Low-sampling rate data-based failure diagnosis by using self-powered system

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Abstract. In recent years, in order to solve critical problems such as global warming and climate change that have been occurring in the world, research on the application of power generation methods which are harmless to the environment has been underway. In this paper, a fault diagnosis method using the self-powered sensing system based on vibration power generation is proposed. Frequency analysis is known as a general failure diagnosis method. However, due to the limitation of the generated power, the sampling period of data acquisition is as large as a few-tenth millisecond. For this reason, it is difficult to use frequency analysis for fault diagnosis using vibration power generation. Therefore, a fault diagnosis system corresponding to an increase in the sampling period is constructed by introducing machine learning. An acceleration sensor used for data acquisition is driven by the vibration power generator attached to factory equipment. The diagnosis is performed by wireless-transmitted acceleration data. By introducing a machine learning strategy into the diagnosis, accurate diagnosis can be performed even for data with low-sampling rate. The effectiveness of the proposed diagnosis method is experimentally evaluated by using the factory equipment.

1. Introduction
In recent years, the idea of how to harvest ambient energy so that it could help in addressing critical issues such as global warming and climate change have been proposed [1],[2]. One of them is vibration power generation that regenerates energy from vibration. Vibration power generation utilizes electromagnetic induction, electrostatic induction, or piezoelectric effect, etc. Piezoelectric elements are mainly used to convert force into electric power. Vibration power generation is being looked on by many researchers [3]-[5]. But this method is currently still under development, and the amount of power generated, and its efficiency is not enough to compete with the likes of solar power generation or small hydraulic power generation. Therefore, in order to use piezoelectric-based vibration power generation as a power source, it becomes necessary to construct a system that can be used for specific self-powered module including power management, sensor and wireless transmission. In this paper, at first energy regeneration is performed from the vibration of factory equipment. The acceleration sensor is then driven by the regenerated energy to acquire three-axis acceleration data. The sampling rate of the measured signals becomes low because the amount of power generated by vibration power generation is limited. A fault diagnosis method of factory equipment for the low sampling rate is proposed and experimentally evaluated.
2. Experimental configuration

2.1. Construction
This section gives an overview of the system used for fault diagnosis based on vibration power generation. In this system, vibration power generation by the vibration of factory equipment is used as a power source for driving a wireless sensor. In this case, due to the driving of the wireless sensor using small power from vibration-based power generation, the sampling period of data is increased about several tens of milliseconds. Therefore, a fault diagnosis method that is suitable for large sampling period is required. Conventional methods of failure diagnosis include frequency analysis and wavelet-based analysis. In frequency analysis, Fourier transforms performed on data. In this method, the difference of state appears in a comparatively high-frequency region. Therefore, the high sampling rate as kilohertz, i.e. microsecond, is required.

In order to solve this problem, in this paper, we are applying feature extraction based on a neural network. The failure diagnosis is performed by learning the acceleration difference between the response when the factory equipment is the normal condition with new cutter blade and just before the failure condition with an ageing cutter blade. Figure 1(a) shows the acceleration response when the device is in normal operation. Figure 1(b) shows the acceleration response just before the failure. Machine learning is performed by feature extraction for such data that is difficult to identify visually. Therefore, it is expected that fault diagnosis is possible by learning the features at the time of normality and just before the fault even if the sampling rate becomes large. In addition, if a failure diagnosis method using low sampling data becomes possible, all the tasks of power supply, data acquisition, wireless transmission and failure diagnosis can be performed by the developed self-powered sensing system.

2.2. Outline of neural network
In this section, the neural network used in the proposed method is described. A neural network is a system in which the information processing function of the brain is modelled, and is composed of three layers of an input layer, an intermediate layer and an output layer. There are basically two main application categories of machine learning using neural networks. The first is a regression problem that predicts the future of continuous data as in stock price analysis. The second is a classification problem that classifies data by learning data features. The learning corresponding to each problem can be performed by changing the function of calculation performed in the output layer. Because of its applicability, neural networks are being studied in various aspects, such as image processing and changes in human emotions, and so on [6]-[9]. As in failure diagnosis, system identification-based strategy has been conducted, and the neural network has attracted attention in recent years [10]. In this method, a recurrent neural network with one intermediate layer whose nodes are ten is used. The initial
values are generated randomly. Data used for learning are acceleration data of factory equipment at the
time in normal condition and in just before failure condition. Considering the cross-validation, both
acceleration data are divided into two parts. The first half is utilized for the learning and the last half for
the evaluation. As a learning method, supervised learning is adopted. In order to set a teacher signal, a
label of zero is assigned to acceleration data of the normal condition, and a label of one is assigned to
that of the failure condition. Learning is performed by comparing the label of the supervised signal and
the output result. In addition, in order to perform feature extraction, the time series of acceleration data
is split appropriately, in this case, 100 samples, and learned into a neural network.

2.3. Data for learning the neural network
In this paper, data with different sampling period are needed to compare the accuracy of fault diagnosis.
The data used in the following experiments are decimated on the existing experimental data with 10μs
sampling period. An example, the original time response with 10μs sampling period, the decimated time
response with 500μs and the decimated time response with 50ms are shown in Figure 2. As a result, the
relationship between the sampling period and the failure diagnosis result can be clearly evaluated.

![Figure 2](image)

**Figure 2.** (a) The original response with 10μs, (b) the decimated time response with 500μs,
(c) the decimated time response with 50ms

3. Failure diagnosis by neural network
Taking the initial value dependency of the weights into consideration, the following results of diagnosis
accuracy shows the average value of five experiments.
3.1. Diagnostic accuracy on one axis
In this section, to confirm the accuracy of failure diagnosis in one axis, the acceleration data of x-direction which has the largest difference in amplitude is applied to the neural network. From this result, in the acceleration data of only one axis, the learning is possible only if the sampling period is small enough as to have 10\(\mu\)s. However, the learning is impossible for the sampling period with milliseconds, i.e., it is difficult to use the vibration power generation as a power source of the sensor.

| Sampling period | Diagnostic accuracy of one axis [%] | Number of sets |
|-----------------|-----------------------------------|----------------|
| 10\(\mu\)s      | 77.2                              | 7000           |
| 50\(\mu\)s      | 53.4                              | 1400           |
| 100\(\mu\)s     | 52.8                              | 700            |
| 500\(\mu\)s     | 53.7                              | 140            |
| 1ms             | 54.6                              | 70             |
| 5ms             | 47.2                              | 14             |

3.2. Diagnostic accuracy on three axis
In order to improve the diagnosis accuracy, three-dimensional acceleration data are combined and learned by the neural network. Table 2 shows the failure diagnosis results for each sampling period. From the result, it can be confirmed that the diagnostic accuracy is improved by the combination of the axis. The accuracy can be held even if the sampling period is extended to 10 times (100\(\mu\)s). However, the sampling period is still short for the self-powered vibration energy harvester.

| Sampling period | Diagnostic accuracy of three axis [%] | Diagnostic accuracy of one axis [%] | Number of sets |
|-----------------|--------------------------------------|------------------------------------|----------------|
| 10\(\mu\)s      | 89.6                                 | 77.2                               | 7000           |
| 50\(\mu\)s      | 76.3                                 | 53.4                               | 1400           |
| 100\(\mu\)s     | 74.9                                 | 52.8                               | 700            |
| 500\(\mu\)s     | 54.1                                 | 53.7                               | 140            |
| 1ms             | 61.8                                 | 54.6                               | 70             |
| 5ms             | 52.8                                 | 47.2                               | 14             |

4. Failure diagnosis result by data preprocessing
In the experiment of the previous section, the acceleration data for learning was individually constructed with 100 samples. In this section, the data used for learning is constructed by shifting the data window with 100 samples for one set of data. Figure 3(a) and (b) show in the previous data constructing method and the proposed data constructing method, respectively. As shown in Figure 3(b), a set of data is produced using a window shift of \(n\) samples while being shifted by \(n\) samples. In this experiment, \(n\) was selected as 1. By introducing this processing, the number of sets of data available for learning and verification of neural networks increases. Furthermore, the problem of phase difference for periodic acceleration learning can also be handled. The range of sampling period is selected from 500\(\mu\)s to 50ms. 500\(\mu\)s is a sampling period when diagnostic accuracy in three axes decreases. 50ms is a sampling period which is large enough to drive a three-axis wireless acceleration sensor powered by vibration power generation. Conditions expect for the data reconstruction are the same as the previous section. Table 3 shows the results for the three-axis acceleration data. Compared to the results of the previous section, it is noted that the number of sets is increased by changing the data acquisition method. Moreover, it can be seen that the diagnostic accuracy is drastically improved and exceeds 80% even in 50ms. In the case of sampling period of 50ms, it lacks in reliability due to the number of groups. But pre-processing of data by time shift improves the diagnostic accuracy and maintains the accuracy even with an increase in the sampling period. Therefore, it can be concluded that failure diagnosis with self-powered wireless sensor node is properly investigated based on the neural network.
Figure 3. (a) Acquisition of data in the previous section, (b) Acquisition method of data in this section

Table 3. Fault diagnosis accuracy by time shift processing

| Sampling period | 500μs | 1ms  | 5ms  | 10ms | 50ms |
|-----------------|-------|------|------|------|------|
| Maximum accuracy [%] | 97.8  | 81.4 | 84.6 | 90.7 | 100  |
| Average accuracy [%]  | 96.4  | 80.5 | 83.6 | 89.6 | 99.0 |
| Number of sets       | 13900 | 6900 | 1300 | 600  | 40   |
5. Conclusion
In this paper, a fault diagnosis method using the self-powered sensing system based on vibration power generation is proposed. In this paper, a fault diagnosis method using the self-powered sensing system based on vibration power generation has been proposed. An acceleration sensor can be driven by the vibration power generator attached to factory equipment. The diagnosis has been performed by using wireless-transmitted acceleration data with low-sampling rate. Machine learning strategy has been introduced into the diagnosis. The effectiveness of the proposed diagnosis method is experimentally evaluated by using the factory equipment. Based on the experimental result, it has been confirmed that high diagnostic accuracy can be achieved even for low-sampling rate data where the frequency analysis is not conducted.

Improvement of vibration power generator efficiency and development of the whole diagnostic system combined with the generator will be planned as future work.

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