Comparison of acoustical features for abnormal sound detection by OCSVM

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Abstract

As a method of inspecting the condition inside the pipe, a skilled engineer can know the abnormality of the pipe by sound. However, it is commonly thought that inspections using sound is difficult because sound is different how to hear depending on the person, and it takes an awful lot of time to examine all machines in a plant. In addition, machine learning came to be used easily on these days. We examine an approach to solve the problem using machine learning. In previous studies, anomalies from bearing noise was detected from acoustic features, using machine learning. In this research, we tried to detect anomalies from the flowing sound which measured on a flowing sound generator using the method. In addition, we used two types of acoustic features and we could determine at a higher rate than in the conventional method.

Keywords: Abnormal sound detection, Flowing sound, Acoustic features, One Class SVM

1. Introduction

In order to operate a machine safely, it is very important to detect abnormalities quickly and accurately. However, it is extremely difficult for a human to keep monitoring the machine, and the detection of abnormalities by humans is unstable due to differences in how they hear. In previous studies, machine learning techniques was used to detect anomalies. Ito et al. was used Mel-Frequency Cepstrum Coefficient (MFCC) as acoustic features, and they detected anomalies from bearing noise using One Class Support Vector Machine (OCSVM) (1). MFCC is one of the acoustical features and is popular as a method of sound recognition. OCSVM is a method to regard normal data as one class and detect other than normal data(2,3). The one of the merits of OCSVM can detect abnormal data by using results of learning only normal data.

In this research, we tried to detect anomalies from the flowing sound which measured on a flowing sound generator. Inspecting the condition inside the pipe is important to prevent pipe clogging. If it becomes possible to judge pipe abnormalities by sound, it will be possible to judge abnormalities in the entire plant together with mechanical abnormalities using a same system. To verify the effectiveness of our system, we made a flowing sound generator and measured the sound flowing through the pipe in a laboratory.

First, we used MFCC as the acoustic feature and tried to detect anomalies from flowing sounds using the machine learning. In this research, a state where the flow rate of water through the pipe is low is regarded as abnormal. However, the conventional method could not detect the condition with low flow rate as abnormal. To solve the problem, we used other acoustic features such as effective value, maximum value, crest factor, modulation value, kurtosis and skewness of the sound. Using those features, we could detect anomalies at a higher rate than in the conventional method.

2. Judgment of abnormal sound

2.1 System overview

If an abnormal sound is required when constructing a judgment system, the introduction cost will increase. Especially, it may also be difficult to collect abnormal sounds. Therefore, in this research, we are examining the judgment system using OCSVM of unsupervised learning method that can judge only with normal sound data. Fig. 1. shows the setup of the judgement system using OCSVM. It can detect outliers as abnormal, it uses acoustic features extracted from measured sound as features for learning. In previous research,
the MFCC has been used as an acoustic feature. Fig. 2. presents the procedure of extracting the feature values. In previous research, MFCC was calculated from every 0.2 seconds of frames obtained by dividing 30 seconds of sound data. First, we used MFCC as the acoustic feature and tried to detect anomalies from flowing sounds using OCSVM

2.2 Flowing sound generator

In this research, the flowing sound was measured with a flowing sound generator. Fig. 3 presents are schematic diagrams of the flowing sound generator. The flowing sound generator has water tanks arranged above and below, and there is a pump for pumping water from the sewage tank. Two water tank are connected by a hose and a pipe with a nominal diameter of 50 mm (inner diameter 51 mm). A flow meter for measuring the flow rate and a valve for operating the flow rate are arranged on the water tank side. Flowing sounds are obtained by a microphone attached to the middle of the pipe.

2.3 Measurement and abnormality judgement

Flowing sound was measured using MATLAB. The sampling frequency is 50 [kHz] and the measurement time is 30 seconds. In this way, we obtained the both high flow rate sounds and low flow rate sounds. To use the proposed system for pipe clogging detection, it is assumed that the sound with high flow rate and low flow rate is normal and abnormal sound respectively. We measured 81 sound data with a flow rate of 9.0 [L / min] and 18 sound data with a flow rate of 2.5 [L / min] to obtain a total of 99 sound data. After those data were divided into 0.2 seconds long, acoustic features (MFCC) was calculated for each data.

2.4 Result and discussion

Fig. 4 shows the experimental results. The horizontal axis represents the data number (1 to 99) and the vertical axis represents the ratio of abnormal sounds (0 to 1.0). The 30-seconds of sound data obtained by one measurement is divided.
into 150 data of every 0.2 seconds length. In OCSVM, normal/abnormal judgment is made for each sound of 0.2 seconds. The ratio of vertical axis in Fig. 4 indicates the percentage of 150 sounds determined to be abnormal. Numbers 1 to 81 in Fig. 4 are the results of using the same data as the training data and test data, then the 1st to 81st sound data should be detected to be normal, and the 82th to 99th sound data should be detected to be abnormal.

In Fig. 4, although the results of the data number from 1 to 81 were judged to be partially abnormal, they were generally judged to be normal. However, the all results of the data number from 82 to 99 were judged to be normal, they are expected to be judged abnormal. In addition, the data immediately after the start of measurement (data numbers from 6 to 8) were determined to be abnormal.

From the experimental results, it was not possible to judge the flowing sound in the same procedure as in the conventional method. Therefore it is necessary to verify the appropriateness for MFCC as acoustic features. Therefore, it is necessary to consider a novel acoustic features.

### 3. Proposed method

#### 3.1 New acoustic features

As a novel acoustic feature, we used the effective value, maximum value, crest factor, modulation value, kurtosis and skewness of the sound. Fig. 5. shows a method of extracting these acoustic feature values. We split 30 seconds of sound data every 0.2 seconds and process with 7 band pass filters. The time domain is transformed into the frequency domain by performing a discrete Fourier transform on those. Then, by taking the logarithm of the data and performing an inverse discrete Fourier transform, the data is converted into a quefrency domain. The effective value, maximum value, crest factor, modulation value, kurtosis and skewness were calculated for each of the time domain, frequency domain, and quefrency domain created in this process, and were used as acoustic features.

#### 3.2 Result and discussion

The same sound data as in Chapter 2 was used, and the details of training data and judgment data were also verified under the same conditions. Fig. 6. shows the results of the proposed method. From these results, while the abnormal sound data was judged to be normal by the conventional method, about 40 to 50% of the results were judged to be abnormal by the proposed method. Although the result of determining the data at the beginning of measurement as abnormal was not changed by proposed method, the number of data detected as abnormal was reduced.

From the experimental results, the proposed method is able to judge that the sound with a low flow rate was abnormal as compared with the conventional method. However, since the ratio of judgments as abnormal is as low as 40 to 50%, it is necessary to improve this part. Specifically,
it is considered that there is a method of reviewing data used as an acoustic features and changing a hyperparameters in OCSVM.

4. Conclusions

In this research, we made a flowing sound generator, and we verified the judgement system of flowing sound. We assumed that the sound with high flow rate is normal and tried to predict that the sound with low flow rate is abnormal sound using conventional method. However, abnormalities could not be correctly determined by the method. To solve the problem, we proposed a method using new acoustic features, and about 40 to 50% were determined to be abnormal by the proposed method. It is considered that the proposed method has the possibility that the rate of judgement an abnormality can be improved by changing the hyperparameters of OCSVM, and the accuracy can be improved by reviewing the acoustic features. In this research, verification was performed using 99 data, but it is necessary to obtain more sound data and to verify assuming various situations.

References

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