Practical Paper

Audio Signal Compression and State Discrimination in a Surround Environment Using Wavelet Transform

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Abstract - When a machine makes an anomalous noise, it is often necessary to take measures such as stopping the factory lines. Thus, we have been making a system to detect machine failure using sounds. The feature of the proposed system is that it converts voice data into an image using wavelet transform, and then uses the image as input to determine anomalies using machine learning. The important thing in this system is the size of the audio data to make it easier to transmit. In addition, the evaluation criteria are based on the learning accuracy of machine learning, rather than the traditional judgment by human ears. In this paper, audio signal compression using wavelet transform is discussed. We will consider reducing the size of audio data without removing abnormal sounds contained in the audio data. The features of abnormal sound on the time-frequency plane by applying some different conversion methods are compared each other. Using images showing the obtained features, machine learning was used to distinguish between normal audio and audio containing abnormalities.

Keywords: Wavelet, Features extract with sound processing.

1 INTRODUCTION

When an abnormality occurs in a machine operating in a factory, it is necessary to stop the factory line in order to deal with the problem. However, this reduces the factory's operating hours, and if the abnormality goes unnoticed for a long period of time, even if the factory line is stopped and measures are taken, it may result in significant losses for the company. Therefore, it is necessary to detect abnormalities or signs related to abnormalities and respond to them quickly.

Factory equipment always makes some kind of noise, and if an abnormality occurs, the machines make sounds that are different from normal sounds. Only experienced engineers can naturally detect the slightest anomalous machine noises, and up until now, maintenance and inspection of equipment at factory production sites has relied on the experience and intuition of veteran engineers. In recent years, due to the influence of generational change in companies, there has been an issue regarding the succession of maintenance work techniques at factories and other work sites. Thus, factories are becoming increasingly smart factories. This technology detects failures and signs of failure in mechanical equipment without relying on human intuition.

In factories and other places, the presence or absence of faults or failures is often based on sounds observed at specific locations, and a system that observes the sounds at relevant locations in a noisy environment and notifies of abnormalities is useful, so various methods have been proposed [1]. Scalograms, which are images of information obtained by wavelet transformation, are used to understand and extract feature values, but there are few examples of directly inputting this into machine learning, and there are no examples of this in a surround environment such as a factory.

We propose an audio compression method for machine learning in this paper. We have proposed a method in which audio data of inside a factory is processed to image data using wavelet transformation, its characteristics are clarified using some processes, and then machine learning is applied [2-4]. By grasping the characteristics from the time variation of the frequency characteristics, the accuracy of judging normality or abnormality could be improved. The important thing in this system is the size of the audio data to make it easier to transmit. A feature of the proposed method is the evaluation criteria for audio compression. The evaluation criteria of audio compression are based on the learning accuracy of machine learning, rather than the traditional judgment by human ears. Data compression is performed so as not to remove features that are important for machine learning in the proposed method.

Figure 1 shows the overall figure of the system we are developing. In the first stage, machine learning is performed using only normal sounds.

First, we apply wavelet transformation to each sound, visualize each sound data. Second, feature extraction processes are applied to the image data. This becomes the input data for machine learning. The wavelet transform uses a basis that shortens the time width at high frequencies and widens the time width at low frequencies, thus providing local frequency information and efficient time-frequency analysis. Time domain is essential for environmental sounds

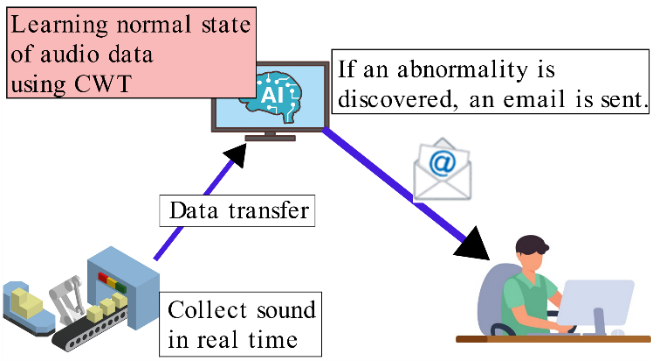

Figure 1: Proposed remote monitoring type system configuration for anomalous sound detection.

and the operating sounds of factory machinery. The AI learned from this input data is used to analyze the voice data collected in real time, and if an event occurs in which abnormal voice is observed, an alert is sent to the administrator (by email, etc.).

An important point in our system is how to collect and transfer audio data. There are multiple machines in a factory and multiple factories, but it is not realistic to install a server for each machine and each factory for the collected data. It is desirable to transfer the collected data in real time and consolidate it on one server. In such a situation, the size of the voice data is important. The smaller the size of the voice data, the easier it is to collect and transfer. However, this requires that the compressed voice data can be analyzed to determine whether it is a normal sound or an abnormal sound. This will make it possible in the future to build a system that stores collected data on the cloud, as shown in Fig. 2, and allows for real-time understanding of the situation from remote locations.

In this paper, we examined the compression method of audio data for anomalous sound detection system in factories for early failure detection using machine learning, thus we will report. In addition, discrimination was performed using images that applied wavelet transform as data for machine learning for abnormal sound detection.

When detecting anomalies using this method, the data is transferred and then analyzed to determine whether or not there is an abnormality; therefore, the proposed system is not suitable for capturing the moment an abnormality occurs and issuing an alarm. However, since the proposed system replaces the work of engineers, who listen to the sounds made by machines when they perform specific actions during inspections and judge the situation, it does not support immediate detection of abnormalities.

In this study, we hypothesize a system that observes and monitors sound, compresses and analyzes the sound using wavelet transform, and aims to verify the possibility and usefulness of applying this to sound source preservation and anomaly detection.

2 WAVELET TRANSFORM

There are two types of wavelet transform. One is continuous wavelet transform(abbreviated as CWT in the following text and figures) and the other is discrete wavelet transform(abbreviated as DWT in the following text and figures).

The wavelet transform is known as a method for analyzing both time and frequency. The wavelet transform is a method that calculates accurate frequency information by increasing the time width in the low-frequency region and calculates accurate time information by decreasing the time width in the high-frequency region. In the wavelet transform, the original waveform is expressed as an appropriate waveform $\Psi(t)$. This $\Psi(t)$ is called the mother wavelet, and the one that is appropriate for the waveform to be analyzed is selected appropriately. The mother wavelets used in this study are Morse, Molet, and Bump for the CWT, and SYM4 and DB4 for the DWT [5].

The CWT has applications such as detecting abnormal signals, and the DWT is used as a standard for image compression, and its applications are being actively discussed.

A typical analysis method used for audio signals is the Fourier transform, which includes frequency information but loses time domain. In contrast, the wavelet transform preserves time information, making it possible to analyze even sudden signal fluctuations. It is also possible to perform flexible operations such as varying the time interval according to the frequency domain, making it possible to perform dynamic analysis according to the situation.

Regarding the selection of the mother wavelet to be used in DWT, Ref. [6] shows the usefulness of Daubechies Wavelet (DB). Also, Ref. [7] shows the usefulness of Symmlet Wavelet (SYM). In this study, we confirmed the usefulness of actually recorded audio data, which may contain environmental sounds not mentioned in the previous studies, and showed the dependency of the compression rate on the parameters.

Waveforms indicating machine abnormalities often show signals with a sudden increase in waveform amplitude. This is similar to the waveform of an electrocardiogram. The SYM4 and DB4 wavelets are particularly suitable for analyzing biological signals, such as detecting the QRS complex in an electrocardiogram (ECG). The QRS complex is the most prominent feature of an electrocardiogram and reflects the deceleration of the left and right ventricles [8]. We therefore believe that SYM4 and DB4, which have been reported to be mother wavelets suitable for ECGs, will also be useful in this research.

In addition, we also verified the effectiveness of other mother wavelets that have been proposed and implemented in Matlab.

3 EXPERIMENT RESULTS: COMPRESSION OF AUDIO SIGNALS USING DISCRETE WAVELET TRANSFORM

3.1 Method of Compression Experiments

An experiment was conducted to confirm the effect of compression using DWT. The following items were confirmed:

1. Amount of file size reduction due to compression

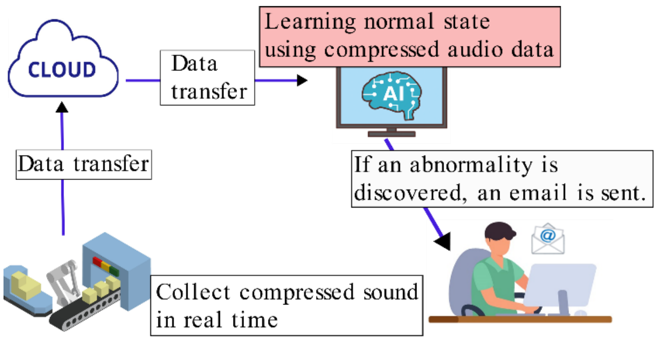

Figure 2: Proposed remote monitoring type system configuration for anomalous sound detection in the future.

2. Dependence of compression rate on mother wavelet
3. Dependence of compression rate on threshold used for analysis
4. Difference in compression rate due to difference in type of sound source

The audio data used in the experiment was collected from various sources [9-11], [12].

The original data was a 10-second uncompressed file with a sampling frequency of 16,000[Hz] . The sound sources include Fan, Pump, Slider, Toy Car, Toy Conveyor, Valve, and Toy Train, and each has a dataset of normal sounds and a dataset that includes abnormal sounds. For audio compression, we used the Wavelet Toolbox in MATLAB R2024.

3.2 File Size Reduction due to Compression

First, we analyzed the normal sound of a fan. We performed a DWT using SYM4 as the mother wavelet. Next, we applied a cut using the same threshold at each of the four frequency decomposition levels, and samples with values below the threshold were set to zero. Fig. 3 shows the chronological waveform diagram of the signal reconstructed based on the coefficient distribution of each decomposition level after cutting. The horizontal axis is the sampling number along the time series, and the vertical axis is the signal amplitude.

The reconstructed data was output as an audio file (wav file), and the audio file was converted to a flac file and compressed.

Figure 3 shows a comparison of the signal waveforms of a normal fan sound before (original) and after (compressed) DWT conversion. The horizontal axis is the number of samplings, which corresponds to time. The vertical axis is the signal amplitude. The first 1000 samples of the sound data are displayed, which corresponds to the first 62.5 milliseconds when converted to time.

The compression effect was evaluated by the compression ratio R. R is calculated as the ratio of the file size when the original audio data was converted to a flac file to the file size when it was converted to a flac file after DWT.

As we continued our analysis, we found that there was audio that had no effect at all from compression. Such audio has a waveform like that shown in Fig. 4. This waveform resembles a giant white noise.

In this case, the compression rate R was 1, meaning no compression was possible. Sounds like this are thought to be found frequently in sound sources such as fans, where the signal is expected to fluctuate at a high frequency. Since this type of waveform is thought to exist in both normal sound data and data containing abnormal sounds, we decided not to consider it noise this time, and to use the data as is for analysis.

The compression ratio R was calculated for 50 normal sound data and 50 abnormal sound data, and the average value was calculated. The error is the standard deviation calculated using the 50 values. For normal fan sounds, the compression rate was $R = 0.820 \pm 0.057$. When abnormal sounds were included, the compression rate was $R = 0.872 \pm 0.042$. SYM4 was used as the mother wavelet, and $T = 0.0017$ was used as the threshold for DWT compression.

This shows that audio data including noise and environmental sounds can be compressed using DWT.

3.3 Dependence on Different Types of Mother Wavelet

In the previous section, SYM4 was used as the mother wavelet for DWT, but we investigated the difference in compression ratio when using DB4, whose usefulness was shown in Ref. [6], [8], and other mother wavelets (bl7, beyl, coif1, fk4, haar, han5.5, mb4.2, vaid). In this case, we used the same threshold value T as in the previous analysis, T=0.0017. The results are shown in Fig. 5.

From this, we found that even with the same sound source, the compression rate varies greatly depending on the type of mother wavelet applied. For han5.5 and vaid, we found that although there was a large error, a low compression rate could be expected. Furthermore, for the Fan data set, SYM4 and DB4 were confirmed to be useful, as shown in Ref. [6] and [7]. It was also found that other mother wavelets can be expected to be useful.

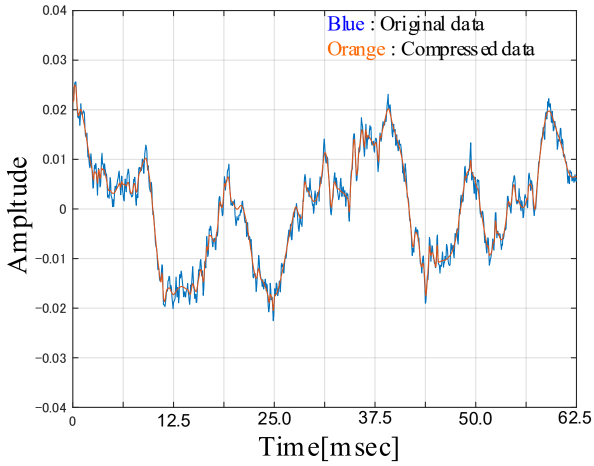

Figure 3: Comparison of Waveform diagram of Normal data using SYM4-Wavelet.

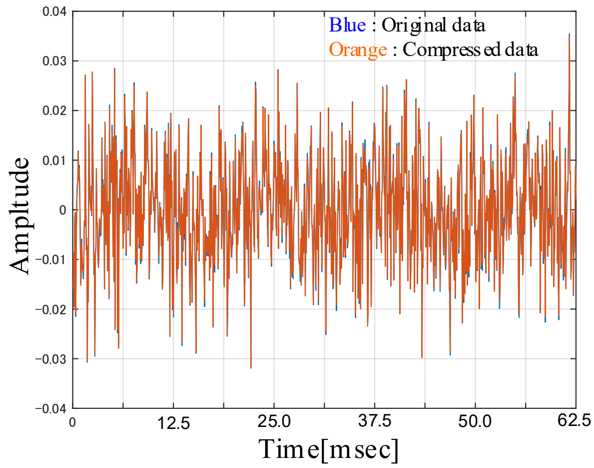

Figure 4: Comparison of Waveform diagram of Normal data using SYM4-Wavelet.

3.4 Dependence of Compression Rate on Threshold used for Analysis

The threshold value (T=0.0017) for compression with DWT was determined by performing compression using Matlab's Wavelet Signal Analyzer. We investigated the dependency of this value on the compression ratio R.

Using the Fan dataset as the sound source, Fig. 6 shows the change in compression ratio R when the threshold is changed. 50 pieces of data were analyzed for each and the average value was calculated.

Looking at this, we can see that the default value (T=0.0017) is exactly at the midpoint where the data size changes rapidly. Increasing the threshold decreases the compression rate R, but when we checked the played back waveform, we could see that it became increasingly distorted.

When compressing with DWT, the determination of the threshold is important. In the analysis that follows, we plotted the compression ratio R vs. the threshold, as shown in the figure, and derived a polynomial fit curve for the graph. Using this equation, we determined the threshold when R was 0.8, and used this value for the analysis. If we were actually archiving audio from a particular factory system, we would need to accurately measure this dependency on the threshold and optimize the value using the methodology used here.

3.5 Difference in Compression Rate due to Difference in Type of Sound Source

To confirm the contents of the previous section, we investigated how the compression rate differs depending on the type of sound source(Fan, Pump, Slider, Toy Car, Toy Conveyor, Valve, and toytrain) when the same threshold is set.

Figure 7 shows the compression rate of each sound source when the threshold is set to T=0.0025. 50 pieces of data for each were analyzed and the average value was calculated.

From this, we found that toytrain and other sound data have an extremely high compression effect.

4 EXPERIMENTAL RESULTS: CONTINUOUS WAVELET TRANSFORM OF COMPRESSED AUDIO DATA

4.1 Comparison of Raw Data and Compressed Data

Next, a CWT was performed on both the normal and abnormal sounds in the compressed voice data to create a scalogram that represents the signal strength on the time and frequency plane.

Figure 8 shows the scalogram of Normal raw data where Morse was used as Mother Wavelet. Fig. 9 shows the scalogram on Compressed data using the DWT of SYM4 Wavelet.

From this, it was found that by first compressing using the discrete wavelet transform, the components corresponding to the white noise that are common to both were suppressed, resulting in a distribution that makes it easier to determine the characteristics.

The abnormal data were analyzed in a similar manner. The results were shows in Fig. 10 and 11. Abnormal data has a high retention rate, but it is observed as a more characteristic figure.

4.2 Dependence on Motherwavelet

To investigate the dependence on Motherwavelet, a similar analysis was performed for two types of Motherwavelet, amor(Morlet) and Bump, in addition to the basic Morse.

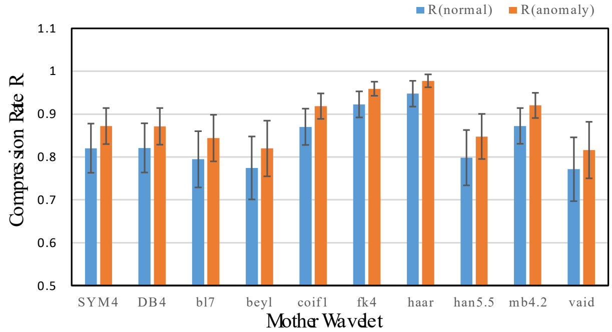

Figure 5: Comparison of Compression Rate R for different mother wavelets.

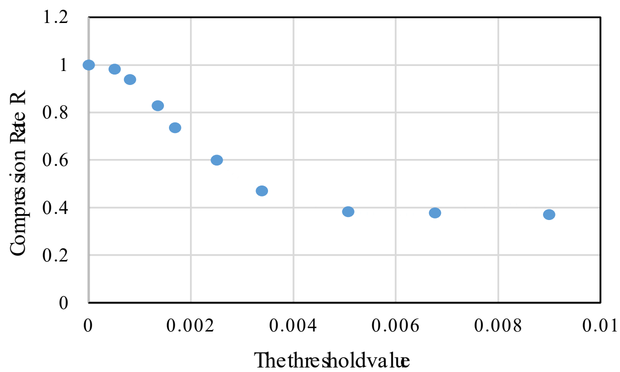

Figure 6: Comparison of Compression Rate R for the threshold value for compression with DWT.

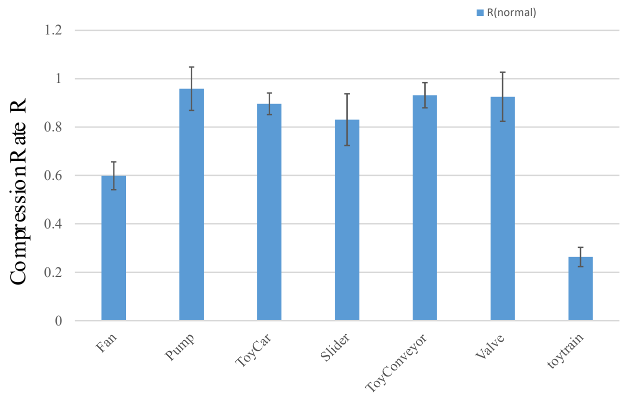

Figure 7: Comparison of Compression Rate R for depending on the type of sound source.

Figure 9 shows the case where the basic Morse-Wavelet were used as Motherwavelets for Normal data analysis, Fig. 12 shows amor(Morlet) and Fig. 13 shows Bump-Wavelet.

From Fig. 12, this scalogram was more widely distributed than in the case of Morse and Bump. So, Morlet was not suitable to handle this data.

From this, it was found that for continuous wavelets, differences in the scalogram appear depending on the mother wavelet.

The abnormal data were analyzed in a similar manner. The results were shows in Fig. 11 ,14 and 15. For Abnormal data, the distribution characteristics were completely different. By comparing Fig. 11 and Fig. 14, as expected, Morlet(amor) was found to be inappropriate for extracting features from this data.

On the other hand, in Fig. 15, the scalogram using Bump-Mother Wavelet, it was found only in a few places, and was very distinctive. Fig. 16 shows the scalogram of uncompressed data transformed by CWT using Bump. We can see that Bump is a wavelet that is quite suitable for extracting features from this Abnormal data.

This can also be derived by comparing Fig. 14(Morlet-Wavelet) and Fig. 15(Bump-Wavelet).

So, it is useful to first identify the wavelet that most clearly shows the characteristics of the target sound source.

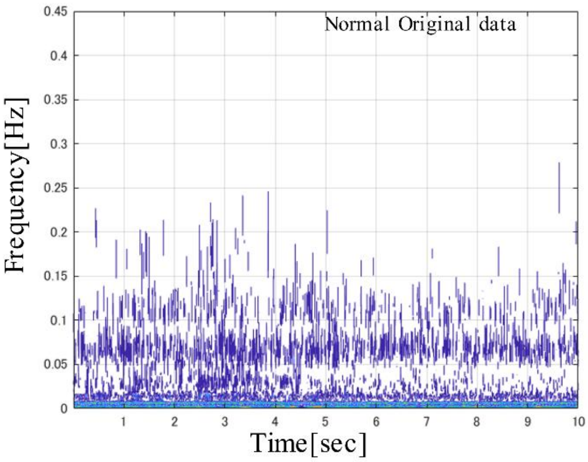

Figure 8: Scalogram of Normal Original Data.

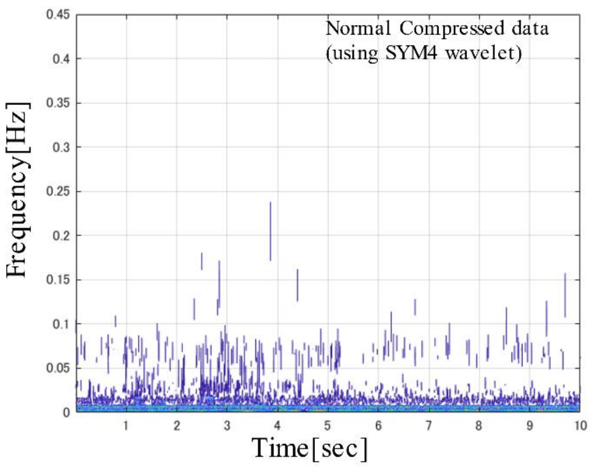

Figure 9: Scalogram of Compressed Normal Data(compressed using SYM4 Wavelet).

Since the range of the distribution of the scalogram is the very characteristics of the sound source, it is possible to use these distribution maps as data for machine learning to build a system that detects and judges abnormalities on behalf of humans.

These results confirmed that the proposed method makes it

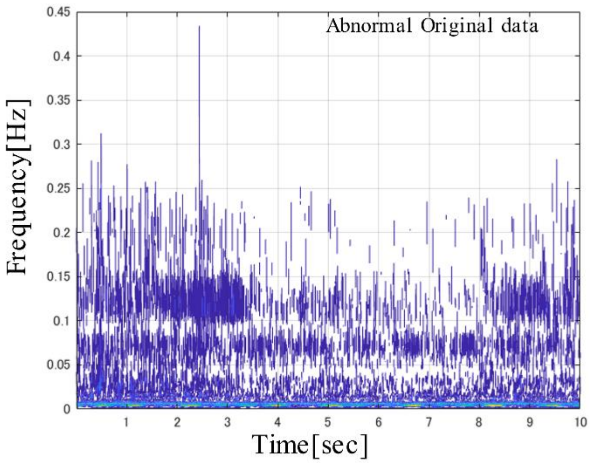

Figure 10: Scalogram of Abnormal Data.

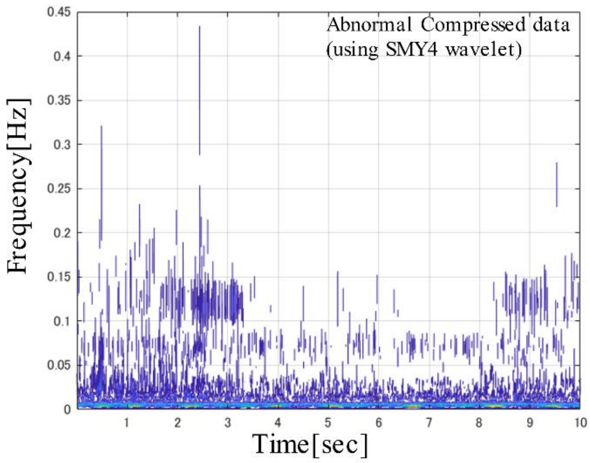

Figure 11: Scalogram of Compressed Abnormal Data(compressed using SYM4 Wavelet).

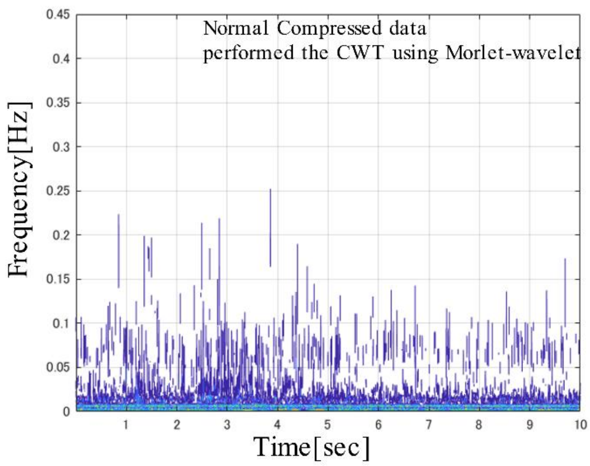

Figure 12: Scalogram of Compressed Normal Data for Morlet-Wavelet (compressed using SYM4 Wavelet).

possible to visually determine whether data is normal or abnormal even after compression, and that the file size can be reduced to 70% of original data.

5 DISTINGUISHING BETWEEN NORMAL AND ABNORMAL USING MACHINE LEARNING WITH SCALOGRAM IMAGES

5.1 Discriminating Audio Signals in a Surround Environment

We used MATLAB R2024a to perform machine learning using scalogram images as input data.

We used VGG16, a neural network with pre-trained weights for image recognition, to perform transfer learning on scalograms. As a dataset, we used 300 images each of normal and abnormal sounds. The trained network was used to classify audio data, and the percentage of data that was successfully classified was used as the validation accuracy. This calculation was performed three times with different random numbers, and the average value was calculated. As a condition for creating the scalogram, the mother wavelet used in the CWT was BUMP, which was found to be useful in the above analysis.

First, we calculated the validation accuracy for data that did not undergo DWT. However, since we assume that machine learning judgments will be made on audio data after it has been compressed using DWT, we also performed machine learning on the compressed data to calculate the validation accuracy.

SYM4 was used as the mother wavelet for DWT.

The types of audio data used were FAN [9-11], PUMP [9-11], and ToyTrain [12].

The results are shown in Table 1.

The validation accuracy for Fan and pump was very low. As previously reported, FAN contains a mixture of waveforms with a compression rate of 1, and various types of sounds are mixed into what is considered normal sound. Therefore, when performing DWT, it is expected that

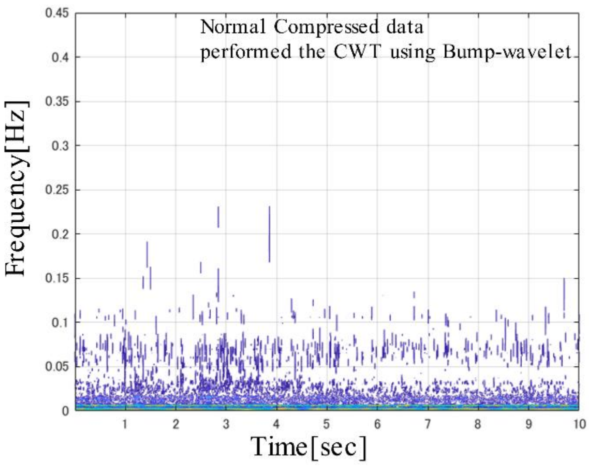

Figure 13: Scalogram of Compressed Normal Data for Bump-Mother Wavelet(compressed using SYM4 Wavelet).

verification accuracy will improve by optimizing parameters, particularly by changing the frequency resolution.

This analysis showed that it is possible to distinguish between normal and abnormal sounds even using data compressed with DWT.

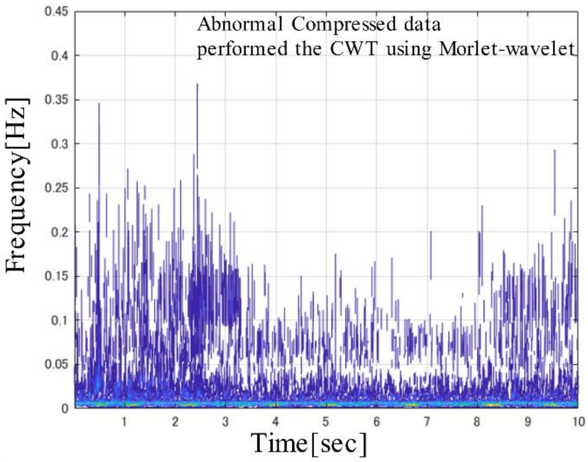

Figure 14: Scalogram of Compressed Abnormal Data for Morlet-Wavelet(compressed using SYM4 Wavelet).

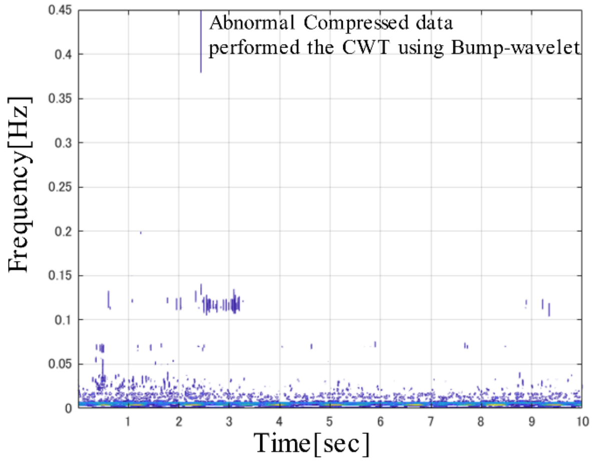

Figure 15: Scalogram of Compressed Abnormal Data for Bump-Wavelet(compressed using SYM4 Wavelet).

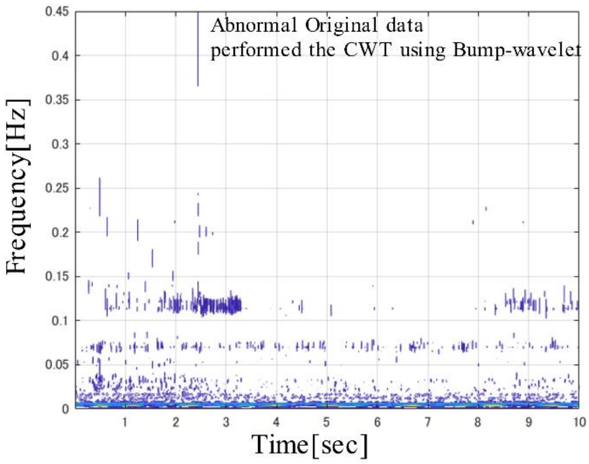

Figure 16: Scalogram of Abnormal Original Data for Bump-Wavelet(Uncompressed data).

It was also found that compression using DWT improves validation accuracy.

5.2 Comparison with Existing Audio Compression Methods

Next, we investigated whether there was a difference in the validation accuracy of machine learning depending on the compression method used to create the scalogram image to be input into machine learning.

To verify subtle differences in validation accuracy, we used the toytrain data, which had high validation accuracy in the previous analysis, changed the random numbers, calculated the validation accuracy 15 or 20 times, and calculated the average value.

Scalograms were created using uncompressed audio signals, audio signals converted to mp3 format (8 kbit/s), audio signals converted to mp3 format (16 kbit/s), and audio signals compressed using DWT (using SYM4-wavelet). Machine learning was then performed using these images as input to determine the verification accuracy for distinguishing between normal and abnormal audio.

The results are shown in Table 2.

This shows that the validation accuracy of anomaly detection using data compressed by DWT is higher than when data is compressed using other methods. Furthermore, it is possible to obtain values equivalent to those obtained when detection is performed using uncompressed data.

Figure 17 is a scalogram of the fan's voice, while Figure 18 is a scalogram of the data compressed with MP3. Comparing the two, it can be seen that Fig. 18 has mostly lost its high frequency range. As a result, information corresponding to the features in the image disappears, which is thought to reduce verification accuracy.

These analyses show that the use of wavelet transform is a useful compression method that can maintain the learning accuracy of machine learning.

6 SUMMARY

In this study, data compression was performed using discrete wavelet transform with SYM4, DB4 and some other mother wavelets. As a result, we found that using wavelet transform is useful as a compression method that can maintain the learning accuracy of machine learning. In addition, by performing continuous wavelet transform on compressed data, we were able to obtain characteristic scalograms in some cases.

We found that it is possible to treat the scalogram of a compressed audio signal as a simple two-dimensional image and use it as input data for machine learning to distinguish between different situations.

We also found that this method can maintain validation accuracy in machine learning.

Table 1: Comparison of validation accuracy using machine learning.

	validation accuracy(%)	
Audio Data	Without Compression	Compressed data
FAN	61.8	67.4
PUMP	89.9	91.1
ToyTrain	99.6	99.7

Table 2: Comparison of validation accuracy using different compression methods.

	Without Compression	Compressed data		
		MP3 8kbit/s	MP3 16kbit/s	DWT
validation accuracy (%)	99.6	95.9	97.7	99.6

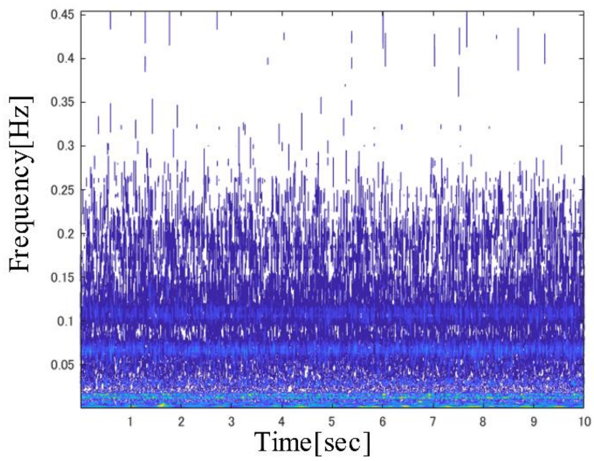

Figure 17: Scalogram of Normal Fan Data without compression.

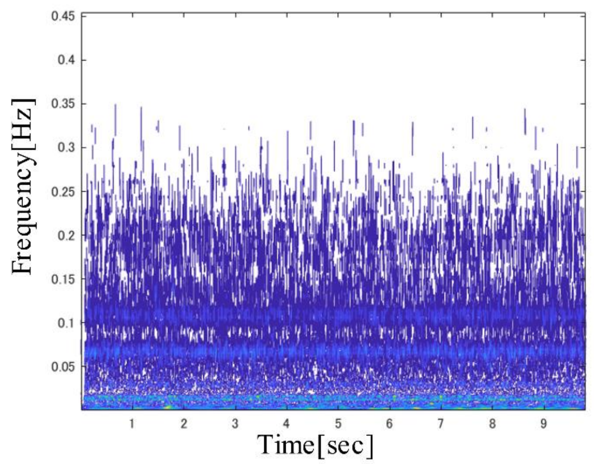

Figure 18: Scalogram of Normal Fan Data with compression using MP3.

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