4th Asia Pacific Conference of the Prognostics and Health Management,
Tokyo, Japan, September 11 – 14, 2023 OS12-07

A Quantitative Analysis of Domain Discrepancies Between General-Speed and Very Low-Speed Bearings and Its Applications to Fault Diagnosis of Very Low-Speed Bearings Using Transfer Learning

Seungyun Lee[1], Sungjong Kim[2], Jiwon Lee[3], Su J. Kim[4], Heonjun Yoon[5], and Byeong D. Youn[6]

[1,2,3,6]*Department of Mechanical Engineering, Seoul National University, Seoul 08826, Republic of Korea*
lsy21400@gmail.com
tjdwhd0423@snu.ac.kr
jwlee2611@snu.ac.kr

[4,6]*OnePredict Inc., Seoul 06160, Republic of Korea*
hippo130@naver.com

[5]*School of Mechanical Engineering, Soongsil University, Seoul 06978, Republic of Korea*
heonjun@ssu.ac.kr

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

ABSTRACT

This paper proposes a fault diagnosis framework for very low-speed bearings using transfer learning. To handle large domain discrepancies between general-speed and very low-speed bearings, the quantitative analysis is performed using operating information and geometries of bearings. From this analysis, the domain discrepancy can be quantitively compared under various speed conditions. Furthermore, a transfer learning technique is proposed to reduce the analyzed discrepancies. The domain discrepancy can be significantly aligned by integrating the operating information and geometries of bearings into transfer learning. Also, the proposed framework is not tailored for the specific algorithm; this means that the framework can be applied to any transfer learning technique regardless of the architecture. The proposed method is validated using two bearing datasets under general-speed and very low-speed conditions. The results show that the domain discrepancy can be quantitatively measured for transfer learning. Additionally, the proposed fault diagnosis framework outperforms the existing methods by aligning domain discrepancies of bearing datasets under large different speeds.

1. INTRODUCTION

Bearings are one of the most frequently failed components in rotary machines. Very low-speed bearings, especially, should be carefully managed, because of their large-scale nature that can cause severe industrial accidents (Jin, Chen, Wang, Han, and Chen, 2021). Therefore, a robust fault diagnosis method is required for these large-scale very low-speed bearings.

Recent research efforts have tried to apply a transfer learning technique for bearing fault diagnosis under different operating conditions (Li, Zhang, Qin, and Estupinan, 2020). Transfer learning can achieve superior performance under insufficient data condition, because it can utilize abundant source domain data with insufficient target domain data. However, it is hard to transfer knowledge from general bearings (i.e. source domain) to very low-speed bearings (i.e. target domain) due to the large domain discrepancies (Ding, Jia, and Zhao, 2021). The speed, load, and specification differences between general and very low-speed bearings should be aligned to apply transfer learning. Therefore, to my best knowledge, there is little research that applies transfer learning to very low-speed bearings.

Thus, this paper proposes a qualitative analysis of different speeds of bearing systems. The domain discrepancies are defined with qualitative values based on operating speeds and geometries of bearings. From the analyzed results, the domain discrepancies can be aligned for fault diagnosis of very low-speed bearings. The remainder of this paper consists of background knowledge on the transfer learning, the proposed framework for analysis of domain discrepancies between bearing systems, the proposed transfer learning technique, experimental validation with bearing datasets, and a conclusion.

2. Proposed Method

In this section, the detailed quantitative analysis technique and domain alignment method are illustrated. The proposed framework for measuring domain discrepancy between general and very low-speed bearings is described in Section 3.1. The measured domain discrepancy can be used for aligning domain discrepancies using transfer learning in Section 3.2.

2.1. Quantitative analysis of domain discrepancy

The domain discrepancy can be defined by rotating speed and characteristic frequency. First, The rotating speeds of bearings represent the number of revolutions in the signal. In the case of general- and very low-speed bearings, there are enormous differences in the number of revolutions. Second, the characteristic frequency can represent the primary fault information in the bearing signals. There are periodic impulse signals which can be utilized for fault diagnosis of bearings. The longer periods can be observed in the very low-speed bearings than in general-speed bearings. Therefore, from the differences in these periods of impulse signals, domain discrepancy can be measured under different speed conditions.

To quantitively measure the domain discrepancy using rotating speed, the speed ratio s can be calculated as follows:

$$s = \frac{\text{Source speed information}}{\text{Target speed information}} \tag{1}$$

where the speed information can be calculated by rotating speed divided by the sampling frequency. s is the final domain discrepancy considering speed information. Similar to the rotating speed, the domain discrepancy can be analyzed by characteristic frequencies as follows:

$$c = \frac{\text{Source characteristic frequency information}}{\text{Target characteristic frequency information}} \tag{2}$$

where the characteristic frequency information can be calculated by characteristic frequency divided by the sampling frequency. From the calculated s and c values, the domain discrepancies can be quantitatively compared.

The quantitative analysis can be performed using s divided c values. It can be helpful to quantify the domain discrepancy between different bearing systems under multiple speed conditions. For example, it is reasonable that transferring scenario from 1500 to 5 rpm is more difficult than 1500 to 50 rpm due to the large domain discrepancy. However, it is hard to compare scenarios from 1500 to 50 rpm and 1000 to 30 rpm. By calculating s/c, if their ratio of characteristic frequency is the same, a former case is 30 and latter case is 33.3. This means that 1000 to 30 rpm shows large domain discrepancy due to the speed information. As described, the proposed method can quantify the domain discrepancy of bearing systems using physical information.

2.2. Domain alignment using transfer learning

To align massive domain discrepancies between general-speed and very low-speed bearings, the obtained domain discrepancies can be used in the process of the transfer learning. First, the target bearing signals are aligned with s values through downsampling. The speed information of the source and target domain can become identical. The raw source data and aligned target data are fed into the feature extractor of the neural network to extract common fault features from the signals. Second, to align the fault information, the c is also used for downsampling. The fault information-aligned target data is fed into the trained feature extractor in the previous process. Consequently, the source and target domain can be effectively used for extracting fault features using the quantitative values; s and c.

The effectiveness of the proposed method can be explained in two ways. First, by incorporating the quantified domain discrepancy between source and target domains, the discrepancy can be reduced in advance using preprocessing. In the case of large domain discrepancies, the data-driven model is hard to converge at the optimum values. Therefore, the preprocessing can be useful for improving the performance of the model. Second, the proposed domain alignment technique can be used as a form of module. This means that the proposed method is model-agnostics; it can be applied to any existing domain alignment methods.

3. Experimental Validation

3.1. Data descriptions

The proposed method is validated with general-speed and very low-speed bearing datasets. The general-speed bearings operate under 1500 rpm, and the very low-speed bearings operate under 15 rpm as described in Table 1. The number of training samples is much larger in the general-speed dataset, because the assumption of transfer learning is sufficient number of source samples and insufficient number of target samples. In addition, the scales of the very low-speed bearings are seven times larger than the general-speed bearings. The transfer scenario is set the general-speed bearings as the source domain, and the very low-speed bearings as the target domain.

Table 1. Meta-information of the used dataset. Each dataset contain normal (N), inner race fault (IF), outer race fault (OF), and rolling element fault (RF) conditions.

Dataset	Speed	Health state	Number of samples (Train/Test)
General-speed	1500 rpm	N/IF/OF/RF	300/80
Very low-speed	15 rpm	N/IF/OF/RF	100/80

3.2. Fault diagnosis performances

The fault diagnosis results of very low-speed bearings are illustrated in Table 2. The proposed model shows superior performances than the existing maximum mean discrepancy (MMD) model, and domain adversarial neural network (DANN) model. This improvement can be achieved by the quantitative analysis of the different speeds of bearing systems and their incorporation to transfer learning procedures.

Table 2. Comparative study for the proposed domain alignment methods through fault diagnosis performance.

Model	Accuracy
MMD	72.00 %
DANN	68.06 %
Proposed model	**76.44 %**

4. Conclusion

This paper proposes the fault diagnosis framework for very low-speed bearings using transfer learning. For the appropriate alignment of large domain discrepancies, the speed and fault information is used for quantitative analysis. These values are also used for the domain alignment process in transfer learning. Consequently, transfer learning can be performed successfully to diagnose very low-speed bearings.

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).

References

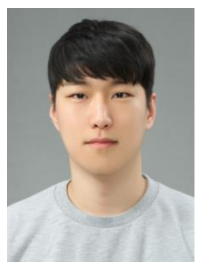
Jin, X., Chen, Y., Wang, L., Han, H., & Chen, P. (2021). Failure prediction, monitoring and diagnosis methods for slewing bearings of large-scale wind turbine: A review. *Measurement*, vol. 172, doi: 10.1016/j.measurement.2020.108855

Li, C., Zhang, S., Qin, Y., & Estupinan, E. (2020). A systematic review of deep transfer learning for machinery fault diagnosis. *Neurocomputing*, vol. 407, pp. 121-135. doi: 10.1016/j.neucom.2020.04.045

Ding, P., Jia, M., & Zhao, X. (2021). Meta deep learning based rotating machinery health prognostics toward few-shot prognostics. *Applied Soft Computing*, vol. 104, doi:10.1016/j.asoc.2021.107211

Biographies

Seungyun Lee is Ph.D. student of Mechanical Engineering at Seoul National University, Seoul, Republic of Korea. He received his B.S degree in biosystem engineering from Seoul National University in 2021. His research areas include artificial intelligence-based mechanical fault diagnosis, physics-informed artificial intelligence, and fault diagnosis of very low-speed bearings. His research efforts result in remarkable awards including Postech Open Innovation Big Data Challenge 2nd Place Winner (2021), Heart Disease AI Datathon Winner (2021), Industrial AI Hackathon Factory Hack Korea 2nd Place Winner (2023), and IEEE PHM Data Challenge Winner (2023).



Sungjong Kim is Ph.D. candidate student at the Seoul National University, Department of Mechanical Engineering in Laboratory for System Health and Risk Management. He received bachelor's degree in mechanical engineering from Seoul National University, Seoul, South Korea, in 2020. His recent research interest is deep learning based bearing fault diagnosis, explainable AI and low speed bearing fault diagnosis. He has been awarded Industrial AI Hackathon Factory Hack Korea (2021) 3rd place Winner and K-AI Manufacturing Data Challenge (2021) 3rd place Winner.

Jiwon Lee received a B.S. degree in mechanical engineering from Sungkyunkwan University, Seoul, South Korea, in 2023. She is currently pursuing an M.S. in the Department of Mechanical Engineering at Seoul National University, Seoul, South Korea. Her research interests include machine learning and deep learning for the diagnostics of bearings.

Su J. Kim received his B.S. degree from Inha University, Incheon, South Korea, in 2015, and Ph.D. degree in mechanical and aerospace engineering from Seoul National University, Seoul, Republic of Korea, in 2022. He is currently data scientist for industrial prognostics and health management(PHM) solutions at OnePredict, Inc. (onepredict.com). His research interests include fault detection, diagnosis, and PHM for industrial systems and rotary machines.

Heonjun Yoon is an assistant professor in the School of Mechanical Engineering at Soongsil University, Seoul, Republic of Korea. Prof. Yoon was a visiting scholar in the George W. Woodruff School of Mechanical Engineering at the Georgia Institute of Technology, Atlanta, Georgia, USA, in 2019-2020. Prof. Yoon received a Ph.D. degree in mechanical and aerospace engineering from Seoul National University, Seoul, Republic of Korea, in 2018. Prof. Yoon has explored three research avenues with great enthusiasm as: piezoelectric vibration energy harvesting, elastic metamaterial, and artificial intelligence-driven design.

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.