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A Review of Deep Learning-Based Intelligent Fault Diagnosis Methods for Rotating Machinery under Small-Sample Conditions

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Abstract

Rotating machinery occupies a central position in modern industrial equipment, and accurate identification of its operating condition is of great significance for ensuring production safety. However, in real-world operating conditions, the high cost of acquiring fault samples, complex service environments, and other difficulties result in extremely scarce available training samples, posing severe challenges to traditional deep learning methods that rely on big data. Therefore, fault diagnosis technology under small-sample scenarios has become a frontier hotspot in both academia and engineering. This paper reviews the research progress on deep learning-based intelligent fault diagnosis methods for rotating machinery under small-sample conditions. It elaborates on the core ideas and current application status of key approaches, including meta-learning, transfer learning, domain generalization, data augmentation, and self-supervised learning, with the aim of providing useful references for subsequent research in this field.

Keywords

rotating machinery, fault analysis, small sample, fault diagnosis, meta-learning, transfer learning, domain generalization, data augmentation, self-supervised learning

1. Introduction

Rotating machinery serves as the core carrier for power transmission and energy conversion in modern industry and is widely applied in major equipment such as aero-engines, wind turbine generators, high-speed train traction systems, and high-end CNC machine tools. Such equipment typically operates for long periods under harsh conditions including high temperature, high pressure, and heavy load, making its critical components prone to fatigue damage or sudden failures. According to statistics, faults in rotating machinery account for approximately 70% of total equipment failures, with gear-related issues contributing about 60% of rotating machinery faults. Once a fault occurs, it not only causes production line shutdowns but may also lead to catastrophic personal injury accidents. Therefore, in-depth research on intelligent fault diagnosis of rotating machinery holds significant theoretical value and practical importance. Data from the China Association of Plant Engineering indicate that a single fault causes average economic losses of 0.1 to 5 million RMB per enterprise. Thus, developing intelligent fault diagnosis for rotating machinery represents an important technical approach.

Traditional fault diagnosis methods for rotating machinery mainly rely on signal processing techniques and domain expert knowledge. Common approaches include spectrum analysis technology, which, however, cannot further reveal the rotational characteristics and fault frequencies of machinery. From the 1960s to 1970s, some simple fault diagnosis instruments emerged successively, but their diagnostic accuracy was very low. Many domestic experts have also made substantial contributions, such as Ren Daqian and Yang Shixi from Zhejiang University who proposed instantaneous frequency calculation methods, and Yu Dejie from Hunan University who conducted in-depth research on morphological component analysis [1]. Nevertheless, these methods have limitations. On one hand, manual feature extraction heavily depends on expert experience and knowledge, and the quality of feature design directly affects diagnostic accuracy. On the other hand, when facing complex and variable operating conditions, traditional methods struggle to adaptively mine deep fault features hidden in signals.

In recent years, the academic community has proposed a series of effective solutions to the problem of fault diagnosis for rotating machinery under small-sample conditions. This paper categorizes existing methods into data augmentation [2], transfer learning, meta-learning, self-supervised learning, and other categories [3], and analyzes the theoretical foundations of each type of method. Finally, it looks forward to future development directions and technical challenges in this field, aiming to provide references for further in-depth research and engineering applications of intelligent fault diagnosis for rotating machinery under small-sample conditions.

2. Task Definition and Main Learning Methods

2.1 Task Definition

The small-sample fault diagnosis task refers to developing a fault diagnosis model with strong generalization capability under the condition of limited training data [4]. Specifically, given a small-sample fault diagnosis task X, X contains a small amount of labeled dataset D_T and related auxiliary dataset D_A. The goal of the small-sample fault diagnosis task is to first train using D_A, then update the model through D_T to adapt to the fault diagnosis requirements [4].

2.2 Learning Methods

At present, the mainstream small-sample fault diagnosis methods primarily include meta-learning, transfer learning, domain generalization, data augmentation, and self-supervised learning. Meta-learning-based small-sample fault diagnosis methods improve the model’s ability for rapid learning and adaptation to new tasks by learning generalizable knowledge across multiple tasks [4]. Transfer learning-based small-sample fault diagnosis methods learn knowledge from one task or specific scenario and transfer it to enable rapid learning and adaptation in a new task. Domain generalization-based fault diagnosis methods train the model on a small number of source domains to learn universal features, enabling generalization to unknown target domains. Data augmentation-based fault diagnosis methods expand the usable dataset by incorporating generative models, noise addition, image transformations, and other techniques, thereby enhancing the model’s learning capability. Self-supervised learning-based fault diagnosis methods develop self-supervised frequency-domain feature extractors based on the task itself, use the model for pre-training, mine latent feature relationships in signals through contrastive learning, and finally fine-tune the model to adapt it to the fault diagnosis task [5].

2.2.1 Meta-Learning-Based Small-Sample Fault Diagnosis Methods

(1) Metric-Based Meta-Learning Methods

These methods mainly consist of two parts: the embedding module and the metric module [6]. The embedding module typically uses a deep learning network to extract sample features. The metric module is generally composed of distance functions, etc., used to calculate the similarity between each sample and query set samples for comparison.

Currently, the main metric-based meta-learning methods include Siamese Networks, Matching Networks, Prototypical Networks, and Relation Networks

A) Siamese Networks

Siamese Networks are the simplest and most commonly used one-shot learning algorithms. As an earlier meta-learning model, they exhibited better performance compared to contemporary models but have relatively inefficient comparison methods, resulting in a larger gap compared to other metric approaches.

The model uses a cross-entropy loss function with L2 regularization. The loss function is expressed as follows:

$$Loss(x_1,x_2) = y(x_1,x_2)\log p(x_1,x_2) + (1-y(x_1,x_2))\log(1-p(x_1,x_2)) + \lambda^T |\omega|^2 \tag{1}$$

where $p(x_1,x_2)$ represents similarity, and $y(x_1,x_2)$ is the label value (0 or 1) [6].

B) Matching Networks

Matching Networks are memory- and attention-based networks capable of rapid learning from samples.

The formula for Matching Networks is as follows:

$$\hat{y} = \sum_{i=1}^{k} \alpha(\hat{x}, x_i) y_i \tag{2}$$

$$\alpha(\hat{x}, x_i) = \frac{e^{c(f(\hat{x}),g(x_i))}}{\sum_{i=1}^{k} e^{c(f(\hat{x}),g(x_i))}} \tag{3}$$

where $\hat{y}$ is the prediction for the query point $\hat{x}$, $\sum_{i=1}^{k}\alpha(\hat{x},x_i)$ is the attention mechanism between $\hat{x}$ and x_i, c(x) represents the cosine distance function, $c(f(\hat{x}),g(x_i))$ represents the cosine distance function, $f(\hat{x})$ is the feature extractor for the query set (a unidirectional LSTM with attention), and $g(x_i)$ is the feature extractor for the support set (a bidirectional LSTM) [6].

C) Prototypical Networks

Prototypical Networks are a metric-learning-based few-shot learning method. They represent samples of each class as prototypes in a metric space and classify a sample into the nearest class based on its distance to the prototypes.

D) Relation Networks

Relation Networks consist of an embedding function and a relation function. The embedding function extracts sample features, while the relation network computes similarity between samples. Unlike other networks, it uses a deep neural network to learn the metric itself, allowing more accurate representation of distances between sample features.

2.2.2 Transfer Learning-Based Small-Sample Fault Diagnosis Methods

Transfer learning is a learning paradigm that fully utilizes knowledge from the source domain and transfers it to the target domain to improve model performance in the target domain.

For example, Zhang et al. proposed a method that first builds a model in a source domain with abundant data and then fine-tunes/adapts the model in a target domain with limited data.

2.2.3 Domain Generalization-Based Small-Sample Fault Diagnosis Methods

Domain generalization trains a model on a certain number of source domains so that it learns common features across those domains, thereby possessing generalization capability when facing unknown target domains. Current domain generalization methods can be divided, according to their mechanisms, into homogeneous domain generalization, federated domain generalization, semi-supervised domain generalization, and imbalanced domain generalization methods [4].

A) Homogeneous Domain Generalization-Based Fault Diagnosis Methods

Homogeneous domain generalization-based fault diagnosis methods represent the most mainstream and mature paradigm in current fault diagnosis research. The core idea is to learn commonalities by training on multiple labeled source domains with different data distributions during the training phase, enabling direct application to unknown domains.

B) Federated Domain Generalization-Based Fault Diagnosis Methods

Federated domain generalization-based fault diagnosis methods aim to decompose fault features into multiple parts while preserving data privacy, allowing collaborative training by different clients (e.g., different factories or equipment) to solve the problem.

C) Semi-Supervised Domain Generalization-Based Fault Diagnosis Methods

Semi-supervised domain generalization-based fault diagnosis methods address scenarios with “extremely few labeled samples and unknown target domains.” They utilize a small amount of labeled data along with unlabeled target domain data to improve data reliability and train the model.

D) Imbalanced Domain Generalization-Based Fault Diagnosis Methods

Imbalanced domain generalization methods aim to address the problem of low diagnostic accuracy caused by class imbalance in real-world data collection [15].

2.2.4 Data Augmentation-Based Small-Sample Fault Diagnosis Methods

The main idea of data augmentation is to expand the quantity of limited samples to train a reliable diagnostic model.

Current data augmentation methods mainly include SMOTE, GAN, and similar techniques [4].

A) SMOTE-Based Fault Diagnosis Methods

SMOTE generates new minority-class samples by interpolating between minority samples and their nearest neighbors, thereby balancing the sample distribution.

B) GAN-Based Fault Diagnosis Methods

GAN takes additional inputs (such as random noise) to generate training samples, which are then used to train the model.

2.2.5 Self-Supervised Learning-Based Small-Sample Fault Diagnosis Methods

Self-supervised learning-based small-sample fault diagnosis methods use large amounts of data for pre-training to enable the model to learn general feature representations. Task-specific modules are then used to fine-tune model parameters to adapt to new tasks [4]. Self-supervised learning approaches mainly include contrastive self-supervised learning and generative self-supervised learning.

A) Contrastive Self-Supervised Learning

Contrastive self-supervised learning minimizes a loss function to bring positive sample pairs closer together while pushing negative samples apart. This is achieved through the following loss function:

$$L = -\log\left(\frac{\exp\left(\frac{sim\left(z_i, z_j\right)}{\tau}\right)}{\sum_{k=1}^{K}\exp\left(\frac{sim\left(z_i, z_k\right)}{\tau}\right)}\right) \tag{4}$$

where L is the contrastive loss, z_i and z_j are feature representations of a positive pair, z_k is a negative sample representation, $sim\left(z_i, z_j\right)$ is a similarity measure function, τ is a temperature parameter controlling distribution smoothness, and K is the number of negative samples [7].

B) Generative Self-Supervised Learning

Generative self-supervised learning enables the model to learn the internal structure and distribution of data by generating data itself, without requiring externally provided labels [4].

3. Development Trends of Small-Sample Fault Diagnosis Methods

Small-sample fault diagnosis methods will, while still relying on data, increasingly incorporate physical principles, expert historical experience, and other knowledge constraints to guide the model, thereby reducing dependence on small samples. They will also introduce noise, temperature, and other factors to enrich model inputs. At the same time, target domain data can be decomposed into multiple data types and assigned to different sensor models for complementary association, yielding more comprehensive and complete equipment state information. In the future, fault diagnosis models with good generalization capability while protecting data privacy will also emerge.

4. Conclusion

This paper systematically reviews the research progress on deep learning-based intelligent fault diagnosis methods for rotating machinery under small-sample conditions, with a focus on analyzing the core ideas, typical algorithms, and application scenarios of five main categories: meta-learning, transfer learning, domain generalization, data augmentation, and self-supervised learning. Although these five categories have already demonstrated good performance in multiple research scenarios, each still faces limitations and distinct challenges. Therefore, as various technologies continue to develop, small-sample fault diagnosis methods will evolve toward greater intelligence, practicality, and precision, providing strong support for the maintenance of complex equipment.

References

[1] Li, L. F. (2015). Research on fault identification and intelligent diagnosis of rotating machinery [Master's thesis, China Jiliang University]. CNKI. https://kns.cnki.net/kcms2/article/abstract?v=zO3wb1M9eky5mQii3rkQ2igyGY_4h3-KZuju03hs8f0Nw89sg-rd8FYZdVpJRzsWVRNKE1EJjNViaGq86VerDe7k3x35Vr5gw5iTo7v4De_AAiHgkeZmirYNSI6Zn9DN6IrSU3ZbsZh-250aeznrHB0ckFA9jenaFLsxgKn05YfrjpZgHZn2Uw==&uniplatform=NZKPT&language=CHS.

[2] Xia, P. C., Huang, Y. X., Wang, Y. X., Liu, C. L., & Liu, J. (2023). Application of discriminative meta-learning method based on data augmentation in cross-device few-shot fault diagnosis. *Scientia Sinica Technologica*, 53(11), 2003-2004.

[3] Zheng, Q. M., Wang, X. M., & Jiang, L. (2025). Research on fault diagnosis method of point machine based on unlabeled self-supervised representation learning. *Journal of Railway Science and Engineering*, 22(01), 404-415. https://doi.org/10.19713/j.cnki.43-1423/u.T20240574.

[4] Wu, K., Wu, J., Shu, Q. M., Shen, W. M., & Song, W. B. (2025). Review of deep learning-based small-sample fault diagnosis methods for rotating machinery. *Chinese Journal of Ship Research*, 20(02), 3-19. https://doi.org/10.19693/j.issn.1673-3185.04175.

[5] Chen, J. X. (2025). Few-shot bearing fault diagnosis based on time-frequency information self-supervised contrastive learning and fusion enhancement [Master's thesis, Yanshan University]. https://doi.org/10.27440/d.cnki.gysdu.2025.000938.

[6] Zhang, R. (2023). Research on fault diagnosis and health assessment of rotating machinery based on meta-learning [Master's thesis, Shijiazhuang Tiedao University]. https://doi.org/10.27334/d.cnki.gstdy.2023.000623.

[7] Song, Y. M. (2024). Research on rolling bearing fault diagnosis method based on self-supervised learning [Master's thesis, Dalian University of Technology]. https://doi.org/10.26991/d.cnki.gdllu.2024.005073.

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Conflicts of Interest

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