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A Fault Detection Approach Based on Sound Signal Analysis for Equipment Monitoring

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ABSTRACT

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Machine fault detection has great practical significance. Compared with the detection method that requires external sensors, the detection of machine fault by sound signal does not need to destroy its structure. The current popular audio-based fault detection often needs a lot of learning data and complex learning process, and needs the support of known fault database. The fault detection method based on audio proposed in this paper only needs to ensure that the machine works normally in the first second. Through the correlation coefficient calculation, energy analysis, EMD and other methods to carry out time-frequency analysis of the subsequent collected sound signals, we can detect whether the machine has fault.

Keywords : Sound Signal, Fault Detection, Time Domain Analysis, Frequency Domain Analysis

I. INTRODUCTION

A. Background and Motivation

Although machines with high accuracy and efficiency are gradually replacing human labor in various industries, we cannot completely avoid the occurrence of errors. It is as important to supervise a machine as to make sure it is working. The simplest method is manual supervision. To ensure the efficiency of supervision, a worker is required to supervise several machines at the same time, which carries a considerable risk of missing out. If every worker is only responsible for one machine, it still needs a lot of labor costs [1]. So intelligent fault monitoring is very necessary.

B. Existing Approach

There are many methods to detect faults. Some need to add external devices such as sensors outside the equipment to detect vibration, current, temperature and other parameters to collect data [2]. For example, Gheorghe Serban [3] detects speaker degradation and other faults by measuring speaker consumption current and external voltage. Many acoustic fault detection methods are often used for a single type of device, and for detecting specific known fault types [1][4][5]. Existing methods detect specific faults by feature extraction and using different machine learning techniques such as such as k-nearest neighbor classifier (KNN), support vector machine classifier (SVM), kernel linear discriminant analysis (KLDA) and sparse discriminant analysis (SDA) [6].

C. Limitations of Existing Art

According to the above, many prior approach have higher requirements for the installation and commissioning of external devices. Using acoustic method to detect faults can effectively avoid the problems caused by the above methods.

Because the working principle of different machines is different and the sound characteristics of different faults are different, many sound-based fault detection methods only aim at specific machine faults. This makes the system in the application scenario has limitations. Even the same type of faults, the monitoring effect of the system is not stable due to different machine models.

II. PROBLEM ANALYSIS AND SYSTEM DESIGN

From experience, it can be seen that the sound is relatively regular on the whole when the machine is working. The sound of a machine will change when it breaks down, and there will be certain trends and patterns in the changes. So it is possible to collect a piece of audio when the machine is working for analysis and the obtained audio is divided into a number of seconds for further processing.

A. Problem Analysis

Through the time-domain waveform of the audio, the changing trend of the sound can be found. We collected a piece of audio from the microphone while the machine was working, and preprocessed it to get the mono data for 10 seconds. In this audio, the machine malfunctioned from the seventh second.

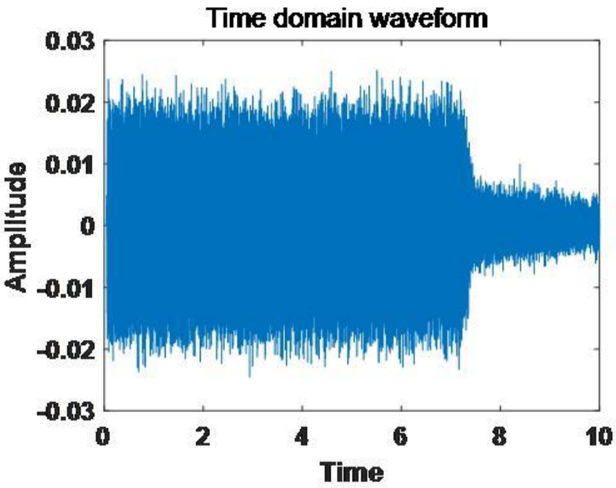


Figure 1. The time-domain waveform.

Figure 1 shows the time-domain waveform of the audio. It can be clearly seen that the image changes from the 7th second, and the trend gradually flattens out.

B. Two Low - Complexity Algorithms

We analyze the feasibility of using low complexity algorithm for fault sound recognition in two ways.

1) Audio Energy Analysis

From Parseval's theorem of the discrete signal, the total energy calculated in the time domain is equal to the total energy calculated in the frequency domain, as shown in Formula (1) .

$$\sum_{0}^{N-1} |x(n)|^2 = \frac{1}{N} \sum_{0}^{N-1} |x(k)|^2 \tag{1}$$

Where $x(n)$ is a time-domain sequence, $x(k)$ is a frequency-domain sequence, N is the sequence length.

The energy per second of this audio can be calculated, as shown in Figure 2.

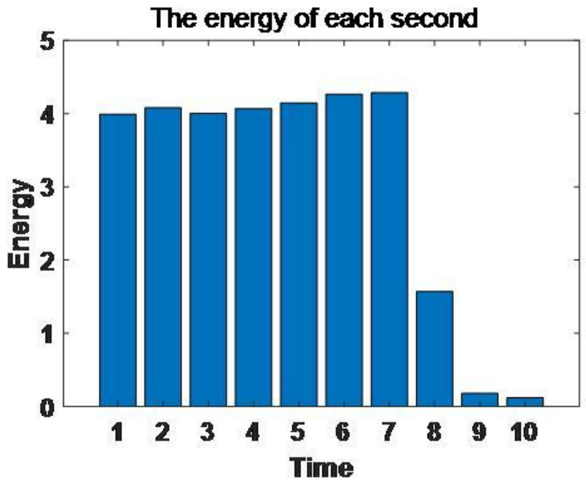


Figure 2. The energy of sound signal

As shown in Figure 2, the energy of this audio from the 8th second is significantly less than that of the previous seconds. But the malfunction started at the 7th second. Although this method can identify the fault, but can not accurately identify the time when the fault occurred.

2) Hilbert–Huang Transform Analysis

The Empirical mode decomposition (EMD) method divides the signals by frequency from high to low sieving into a series of sum of IMF components. After the original signal is decomposed by EMD, the instantaneous frequency can be obtained by applying Hilbert–Huang transform to the decomposed IMF components. Then the instantaneous spectrum of all IMF components is synthesized to obtain the signal's Hilbert spectrum, as shown in Figure 3.

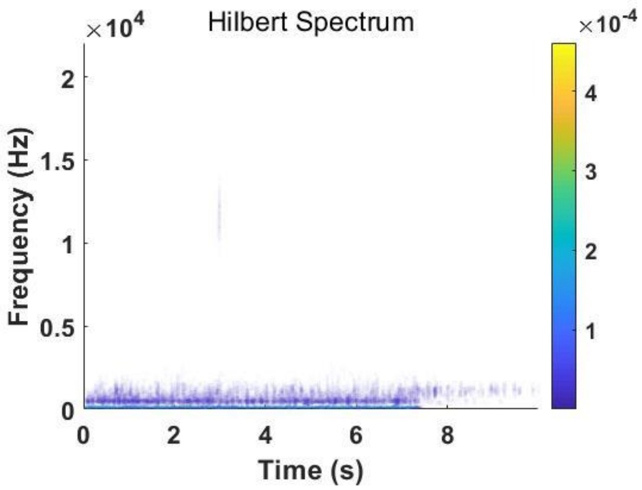


Figure 3. The instantaneous energy diagram of each point in the IMF

In the image, the frequency and energy change at the 7th second, but there is interference between the frequencies, and the computation is large.

C. Correlation Coefficient Analysis

The two low-complexity Algorithms mentioned above have some drawbacks. When a machine breaks down, if the sound changes a lot in a short period of time, there is an obvious error in using energy to identify the fault. The Hilbert - Huang transform is computationally complex and requires a high level of hardware performance, which adds to the cost.

So we use a correlation algorithm to realize the fault detection based on audio.

We divided the 10 seconds audio into 10 equal lengths of 1 second each, and 10 data sets of 44,100 lengths, numbered from α_1 to α_{10} . Then we use Formula (2) to calculate the correlation Coefficient of two adjacent sets of data.

$$r(\alpha_i, \alpha_{i+1}) = \frac{Cov(\alpha_i, \alpha_{i+1})}{\sqrt{Var[\alpha_i]Var[\alpha_{i+1}]}} \qquad (2)$$

In Formula (2), i is the number of seconds. $Cov(\alpha_i, \alpha_{i+1})$ represents the covariance of the two. $Var[\alpha_i]$ is the variance. The corresponding results are stored in $\rho_{i,i+1}$.

Correlation coefficient is a statistical index to reflect the degree of correlation among variables. We focus on the value of the coefficient, not the direction of correlation. Thus, the correlation coefficient for every two seconds is calculated as shown in Table I after taking the absolute value.

TABLE II. THE CORRELATION COEFFICIENTS OF PER TWO SECONDS

$\rho_{i,i+1}$	**Correlation coefficient**
$\rho_{1,2}$	0.4308
$\rho_{2,3}$	0.4564
$\rho_{3,4}$	0.7102
$\rho_{4,5}$	0.4741

$\rho_{5,6}$	0.5601
$\rho_{6,7}$	0.5760
$\rho_{7,8}$	0.1887
$\rho_{8,9}$	0.0591
$\rho_{9,10}$	0.0520

Where $\rho_{1,2}$ represents the absolute value of the correlation coefficient between the first and second seconds, and the like.

The failure of this audio is known to begin at the seventh seconds. In the above table, the values starting from $\rho_{7,8}$ are all significantly less than the previous 6 values.

To improve the accuracy of our judgment, we took the first second of audio and divided it into 10 equal bands, each with a length of 100 milliseconds, numbered from β_1 to β_{10} .

All the audio in the first second is produced when the machine is working properly. We calculate the correlation coefficient between any two of these 10 audio segments in the same way and get the mean E_r . E_r has a value of 0.4325.

$$\gamma = \lambda E_r \tag{3}$$

In Formula (3), γ is the threshold to determine whether the machine is malfunctioning. Where λ is the coefficient of accuracy. The criteria are shown in Formula (4).

$$\begin{cases} \rho_{\mathrm{i,i+1}} \geq \gamma, 0 \\ \rho_{\mathrm{i,i+1}} < \gamma, 1 \end{cases} \tag{4}$$

Where the 0 means the machine is working properly and the 1 means the machine is malfunctioning. And the result of $\rho_{\mathrm{i,i+1}}$ corresponds to the working condition of seconds $i+1$. We set the value of λ to 0.5, and the result is shown in Table II.

TABLE II

THE CORRELATION COEFFICIENTS OF PER TWO SECONDS

$\boldsymbol{\rho}_{\mathbf{i,i+1}}$	**The Second**	**Working condition**
$\rho_{1,2}$	2	0
$\rho_{2,3}$	3	0
$\rho_{3,4}$	4	0
$\rho_{4,5}$	5	0
$\rho_{5,6}$	6	0
$\rho_{6,7}$	7	0
$\rho_{7,8}$	8	1
$\rho_{8,9}$	9	1
$\rho_{9,10}$	10	1

As shown in the table above, the results show that the machine malfunctioned from the 8th to 10th seconds.

III. EXPERIMENT AND CONTRAST

A. Experimental Data Collection

We fixed the microphone at a distance of 5 cm from the target machine, to ensure that the sound acquisition process does not affect the operation of the machine. The data is pre-processed to ensure that each audio is 10 seconds, and the sound recorded in the first second is during normal operation. We selected three different types of machines and marked them as A, B, and C. Each machine was given two sets of 10 second audio recordings, labeled 1 and 2. At the same time we record each group of data corresponding to the working state of the machine, as shown in Table III.

TABLE III. EXPERIMENTAL DATA AND WORKING STATE OF EACH MACHINE

Machine	**Audio number**	**Starting and ending time of fault**
A	1	Normal working
	2	8 to 10 seconds
B	1	3 to 6 seconds
	2	4 to 8 seconds
C	1	2 to 6 seconds
	2	7 to 10 seconds

The audio A1 in the table above is 10 seconds of data collected while the Machine A is working normally. The audio A2 is 10 seconds of data collected on Machine A, where a failure occurred from 7th to 8th seconds. It's the same with the others.

B. Experimental Results

1) The Result of Correlation Coefficient Analysis

In Formula(3), we take the value of λ to be 0.5. The test results of the working state of the machine are shown in Table IV.

TABLE IV. DETECTION RESULTS BY CORRELATION COEFFICIENT ANALYSIS

Sounds of each machine		**Second**									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
A	**1**	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	1	1	1
B	**1**	0	1	0	1	1	1	0	1	1	0
	2	0	0	0	0	0	1	1	0	1	0
C	**1**	0	1	1	1	1	1	1	1	1	1
	2	0	0	1	1	1	0	1	1	1	0

In the table above, the 0 means the machine is working properly and the 1 means the machine is malfunctioning. For A1, the test results are all normal within 10 seconds. For A2, the results show that the failure occurred from 7th to 8th seconds. For Machine B and C, there are some errors in the test results. The detection accuracy for each second is 73.3% and failure omission rate is 8.3%

2) The Result of Audio Energy Analysis

In order to present the results in numerical form as well, we use Formula (5) as the criterion.

$$\begin{cases} E_i \geq \mu E_1, 0 \\ E_i < \mu E_1, 1 \end{cases} \tag{5}$$

Where E_i means the energy of second i. μ is the coefficient of accuracy and we take a value of it to be 0.5. In the test results, 0 indicates that the machine is working normally, and 1 indicates that the machine is malfunctioning. The test results of the working state of the machine are shown in Table V.

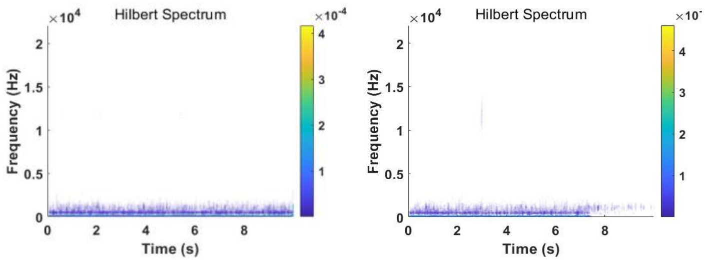
TABLE III. DETECTION RESULTS BY AUDIO ENERGY ANALYSIS

Sounds of each machine		**Second**									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
A	**1**	0	0	0	0	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	1	1	1
B	**1**	0	0	0	1	0	0	0	0	0	0
	2	0	0	0	0	0	0	0	0	0	0
C	**1**	0	0	0	0	1	0	0	0	0	0
	2	0	0	0	0	0	0	0	1	1	1

As can be seen from the table above, this method is also correct for machine A. But for machine B and C, the error is large. The detection accuracy for each second is 76.7% but failure omission rate is 21.7%.

3) The Result of Hilbert–Huang Transform Analysis

The Hilbert–Huang transform method has a large amount of calculation, and the results of Hilbert–Huang transformation of each data in the experiment are shown in Figure 5.



A1 A2

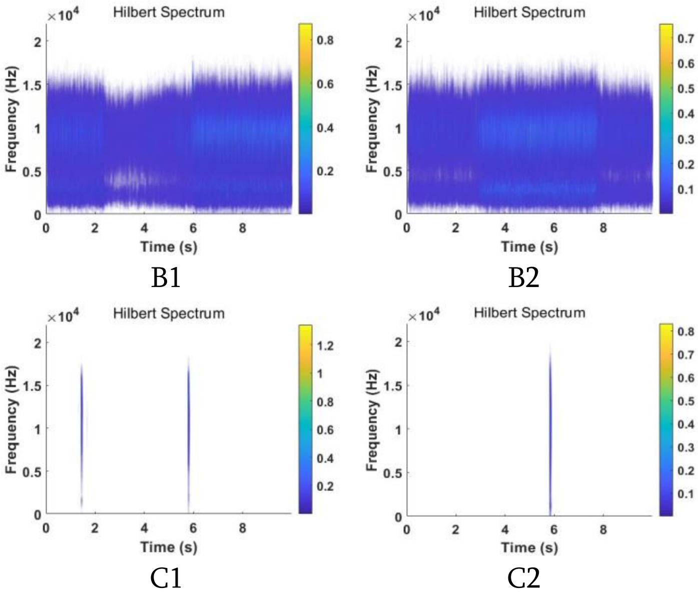


Figure 4. the results of Hilbert–Huang transformation of each data in the experiment

As A1 and A2 in Figure 4 show, for Machine A, the time of failure can be determined by the disappearance of a frequency. As shown in Figures B1 and B2 in figure 4, for Machine B, the time of failure can be determined by the change in the energy represented by the color of the image. As C1 and C2 in figure 4 show, for Machine C, the start and stop time of a failure can be determined by the appearance of the energy represented by the color. Therefore, it is difficult to use the same method to detect different machine faults.

C. Analysis of Experimental Results

The method of Hilbert–Huang Transform analysis has a large amount of computation and can not be well applied to all kinds of equipment. For different machine faults, both of correlation coefficient analysis and audio energy analysis have similar detection accuracy , but the failure omission rate of the latter is much higher than the former. In the practical application scenario, if the machine failure is not detected in time, it may cause huge economic loss and even threaten the worker's health. Therefore, from the point of view of ensuring that the failure is found as far as possible, the method of correlation coefficient analysis is better.

IV. RELATED WORK

Acoustic based fault detection methods are often used for a fixed type of equipment, such as bearings, motors, etc., and for detecting specific known fault types. The commonly used methods of sound fault recognition involve more complex calculation, such as using wavelet transform to process sound signals [7]. Some detection methods use neural networks and other popular technologies, such as Feng Tao[8]'s micro motor fault diagnosis method based on CNN and sound time-frequency characteristic map, which needs to prepare a large number of data to build the model, and the time and calculation costs are also large. Amarnath used artificial neural networks (ANNs) and support vector machines (SVMs) to monitor gear transmission. The features extracted from the measured vibration and sound signals were mean, root mean square (rms), variance, skewness, and kurtosiswere used as an input features [9]. Yongzhi Qu's team proposed a novel method named augmented deep sparse autoencoder (ADSAE), which can be used to diagnose the gear wearing fault with relatively few raw vibration signal data [10]. They also proposed a fully unsupervised feature extraction method for “meaningful” feature mining, named disentangled tone mining, which can effectively extract the hidden “trend” associated with machinery health state [11]. Nowadays, the way of monitoring fault by sound signal has been applied in more professional scenes. To recognize HV circuit breaker fault, Yang used K-S test to search the intervals where the amplitude distributions of fault signals and normal signals were very different. By analyzing a number of characteristics of the maximum contribution, the mechanical fault diagnosis was achieved [12]. Jonguk extracted mel-frequency cepstrum coefficients (MFCCs) from audio data and employs support vector machines (SVMs) for early detection and classification to efficiently detect and diagnose faults in railway condition monitoring systems[13]. Mollasalehi Ehsan analyzed tower vibration signals by using Empirical Mode Decomposition to indicative fault diagnosis of the wind turbine tower [14]. Luo identify the insulation state of vacuum circuit breaker by the method of using of MFCC feature extraction based on Fisher criterion and one-class support vector machine [15].

V. CONCLUSION

In this paper, we propose a series of machine fault detection methods based on audio, which have universal applicability. Without destroying its original structure, only microphone is used to collect the working sound of the machine. By segmenting the audio, only one segment of normal working data is needed to detect the subsequent working sound with an accuracy of 73.3%. Experiments show that this method can be applied to many kinds of equipment and can detect unknown faults. And this method has a low failure omission rate, can better maintain the good working condition.

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