IDENTIFYING CHANGES IN DYNAMIC CHARACTERISTICS DUE TO FRACTURE OF A DIAGONAL MEMBER OF A 9-SPAN CONTINUOUS STEEL TRUSS BRIDGE FROM TRAFFIC-INDUCED VIBRATIONS

S. KITAUCHI*, C.W. KIM†, K.C. CHANG and K. SUGIURA

Department of Civil and Earth Resources Engineering, Graduate school of Engineering, Kyoto University, Japan

ABSTRACT

This study is intended to identify changes in dynamic characteristics of a 9-span continuous steel truss bridge due to fracture of a diagonal member by measuring vehicle-induced vibrations of the bridge. On-site damage experiment was carried out on the bridge before and after applying damage. At first, the dynamic characteristics of the bridge are identified by means of Auto-Regressive (AR) model. Second, an automated way of identifying dynamic characteristics was investigated, aiming the practical use of the identification method for damage diagnosis. Observations through this study demonstrate difficulties of utilizing dynamic characteristics for structural diagnosis of bridges and also clarify problems to be solved.

Keywords: vehicle-induced vibration, system identification, structural diagnosis, autoregressive model, outlier analysis.

1. INTRODUCTION

Damage in bridges has been reported in many countries due to deterioration, aging, heavy loads, etc. Bridge owners have shown great interests in the vibration-based structural health monitoring (SHM) (Doebling et al. 1996; Deraemaeker et al. 2007) which is expected to provide more efficient method of SHM comparing to visual-based ones.

In the vibration-based SHM of bridges, what must be clarified is how damage changes the dynamic characteristics such as natural frequency, damping constant and mode shape. In order to detect changes in dynamic characteristics due to damage, we need to map those characteristics of intact (reference) state into those of damage state. How to inspect bridges efficiently is another keen technical issue, considering a huge number of bridges, urgent needs for inspecting those bridges and short of skillful technical experts. Therefore, it is important to develop a damage detection method of bridges which can be utilized even by non-professional engineers. In other words, a problem remained to be solved is to identify dynamic characteristics of bridges automatically, since without

* Presenter: Email: kitauchi.soutarou.43e@st.kyoto-u.ac.jp

† Corresponding author: Email: kim.chulwoo.5u@kyoto-u.ac.jp

automation it is difficult to cover all the bridges which need to be inspected. It is noteworthy that considering a large portion of short to medium span bridges in whole bridge stocks, the traffic-induced vibration which is dominant on those bridges should be used in SHM of those short to medium span bridges.

Hence this study, at first, is intended to identify the dynamic characteristics of a steel bridge utilizing multivariate and singlevariate AR model (Okabayashi et al. 2003; Okabayashi et al. 2007; Kim et al. 2012) in order to clarify how fracture in a steel truss member leads to change in dynamic characteristics. Mahalanobis-Taguchi system (MTS), which is one of the supervised learning schemes, is also adopted to make a decision on structural diagnosis of the bridge. This study also discusses an automated way of identifying modal parameters so that even non-professional people utilize the identification approach, aiming the practical use of the approach for structural diagnoses of bridges. In order to verify validity of the proposed approach, a damage experiment was carried out on a real 9-span continuous bridge which will be removed after the experiment.

2. ON-SITE DAMAGE EXPERIMENT

On-site damage experiment was carried out on 9-span continuous steel truss bridge shown in Figure 1. Only the sixth span from the A1 abutment was examined. Two different damage scenarios, healthy and damage, were considered. Artificial damage was applied by severing the diagonal member. 14 accelerometers were installed to measure vertical acceleration responses and accelerometers were relatively more densely deployed near the damage member as shown in Figure 2. Two different patterns of sensor grouping were considered in damage detection as shown in Table 1 where Pattern 1 and Pattern 2 denote the pattern of sensor grouping. Total weight of the test vehicle is about 256kN. Scenarios of moving vehicle test are shown in Table 2.

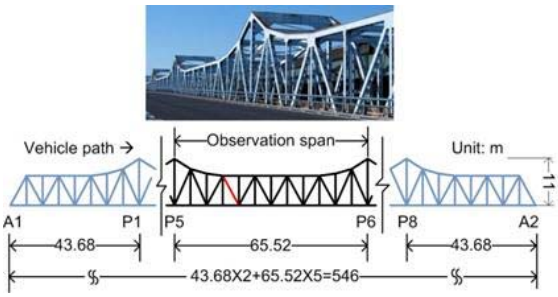

Figure 1: Elevation views of observation bridge.

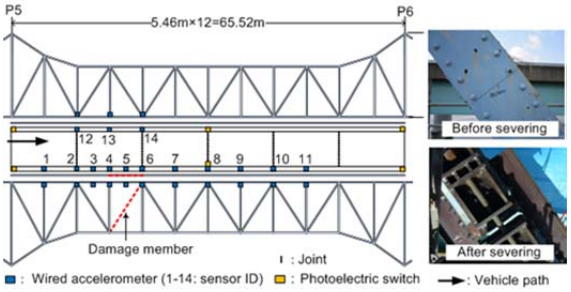

Figure 2: Sensor deployment map and artificial damage.

Table 1: Two sensor grouping patterns.

Pattern 1	Sensors from 4 and 6 to 11 are considered as single group.										
Pattern 2	Sensor group	A	BC	DE	F	G	H	I	J	K	L
	Sensor No.	1 & 2	2 & 4	4 & 6	6 & 7	7 & 8	8 & 9	9 & 10	10 & 11	12 & 13	13 & 14

Table 2: Scenarios of moving vehicle test.

Scenarios	Speed	The number of observations	
		Intact	Damage
SCN1	20km/h	7	6
SCN2	40km/h	7	6
SCN3	SCN1+SCN2	14	12

3. IDENTIFICATION OF DYNAMIC CHARACTERISTICS

3.1. Identification by multivariate AR model

Changing the model order, the linear dynamic model system is modeled by multivariate AR (MAR) model (Okabayashi et al. 2007; Kim et al. 2012). Figure 3 shows a Stabilization Diagram derived from MAR model and singular value spectrum under SCN2. There are stably identified frequencies which do not vary much with respect to model order. Checking all those stably estimated dynamic characteristics visually, two frequencies 2.0Hz and 7.6Hz (see Figure 4) are considered in this study. Then, the dynamic characteristics corresponding to the two modes are identified in all data.

COMAC values are estimated in order to detect the damage location. Figure 5 shows the COMAC with respect to each observation point, and also shows that the COMAC values around damage location are relatively small. Thus, mode shape may be useful for damage location detection. On the other hand, changes in frequency and damping constant are observed, but more observations are necessary to make a decision on the health condition of the bridge.

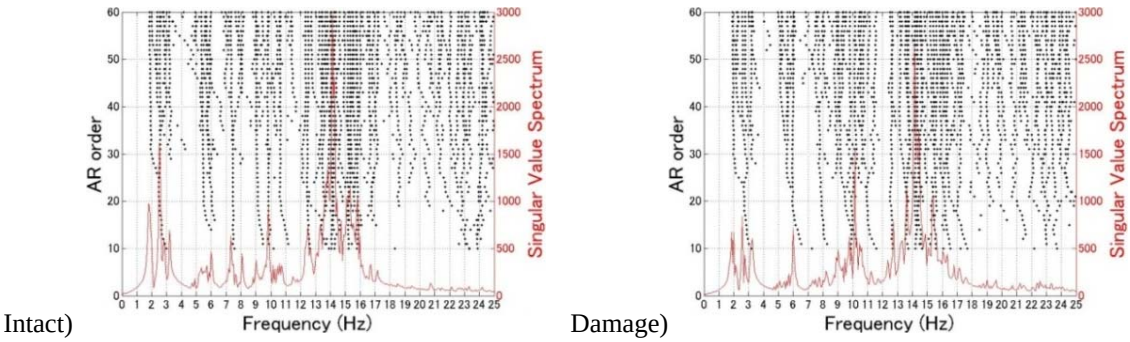

Figure 3: Stabilization Diagram and singular value spectrum under SCN2.

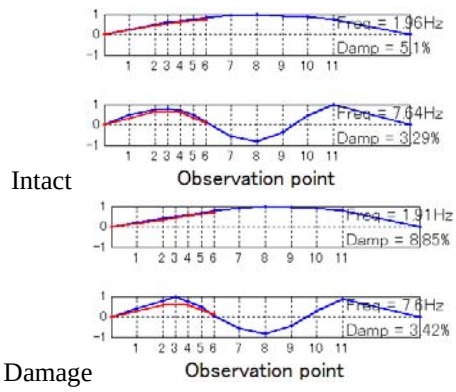

Figure 4: Average mode shapes of two dominant modes and corresponding freq. and damp.

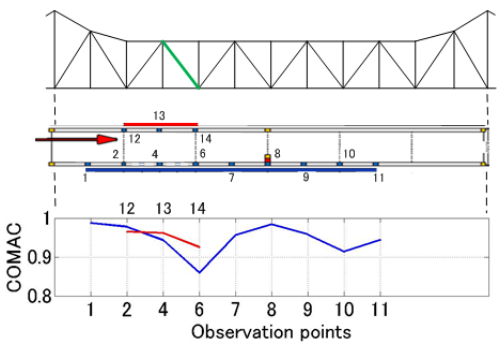

Figure 5: COMAC of the observation span w.r.t. each observation point.

3.2. Identification by singlevariate AR model

Frequency and damping constant are also identified by singlevariate AR (SAR) model. In a preliminary investigation, it was observed that SAR model under optimal model order identified even spurious values. Therefore, this study adopts 45 as the model order because SAR model under the model order of 45 could reduce the spurious values and provide those dominant frequencies estimated by MAR model; dominant frequencies near 2.0Hz and 7.6Hz were identified.

3.3. Mahalanobis-Taguchi System (MTS)

In order to emphasize potential change in frequency and damping constant due to damage for damage detection, the Mahalanobis-Taguchi System (MTS) is adopted as a tool for a multivariate outlier analysis, which is used in diagnostic applications to make quantitative decisions by constructing a multivariate measurement scale called Mahalanobis distance (hereafter MD) (Taguchi and Jugulum 2000).

3.3.1. Algorithm of MTS

In the MTS, the Mahalanobis space (MS) is obtained using the standardized variables of normal data. The MS can be used to discriminate normal and abnormal data.

In applying MTS, firstly we have to construct a measurement scale with MS as a reference: this is done using the data from a normal group and calculating their MDs, whose value should be close to 1. The standardized normal data are obtained using equation (1).

$$z_i^p = \frac{x_i^p - \mu_i}{\sigma_i} \tag{1}$$

where z_i^p indicates the standardized *p*-th tuple of normal data for *i*-th variable; x_i^p, the *p*-th tuple of normal data for *i*-th variable; $\mu_i\left(= \left(\sum_{p=1}^{n} x_i^p\right)/n\right)$, mean value of the *i*-th variable defined as; and $\sigma_i\left(= \frac{1}{n}\sqrt{\sum_{p=1}^{n}\left(x_i^p - \mu_i\right)^2}\right)$, the standard deviation of *i*-th variable. If $\mathbf{Z}_p = \left(z_1^p, z_2^p, \cdots, z_k^p\right)$ and $\mathbf{C} \in \mathbb{R}^{k\times k}$ denotes correlation matrix for *k* standardized variables, then MD calculated for the *p*-th tuple of normal data in a sample size *n* with *k* variable is given by

$$MD_p = D_p^2 = \frac{1}{k}\mathbf{Z}_p\mathbf{C}^{-1}\mathbf{Z}_p^T \tag{2}$$

Next, the signal space is obtained from abnormal data or newly monitored data. Abnormal data are also standardized utilizing mean and standard deviation values of the normal data as

$$y_i^p = \frac{w_i^p - \mu_i}{\sigma_i} \tag{3}$$

The $\overline{MD}_p$ of the normalized abnormal data in the signal space can be defined by equation (4) from the normalized abnormal data and **C**, which is obtained from known data. If newly monitored data is abnormal, the $\overline{MD}_p$ should be considerably greater than one.

$$\overline{MD}_p = \overline{D^2}_p = \frac{1}{k}\mathbf{Y}_p\mathbf{C}^{-1}\mathbf{Y}_p^T \ \left(\text{where } \mathbf{Y}_p = \left(y_1^p, y_2^p, \cdots, y_k^p\right)\right) \tag{4}$$

The required conditions to utilize MTS are as follows: the number of variables k of normal data is equivalent to that of abnormal data; n is larger than k; and σ_i is not zero.

This study utilizes the outliers crossing a threshold for structural damage diagnosis. In deciding the threshold, the largest and smallest values of MD taken from the cross-validation (Bishop 2006) were removed, and the trimmed mean value was adopted as the threshold using (n-2) MD distances to reduce the effect of outliers on the MDs.

3.3.2. Damage detection by MTS

Damage detection of the bridge is carried out applying MTS for detecting change in frequency and damping constant. The MTS requires a rather larger number of observations than the number of variables or sensors. However only a limited number of runs were carried out in the field experiment in order to reduce time and cost. Therefore this study utilized data from sensor groups to reduce the number of sensors which is considered as the number of variables in MTS. The SCN3 (see Table 2) which is the scenario combining SCN1 and SCN2 is also considered in order to increase the number of observations.

In applying MTS for damage detection of the bridge, two different patterns of sensor grouping were considered as shown in Table 1: Pattern 1 uses all the data from the 7 observation points, 4 and 6 to 11, for the damage detection; Pattern 2 uses the observation points except the two observation points near the damaged member, points 3 and 5, to examine the feasibility of detecting damage location without considering data from the sensors near the damage.

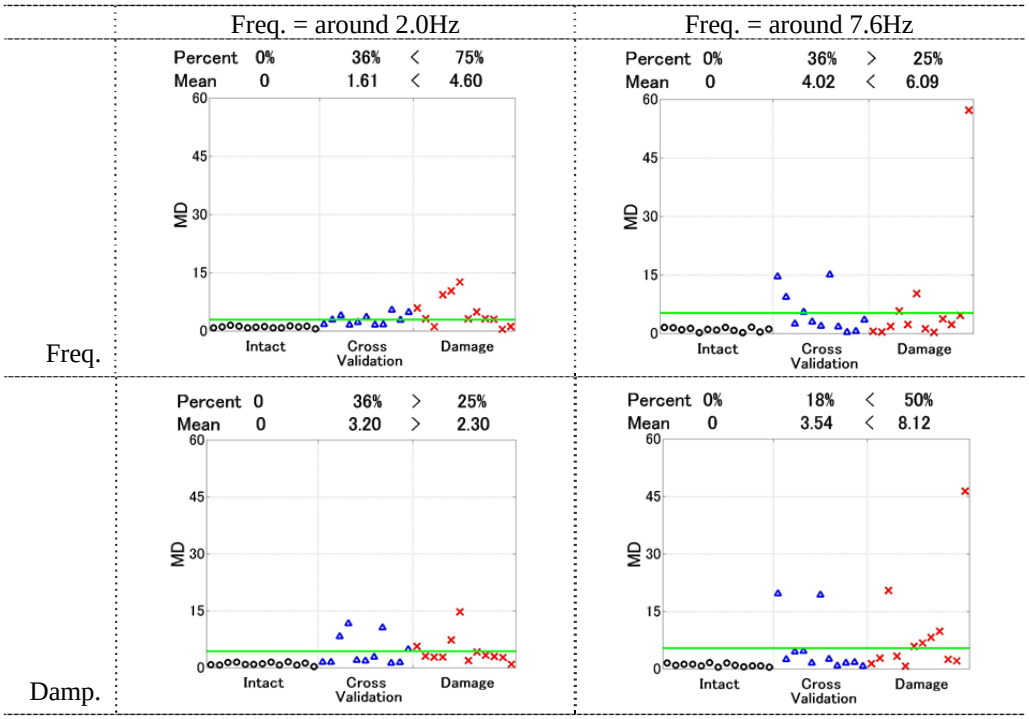

Figure 6: MDs of each dynamic characteristic under SCN3 of Pattern 1.

Results of MTS considering Pattern 1 is shown in Figure 6, in which the green horizontal line denotes the threshold. Figure 6 shows that the frequency around 2.0Hz and damping constant which corresponding to the frequency around 7.6Hz lead to clear change caused by damage of the bridge: MDs' crossing percentage of threshold in the Damage is bigger than that in the Cross Validation and mean length of MDs in the Damage is also bigger than that in the Cross Validation. However the other results show difficulty of detecting anomaly by the MTS.

Damage location detection is carried out using sensor grouping Pattern 2, and mean length of MDs are plotted as shown in Figure 7. Since the probability of crossing the threshold in the Damage is higher than that in the Cross Validation, only mean length of MDs are shown in Figure 7. It was expected that the mean value of MD of sensor group near the damage will be dominant. However Figure 7 shows that it is difficult to detect damage location by the MTS because dominant mean MDs are not appeared around damage location group 'DE'.

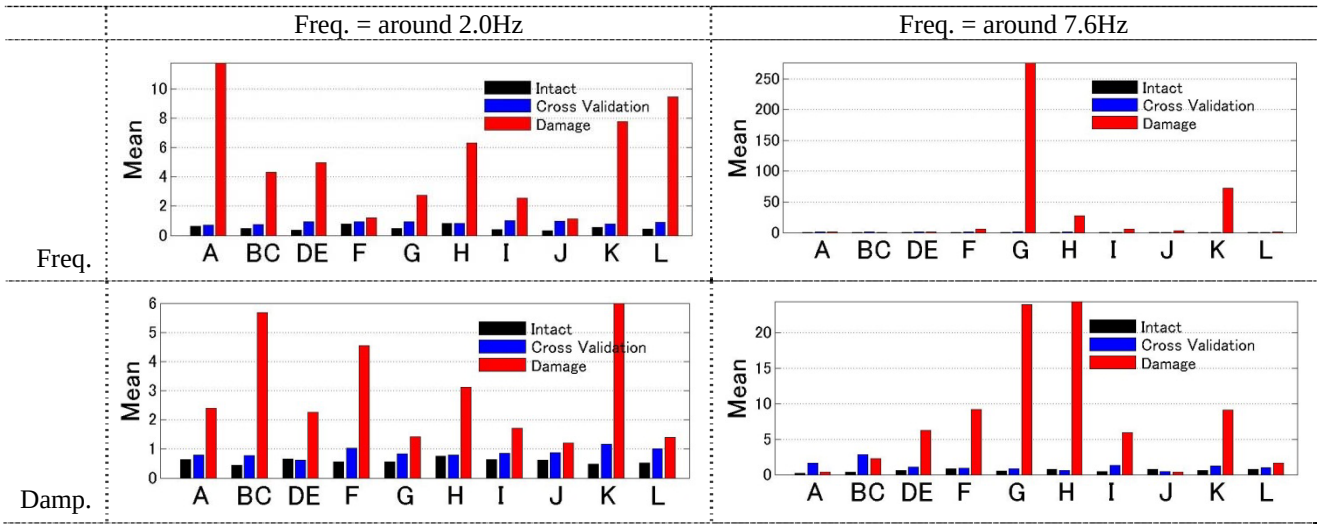

Figure 7: MDs' mean length of each dynamic characteristic under SCN3 of Pattern 2.

4. AUTOMATIC IDENTIFICATION OF DYNAMIC CHARACTERISTICS

Aiming the practical use of dynamic characteristics for damage detection, it is important to identify those characteristics automatically. Therefore, this section describes a method to identify dynamic characteristics of the observation bridge automatically. Typically, in the modal parameter-based damage detection, one way to compare the dynamic characteristics is to map mode shapes before and after applying damage. Therefore, if we can automatically estimate mode shapes of intact and damage states which match with each other, there is a possibility that the automatic identification method would be useful for damage detection.

The linear dynamic system is modeled by the MAR model as previously mentioned. In order to realize an automatic estimation of dynamic characteristics, utilizing an optimal MAR model is convenient since we have to decide the order of MAR model somehow. In this study, model order is

determined by Akaike Information Criterion (AIC) which helps getting an optimal order, and an automatic extraction of stable dynamic characteristics is performed. As a first step, extraction of the dynamic characteristics whose frequencies are stable is carried out. Specifically, focusing on a frequency f_k, extract all the frequencies falling into the range $[f_k\times(1-f^*)\ f_k\times(1+f^*)]$ and if the number of those frequencies are bigger than the half of total running times, those frequencies are considered as stable. After performing the first step, extraction of the dynamic characteristics whose mode shapes have high correlation is carried out. Specifically, focusing on a mode shape ϕ_k, extract all the mode shapes ϕ_l which satisfy the following criterion: $\mathrm{MAC}^*<\mathrm{MAC}(\phi_k,\phi_l)$. $\mathrm{MAC}(\phi_k,\phi_l)$ is the modal assurance criteria (MAC) between ϕ_k and ϕ_l. In this study, the values of f^* and MAC^* were adopted as 0.01 and 0.95 respectively.

Finally extracted dynamic characteristics are shown in Figure 8. Though in some cases, the estimated modes in intact and damage state are same, in most cases, the number of identified modes is different. It shows difficulty to utilize dynamic characteristics for damage detection even utilizing an automatic approach.

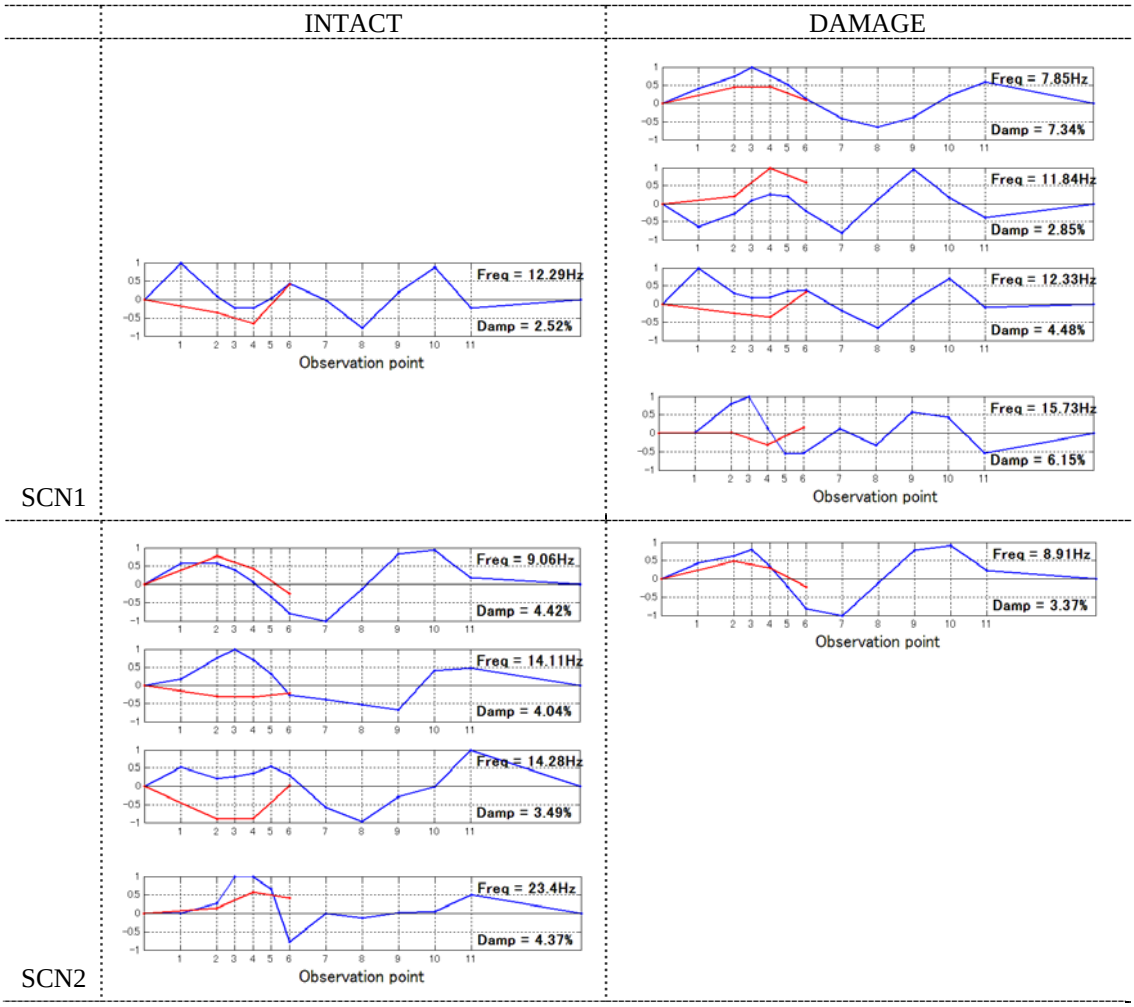

Figure 8: Stably estimated dynamic characteristics.

5. CONCLUSIONS

This study identified changes in dynamic characteristics due to fracture of a diagonal member of a 9-span continuous steel truss bridge by measuring vehicle-induced vibration of the bridge. A method to identify dynamic characteristics automatically was also investigated aiming the practical use of the method for damage diagnosis. Utilizing MAR model with the model order decided by a trial-and-error approach, changes in the dynamic characteristics could be identified by COMAC. The MTS was applied to the identified dynamic characteristics by SAR model and showed that the MTS also could detect anomalies in some cases but failed to detect damage location.

Observations through this study show that difficulty to utilize dynamic characteristics for damage detection even utilizing an automatic approach unless we have an efficient way of deciding allowable variances of each dynamic characteristic, although this study shows feasibility of utilizing dynamic characteristics in damage detection which can be automatically estimated by AR model under optimal model order. Therefore it would be a keen issue to develop a new damage sensitive feature as an automatic way of estimating the damage sensitive feature.

6. ACKNOWLEDGMENTS

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