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Cantilever damage evaluation using impedance-loaded SAW sensor with CWT and machine learning

連続ウェーブレット変換および機械学習を用いたインピーダンス負荷 SAW センサによる片持ち梁の損傷評価

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1. Introduction

Wireless and passive surface acoustic wave (SAW) sensors[1] are expected to be used for continuous health monitoring of large structures such as bridges because of their small size and low cost and the ability to use impedance sensors without power supply. However, an evaluation method for the health monitoring has not been fully investigated. It is difficult to detect micro-defects even in the absence of disturbance.

In this study, continuous wavelet transform (CWT) and machine learning[2] are applied to evaluate vibration data of a cantilevere beam. Compared with our previous method[1], frequency variation over time are obtained from CWT results. Also, the machine learning is adapted to distinguish damaged cantilevers.

2. Measurement system

In this study, 13.5 MHz SAW sensor was used. Interdigital transduces (IDT) and IDT type reflector were fabricated on 128YX-$LiNbO_3$. A pressure sensor was connected to the IDT type reflector. The vibration of the cantilever beam made of polyethylene terephthalate (PET) resin was measured using the pressure sensor. Detail measurement method is written in ref. 1.

3. Continuous wavelet transform (CWT)

The CWT is a frequency analysis method, which represents an arbitrary waveform by scaling and translating a specific waveform called the mother wavelet. Unlike the Fourier transform, the CWT is suitable for aperiodic vibration analysis because it can retain the time information and has higher resolution than the short-time Fourier transform, which is also time-frequency analysis. **Fig. 1** shows a typical CWT result obtained from the pressure sensor -loaded SAW sensor[1].

In our previous studies[1], the natural frequency from the FFT and the attenuation coefficient of damped vibration were used for evaluating the cantilever. For the CWT, the natural frequencies can be obtained as a function of time, as shown in Fig. 1. Moreover the attenuation coefficients at each frequency can be obtained. In addition, as shown in Fig. 1, a constant-amplitude disturbance occurs at around 20 Hz. It is considered to be an effective method in a real environment with a high noise level.

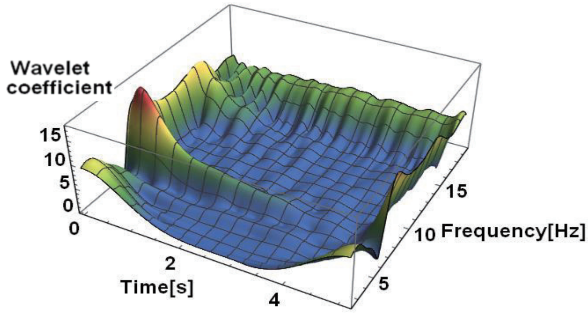

Fig. 1 Typical CWT result.

4. Analysis of attenuation at each frequency

Attenuation at each frequency obtained by the CWT was studied. We found that the attenuation at each frequency was classified into three categories: 1) exponential damping is that the amplitude gradually attenuates from high value, 2) linear damping is rapid attenuation from low value, and 3) mixed damping includes the intermediate characteristics. We considered that the exponential damping occurs mainly around the natural frequency and the linear damping occurs in other regions. As the linear damping depends on the initial conditions of vibration generation, its amplitude and damping coefficient are highly variable. On the other hand, since the exponential damping depends on the properties of the material, the same results can be obtained for the same material and shape regardless of the initial conditions of vibration. Furthermore, since the proportion of the exponential damping increases with the expansion of the defect, it is considered that a more accurate defect detection is possible by focusing on the frequency of exponential attenuation obtained by the continuous wavelet transform and making use of these properties.

5. Machine Learning Classification

Defects in PET resin plates were detected

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using the machine learning with the attenuation coefficients for each frequency obtained by the CWT. An example of the dataset used is shown in **Table 1**. In the table, the values of 0 and 1 in the defect column mean absence and presence of defect, respectively. Attenuation coefficients at 8.97, 7.71, and 7.55 Hz obtained by the CWT show the feature values. Only the attenuation coefficients of the exponential damping were focused. The other feature values for the two types of the damping were set to zero. The attenuation coefficients for the exponential damping were used in the reciprocal number form, so that the decay was rapid and linear when it approaches zero, and becomes more gradual and exponential when it increases. In this study, 69 data were used. In those, 23 data were obtained from defect-free cantilever. The number of dimensionalities of the features is 19.

Table 1. Datasets used for machine learning

Name	Defect	Attenuation coefficient		
		8.97Hz	7.71Hz	7.55Hz
Data1	0	0	0.858	0.906
Data2	0	0	0.774	0.791
Data3	1	0	1.766	1.74

In the analysis, we used three types of machine learning models: support vector machine (SVM), random forest, and LightGBM (light gradient boosting machine). The SVM is a commonly used machine learning model. The LightGBM is an advanced form of the random forests, because it is a binary classification problem to discriminate whether there are defects or not and because the data for teachers can be used. Each hyperparameter is optimized through a prior grid search.

Each model was evaluated by using cross-validation, where the data set was randomly divided and the teacher's data and test data were swapped out for training and testing from three different perspectives: Accuracy(Acc), Log Loss, and Area Under Curve (AUC). The Acc represents the absolute number of correct answers. The Log Loss represents the deviation between predicted and actual values. The AUC is the number of correct answers considering the bias between classes calculated from the area under the ROC curve. In addition to the normal data set, we also performed the same evaluation on a data set where each data feature was normalized from 0 to 1. **Tables 2** and **3** show the evaluation results for each model in the normal data set and for the normalized data set, respectively.

Table 2. Evaluation results for each model.

Model	Acc	Log Loss	AUC
SVM	0.654	0.519	0.941
Random Forest	0.654	0.546	0.729
LightGBM	0.885	0.530	0.853

Table 3. Evaluation results after normalization.

Model	Acc	Log Loss	AUC
SVM	0.654	0.440	0.729
Random Forest	0.692	0.445	0.856
LightGBM	0.769	0.384	0.879

From the tables, it is found that the accuracy of about 89% was obtained for the ACC using LightGBM, which was considered to be sufficiently accurate for practical use based on the log loss and AUC values. On the other hand, the accuracy of the SVM and Random Forest was below 70% for ACC. However, considering other indicators, further improvements can be expected by adjusting the hyperparameters and changing the measurement conditions. Although normalization contributes to the improvement in Log Loss, its impact on ACC is insignificant. Therefore, not only the value of the attenuation coefficient, but also the distribution of exponential/linear attenuation is considered to be an important factor for defect identification. We observed a frequency shift in the shape of the attenuation due to the expansion of the defect. This means that the prediction of the regression of not only the presence or absence of the defect, but also its diameter and shape by increasing the number of data.

6. Conclusion

In this study, we found that the combinations of the impedance-loaded SAW sensor with the CWT and machine learning are an effective method for the health monitoring of the structure. In the future, we would like to study the implementation of regression prediction and defect detection under more realistic conditions.

Acknowledgment
In this study, we used alumni data measured for the same structures.

References

1. M. Oishi et al., Jpn. J. Appl. Phys. 55, 07KD06 (2016).
2. A. Géron, Hands-On Machine Learning with Scikit-Learn and TensorFlow(OREILLY, 2018)