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Damage evaluation of fixed beams at both ends for bridge health monitoring using surface acoustic wave device
弾性表面波素子を用いた 橋梁ヘルスモニタリングのための両端固定梁の損傷評価

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1. Introduction

In recent years, the aging of infrastructure facilities such as bridges built during the period of rapid economic growth has become a serious problem. In this paper, we propose a structural health monitoring system using surface acoustic wave (SAW) sensors. Impedance-loaded passive SAW sensors have the advantage that they can be used wirelessly and without power supply when combined with impedance-changing sensors. At present, we are mainly investigating the method of evaluating the health of bridges.

In our previous research[1], we conducted experiments on cantilevered beams made of polyethylene terephthalate (PET) resin, which simulate bridges. However, since a cantilever beam made of PET resin is insufficient to simulate a bridge, in this study, a fixed beam made of an aluminum alloy (A5052) plate at both ends was used to simulate a bridge. In addition, unsupervised machine learning k-means clustering and One-Class Support Vector Machine (OCSVM), which is one of the anomaly detection methods, were used for damage discrimination.

2. Experimental method

The experimental system used in this study is shown in **Fig. 1**, where the frequency of the SAW device is 13.5 MHz and the IDT is fabricated on 128°YX-$LiNbO_3$. A variable-capacitance diode and a vibration energy harvester were connected to the IDT reflector as an impedance-changing sensor. The vibration energy harvester converts the acceleration of the beam into a voltage change, and the variable-capacitance diode converts the voltage change into a capacitance change. This is how the system detects the vibration of the beam. In the vibration experiment, the oscilloscope was used to measure for one second. A vibration exciter was used to excite the beam at 20 Hz for about 0.3 seconds, and then the vibration exciter was stopped to measure the damping. The dimensions of the beams are shown in **Fig. 2**. 10 measurements were carried out at each of the three points shown in Fig. 2. Two holes with a diameter of 20 mm were made in the beam to simulate damage, and the presence or absence of the holes was used to detect damage.

The measured vibration data were then subjected to continuous wavelet transform (CWT) to obtain both time and frequency information. The detailed explanation of CWT is omitted because it is the same as in the previous study[1].

In addition, the data at each frequency of CWT is approximated using the exponential function,

$$y = A \exp(-\alpha x) \tag{1}$$

Here, α is the attenuation coefficient and A is the amplitude. Based on the attenuation coefficient, a database for machine learning was developed.

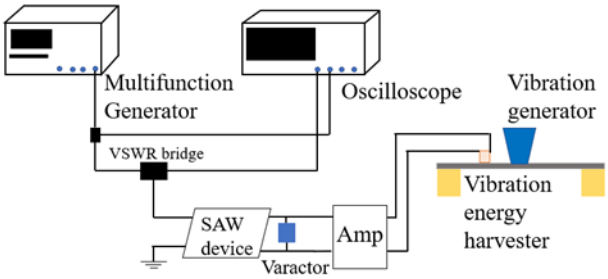

Fig. 1 Experimental system

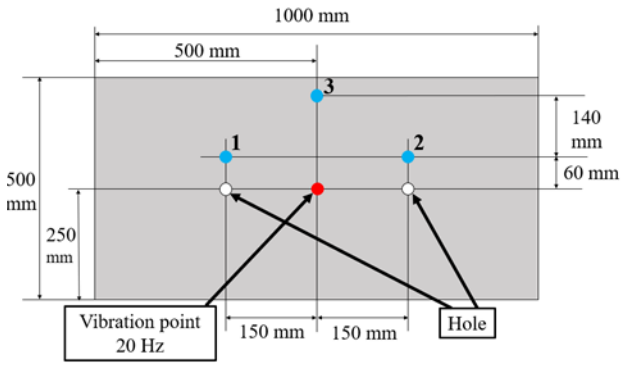

Fig. 2 Beam dimensions

3. Classification by Unsupervised Machine Learning

In this study, we used k-means clustering, a typical unsupervised machine learning method, and OCSVM, a well-known anomaly detection method, to classify the presence of damage. The machine learning was implemented using

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scikit-learn[2], an open-source Python library. To classify the data, we normalized the dataset by columns. When the array of data is a_i, the normalized data $a_{i,Normalization}$ is as follows.

$$a_{i,Normalization} = \frac{a_i - \min(a)}{\max(a) - \min(a)} \quad (2)$$

The results of k-means clustering were evaluated using the ARI (Adjusted Rand Index), which indicates that the clustering is random when it is close to 0 and accurate when it is close to 1. On the other hand, the results of OCSVM were evaluated by ACC (Accuracy), which indicates the number of correct answers. **Figures 3** and **4** show the results of k-means and OCSVM with the data normalized by columns according to Eq. (2), summarized in a stacked bar.

For the k-means clustering, ARI = 0.93, indicating high accuracy. From these results, we confirmed that it is possible to discriminate damage with and without holes using unsupervised machine learning. However, if there is a bias in the number of data with and without holes, the accuracy may deteriorate drastically. **Figure 5** shows the clustering result when the number of data with holes is small, ARI = 0.31, which is much worse. This may be due to the fact that the center of gravity between the data, which is the criterion for determining the similarity of the data, may no longer function due to the bias in the data. This problem is unavoidable because clustering determines clusters based on the center of gravity of the data. Even if we consider implementing it in a real environment, it is hard to imagine that both data with and without defects will be equal. Therefore, we believe that k-means clustering is not suitable for health monitoring in a real environment.

OCSVM was also able to achieve high accuracy with ACC = 96 %. The results in Figure 4 show that the data without holes can be classified as normal data and the data with holes can be classified as outliers. In addition, unlike k-means clustering, OCSVM can be trained using only the without hole data, so it does not need to take into account the bias of the data. Therefore, it is suitable for health monitoring systems.

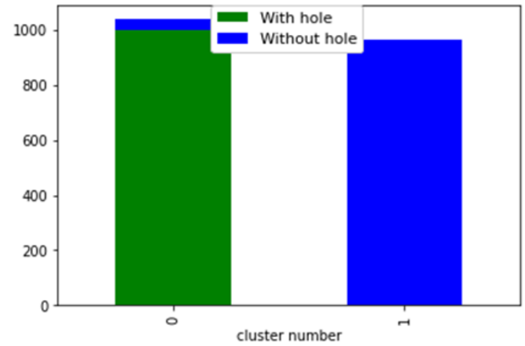

Fig. 3 k-means clustering (ARI = 0.93)

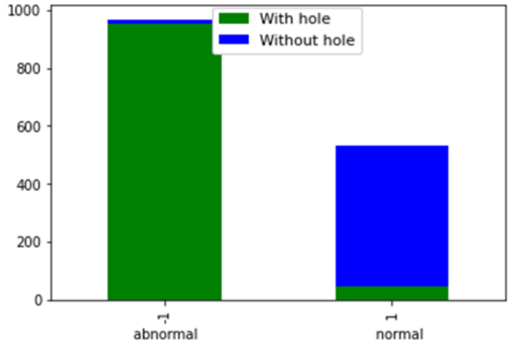

Fig.4 OCSVM (ACC = 96 %)

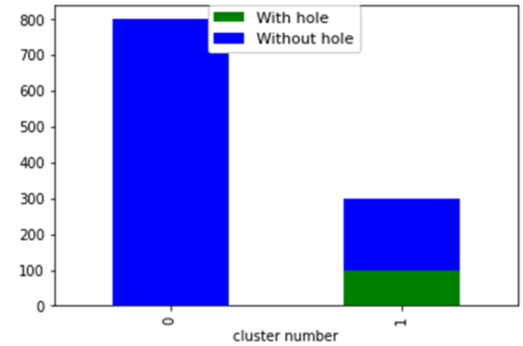

Fig. 5 k-means clustering when there are few data with hole (ARI = 0.31)

4. Conclusion

Damage assessment of fixed beams at both ends for bridge health monitoring using impedance-loaded SAW sensors was conducted. The results of this study showed that classification by unsupervised machine learning is possible. In particular, we showed that OCSVM is suitable for bridge health monitoring. In the future, we aim to increase the number of defect types and classify various types of defects, and to conduct demonstration experiments in real environments.

Acknowledgment

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References

1. S. Suzuki et al., Jpn. J. Appl. Phys., vol. 60, SDDC09 (2021).
2. https://scikit-learn.org/