International Journal of GEOMATE, Feb., 2019 Vol.16, Issue 54, pp.62 - 67
Geotec., Const. Mat. & Env., DOI: https://doi.org/10.21660/2019.54.4840
ISSN: 2186-2982 (Print), 2186-2990 (Online), Japan

DAMAGE DETECTION OF TRUSS STRUCTURES BY APPLYING MACHINE LEARNING ALGORITHMS

*****Koji Unno, Atsushi Mikami, and Masaki Shimizu

Department of Civil Engineering, Faculty of Engineering, Tokai University, Japan

*Corresponding Author, Received: 02 Oct. 2018, Revised: 30 Nov. 2018, Accepted: 31 Dec. 2018

ABSTRACT: Infrastructures including bridges constructed in the period of high economic growth are getting older. For the damage detection of truss structures, this study assumes to utilize vibration signals obtained from sensors installed into the bridges. By preparing damaged and non-damaged bridge structures, large quantities of response data are generated. AR (Auto-Regressive) model is then applied to the time signals to extract the structure's soundness characteristics. Here, AR coefficients are values in which damaged structural characteristics are reflected. Then, the machine learning technique is applied to the AR coefficients to classify the structures into damaged and non-damaged ones. Results showed that the machine learning method successfully detected the damage of truss members. This kind of SHM (Structural Health Monitoring) technology is expected to contribute to early damage detection and preventive maintenance of bridges leading to increase the accuracy of the damage detection of truss structures with low costs and fewer efforts for maintenance.

Keywords: Damage detection, Machine learning, AR model, Decision tree

1. INTRODUCTION

In Japan, infrastructures including bridges constructed in the period of high economic growth are getting older. Ministry of Land, Infrastructure, Transport and Tourism (MLIT) requires bridge administrators to make a short-range visual inspection of bridges more than once in every 5 years. Aged bridges tend to need more maintenance which requires additional costs and human labors. However, maintenance engineers are insufficient in number compared with the numbers of aged bridges. One solution to resolve the problem is to use sensors and signal processing techniques to detect damaged members and their damage level of the structures.

Our research group is tackling the damage detection problem of aged structures on the assumption of using sensor data.

Shimizu et al. conducted eigenvalue analysis to fully utilize the sensor data, aiming to find optimum sensor arrangement [1].

This study assumes to utilize vibration signals obtained from sensors installed into the bridges. The machine learning algorithm is applied to the sensor data to detect damage. By preparing damaged and non-damaged bridge structure models, large quantities of response data are generated giving random input motion at the base. AR model is then applied to the time signals to extract the structure's characteristics. Here, AR coefficients are values in which damaged structural characteristics are reflected. Then, the decision tree technique is applied to the AR coefficients to classify those structures into damaged and non-

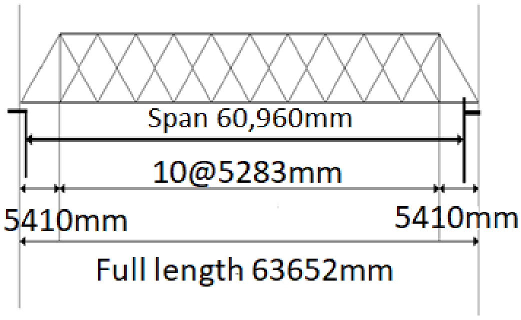
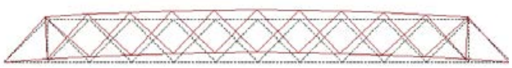
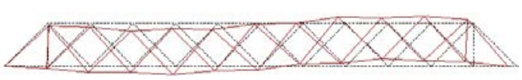


Fig. 1 Hayakawa Bridge (Hakone Tozan Railway)

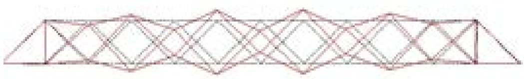


1st mode 3.2065Hz.

2nd mode 10.493Hz



3rd mode 13.821Hz



4th mode 15.569Hz

Fig. 2 The 1st to 4th mode of natural vibration [1]

Table 1 Parameters prescribing the Hayakawa Bridge truss members

Parameter	Breadth	Height	Sectional area	Poisson's ratio	Elastic modulus
Unit	400mm	500mm	20000mm^2	0.3	206GPa

damaged ones. This kind of SHM (Structural Health Monitoring) technology is expected to contribute to early damage detection and preventive maintenance of bridges [2].

2. TRUSS BRIDGE TO BE ANALYZED

The bridge structure in this study is Hayakawa bridge administrated by Hakone Tozan Railway Co. Ltd. shown in Fig.1. It is a double Warren truss bridge which length is approximately 63 meters, constructed in 1888. The truss bridge is a typically aged railway bridge in Japan. Wrought iron was used for the material [3].

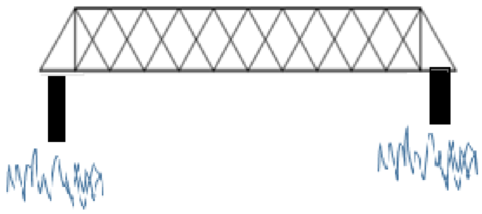
3. MODELING AND ANALYSIS

To model the structure, finite element method is used. The model was analyzed by two-dimensional finite element method using the software, TDAPIII [4]. For the damage detection of structures, this study assumes to utilize vibration signals obtained from sensors installed into the bridges. By preparing damaged and non-damaged truss bridges, large quantities of response data are generated. Machine learning algorithms are then applied. This study referred to the MATLAB Web seminar for the application of machine learning algorithms [5], [6].

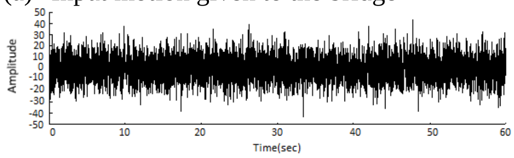
4. DYNAMIC ANALYSIS OF THE TRUSS STRUCTURE

Parameters that prescribe the Hayakawa bridge model are shown in Table 1. Fig.2 shows 1st to the 4th mode of the truss structure. 1st mode frequency is 3.2065Hz. 2nd mode frequency is 10.493Hz. 3rd mode frequency is 13.821Hz. 4th mode frequency is 15. 569Hz. Stationary random input motion is given to the base of the prepared structures as shown in Fig.3 (a), (b). The duration time is 60 second and time increment is 0.01 second, hence the input motion is consisting of 6000 data. Acceleration responses from bottom chord member were calculated and accumulated in the database. Both damaged and non-damaged structures were prepared, ranging the damage level from 10% to 90% of the reduction of elastic modulus. Examples of the responses for damaged and non-damaged structures are shown in Fig.3(c), (d), respectively.

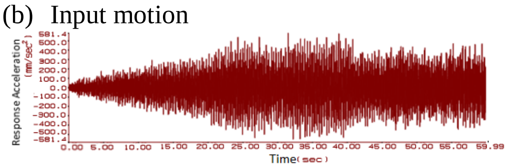
5. AUTOREGRESSIVE MODEL



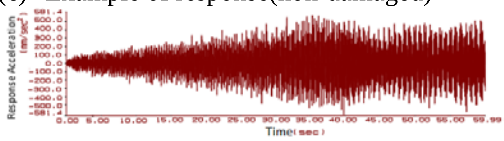
(a) Input motion given to the bridge



(b) Input motion



(c) Example of response(non-damaged)



(d) Example of response(damaged)

Fig. 3 Input motion and response

Autoregressive model (AR model) is then applied to the accumulated signals in this study. As shown in Eq (1), the model, depending on its own previous values, regresses a value from the time signals. The order of the AR model was set as 10th.

$$Xn = a_0 + \sum_{i-1}^{N} a_i X_{n-i} + \varepsilon_t \quad (1)$$

where a_0 is the constant term. a_i is a parameter of the model. ε_t is white noise. The responses include both from damaged and non-damaged truss structures. AR coefficients were then calculated for both damaged and non-damaged structures, then the coefficients were saved for the machine learning process.

6. PREPARATION OF DATA FOR THE MACHINE LEARNING

As a signal input to the AR model, the portions regarded as stationary were extracted and used. As shown in Fig.4, a total of 4000 data points out of 6000 data points were extracted, and they are divided into 40 sections. Aforementioned AR

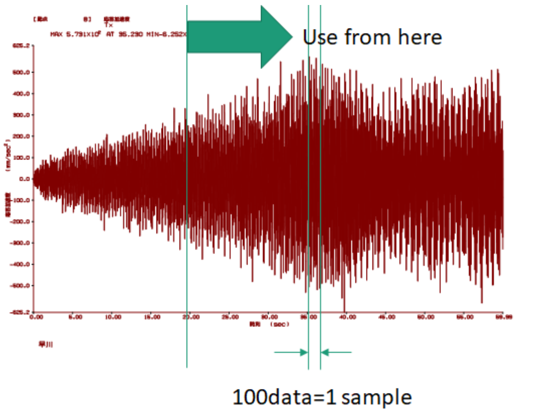


Fig. 4 Example of inputs for an autoregressive model

model was then applied to the data that includes both damaged and non-damaged cases. Then, AR coefficients were determined.

Fig.5 shows the AR coefficients by taking the order of the coefficients (up to 10th mode) on the horizontal axis. It seems that we may be able to find the difference between damaged and non-damaged cases by taking the AR coefficients as feature quantities. Fig.6 shows the contributions of each mode of AR coefficients. As the order of the modes becomes higher, the contributions drastically decrease. Hence, this study focused only on the first and second mode. Those determined AR coefficients include non-significant coefficients, hence, dimension reduction technique (PCA: Principal Component Analysis) is utilized here.

Fig.7 represents the results of the principal component analysis (PCA) by looking at the first and the second components. Clearly, we can divide the data plots into two groups, therefore, the method is capable of discriminating damaged cases from non-damaged ones. It is of importance for efficient computation to conduct data compression as machine learning tend to use enormous data. The dimension of the data was reduced from 10 to 2 by PCA in this study as shown in Fig.8. The total data is classified into two groups: data to be studied by the machine learning algorithms and data to test the performance of the machine learning algorithm.

7. MACHINE LEARNING

To discriminate damaged structures from non-damaged cases, the machine learning algorithm is utilized. As a simple method to achieve the purpose, the decision tree method is applied to the data shown in Fig.8. The series of the analytical procedure including AR, PCA, etc., leading to machine learning is commonly used procedures (e.g., [7]).

8. RESULTS

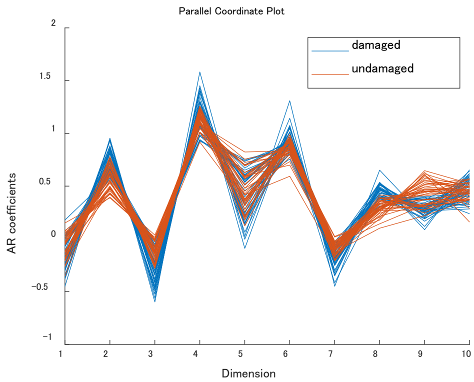


Fig. 5 Parallel coordinate plot

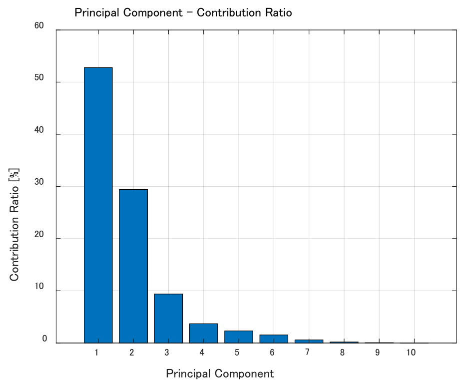


Fig. 6 Contribution rate

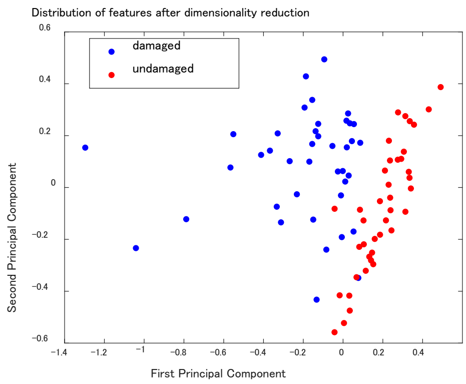
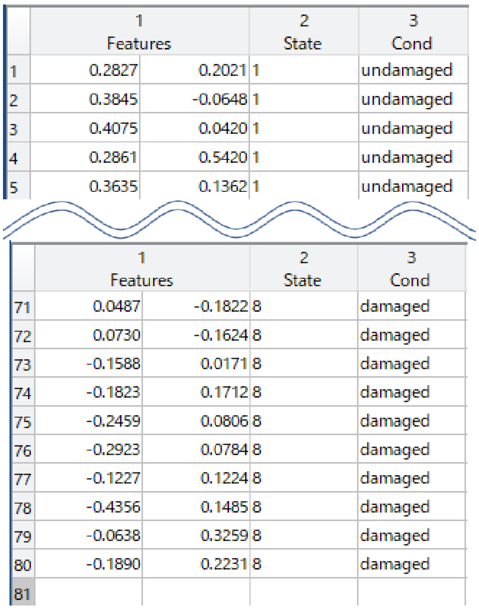


Fig. 7 Dimensionality reduction

8.1 Detection of damage considering only damage to one member

Shimizu et al. [1] paid attention to the variation of the natural frequency of the entire structure due to the deterioration of a member. However, natural frequencies are not always sensitive to the damage considered [1], [8]. Hence, this study attempts to perform a different method, i.e., machine learning. Fig.9 shows an example of the result of the decision tree method. The numbers are thresholds determined by the algorithm. Based on the



	1 Features		2 State	3 Cond
1	0.2827	0.2021	1	undamaged
2	0.3845	-0.0648	1	undamaged
3	0.4075	0.0420	1	undamaged
4	0.2861	0.5420	1	undamaged
5	0.3635	0.1362	1	undamaged

	1 Features		2 State	3 Cond
71	0.0487	-0.1822	8	damaged
72	0.0730	-0.1624	8	damaged
73	-0.1588	0.0171	8	damaged
74	-0.1823	0.1712	8	damaged
75	-0.2459	0.0806	8	damaged
76	-0.2923	0.0784	8	damaged
77	-0.1227	0.1224	8	damaged
78	-0.4356	0.1485	8	damaged
79	-0.0638	0.3259	8	damaged
80	-0.1890	0.2231	8	damaged
81				

Fig. 8 An example of calculated AR coefficients

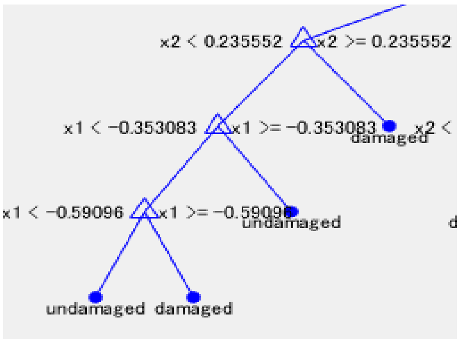


Fig. 9 Decision tree

threshold number, calculated responses are classified into damaged and non-damaged structures.

Table 2-4 shows results obtained by applying the decision tree for the upper chord, diagonal and bottom chord members, respectively. Here, Table 3 is the result corresponding to Fig.9. Fig.10 (a)-(c) shows the results of the relation between the first and the second principal components for the upper chord, diagonal and bottom members, respectively. Blue dots stand for damaged cases and red dots non-damaged cases. It seems that we can distinguish the damaged structures from non-damaged structures from these figures by setting threshold values properly. The applied decision tree method automatically determines the threshold values.

Table 2 Upper chord member

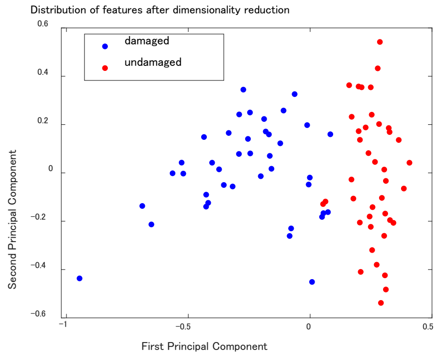
Items	Estimate_ damaged	Estimate_ undamaged
damaged	19	0
undamaged	0	21

Table 3 Diagonal member

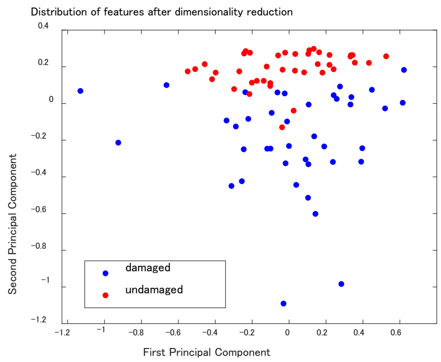
Items	Estimate_ damaged	Estimate_ undamaged
damaged	20	2
undamaged	2	16

Table 4 Bottom chord member

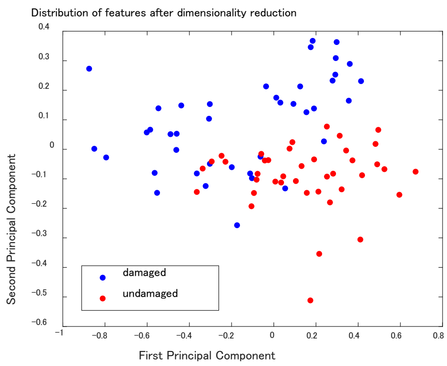
Items	Estimate_ damaged	Estimate_ undamaged
damaged	20	2
undamaged	2	16



(a) Upper chord member



(b) Diagonal member

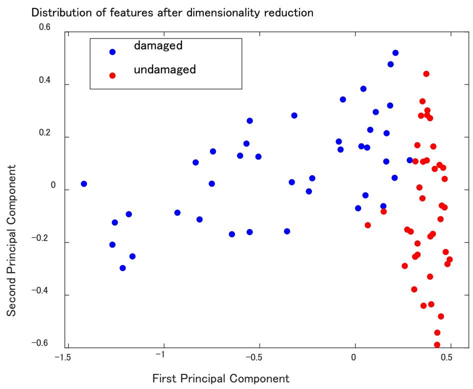


(c) Bottom chord member

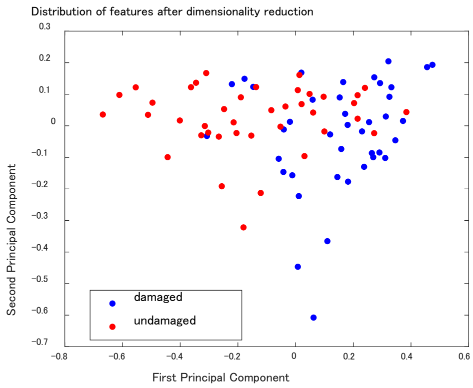
Fig. 10 Result of detection of damage considering only damage to one member

8.2 Principal component analysis of the degree of damage when specified on an upper chord member

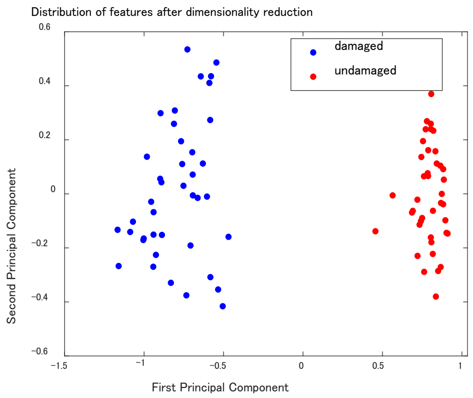
Fig.11 (a)-(c) show the results of principal component analysis when the degree of damage for an upper chord member changed. Based on this damage, results were obtained as shown in Table 5-7. Damage classification becomes difficult when the damage level decreases.



(a) 10% damage



(b) 50% damage



(c) 90% damage

Fig. 11 Principal component analysis of degree of damage when specified on an upper chord member

Table 5 10% damage

Items	Estimate_ damaged	Estimate_ undamaged
damaged	16	4
undamaged	8	16

Table 6 50% damage

Items	Estimate_ damaged	Estimate_ undamaged
Damaged	21	0
undamaged	0	19

Table 7 90% damage

Items	Estimate_ damaged	Estimate_ undamaged
damaged	24	0
undamaged	0	16

9. CONCLUSIONS

For the damage detection of truss structures, this study assumed to utilize vibration signals obtained from sensors installed into the bridges. By preparing damaged and non-damaged bridge structures, large quantities of response data were generated. AR model was then applied to the time signals to extract the structure's soundness characteristics. Here, AR coefficients are values in which damaged structural characteristics are reflected. Then, as a machine learning technique, the decision tree method was applied to the AR coefficients to classify the structures into damaged and non-damaged ones. Results showed that the decision tree method successfully detected the damage of truss members. This method is expected to contribute to automatically find deterioration of a member for aged truss structures with fewer costs and labors.

10. ACKNOWLEDGMENTS

This study used TDAPIII developed by Ark Information System.

11. REFERENCES

[1] Shimizu, M., Mikami, A. and Unno, K., Damage Detection of Truss Structures Based on Vibration Characteristics, 4th International Conference on Science, Engineering and Environment(SEE), 2018, pp. 752-757.

[2] MLIT, White Paper on Land Infrastructure, Transport and Tourism in Japan, 2014.

[3] Sekino, M., Hakone Tozan Line Hayakawa Bridge, Bridge and Foundation Engineering, Truss Bridge Feature, Kensetsutosho, Vol. 27, No. 8, 1993, p. 167 (in Japanese).

[4] Ark Information Systems, INC., Users' Manual, 2017 (in Japanese).
[5] MathWorks, Sensor data analysis and machine learning - Anomaly detection from vibration data - web seminar, 2015 (in Japanese), https://jp.mathworks.com/videos/sensor-data-analysis-and-machine-learning-anomaly-detection-using-vibration-data-100241.html (accessed on 2018-05-20).
[6] Figueiredo, E., Park, G., Figueiras, J., Farrar, C. and Worden, K., Structural Health Monitoring Algorithm Comparisons Using Standard Data Sets, Los Alamos National Laboratory Report: LA-14393, 2009.
[7] Goi, Y. and Kim, C-W., Damage Detection of a Truss Bridge Utilizing a Damage Indicator from Multivariate Autoregressive Model, Journal of Civil Structural Health Monitoring, 7(12), 2017, doi:10.1007/s13349-017-0222-y.
[8] Yoshioka, T., Harada, M., Yamaguchi, H. and Itou, S., A Study on the Vibration Characteristics Change of the Steel Truss Bridge by the Real Damage of Diagonal Member, Journal of Structural Engineering, Vol.54A, 2008, pp. 199-208 (in Japanese).