Simulation-driven Bearing Fault Diagnosis for Condition monitoring without Faulty Data

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ABSTRACT

The failure of rolling element bearings in complex mechanical systems is a significant cause of mechanical failures, leading to decreased productivity and safety risks. Deep learning has shown promising results in bearing fault diagnosis, but the predictive performance depends on high-quality data. Domain adaptation has been studied to solve this problem, but it still has limitations when applied to real-world industrial applications. In this study, we propose a deep learning-based domain generalization framework for bearing fault diagnosis using the bearing simulation model and adversarial data augmentation method. The proposed framework was validated on a real bearing fault dataset and showed promising results in improving diagnostic performance in cases where fault data cannot be obtained or when dealing with unlearned target domains. This approach has the potential to improve industrial maintenance systems by obtaining improved generalization performance in the absence of fault datasets.

1. INTRODUCTION

Rolling element bearings contribute significantly to overall productivity in rotating machinery, but they are vulnerable to external influences such as acidic liquid corrosion, lubricant deficiency, and plastic deformation due to harsh working environments and long operating times. The failure of bearings in complex mechanical systems accounts for approximately 30% of entire mechanical failures, which cause serious time consumption, a decrease in productivity, and the risk of fatal accidents (Zhang, 2020). As a result, bearing fault diagnosis is being highlighted as an essential research field in modern industrial maintenance systems.

Deep learning, which has shown promising results in a variety of fields, has been applied to condition monitoring, demonstrating predictive performance and generalization ability that outperforms existing signal processing-based studies (Shao, 2018; Chen, 2017; Zheng, 2019). However, implementing an accurate predictive model based on deep learning presents a challenge because it requires high-resolution and high-quality data.

In order to solve these problems, deep learning-based bearing fault diagnosis has been studied in the field of domain adaptation over the past few years (Chen, 2020; Li, 2019). Domain adaptation is to transfer knowledge learned from the labeled training data (i.e., source domain) to the unlabeled data (i.e., target domain) in order to minimize domain discrepancy and improves the diagnostic performance of the target domain. It showed excellent performance by solving difficulties arising from data acquisition, including building big data in various domains or acquiring fault data. However, domain adaptation also has some limitations in application to actual machine diagnosis. First, characteristic fault frequencies can change according to the alignment and looseness of the shaft and size of the bearing elements so that the vibration signal of the bearing shows a clearly different data distribution for each machine. Therefore, bearing fault diagnosis is impossible when fault data cannot be acquired, such as in new equipment. Second, even if fault data for target domains are acquired, domain adaptation cannot be diagnosed with good generalization performance for new unlearned target domains.

In this study, we introduce the domain generalization framework that learns simulation data for bearing fault diagnosis. The proposed framework aims to diagnose when there is no fault dataset for the target domain, which has two characteristics: generation of a bearing simulation dataset for learning of deep learning model and an adversarial data

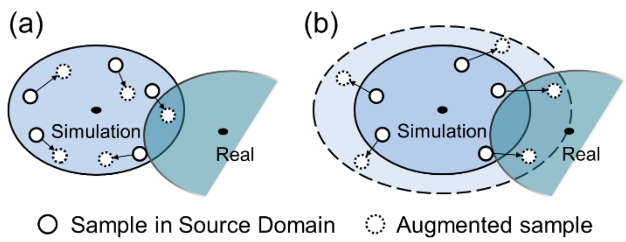

Figure 1. Illustration of the proposed domain extension. (a) general data augmentation. (b) the proposed adversarial data augmentation.

augmentation method for bearing fault diagnosis of unlearned target domains. The effectiveness of this method was validated in experiments on a rolling-element bearings defect dataset.

2. PROPOSED METHOD

2.1. Bearing Simulation Model

Localized bearing fault vibration response can be viewed as a complex mix of contributions modeled by a secondary cyclo-stationary process. When this non-stationary condition is considered, the vibration signal can be described as a periodic impulse excitation signal (Antoni, 2007; Liu, 2021):

$$x(t) = \sum_{i=0}^{i=N} h(t - iT - \tau_i) q(iT) A_i + n(t) \quad (1)$$

where $h(t)$ denotes the impulse response, i is the sequential number of impulse excitation, T and t is the time interval between two impulse excitation and is discrete time variable, respectively. τ and A are the uncertainties on the inter-arrival time and the magnitude. Finally, $q(t)$ and $n(t)$ represents the periodic modulation generated by the load distribution and the environment noise, respectively.

2.2. Adversarial Data Augmentation Algorithm

In many domain adaptation studies, the bearing fault diameter was also designated as the label class. However, since the difference in distribution between simulation and actual data is large, and it is difficult to generate simulation signals according to fault diameters, this study generates and learns simulation signals for four categories (e.g., healthy, inner race fault, outer race fault, and rolling element fault) and infers them for the target domain.

The proposed framework aims at data augmentation in a direction that can expand the data distribution by generating outside the distribution learned by the deep learning model, which is different from the existing data augmentation that generates data within the distribution, as shown in Fig. 1. Therefore, augmented domains improve the capacity and generalization performance of deep learning-based

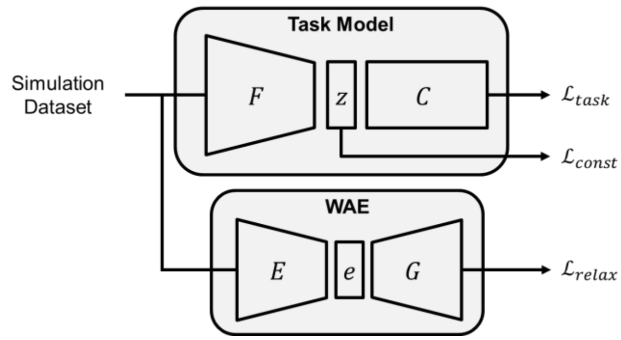

Figure 2. The architecture of the proposed framework.

diagnostic models by mimicking unseen target domains as much as possible.

To achieve this goal, we propose the proposed framework that follows the architecture presented in (Qiao, 2020), as shown in Fig. 2. The proposed framework consists of two architectures, and the overall loss function is formulated as follows:

$$\mathcal{L} = \mathcal{L}_{task}(\omega; x) - \alpha \mathcal{L}_{const}(\omega; z) + \beta \mathcal{L}_{relax}(\psi; x) \quad (2)$$

where $\mathcal{L}_{task}$ is the classification loss, $\mathcal{L}_{const}$ is semantic consistency constraint to prevent changes in the labels of adversarial examples generated to augment the data outside the data distribution, and $\mathcal{L}_{relax}$ guarantees large domain transportation, generating data that is as fictitious yet challenging as possible. ω and ψ are parameters of task model (i.e., general convolutional neural network, CNNs) and Wasserstein autoencoder (WAE), respectively.

Given the objective function $\mathcal{L}$, we employ an iterative way to generate the adversarial samples x^{+} in the augmented domain S^{+}:

$$\mathrm{x}_{t+1}^{+} \leftarrow \mathrm{x}_t^{+} + \gamma \nabla_{x_t^{+}} \mathcal{L}(\omega, \psi; x_t^{+}, z_t^{+}) \quad (3)$$

where γ is the learning rate of gradient ascent. A small number of iterations are required to produce sufficient perturbations and create desirable adversarial samples. $\mathcal{L}_{const}$ and $\mathcal{L}_{relax}$ proposed in the overall loss function are as follows:

$$\mathcal{L}_{const} = \frac{1}{2} \|z - z^{+}\|_2^2 + \infty \cdot 1\{y \neq y^{+}\} \quad (4)$$

$$\mathcal{L}_{relax} = \frac{1}{2} \|x - x^{+}\|_2^2 \quad (5)$$

where $1\{\cdot\}$ is the 0-1 indicator function and $\mathcal{L}_{const}$ will be ∞ if the class label of x^{+} is different from x.

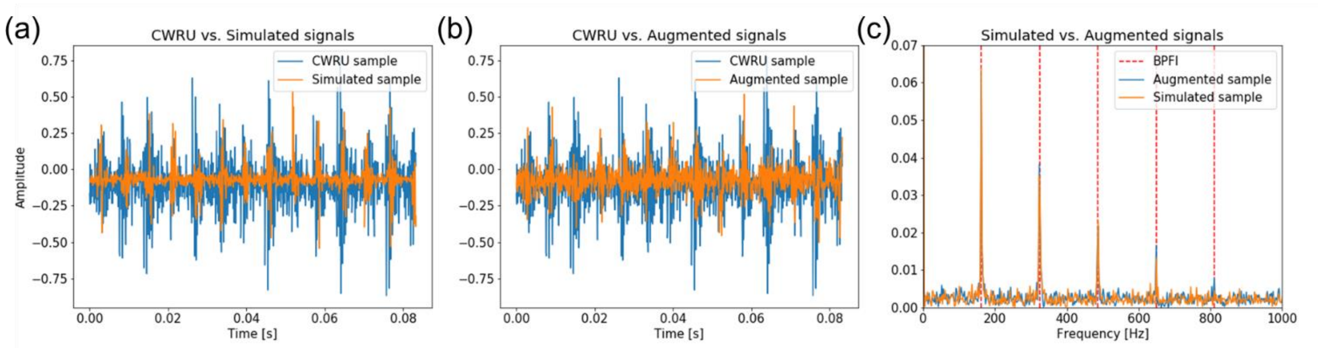

Figure 3. Visualization of simulated, augmented, and real signals. (a) Comparison of real and simulated time signals. (b) Comparison of real and augmented time signals. (c) Comparison of simulated and augmented frequency components.

Table 1. Operating conditions of CWRU dataset.

	Condition 1	Condition 2	Condition 3	Condition 4
Speed (rpm)	1797	1772	1750	1730
Load (HP)	0	1	2	3

Table 2. CWRU dataset classification results.

Method	Source data	Target data	Accuracy (%)
Base method	Simulation	Condition 1	46.97
		Condition 2	60.77
		Condition 3	59.81
		Condition 4	46.47
Proposed method	Simulation	Condition 1	73.41
		Condition 2	78.29
		Condition 3	71.91
		Condition 4	70.66

3. Results and Discussions

3.1. Experiment Setting

The effectiveness of the proposed framework was validated using an experimental bearing dataset from the Case Western Reserve University (CWRU) in the United States. The bearings in the dataset were artificially damaged using various methods in different locations. Acceleration measurements have been captured on the drive-end bearings with a sampling frequency of 12kHz. The signal length is equally split into 2048 lengths without overlapping.

3.2. Experiment Results

In this section, we demonstrate that simulated signals that mimic real-world machine signals, as well as the proposed deep learning-based augmentation signals, are generated while accurately reflecting the physical properties of actual bearings. Fig. 3 shows the inner race fault class's simulated, augmented, and real signals. Simulated signals show that the characteristic frequencies match real signals with the same bearing specifications, which is explained that simulated signals reflect the mechanical properties of the actual bearing well. However, simulated signals are difficult to reflect the individual characteristics of real signals, such as mechanical looseness, imbalance, and environmental noise. Fig. 3 (b) compares real signals with augmented signals generated by adversarial training. Augmented signals reflect characteristic frequencies of the inner race fault while showing that more complex signals can be generated. These results imply that realistic but challenging signals can be generated by gradually extending the data domain from simulated signals that mimic characteristic frequencies.

We compare the base model in which simulated signals are learned to the proposed method in which augmented signals are generated and learned to demonstrate the validity of the proposed framework. Table 1 lists the information on the operating conditions of CWRU dataset classified into four categories. Since characteristic frequencies and amplitudes of actual bearings change depending on the operating conditions, diagnostic performance is compared for each condition and presented in Table 2. The proposed method not only improves average accuracy by 20.06 % compared to the basic method, but also it also shows exceptional diagnostic performance under all conditions. In addition, the trend of diagnostic performance of the proposed method and the base method has a similar tendency according to each condition. This result implies that augmented signals generate vibration signals with various information that simulated signals did not have while accurately reflecting the information of the impulse excitation signals that simulated signals did have.

4. Conclusion

In this study, we propose a domain generalization framework for bearing fault diagnosis when no fault dataset exists for the actual bearing. The proposed framework aims to generate fictitious but challenging bearing fault signals by combining simulated signals of bearing failure used for learning and a deep learning method to perform adversarial data augmentation. The proposed method outperformed the base method learned with simulated signals, and it was demonstrated that augmented signals retain information about the physical properties of simulated signals as well. However, for the condition with low accuracy in the base method, the proposed method also had low accuracy compared to other conditions, implying that additional research on domain extension should be conducted. In addition, future work will be performed, such as comparison with domain adaptation methods and validation of datasets other than CWRU. We believe that the proposed method will help overcome the problem in the absence of fault data.

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