Sequential Domain Adaptation for Fault Diagnosis in Rotating Machinery

Yong Chae Kim[1], Jin Uk Ko[2], Jinwook Lee[3], Taehun Kim[4], Joon ha Jung[5], and Byeng D. Youn[6]

[1,2,3,4,6]*Department of Mechanical Engineering, Seoul National University, Seoul, 08826, Republic of Korea*
313nara@snu.ac.kr
coolstyle@snu.ac.kr
ljw723@snu.ac.kr
crwon3633@snu.ac.kr
bdyoun@snu.ac.kr

[5]*Department of Industrial Engineering, Ajou University, Suwon 16499, Republic of Korea*
joonha@ajou.ac.kr

[6]*Institute of Advanced Machines and Design, Seoul National University, Seoul 08826, Republic of Korea*
bdyoun@snu.ac.kr

[6]*OnePredict Inc., Seoul, 08826, Republic of Korea*
bdyoun@snu.ac.kr

ABSTRACT

Fault diagnosis of mechanical systems is essential to minimize damage in industrial sites. With the recent development of computer and IoT technologies, deep learning-based fault diagnosis has been widely studied. However, in industrial sites, the performance of deep learning-based fault diagnosis algorithms is degraded by the problem of domain shift, where the distribution of data varies depending on the operating conditions of the mechanical system, and the problem of unlabeled data. In this paper, we propose a sequential domain adaptation to solve these problems. The main contribution of the proposed method is to allocate priority in the high-dimensional latent space in addition to the traditional model to reduce the distribution discrepancy under different operating conditions. By prioritizing, the proposed method performed well for conditions that are difficult to adapt reliably. The proposed method is validated on open-source datasets. The results show that the proposed method outperforms compared to other algorithms.

1. INTRODUCTION

Rotating machinery is used in industrial sites, such as power plants and factories, which are essential for national infrastructure and corporate production systems (Lee, J., Kim, M., Ko, J.U., Jung, J.H., Sun, K.H., & Youn, B.D., 2022). Mechanical system failures occur due to various uncertainties, such as operational uncertainties. When a machine failure occurs, it causes significant economic damage to our society. Therefore, diagnosis is essential for the reliability and safety of mechanical systems. With the recent development of IoT technology, it has become possible to collect vast amounts of data. Deep learning-based fault diagnosis using a large amount of vibration data is being widely researched. Many studies on deep learning-based fault diagnosis have shown high performance; however, these studies were conducted under the assumption that the distribution of training and test data is similar. In realistic industrial scenarios, this assumption is not satisfied, and there are two issues: 1) Domain shift: The distribution of data changes due to different operating conditions. 2) Unlabeled data: Although there is a large amount of data in industrial sites, most of the data is stored without labels. In this paper, we propose sequential domain adaptation to ensure high performance for the two issues in real industrial scenarios. The main contribution of the proposed method is assigning priority to the high-dimensional latent space in addition to the traditional model, reducing distribution mismatch under various operating conditions. The proposed method showed excellent performance even under difficult conditions that are difficult to adapt stably, by assigning priority. The proposed method

*Corresponding Author: Joon ha Jung (joonha@ajou.ac.kr) & Byeng D. Youn (bdyoun@snu.ac.kr)

was validated on an open-source dataset, and as a result, it showed superior performance compared to other algorithms.

2. PROPOSED METHOD

The proposed method uses a domain adversarial neural network (Ganin, Ustinova, Ajakan, Germain, Larochelle, Laviolette, Marchand, & Lempitsky, 2016) and employs the maximum mean discrepancy method to calculate the difference in the distribution of the latent vectors. The domain adversarial neural network is an algorithm that uses a gradient reversal layer to help the extractor extract domain invariant features. Similarly, the maximum mean discrepancy maps high-dimensional latent vectors to Hilbert space to calculate the difference in distribution, and by reducing it, the extractor can extract domain invariant features. The proposed method adds one new method to these. We introduced a new sequential adaptation loss function to prioritize the conditions.

2.1. Sequential adaptation loss function

The sequential adaptation loss function goes through two steps. First step: Assign a region to the source domain for prioritization. We can find the centroid of the source data in a high-dimensional latent vector and calculate the number of target instances that are close to the centroid for a Euclidean distance. Second step: Calculate the Euclidean distance by prioritizing the number of target instances in decreasing order and backpropagate with the loss function as follows:

$$d(F(\mathbf{X}_T^{(i)})) = \begin{cases} \left|F(\boldsymbol{X}_i^T) - \mu_c\right| & if\ \ F(\mathbf{X}_T^{(i)}) \in R_{\text{priority}} \\ 0 & if\ \ F(\mathbf{X}_T^{(i)}) \notin R_{\text{priority}} \end{cases} \quad (1)$$

$$\mathcal{L}_S = \frac{1}{m^T} \sum_i^{m^T} d(F(\mathbf{X}_T^{(i)})) \quad (2)$$

where $\mathbf{X}_T^{(i)}$ is the input data of target data, μ_c is the centroid of source data, F is the extractor, c is the condition, m^T is the number of the target data, and R_{priority} is the region of priority region. The model is stabilized by updating the most distant target instances first.

2.2. Result

As validation datasets, we used the CWRU (C) and IMS (I) datasets, which are open-source data. Each dataset operates under different operating conditions and has different part sizes. For all two data types, there are four classes: normal (N), ball element fault (B), inner race fault (IF), and outer race fault (OR). Both source and target data consisted of 12000 training data and 4000 test data. The results are shown in Table 1 with accuracy and standard error for five attempts. The proposed method shows high performance compared to other algorithms: CNN, domain adversarial neural network (DANN; Ganin, Ustinova, Ajakan, Germain, Larochelle, Laviolette, Marchand, & Lempitsky, 2016), deep convolutional transfer learning network (DCTLN; Guo, Lei, Xing, Tan & Li, 2018).

Table 1. Result of the proposed method.

Acc (%)	C→ I	I→ C	Average
CNN	51.73±4.5	49.80±0.8	50.76
DANN	72.44±5.1	78.98±5.3	75.71
DCTLN	80.65±5.4	94.07±4.9	87.36
Proposed	**99.32±0.7**	**100±0.0**	**99.66**

3. CONCLUSION

We proposed the sequential domain adaptation that can extract domain-invariant features. The core of the algorithm is to reduce the distribution discrepancy between the two domains by assigning the priority region of the latent space and adding a loss function for the distance. Compared with the other conventional algorithms, the proposed method showed high performance. However, the proposed method assumes that the source and target have the same label space. In the future, we will develop an algorithm that can be used when the label space differs.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea Government (MSIT) (No. 2020R1A2C3003644) and Korea Institute for Advancement of Technology (KIAT) grant funded by the Korea Government (MOTIE) (P0008691, HRD Program for Industrial Innovation).

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Yong Chae Kim received the B.S. degree in mechanical engineering from Yonsei University, Seoul, South Korea, in 2022. He is currently pursuing the M.S. in the Department of Mechanical Engineering at Seoul National University, Seoul, South Korea. His research interests include machine learning and deep learning for diagnostics of rotating machinery.

Jin Uk Ko received a B.S. degree in mechanical engineering from Seoul National University, Seoul, South Korea, in 2017. He is currently pursuing a Ph.D. degree in the Department of Mechanical Engineering at Seoul National University, Seoul, South Korea. His research interests include machine learning and deep learning for anomaly detection and diagnostics of rotating machinery.

Jinwook Lee received the B.S. degree in mechanical engineering from Hanyang University, Seoul, South Korea, in 2019. He is currently pursuing a Ph.D. degree in the Department of Mechanical Engineering at Seoul National University, Seoul, South Korea. His research interests include machine learning and deep learning for diagnostics of rotating machinery.

Taehun Kim received the B.S. degree in mechanical engineering from Hanyang University, South Korea, in 2021. He is currently pursuing the M.S. degree in the Department of Mechanical Engineering at Seoul National University, South Korea. His research interests include machine learning and deep learning for the diagnosis of rotating machinery.

Joon Ha Jung is currently serving as an assistant professor of industrial engineering at Ajou University. He holds a BSc and a PhD in mechanical engineering from Seoul National University, which he obtained in 2012 and 2019, respectively. Prior to joining Ajou University, he worked as a senior researcher at the Korea Institute of Machinery and Materials (KIMM). Professor Jung's primary research focus is on fault diagnosis for rotating machinery, and he is also engaged in research activities that uses machine learning and deep learning.

Byeng D. Youn is the Full Professor of Mechanical Engineering at Seoul National University (SNU) and the founder and CEO of OnePredict, Inc. (onepredict.com). Prof. Youn received the B.S. degree in mechanical engineering from Inha University, Incheon, South Korea, in 1996, the M.S. degree in mechanical engineering from Korea Advanced Institute of Science & Technology, Daejeon, South Korea, in 1998, and the Ph.D. degree in mechanical engineering from the University of Iowa, Iowa City, IA, USA, in 2001. His current research includes prognostics and health management (PHM), engineering design under uncertainty, and energy harvester design. His dedication and efforts in research have garnered substantive peer recognition, resulting in many notable awards including the Commendation of Prime Minister (2019), the Shin Yang Academic Award from Seoul National University (2017), the IEEE PHM Competition Winner (2014), the PHM Society Data Challenge Winners (2014, 2015, 2017, 2019), the Best Paper Award of ICMR2019 (2019), the PHMAP 2019 PHM Data Challenge Competition 3rd Place Winners (2019), the Front Cover and Featured Article of Journal of Applied Physics (2020), the Industrial AI Hackathon Factory Hack Korea 2021 Winners (2020), among others.