value density; (2) Low availability. This leads to a shortage of effective data for deep learning modeling, and the accuracy of fault diagnosis models decreases. In order to solve the above problems, experts and scholars try to use new theories and technologies to solve the problem of data sparseness. In this process, transfer learning has gradually attracted wide attention from experts both at home and abroad.

Transfer learning is a development in the field of machine learning, which aims to solve the learning problem with few labeled samples in the target domain. It first stores the existing problem solving model, and then applies it to other similar problems, that is, transfer the data or knowledge structure from the relevant domain, and then use the data in the target field to train the model to complete the required learning task. It has been successfully applied in the fields of image recognition, text mining, biological imaging [13]-[16] and other fields. The core idea of transfer learning is to use the knowledge learned in one task to improve the performance of the similar tasks. The more similar the two areas are, the easier the transfer process will be. Otherwise, it will be more difficult, and even negative transfer may occur [13]. In the field of fault diagnosis, researchers hope to use the transfer learning theory to transfer the existing fault diagnosis model to the similar field, in order to solve the problem of insufficient or difficult to obtain fault data in the actual working conditions. This paper mainly analyzes and summarizes the research of transfer learning in the field of equipment fault diagnosis based on deep learning, expounds the relationship between existing research and the results achieved, and finally proposes future development directions and suggestions for improvement.

2. Classification of transfer learning
Currently, there are two common transfer learning classification methods, which are classified by whether the target domain has labels, and classified by learning methods.

2.1. Classified by whether the target domain has labels
Under this classification, transfer learning can be divided into inductive transfer learning, transductive transfer learning and unsupervised transfer learning.

Table 1 shows the transfer learning classification according to whether the target domain has labels.

| Classification             | Data                                   | Task                | Source domain label data | Target domain label data |
|----------------------------|----------------------------------------|---------------------|--------------------------|-------------------------|
| Inductive transfer learning| Can be the same or different           | Different but related| Have                     | Have                    |
| Transductive transfer learning| Different but related                  | The same            | Have                     | Little or none          |
| Unsupervised transfer learning| Different but related                | Different but related| None                     | None                    |
2.2. Classified by learning methods
Under this classification, transfer learning can be divided into four categories: sample-based, feature-based, model-based, and relationship-based transfer learning.

Table 2 shows the types of transfer learning classified by learning methods.

| Classified by learning method | Data requirements between fields | Main idea | Departure level |
|-------------------------------|---------------------------------|-----------|----------------|
| Sample-based                  | Require high similarity         | Adjust weights to reduce inter-domain differences | Data level |
| Feature-based                 | No request                      | Find features to minimize domain differences | Data level |
| Model-based                   | No request                      | Check if the model shares hyperparameters | Model level |
| Relationship-based            | Need analogical relation        | Knowledge mapping | Data level |

3. Applications of Transfer Learning in the Field of Fault Diagnosis
In actual industrial systems, complex environments and variable operating conditions are common, which makes equipment state data obtained from sensors complex. The researchers introduced transfer learning to solve the difficulty in modeling deep learning caused by sparse training samples. At present, the application of transfer learning in fault diagnosis is mainly divided into two situations: transfer diagnosis between different working conditions and transfer diagnosis between different devices.

3.1. Transfer diagnosis between different working conditions
Transfer learning can transfer existing knowledge into similar but unrelated fields, which can effectively solve the problem of scarcity of available data caused by external environment interference and inability to obtain target data in a specific state. In order to improve the fault identification accuracy of the training model, the researchers transferred the relevant data of the machine under different working conditions as auxiliary data set, constructed and trained the relevant diagnosis model, and realized the fault diagnosis when the data was scarce.

3.1.1 Instance based Transfer Learning
The instance based transfer learning method uses data similar to the target domain to construct relations between data, and provides fault classification features for transfer learning, which helps train the model and improve the accuracy of fault diagnosis.

Bearing is the core component of rotating machinery, and its health condition has a great influence on the performance of equipment. Chen Chao et al. [17] in order to solve the problem of too little data that can be used to establish bearing fault diagnosis models in engineering, they proposed an improved least square support vector machine (LSSVM) transfer learning method based on auxiliary data. The target bearing data is similar but the distribution characteristics of the auxiliary bearing data are different, and the fault diagnosis model is constructed to improve the fault diagnosis performance. To solve the problem that fault information of low-speed bearings is difficult to obtain, MD Junayed Hasan et al. [18] successfully reduced the difficulty of feature extraction of variable speed bearings by using spectrum imaging method based on acoustic emission signals and combining with convolutional neural network based on transfer learning.

3.1.2 Feature based Transfer Learning
Feature based transfer learning focuses on similar expressions in the process of transfer. It is similar to a feature extractor, which is used to extract similar expressions in different fields and place them in the same feature space.

The selection and extraction of fault features is a key part of diagnosis technology, but the signals are mixed and the features are difficult to distinguish when the machine is running. Therefore, Long
Wen et al. [19] used a feature extraction algorithm based on three-layer sparse auto-encoding (SAE), combined with the third data set without label to extract the hidden common features between the two domains, and successfully improved the prediction accuracy. In the face of the problem of feature extraction under variable working conditions, Qian Weiwei et al. [20] proposed an improved joint distribution adaptive (IJDA) method to achieve the simultaneous alignment of edge distribution and conditional distribution of the data set, successfully extracted the fault features of rotating machinery under variable working conditions and completing the fault diagnosis. In order to expand the range of feature extraction, Zhang ming et al. [21] built a model to learn domain invariant features across domains, and completed fault diagnosis of bearings in different working conditions through transfer.

3.1.3 Model based Transfer Learning
Model based transfer learning shares some model parameters in the source domain and target domain, and then modifies each parameter to generate a new model according to the specific requirements of the target domain.

The use of deep learning for fault diagnosis requires a large amount of data and time to train the model. Although the model has high diagnostic accuracy, it does not have applicability, so it needs to be retrained every time it faces new diagnostic problems. In order to save computing resources, the existing model is transferred into the similar field, and then the data of the target field is used to fine-tune parameters to form a new network, so as to reduce the model training time and improve accuracy by using the data of different conditions. This model which based on transfer learning strategy has been widely applied successfully [22]-[27]. Based on the above steps, Shao Siyu [22] and Wen Long [25] used wavelet transform and other methods to convert the original signals into image signals, and then used CNN to extract image features to train the network. Zhang Rang [23] and Cao Pei [24], aiming at the problem of missing data, transferred the training model from similar data domains, and then fine-tuned the parameters to obtain a new network. Xu Yan [27] proposed a digital twin auxiliary fault diagnosis model, which combines virtual space with physical space to ensure diagnosis accuracy, save time and cost, and finally realize real-time monitoring and predictive maintenance.

The above methods solve the problem of scarcity of training samples by transferring data and models, and focuses on analyzing historical data, which is time-consuming and cannot be used for real-time diagnosis. In this regard, there have been several online fault diagnosis methods based on physical model and achieved certain results [28]-[31], but they are not applicable to complex machinery. Therefore, some scholars have studied online diagnosis methods based on data-driven to achieve online diagnosis. Xu Gao Wei et al. [32] proposed an online fault diagnosis method based on deep transfer convolutional neural network (TCNN) framework. During model training, firstly the original signals were converted into images. Secondly the online CNN was constructed to automatically extract features and classify faults. Finally, several off-line CNNs were constructed and their shallow structures were transferred to online CNNs, which not only improved the real-time performance of the model, but also achieved the required diagnostic accuracy within the limited training time.

3.1.4 Summary of Transfer diagnosis between different working conditions
It can be seen from the above research that the technology of transfer diagnosis between different working conditions of the same machine has been relatively mature at present, and the results show that: ① the fault information of related machinery can be identified by using the existing fault diagnosis knowledge; ② A large amount of computation and time resources can be saved by transferring the model or feature knowledge of the similar domain, and the fault diagnosis accuracy of the transfer model is higher.

3.2. Transfer diagnosis between different devices
Different from the transfer diagnosis between different working conditions, the transfer diagnosis of different machines is closer to reality. It is not based on a certain assumption, that is, the effective data available for the same equipment under a certain working condition is sufficient [33]. This assumption
is inconsistent with the actual engineering application. Therefore, it is of great practical significance to study the diagnostic methods of transfer between different machines.

It is often difficult to obtain and use detection data during machine operation in engineering, existing transfer learning research applications are mostly limited to the transfer of data in different working conditions between the same machine. For this, Lei Ya Guo [33] and Yang Bin et al. [34] using feature based transfer learning, designed a shared network in the field, and transferred the complete fault diagnosis knowledge obtained from laboratory machinery, to identify the health status of the actual machine, make up for the lack of engineering data and improve the fault recognition accuracy of the training model. Guo Liang et al. [12] proposed a deep convolutional transfer learning neural network model (DCTLN), including condition recognition and domain adaptation modules, to learn features of domain invariance, and finally realized effective fault classification for unlabeled data of different machines.

Studies above show that it is necessary to carry out transfer diagnosis for different machines in the face of complex conditions in working conditions, which will effectively solve the problem that the fault state data is difficult to obtain, and leads to the failure to build fault diagnosis model. At the same time, with the development of this field, the ultimate goal is to realize the use of a few mature models to complete the fault diagnosis of many kinds of machines, that is, to achieve the generalization of modules.

3.3. Explanation and comparison of the two situations
According to the previous statement, it can be seen that the current application of transfer learning in mechanical fault diagnosis mostly focuses on the transfer diagnosis between different working conditions of the same machine, while there are few studies on the transfer between different machines. Although the former has achieved many results with the efforts of researchers, these achievements still have certain requirements for the amount of data that the machine needs to obtain under a certain working condition, and this assumption is often difficult to achieve in actual working condition. In contrast, if the ability to transfer diagnosis between different machines can be drilled in depth, the amount of data required will be greatly reduced, and when the model or algorithm has the ability to learn and use the invariance of fault characteristics across domains, people will be able to grasp the health condition of equipment effectively to prevent the happening of the major fault accident.

4. The development direction of deep transfer learning in the field of fault diagnosis
Transfer learning relaxes the data requirements for training models based on the deep mining and automatic extraction of fault features in deep learning. By transferring data or mature models from adjacent fields into target fields, it is not only close to the fact that it is difficult to obtain fault data in real engineering, but also greatly reduces the calculation and time cost of training models. Although there are many advantages, the theory of transfer learning is still in the development stage compared with deep learning which has been widely and maturely used, and there is also a lot of room for the development of fault diagnosis technology based on transfer learning:

1) Applications in general testing of machine. In actual engineering, the number and types of mechanical equipment are increasing, and it is impossible to use machine learning methods such as deep learning to complete the fault diagnosis of all the equipment. However, by using the concept of transfer learning. Firstly we can collect the machine fault information of different but similar fields and study uniformly. Secondly we can explore common features of this type of machine. Finally, one or a few fault diagnosis models can be used to complete the analysis of more equipment, this will be an important development direction for practical engineering applications.

2) Applications in real time fault diagnosis. The purpose of mechanical fault diagnosis is to be able to identify the health condition of the equipment, and the speed of diagnosis is naturally required. In order to improve the efficiency of model training, it is considered to use transfer learning to learn more representative features from different working conditions and different devices, or even to directly transfer mature models in similar fields to the target field, and then fine-tune parameters to form
the target model in combination with the actual situation, so as to reduce the demand of computing data and the time to build the model. On the basis of the above steps, we can complete fault classification or even online diagnosis in a relatively short time.

(3) Applications of automatic update of fault information. The fault types of different machines and equipment vary greatly and will change over time, so it is impossible to calibrate all the fault types manually. Faced with the situation that a large number of new faults continue to occur with the operating conditions in actual working conditions, by designing a new knowledge retention strategy and transfer method, the machine will have the ability to learn for life, and continuously transfer the labeled data from different learning tasks, finally it can automatically update the fault types and information, greatly improve the safety and economic efficiency.

5. Conclusion
In this paper, the application of deep learning in equipment fault diagnosis is analyzed and summarized. On this basis, transfer learning is introduced to solve the existing shortcomings. It is of great significance to introduce transfer learning to realize universal detection for complex engineering environment. With the continuous development of transfer learning theory, the realization of a wider range of fault diagnosis will become a reality, and the support ability of mechanical equipment will keep improving.

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