Deep Fusion Attention Learning Method for Rotating Machinery Fault Diagnosis Based on Two Stage Neural Network

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Abstract: Under different working conditions, there are obvious differences in the fault characteristics of machinery, which directly leads to the failure of the model trained under a single working condition. Considering that there are often multiple working condition data sets in real scenarios, how to make full use of multi-source data sets to ensure model generalization performance becomes the key to fault diagnosis. Aiming at the problems of limited depth, lack of feature extraction ability and poor generalization ability of current multi-source models, an improved deep transfer learning algorithm called Two-Stage Deep Fusion Attention Transfer Network (TS-DFATN), is studied and proposed. The main network extracted shared features across various datasets, followed by multiple sub-networks to extract distinctive features from each dataset. A dual attention network was added to the subnetwork to enhance the capability of extracting local features. Meanwhile, based on explainable artificial intelligence technology, an advanced class activation map algorithm is used to highlight the areas in the image that contribute the most to the model's prediction. This approach was evaluated on the public bearing dataset and gearbox dataset, demonstrating enhanced model accuracy and better generalization.

Introduction

Considering the complexity of the feature distribution in different working condition datasets, the one-to-one transfer method is no longer sufficient to meet the requirements of model generalization. Therefore, it becomes particularly important to use a method that allows multiple source domains to learn together. However, most fault diagnosis methods for transfer learning rely solely on a single dataset for knowledge transfer, without considering the assistance of multiple datasets to improve model generalization performance. In order to fully extract the potential features of multi-source datasets, including common features and differential features, this paper proposes a novel multi-source transfer algorithm for rotating machinery fault diagnosis. The algorithm combines time-frequency analysis for data preprocessing to obtain a representation spectrogram with time-frequency domain information. The method designs a special two-stage network structure. The primary network is based on the ResNet-50 residual neural network as the backbone network to extract the common features of the dataset. The secondary sub-network is designed based on a convolutional neural network and internally incorporates a dual-attention fusion network (DANet) to enhance the ability to extract differing features from the source domain dataset. The subnetwork performs a one-to-one matching based on the number of source domain datasets. At the same time, during the network training process, multiple loss functions were designed, including migration loss and classifier distance loss, in order to reduce the data distribution differences between multiple source domains and the target domain.

Contributions

1) A special data preprocessing method has been designed to extract key time-frequency features from the raw time series signal, which will be used as input for the deep transfer learning network.

2) A special two-stage network structure has been designed, with the main network used to extract general data features and the sub-network used to extract differentiated features. In order to enhance the ability to extract differentiated features, a dual-attention fusion network has been added.

3) The overall loss calculation method for the network is designed to include transfer loss and multi-classifier distance loss for network training.

4) Experimental tests were conducted on the dataset under multiple operating conditions, and the results demonstrated the excellent performance of the method.

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Method

The main improvement points of the method

- **Data preprocessing**: the time-frequency graph is obtained by time-frequency processing of the original time series data of multiple source domain data sets and target domain data sets.
- **Network structure**: the pre-trained model of ResNet-50 residual neural network is used as the main network of general feature extraction, that is, the first-level master network. At the same time, for multiple source domain data sets, independent subnetworks are designed to extract the difference features of each data set.
- **Model loss functions**: several loss functions are designed, including classification loss, migration loss and multi-classifier distance difference loss.
- **Model training and inference**: the preprocessed source domain samples and target domain samples were input into the first-level main network for model training, and the calculated features of the first-level main network were used for loss calculation in the second-level sub-networks that were input into their respective data sets. The dual attention network obtains the location information and channel information, and fuses them. The network parameters were updated iteratively through back propagation to complete the training process.

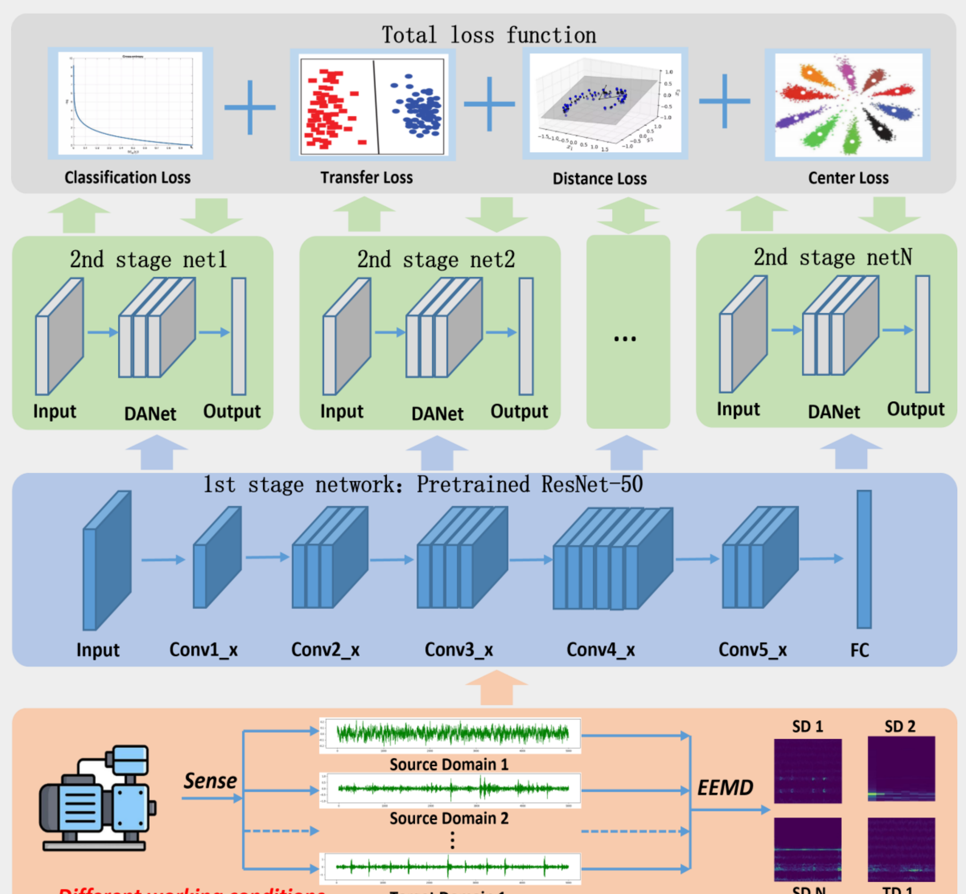

Fig.1. Frame diagram of the proposed method

Evaluation

In order to test the transfer performance of fault diagnosis model in multi-source domain scenario. Here, we designed the following experiment. The experiment uses multiple source domain data sets to test the performance of the proposed method, including the cases under different loads and the cases under different sensor locations.

A. Different load conditions

It can be seen that compared with the latest research results, the proposed method has the best performance under different loads.

B. Different sensor installation positions

It can be seen that compared with the latest research results; the proposed method has the best performance under different sensor position.

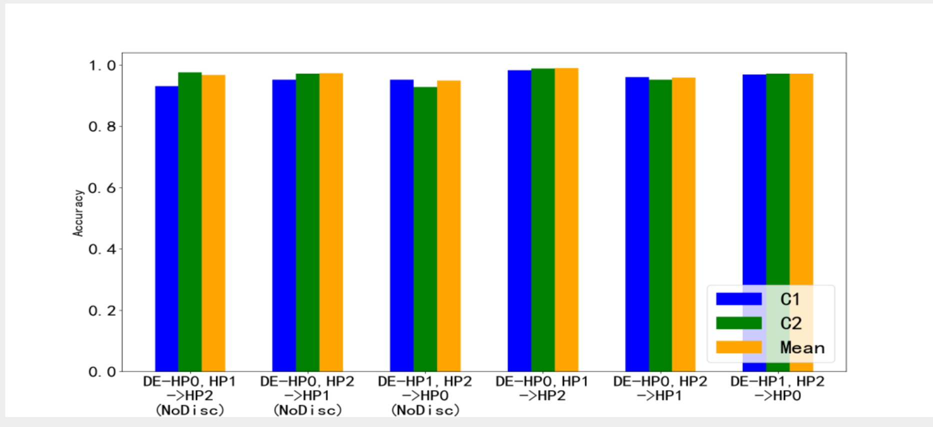

Fig.2. The comparison of models with distance loss

	DE-HP0, DE-HP1 ->DE-HP2	DE-HP0, DE-HP1 ->DE-HP3	DE-HP2, DE-HP3 ->DE-HP1	Average
DDC [24]	0.955	0.940	0.902	**0.932**
DAN [25]	0.985	0.988	0.942	**0.972**
DeepCoral [26]	0.982	0.974	0.954	**0.970**
MFSAN [27]	1.00	0.990	0.987	**0.992**
TS-DFATN	0.995	0.993	0.996	**0.995**

Tab.1. THE COMPARISON OF RECENT RESEARCH RESULTS UNDER DIFFERENT LOADS

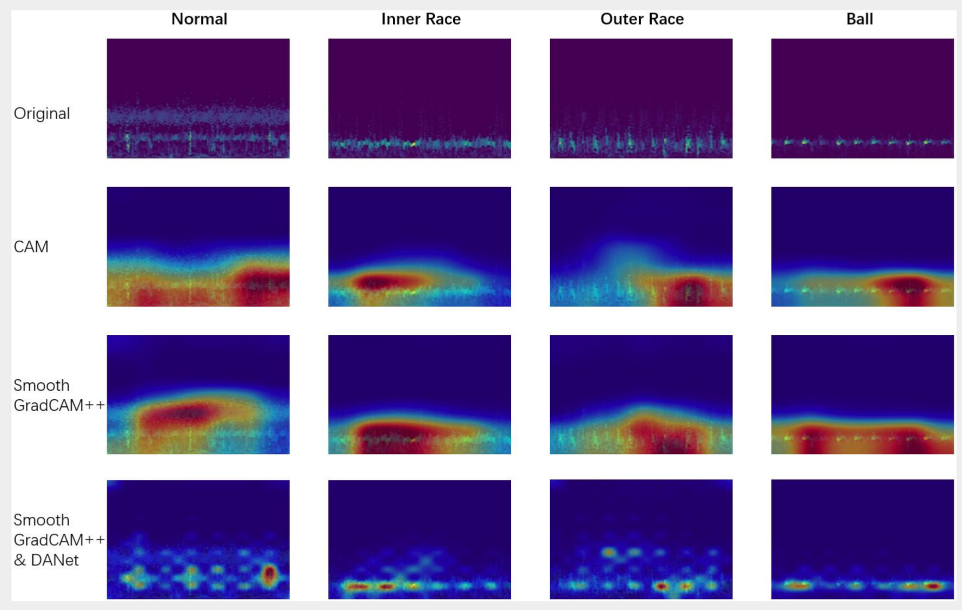

Fig.3. The visualization of network feature maps by SmoothGradCAM++

Conclusion

This paper presents a study on an enhanced fault diagnosis algorithm that utilizes a time-frequency graph and a pre-training model of ResNet-50 residual neural network for model adaptation. The proposed method first preprocesses the original time series data and obtains the time-frequency diagram as the input for the deep neural network. The ResNet-50 pre-training model is used as the main network for feature extraction, and several loss functions are designed to minimize the differences between data categories and the loss of adaptive transfer. At the same time, multiple hyperparameters are optimized, which not only improves the accuracy of the fault diagnosis model but also significantly reduces the training time.

References

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