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Long-term monitoring of a steel girder bridge and a Bayesian approach to assess change in bridge condition

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ABSTRACT

This study is intended to investigate a way to consider changes in temperature and vehicle weight as environmental and operational factors for long-term bridge health monitoring by applying a Bayesian approach to long-term monitoring data. The Bayesian approach consists of three steps: step 1 is to identify damage indicators from coefficients of the auto-regressive model as a damage-sensitive feature; step 2 is to obtain residuals by means of the Bayesian regression; step 3 is to make a decision based on the residuals utilizing the 95% confidence interval and the Bayesian hypothesis testing. Observations through the study demonstrate that the Bayesian regression considering both temperature and vehicle weight led to more accurate results than that considering only temperature. Validity of using the data observed at a specified time to reduce the influence of traffic loads can be confirmed. In the Bayesian hypothesis testing utilizing data from the healthy bridge, the probability of the bridge damage was judged as 'very small'.

1. INTRODUCTION

Maintaining and improving civil infrastructures including bridge structures are keen technical issues in many countries. Developing an effective maintenance strategy relies on a timely decision on the health condition of the structure. Structural health monitoring (SHM) using vibration data has been recognized as one of the promising technologies for providing a timely decision on the bridge health condition. Most precedent studies on SHM specifically examine changes in modal properties of structures. The fundamental concept of this technology is that modal parameters are functions of structures' physical properties. Therefore, a change in physical properties,

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such as reduced stiffness resulting from damage, will detectably change these modal properties (Deraemaeker 2007, Dilena 2011 and Kim 2012). In fact, many techniques to identify the hidden information of structural integrity in the vibration data have been proposed to diagnose bridge structures, and have been successfully applied in controlled environments such as laboratories. However, real bridge structures are subject to changing environmental and operational conditions that affect of structural integrity information during a long in-service period. The signals affected by those effects lurk in the measured vibration data and disguise themselves as structural responses (Peeters 2001, Sohn 2003, Deraemaeker 2007, and Kim 2011). Therefore, how to consider those environmental and operational effects in long-term bridge health monitoring is a crucial issue.

This study is intended to investigate a way to consider changes in temperature and vehicle weight as environmental and operational factors for the long-term BHM by means of a Bayesian approach, which is an improvement from previous researches considering only temperature as an environmental factor by Kim (2011, 2013a and 2013b). The Bayesian approach consists of three steps. Step 1 is to identify damage indicators (DI) from coefficients of the auto-regressive (AR) model as a damage-sensitive feature utilizing bridge acceleration data (Nair 2006 and Kim 2012 and 2013c). Since AR coefficients are closely related to bridge vibration properties, the DI from AR coefficients changes depending on the bridge structural condition and the environmental and operational conditions. The DI is identified automatically unlike frequency, damping constant and mode shape. Step 2 is to obtain residuals by means of the Bayesian regression utilizing the DI identified in step 1 (observed DI), and environmental and operational data (Bishop 2006). The residuals are differences between observed DI and DI predicted by the Bayesian regression (predicted DI). In this study, the regression analysis is applied to consider environmental and operational effects. Especially the Bayesian regression is more accurate than linear regression (Bishop 2006). Step 3 is to make a decision based on the residuals utilizing the 95% confidence interval and the Bayesian hypothesis testing (Sankararaman 2011).

This study applies the Bayesian approach to the long-term monitoring data of a short span steel girder bridge. The monitoring data are data measured at a seven-span plate-Gerber bridge during approximately one year. This study focuses on the effects of temperature and vehicle weight because the effects of temperature and vehicle weight dominate in short span bridges. The bridge weigh-in-motion (BWIM) system (Tamakoshi 2004) is installed in the bridge. Moreover, the study utilizes the monitored data at a specified time to reduce influences from varying traffic load, since the BWIM system on the observed bridge suggested that dividing the monitoring data according to a specific time resulted in a weak correlation between DI and vehicle weight (Heng 2011). Also, a noteworthy point is that all the data is taken from the healthy bridge, since no damage and deterioration was reported during the monitoring period. The influence of environmental and operational factors is investigated by comparing three cases: case A is to consider temperature and vehicle weight utilizing data monitored at a non-specified time; case B is to consider temperature utilizing data monitored at a non-specified time; and case C is to consider temperature utilizing data monitored at a specified time.

2. DAMAGE INDICATOR FROM AR COEFFICIENTS (STEP 1)

Step 1 is to identify observed DI (DI_{ob}) from coefficients of AR model as a damage-sensitive feature utilizing bridge acceleration data. Linear dynamic systems can be idealized using the AR model shown in Eq. (1) (Kim 2012).

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

where $y(k)$ denotes output of a system, a_i is the i-th AR coefficient, p is the optimal AR order and $e(k)$ indicates an error. The optimal AR order, which is obtainable by means of AIC, is used in this study (Gersch 1973). AIC is given by Eq. (2).

$$\mathrm{AIC} = n\log\left(2\pi E^2\right) + 2(m+1) + n \tag{2}$$

where n indicates the number of data, m represents AR order, and E^2 means square of prediction error. The AIC consists of two terms; the first term is a log-likelihood function and the second term is a penalty function for the number of the AR order. A damage indicator (DI) from AR coefficients defined by Eq. (3) is adopted as a damage sensitive feature (Nair 2006 and Kim 2013c).

$$\mathrm{DI} = \frac{|a_1|}{\sqrt{a_1^{\,2} + a_2^{\,2} + a_3^{\,2}}} = \left(\mathrm{DI_{ob}}\right) \tag{3}$$

Since AR coefficients are closely related to bridge vibration properties, the DI changes depending on the bridge structural condition and the environmental and operational conditions. Nair (2006) shows that the first three AR coefficients are the most significant among all the coefficients of the AR model. Kim (2013c) also observes that the DI, considering up to the third order of AR coefficients, is a promising parameter in BHM, since the DI is observed to be the most sensitive to damage through a bridge-moving vehicle laboratory experiment. Moreover, the DI can be identified automatically unlike frequency, damping constant and mode shape.

3. BAYESIAN REGRESSION TO CONSIDER ENVIRONMENTAL AND OPERATIONAL FACTORS (STEP 2)

Step 2 is to obtain residuals by means of the Bayesian regression utilizing observed DI (DI_{ob}), and environmental and operational data (Bishop 2006). The residuals are differences between observed DI and DI predicted by the Bayesian regression (predicted DI (DI_{pr})). In this study, the regression analysis is applied to consider environmental and operational effects. Especially the Bayesian regression is more accurate than linear regressions (Bishop 2006). The Bayesian regression also is useful to examine long-term monitoring data effectively because it can be updated online.

Assuming observations from a deterministic function with Gaussian noise (ε), the target function is written as Eq. (4).

$$t = y(\mathbf{x}, \boldsymbol{\omega}) + \varepsilon \tag{4}$$

where **x** is an input vector, and the corresponding target is denoted as *t*. In this study, observed DI is used for *t*, and environmental and operational factors, e.g. temperature and vehicle weight are used for **x**. Then ε follows the normal distribution. Regression models can be represented by Eq. (5).

$$y(\mathbf{x}, \boldsymbol{\omega}) = \sum_{i=0}^{M-1} \omega_i \phi_i(\mathbf{x}) = \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{\varphi}(\mathbf{x}) \tag{5}$$

where ω_i stands for a model parameter and $\phi_i(\mathbf{x})$ is known as a basis function. *M* indicates the order of the model equation. $\boldsymbol{\omega}$ and $\boldsymbol{\varphi}(\mathbf{x})$ stand for vector of model parameters and basis matrix respectively. T indicates the transpose of a matrix. The optimal model parameter ($\hat{\boldsymbol{\omega}}$) is estimated by virtue of Bayes' theorem (Bishop 2006). Moreover, the predictive distribution for *t* normally distributed is obtained. The mean of the predicted distribution is represented by Eq. (6).

$$\bar{\hat{t}} = \overline{\hat{\boldsymbol{\omega}}}^{\mathrm{T}} \boldsymbol{\varphi}(\mathbf{x}) = \left(\overline{\mathrm{DI}}_{\mathrm{pr}}\right) \tag{6}$$

where $\hat{t}$ stands for the mean of the predicted value and the bar on the top of a character indicates the mean of the character. In this study, residuals (*r*) are defined as Eq. (7)

$$r = \bar{t} - \bar{\hat{t}} = \left(\overline{\mathrm{DI}}_{\mathrm{ob}} - \overline{\mathrm{DI}}_{\mathrm{pr}}\right) \tag{7}$$

This study assume that *r* follows normal distribution.

4. DECISION-MAKING BASED ON RESIDUALS (STEP 3)

4.1 Utilizing the 95% confidence interval

This study adopts the probability of the residuals fitting within the 95% confidence interval to assess the accuracy of the regression analysis. The threshold for the 95% confidence interval is represented by Eq. (8).

$$\bar{r} \pm 1.96 s \tag{8}$$

where *s* indicates the standard deviation of the residuals. The 95% confidence interval means that the interval contains 95% of the residuals of signals taken from the healthy bridge. Therefore, if the probability is much less than 95%, there might be some changes in the health condition of the bridge. The probability is considered as a parameter for fault detection of the bridge.

4.2 Utilizing the Bayesian hypothesis testing

This study adopts the Bayesian hypothesis testing to detect damage in BHM (Sankararaman 2011). This study assumes that the null hypothesis (H_0) is 'no damage' and the alternate hypothesis (H_1) is 'damage', and they are defined by Eq. (9) and Eq. (10).

$$\mathrm{H}_0 : \bar{r} = 0 \tag{9}$$

$$\mathrm{H}_1 : \bar{r} \neq 0 \tag{10}$$

Damage detection can be achieved through the use of Bayes factor (*B*), which is defined as the ratio of likelihood of the two scenarios: 'damage' and 'no damage' as follow.

$$B = \frac{p(\mathbf{D} \mid \mathrm{H}_1)}{p(\mathbf{D} \mid \mathrm{H}_0)} \tag{11}$$

where **D** refers to the data on the residuals obtained during health monitoring. Moreover, Jiang (2008) derived the expression for *B* shown in Eq. (12).

$$B = \frac{1}{\sqrt{N+1}} \exp\left(\frac{N^2 \bar{r}^2}{2(N+1)s^2} \right) \tag{12}$$

where *N* denotes the number of the data. If the Bayes factor is greater than 1, it implies that the data favor the hypothesis H_1 and hence suggests that there is damage. If the Bayes factor is less than 1, then there is no damage. According to Jeffreys (1998), a Bayes factor such that $1<B<3$ is 'barely worth mentioning', $3<B<10$ is 'substantial', $10<B<30$ is 'strong', $30<B<100$ is 'very strong', and $B>100$ is 'decisive'. In other words, $B<1$ is 'nothing (no damage)', $1<B<3$ is 'very small', $3<B<10$ is 'small', $10<B<30$ is 'strong', $30<B<100$ is 'very strong' and $B>100$ is 'decisive (damage)'.

5. LONG-TERM MONITORING ON A STEEL GIRDER BRIDGE

This study utilizes data monitored at a short span steel girder bridge during approximately one year. The seven-span plate-Gerber bridge shown in Fig. 1 is the observed bridge, which is located on a busy national road in Japan. The bridge properties are summarized in Table 1. Elevation and plan views with sensor locations on the observation span are shown in Fig. 2. Therein, UA-1, UA-2, DA-1 and DA-2 stand for accelerometers to measure acceleration responses of steel girders on up and down lanes. The sampling rate is 200 Hz for acceleration measurements.

Thermometers are denoted by T-5 and T-6. Temperature is measured once every hour. The BWIM system (e.g. Tamakoshi et.al. 2004) is installed in the bridge, and this study also utilizes the estimated vehicle weight. This study focuses on the effects of temperature and vehicle weight for the effects of temperature and vehicle weight dominate in short span bridges. This study examined data measured at 7:00, 13:00 and 19:00 on every Wednesday and Sunday for about one year (6^{th} August 2008 to 21^{st} June 2009); the number of measurements is 276. The reason for investigating data monitored at those times is to represent changes of vehicle characteristics in the data. Moreover, the study utilizes the monitored data at a specified time to reduce the influence of varying traffic loads, since the BWIM system on the observed bridge suggested that dividing the monitoring data according to a specific time resulted in a weak correlation between DI and vehicle weight (Heng 2011). Also, a noteworthy point is that all the data is taken from the healthy bridge since no damage and deterioration was reported during the monitoring period.

Table 1 Properties of the observation bridge

Construction year		1960
Bridge length (m)		186.4
Span length (m)	Hanging girder	16.0
	Anchorage girder	40.8
Width (m)		8.0

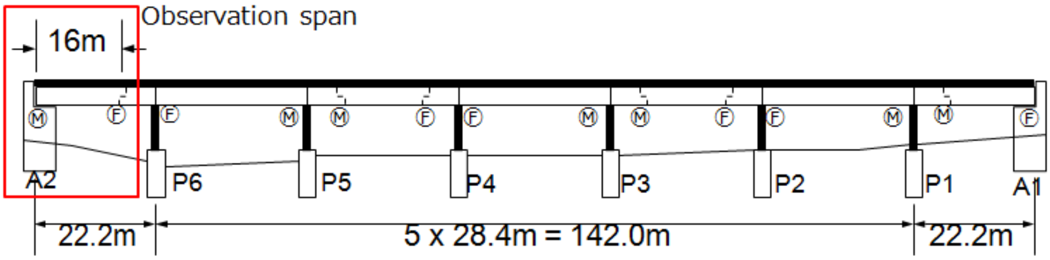

Fig. 1 Observation bridge.

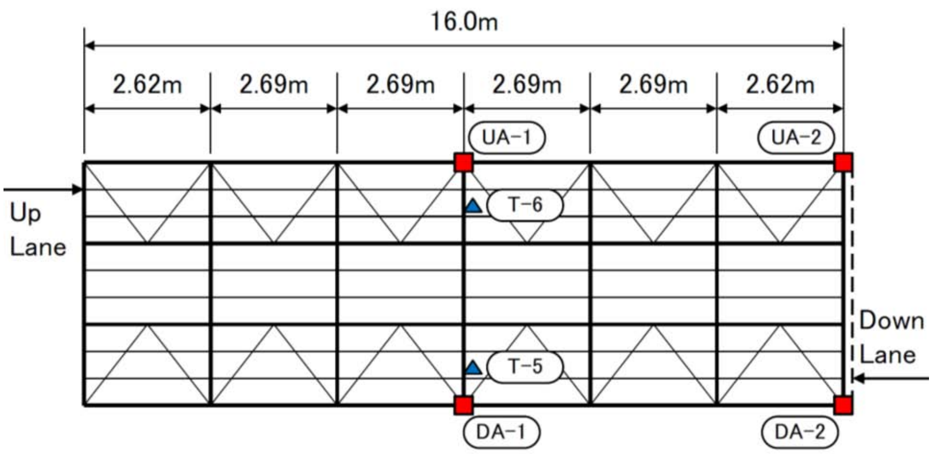

Fig. 2 Sensor locations on the observation span.

6. APPLICATIONS AND DISCUSSION

This study applies the Bayesian approach to the long-term monitoring data of a short span steel girder bridge. The influence of environmental and operational factors is investigated by comparing three cases summarized in Table 2. Herein, the data monitored at a non-specified time and those at a specified time indicate data monitored at 7:00, 13:00 and 19:00 on Wednesdays and Sundays (N=276) and those at 7:00 on Wednesdays (N=46) respectively. This study adopts Eq. (13) in case A and case B, and Eq. (14) in case C as the regression model equation (Eq. (5)).

$$y(\mathbf{x},\boldsymbol{\omega}) = \omega_0 + \omega_1 x_1 + \omega_2 x_2 \quad (M = 3) \tag{13}$$

$$y(\mathbf{x},\boldsymbol{\omega}) = \omega_0 + \omega_1 x_1 \quad (M = 2) \tag{14}$$

where ω_1, ω_2, and ω_3 stand for model parameters, x_1 denotes temperature, and x_2 denotes vehicle weight. The M indicates number of model parameters to be estimated. This study adopts the simplest basis function because the physical meaning of the model equation is not known.

This study identifies 100 DI's from blocks of acceleration data obtaining by means of moving time windows as shown in Fig. 3. The DI's identified at the sensors of UA-1 monitored at 7:00, 13:00 and 19:00 on Wednesdays and Sundays are shown in Fig. 4, and those monitored just at 7:00 on Wednesdays are shown in Fig. 5.

Temperatures measured on up lane monitored at 7:00, 13:00 and 19:00 on Wednesdays and Sundays are shown in Fig. 6, and those monitored at 7:00 on Wednesdays are shown in Fig. 7. Fig. 6 and Fig. 7 show that the change in temperature during ten months is about 30 degrees Celsius.

The Bayesian regression of this study considered sum of weights of vehicles traveling on the bridge during the time block used in estimating the DI. The transitions of vehicle weight on up lane at 7:00, 13:00, and 19:00 on Wednesdays and Sundays are shown in Fig. 8, and those at 7:00 on Wednesdays are shown in Fig. 9. Fig. 8 and Fig. 9 show that the variance of vehicle weight at a specified time is smaller than that at a non-specified time.

Fig. 11, Fig. 12 and Fig. 13 show the predicted DI and the residuals at the sensor of UA-1 in cases A, B and C respectively, in which $\hat{\sigma}$ stands for the standard division of the predicted DI. The horizontal red lines in the graph of the residuals indicate the 95% confidence interval of the residuals.

Table 2 Three cases to consider in this study

<table>
<tr><th></th><th>Considered factors</th><th>Observed data</th></tr>
<tr><td>Case A</td><td>Temperature & vehicle weight</td><td rowspan="2">Non-specified time
(7:00, 13:00 & 19:00
on Wednesdays & Sundays: N=276)</td></tr>
<tr><td>Case B</td><td rowspan="2">Temperature</td></tr>
<tr><td>Case C</td><td>Specified time
(7:00 on Wednesdays: N=276)</td></tr>
</table>

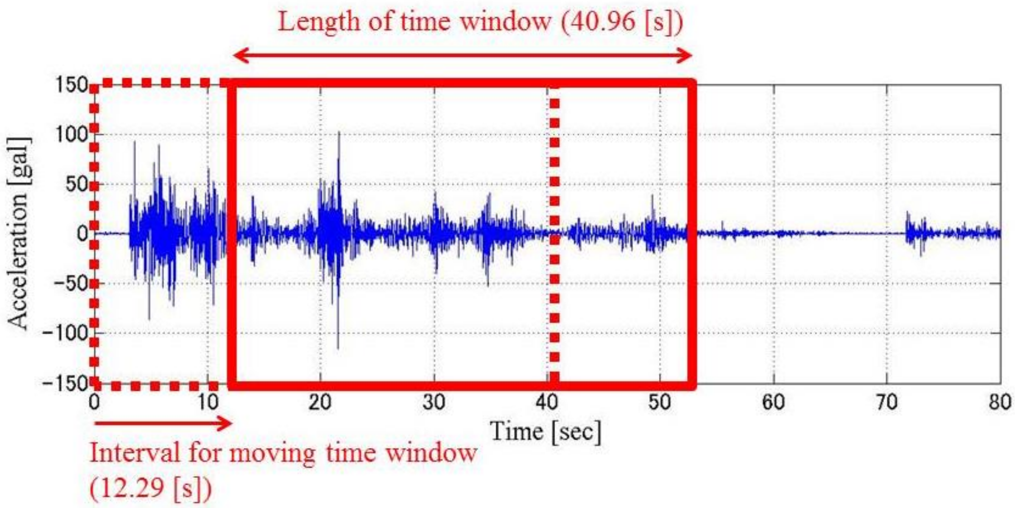

Fig. 3 Time windows to identify DI

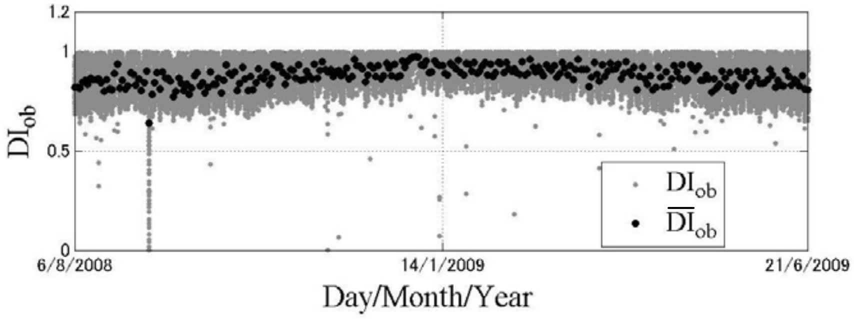

Fig. 4 DIs monitored at 7:00, 13:00 and 19:00 on Wednesdays and Sundays at UA-1

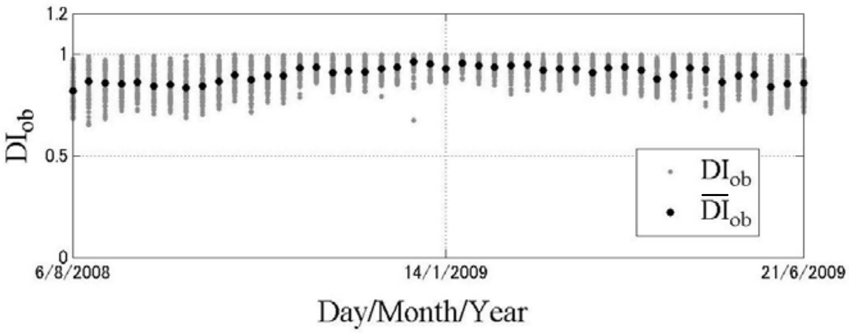

Fig. 5 DIs monitored at 7:00 on Wednesdays at UA-1

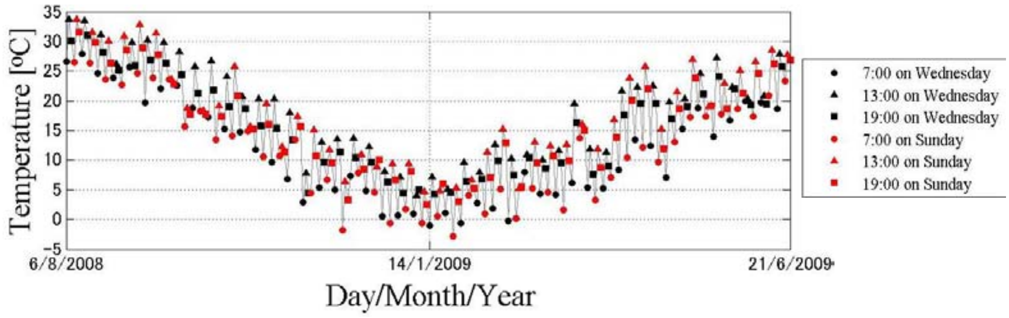

Fig. 6 Temperature monitored at 7:00, 13:00 and 19:00 on Wednesdays and Sundays on up lane

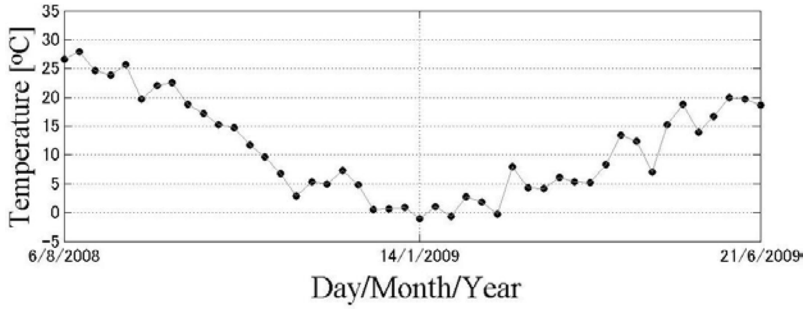

Fig. 7 Temperature monitored at 7:00 on Wednesdays on up lane

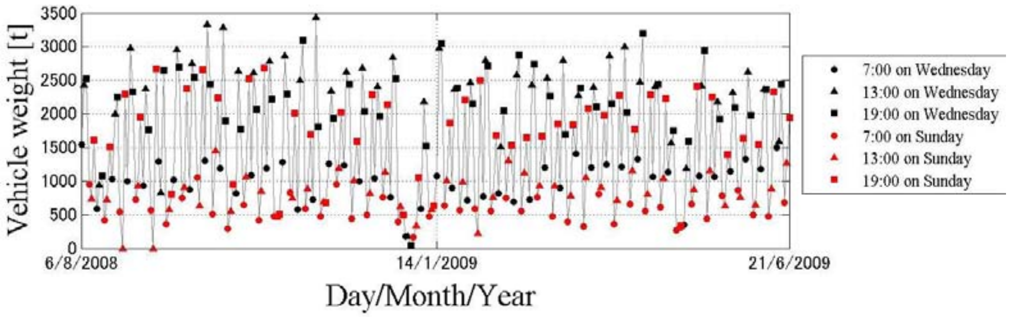

Fig. 8 Vehicle weight at 7:00, 13:00 and 19:00 on Wednesdays and Sundays on up lane

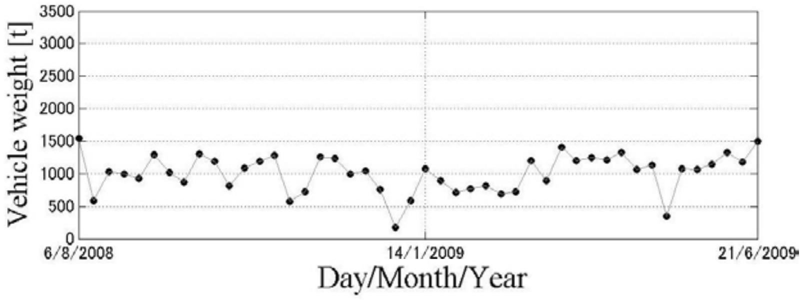

Fig. 9 Vehicle weight at 7:00 on Wednesdays on up lane

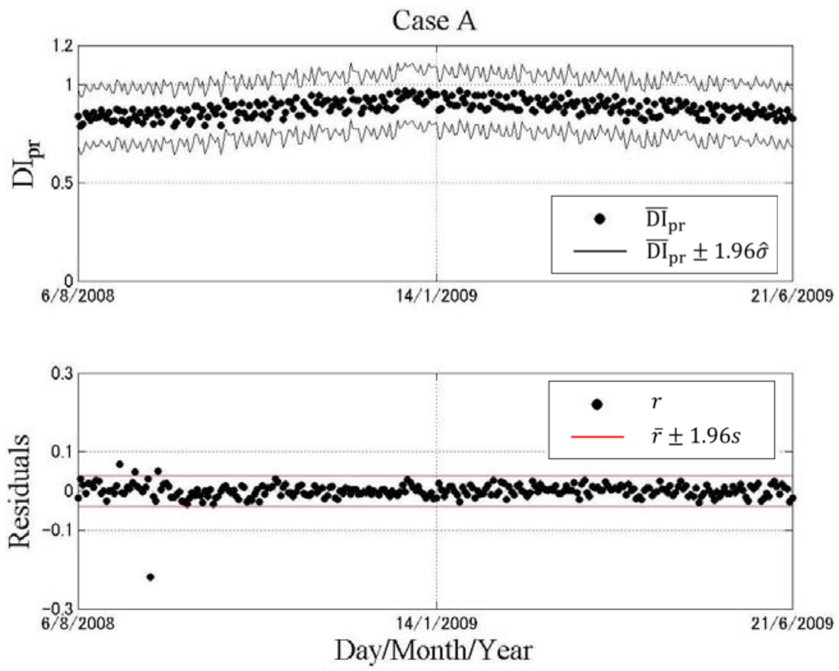

Fig. 10 Predicted DIs and residuals at UA-1 in case A

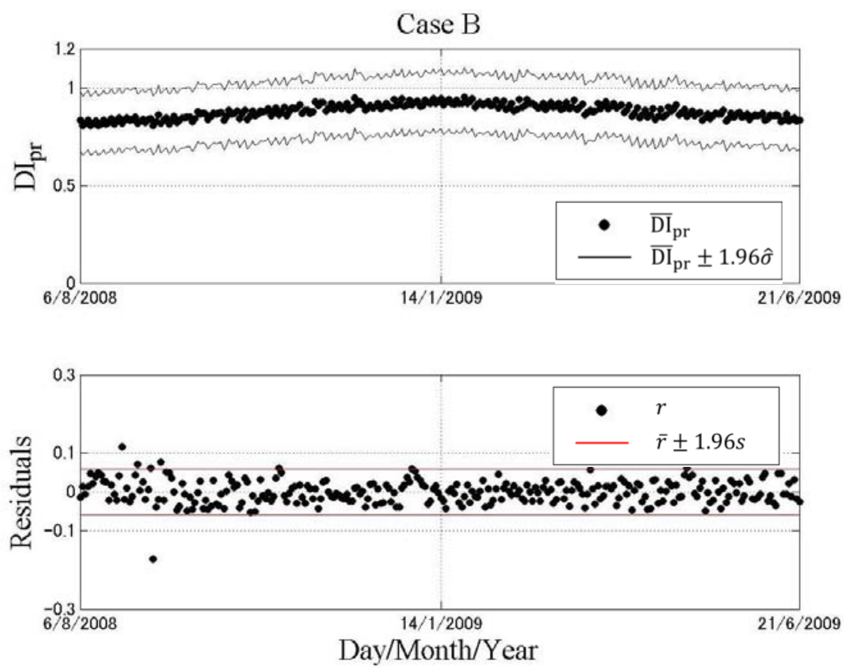

Fig. 11 Predicted DIs and residuals at UA-1 in case B

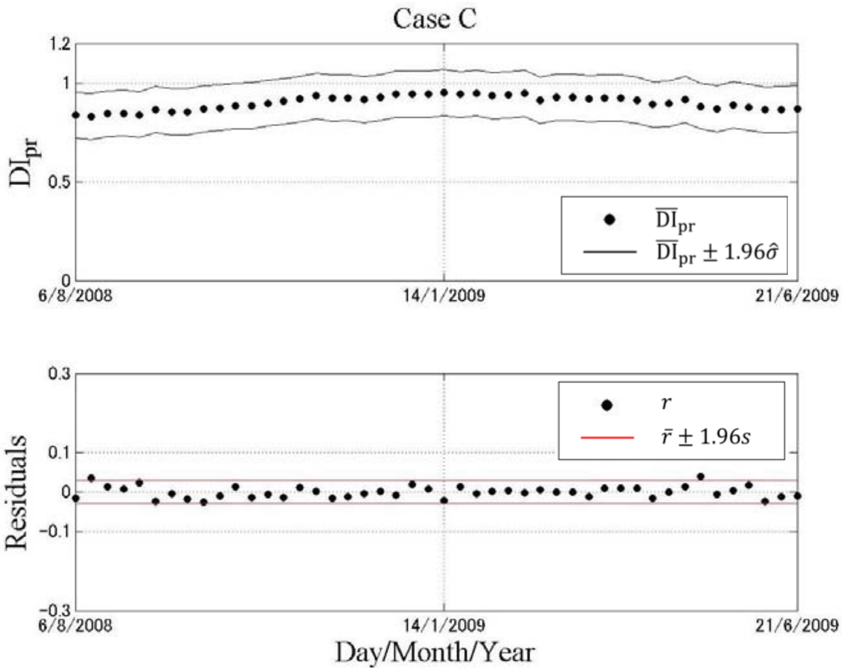

Fig. 12 Predicted DIs and residuals at UA-1 in case C

Table 3 Probability of the residuals in cases A, B and C fitting within the 95% confidence interval regarding case A

	UA-1	UA-2	DA-1	DA-2
Case A	98.6%	96.0%	97.5%	97.8%
Case B	83.3%	94.2%	97.5%	95.7%
Case C	97.8%	100%	100%	100%

6.1 Utilizing the 95% confidence interval

Table 3 shows the probability of the residuals in cases A, B and C fitting within the 95% confidence interval regarding case A at the sensors of UA-1, UA-2, DA-1 and DA-2. Comparing cases A and B, it is clear that the probability in case A is greater than that in case B at the sensors of UA-1, UA-2, and DA-2. It demonstrated that the regression analysis considering both temperature and vehicle weight as environmental and operational factors leads to more accurate results than that considering only temperature as an environmental factor. Comparing cases B and C, it is apparent that the probability in case C is bigger than that in case B at all sensors. In other words, the probability considering only temperature utilizing data monitored at a non-specified time is smaller than that utilizing data monitored at a specified time. Therefore, it showed validity of using the data observed at a specified time to reduce the influence of traffic loads. Taking the fact that the impracticality of applying a BWIM system to monitor traffic load to every bridge into consideration, the monitoring method considering data at a specified time to reduce traffic effects could be practical.

Table 4 Bayes factor of the Bayesian hypothesis testing in cases A, B and C

	B
Case A	1.06
Case B	1.06
Case C	1.15

6.2 Utilizing the Bayesian hypothesis test

Table 4 shows Bayes factor of the Bayesian hypothesis testing at the sensors of UA-1 in cases A, B and C. Those Bayes factors at the sensors of UA-2, DA-1, and DA-2 were same results as Table 4. The Bayes factor was $1<B<3$ as shown in Table 4. Therefore, the damage probability of the observation bridge is ‘very small’. This is natural result, since no damage and deterioration was reported during the monitoring period. However, the results obtained by comparing cases are different from those of utilizing the 95% confidence interval. Therefore, more investigations about the Bayesian hypothesis test are needed.

7. CONCLUSIONS

This study investigated a way to consider changes in temperature and vehicle weight as environmental and operational factors for long-term bridge health monitoring by applying a Bayesian approach to long-term monitoring data. The Bayesian approach consists of three steps: step 1 is to identify damage indicators from coefficients of the AR model as a damage-sensitive feature; step 2 is to obtain residuals by means of the Bayesian regression; step 3 is to make a decision based on the residuals utilizing the 95% confidence interval and the Bayesian hypothesis test. Observations through this study could be summarized as follows.

(1) The Bayesian regression considering both temperature and vehicle weight led to more accurate results than that considering only temperature.

(2) Validity of using the data observed at a specified time to reduce the influence of traffic loads can be confirmed.

(3) In the Bayesian hypothesis testing utilizing data from the healthy bridge, the damage probability of the bridge was judged as ‘very small’.

The bridge is still under a long-term monitoring program, and thus the next step for this study is to analyze that long-term monitoring data utilizing the Bayesian regression.

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