Misalignment Diagnostic System for Linear Motion Robots Using Long Short-Term Memory

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***Abstract*—Linear-motion robots are commonly used for positioning or part-transfer operations in the automation industry. However, such robot systems may suffer mechanical defects, which compromise the performance of the equipment and generate noise and vibration. Human workers are usually placed in charge of anomaly diagnosis for linear robots; however, the results of such diagnoses vary depending on the skill level of the individual in charge. Many attempts have recently been made to utilize artificial intelligence to diagnose anomalies in industrial devices. This study presents a system that can automatically diagnose linear rail misalignment and ball screw misalignment in linear robots using a Long Short-Term Memory (LSTM)-based deep learning model. The time sequence of the statistical feature parameters obtained from acceleration sensor data was used as the input for the LSTM model. Furthermore, the proposed method was validated experimentally. A comparative test with an artificial neural network using signal feature values as input and a 2D-Convolutional Neural Network (CNN) using a spectrogram as input confirmed that the proposed method is effective at anomaly detection. Thus, this method can be used to diagnose anomalies in industrial robots.**

***Keywords*—linear motion robot, long short-term memory, misalignment diagnosis, linear rail misalignment, ball screw misalignment**

I. Introduction

Linear motion robots are commonly used as part of automation systems for positioning or part transfer operations. However, mechanical defects may occur in such robot systems during system assembly or long-term operation, thereby reducing the performance of the entire automation system and generating noise and vibration. Therefore, companies that produce linear robot equipment try to maintain a certain level of quality management by inspecting the manufactured system. Until now, human workers have mainly been responsible for judging the presence of anomalies by investigating the system status, but the detection accuracy depends on the operator's skill level. Alternatively, automatic diagnostic methods have been explored in which devices detect anomalies through an expert system or machine learning. Among these methods, vibration diagnosis technology, which automatically detects anomalies from the vibration signals generated during operations, has been studied for a long time. Much research has been conducted to detect anomalies in the outer and inner races of ball bearings based on the vibration signals for motors and turbines. Methods of detecting faults using the envelope spectrum of a vibration signal [1], wavelet transformation [2], machine learning [3], and recently deep learning [4] have been proposed. The vibration signal of a ball bearing has cyclostationary properties, where the same frequency distribution repeats periodically when the rotation speed is constant. Additionally, the detection of anomalies is mainly achieved using these cyclostationary characteristics [1]. On the other hand, little research has been conducted on the diagnosis of anomalies in linear motion robots. In robots, it is challenging to find fault characteristics in the frequency response because the frequency response includes the natural vibration of the robot body. Moreover, because robot systems are subject to friction and considerable uncertainty [5], obtaining an intrinsic vibration model is difficult. Studies on linear robots have mainly focused on structural vibration characteristics [6]. Research that has been performed on anomaly diagnosis in linear robots include a study on detecting flaking of bearings that support a linear motion guide [7] and another to detect anomalies in the bearing of the rotation axis [8]; these two studies used transfer learning [9] and performed binary classification into two classes: abnormal or normal. Artificial intelligence performs effectively in systems with uncertainty [10].

This study presents an automatic diagnosis method to detect misalignments in 1-axis linear motion robots for semiconductor equipment. The proposed method uses a time sequence of statistical feature parameters of vibration signals and a Long Short-Term Memory (LSTM) to detect misalignments. Misalignment of Linear Motion (LM) rails and ball screws, which frequently occur in linear motion robots and are stipulated by the robot manufacturer to be within the allowable range, are detected by constructing a multi-classifier. In the author's previous research, a study was conducted to detect anomalies by inputting the spectrogram image of the entire vibration signal into the CNN-based VGG-19 transfer learning model [11]. However, with this approach, a large amount of data was

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needed to train the model. Moreover, due to the nature of industrial devices, it was difficult to obtain sufficient training data, which resulted in unsatisfactory diagnosis accuracy. To solve this problem, we propose a lightweight anomaly diagnosis method based on LSTM and a time sequence of feature parameters of vibration signals. LSTM, a type of Recurrent Neural Network (RNN), has an input gate, a forget gate, and an output gate. Similar to the RNN, it has a chain-type structure, but it can store information for a longer period than the RNN and exhibits excellent performance in classification tasks using time sequences as input [12]. Vos used LSTM regression to detect abnormalities in the helicopter rotation axis, while Khorram used a CNN+LSTM to detect bearing faults [13].

This study aims to develop a lightweight vibration signal-based anomaly diagnosis system that can be used for robots. While the robot is driven along a predefined trajectory, the time sequence of the statistical feature parameters of the acceleration signal is obtained, and this sequence is input to the trained multi-channel input LSTM to diagnose anomalies. This feature differentiates the proposed technique from existing methods. The remainder of the paper is structured as follows. Section II describes the proposed automatic diagnosis method for the 1-axis linear robot, and Section III describes the composition of the data set and experiment results. Finally, the conclusions are drawn in Section IV.

II. METHODS

A. Configuration of the Misalignment Diagnostic System

The target of the diagnostic system proposed in this study is a 1-axis linear robot for semiconductor wafer transfer, as shown in Fig. 1. The vibration signal was collected using an acceleration sensor, which was mounted on the mover of the linear robot. The sampling frequency of the acceleration sensor is 48 KHz. Misalignments in the ball screw axis and linear rail may arise in linear robots, which can cause abnormal vibration. The ball screw and linear rail alignment errors are defined in Fig. 2, and the structure of the proposed diagnostic system is shown in Fig. 3. Linear rail misalignment is a horizontal displacement value, while ball screw rail misalignment is a combination of vertical and horizontal displacements. The measured vibration signal was transmitted to a PC, and the feature parameters were extracted. Moreover, the type of anomaly was determined using a pre-trained classifier.

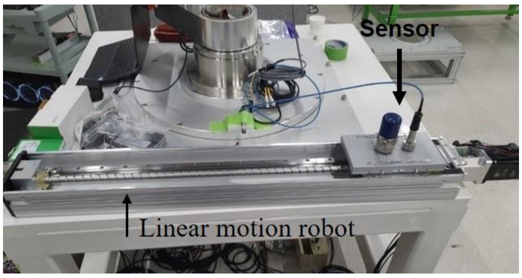


Fig. 1. Misalignment diagnostic system.

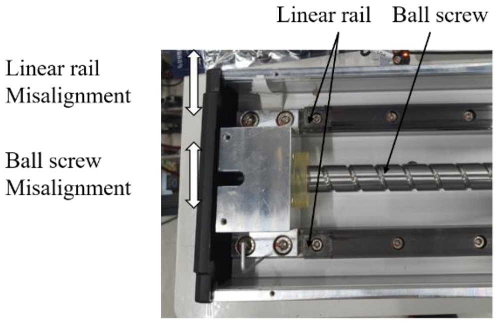


Fig. 2. Linear rail and ball screw misalignments definition.

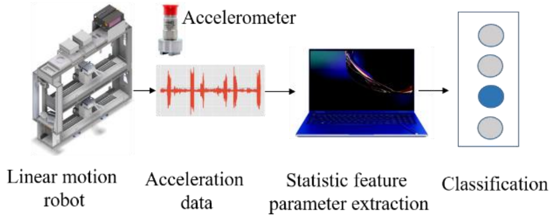


Fig. 3. Structure of the proposed diagnostic system.

B. Feature Parameters of the Vibration Signal

To detect anomalies, the vibration data was collected while a robot moved in a trajectory, including acceleration, deceleration, and constant speed operation. In this study, the entire trajectory comprised one round trip, and each driving section was divided into seven subsections, as shown in Fig. 4. The maximum speed was experimentally chosen so that the anomalies could be diagnosed easily. The vibration signals from ball screw misalignment, linear rail misalignment, and the normal-state linear robot are shown in Fig. 5, and the fast Fourier transform results of each signal are shown in Fig. 6. Although there were obvious differences in acceleration and frequency distribution depending on each anomaly, it was difficult to find a regularity that could detect anomalies in the time domain or frequency domain waveform for all the measured signals.

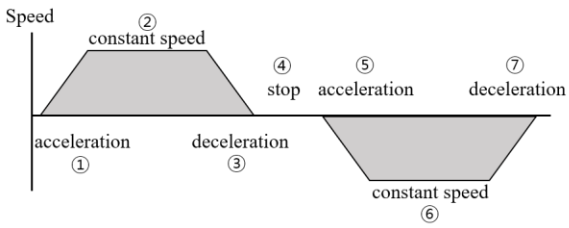
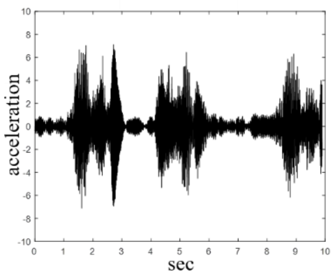


Fig. 4. Trajectory for data acquisition.



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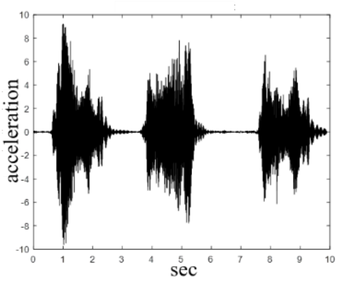

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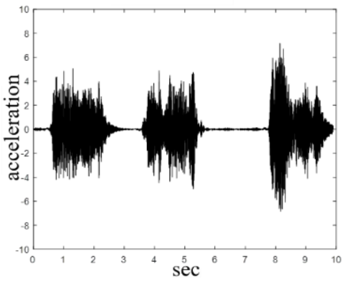
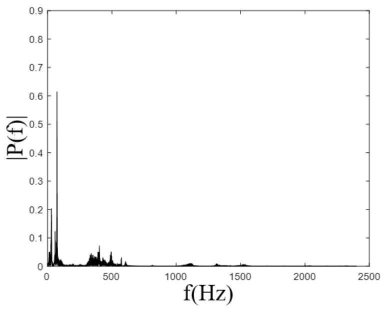


(c)

Fig. 5. Vibration signal: (a) Ball screw misalignment; (b) Linear rail misalignment; (c) Normal.



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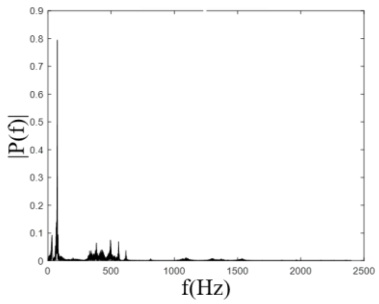

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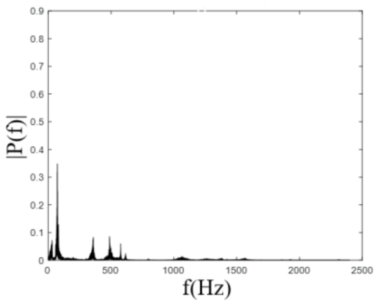


(c)

Fig. 6. Fourier transform results: (a) Ball screw misalignment; (b) Linear rail misalignment; (c) Normal.

Existing anomaly detection methods for industrial equipment use various techniques, including statistical methods, artificial neural networks, and deep learning, in the frequency or time domain [12]. In Ref. [14], the statistical feature parameters of the signal were calculated and then input into an artificial neural network to detect anomalies. In this study, the following six feature values among commonly used feature parameters were used: peak value, skewness, Kurtosis, crest factor, clearance factor, and impulse factor, as defined in Table I. When fewer parameters were used, the classifier did not show sufficient accuracy. In Table I, *n* denotes the data length of the detected discrete vibration signal *x*, and x_i denotes *i*-th sampled data of *x*. The feature parameter vector of the signal gathered in the entire driving section, *X*, can be defined through Eq. (1).

$$X = \{x_p, x_{skew}, x_{kurt}, x_{crest}, x_{clear}, x_{IF}\} \tag{1}$$

Let X_j denote the vector that collects the feature parameters extracted from the *j*-th driving section. Then, X_{aug} is defined as the vector that collects all X_js for *N* sections (*N* = 7 in this study), as shown in Eq. (2).

$$X_{aug} = \{X_1, X_2, .., X_j, .., X_N\} \tag{2}$$

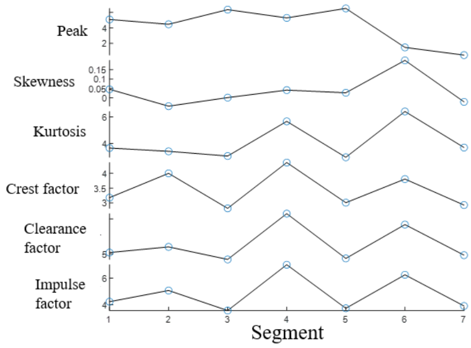
Let x_{p_j} denote the peak value extracted from the vibration signal of the *j*-th driving section, and $X_p = \{x_{p_1}, x_{p_2} \dots x_{p_j} \dots x_{p\_N}\}$ is the vector that collects $x_{p\_j}s$. For other feature parameters, $X_{skew}, X_{kurt}, X_{crest}, X_{clear}$, and X_{IF} are defined in the same way. Finally, X_{seq} is defined as a two-dimensional matrix that combines these vectors as shown in Eq. (3).

$$X_{seq} = \{X_p{}^T, X_{skew}{}^T, X_{kurt}{}^T, X_{crest}{}^T, X_{clear}{}^T, X_{IF}{}^T\}^T \tag{3}$$

TABLE I. STATISTICAL FEATURE PARAMETERS

Feature	**Equation**
Peak value	$x_p = \max_i \lvert x_i \rvert$
Skewness	$x_{skew} = \dfrac{\frac{1}{n}\sum_i^n (x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_i^n (x_i - \bar{x})^2\right)^{3/2}}$
Kurtosis	$x_{kurt} = \dfrac{n\sum_i^n (x_i - \bar{x})^4}{\left(\sum_i^n (x_i - \bar{x})^2\right)^2}$
Crest factor	$x_{crest} = \dfrac{x_p}{\sqrt{\frac{1}{n}\sum_i^n x_i{}^2}}$
Clearance factor	$x_{clear} = \dfrac{x_p}{\left(\frac{1}{n}\sum_i^n \sqrt{\lvert x_i \rvert}\right)^2}$
Impulse factor	$x_{IF} = \dfrac{x_p}{\frac{1}{n}\sum_i^n \lvert x_i \rvert}$

In existing studies on anomaly detection, the anomalies were diagnosed using classifiers such as artificial neural networks or support vector machines using the feature vector X or X_{aug} as the input. On the other hand, in this study, we constructed a classifier that utilized the time sequence of the feature parameters, X_{seq}, as the input. Fig. 7 depicts a X_{seq} collected from a robot with a ball screw alignment error, linear rail alignment error, and the normal state.



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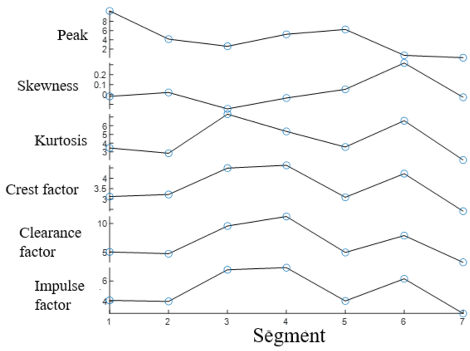

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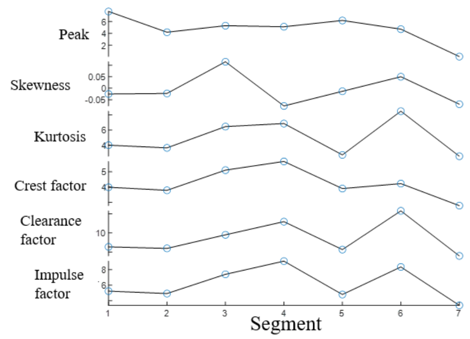

(c)

Fig. 7. Feature value sequence: (a) Ball screw misalignment; (b) Linear rail misalignment; (c) Normal.

The block diagram of the proposed misalignment diagnostic system is shown in Fig. 8. First, a trajectory that was favorable for diagnosing anomalies was selected experimentally, and a feature parameter sequence was constructed from the vibration data obtained by moving the robot according to the designated trajectory. This feature parameter sequence was input into a pre-trained LSTM to determine the presence and type of the anomaly. Fig. 9 shows the structure of the multi-channel input 1D LSTM classifier.

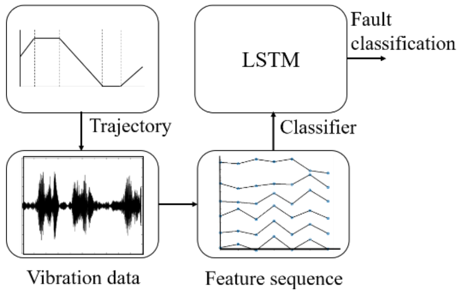

Fig. 8. Block diagram of the proposed diagnostic system.

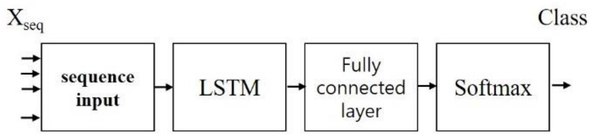

Fig. 9. Block diagram of the LSTM classifier

C. *Previous Research Review for Comparison*

In the author's previous research, the entire vibration signal was short-time Fourier transformed, and a spectrogram was obtained to visualize the signal along the two dimensions of the time axis and frequency axis from this transformed result. The presence and type of the anomaly were classified using a VGG-19-based image classification model [11]. Fig. 10 shows the VGG-19-based misalignment diagnostic system of the previous research. The obtained diagnosis accuracy, 78%, was lower than expected, which was assumed to be due to an insufficient data set.

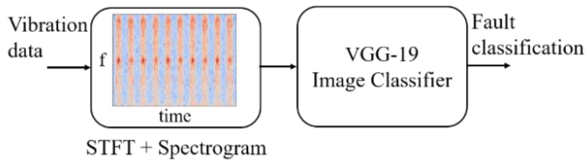

Fig. 10. VGG-19 based misalignment diagnostic system [11].

III. Results

For training, 130 units of raw data were used, and the number of units of test data was 50. The total displacement of the LM guide was 750 mm, and the vibration data was measured at the moving speeds of 550 mm/s, 600 mm/s, and 650 mm/s, which showed the highest diagnostic accuracy. A robot with rail misalignment, ball screw misalignment, and normal state were driven according to the trajectory in Fig. 4. Then, the acceleration signals were gathered and the feature parameters were extracted to form a data set. The linear rail misalignment was approximately between 0.05 mm and 0.1 mm, and the ball screw misalignment was between 0.3 mm and 0.6 mm. The allowable linear rail misalignment range was within 0.02 mm and, in the case of the ball screw misalignment, it was within 0.1 mm. These allowable clearance ranges were stipulated internally by the manufacturing company. The to-be-classified anomalies were divided into three classes—normal, LM rail misalignment, and ball screw misalignment—and were trained and tested. For comparison, the following methods were also tested, and the structures and features of each method are listed in Table II. All experiments using Methods 1–4 were conducted on a PC using MATLAB, which can be used to create programs for distribution [15].

TABLE II. CLASSIFIER STRUCTURE

Method	Structure/ Training method	Classification time/ Data size
Image classification	Re-trained VGG-19/ Adam Optimizer, Max Epoch 150	1.86 s/ 224 by 224 pixels image
Method 1	3 Layer ANN Inner layer size 40, 20	0.96 ms/ vector of 6 floats
Method 2	3 Layer ANN Inner layer size 40, 20	4.81 ms/ vector of 42 floats
Method 3	1D CNN Filter size 5, 32 filter/ Adam Optimizer, Max Epoch 50	15.2 ms/ 6 × 7 float matrix
Method 4	1D LSTM with 6 channel input Hidden unit 120/ Adam Optimizer, Max Epoch 50	7.76 ms/ 6 × 7 float matrix

(1) Image classification: Image classification using a spectrogram as the input [11]
(2) Method 1: Artificial neural network classifier with feature parameter vector, X, as the input
(3) Method 2: Artificial neural network classifier with the augmented feature parameter vector, X_{aug}, as the input
(4) Method 3: Convolutional Neural Network (CNN) with the feature parameter sequence matrix, X_{seq}, as the input
(5) Method 4: The proposed method, LSTM, with the feature parameter sequence matrix, X_{seq}, as the input

The model of the proposed method is a 1D LSTM and has 120 hidden units. Adam Optimizer was used for training, and the maximum epoch was set to 50. The classification time is the time required for judgment and was measured on a 2.4 GHz PC. Since the anomaly diagnosis is an offline operation, the classification is made quickly enough no matter which model is used.

The accuracy, sensitivity and specificity of a classifier are defined as Eqs. (4)–(6), where, TP is true positive, TN is true negative, FP is false positive, and FN is false negative [16].

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{4}$$

$$sensitivity = \frac{TP}{TP+TN} \tag{5}$$

$$specificity = \frac{TN}{TN+FP} \tag{6}$$

The diagnostic accuracies of the implemented method are shown in Table III. Each accuracy is the average value after repeating training and test three times. The results of spectrogram image classification method were reproduced from [11], and these were the results of using data sets different from those in this paper. However, the ranges of misalignments were the same.

TABLE III. DIAGNOSTIC ACCURACY

Method	Input data	Accuracy (%)
Image classification	Spectrogram	78.0 [11]
Method 1	Feature vector, X	77.4
Method 2	Augmented feature vector, X_{aug}	86.7
Method 3	Feature vector sequence, X_{seq}	88.4
Method 4	Feature vector sequence, X_{seq}	95.6

The proposed method had an accuracy of 95.6%, which is superior to the accuracy of other methods. Fig. 11 shows a confusion chart of each method. With the proposed LSTM model, there were still cases where linear rail alignment anomalies were judged as normal. The specificity and sensitivity of each method are compared in Table IV. In the anomaly diagnosis of industrial equipment, if a normality is incorrectly judged to be abnormal, the test can be re-run to obtain the correct result. However, the converse situation can compromise quality control. Therefore, the specificity of the "Normal" class must be high. As this specificity value for the proposed method is 0.936, this method offers better performance than other neural network-based methods.

	Ball screw	Linear rail	Normal
Ball screw	0.529	0.341	0.129
Linear rail	0.118	0.812	0.071
Normal	0.025	0.0	0.975

(a)

	Ball screw	Linear rail	Normal
Ball screw	0.824	0.153	0.024
Linear rail	0.047	0.788	0.165
Normal	0.013	0.0	0.988

(b)

	Ball screw	Linear rail	Normal
Ball screw	0.882	0.106	0.012
Linear rail	0.0	0.777	0.224
Normal	0.0	0.0	1.0

(c)

	Ball screw	Linear rail	Normal
Ball screw	1.0	0.0	0.0
Linear rail	0.0	0.871	0.129
Normal	0.0	0.0	1.0

(d)

Fig. 11. Confusion chart: (a) Method 1 (ANN + X); (b) Method 2 (ANN + X_{aug}); (c) Method 3 (CNN + X_{seq}); (d) The proposed method.

TABLE IV. SPECIFICITY AND SENSITIVITY

Method	Class	Specificity	Sensitivity
Method 1	Ball screw	0.926	0.530
	Linear rail	0.815	0.811
	Normal	0.870	0.975
Method 2	Ball screw	0.967	0.823
	Linear rail	0.922	0.788
	Normal	0.895	0.987
Method 3	Ball screw	1.000	0.882
	Linear rail	0.947	0.776
	Normal	0.875	1.000
Method 4	Ball screw	1.000	1.000
	Linear rail	1.000	0.871
	Normal	0.936	1.000

IV. Conclusion

This study presents an automatic diagnosis method using vibration signals to diagnose misalignments in 1-axis linear robots for semiconductor equipment. The purpose of this study was to automatically perform anomaly detection, which has been performed by human workers so far. The automatic diagnosis of bearings in rotational machines using vibration signals has been studied for a long time; however, little research has been conducted on diagnosing anomalies in 1-axis linear robots. This study's contribution is to propose a diagnostic method that operates according to the following sequences: First, vibration signals were obtained by driving a robot according to a predefined trajectory. Thereafter, the time sequences of the feature parameters were calculated, and, finally, misalignment anomalies were classified through LSTM. Compared to the previous diagnosis method where a spectrogram was used with 224 by 224 pixels [11], the method proposed by this study has a smaller data size, 42 float values per data, which proves advantageous for small-scale manufacturers of automated systems. The proposed method was confirmed to achieve an accuracy of 95.6%, which represents an improvement over the 78.0% accuracy of the existing spectrogram image classifier. Moreover, it outperforms classical artificial neural networks and a CNN classifier that use feature values as input, with accuracies of 77.4%, 86.7%, and 88.4%. Additionally, the specificity of the "Normal" class was 0.936 when using the proposed method. Because this value is higher than that for other methods, the proposed method is more reliable for use as an industrial diagnostic system. However, the misalignment values used in the experiment were severe compared to the allowable range considered normal. For industrial use, there is a need to further improve diagnosis precision. To use the automatic diagnostic system industrially, it is essential to secure higher reliability and precision; however, diagnostic methods using artificial intelligence can be potentially used to diagnose anomalies in various industrial devices.

In the future, we plan to verify the effectiveness of the proposed diagnostic method for multi-DOF robots. Moreover, improving diagnostic accuracy is another target. Explainable AI, which constitutes the basis for the judgments rendered by a neural network, is another important research topic. Further, we plan to identify feature parameters and operating conditions that contribute to abnormality detection.

Conflict of Interest

The authors declare no conflict of interest.

Acknowledgment

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References

[1] R. Randall and J. Antoni, "Rolling element bearing diagnostics," *Mechanical Systems and Signal Processing*, vol. 25, pp. 485–520, 2011.

[2] P. Kankar, S. Sharma, and S. Harsha, "Rolling element bearing fault diagnosis using wavelet transform," *Neurocomputing*, vol. 74, pp. 1638–1645, 2011.

[3] H. Zhao, Y. Gao, H. Liu, and L. Li, "Fault diagnosis of wind turbine bearing based on stochastic subspace identification and multi-kernel support vector machine," *Journal of Modern Power Systems and Clean Energy*, vol. 7, no. 2, pp. 350–356, 2019

[4] S. Zhang, S. Zhang, B. Wang, and T. Habetler, "Deep learning algorithms for bearing fault diagnostics—A comprehensive review," *IEEE Access*, vol. 8, pp. 29857–29881, 2020.

[5] Z. Hazem, M. Javad Fotuhi, and Z. Bingül, "A comparative study of the friction models with adaptive coefficients for a rotary triple inverted pendulum," in *Proc. 2018 6th International Conference on Control Engineering & Information Technology (CEIT)*, Istanbul, Turkey, 2018, pp. 1–6.

[6] Y. Yi, Y. Kim, J. Choi, J. Yoo, D. Lee, and S. Lee, "Micro-scale vibration phenomena in a linear motion guide having rolling elements," *Transactions of the Korean Society for Noise and Vibration Engineering*, vol. 14, no. 10, pp. 1029–1034, 2004.

[7] S. Cho, S. Kim, and J. Choi, "Transfer learning-based fault diagnosis under data deficiency," *Applied Sciences*, vol. 10, no. 21, p. 7768, 2020.

[8] J. Yun, M. Kim, G. Koo, and C. Shin, "Fault diagnosis and analysis based on transfer learning and vibration signals," *IEMEK Journal of Embedded Systems and Applications*, vol. 14, no. 6, pp. 287–293, 2019.

[9] M. Shaha and M. Pawar, "Transfer learning for image classification," in *Proc. 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, Coimbatore, India, 2018, pp. 656–660.

[10] A. Arab and Y. Mousavi, "Optimal control of wheeled mobile robots: From simulation to real world," in *Proc. 2020 American Control Conference (ACC)*, Denver, CO, USA, 2020, pp. 583–589.

[11] S. Hong, Y. Lee, A. Park, and C. Moon, "A diagnosis system of misalignments of linear motion robots using transfer learning," *Journal of the Convergence on Culture Technology*, vol. 10, no. 3, pp. 801–807, 2024.

[12] K. Vos, Z. Peng, C. Jenkins, M. Shahriar, P. Borghesani, and W. Wang, "Vibration-based anomaly detection using LSTM/SVM approaches," *Mechanical Systems and Signal Processing*, vol. 169, 108752, 2022.

[13] A. Khorram, M. Khalooei, and M. Rezghi, "End-to-end CNN + LSTM deep learning approach for bearing fault diagnosis," *Appl. Intell.*, vol. 51, pp. 736–751, 2021.

[14] B. Sreejith, A. Verma, and A. Srividya, "Fault diagnosis of rolling element bearing using time-domain features and neural networks," in *Proc. 2008 IEEE Region 10 and the Third International Conference on Industrial and Information Systems*, 2008, pp. 1–6.

[15] Z. Hazem, "Study of Q-learning and deep Q-network learning control for a rotary inverted pendulum system," *Discover Applied Sciences*, vol. 6, no. 2, 49, 2024.

[16] K. Chu, "An introduction to sensitivity, specificity, predictive values and likelihood ratios," *Emergency Medicine*, vol. 11, no. 3, pp. 175–181, 1999.