Time Shifting Data Augmentation to Alleviate Class-Imbalance Problem for Cross-Domain Bearing Fault Diagnosis

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ABSTRACT

This paper presents a new cross-domain fault diagnostic method for rolling element bearings with class-imbalanced datasets. The key idea to alleviate the class imbalance problem is the incorporation of the data augmentation strategy. This study proposes a new data augmentation technique, namely, time shifting data augmentation (TS-DA). Synthetic data is generated to balance the number of normal and fault data. The validity of the proposed method is evaluated using a dataset from the bearing testbed. The results show that the proposed method augments different types of bearing fault data effectively and outperforms existing methods under the class imbalance problem.

1. INTRODUCTION

Bearings are machine components used as a core part in rotating machines. Bearing fault diagnosis is sometimes required in safety-related and mission-critical systems as bearing defects can lead to significant consequences.

The operating conditions of rotating machines often vary due to various reasons. Conventional fault diagnostic methods showed poor performance for the cross-domain problem. To address this issue, transfer learning was studied recently. Different transfer learning methods were developed such as maximum mean discrepancy-based domain adaptation method (Long et al., 2015) and domain adversarial method (Ganin & Lempitsky, 2015). However, Existing studies assumed that a sufficient number of fault data is available. It is commonly observed that normal data in rotating machinery is abundant, whereas fault data is limited. It is worth noting that fault data can only be obtained when a machine failure occurs. Existing methods mostly address the cross-domain problem only.

In this study, a deep learning model is used to address the cross-domain problem when bearing fault data is limited. A one dimensional convolutional neural network (1D-CNN) is used as a baseline model with domain adaptation to extract features from bearing data. The time shifting data augmentation (TS-DA) technique is used to augment the limited number of fault data. The model is implemented to address various operating condition situations.

The subsequent sections of this paper are organized as follows. The proposed method is described in Section 2. The bearing data used to validate the proposed method follows in Section 3. Section 4 shows the results and discussions. Finally, Section 5 presents the conclusion with future work.

2. PROPOSED METHOD

The concept of TS-DA is presented in Figure 1. The original vibration data from rotating machines with defective bearings is augmented by moving a certain number of data points in the original vibration data along with the time axis. This strategy for the fault data augmentation is reasonable considering the characteristic of rotating machines with bearing defects. When a rotating machine operates, fault-specific patterns that occur periodically are created by the rolling action of the defective bearing surfaces.

The architecture of the fault diagnostic model is shown in Figure 2. A 1D-CNN model is utilized as a baseline model that consists of two modules: (1) pseudo-label data augmentation and (2) domain adaptation. The vibration data from the bearing is initially input into the model. Then, pseudo-labels are assigned to unlabeled target data. TS-DA is implemented to the fault data. The augmented data is used to train the 1D-CNN model. The training objective is to minimize the summation of the cross entropy and class-wise central moment discrepancy for the classification loss and the domain adaptation loss, respectively. The proposed model was trained to classify ten classes with different

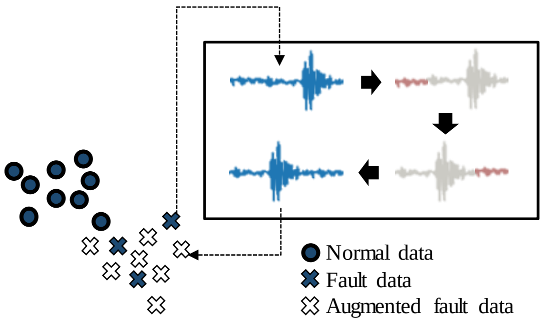

Figure 1. Concept of the proposed time shifting data augmentation technique

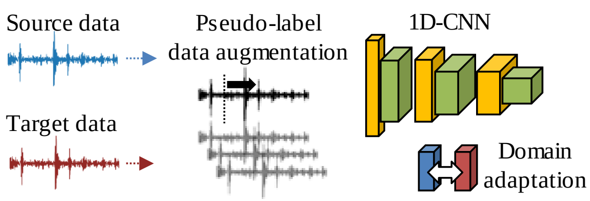

Figure 2. Flowchart of the proposed method

Table 1 Model architecture

Layer	Output size	Parameter
Input	1-[1200×1]	-
Conv1	4-[593×1]	Kernel 16×1, Stride 2, ReLU
Pool1	4-[295×1]	Kernel 4×1, Stride 2
Conv2	8-[146×1]	Kernel 4×1, Stride 2, ReLU
Pool2	8-[72×1]	Kernel 4×1, Stride 2
Conv3	16-[35×1]	Kernel 4×1, Stride 2, ReLU
Pool3	16-[16×1]	Kernel 4×1, Stride 2
Flatten	256×1	-
FC1	128×1	-
FC2	C×1	-
Softmax	C	-

bearing conditions. The details of the proposed model architecture are shown in Table 1. Adam optimizer is used with learning rate 10^{-3}. For training, the number of epoch is set to 200 and batch size 256. Class-wise central moment discrepancy moment is set to 7 and domain adaptation loss weight is set to 0.1. After initializing model parameters, mini batches are sampled from the source and target data. To handle the unlabeled target data, pseudo-labels are generated for each mini-batch. For fault data, TS-DA is conducted. Using the augmented source and target data,

Table 2 Description of datasets

Dataset	Health conditions	Operating condition: Rotational speed	Operating condition: Loading condition
CWRU A	N/B/IR/OR	1797 rpm	0 hp
CWRU B	N/B/IR/OR	1772 rpm	1 hp
CWRU C	N/B/IR/OR	1750 rpm	2 hp
CWRU D	N/B/IR/OR	1730 rpm	3 hp

forward propagation is calculated. This process is repeated until the convergence criteria are met.

3. DATASET

The proposed method was evaluated using the Case Western Reserve University (CWRU) dataset collected from the bearing testbed data. CWRU consists of four types of faults; normal (N), ball fault (B), inner raceway fault (IR) and outer raceway fault (OR). Artificially seed faults were created with lengths of 0.007, 0.014, and 0.021 inches. The dataset was constructed using the vibration data acquired under each condition. A single datum was acquired by the sliding window to the vibration signals. The single datum consisted of 1,200 sample points. Ten bearing conditions have 1,000 data of vibration signals individually. The quantities of normal bearing training source and target data are 700 and 700, respectively. For the fault data, a particular portion of the original vibration signals was randomly extracted for the class imbalanced conditions. For example, when the imbalance ratio is 0.01, the quantities of ball fault training source and target data are 7 and 7, respectively. The quantities of test data samples in the target domain is 300 for data with any health condition. Domain adaptation tasks were conducted between two different operating conditions with class imbalanced data, i.e., CWRU A → CWRU B. Details of the datasets are shown in Table 2.

4. RESULTS AND DISCUSSION

The results of the proposed model in various imbalanced scenarios are shown in Figure 3. From the results, it was confirmed that the proposed model presented a high performance of over 93% even as the imbalance was severe. The performance of the proposed method was compared with those of state-of-the-art domain adaptation methods as shown in Figure 4. For domain adaptation tasks, experiments were repeated ten times and the average accuracy was calculated. From the results, existing methods do not perform well when the imbalance ratio becomes severe. However, the proposed method shows robust performance even under low imbalance ratios.

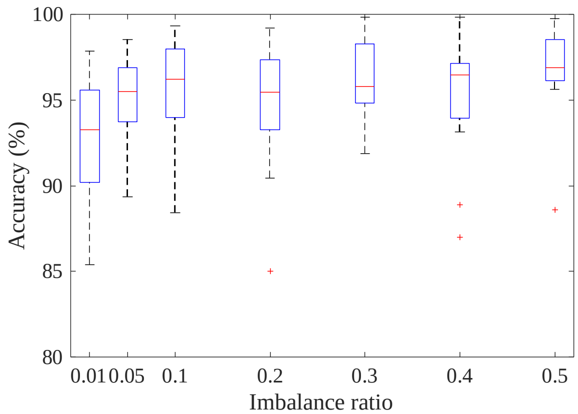

Figure 3 Accuracy of the proposed method with various imbalance ratios

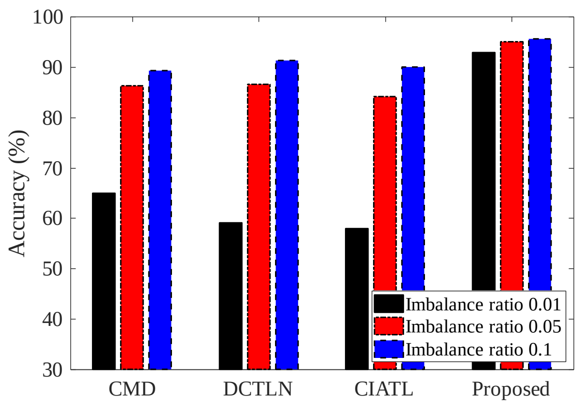

Figure 4 Comparison of accuracy using CWRU dataset

5. Conclusion

This paper presents a new data augmentation technique for enhanced cross-domain bearing fault diagnosis with class-imbalanced datasets. The proposed fault diagnostic method was evaluated on the CWRU testbed dataset under class-imbalance and various operating conditions. The authors found that the proposed time shifting data augmentation (TS-DA) technique is very powerful to overcome the dearth of fault data. Even in extremely imbalanced conditions (e.g., imbalance ratio of 0.01), the diagnostic accuracy of the proposed method was over 93% for the datasets.

The benefit of the proposed TS-DA was evident. Nonetheless, the TS-DA presented one limitation. It was found that, when the number of original samples is very small (e.g., five samples), the proposed method can be ineffective. In future, advanced data augmentation techniques will be studied further.

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References

Long, M., Cao, Y., Wang, J., & Jordan, M. (2015). Learning transferable features with deep adaptation networks. *International Conference on Machine Learning*, pp. 97-105.

Ganin, Y., & Lempitsky, V. (2015). Unsupervised domain adaptation by backpropagation. *International Conference on Machine Learning*, pp. 1180-1189.

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