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An Experiment on Anomaly Detection for Fault Vibration Signals Using Autoencoder-Based N-Segmentation Algorithm

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ABSTRACT

Most manufacturing facilities driven by motors generate vibration and noise representing critical symptoms against facility malfunctioning conditions in the manufacturing industry. Due to the difficulty of obtaining abnormal data from facilities in manufacturing sites, many prior researchers who have studied predicting facility faults have adopted unsupervised learning-based anomaly detection approaches. Although these approaches have a strength requiring only data on from facility normal behaviors, it is not clear that the anomalies detected by an anomaly detection model are due to the real component faults. Also, the model performance is likely to change according to the diverse abnormal conditions of the given facility. In this paper, we took an experiment with a fault vibration simulator to measure the anomaly detection performance of a one-dimensional convolutional autoencoder model with different fault conditions. In the experiment, we used four different abnormal conditions: imbalance, misalignment, looseness, and bearing faults, which are the most frequently occurring facility component failures from the rotating machineries. Data were gathered from the simulator with the IEPE(Integrated Electronics Piezo-Electric) type sensor. We proposed the N-Segmentation algorithm that performs anomaly detection in segmented frequency region according to corresponding component faults for better anomaly detection performance. In conclusion, the proposed algorithm showed about 15 times better anomaly detection rate than not applying it.

1. INTRODUCTION

Artificial Intelligence (AI) technologies are adopted in various field domains to replace human beings or improve legacy systems. The manufacturing sector has also gradually tackled AI-based anomaly detection (AD) approaches for facility monitoring and fault detection. (Kumar, Khalid, & Kim, 2022; Zhang, Lin, Liu, Zhang, Yan, & Wei, 2019). AI-enabled facility monitoring systems are necessary to improve productivity, reduce costs, and ensure worker safety in manufacturing sites. Facility anomaly is an abnormal condition where defects or failures occur, and it can be determined and predicted by analyzing physical data measured during the facility operation from physical sensors such as those of vibration, current, and temperature. Since motors drive most manufacturing facilities, they generate various vibration signals during operation. These vibration signals represent a valuable basis for predicting whether the facility is in normal operations or defective status. When the vibration increases or becomes excessive, certain mechanical trouble has usually occurred. Since the vibration does not increase or become excessive for no reason, it is considered an indicator of machinery malfunction (Shreve, 1994). However, since the types of facility defects or failures are so diverse, obtaining sufficient data on facility defects and failures in manufacturing sites is impractical (Hiruta, Maki, Kato, & Umeda, 2021; Li, Li, & Ma, 2020). As a result, unsupervised learning approaches that use only data acquired when the facility is in a normal condition are very practical.

As the fault situations are diverse and unsupervised AD models require reconstruction of input signals, there are two important considerations, namely, types of faults (Thi, Do, Jung, Jo, & Kim, 2020) and the reconstruction range (Amarbayasgalan, Pham, Theera-Umpon, & Ryu, 2020). Considering these points, we conducted a vibration AD test using a fault vibration simulator and an Integrated Electronics Piezo-Electric (IEPE) type vibration sensor. We collected the vibration data of the simulator's normal signals and abnormal signals generated under normal operation and conditions of imbalance, misalignment, looseness, and bearing faults. Then, we trained the normal signals with a one-dimensional convolutional autoencoder (1-D CAE) and measured the AD performance by normal signals and fault signals. We introduce the N-segmentation algorithm for the better AD performance, which performs it by segmenting the frequency range into N different regions. The proposed algorithm can detect fault vibration signals with improved performance.

2. BACKGROUND

AI models are classified as supervised or unsupervised learning, depending on whether labels are used during the learning process. Applying supervised learning to AD requires data for all types of anomalies. Since gathering anomaly data for enough training is practically impossible, unsupervised learning using only the normal-condition data of the facility is more suitable, and the Autoencoder (AE) is representative of unsupervised learning (Lee, Lee, & Kim, 2024; Wei, Jang-Jaccard, Xu, Sabrina, Camtepe, & Boulic, 2023). AE is an AI model that learns how to produce output data as close as possible to the input data without data labels. Using a difference between the input data of the AE and the reconstructed data generated by the output data of the AE detects anomalies. In this case, the reconstruction error, the difference between the input data and the output data of the AE, is calculated by error functions such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE).

Various research has been performed regarding AD using fault vibration signals. Wisal and Oh (2023) developed a new deep learning algorithm that utilized ResNet and convolutional neural networks to detect the unbalance of a rotating shaft for both binary and multiclass identification. Kamat et al. (2021) used random forest, artificial neural network, and AE to detect the bearing fault. Their experiment showed the AE provides the highest accuracy of 91% over the others. Ahmad et al. (2020) has taken experiment with AD for rotating machines by comparing a long short-term memory-based AE (LSTM-AE) and an isolation forest model. The experimental results on real-world datasets showed that the LSTM-AE achieved an average f1-score of 99.6%. Most previous works focused on developing the model achieving high accuracy for AD, but they are suggested within the limited fault environment or dataset.

In vibration accuracy for condition monitoring, an IEPE-type sensor is usually capable of more precise vibration measurement than a Micro-Elector-Mechanical System (MEMS) type sensor. (Hassan, Panduru, & Walsh, 2024). In the previous research regarding AD by frequency segmentation, Park & Lee (2022) successfully performed AD by synthesizing the frequency domain data of the IEPE-type vibration sensor collected from the printing facility and the virtual frequency signals. However, for the objective performance evaluation of the approach, it is necessary to utilize data collected in a simulator environment like actual facilities, not a virtual signal.

3. PROPOSED ALGORITHM

We propose the N-Segmentation algorithm that detects abnormal vibration signals by segmenting the frequency domain measured by a vibration sensor into N frequency ranges. The algorithm uses N reconstruction errors and N thresholds to determine anomalies in the target vibration signal. The algorithm predicts whether the frequency section corresponding to each segment is a normal or an anomaly using the threshold that is the maximum reconstruction error value of the segment. Therefore, the algorithm can perform not only AD of the target signal but also AD of the segments. In other words, it can present additional information on which segment of the entire frequency range has an anomaly occurred. Here, N, the number of segmented frequency ranges, is a kind of hyperparameter designated by analysts, so applying various N values is necessary to measure the performance of a model like 1-D CAE through the proposed algorithm. Figure 1 shows a schematic diagram of the proposed algorithm when N is 4.

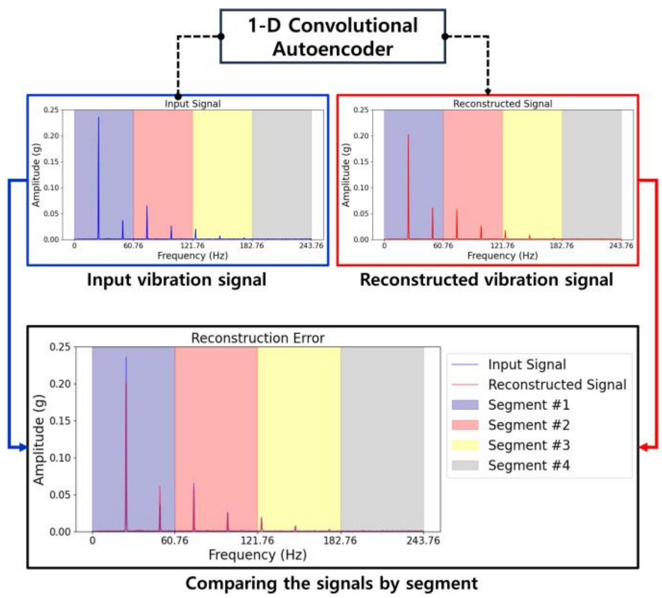


Figure 1. N-Segmentation Algorithm (N=4)

3.1. 1-Dimensional Convolutional Autoencoder

1-D CAE is an AE composed of encoders and decoders using one-dimensional convolutional layers (Zhang, Wang, Yi, Wang, Liu, & Chen, 2021). Convolutional layers can learn the data with high accuracy when the data size is constant, such as image data with two-dimensional data shape of width and height in pixels. Compared with two-dimensional images, as one-dimensional input vectors like vibration signals contain intuitive data characteristics, it is a great opportunity to use deep learning-based methodology for AD (Chen, Yu, & Wang, 2020). In the case of the frequency domain data used in this study, a 1-D CAE model is applied to capture the status of the simulator with the vibration signal having one-dimensional 1024 numerical data. We developed the 1-D CAE model that consists of two 1-D convolution layers as encoder and two 1-D transposed layers as decoder using Python 3.10.9 and TensorFlow 1.12.0. Table 1 shows the structure of the model and hyperparameters.

Table 1. Structure of the model and hyperparameters

Layer	# of Filters	Kernel Size	Activation Function
1-D Conv.	64	8	RELU
1-D Conv.	32	8	RELU
1-D Trans. Conv.	64	8	RELU
1-D Trans. Conv.	1	8	-

Since MSE and RMSE can lead to higher weights given to higher errors, the model tends to be more sensitive to noise that might cause false positives (Kang, Kim, Kang, & Gwak, 2021). In the reconstruction loss function for AE-based AD models, MAE is more appropriate than the other two functions (Xu, Jang-Jaccard, Singh, Wei, & Sabrina, 2021). Therefore, the loss function used in the training process using the model is MAE in Eq. (1). Here, n denotes the number of numeric values contained in one vibration signal. X' denotes the reconstructed signal from the model, and X denotes the input signal to the model.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|X'_i - X_i| \tag{1}$$

3.2. Thresholds

Unsupervised learning-based AD requires a threshold to determine whether the vibration signal represents an anomaly. In the existing AD using AE, the maximum reconstruction error value (Kang, Kim, Kang, & Gwak, 2021; Wei, Jang-Jaccard, Xu, Sabrina, Camtepe, & Boulic, 2023) or the 3-sigma value (Lee, Lee & Kim, 2024; Panza, Pota, & Esposito, 2023) among the reconstruction errors of the training data has been set as a threshold. In this case, the threshold has to be only one. However, in the proposed method, thresholds are generated as many as the number of segments N. Figure 2 shows the reconstruction error distributions as a histogram for each segment of the training data when N is 4. The red vertical line in each histogram in Figure 2 represents the maximum reconstruction error used as a threshold to determine the anomaly in the segment.

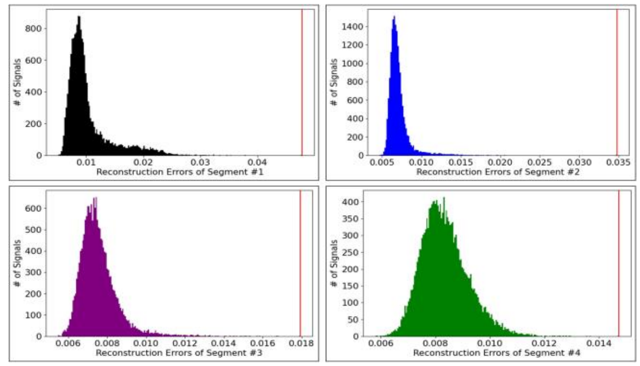


Figure 2. Reconstruction error distributions and thresholds (N=4)

3.3. Anomaly Detection

The proposed algorithm uses all N thresholds to detect the fault vibration signals among the test signals. If all the N reconstruction errors in the N segments of a target signal are lower than the corresponding thresholds, the signal is considered normal. Otherwise, it is a fault vibration signal. Figure 3 shows an example of the AD process of the proposed algorithm when N=2.

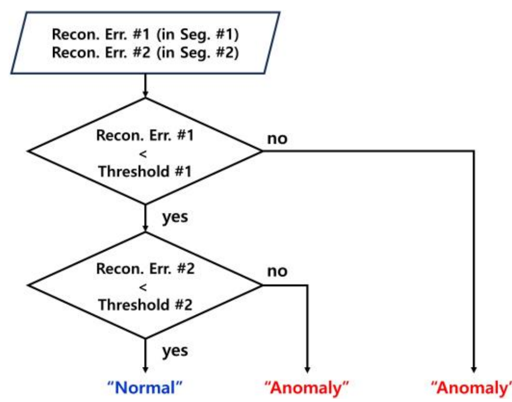


Figure 3. Process of anomaly detection (N=2)

The true-positive rate (TPR) in Eq. (2) was set to measure the performance of AD. Here, TP is the number of correctly predicted vibration signals, and FN is the number of incorrectly predicted ones.

$$TPR = \frac{TP}{TP + FN} \tag{2}$$

4. Experiment

4.1. Setup

The vibration signals were gathered with a fault vibration simulator and an IEPE-type sensor for about two months. The simulator is the AST-VFS product of AST company of the Republic of Korea, and the sensor is the Model 131.02

product of VibraSens company of France. The vibration signals were collected every two minutes and obtained by Vib-AiR, the wireless health monitoring solution of RESHENIE company of the Republic of Korea, through open platform communication-unified architecture (OPC-UA) protocol (Schleipen, Gilani, Bischoff, & Pfrommer, 2016). Figure 4 shows the experimental environment. In Figure 4, R and L in parentheses mean Right and Left, respectively. The sensor (red square in Figure 4) was set on the top of the right-bearing housing of the simulator (blue square in Figure 4). The sensor can collect vibration signals in three-axis directions. In the experiment, only the Y-axis signals, which is the direction of rotation of the motor (the orange arrow in Figure 2), were used.

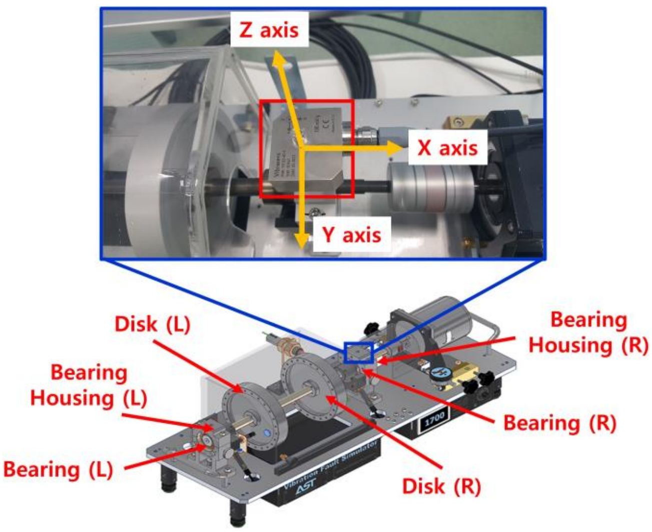


Figure 4. The fault vibration simulator and the IEPE sensor

4.2. Data Description

The dataset includes normal vibration signals at the motor rotation speed of 1,500 RPM and four fault vibration signals: imbalance, misalignment, looseness, and bearing faults. Table 2 summarizes the 16 simulator settings for generating fault signals. In Table 2, settings #1 to #6 are the conditions for the imbalance. Setting #7 is for the misalignment. Settings #8 to #10 are for the looseness. Finally, settings #11 to #16 are for the bearing faults.

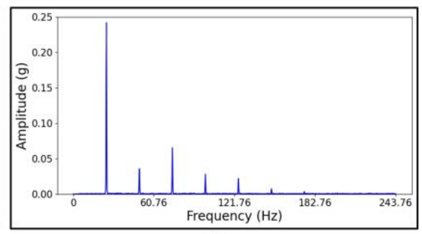
Table 2. Simulator settings for the faults

No	Setting
#1	Attaching 1.7g mass to the right disk
#2	Attaching 1.7g mass to the left disk
#3	Attaching 1.7g mass to each disk
#4	Attaching 6.25g mass to the right disk
#5	Attaching 6.25g mass to the left disk
#6	Attaching 6.25g mass to each disk
#7	Set to 1.2mm
#8	Loosening the left bearing housing
#9	Loosening the right bearing housing
#10	Loosening both bearing housing
#11	Applying outer wheel defect bearing to the left
#12	Applying outer wheel defect bearing to the right
#13	Applying inner wheel defect bearing to the left
#14	Applying inner wheel defect bearing to the right
#15	Applying ball defect bearing to the left
#16	Applying ball defect bearing to the right

One vibration data has 1,024 features that are numerical values representing amplitudes of each frequency from 0 to 243.76Hz. Figure 5 (a) is an example of the normal vibration data, and Figure 5 (b) is the result of visualizing it.

Frequency	Amplitude
0	0.000009
0.24	0.000015
0.71	0.000020
:	:
243.29	0.000458
243.52	0.000239
243.76	0.000327

(a)



(b)

Figure 5. An example of the normal data

Figure 6 shows the sample fault signals collected from the simulator using the sensor. Figure 6 (a), Figure 6 (b), Figure 6 (c), and Figure (d) are the results of the visualization of the signals collected under the imbalance of setting #1, the misalignment of setting #7, the looseness of setting #8, and the bearing fault of setting #11, respectively. These fault signals in Figure 6 showed different patterns in the number of peaks and amplitude values of peaks compared to the normal vibration signal in Figure 5(b). However, most frequencies in all signals showed very low amplitudes close to zero, except for a few frequencies. These frequency data characteristics affect the reconstruction results of the model and can consequently influence the AD performances.

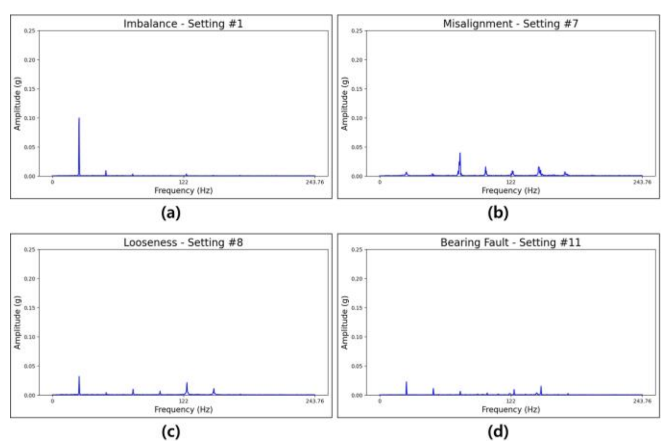


Figure 6. Example of the fault signals

A total of 21,365 vibration signals were collected from the simulator, of which 17,624 (82.5%) vibration signals were used as training data and 3,741 (17.5%) vibration signals as test data. Table 3 shows a detailed description of the dataset. Normal vibration signals of 17,624 training data and 481 test #1 data in Table 3 were generated when the motor in the simulator rotated at 1,500 RPM without applying fault condition settings described in Table 2. Test data used in tests #2 to #17 in Table 3 were generated from the operating conditions of the simulator with settings #1 to #16 in Table 2, respectively. In summary, the AD performances were measured with TPR for a total of 17 test cases (tests #1 to #17 in Table 3) in the experiment. The experiment was conducted in two cases: with and without the proposed algorithm.

Table 3. Description of the dataset

Purpose		Type	# of Data
Training		Normal	17,624
Test	#1	Normal	481
	#2	Imbalance (setting #1)	154
	#3	Imbalance (setting #2)	279
	#4	Imbalance (setting #3)	120
	#5	Imbalance (setting #4)	213
	#6	Imbalance (setting #5)	230
	#7	Imbalance (setting #6)	184
	#8	Misalignment (setting #7)	241
	#9	Looseness (setting #8)	319
	#10	Looseness (setting #9)	118
	#11	Looseness (setting #10)	265
	#12	Bearing Fault (setting #11)	138
	#13	Bearing Fault (setting #12)	251
	#14	Bearing Fault (setting #13)	127
	#15	Bearing Fault (setting #14)	269
	#16	Bearing Fault (setting #15)	196
	#17	Bearing Fault (setting #16)	156

5. EXPERIMENTAL RESULTS

5.1. Anomaly Detection without N-Segmentation

Figure 7 shows the results of AD for the test data (Test #1 to #17 in Table 3) when the N-Segmentation algorithm is not applied. The blue dots and the red horizontal line in Figure 7 represent the MAE values for the test data and the threshold, respectively. Therefore, the dots above the threshold line mean predicted anomalies. The normal vibration signals (Test #1 in Figure 6) were exactly predicted as normal vibration signals. On the other hand, the performance of AD for the fault vibration signals (Test #2 to Test #17 in Figure 7) was too low. A few data were detected as anomaly signals in misalignment (Test #8 in Figure 7) and looseness (Test #10 and Test #11 in Figure 7), where TPRs were measured as 0.21, 0.19, and 0.05, respectively. Except for these cases, no detection was made for the rest of the anomalies. Overall, AD performances with the traditional approach using the model were too poor.

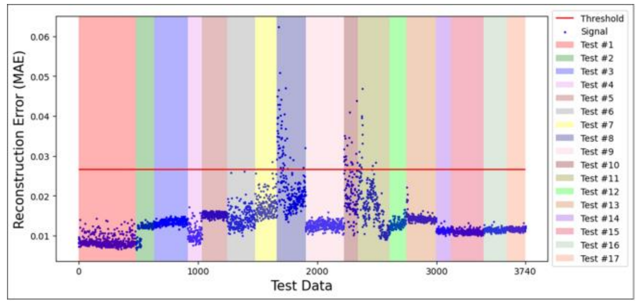


Figure 7. Result of anomaly detection without N-Segmentation

5.2. Anomaly Detection with N-Segmentation

As mentioned in Section 3.3, the proposed algorithm finally determines an anomaly signal by OR operation of AD results in segmented frequency ranges. Since the IEPE sensor collected a frequency signal of 0-243.76Hz, the segments are made by dividing the frequency range evenly. Figure 8 shows AD results in the segmented frequency ranges when N is 4: 0~60.76Hz (Figure 8 (a)), 61~121.76Hz (Figure 8 (b)), 122~182.76Hz (Figure 8 (c)), and 183.76Hz (Figure 8 (d)). In the example, as shown in Figure 8 (c) and Figure 8 (d), the proposed algorithm can detect most anomalies belonging to misalignment (Test #8 in Figure 8 (c)) and imbalance (Test #5 and Test #7 in Figure 8 (d)) compared to Figure 7. AD performance with the proposed algorithm has improved dramatically in these faults compared to the results of Figure 7.

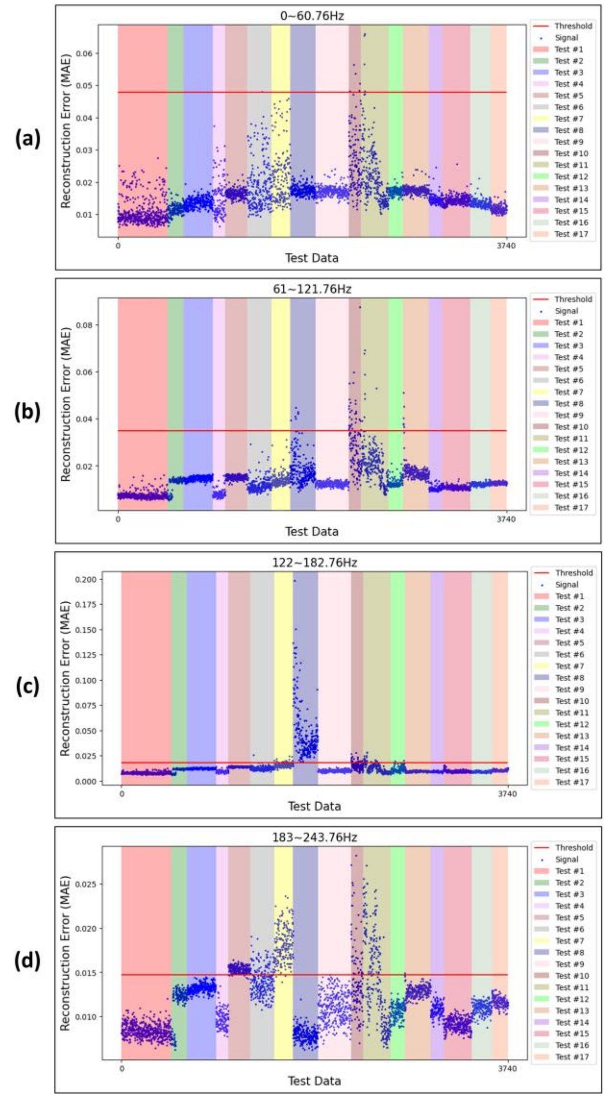


Figure 8. Result of anomaly detection with N-Segmentation (N=4)

As mentioned before, because N is a kind of hyperparameter, the proposed algorithm needs to be confirmed by changing N. Figure 9 shows the AD performance of the algorithm according to the change in the N value. When N is zero in Figure 9, the TPRs indicate AD results of not applying the proposed algorithm. The AD performance with N-Segmentation shows higher TPR scores than without it in all fault cases: imbalance (Figure 9 (a)), misalignment (Figure 9 (b)), Looseness (Figure 9 (c)), and Bearing Faults (Figure 9 (d)). Especially when N was 8, the TPRs for imbalance (Test #7) and misalignment (Test #8) improved dramatically from 0.01 to 0.99 and 0.21 to 1, respectively. In this case, the TPR for all fault signals was 0.40, and the proposed algorithm detected 1,301 anomalies among a total of 3,260 anomalies. On the other side, the traditional approach without the proposed algorithm just detected 87 anomalies.

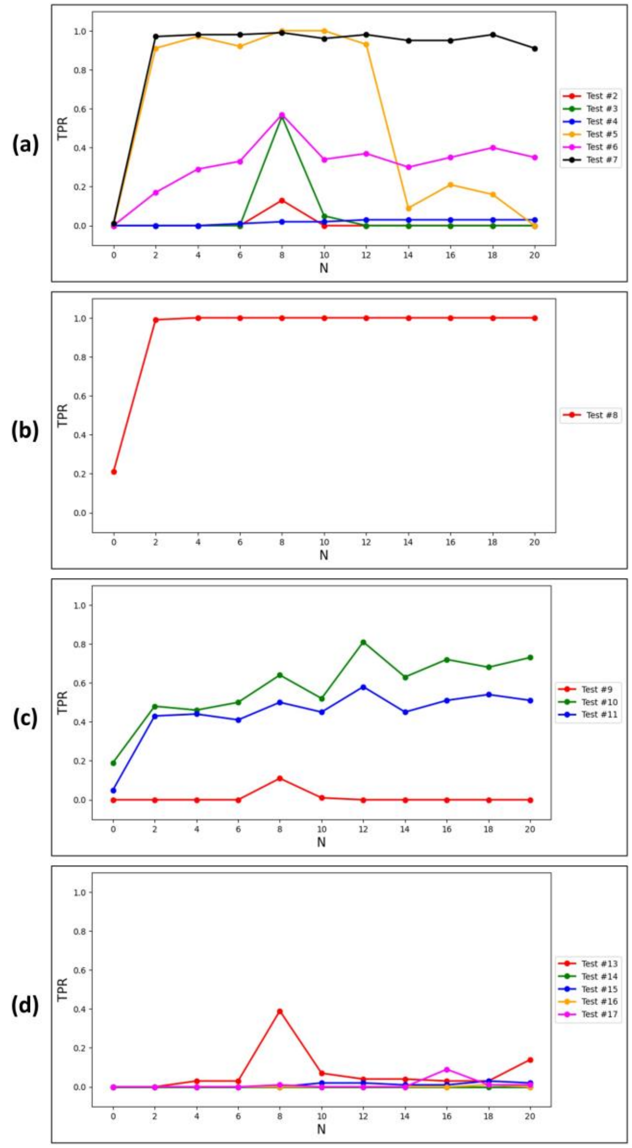


Figure 9. Performance of anomaly detection by N

6. DISCUSSION

The results of the experiment can be summarized as follows. First, the N, the number of segmentations, did not affect the AD performance for the normal vibration signals in the test data. Regardless of N, the TPRs for the normal vibration signals were always measured as 1. Second, even if anomaly signals were the same fault type, the TPRs for the same fault signals showed differences according to the specific settings. Overall, anomaly signals measured in higher physical changes near the sensor were relatively better detected (see Table 2, Table 3, and Figure 9). Therefore, when detecting facility faults using a vibration sensor, the position of the sensor must be carefully determined. Third, the proposed algorithm can improve the performance of the unsupervised-based AD. In our experiment, the proposed algorithm detected about 15 times fault vibration signals in the best case (N=8) than N=0. Even in the worst case (N=14), it could detect fault vibration signals more than 8 times. Fourth, the proposed algorithm not only detects the fault vibration signals with better performance but also provides additional information about the frequency range in which the anomaly occurred (see Figure 8). This information can be used to predict the type of facility failure.

7. Conclusions and future work

In this paper, we proposed the N-segmentation algorithm, which uses segmented frequency ranges to enhance facility fault detection performance. To measure the algorithm performance, we collected the frequency domain data of the vibration signal with the fault vibration simulator using the IEPE-type sensor. We trained the normal vibration data in the collected vibration signal using the 1-D CAE model and performed AD for the normal vibration data and four types of fault vibration data: imbalance, misalignment, looseness, and bearing faults. We detected up to 15 times more anomalies with the proposed algorithm than without it. The results show that the proposed algorithm is effective in AD for fault vibration signals. However, this study has limitations in applying only the 1-D CAE model and experimenting in the simulation environment. In future research, we aim to improve the proposed algorithm by comparing other machine learning models, and we will adopt it to facilities and equipment operating in real manufacturing sites.

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References

Ahmad, S., Styp-Rekowski, K., Nedelkoski, S., & Kao, O. (2020). Autoencoder-based condition monitoring and anomaly detection method for rotating machines. *In 2020 IEEE International Conference on Big Data (Big Data)* (pp. 4093-4102). IEEE.

Amarbayasgalan, T., Pham, V. H., Theera-Umpon, N., & Ryu, K. H. (2020). Unsupervised anomaly detection approach for time-series in multi-domains using deep reconstruction error. *Symmetry*, 12(8), 1251.

Chen, S., Yu, J., & Wang, S. (2020). One-dimensional convolutional auto-encoder-based feature learning for fault diagnosis of multivariate processes. *Journal of Process Control*, 87, 54-67.

Hassan, I. U., Panduru, K., & Walsh, J. (2024). An In-Depth Study of Vibration Sensors for Condition Monitoring. *Sensors*, 24(3), 740.

Hiruta, T., Maki, K., Kato, T., & Umeda, Y. (2021). Unsupervised learning based diagnosis model for anomaly detection of motor bearing with current data. *Procedia CIRP*, 98, 336-341.

Kamat, P., Marni, P., Cardoz, L., Irani, A., Gajula, A., Saha, A., Kumar, S. & Sugandhi, R. (2021). Bearing fault detection using comparative analysis of random forest, ANN, and autoencoder methods. *In Communication and Intelligent Systems: Proceedings of ICCIS 2020* (pp. 157-171). Springer Singapore.

Kang, J., Kim, C. S., Kang, J. W., & Gwak, J. (2021). Anomaly detection of the brake operating unit on metro vehicles using a one-class LSTM autoencoder. *Applied Sciences*, 11(19), 9290.

Kumar, P., Khalid, S., & Kim, H. S. (2023). Prognostics and Health Management of Rotating Machinery of Industrial Robot with Deep Learning Applications—A Review. *Mathematics*, 11(13), 3008.

Lee, Y. K., Lee, S., & Kim, S. H. (2024). Real-Time Defect Monitoring of Laser Micro-drilling Using Reflective Light and Machine Learning Models. *International Journal of Precision Engineering and Manufacturing*, 25(1), 155-164.

Li, X., Li, X., & Ma, H. (2020). Deep representation clustering-based fault diagnosis method with unsupervised data applied to rotating machinery. *Mechanical Systems and Signal Processing*, 143, 106825.

Panza M. A., Pota M., & Esposito, M. (2023). Anomaly Detection Methods for Industrial Applications: A Comparative Study. *Electronics*. 2023; 12(18)

Park, K., & Lee, Y. (2023). Anomaly Detection in a Combined Driving System based on Unsupervised Learning. *Journal of the Korean Society for Precision Engineering*, 40(11), 921-928.

Schleipen, M., Gilani, S. S., Bischoff, T., & Pfrommer, J. (2016). OPC UA & Industrie 4.0-enabling technology with high diversity and variability. *Procedia Cirp*, 57, 315-320.

Shreve, D. H. (1994). Introduction to vibration technology. *Proceedings of Predictive Maintenance Technology Conference*. November.

Thi, N. D. T., Do, T. D., Jung, J. R., Jo, H., & Kim, Y. H. (2020). Anomaly detection for partial discharge in gas-insulated switchgears using autoencoder. *IEEE Access*, 8, 152248-152257.

Wei, Y., Jang-Jaccard, J., Xu, W., Sabrina, F., Camtepe, S., & Boulic, M. (2023). LSTM-autoencoder-based anomaly detection for indoor air quality time-series data. *IEEE Sensors Journal*, 23(4), 3787-3800.

Wisal, M., & Oh, K. Y. (2023). A New Deep Learning Framework for Imbalance Detection of a Rotating Shaft. *Sensors*, 23(16), 7141.

Xu, W., Jang-Jaccard, J., Singh, A., Wei, Y., & Sabrina, F. (2021). Improving performance of autoencoder-based network anomaly detection on nsl-kdd dataset. *IEEE Access*, 9, 140136-140146.
Zhang, L., Lin, J., Liu, B., Zhang, Z., Yan, X., & Wei, M. (2019). A review on deep learning applications in prognostics and health management. *IEEE Access*, 7, 162415-162438.
Zhang, Y., Wang, Y., Yi, Y., Wang, J., Liu, J., & Chen, Z. (2021). Coupling matrix extraction of microwave filters by using one-dimensional convolutional autoencoders. *Frontiers in Physics*, 521.

BIOGRAPHIES

Kichang Park received his M.S. and Ph.D. in Computer Science from Chonnam National University, the Republic of Korea, in 2003 and 2013, respectively. He has a background as a software engineer in the manufacturing industry and is currently working as an artificial intelligence professional at the Intelligent Manufacturing Technology Institute, RESHENIE Co. Ltd. His current research interest is AI-based anomaly detection for manufacturing facilities.

Yongkwan Lee is a Professor at the Tech University of Korea and founder of manufacturing AI solution company, RESHENIE Co. Ltd. He finished Bachelor's and Master's course at Kumoh National University of Technology, the Republic of Korea and got a Ph.D. degree in St. Petersburg State Polytechnic University, Russia. His research interest is manufacturing artificial intelligence, facility diagnosis technology, and smart-manufacturing solutions.