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Multi-Label Fault Diagnosis of Rotary Machine via Domain Adversarial Neural Network-Based Domain Generalization Targeting High Range Rotating Speed

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Abstract

Research on deep learning has been increasing in recent years in the field of fault diagnosis in rotary machine. However, compared to training data, real world data is collected from different system conditions and environments. Therefore, real world data has different data distribution and various noise with the training data, leading to domain shift between data. Due to the problem mentioned above, deep learning often fails to apply on industrial data. Domain generalization is an emerging deep learning technique to generalize domain discrepancy. In this study, domain adversarial neural network (DANN)-based domain generalization is proposed for multi-label fault diagnosis of rotary machine. Frequency domain image data were generated via implementing short time fourier transform (STFT) to the sensor data collected from the test rig. Then, the features are utilized as training data to diagnosis multi-label fault via DANN-based domain generalization. Moreover, the upper boundary of rotating speed domain of the rotary machine where domain generalization can effectively diagnosis multi-label fault is suggested.

1. Introduction

According to Chongchong et al.(2021), compared with the past, as rotating machines become more and more complex, sudden failure causes great economic loss or human injury. Therefore, according to Yixiao et al.(2020) prognosis health management of rotating machinery in modern industry is becoming more and more important. Accurate fault diagnosis can reduce machine maintenance costs, ensure safety, and reduce fault losses. Model-based fault diagnosis methods were mainly used in the past to simulate system fault phenomena through physical modeling. However, this method requires expert knowledge and cannot be interpreted non-linearly thus difficult to apply to noisy real-world models.

In recent studies, a data-driven fault diagnosis method that diagnoses faults by deep learning using experimental data is mainly used. Data-driven fault diagnosis will perform better if training and test data have the same distribution. However, according to Ishaan et al.(2020) most test data are obtained under different environmental conditions to the training data, which leads to various noise by each test data. Moreover, according to Xiang et al.(2020) discrepancy exists in data distribution because not all machine has identical driving conditions such as rotation speed and applied load. Since data with such out-of-distribution is usually not available in the training, data-driven fault diagnosis is of limited use in practical applications.

In this study, domain adversarial neural network (DANN)-based domain generalization is proposed to find invariant features of multiple source domains and advance multi-label fault diagnosis of unseen out-of-distribution target domains of rotating machinery. We also propose a guide on how far from the source domain to the target domain the domain generalization can be applied. The overall process is illustrated in Fig.1. Frist, sensor data is collected from the test rig consisting rotary machine. Then, the time domain signal data is transformed to frequency domain image data via short time fourier transform (STFT). Lastly, DANN-based domain generalization diagnoses multi-label fault. The novelty of this research is as follows.

1. We propose a DANN-based domain generalization that enables multi-label fault diagnosis of rotating machinery. Every fault is classified within complex fault scenario, aiding accurate health condition maintenance.
2. Domain generalization is applied on various combination of source and target domain. The source domain boundary is suggested to obtain high performance of fault diagnosis at high range rotating

speed domain, providing guide of implementing domain generalization.

The remainder of this paper is organized as follows. Section 2 describes detailed rotating machinery experimental data measurement methods and data preprocessing methods. Section 3 performs experimental data fault diagnosis to validate the proposed domain generalization methodology. Finally, Section 4 concludes the paper and describes possible future improvements of this study.

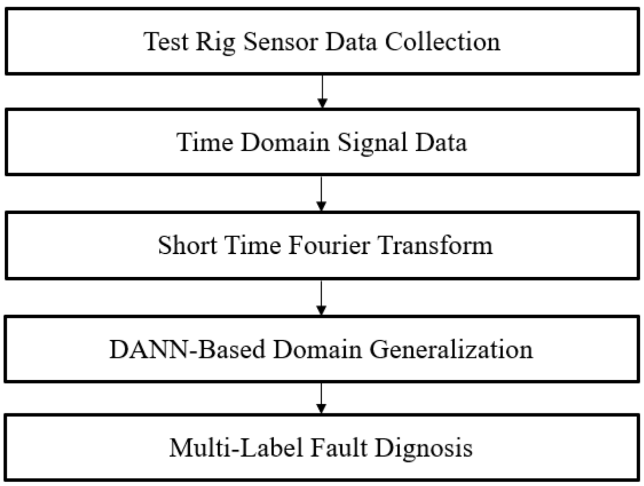

Figure 1. Flowchart of proposed methodology

2. Data Collection and Preprocessing

For this study, as shown in Fig. 2, a test rig consisting of an induction motor and a gearbox was used to generate fault data. The induction motor is run at a wide range of motor rotation speeds (400, 500, 600, 700, 800, 900 rpm) and is connected to the reduction gear with a ratio of 1:8.25. The vibration acceleration is measured in the vertical direction via an accelerometer in the bearing installed after the reduction gear at a sampling rate of 512 Hz, which is higher than the minimum required sampling rate according to the Nyquist theorem. There are total of three health states for the test rig, listed in Table 1 along with their rotation speed. Faulty parts include induction motors with defective inner ring bearings and unbalanced rotor.

To validate the proposed methodology, we utilize the vibration acceleration measured from the test rig as input data. Next, classify the rotational speed of the motor as a domain label and the health condition as a class label. Thus, the purpose of domain generalization is to classify class labels well throughout different domain labels. 800 data were measured for each health status class. Therefore, there are 2400 data for each motor rotation speed domain, and each data consists of 512 data points.

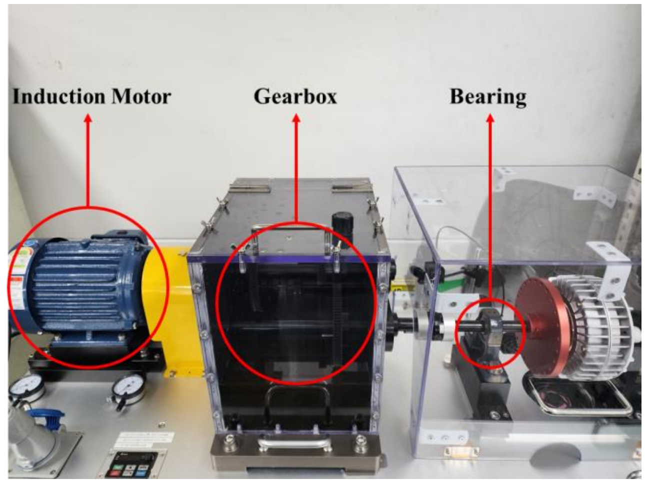

Figure 2. Experiment test rig.

Table 1. Test rig experiment scenario.

Rotation speed	Induction motor	
	Bearing	Rotor
400 500 600 700 800 900	Normal Inner Race Fault	Normal Rotor Unbalance

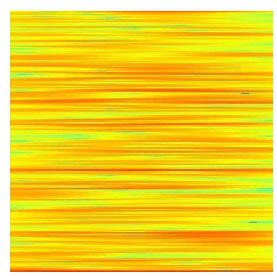

Figure 3. Frequency domain image data generated via STFT.

The measured experimental data are consisted of time series vibration acceleration data. However, the raw signal data is collected from a model running with a constant cycle. Therefore, it is reasonable to expect frequency domain data having more useful fault information compared to the time domain data. For this purpose, STFT is applied on the time domain raw signal data to change into the frequency domain image data. STFT applied frequency domain image data enables analysis on the frequency of the data respect to all timeline. Thus, frequency domain image data enhances fault diagnostic feature extracting performance during neural network training process. The STFT is implemented with a window length of 512 and hop length 16, generating 308x308 pixel size image data as shown in figure 3.

3. Domain Generalization

DANN, studied by Yaroslav et al.(2016), adapts an existing domain with prior information to a new information-deficient, identical and independently distributed (i.i.d.) domain through an adversarial learning method. In the field of engineering, DANN is utilized to solve the domain shift problem of fault diagnosis between existing source domain and target domain. However, DANN has the drawback of requiring target domain data during training. DANN-based domain generalization leverages multiple source domains for training without the need to use target domain data for training. Finding domain invariant features from multiple source domains enables fault classification of unseen out-of-distribution domains.

The proposed DANN-based domain generalization neural network consists of a feature extractor, label classifier and domain discriminator layer, as shown in Figure 4. Feature extractor is consisted of convolutional layers to collect useful features from an embedding space. Then, label classifier and domain discriminator classify the class label and domain label respectively from the extracted features in the embedding space. Adversarial learning between the label classifier and the domain discriminator is carried, with the label classifier trained in the direction where the class labels are well classified, and the domain discriminator trained in the direction where the domain labels are not well classified. As a result, we can find invariant features in multiple source domains and classify unseen target domains. The overall loss function for the DANN-based domain generalization architecture can be expressed as Eqs. (1). Then, parameters are optimized expressed as Eqs. (2-3) so that L_c is minimized and L_d is maximized to find domain invariant features.

$$L(\theta_f,\theta_c,\theta_d) = L_c(\theta_f,\theta_c) - \lambda L_d(\theta_f,\theta_d), \tag{1}$$

$$(\theta_f,\theta_c) = arg\min_{\theta_f,\theta_c} L(\theta_f,\theta_c,\theta_d), \tag{2}$$

$$\theta_d = \operatorname*{argmax}_{\theta_d} L(\theta_f,\theta_c,\theta_d), \tag{3}$$

where L_c and L_d refer to the label classifier loss and domain discriminator, respectively. θ_f , θ_c and θ_d refer to the parameters of feature extractor, label classifier and domain discriminator, respectively. λ refers to the tradeoff parameter. Specific loss functions for L_c and L_d are expressed in Eqs. (4-5).

$$L_c = -\frac{1}{n}\sum_{i=1}^{n} y_i \cdot \log(C(F(x_i)) + (1-y_i)\cdot \log(1 - C(F(x_i)), \tag{4}$$

$$L_d = -\frac{1}{n}\sum_{i=1}^{n} d_i \cdot \log(D(F(x_i)), \tag{5}$$

where n refers to the total number of data, x_i, y_i and d_i refer to the ith data, label, and domain, respectively. F, C and D refer to the feature extractor, label classifier and domain discriminator, respectively.

4. Domain Generalization

In this study, we trained DANN-based domain generalization with various test type combination of source and target domains as illustrated in Table 2. The corresponding multi-label fault diagnosis accuracy result of the target domains is shown in Table 3.

Test type A's target domain 500, 700 and 900 RPM classification accuracy is 95.7, 77.3 and 55.7% respectively. Test type B's target domain 500, 600, 800 and 900 RPM classification accuracy is 79.0, 88.3, 46.7 and 34.3% respectively. Test type C's target domain 500, 700, 800 and 900 RPM classification accuracy is 97.3, 67.3, 54.3 and 47.7% respectively. The target domains inside the boundary of source domains tend to have higher classification accuracy compared to the target domains outside. This is because there are more source domains to reference which has more similar distribution. Moreover, the farther the target domain is to the source domains, the classification accuracy is lower. From test type B and C, as target domain rpm becomes higher, the classification accuracy decreases about 10%. This is also shown from test type A and B, where 500 rpm domain classification accuracy decreased as the referencing source domain has changed to a higher rpm domain from 600 to 700. This is also due to the similarity decrease between the source and target domains. However, from test type A, target domain 500 rpm has higher classification accuracy than 700 rpm even though they both have source domains at the under and upper rpm. The reason for this is that the higher the rpm, the higher the noise in the data. Therefore, having good classification performance at high rpm is hard. Lastly, test type C has a higher classification accuracy at the upper rpm of the highest source domain than test type B. Source domains of test type C are closer and more similar than test type B, allows finding the domain invariant feature to be easier. Thus, considering the source domain combination is an important factor in advancing classification performance.

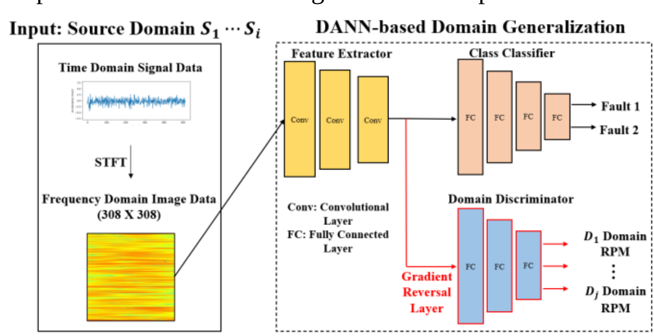

Figure 4. DANN-based domain generalization architecture.

Table 2. Source and target domains combination.

Test Type	Source Domain (RPM)	Target Domain (RPM)
A	400, 600, 800	500, 700,900
B	400, 800	700, 800,900
C	400, 600	600, 700, 800, 900

Table 3. Target domain fault diagnosis accuracy result.

Test Type	Target Domain (RPM)				
	500	600	700	800	900
A	95.7%	-	77.3%	-	55.7%
B	79.0%	88.3%-	-	46.7%	34.3%
C	97.3%	-	67.3%	54.3%	47.7%

5. Conclusion

In this study, we perform multi-label classification of unseen out-of-distribution domain data of rotating machinery via DANN-based domain generalization. We confirmed that the accuracy of the classification of the target domain existing within the source domain RPM interval was high, but the accuracy of the domains existing elsewhere was low. Moreover, the proposed methodology suggests the upper boundary of the out-of-distribution target domain to successfully diagnose fault. Finally, the following additional studies are possible. We would like to secure more diverse failure mode domains, select more general features, and develop a more robust model. In addition, we are looking for classification models with higher performance via other algorithmic neural networks rather than DANN-based neural networks.

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References

Ishaan, G., & David, L. (2020). In search of lost domain generalization. arXiv preprint arXiv:2007.01434. doi:10.48550/arXiv.2007.01434

Chongchong, Y., Yaqian, N., Yong, Q., Weijun, S., & Xia, Z. (2021) Multi-label fault diagnosis of rolling bearing based on meta-learning. *Neural Computing and Applications*, vol. 33, pp. 5393-5407. doi:10.1007/s00521-020-05345-0

Yaroslav, G., Evgeniya, U., Hana, A., Pascal, G., Hugo, L., Francois, L., Mario, M., & Victor, L. (2016). Domain-adversarial training of neural networks. *Journal of Machine Learning Research*, vol. 17, pp. 2096-2030.

Xiang, L., Wei, Z., Hui, M., Zhong, L., & Xu, L. (2020). Domain generalization in rotating machinery fault diagnostics using deep neural networks. *Neurocomputing*, vol. 403, pp. 409-420. doi:10.1016/j.neucom.2020.05.014

Yixiao, L., Ruyi, H., Jipu, L., Zhuyun, C., & Weihua, L. (2020). Deep semisupervised domain generalization network for rotary machinery fault diagnosis under variable speed. *IEEE Transactions on Instrumentation and Measurement*, vol. 69, pp. 8064-8075. doi:10.1109/TIM.2020.2992829

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