Global-Local Continual Transfer Network for Intelligent Fault Diagnosis of Rotating Machinery

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Abstract

Existing fault diagnosis methods face three fundamental challenges when deployed under dynamic environments: limited continuous diagnostic capability, poor generalization, and inadequate protection on data privacy. To address these problems, we develop a novel continual fault diagnosis framework named Global-Local Continual Transfer Network (GLCTN) for classifying unlabeled target samples under varying working conditions without accessing source samples. To this end, the proposed GLCTN incorporates a consistency loss and a mutual information loss to facilitate the transfer of learned diagnostic knowledge from one domain to another domain. Moreover, a dual-speed optimization strategy is employed to retain the acquired diagnostic knowledge while empowering the model to acquire new information. Experiments conducted on an automobile transmission dataset demonstrate that the proposed GLCTN achieves robust diagnostic performance across multiple continuous transfer diagnostic tasks.

1. Introduction

Data driven-based intelligent fault diagnosis (IFD) methods have been implemented in various high-end equipment, including wind turbines, airplanes, high-speed trains, to name a few. Precision IFD models are essential for ensuring the reliable operations of mechanical equipment, reducing machine breakdowns, and minimizing economic losses (Li et al., 2024). Consequently, the development of precision IFD models has become a key research focus in the field of machinery fault diagnosis.

Deep learning (DL), a crucial branch of machine learning, has garnered widespread attention in recent years and it has achieved significant success in machinery fault diagnosis (Yan et al., 2023). For example, Zhou et al. (2022) proposed a probabilistic Bayesian DL framework to improve the reliability of diagnostic results for rotating machinery. Zhang et al. (2023) proposed an end-to-end DL framework for the IFD of wind turbine gearboxes under non-stationary conditions.

Despite the rapid progress, DL models experience significant performance degradation when applied to testing conditions with distributions different from the training data. To overcome the poor generalization of DL models, transfer learning (TL) has been leveraged along the development of IFD models. The key idea of TL is to apply learned knowledge to address a similar but distinct task. In machinery fault diagnosis, researchers have combined DL with TL to leverage DL's feature extraction capabilities and TL's knowledge transfer ability simultaneously as a means of enhancing the generalization performance of IFD models. For example, Chen et al. (2023) proposed a deep parameter-free reconstruction classification network to solve the fault classification problem of bearing under different working conditions. Li et al. (2020) proposed a two-stage transfer adversarial network for detecting the multiple unknown faults in the unlabeled target samples. Zhao et al. (2022) utilized extreme learning machine and TL techniques to achieve the IFD of the aero engine. Meanwhile, continual learning (CL) is introduced to improve the continuous diagnostic ability of IFD models. Inspired by the continuous learning ability of humans, CL enables the model to learn continuously from new data without the need of retraining the entire model. This capability is well-suited for the diagnostic requirements of mechanical equipment in continuous operation. Li et al. (2023) proposed a deep continual TL method to address continuous diagnosis problems for IFD models. The proposed framework can work well for increasing new faults of unlabeled target samples. Wang et al. (2019) proposed an incremental transfer fault diagnosis method to reconstruct the new process diagnosis model, which can recognize the new fault classes in multiple phases.

Even though the above-mentioned methods have yielded promising experimental results, a central issue remains: the necessity for joint training on fault samples from both the source and target domains to enable the model in handling fault types from both domains simultaneously. With growing awareness of data privacy protection, ensuring the full utilization of data from various sources without data sharing is a research direction worthy of investigation. Therefore, this study investigates a more challenging and practical scenario termed as a source-free continual transfer. To this end, we propose a novel Global-Local Continual Transfer Network (GLCTN) for the continuous diagnosis of mechanical equipment. The proposed GLCTN not only enables continuous diagnosis under varying operating conditions, but also facilitates intelligent diagnosis of unlabeled target samples without accessing the source samples. In particular, a consistency loss and a mutual information loss are introduced into the proposed GLCTN to transfer the learned knowledge for equipment diagnostics. Meanwhile, a dual-speed optimization strategy is utilized to preserve the learned diagnostic knowledge and endow the model with the ability to acquire new knowledge. Experimental results demonstrate that the proposed GLCTN is a promising tool for continual machine monitoring.

2. METHODOLOGY

2.1. Problem Formulation

In this study, a source-free continual transfer problem is investigated, and it includes a source domain $D_s = \{x_s^i, y_s^i\}_{i=1}^{n_s}$ and multiple target domains $\{D_t^1, D_t^2, \cdots, D_t^k\}$. In each stage, a target domain dataset $D_t^k = \{x_t^{k,i}\}_{i=1}^{n_t}$ is sequentially fed into the diagnostic model, where n_s and n_t represent the number of fault samples from the source and target domains, respectively. The source and the target samples are collected from different data distributions, $P(x_s^i, y_s^i) \neq Q(x_t^{k,i})$. Due to the consideration of data privacy protection, source samples are only used to initialize the network parameters during the model pre-training process. The goal of this study is to develop a continual intelligent diagnostic model that can continually classify unlabeled target samples without accessing any source samples.

2.2. Overview of the Proposed GLCTN

The architecture of the proposed GLCTN is presented in Fig. 1, and it includes a pre-training process and a continual diagnosis process. In the pre-training process, the labeled source samples are utilized to train the source model. At a high level, the source model consists of a feature extractor M_s and a fault classifier C_s. It is worth noting that the pre-training process is a classical fault classification problem, where a standard cross-entropy loss function is used for model training.

After the pre-training process, multiple diagnostic subdomains are sequentially fed into the continual diagnostic model for continuous diagnosis in the target domain. The unlabeled target samples are fed into the continual diagnostic model. Unlike the source model, the continual diagnostic model has two sub-models, a global model M_g and a local model M_l. The global model M_g is used to preserve the learned diagnostic knowledge, while the local model M_l is utilized to learn new knowledge from the current phase. In particular, a consistency loss function and a mutual information loss function are used to train the model. Meanwhile, a dual-speed optimization strategy (Feng et al., 2023) is introduced into the proposed GLCTN to retain the learned diagnostic knowledge and empower the model to handle faults in other operating conditions. Specifically, the local model M_l is updated rapidly using Stochastic Gradient Descent (SGD) after each batch. In contrast, the global model M_g is slowly updated by performing the Exponential Moving Average (EMA) between the global model in the previous phase and the local model in the current phase at the end of each epoch. Therefore, the updates for the global model and the local model are performed as follows.

For global model:

$$M_g \leftarrow m * M_g + (1 - m) * M_l \tag{1}$$

For local model:

$$M_l \leftarrow M_l - \eta * \nabla_{M_l}[L_{\text{cons}} - \lambda L_{\text{MI}}] \tag{2}$$

2.3. Network Architecture

In this study, a one-dimensional convolutional neural network (1D-CNN) serves as the backbone feature extractor to elicit representative features from the source and target domains. In particular, four convolutional blocks are initially stacked with each block incorporating a convolutional layer and a batch normalization (BN) layer for enhanced training efficiency. Following the two convolutional blocks, a MaxPool layer is introduced to reduce the data dimension while preserving the crucial spatial information. Next, the extracted representative features are flattened and fed into a fully connected (FC) layer. The fault classifier contains two FC layers with a *SoftMax* activation applied for fault classification. It is noteworthy that the model structure of the global and local models is exactly the same as that of the source model to facilitate the transfer of diagnostic knowledge learned from the source domain to the target domain.

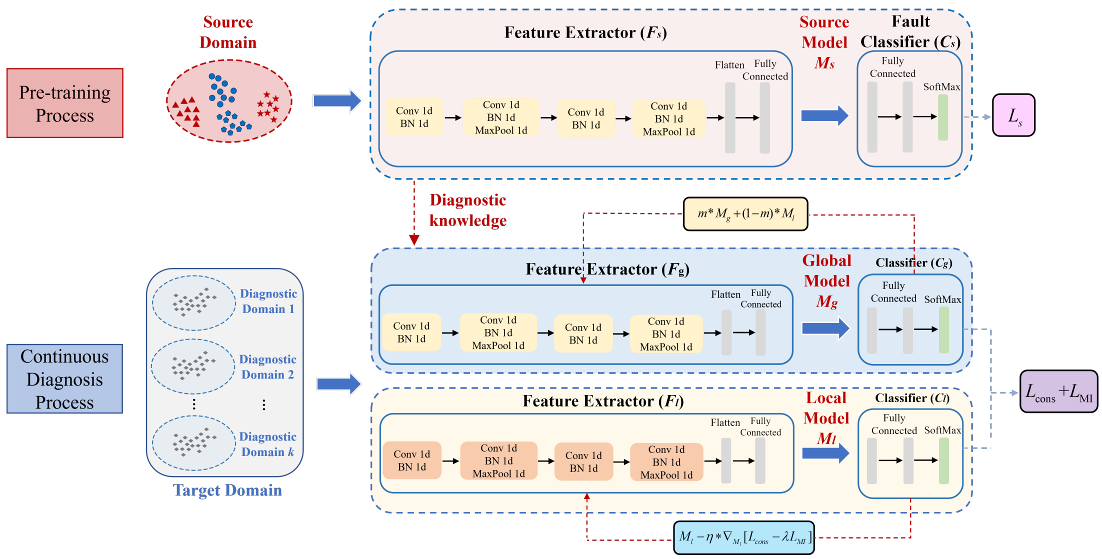


Figure 1. Overview of the proposed GLCTN.

2.4. Loss Function

2.4.1. Source Supervision

In the pre-training process, the optimization objective is to minimize the classification error under source domain. The standard cross-entropy loss function L_s is used to drive the learning:

$$L_s = -\frac{1}{n_s}\sum_{i=1}^{n_s}\sum_{j=1}^{N_c}\mathbf{1}\{y_s^i = j\}\log\frac{e^{x_s^{c,i,j}}}{\sum_{\mathrm{k}=1}^{\mathrm{N_c}} e^{x_s^{c,i,k}}} \tag{3}$$

where $x_s^{c,i,j}$ denotes the j-th element of the output vector in the fault classifier, taking the i-th source sample as input, and N_c represents the number of fault categories in the source domain.

2.4.2. Consistency Loss

After the pre-training process, the model parameters of global model M_g are copied from the source model M_s to retain the diagnostic knowledge obtained from the source domain. For an unlabeled fault sample $x_t^{k,i}$ from the current diagnostic domain, the corresponding pseudo label $\tilde{y}_t^{k,i}$ is generated using the global model M_g. In this study, the fault sample's classification score is considered as the corresponding pseudo label. The pseudo label can be generated as follows:

$$\tilde{y}_t^{k,i} = \mathrm{softmax}((h_g(x_t^{k,i}))/\tau) \tag{4}$$

where τ is a temperature parameter and h_g denotes the classification score from the classifier C_g, and softmax represents the softmax loss function.

To ensure the accuracy of the pseudo label, a data augmentation technique is adopted in the proposed GLCTN. Specifically, we add random noise to the raw vibration signal, and the augmented fault sample is defined as $\tilde{X}_t^{k,i} = \{x_t^{k,i}, \tilde{x}_t^{k,i}\}$ with pseudo label $\tilde{Y}_t^{k,i} = \{y_t^{k,i}, \tilde{y}_t^{k,i}\}$. According to the definition of knowledge distillation, the consistency loss function L_{cons} can be defined as follows:

$$L_{\text{cons}}(\tilde{X}_t^{k,i}, \tilde{Y}_t^{k,i}, M_l) = D_{\text{KL}}(\tilde{Y}_t^{k,i} \parallel h_l(\tilde{X}_t^{k,i})) \tag{5}$$

where $D_{\text{KL}}(a \parallel b)$ presents the KL divergence that is used to measure the similarity between a and b.

2.4.3. Mutual Information Loss

Mutual information (MI) loss is a typical loss function in machine learning used to quantify the degree of dependence between two random variables (Kraskov, Stögbauer, & Grassberger, 2004). In essence, MI estimates the shared information between two random variables by measuring how much information knowing the value of one variable tells us about the other variable. Maximizing MI helps model to learn more meaningful feature representations. For a batch augmented sample $\{\tilde{X}_t^{k,i}\}_{i=1}^b$, the MI loss function L_{MI} is calculated in this study:

$$L_{\text{MI}}(\{\tilde{X}_t^{k,i}\}_{i=1}^b, M_l) = -\frac{1}{b}\sum_{i=1}^{b} D_{KL}(h_l(\tilde{X}_t^{k,i}) \parallel \tilde{h}_l) \tag{6}$$

where $\tilde{h}_l = \frac{1}{b}\sum_{i=1}^{b} h_l(\tilde{X}_t^{k,i})$ is a predicted result.

In summary, the overall loss function of the continuous diagnosis process is defined as follows:

$$L_{all} = L_{\text{cons}} + \gamma L_{\text{MI}} \tag{7}$$

3. EXPERIMENTAL VALIDATION

3.1. Dataset Descriptions

Experiments were conducted on an automobile transmission (AT) test platform to validate the performance of the proposed method. The SG135-2 AT used in the experiment is a three-axis, five-speed transmission. The test bench is capable of simulating various operating conditions. Specifically, the test bench simulated four speeds: 500 rpm, 750 rpm, 1000 rpm, and 1250 rpm while the load torque was set to 0 Nm and 50 Nm. The type of fault bearing is NUP311EN. Two inner ring faults (IRF), with depths of 1 mm and widths of 0.2 mm and 2 mm, were injected in two distinct NUP311EN bearings through wire-cut processing. Three kinds of gear faults were simulated. The simulated fault categories of AT are shown in Table 1 encompassing a total of nine different fault categories. The vibration acceleration sensor was fixed on the housing of the AT output shaft, and the sampling frequency was set at 24 kHz.

Table 1. Detailed information of fault categories on the AT dataset.

Labels	Bearing fault	Gear fault	Marks
0	Normal	Normal	NO-NOR
1	Normal	Single tooth fault	NO-SIT
2	Normal	Mild tooth fault	NO-MIT
3	Normal	Moderate tooth fault	NO-MOT
4	0.2mm IRF	Normal	0.2 IRF-NOR
5	0.2mm IRF	Single tooth fault	0.2 IRF-SIT
6	0.2mm IRF	Mild tooth fault	0.2 IRF-MIT
7	0.2mm IRF	Moderate tooth fault	0.2 IRF-MOT
8	2mm IRF	Single tooth fault	0.2 IRF-SIT
9	2mm IRF	Moderate tooth fault	0.2 IRF-SIT

3.2. Study Design

To validate the effectiveness of the proposed GLCTN, seven different continual transfer diagnostic tasks are devised encompassing variations in speeds, loads, and combinations of speeds and loads. The detailed information of seven continual transfer diagnostic tasks is summarized in Table 2. Taking T1 as an example, the working condition of the source domain is 500rpm with 50Nm, while the target domain includes multiple diagnostic domains. As indicated in Table 3, with the increasing number of phases, the number of diagnostic domains in the target domain is also increasing. This setup closely aligns with the actual operation of mechanical equipment.

In this study, 200 labeled source samples are available for training under each fault category, and 200 unlabeled target samples are utilized in each diagnostic domain to characterize the target domain. The experimental results are averaged by ten trials to mitigate the impact of randomness. The training epoch is 30, and the learning rate is set to 0.001. The experiment is conducted on a workstation with an NVIDIA GeForce GTX 1660 Ti GPU, and the PyTorch deep learning platform is employed for programming.

Table 2. Details of the continual transfer tasks.

Tasks	Source domain	Target domain
T1	500-50	750-00/750-50/1000-00 /1000-50/1250-00/1250-50
T2	750-00	750-50/1000-00/1000-50 /1250-00/1250-50/500-50
T3	750-50	1000-00/1000-50/1250-00 /1250-50/500-50/750-00
T4	1000-00	1000-50/1250-00/1250-50 /500-50/750-00/750-50
T5	1000-50	1250-00/1250-50/500-50 /750-00/750-50/1000-00
T6	1250-00	1250-50/500-50/750-00 /750-50/1000-00/1000-50
T7	1250-50	500-50/750-00/750-50 /1000-00/1000-50/1250-00

Table 3. Details of task T1 in each phase.

Phases	Source domain	Target domain
1	500-50	750-00
2		750-00/750-50
3		750-00/750-50/1000-00
4		750-00/750-50/1000-00 /1000-50
5		750-00/750-50/1000-00 /1000-50/1250-00
6		750-00/750-50/1000-00 /1000-50/1250-00/1250-50

3.3. Baselines

To validate the superiority of the proposed GLCTN, four different methods are considered in this study for comparison. The details of compared approaches are introduced as follows:

- ***Baseline***. The pre-trained source model is directly applied to multiple target domains.
- ***SHOT***. As a typical source-free domain adaptation method, source hypothesis transfer (SHOT) (Liang, Hu, & Feng, 2020) has achieved high performance for image recognition. This comparison can demonstrate the superiority of the CL in the proposed GLCTN.
- ***USF***. To handle the cross-domain fault diagnosis problem with data protection limitation, Zhang et al. (Y. Zhang, Wang, & He, 2023) proposed an unsupervised source-free (USF) method. It has been proven that USF performed well on two rotating datasets, and it can also detect unknown faults in the target domain.
- ***G-SFDA***. The Generalized source-free domain adaptation (G-SFDA) method (Yang, Wang, Van De Weijer, Herranz, & Jui, 2021) is an effective method that works

well for continually detecting images from different domains in computer vision. This approach is employed to illustrate the superiority of the dual-speed optimization strategy.

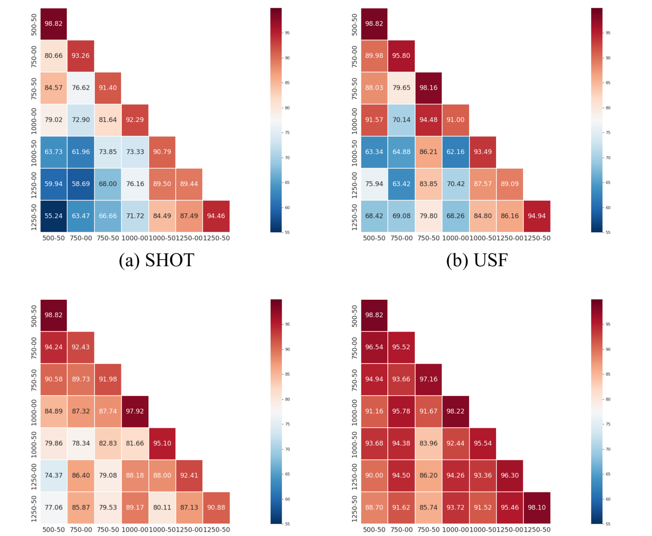
3.4. Experimental Results

The experimental results of different methods are summarized in Table 4. Overall, the proposed GLCTN achieved satisfactory results in all the continual transfer diagnostic tasks with an average diagnostic accuracy of 94.06%. In contrast, the baseline method, relying solely on diagnostic knowledge extracted from the source domain, struggles to adapt to the diagnostic scenarios in the target domain and yields an average accuracy of only 64.09%. This highlights the limited generalization capability of DL-based intelligent fault diagnosis methods. Although both the SHOT and USF methods do not require the merging of source and target domain samples to train the model, but they lack continuous diagnosis capability. As a result, these two methods only achieve a diagnostic accuracy of 73.05% and 77.39%, respectively. The G-SFDA method achieved relatively competitive experimental results with an average diagnostic accuracy of 84.47%, but its diagnostic accuracy still falls behind GLCTN by a large margin. This also demonstrates the advantage of the global and local models in the proposed GLCTN.

Table 4. Testing accuracies (%) of different methods in different diagnostic tasks.

Tasks	Baseline	SHOT	USF	G-SFDA	GLCTN
T1	63.81	74.79	78.78	84.25	92.12
T2	62.77	69.74	79.08	85.52	95.73
T3	56.05	67.66	77.88	83.51	92.07
T4	67.47	76.16	78.04	86.34	94.67
T5	69.70	77.48	81.72	83.62	94.83
T6	60.09	68.98	69.10	82.42	93.93
T7	68.74	76.53	77.14	85.60	95.09
Average	64.09	73.05	77.39	84.47	94.06

To demonstrate the effectiveness and superiority of the dual-speed optimization strategy in each phase, we present the diagnostic accuracy achieved by each method in each phase. Due to space constraints, we illustrate the experimental results in T1. The diagnostic results of the SHOT, USF, G-SFDA and GLCTN in each phase are shown in Figure 2. From the experimental results, it can be observed that as the number of phases increases, the USF method's degree of forgetting diagnostic knowledge also increases. Precisely, in the last stage, SHOT has almost forgotten half of the initially learned knowledge. While the G-SFDA method exhibits good diagnostic accuracy in phases 1 to 3, its accuracy significantly decreases in phase 5. This indicates that the G-SFDA method cannot retain learned diagnostic knowledge over an extended period. In contrast, the proposed GLCTN maintains an accuracy of around 90% in each phase, indicating its strong ability to retain previously learned knowledge.



(a) SHOT (b) USF (c) G-SFDA (d) GLCTN

Figure 2. Experimental results of different methods in each phase.

4. CONCLUSION

This paper proposes a novel GLCTN for machinery IFD. Different from most existing IFD approaches where the source samples are available for model training, the unlabeled target samples are accurately diagnosed without any source sample. Moreover, the proposed GLCTN addresses the continuous diagnosis of mechanical equipment under variable working conditions using the consistency loss function, the mutual information loss function and the dual-speed optimization strategy. Experimental results on an automobile transmission dataset are used to validate the performance of the proposed GLCTN. Computational comparisons suggest that the proposed approach achieves satisfactory fault diagnosis results in multiple continual transfer diagnosis tasks.

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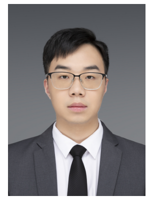

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