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Learnable wavelet transform and domain adversarial learning for enhanced bearing fault diagnosis

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Unsupervised domain adaptation techniques have been widely used to detect the health conditions of rolling bearings. Despite the importance of cross-domain fault diagnosis, it has not received much attention for applications in noisy environments. To address this issue, we propose a novel architecture that combines learnable wavelet packet transform with domain adversarial neural networks (DANN-LWPT). The proposed method involves utilizing the learnable wavelet packet transform (LWPT) and wavelet packet transform (WPT) to decompose and reconstruct signals from the source and target domains. These reconstructed signals are then fed into a domain adversarial neural network (DANN). We introduce a guidance loss that dynamically enforces similarity between the source and target domain signals in the time-frequency domain during the process of decomposition and reconstruction, promoting the learning of domain-invariant and discriminative features. We compare our proposed method with other representative domain adaptation approaches, and the results of the evaluation show its superiority.

Keywords: Rolling bearing, Fault diagnosis, Unsupervised domain adaptation, Learnable wavelet packet transform.

1. Introduction

With the great demand for higher reliability and safety of increasing number of industrial machines, unsupervised domain adaptation (UDA) fault diagnosis techniques have been developed rapidly and applied widely. However, most UDA methods that perform well are designed for low-level noise data in laboratory environments (Zhao et al. 2021). In real-world scenarios, the performance of these methods may significantly deteriorate due to the presence of various types and levels of noise during signal acquisition.

The recently proposed LWPT algorithm can automatically learn meaningful and sparse features of raw signals (Frusque and Fink 2022). Inspired by this, an architecture that combines learnable wavelet packet transform with domain adversarial neural network (DANN-LWPT) is proposed for fault diagnosis of rolling bearings under noisy environment.

2. Method

Fig. 1 illustrates the overall framework of our proposed DANN-LWPT. The first step involves feeding separately the source and target signals into the separate encoders of LWPT and WPT modules for signal decomposition, obtaining learnable wavelet coefficients and traditional wavelet coefficients, respectively. In the second step, the learnable wavelet coefficients and traditional wavelet coefficients are separately reconstructed into time-domain signals by the decoders of LWPT and WPT modules. During the learning process, the features of the learnable wavelet coefficients dynamically approximate the features of the traditional wavelet coefficients during the learning process, under the guidance loss L_G, which is expressed as:

$$L_G = \sum_{j=1}^{2^L} \left| \mathrm{E}\left[\frac{1}{B}\sum_{i=1}^{B}\left|c_{i,j}^{s}\right|\right] - \mathrm{E}\left[\frac{1}{B}\sum_{i=1}^{B}\left|c_{i,j}^{t}\right|\right] \right| \quad (1)$$

where L is the number of decomposition layers in LWPT and WPT modules, $\mathrm{E}[\cdot]$ represents the expectation of the elements from a vector, B is the batch size, $c_{i,j}^{s}$ and $c_{i,j}^{t}$ are the wavelet coefficients of the j-th output node of the i-th source domain sample and target domain sample, respectively.

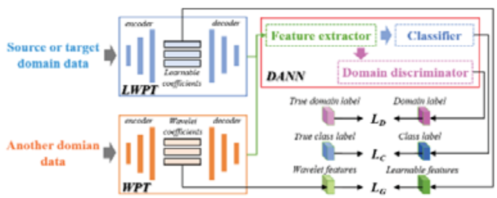

Fig.1 Architecture of the proposed method.

In the last step, the reconstruction signals of the source and target domains are fed into a typical domain adversarial neural network (DANN) (Zhao et al. 2021), which consists of a feature extractor, a domain discriminator, and a classifier. The total loss function of the DANN-LWPT can be defined as:

$$L = L_C + \lambda L_D + \mu L_G \tag{2}$$

where L_C is the classification loss, L_D is the domain discriminator loss, λ and μ are the trade-off parameters.

3. Results

We utilize the vibration data of the drive end bearing of the CWRU dataset with a sampling frequency of 12 kHz, which contains four operating states (0, 1, 2, 3) and ten bearing states (one normal state and three fault types including inner fault, ball fault and outer fault with three different fault sizes).

We segment the original vibration signals into sub-samples using a sliding window of length 1024 without overlapping between adjacent samples. We randomly select 80% of the samples for each bearing state as the training set and the remaining 20% as the test set.

To imitate the case of noisy environments, we added white Gaussian noise to all target domain data to maintain a signal-to-noise ratio of -5. To evaluate the performance of the proposed DANN-LWPT, we compare it with four other methods (Zhao et al. 2021), including correlation alignment (CORAL), multi kernels maximum mean discrepancy (MK-MMD), DANN, and joint maximum mean discrepancy (JMMD). For the DANN-LWPT, it is worth noting that in order to denoise the noisy target domain data and make them similar to those of the noise-free source domain data, we fed the target domain data into the LWPT module and the source domain data into the WPT module. Table 1 presents the mean and the standard deviation of the classification accuracy for three transfer tasks after calculating with five random seeds. The baseline in the table contains only a feature extractor and a classifier, whose architectures are consistent with those two modules in DANN.

Table 1. Classification results of noisy CWRU dataset.

Task	$Q_{0\to1}$	$Q_{0\to2}$	$Q_{0\to3}$
Baseline	16.6%±4.1%	24.2%±4.3%	18.3%±5.2%
CORAL	11.9%±2.2%	10%±0.0%	15.3%±4.2%
MK-MMD	47.4%±8.3%	45.5%±4.5%	33.4%±5.9%
DANN	65.8%±4.7%	61.8%±5.2%	45.0%±10.7%
JMMD	24.8%±4.5%	27.3%±4.0%	22.5%±3.2%
DANN-LWPT	**78.8%±1.6%**	**82.9%±1.2%**	**64.4%±0.9%**

As shown in Table 1, the proposed DANN-LWPT achieves the highest diagnostic accuracy in all three cross-domain tasks, with an improvement of 13.0% to 72.9% compared to other methods.

4. Conclusion

By utilizing the DANN-LWPT method, UDA for fault diagnosis can be achieved in noisy scenarios. In summary, our findings suggest that 1) promoting domain alignment through enforcing similarity between the representations of source and target data in the time-frequency domain can be effective; and 2) the proposed DANN-LWPT method outperforms other DA methods for fault diagnosis in noisy conditions.

References

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