Verification of Determination Possibility using Convolutional Autoencoder for Machine Tool Abnormality Detection

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Abstract

The purpose of this research is to clarify the cause of failure and to improve the accuracy of abnormality detection by predicting the noise added to the machine tool from the results of the convolutional autoencoder. Data obtained from an acceleration sensor mounted on the machine tool are reconstructed using a convolutional autoencoder, and the average absolute error is calculated. The maximum value of the average absolute error of the training data is used as the threshold value for abnormality detection. Multiple simulated data with different amplitude values based on a composite sine wave with a specific frequency and random numbers within a specified amplitude value were verified. In this paper, the characteristics of each type of noise and the parameters of the optimal model were examined from error rate and error distribution.

Keywords: machine tools, deep learning, anomaly detection, convolutional autoencoder, noises

1. Introduction

In factories, machine failures can be categorized as sudden breakdowns and deteriorating faults [1]. Preventing failures proactively during maintenance is exceptionally challenging, and excessive maintenance or machine breakdowns can result in significant losses for companies. Examples include production downtime leading to manufacturing time losses, increased labor costs due to stoppages, and the generation of defective products. The purpose of this study is to reduce losses and enhance productivity by providing maintenance timing suggestions and early detection of abnormalities in machining equipment.

In collaboration with businesses, this research involved installing acceleration sensors on machining equipment used in semiconductor manufacturing. The data acquired from the sensors is in the form of continuous time-series data. Since explicit abnormal judgments are significantly fewer than normal data, it is necessary to perform anomaly detection without explicit labels for normal and abnormal data. Consequently, anomaly detection was conducted using a convolutional autoencoder [2].

Initially, the machine with the attached sensor experienced a breakdown, and there were no prospects for its reprocessing. Subsequently, the sensor was transferred to a similar type of machining equipment. After the transfer, only normal data was obtained from the factory's machines. As abnormal data obtained before the transfer exhibited specific frequency components, simulated data resembling those characteristics was generated. Parameters for multiple models were created based on different numbers of training data, and abnormal detection was verified by introducing specific noise to the training data [3] to assess how much noise is required to detect anomalies. Moreover, considering the possibility of identifying malfunctioning machine components by pinpointing the noise, we investigated the distribution of reconstruction errors.

2. Proposed method

The proposed method consists of two steps: Learning and parameter saving, and Testing validation.

2.1. Learning and parameter saving

Initially, a convolutional autoencoder was created by referencing the Keras tutorial [4] for parameter

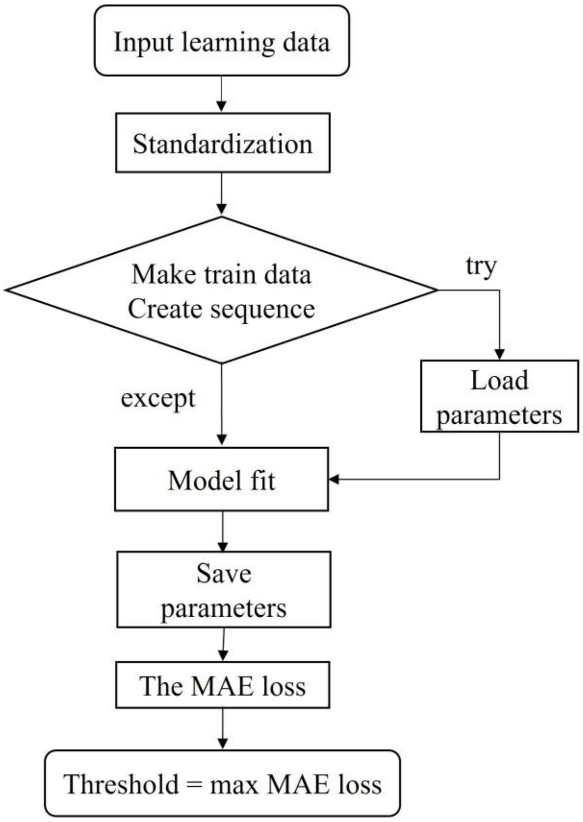

Fig. 1. Flowchart of learning and parameter saving

inheritance (Fig. 1). The training data was standardized using the mean and standard deviation of the data. A sequence with a timestep of 100 was generated using a sequential model, and training was conducted. A callback was implemented to halt training if the validation loss did not improve for five consecutive epochs. The hyperparameters were set as follows: epochs = 5, batch size = 4096, and validation split = 0.1.

After training, the parameters were saved, and the model was used to reconstruct the training data. The absolute mean error between the actual data and the reconstructed data for each sequence was calculated, and the maximum value was set as the threshold for testing.

2.2. Testing validation

The process involves extracting one CSV file at a time from the dataset. The training data is then standardized using the mean and standard deviation of the respective file. Test data is reconstructed using the specified model parameters. For each sequence, the absolute mean error between the test data and the reconstructed data is calculated. Instances where this error exceeds the predefined threshold are considered anomalies. (Fig. 2)

3. Experiment

The sampling frequency of the experimental data was 500Hz, and each file contained 600,000 data points (equivalent to 20 minutes) with columns for time (s), x (m/s^2), y (m/s^2), and z (m/s^2). For this study, only the time (s) and x (m/s^2) columns were utilized. To assess the accuracy of each parameter, twelve CSV files were utilized for training. The process depicted in Figure 1 was repeated twelve times, and the resulting parameters were saved. The model parameters were denoted as model_1, model_2, ..., model_n corresponding to the number of training data (n). With an epoch count of 5 per training, a total of 60 training iterations were conducted as the process was repeated 12 times. (Fig. 3).

Analyzing the frequency components of normal and abnormal data obtained from the machine before the transfer revealed that normal data covers a wide frequency range, whereas abnormal data is concentrated in the high-frequency band. The results of the FFT (Fast Fourier Transform) applied to normal and abnormal data are shown in Fig. 4.

Based on these results, a composite wave of sine waves with specific frequencies was added to the initial training data to create simulated abnormal data. The added composite waves consisted of low frequencies at 40Hz and 90Hz, and high frequencies at 410Hz and 460Hz.

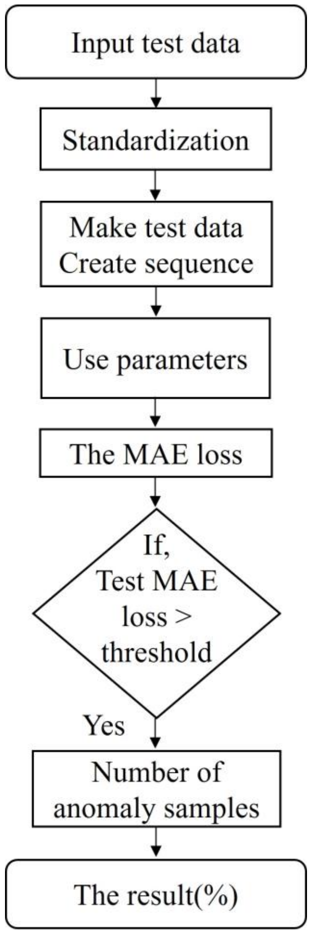

Fig. 2. Flowchart of testing validation

Fig. 3. Loss function

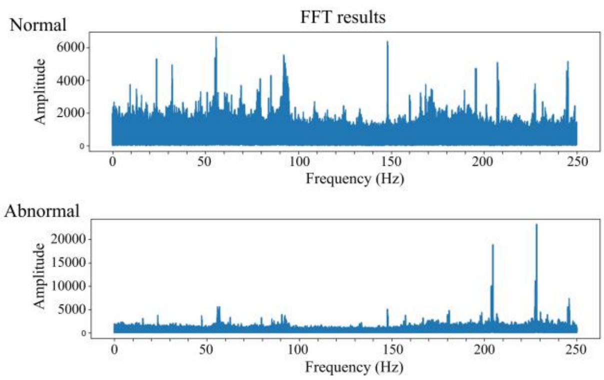

Fig. 4. Frequency analysis results of normal and abnormal data

Additionally, simulated data was generated by adding random numbers within specified maximum and minimum values. The specified absolute values for amplitude and random numbers ranged from 0.1 to a maximum of 0.8.

3.1. Testing validation

Test the three types of simulated data using twelve parameters (model_n) with varying amounts of training data. Based on the results, examine the optimal amount of training for anomaly detection.

3.2. Testing validation

Detect the three types of simulated data using the best parameters. Based on the results, evaluate how well anomalies are detected when various levels of noise are added and investigate the threshold for anomaly detection.

3.3. Testing validation

When the three types exhibit the same error rate, illustrate the distribution of the mean absolute errors between the actual data and the reconstructed data for each type. Compare the mean absolute errors when the error is approximately 10% and investigate whether there are any distinctive features in the distribution due to the added noise.

4. Results

4.1. Parameter Comparison

The order of accuracy in detecting anomalies for abnormal data is as follows:

- Low-frequency components: model_3, model_5, model_11, model_2 (Fig. 5)
- Random noise: model_3, model_11, model_12, model_5 (Fig. 6)
- High-frequency components: model_11, model_12, model_10, model_3 (Fig. 7)

For data with added low-frequency components and random noise, the parameters of Model_3, trained using three datasets, exhibited the most effective anomaly detection. Regarding data with added high-frequency component noise, Model_11, trained using eleven datasets, demonstrated the most proficient anomaly detection.

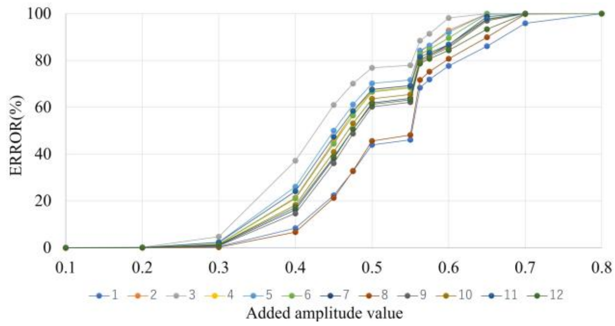

Fig. 5. Parameter comparison (Low-Frequency component)

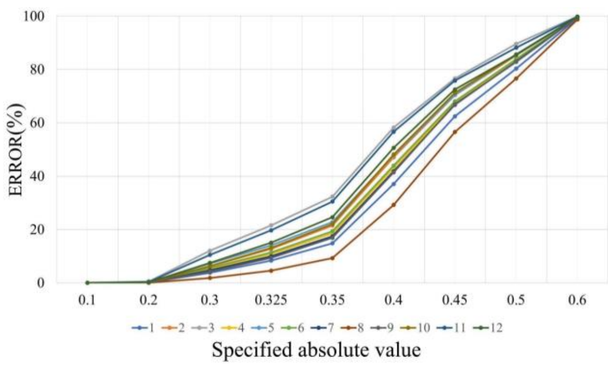

Fig. 6. Parameter Comparison (Random Data)

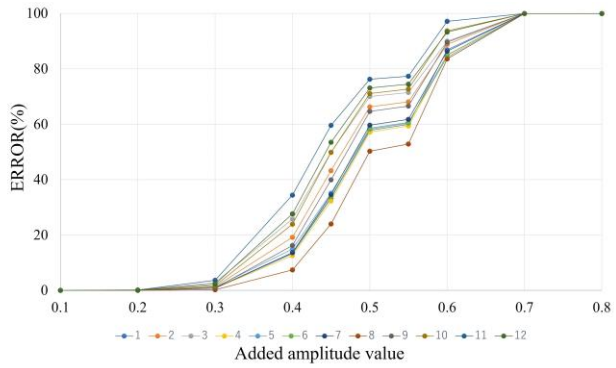

Fig. 7. Parameter Comparison (High-Frequency Component)

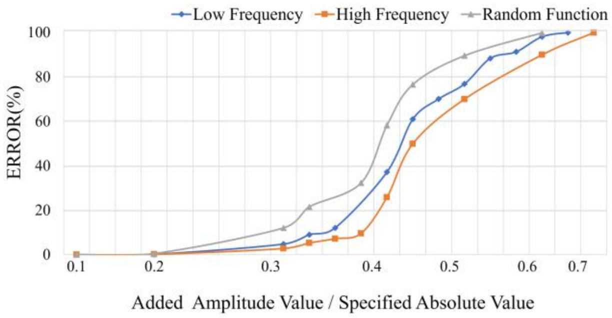

Fig. 8. Comparison of Model_3

4.2. Simulated Data Comparison

Based on the results from 4.1, a comparison of the three types of simulated data was performed using model_3 (Fig. 8). For all three types, errors reached 10% when the additional amplitude and specified absolute values ranged from 0.3 to 0.4. Additionally, it was observed that errors sharply increased for values equal to or greater than 0.4.

4.3. Noise Identification

When the error is approximately 10%, the distribution of actual data and reconstructed data for the three types is shown. Additionally, when the error is approximately 10%, the amplitude of the synthesized wave for low-frequency is 0.325, for high-frequency is 0.35, and the specified absolute value for random data is 0.3 (Fig. 9, Fig. 10 and Fig. 11). Differences in items such as mean, median, standard deviation, minimum, 25th percentile, 75th percentile, and maximum, based on the obtained basic statistical information, are on the order of one-thousandth. It can be observed from the distribution that when the anomaly rate is the same, there is little difference.

5. Conclusion

In the experimental data, step count, and hyperparameters employed in this study, the parameters of model_3 and model_11 demonstrated high accuracy in anomaly detection. From this, it was found that under the current conditions, abnormalities could be detected with high accuracy if three or 11 or more pieces of normal data, each with a total of 600,000 pieces of data, were trained.

From experiments using parameters trained three times, it was observed that, irrespective of whether the noise is periodic, high-frequency, or low-frequency, anomalies were detected when noise with an amplitude value or specified absolute value exceeding 0.3 was introduced. While it was not possible to identify the characteristics of the noise from the distribution of reconstruction errors, it is possible to estimate the amplitude of the added noise from the error percentages.

Currently, data is being measured in the factory and saved in specific files. Processing is set to analyze the second-to-last CSV file every 20 minutes. If anomalies are detected above 10%, the number 1 is added to the array; if below 10%, the number 0 is added. An alert is triggered when anomalies are detected continuously three times, and the array is output daily.

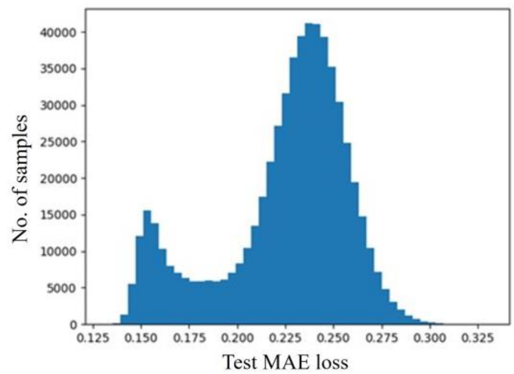

Fig. 9. Low Frequency- Additional Amplitude 0.325

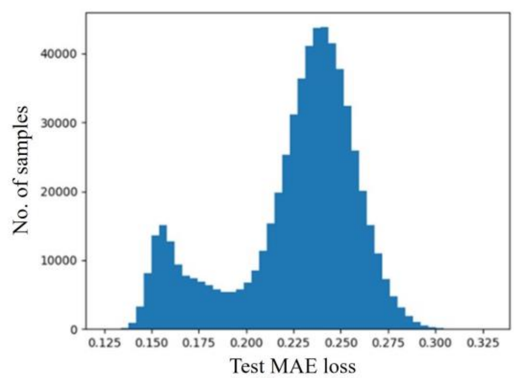

Fig. 10. High Frequency- Additional Amplitude 0.35

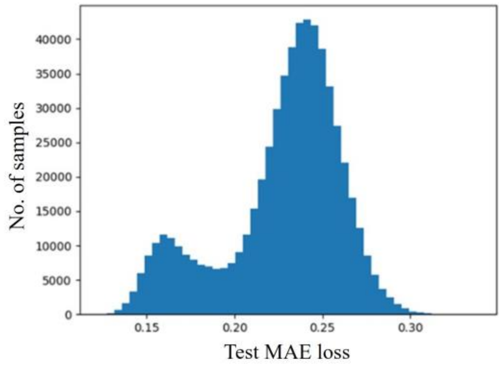

Fig. 11. Random- Specified Absolute Value 0.3

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Authors Introduction

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