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The Review of Bearing Fault Diagnosis Technology Based on Machine Learning

Yi Jiang

Department of College of Information and Mechanical and Electrical Engineering, Hunan International Economics University, ChangSha,410000, China

***Corresponding author**: Yi Jiang*

Abstract: This paper reviews the development and applications involving bearing fault diagnosis technology based on machine learning and deep learning and explores the limitations of traditional fault diagnosis methods and advantages of machine learning technology in improving diagnostic accuracy and efficiency. The study represents that these technologies can effectively extract and learn features from vibration signals for high-precision fault diagnosis through in-depth research into the application of models like support vector machines, convolutional neural networks, and long short-term memory networks. It also summarizes the deep learning research results in bearing fault diagnosis up to now, points out the superior performance of it in complex working conditions, and highlights its role in improving mechanical equipment reliability and safety, both played and to be played.

Keywords: Bearing Fault Diagnosis; Machine Learning; Deep Learning; Convolutional Neural Network; Long Short-Term Memory Network

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1. Introduction

1.1 Research Background and Importance

With the rapid development of modern industrial technology, bearings, as one of the most important parts of mechanics and electrical equipment, play a critical role in the top running status of the health of the system with respect to security and reliability. However, bearings are easily prone to definite faults, such as fatigue spalling, wear, and poor lubrication, because of the complicated working environment and harsh operating conditions. If those faults are undetectable and handled in time, they can cause serious economic losses or even catastrophic accidents [1]. Conventional methods of diagnosing bearing faults mainly depend on signal processing technologies, such as spectrum analysis and waveform analysis. Those traditional methods usually need expert experience for manual characteristic extraction and present poor performance in noisy environments [2]. Hence, improving the accuracy and real-time performance of bearing fault diagnosis becomes an important issue for researchers.

In recent years, the rapid development of machine learning technology has provided new solutions for bearing fault diagnosis. By utilizing a large amount of historical data and advanced algorithms, machine learning can automatically extract fault features from complex signals and effectively distinguish different fault types. This not only improves the accuracy of fault diagnosis, but also greatly reduces the dependence on expert experience [3]. In particular, the introduction of deep learning technology has enabled unsupervised learning, convolutional neural network (CNN) and other methods to show superior performance in bearing fault diagnosis. They can automatically extract multi-level feature representations from raw signals, thereby achieving more accurate fault diagnosis [4]. Therefore, the research on bearing fault diagnosis technology based on machine learning has important academic value and application prospects.

1.2 Research Objectives

In this paper, the bearing fault diagnosis technology supported by machine learning is systematically reviewed, and the advantages and challenges it has caused in fault feature extraction, model selection, and diagnostic accuracy are analyzed. It first reviews the traditional methods of bearing fault diagnosis, which will lay a theoretical basis for the subsequent research process. The latter part of the paper elaborated in detail on the application of machine learning technology in bearing fault diagnosis, where the focus was put on the application status and the advantages and disadvantages of mainstream algorithms of the support vector machine (SVM), neural network (NN), and convolutional neural network (CNN). The last part addressed the latest advancements in deep learning technology in this area and analyzed how this has improved over the traditional methods. Finally, by summarizing the limitations of current research, this paper will propose possible future research directions in order to provide valuable reference and guidance for researchers in related fields.

2. Basics of Bearing Fault Diagnosis Technology

2.1 Types of Bearing Faults

As a key component in rotating machinery, bearings may suffer from a variety of faults during long-term operation, mainly including rolling element fatigue spalling, inner and outer ring cracks, cage damage, poor lubrication, etc. Rolling element fatigue spalling is the most common form of failure, usually due to the long-term alternating stress on the material surface, which eventually leads to material fatigue and shedding, thereby generating vibration and noise [5]. Cracks in the inner and outer rings may be caused by overload, excessive temperature or material defects. These cracks will gradually expand and eventually lead to bearing failure [6]. In addition, cage damage is usually related to abnormal loads, poor lubrication or improper installation. Once the cage is damaged, it may cause the rolling elements to be unable to position correctly, thereby aggravating bearing wear and failure [7]. Poor lubrication is another common type of failure. It may be caused by insufficient lubricant, lubricant degradation or improper lubricant selection, which will increase friction and temperature, thereby accelerating bearing wear and failure [8].

Different types of faults often exhibit different vibration and noise characteristics. Therefore, identifying the type of bearing fault is crucial for formulating maintenance strategies and preventing potential equipment failures. In recent years, with the development of vibration signal analysis technology, researchers have been able to more accurately identify and classify bearing fault types, thereby improving the reliability and safety of mechanical systems [9].

2.2 Introduction to Traditional Fault Diagnosis Methods

Traditional bearing fault diagnosis methods mainly rely on signal processing techniques such as time domain analysis, frequency domain analysis and time-frequency analysis. These methods analyze the vibration signals generated during the operation of the bearing and extract characteristic parameters to determine the health of the bearing [10]. Time domain analysis methods usually identify anomalies by calculating the statistical characteristics of vibration signals, such as mean, variance, peak factor, and kurtosis [11]. These methods are easy to implement, but they have certain limitations when dealing with complex fault modes. Frequency domain analysis methods convert vibration signals from time domain to frequency domain through Fourier transform, identify the amplitude of specific frequency components, and detect fault characteristics [12]. This method is effective in dealing with periodic fault characteristics, but has limited processing capabilities for non-stationary signals.

In addition, time-frequency analysis methods such as short-time Fourier transform (STFT) and wavelet transform (WT) can analyze signals in both time domain and frequency domain, providing more detailed fault information, especially when dealing with non-stationary signals [13]. However, traditional methods usually rely on manually selected feature parameters, and the analysis process is complex and susceptible to noise interference, so they still face challenges in practical applications. Nevertheless, these methods have laid an important theoretical foundation for subsequent diagnostic technologies based on machine learning and deep learning.

3. Application of Machine Learning in Bearing Fault Diagnosis

With the continuous development of machine learning technology, researchers have gradually applied machine learning to bearing fault diagnosis for improving diagnosis accuracy and efficiency. Machine learning is capable of learning from a huge amount of historical data to gain knowledge about mode and set up complicated mapping relations between data and fault types effectively for fault prediction and diagnosis in unknown environments [14]. Traditional methods of fault diagnosis are based on expert experience and manual feature extraction; machine learning can automate it and greatly reduce the dependence on human intervention. Currently, various machine learning approaches have been used in bearing fault diagnosis, among which are supervised learning, unsupervised learning, and semisupervised learning.

Among the supervised learning methods, algorithms like support vector machines and random forests have become very prevailing tools in bearing fault diagnosis due to their good performance in classification. For example, Zhang et al. used an SVM method combined with signal processing technology to realize effective bearing fault diagnosis; its accuracy was far better than that of traditional methods [15]. Meanwhile, the development of neural networks (NN), and especially deep neural networks (DNN), is able to learn and represent complex patterns. Li et al. further pursued the studies on convolutional neural networks (CNN) for improving the accuracy and robustness in fault diagnosis on large-scale bearing fault datasets [16].

So, these methods like autoencoders and K-means' unsupervised learning work absolutely perfectly under conditions of scarcess labeled data. All in all, autoencoders compress and reconstruct data; without labels, feature representation of data may learn and use these for anomaly detection. According to Xie et al., autoencoders can capture key features from signals of bearing vibration and, in this way, clearly identify the fault types in them [17]. Moreover, these semi-supervised learning methods are the best composition of supervised learning and unsupervised learning. Under the condition of small amounts of labeled data and large amounts of unlabeled data, these methods could make full use of data resources and improve the accuracy of diagnoses.

Figure 1: Fault diagnosis flow chart based on machine learning

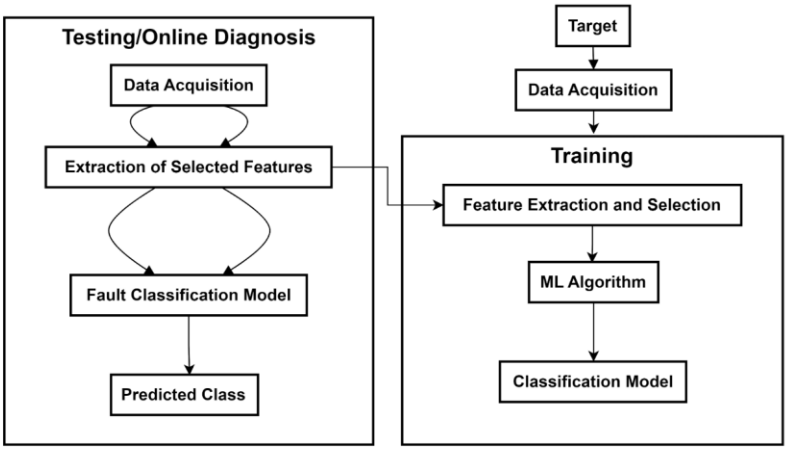

Figure 1 shows the process of bearing fault diagnosis based on machine learning, including the training phase and the test/online diagnosis phase. In the training phase, data is first obtained from the target system, and representative features are extracted through feature extraction and selection steps. These features are then used to train the machine learning algorithm to finally generate a classification model. In the test or online diagnosis phase, the classification model classifies the fault type and predicts the fault category through new data collection and feature extraction steps combined with the trained classification model.

4. Fault Diagnosis Technology Based on Deep Learning

4.1 Convolutional Neural Network (CNN)

Convolutional neural network (CNN) has been widely used in the field of bearing fault diagnosis in recent years due to its excellent performance in image processing and feature extraction. CNN can automatically learn and extract multi-level features from signals without manually designing feature extractors, which greatly improves the accuracy and efficiency of fault diagnosis[18]. For example, Jia et al. used the CNN model to extract features and classify faults from bearing vibration signals in their research, and showed high diagnostic accuracy under different working conditions[19]. The hierarchical structure of CNN enables it to perform well in processing large-scale, high-dimensional vibration signals, and can capture the spatial and frequency characteristics of the signal, thereby achieving efficient fault diagnosis. In addition, combined with technologies such as data enhancement and transfer learning, CNN also shows excellent performance in small sample scenarios [20].

4.2 Long Short-Term Memory Network (LSTM)

Long Short-Term Memory Network (LSTM) is a recurrent neural network (RNN) designed specifically for processing sequence data, and its application in fault diagnosis has attracted more and more attention. LSTM can effectively memorize and capture the time dependency and long-term dependency in the signal, so it is particularly suitable for processing non-stationary and time series data [21]. Wu et al. modeled the bearing vibration signal through LSTM and successfully captured the key time dependency features in the signal, thereby significantly improving the accuracy of fault identification [22]. In addition, LSTM shows superior robustness and adaptability when processing complex signals generated by long-term operation, and can effectively deal with nonlinear features that are difficult to handle by traditional methods [23]. This makes LSTM an important tool in modern intelligent fault diagnosis systems, especially in fault prediction under long time series and complex working conditions.

5. Conclusion

This paper systematically reviews and analyzes bearing fault diagnosis technology based on machine learning and deep learning, and deeply explores the current mainstream fault diagnosis methods and their performance in practical applications. Studies have shown that the application of machine learning, especially deep learning technology, in bearing fault diagnosis not only significantly improves the accuracy and efficiency of fault identification, but also reduces the dependence on human experience and manual feature extraction to a certain extent. Deep learning models such as convolutional neural networks (CNN) and long short-term memory networks (LSTM) have greatly improved the fault diagnosis capabilities under complex working conditions by automatically extracting and learning features from signals, providing strong support for practical industrial applications. However, despite significant progress, existing research still faces some challenges and limitations that deserve further exploration and resolution.

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