A study on the types of sensors for machine anomaly analysis and their effectiveness

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Abstract—**Machine failures can lead to major losses, such as production line shutdowns and quality degradation. Research into failure prediction and anomaly detection is being conducted widely, driven by the need to know the signs of equipment and machinery failure before they occur. This method uses sensors to collect machine status data and use that data to detect signs of failure. It is hoped that the use of AI will enable objective, highly accurate failure prediction and anomaly detection. Sensors are crucial here. Depending on their installation location, there may be issues with the reliability of the data obtained, and signal lines such as power and LAN lines may get in the way of the machinery, making them a key component when considering actual system operation. This paper reports on the results of a study focusing on sensors.**

Keywords—**Anomaly Detection, Vibration sensors, Sound source separation, Millimeter wave radar.**

I. INTRODUCTION

Machine failures can lead to significant losses, such as production line shutdowns and quality degradation. Therefore, research into failure prediction and anomaly detection is actively underway, driven by the need to identify signs of equipment and machine failures in advance. This involves moving away from traditional management methods relying on the wisdom of experts and shifting to a system of numerical management that enables factories to be maintained and managed with a small number of staff. Numerical management uses sensors to collect machine status data and uses that data to detect signs of failure. It is expected that the use of AI will enable objective and highly accurate failure prediction and anomaly detection. We have been working on AI-based anomaly detection technology for factory machinery [1, 2]

Sensors play a crucial role. The most common type of sensor is the vibration sensor. Vibration sensors are installed directly on machines to measure their vibrations and identify abnormalities [3, 4]. However, depending on the installation location, there are issues with the reliability of the data they obtain. While it would be ideal if they could be installed directly at the problem location, this is often not possible, resulting in indirect measurements. Furthermore, signal lines such as power lines and LAN cables may interfere with the machine. While wireless and battery-operated sensors have become available in recent years, they require regular charging, which requires a lot of effort.

Acoustic detection is a common method for detecting machine anomalies, as sensor installation is minimal and retrofitting is easy [1, 2, 5]. However, in factories, microphones pick up ambient noise. Furthermore, because vibrations are often transmitted as sound, the volume of the sound signaling an anomaly is often low. In other words, anomaly detection using microphones (acoustics) is susceptible to site-specific noise conditions, such as environmental noise, the presence of multiple machines, and sound obstruction and reverberation.

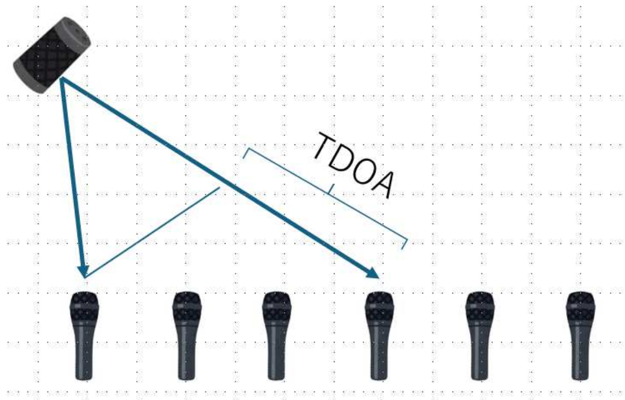

Figure 1. How a microphone holon array can identify the location of a sound source.

In recent years, research has been conducted into sound source separation and sound source collaboration using microphone arrays [6, 7]. Sound source separation using microphone arrays involves spatially arranging multiple microphones, each picking up the same sound at slightly different times, to estimate sound direction and separate sound sources. Figure 1 shows an illustration of the operation of a microphone holon array. When there is one sound source and multiple microphones, there will be a time difference of arrival (TDOA) between the sounds received by each microphone. This method makes it possible to emphasize the sound of interest and attenuate other sounds, making it possible to collect sound by focusing on the location of the machine being investigated. Using an array makes it possible to identify "which machine (which part) is making an abnormal sound," which is difficult to do with a single microphone, making it easier to narrow down the targets for inspection and maintenance. In this paper, we investigate whether abnormal sound analysis can be performed using a microphone array and report the results.

II. Abnormal Sound Analysis Flow

Since breakdowns do not occur frequently in factories, only normal sounds are used for learning. During operation, audio is continuously collected from a microphone. This section is designed to be able to collect not only sound but also vibration waveforms using a vibration sensor. The sound is then converted into an image using a wavelet transform. Wavelet transform has high frequency resolution, can acquire time-series information, and can be confirmed as an image, making it a good fit for current deep machine learning. Figure 2 shows the abnormal sound analysis flow we use.

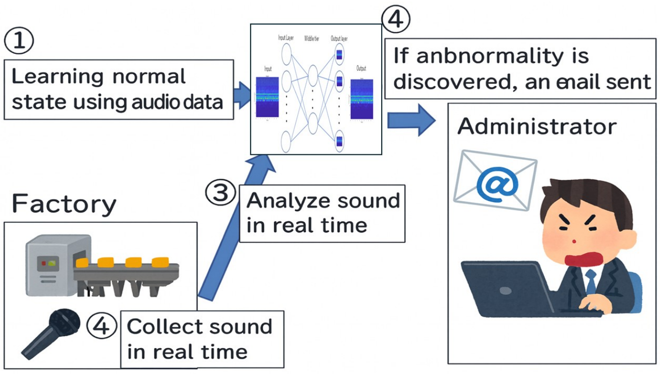

Figure 2. Factory abnormal sound analysis flow.

The machine learning steps are as follows:

1. Sound is saved as a separate file every few tens of seconds, and a wavelet transform is applied to convert the image data.
2. Images created from normal sound are used as input, and training is performed to create a model.

The operational steps are as follows:

1. Sound is saved as a separate file every few tens of seconds, and a wavelet transform is applied to convert the image data.
2. The converted images are input into the trained model, which then determines whether the sound is abnormal or normal.

III. Experimental Preparation Using Microphone Array

We conducted an experiment to investigate whether sound collection using a microphone array is applicable to the abnormal sound analysis flow we propose. We prepared several PC fans, created a fan with some of the blades cut off, and compared it with a fan with no modification to check whether there was a difference in the collected sound. The right side of Figure 3 shows a diagram of a low-voltage source connected to a fan in order to change the power supply voltage given to the fan, and on the right are photographs of a normal fan and a fan with the blades cut off. Figure 4 shows a diagram of the experiment using a fan and microphone array. The fan was placed on a desk, 50 cm away from the microphone array, and measurements were taken. The microphone array used was a commercially available one equipped with 64 MEMS digital microphones.

Figure 3. The fan used in the experiment. The power supply voltage can be changed.

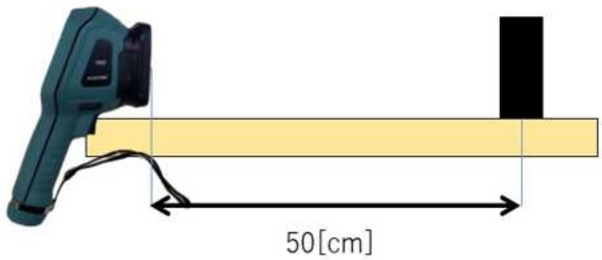

Figure 4. Experimental layout of the fan and microphone array. Measurements were taken at a distance of 50 cm.

IV. Experimental Results using Microphone Array

The tests were carried out to verify whether changes due to power supply voltage could be confirmed and whether a normal fan could be distinguished from one with a broken blade.

The following shows the results of an investigation into how the sound of a fan changes when the power supply voltage applied to the fan is changed. The power supply voltage was changed in 1V increments from 4V to 11V. The results are shown in Figure 5. The horizontal axis is power supply voltage, and the vertical axis is the sound volume in dB. Measurements were taken twice, once from the front of the fan and once from the side. As can be seen from the graph, the sound volume increases as the power supply voltage increases.

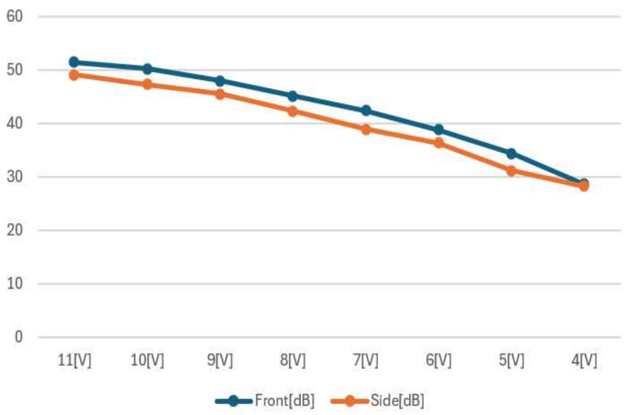

Figure 5. Results of changing the power supply voltage applied to the fan.

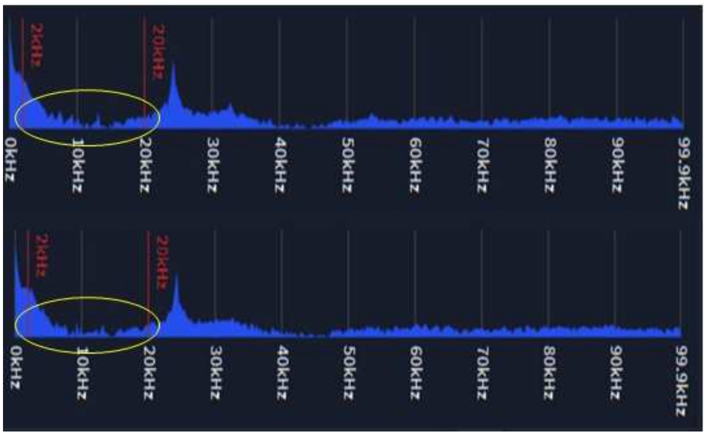

Figure 6. The results of a frequency analysis of the sound of a normal fan. The top shows the result of measurement from the front, and the bottom shows the result from measurement from the side

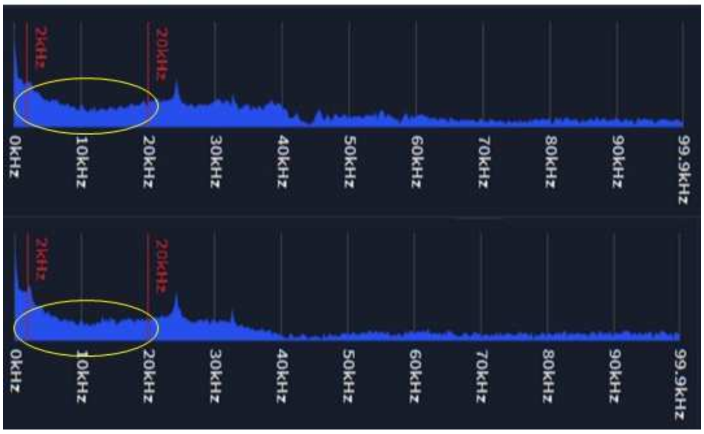

Figure 7. The results of a frequency analysis of the sound of a fan with broken blades. The top shows the result of measurement from the front, and the bottom shows the result from measurement from the sideThe fan used in the experiment. The power supply voltage can be changed.

Figure 6 shows the results of a frequency analysis of the sound of a normal fan. The top image shows the results from measurements taken from the front, and the bottom image shows the results from measurements taken from the side. Figure 7 shows the results of a frequency analysis of the sound of a fan with broken blades. The top image shows the results from measurements taken from the front, and the bottom image shows the results from measurements taken from the side. A difference can be seen around 10 kHz. These results confirm the high possibility of using a microphone array to analyze abnormal noise.

V. CONCLUSION

Sensors installed on machines, such as vibration sensors, are difficult to use in actual work sites due to issues such as installation location, so analysis using sound is widely used. When collecting sound in a factory, environmental sounds are also collected, so filtering must be written. Sound collection using a single microphone, which has been used until now, makes it difficult to filter out environmental sounds, making it difficult to capture sounds from specific parts of the machine. Therefore, an experiment was conducted to see if it is possible to use a microphone array to remove environmental sounds and collect sounds from the desired parts for abnormal sound analysis. The results of the experiment confirmed that there is a high possibility that this method can be used.

ACKNOWLEDGMENT

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