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Damage detection of a steel truss bridge through on-site moving vehicle experiments

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ABSTRACT: This study investigated feasibility of vibration-based bridge health monitoring (BHM) of a real steel truss bridge utilizing vehicle-induced vibrations of the bridge. A time series model was identified from vehicle-induced vibrations, and a damage-sensitive feature was extracted from linear system parameters of the time series model. Mahalanobis-Taguchi system (MTS) was adopted to emphasize change in the damage-sensitive feature due to damage. It was possible to detect damage location by densely deploying sensors near the damaged member, even though removing the information from the sensors near the damaged member in the MTS led to fault information on damage location. More comprehensive investigations are needed to clarify the reason to fail in detecting damage location after removing the sensors near the damaged member in consideration. However, feasibility of damage detection utilizing the damage detection approach encourages applying the approach to real world problems.

1 INTRODUCTION

The collapse of the I-35W Mississippi River bridge in Minneapolis, Minnesota, USA on August 1, 2007, (National Transportation Safety Board 2008) was an unprecedented shock to the civil engineering community. After the incident, damaged truss members in truss bridges have been found by bridge inspections even in Japan. The importance and need for bridge inspection and monitoring has increasingly become more apparent aftermath of these events.

Among the inspection and monitoring, bridge owners have been captivated by vibration-based bridge health monitoring (BHM) since vibration-based BHM is expected to provide more efficient way comparing to visual inspections. Most precedent studies on vibration-based bridge health monitoring (BHM) specifically examine change in modal properties and quantities of bridges (e.g. Salawu 1997, Doebling et al. 1998, Deraemaeker et al. 2007). Fundamental concept of this technology is that modal parameters are functions of structure’s physical properties. Therefore, a change in physical properties, such as reduced stiffness resulting from damage, will detectably change these modal properties.

In identifying modal parameters, many studies utilize a linear time-series model (e.g. He & De Roeck 1997, Carden & Brownjohn 2008, Kim et al. 2012). However there are drawbacks yet in modal parameter-based bridge diagnosis using the time series model: the optimal time series model identified from vehicle-induced vibration of bridges usually comprises a higher order term which is easily affected by noises, and the optimal model detects even numerical parameters which lead to spurious system frequencies and damping constants. In fact those spurious system parameters make it difficult to choose proper modal parameters affected by structural damage. Nair et al. (2006), thus, investigated feasibility of a damage-sensitive feature, which is derived from linear system parameters of the AR model, to cope with the drawback of the modal parameter-based damage detection by utilizing data from the ASCE benchmark test on a model building. Kim et al. (2013) examined feasibility of the damage-sensitive feature for the BHM of bridges through a laboratory moving vehicle experiment on a model bridge. Both investigations show feasibility of the damage-sensitive feature from coefficients of the AR model for SHM and BHM within the laboratory scale, while verifying the validity of the BHM for real bridges is a crucial technical issue.

The authors have a chance to conduct a damage experiment on a real nine-span continuous steel truss bridge which is planned to be removed. This study investigates feasibility of a vibration-based bridge health monitoring on the real steel truss bridge utilizing the damage-sensitive feature extracted from vehicle-induced vibrations of the bridge. Potential changes in the damage-sensitive feature due to damage are emphasized by the Mahalanobis-Taguchi system (MTS) (Taguchi & Jugulum 2000, Kim et al. 2013). This paper also discusses both implications and limitations of the approach in terms of real world applications.

2 DAMAGE-SENSIVITIY FEATURE FROM AR COEFFICIENTS

The linear dynamic system can be modeled by the AR model (e.g. Ljung 1999, Kim et al. 2012) as

$$y(k) + \sum_{\mathrm{i}=1}^{\mathrm{p}} a_i y(k-i) = e(k) \tag{1}$$

where $y(k)$ denotes the output of the system, a_i is the i-th order AR coefficient and $e(k)$ indicates an error term. The coefficient a_p is a pole of the system because the z-transformation of Equation 1 can be written as

$$Y(z) = H(z)E(z) = \frac{1}{1+\sum_{i=1}^{p} a_i z^{-i}} E(z) \tag{2}$$

where $Y(z)$ and $E(z)$ are z-transformations of $y(k)$ and $e(k)$, $H(z)$ is the transfer function of the system in the discrete-time complex domain, and z^{-i} denotes the forward shift operator.

Values of z in which the elements of the transfer function matrix show infinite values are the poles. This means that the denominator of the transfer function is the characteristic equation of the dynamic system, given as

$$z^p + a_1 z^{p-1} + a_2 z^{p-2} + \cdots + a_{p-1} z + a_p = 0 \tag{3}$$

The poles on the complex plane are associated with the frequency and damping constant of the dynamic system of structures, as follows:

$$z_k = \exp\left(-h_k \omega_k \pm j\omega_k \sqrt{1-h_k^2}\right) \tag{4}$$

where h_k and ω_k are the damping constant and circular frequency, respectively, of the k-th mode of the system, and j represents the imaginary unit.

It should be noted that AR coefficients can be defined by sums and products of its roots z_k shown in Equation 4 according to Vieta's formula (Bold 1982). In other words, AR coefficients are directly associated with the modal parameters such as ω_k and h_k in Equation 4, and AR coefficients are also affected by damage. Therefore the parameter from AR coefficients is adopted as a damage-sensitive feature and defined as

$$\mathrm{DI}_j = \frac{|a_1|}{\sqrt{\sum_{i=1}^{j} a_i^2}} \tag{5}$$

where a_i denotes the i-th AR coefficient and DI_j is the damage indicator that considers up to the j-th AR coefficient. If we consider $j = 3$ then the DI_3 is the same with that of Nair et al. (2006).

3 MAHALANOBISI-TAGUCHI SYSTEM FOR FAULT DETECTION

The Mahalanobis-Taguchi System (MTS) (Taguchi & Jugulum 2000) is one of the pattern recognition methods, which is used in diagnostic applications to make quantitative decisions by constructing a multivariate measurement scale called Mahalanobis distance (hereafter MD). In the MTS, the Mahalanobis space (MS) is obtained using the standardized variables of normal data. The MS can be used to discriminate between normal and abnormal data.

In applying the MTS, firstly a measurement scale with the MS needs to be constructed 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 6.

$$z_i^p = \frac{x_i^p - \mu_i}{\sigma_i} \tag{6}$$

where z_i^p indicates the standardized p-th tuple of normal data for j-th variable; x_i^p, the p-th tuple of normal data for i-th variable; $\mu_i \left(= \frac{1}{n}\sum_{p=1}^{n} x_i^p\right)$, mean value of the i-th variable; 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

$$MD_p = D_p^2 = \frac{1}{k}\mathbf{Z}_p^T\mathbf{C}^{-1}\mathbf{Z}_p \tag{7}$$

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

$$y_i^p = \frac{w_i^p - \mu_i}{\sigma_i} \tag{8}$$

The $\overline{MD}_p$ of the normalized abnormal data, $\mathbf{Y}_p = \left(y_1^p, y_2^p, \cdots, y_k^p\right)$, in the signal space can be defined by Equation 9 from the normalized abnormal data and $\mathbf{C}$, which is obtained from known data. If newly monitored data is abnormal the $\overline{MD}_p$ should be considerably greater than one.

$$\overline{MD}_p = \overline{D^2}_p = \frac{1}{k}\mathbf{Y}_p^T\mathbf{C}^{-1}\mathbf{Y}_p \tag{9}$$

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

4 FIELD EXPERIMENT

On-site damage experiments are conducted on a real steel truss bridge shown in Figure 1 which is a nine span continuous Gerber-truss bridge. The observation span is the sixth span from the

A1 abutment. The roadway roughness condition was poor especially on expansion joints as well as on construction joints of precast RC decks for the bridge has not been maintained for quite a while. Figure 2 shows accelerometer deploying map and artificial damage into a diagonal tension member. Measured accelerations are used in the damage detection. Sensors are densely placed around the damaged member. Four different sensor groupings, Group 1, Group 2, Group 3 and Group 4, are considered. Chapter 5 depicts more details about the sensor grouping.

The same cargo truck with a tandem axle was used in the experimental campaign over two days. Vehicle weights were slightly different from 253kN to 258kN, but effects of the small difference in the vehicle's axle load to the bridge response were assumed to be negligible. The axle distance between front and tandem axles was 6.5m. Photoelectric switches mounted on the entrance, center and exit of the span were used to estimate position and speed of the passing vehicle. Vehicle drop tests were conducted to estimate the natural frequencies of the vehicle. A rubber mat with thickness of 5cm was prepared on which the vehicle was put for the drop test, and the vehicle was then dropped from the mat. The free vibrations were measured when the vehicle landed on the ground. A noteworthy point on the drop test is that the measured acceleration faded-out so fast by high damping of the suspension of the vehicle that led to low resolution in FFT. The drop test showed that two dominant frequencies at 1.0 Hz and 3.0 Hz for bounce motion on the front axle, and at 1.5 Hz and 3.5 Hz for that on the tandem axle. Those for hop motions appeared around 12 Hz for the front axle and 14 Hz for the rear axle.

Vehicle-induced vibrations of the bridge before and after severing the member were measured and used in damage detection of the bridge. During the experiment, 18 runs were carried out for the healthy bridge which comprises 4 runs under vehicle speed of 10 km/h, 7 runs under vehicle speed of 20 km/h and 7 runs under vehicle speed of 40 km/h. For the damaged bridge, 15 runs were carried out, which comprises 3 runs under vehicle speed of 10 km/h, 6 runs under vehicle speed of 20 km/h and 6 runs under vehicle speed of 40 km/h.

It was hard to measure free vibrations of the observation span, since the observation span locates on the central part of the 9 span-continuous bridge and the responses measured after the vehicle leaving the bridge was too weak to measure without utilizing high resolution accelerometers. On the other hand, a preliminary eigenvalue analysis of the bridge and the vehicle's dynamic properties taken from the drop test were used to identify the dominant frequency affected by the moving vehicle from vehicle-induced vibration data of the bridge. Therefore this study utilizes the vehicle-induced vibration data to examine dynamic characteristics of the bridge (accurately, dynamic characteristics of the bridge affected by the vehicle-bridge interaction). This study even tries to identify dynamic properties of the bridge as those fundamental dynamic properties such as frequency, damping constant and mode shapes provide useful information to understand the dynamic behavior of bridges, although identifying the dynamic properties of the bridge is not the aim of this study.

Figure 3 shows the measured acceleration responses at the observation points 4 and 14 as an example before and after applying damage under vehicle speed of 40km/h. Figure 4 shows a stabilization diagram combined with singular value spectrum taken from the frequency domain decomposition (FDD) (Brincker et al. 2000). The stabilization diagram showed dominant frequencies near 1.96Hz, 2.5Hz, 7.64Hz, and 14Hz, in which the dominant frequencies near 2.5Hz and 14Hz may be the contribution from the vehicle's bounce and hop motions. Wavelet analysis of acceleration responses of the bridge and vehicle also demonstrated that the dominant frequency near 14 Hz is resulted from excessive hop motions of the vehicle caused by the poor pavement especially on the joints, which is omitted in this paper for the sake of brevity. It is clear that the stabilization diagram derived from the vehicle-induced vibration also comprises spurious frequencies which are possibly not relevant to the bridge.

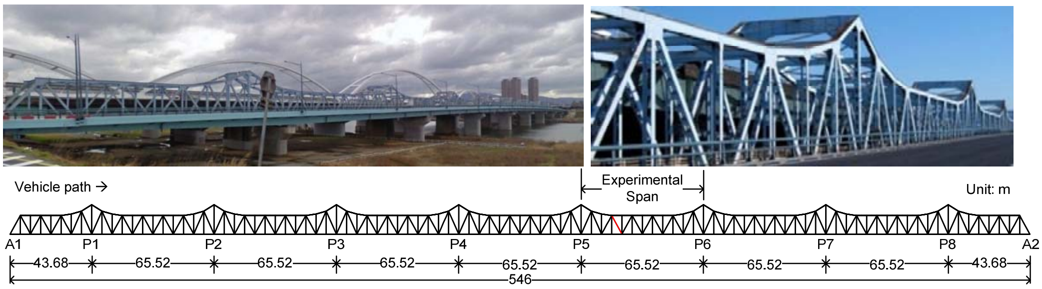


Figure 1. Experimental bridge.

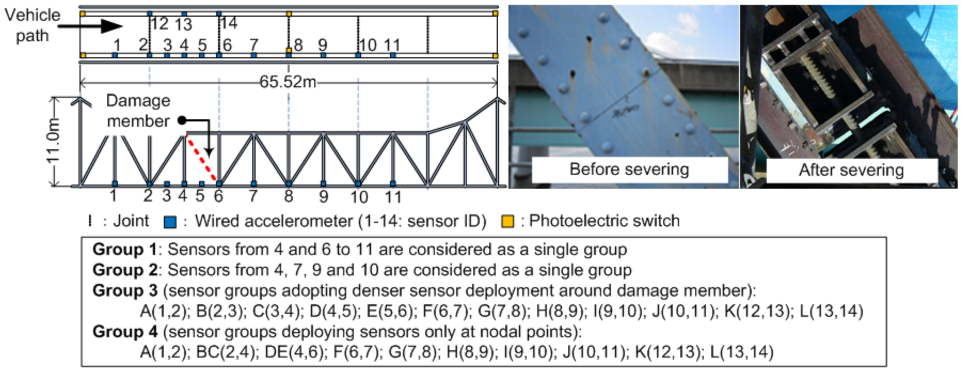
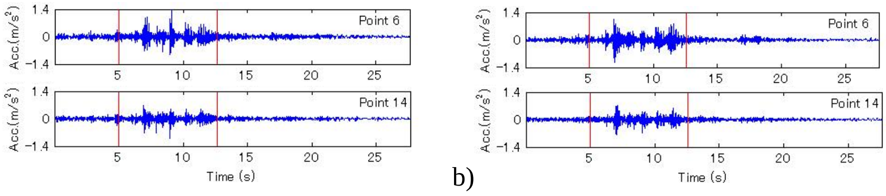
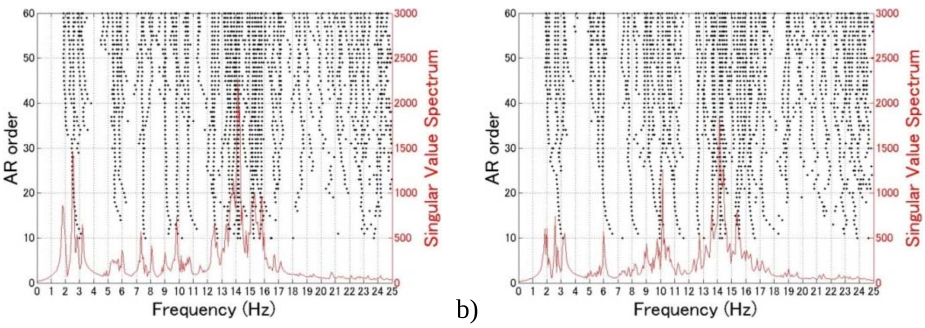


Figure 2. Sensor deploying map and damaged member.



a) b)

Figure 3. Vehicle-induced vibrations: a) Healthy (v=40 km/h, Run3); b) Damage (v=40 km/h, Run3).



a) b)

Figure 4. Stabilization diagram from vehicle-induced vibration data: a) Healthy (v=40 km/h, Run3); b) Damage (v=40 km/h, Run3).

5 DAMAGE DETECTION UTILIZING MAHALANOBIS-TAGUCHI SYSTEM

Damage detection of the bridge was carried out utilizing the DI as a damage-sensitive feature which is defined in Equation 5 and MTS depicted in Chapter 4. The DI_3 (Nair et al. 2006) was adopted although there is no definite rule to decide the optimal DI. In fact Kim et al. (2013) applied Akaike's Information Criteria (Gersch et al. 1973) and decided the most sensitive order corresponding to any damage although to measure dynamic responses of damaged bridges before it happened is not practical. It is noteworthy that the first AR coefficient is the most dominant among the coefficient and the influence of higher order coefficients decreases drastically with respect to time (Kim et al. 2013).

In applying the MTS to damage detection of the bridge, four different sensor groupings were adopted: Group 1 utilizes the observation data from the seven observation points, 4 and 6 to 11; Group 2 utilizes all the observation data from the four observation points, 4, 7, 9, 11; Group 3 utilizes the data from two adjacent observation points for detecting even the damage location; finally Group 4 utilizes the observation points except the two observation points near damaged member, points 3 and 5 in Group 3, to examine feasibility of detecting damage location without considering data from the sensors near the damaged member. It is noteworthy that the MTS requires enough observations which should be greater than the number of the variable although it is not easy to conduct plenty of runs in this field experiment. Therefore this study used data from sensor groups since reducing number of variables in the MTS leads to relative increase of number of observations.

Results of applying the MTS considering Group 1 and Group 2 are shown in Figure 5, in which the red horizontal line denotes the threshold. The *n*-fold cross-validation was adopted for assessing how the results of a statistic analysis will generalize to an independent data set (Bishop 2006). In deciding the threshold, the largest and smallest values of MDs taken from the cross validation were removed, and the trimmed mean value was adopted as the threshold using (*n*-2) MDs distances to reduce the effect of outliers on the MDs in the normal data. Figure 5 shows that most of all the MDs crossed the threshold, and indicates high possibility of anomalous events in the bridge. It is clear that for Group 2 the probability of MDs of the *n*-fold cross-validation crossing the threshold is lower than that of Group 1, which indirectly proves the fact that more observations can provide more stable results. It is noteworthy that other sensor groupings were investigated and deduced same conclusion, which is omitted for the brevity.

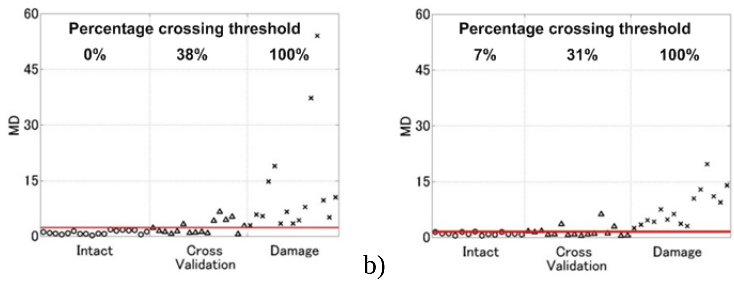


Figure 5. MDs of DI: a) Group 1; b) Group 2.

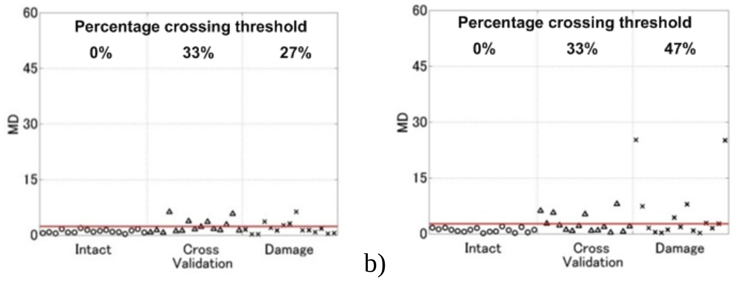


Figure 6. MDs of frequency of Group 1: a) 1.96Hz; b) 7.64Hz.

a)
b)

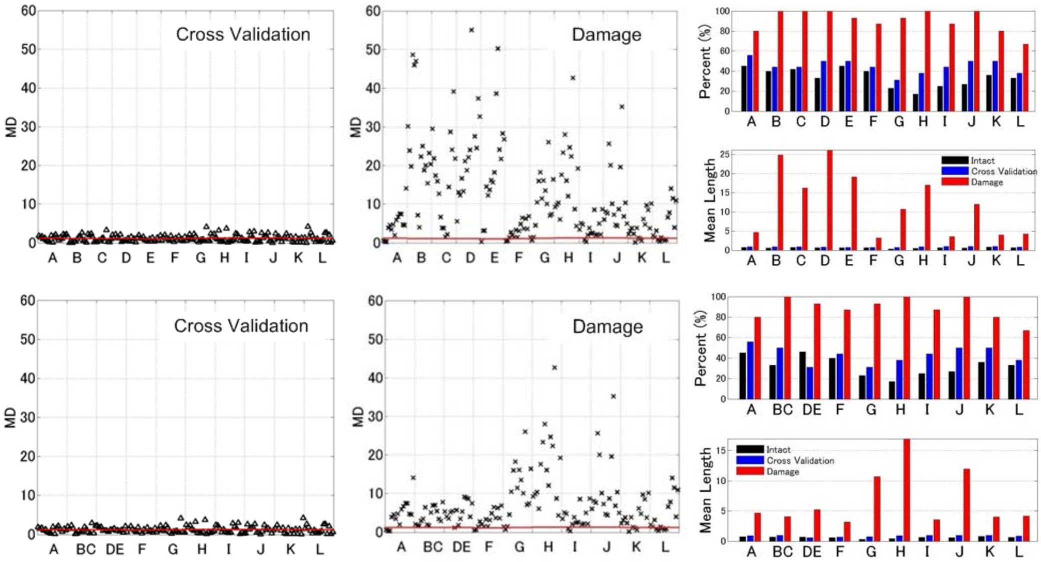


Figure 7. MDs of DI, percentage of MDs crossing the threshold, and mean length from the threshold of the MDs which cross the threshold: a) Group 3; b) Group 4.

MDs of the frequency considering Group 1 are shown in Figure 6. It demonstrates difficulty of detecting anomalous event from the MDs of 1.96 Hz, while MDs of 7.64Hz led to a little higher probability to detect the damage event compared to those of 1.96Hz but still lower than those from DI. For those of damping constants corresponding to 1.96Hz the MDs led to a higher possibility than those corresponding to of 7.64Hz differently from tendency of the frequency. However fault detecting performance is still very low compared to the DI. Those results from damping constants are omitted for brevity.

Detecting the damage location was carried out using Group 3. The results are summarized in Figure 7a) with the percentage of MDs crossing the threshold as wells as the mean length of the MDs. Apparently the probability of crossing the threshold is higher at the group considering the observation points near the damaged member. Success of detecting the damage location is natural since the result even considers data of two additional sensors deployed near the damaged member. However it is quite an ideal situation to predict damage and deploy sensors around the damage suspected member for monitoring. A remaining question to be answered, thus, would be feasibility of identifying damage locations when sensors are deployed at the panel points. Therefore, this study examined feasibility of detecting damage location utilizing Group 4 which excludes two observation points near damaged member (points 3 and 5) from Group 3. The results are summarized in Figure 7b), which shows difficulties in detecting the damage location despite of providing information about anomaly in observation data.

There is no doubt to say that how to decide the optimal number and location of sensors is also an important issue in SHM. However this paper does not discuss about the optimal sensors since that is beyond the scope of this study.

6 CONCLUDING REMARKS

This study investigated feasibility of a vibration-based bridge health monitoring of a real steel truss bridge utilizing vehicle-induced vibrations of the bridge. To overcome a drawback of utilizing conventional dynamic properties as a damage-sensitivity feature, this study used a damage-sensitive feature derived from linear system parameters of a time series model. The MTS was applied to emphasize change in the damage-sensitive feature due to damage.

The DI, the damage-sensitive feature derived from the coefficient of the AR model, combining with the MTS was successfully applied to detect damage in the real steel truss bridge even utilizing vehicle-induced vibration data. Denser sensor deployment near the damaged member led to feasibility of detecting a damage location by means of the MTS. However identifying the damage location was unsuccessful after excluding the sensors near the damaged member in the damage detection procedure.

More comprehensive investigations are needed to clarify the reason to fail in detecting damage location after excluding the sensors near the damaged member in consideration. Deciding optimal number of sensors is another future challenge. However the proposed damage detection approach is nonetheless applicable to BHM of real truss bridges.

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