The fault re-decision method based on the different decreasing functions

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Original Article

Keywords: fault diagnosis, key-delay

Posted Date: April 9th, 2021

DOI: https://doi.org/10.21203/rs.3.rs-306546/v1

Abstract

The fault diagnosis method (FDM) is widely used in machine operation and maintenance. However, the wrong decision made by the FDM might cause the machine unnecessarily to shut down. To reduce the number of false alarms, this paper proposes a fault re-decision method based on the key-delay technology. The original data from sensors are inputted into the inner fault diagnosis method (IFDM) and the proposed method only employs the results from the IFDM as the input. Then according to the improved key-delay technology and comprehensive consideration of current result and previous results, the re-decision is given. To illustrate the proposed method, a case study on gear is presented in this paper, which shows that the proposed method does decrease the false negative rate.

1 Introduction

Table 1. Nomenclature

Abbreviation	Full phrase
FDM	fault diagnosis method
IFDM	inner fault diagnosis method
EMD	empirical mode decomposition
IMF	intrinsic mode functions
EAED	extreme average envelope decomposition
LS-SVM	least-square support vector machine
SVM	support vector machine
ELM	extreme learning machine
DNN	deep neural network
CNN	convolutional neural network
DBN	deep brief network
SCM	single-chip microcomputer
ANN	artificial neural network

Nowadays, industry has become one of the most important things to a country. The machine plays an important role in the modern industry. With the development of science and engineering, more and more sensors have been placed in the machines. Using the data generated by the sensors, many FDMs have been developed. As the time goes on, the FDMs have also been improved. In the era of the Industrial Revolution when people used the machine on a large scale for the first time, the workers rely on manual observations of the machine to determine whether it is on a normal status. After some time, people get to know some machine principles. They started to use some features to judge the operating status of a machine. The data from the machine, such as acceleration, is collected and analyzed with various methods, such as empirical model decomposition (EMD) [1]. Recently, the machine learning technology is a hot topic and has been used widely in fault diagnosis. Although many FDMs could achieve over 95% accuracy [2], noise or other factors may still cause false alarms. A false alarm may interrupt the normal operation of a device and lead to the damages of people and property. Therefore, it is necessary to avoid the occurrence of false alarms, e.g., reducing the false negative rate.

Blanke et al. [3] shows how violations of normal behavior of main components can be detected and isolated for a complex automation system with the use of a functional service philosophy and fault accommodation techniques. Parey et al. [4] applied EMD to decompose signal into intrinsic mode functions (IMFs), then variable cosine window was used for IMFs to minimize boundary distortion problem and statistical parameters of IMFs were used for gearbox diagnosis. In [5], Hu et al. proposed a new method combining the multi-masking empirical mode decomposition and fuzzy c-means clustering to do fault diagnosis. A set of experiment in wind turbine was used to verify its validity and high accuracy. HerTerng et al. [6–7] applied the chaotic system and fractal theory to the ball-bearing fault diagnosis. In [8], extreme average envelope decomposition (EAED) method is presented based on EMD aiming at the problems of mode mixing and low decomposition accuracy.

Machine learning theories have been applied widely for machine fault diagnosis in recent years [9–11]. In Heydarzadeh and Nourani [12], a model-based method is adapted into a data-driven method. A least-square support vector machine (LS-SVM) is used to generate system residuals, which are analyzed by discrete wavelet transform to detect the sensor faults and plant faults. Li et al. [13] proposed a new diagnosis model based on the wavelet packet decomposition approach and support vector machines. An intelligent time-adaptive ensemble extreme learning machine (ELM) based data-driven FDM for sensors in power drive systems is proposed in Gou et al. [14].

With the development of massive computing ability of modern computers, deep learning has become a hot topic in fault diagnosis. deep neural network (DNN) and other deep learning theories are used for the fault diagnosis [15–19]. A DNN-based intelligent method using massive related data for training is proposed by Jia et al. [20] to diagnose the faults of a rotating machinery. Janssens [21] extracted the absolute amplitudes of the frequency spectrum using two accelerometers and a convolutional neural network (CNN) with one convolutional layer was designed to learn useful features for bearing fault detection. Chen et al. [22] proposed a novel approach by integrating CNN and ELM to diagnose faults of motors and gearboxes. To extract features with high quality, a deep learning approach based on deep belief networks (DBN) is developed to learn features from frequency distribution of vibration signals in [23].

The FDMs mentioned above could achieve the accuracy rate from 60% to 95% [2], but false alarms still can occur. It is difficult to change their structures or hyperparameters to reduce the false negative rate and keep the accuracy rate unchanged at the same time.

To overcome the aforementioned weakness, a new method named fault re-decision method based on the key-delay technology is proposed for decreasing the false negative rate at the cost of a loss in fault response speed. Experimental results demonstrate the effectiveness of the proposed method in decreasing the false negative rate of the FDM. The main contributions of this paper are summarized as follows.

1) The IFDM is considered as a digit key. The results given by the IFDM are considered as the actions of the digit key. Thus, the normal results and abnormal results given by the IFDM are regarded as two states

of “off” and “on”, respectively. It makes the IFDM abstract and improves its versatility.

2Compared with the origin key-delay method that uses a single result, our proposed method uses several following results given by the IFDM, which makes the results more reliable.

3) This method uses different rates for increasing and decreasing. In this paper, a constant rate is used for increasing and the rate for decreasing is determined by the decreasing function. The differences between the rates for increasing and decreasing play a major role in this method.

Section 2 details the basic of the proposed method and the proposed method is laid out in section 3. An experiment is implemented to verify the proposed method with the real data in section 4 and section 5 concludes this paper.

2 The Basic Of Proposed Method

In this paper, it assumes that the distribution of the wrong results from the IFDM is uneven and unknown. Since if the wrong diagnosis results are distributed evenly and known, we would use some kinds of methods or tools, such as giving an opposite input based on their known interval, to eliminate the effects of noise and get the right diagnosis result.

The single-chip microcomputer (SCM) is a single chip of silicon that contains the processor, memory and input/output logic. The SCM system is mainly consisted of the SCM and other components, such as power supply and RS−232 serial port. Due to the SCM system’s low energy consumption, low cost, and other advantages, it is widely used as a controller in many areas, including home appliances, wearable devices and so on.

As an input device, the key plays an important role in human-computer interaction. People could use it to input numbers and letters. However, a problem how to judge whether the key is on affects the efficiency of the SCM system at early stages. The key usually consists of two contacts and a connector. Its structure diagram is shown in Figure 1 (a). When the two contacts are connected by the connector, the key is on and the link is open, otherwise, it is off.

Ideally, the switching process should be completed instantly, which is shown in Figure 1(b). But in reality, there will be voltage fluctuations, which is shown in Figure1(c), throughout the whole process if no corresponding measures are taken. Due to these fluctuations, the SCM may get a wrong conclusion about the status of the key. Even worse, as the time goes by, the conclusion may change continuously between these two states, which might affect the normal operation of the system or even damage the entire system.

To address this problem, the key-delay technology is proposed. It uses a time delay to eliminate the effects brought by the fluctuations. When the SCM system detects a signal that shows the state of the key is changing from A to B, a delay starts and the delay time is determined by the program. After the delay, the SCM system would try to detect the signal again. If the final signal shows the key is on the

state B, that the key is truly on state B will be obtained. But if the final signal shows the key is still on the state A, the SCM system would conclude that the previous signal was caused by noise. The flowchart is shown in Figure 2.

3 The Proposed Method

00The architecture of the proposed re-decision method is illustrated in Figure 3. In the proposed method, the results from the IFDM are used as the input of the whole re-decision method. Then, the process goes on depending on the judgements of the input. Finally, a re-decision result is given. The detailed processes of this method are described in Figure 3.

where f(x) is the decreasing function; N is the delay time; OK is the timer; R is the total fault number; FA is the A type fault number.

In the proposed method, one decreasing function and two variables named “R” and “N”, respectively, are important. The decreasing function produces decreasing value. “R” represents the reliability of the results determined by the IFDM that shows the monitored machine system is abnormal. If “R” is 0 or other small number, it means that the result has a low reliability, otherwise, it is highly reliable. The proposed method uses “R” as the input of the decreasing function to calculate magnitude of the decrease. “N” represents the counting distance from the next alarm and is the sum of the decreasing function. It is obtained by the following equations:

$$N = f1+f2+f3+\ldots+f(n) \quad (1)$$

where f denotes the decreasing function, n is the delay number.

Like the key-delay technology for SCM system, before the method runs, the delay number should be set to an appropriate value. It is determined based on the experience and situation. In the proposed method, the delay number means that if the number of the results from the IFDM which show the monitored machine system is in an abnormal state is equal to the delay number, an alarm will be send out by the proposed method.

After setting the delay number, the IFDM and the proposed method run together. The data from the sensors in the monitored machine system is input into the IFDM and the results from the IFDM are input into the proposed method. According to the different types of the results, the results from the IFDM that show the monitored machine system is in normal operation are considered as “0” and those noted as faulty by the IFDM are regarded as 1, 2, 3, etc. based on the fault type. This step ignores the details of the IFDM and only cares about the results of it, e.g., the proposed method simplifies the IFDM and improves its own versatility.

If the input is 0, which means the IFDM thinks the monitored machine system is running normally, the proposed method will determine whether OK is equal to N. If equal, “R” and other variables are reset to their initial values. If not, OK plus one. If the input is not 0, which means the IFDM thinks the monitored

machine system is running abnormally, the proposed method will reduce OK by the decreasing function value.

OK = OK-fR

where f is the decreasing function, and R is its input.

Then the proposed method will determine whether the new OK is less than or equal to 0. If so, an alarm will be sent out and all variables will be reset to their initial values. If not, “R” plus one.

4 Experiment Analysis

4.1 Parameters setting strategy

The false negative rate is calculated by

$$false\ negative\ rate = \frac{the\ false\ negative\ number}{the\ ture\ positive\ number + the\ false\ negative\ number} \qquad (2)$$

In the algorithm flowchart of the proposed method, the delay time and the decreasing function are the most important parameters. The value of the delay time directly determines the response time to fault. And the decreasing function determines the distance to decrease. It not only has an impact on the false negative rate, but also on the response time. Therefore, it is necessary to choose those two parameters appropriately. Because the relationship between the false negative rate and the response time is similar to that between the precision and the recall in machine learning, referring to the F1-score, a score is set up by us:

$$F_\beta = \frac{(1+\beta^2) * the\ false\ negative\ rate * the\ response\ time}{\beta^2 * the\ false\ negative\ rate + the\ response\ time} \qquad (3)$$

where β represents the different weight of the false negative rate and the response time. It could be set to different value according to the need. Because in the experiments we consider the false negative rate and the response time equally, β is set to 1. So the formula becomes the following form:

$$F_1 = 2 * \frac{the\ false\ negative\ rate * the\ response\ time}{the\ false\ negative\ rate + the\ response\ time} \qquad (4)$$

Different from the precision and the recall in machine learning, we would like the false negative rate and the response time both to be small. So, the smaller the value of F1 score, the better.

4.2 A case study on gear about fault re-decision

00The experiments were performed on the rolling bearing bench shown in Figure 4. Artificial fault was imposed both on the gearings and the outer race of the test bearings.

In this experiment, the shaft rotational speed and sampling frequency were set to be 1800 rpm and 25600 Hz, respectively. The magnetic brake load is set as 2A. The data acquisition system is consisted of four channels, with three acceleration signals and one torque signal. The sensors placed in the different positions on the machine. The original signals are shown in the Figure 5. The red line represents the signals collected under normal conditions, while the blue one represents those collected under the conditions that there is a broken tooth in the 00000000gear.

The SVM model is used as the IFDM. The normal signal and the abnormal signal each take the first 12000 data points for training. And 10000 data points from the normal signal is used as test data. After training, the SVM model could achieve 64.83% accuracy without the proposed method. It is not a satisfying result because its false negative rate is 35.17% according to the formula (2), which means the monitored machine system might often be shut down when it should be run normally.

When one sample is input, the SVM model firstly gives an initial result. Then, the initial result will be handled by the proposed method instead of being used directly to control the machine. Through the re-decisioning process, which not only considers the current results but comprehensively considers the previous results, the proposed method would give a final result about the status of machine.

0000With our proposed method, the false negative rate decreases from 35.17% to 13.46%, which is shown in Figure 6. The best false alarm rate is 1.83%, using “f(x) = log(x+1)" as the decreasing function and 10 as the delay time. When the delay time is less than or equal to 6, the false negative rates of four decreasing functions all go down. But if the delay time is bigger than 6, the false negative rates remain unchanged at 3.48% with the decreasing function of “f(x) = 2^x" and at 2.88% when it is “f(x) = x^2" (see the blue bars and the red bars in the Figure 6). It indicates that our proposed method works.

It could be seen in Figure 6 that for all the decreasing function, their F1-scores are smallest when the response time is 1. However, when the response time is bigger than 5 and as the response time increases, the F1-scores for the decreasing functions of “f(x) = x” and “f(x) = log(x+1)" are both decreasing while the other two keep rising (see the yellow line and the purple line in Figure 6). Therefore, the proposed method was carried on again with a larger delay time, whose false negative rates and F1-socure are shown in Fig 7. As expected, their F1-scores keep go down (see the yellow line and the purple line in the Figure 7). However, even when the delay time is 20, their F1-scores are still larger than that when the delay time is 1.

0000Summary, the proposed method could achieve a significant reduction in the false negative rate. For a low false negative rate and a relatively low F1 score, we recommend using the f(x) = x as the decreasing function and 10 as the delay time, which could reduce the false negative rate from 35.17% to 1.89% in current experiment.

5. Conclusions

In this paper, a new fault re-decision method is proposed based on the key-delay technology.

1) Different from those methods which change their hyperparameters, the proposed method does not change anything of the IFDM, and just deals with the result sequence directly. A set of re-decision rules are used to obtain the final results.

2) The proposed method is aimed to solve the false alarm problem in fault diagnosis, which can cause an unexpected shut down of the equipment and may even cause loss of life and property.

3) The proposed method proved its ability to decrease the false negative rate and keep the accuracy rate within acceptable ranges under various conditions. In the best case, the false negative rate dropped from 35.17% to 1.89%.

In the future, some questions are needed to reinvestigate. For example, why do the results with some decreasing functions keep constant and which one is more important for decreasing the false negative rate, the decreasing function or the delay time?

Declarations

Acknowledgements

Not applicable

Funding

This research is supported by National Natural Science Foundation of China (12032017, 11790282), National Key R&D Program of China (2020YFB2007701), National Defense Science and Technology Key Project of China, Hebei Youth Top Notch Talent Program (BJ2017047) and Postgraduate Innovation Support Project of Shijiazhuang Tiedao University (YC2021035).

Authors' contributions

BR was in charge of the whole trial; JYC wrote the manuscript; GL and ZXJ provided guidance and discussion in theory. All authors read and approved the final manuscript.

Competing interests

The authors declare no competing financial interests.

Availability of data and materials

The datasets supporting the conclusions of this article would be got when you contact with JYC.

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Figures

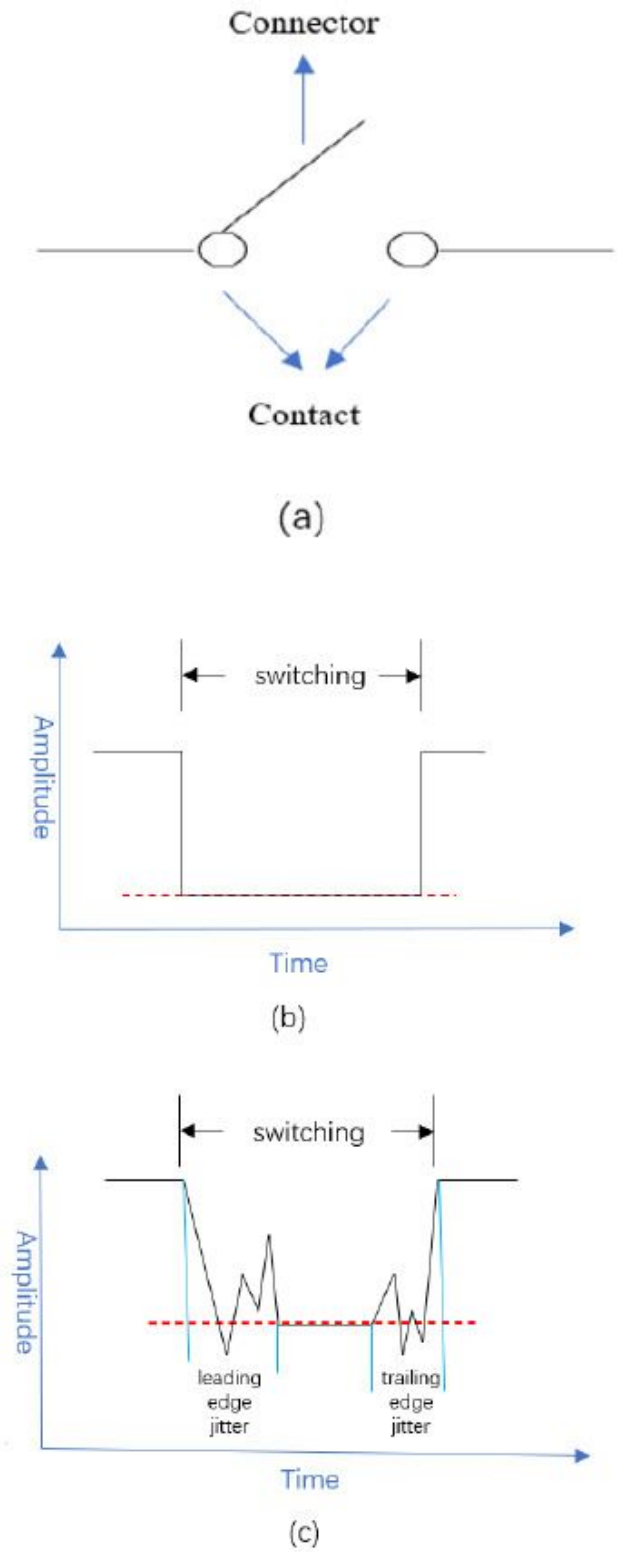

Figure 1

(a) key structure, (b) ideal situation, and (c) actual situation

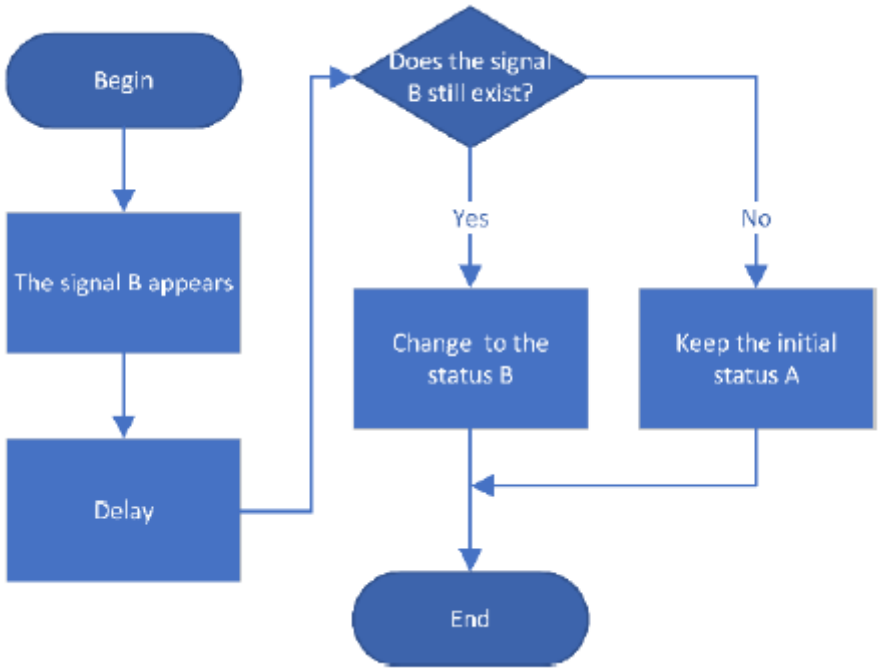

Figure 2

Flowchart

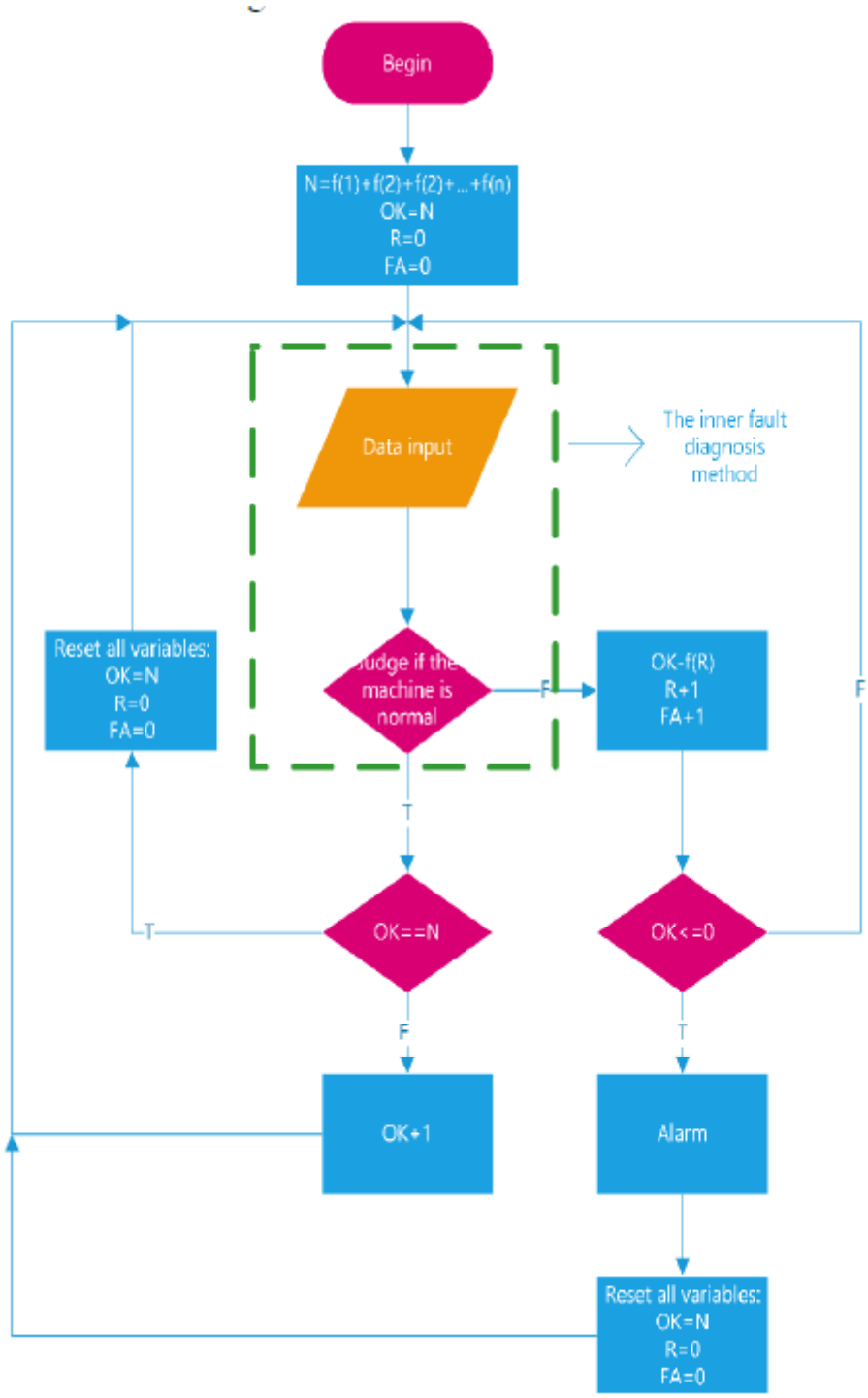

Figure 3

The flowchart of proposed method

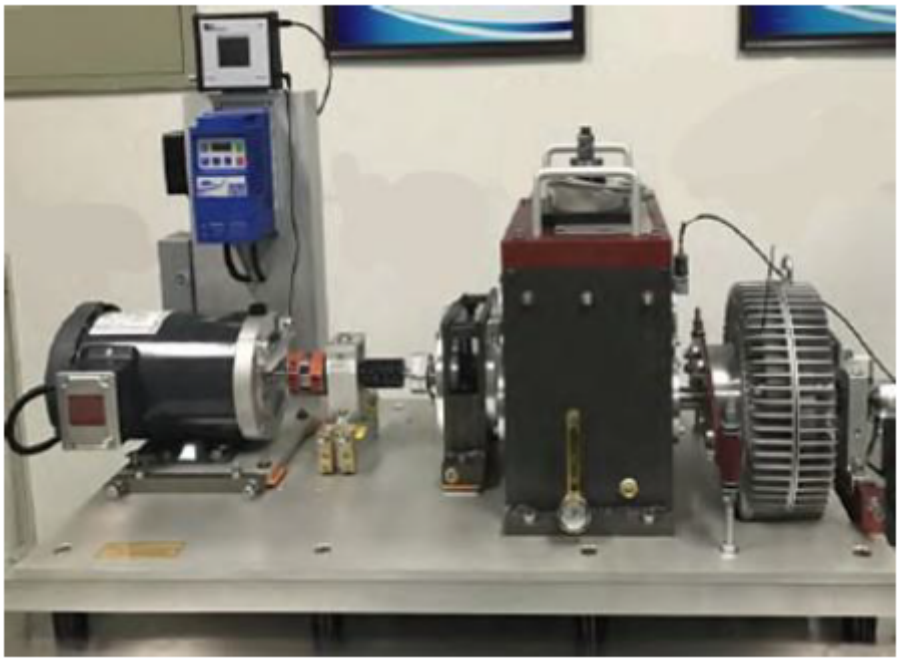

Figure 4

Experiment device

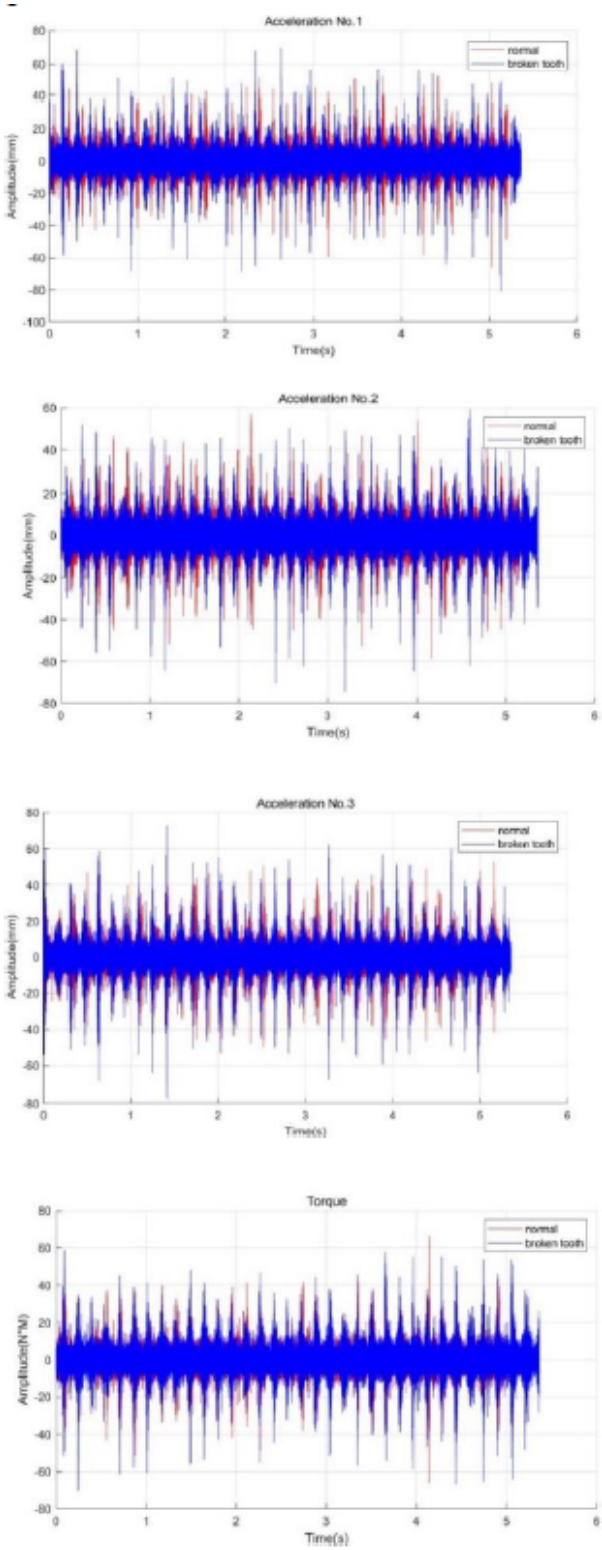

Figure 5

The original signal

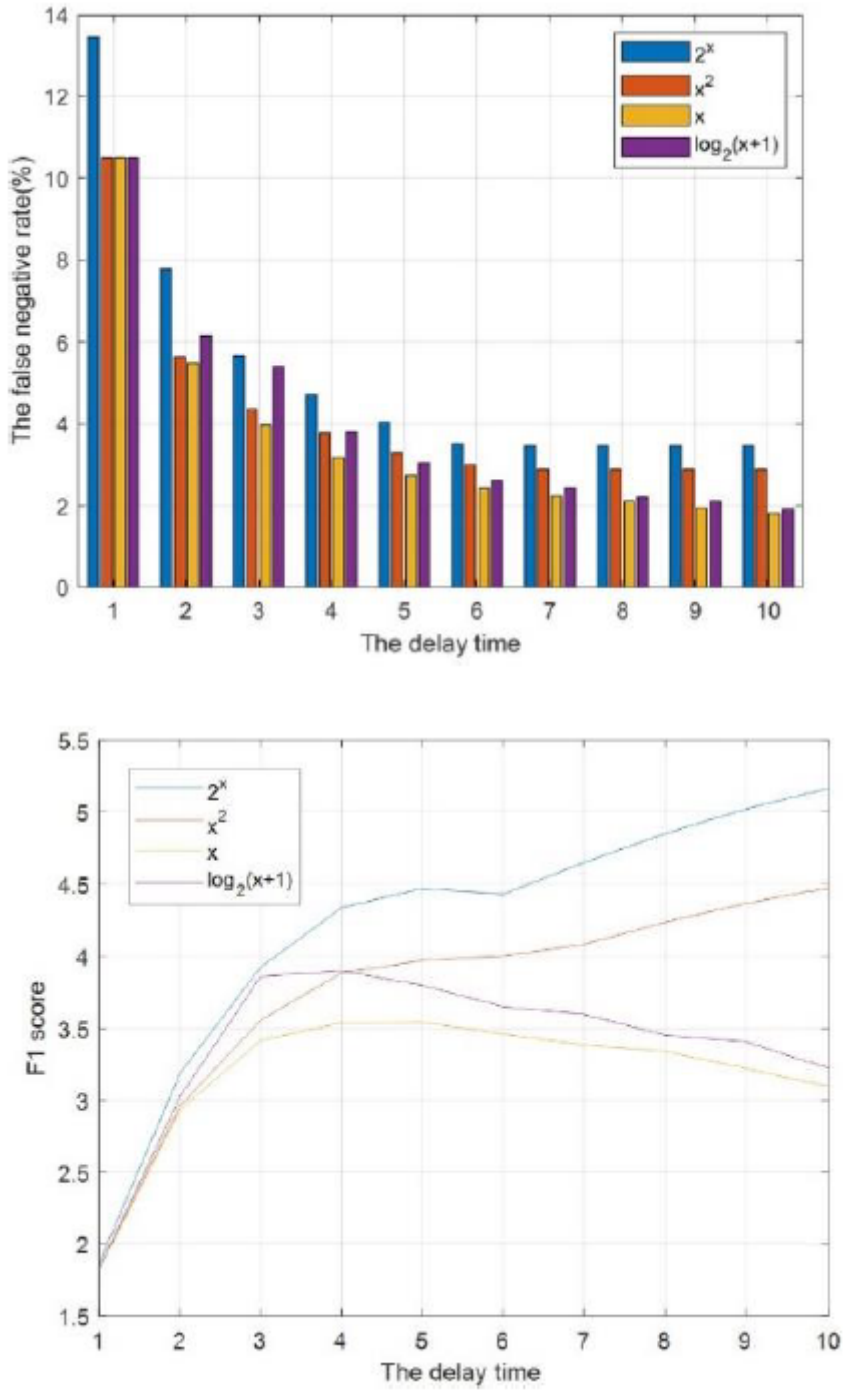

Figure 6

Experiment result

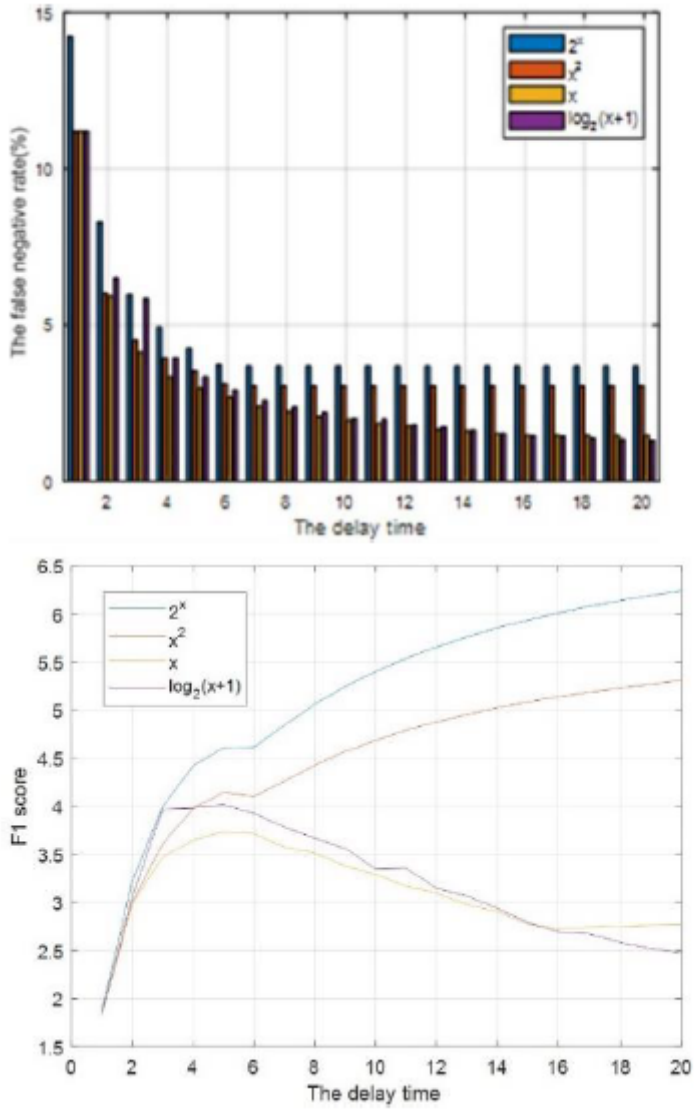

Figure 7

The result of more delay time