A Real-time Stochastic Scour Detection for Railway Bridge

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ABSTRACT: This study aims to propose a real-time stochastic scour detection (SSA) of railway bridges by means of ambient vibration monitoring. A remote ambient vibration monitoring system is deployed in a railway bridge to measure ambient vibration. To detect the scour from the ambient vibrations, a non-Gaussian approach is proposed since the identified frequencies are scattering and the probability distribution of the identified frequencies sometimes show non-Gaussian distribution with fat tails. Observations from the ambient vibration data before and after a flood event showed that target frequency was slightly decreased under the increase of water surface during swollen river water period. However, the decreased frequency recovered once the water surface level decreased to normal river water level. The proposed real-time SSA showed an extremely low probability of scour of the target bridge due to the swollen river water period.

1. INTRODUCTION

Many Japanese railway companies adopt an impact test on the railway bridge pier to detect occurrences of scour focusing on changes in frequencies despite its labor-intensive and time-consuming approach. Moreover, the impact test is inapplicable for real-time monitoring during heavy rains. Real-time scour monitoring using bridge vibrations thus has been considered an alternative method to the conventional impact test (Kim et al. 2017). Since changes in the stability of the pier foundation link to changes in natural frequencies for the rocking motion of the pier, identification of modal frequency is the first step for vibration-based scour detection.

This study proposes a real-time scour monitoring system comprising an edge computing system, a remote data-delivering function, and a cloud system for alarming scour occurrence. A fast Bayesian FFT (Au 2011) is adopted for the modal identification from microtremor measurement, which provides higher identification accuracy and statistical information about the identification.

Table 1: Soundness index of scour.

Soundness Index	Category	Scour Assessment
$\kappa \leqq 0.70$	A1	scour
$0.70 < \kappa \leqq 0.85$	A2	progressing
$0.85 < \kappa \leqq 1.00$	B	low chance
$1.00 < \kappa$	S	healthy

The estimated posterior distribution of the target frequency is used for real-time scour detection. Two approaches are investigated. One is the method utilizing an index from the ratio of newly identified frequency to that of a healthy state. The possibility of the scour is estimated by comparing the index with a scour assessment scale specified in the Japanese guideline (Ministry of Land, Infrastructure, Transport and Tourism, Railway Bureau 2007). Table 1 shows the sound index in the Japanese guideline. The other is the method utilizing probability distributions of the identified frequency during the normal river water

Table 2: Parameter of stable distribution.

Parameter	Range	Remarks
α	$0 < \alpha \leq 2$	Characteristic exponent
β	$-1 \leq \beta \leq 1$	Skewness parameter
γ	$0 < \gamma < \infty$	Scale parameter
d	$-\infty < d < \infty$	Location parameter

period (hereafter "normal period") and swollen river water period (hereafter "swollen period").

Real-time processing, a so-called online process, for stochastic scour detection is proposed, and for comparison, batch processing, a so-called offline process, for stochastic scour detection is also discussed. To describe the probability density function (PDF) of observed frequencies the Levy flight distribution (Adler et al. 1996), which is useful to describe the fat-tailed distribution, is adopted.

2. LEVY-FLIGHT DISTRIBUTION

The PDF of the Levy flight distribution of the frequency during the normal period is estimated, and the parameters of the PDF of the Levy flight distribution are identified by the maximum likelihood estimation (MLE). The characteristic function of the Levy-flight distribution is given by Eq. (1).

$$\Psi(t, \alpha, \beta, \gamma, d) = E\left(e^{-itZ}\right) \tag{1}$$

where the characteristic exponent α determines the rate of decay, *i.e.*, if it becomes smaller the tails get fatter. While the parameter β is an indication of the skewness of the distribution, with $\beta = 0$ corresponding to the symmetric case. The parameters γ, and d simply translate and scale the distribution but have no effect on its shape. The location parameter d equals the median of the PDF. Z is the random variable and t denotes the parameter for the characteristic function (Adler et al. 1996). The parameters used in the Levy flight distribution are summarized in Table 2.

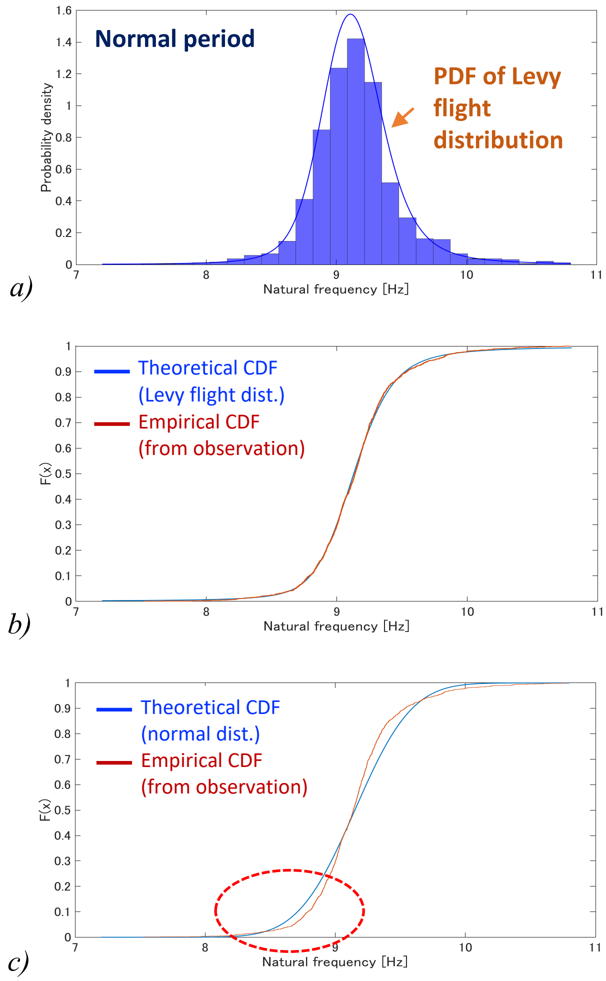

Figure 1: CDF of the observed frequency in normal river water period (red line): a) Histogram of observed frequency and fitting to Levy flight distribution; b) CDF of the Levy flight distribution (blue line); c) CDF of the normal distribution (blue line).

The PDF of the Levy flight distribution is represented as $S_N(\alpha_N, \beta_N, \gamma_N, d_N, \mathrm{Z})$ which is the inverse transformation of the characteristic function shown in Eq. (1). The parameters of PDF of the Levy flight distribution under normal conditions (S_N) were estimated by means of the MLE.

Since the number of data samples of the observed frequency during the swollen period is small, it was quite difficult to grasp the whole picture of the PDF. Therefore, measured ambient vibration was overlapped in order to increase the number of data samples for system identification, and 50% of the data block was overlapped. Then the PDF of the observed frequency from the overlapped data samples, $S_F(\alpha_F, \beta_F, \gamma_F, d_F, \mathrm{Z})$, was estimated in the same manner to the normal period.

2.1. Normal river water period

An example of the CDF of S_N is shown in the blue line of Figure 1b) while the red line shows the CDF of the observed frequency in the normal period. For comparison, the CDF following a normal distribution is shown in Figure 1b). From Figure 1a), it is obvious that the CDF curve of the Levy flight distribution matches well, especially at tails, with that of the observed CDF. On the other hand, Figure 1c) demonstrates that the tails in the normal distribution do not match well with the observed one, leading to a poorer accuracy in scour assessment. It is noted that identified parameters for the example shown in Figure 1 were $\alpha_N = 1.59$, $\beta_N = 0.32$, $\gamma_N = 0.18$ and $d_N = 9.11$.

2.2. Swollen river water period

An example of the CDF of S_F is shown in the blue line of Figure 2b). For comparison, the CDF assumed to follow normal distribution is shown in Figure 2c). Similar to the normal period, it is obvious that the CDF curve of the Levy flight distribution matches well with that of the observed CDF while the tails in the normal distribution do not match well with the observed one. It is noted that identified parameters for the example shown in Figure 2 were $\alpha_F = 1.62$, $\beta_F = 0.94$, $\gamma_F = 0.14$, and $d_F = 8.99$.

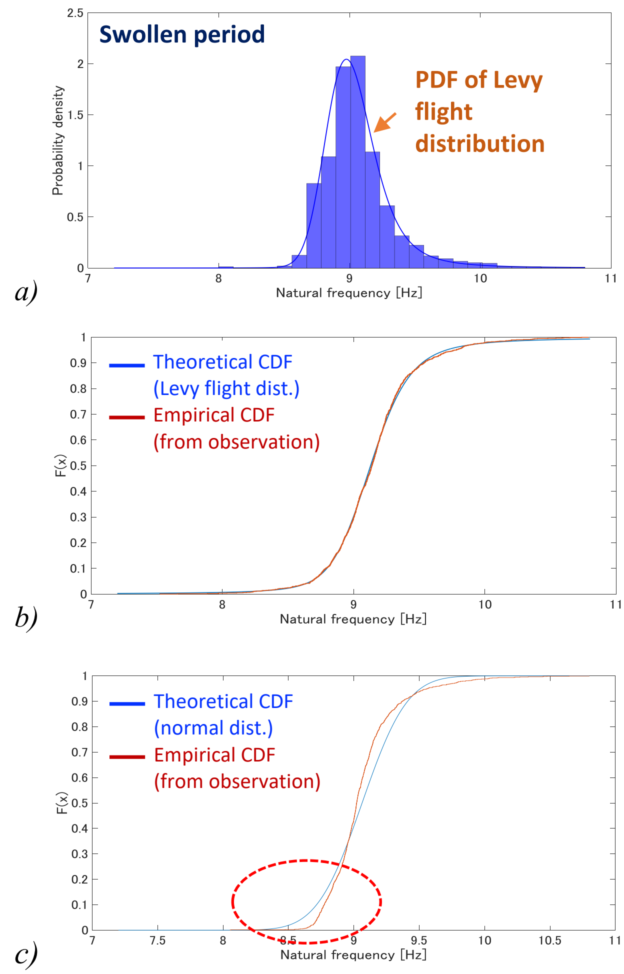

Figure 2: CDF of the observed frequency in swollen river water period (red line): a) a) Histogram of observed frequency and fitting to Levy flight distribution; b) CDF of the Levy flight distribution (blue line); c) CDF of the normal distribution (blue line).

3. REMOTE SCOUR MONITORING SYSTEM

The remote monitoring system comprises triaxial accelerometers, an edge computing system, data delivering module, and a stochastic scour assessment system. Using this system, there is no need to dispatch engineers to the bridge during flood events, while changes in the target frequency of the observation piers are remotely monitored for scour detection. Instead of a conventional impact test that detects changes in frequency from the free vibration, the remote monitoring system examines the ambient vibration. The monitored ambient vibration signals are processed and the target frequency is identified in the edge computing system, and the identified frequencies are sent to a cloud computing system via a mobile phone network (see Figure 3). In cloud computing, the possibility of scour is estimated, and send out warnings as needed. In another implementation, it is also possible to identify the target frequency on a cloud server without installing an edge computer.

Furthermore, by adding a water level sensor to the system, it is possible to analyze the relationship between water level and identified frequency.

4. SCOUR MONITORING OF A RAILWAY BRIDGE

The monitoring bridge is a steel plate girder railway bridge with a span length of 22.5 m, a pier height of 9 m, and a width of 3 m, designed for a single railway track. The photo of the target pier is shown in Figure 4. 13 triaxial sensors were installed on the top of the pier and connecting girders during the impact test, while all sensors except two sensors installed upstream and downstream of the pier top were removed after the impact test. Figure 5 shows the sensor deploying map. Two sensors left on the pier top (sensors ①-① and ①-③) are used for long-term ambient vibration monitoring. The sampling frequency of the measurement is 200Hz.

Modal parameters of the monitoring pier such as frequency, damping ratio, and mode vector were first identified from the vibration data during the impact test. The dominant frequency for the rocking mode was identified as 9.2 Hz. The scour assessment needs vibration data not only from the normal period but also from the swollen period. Figure 6 shows examples of ambient vibration observed during the normal period whose amplitude was less than 0.1 gal. During the swollen period, it was around 1 gal caused by rising water and increasing speed of river flow. The fast Bayesian FFT is used to identify the posterior probability of modal parameters from ambient vibrations.

This study examines the ambient vibrations monitored on 30th September 2018 and 1st October 2018 as data during the swollen period. Figure 7a) shows the change in water level per five minutes from noon on September 30 to noon

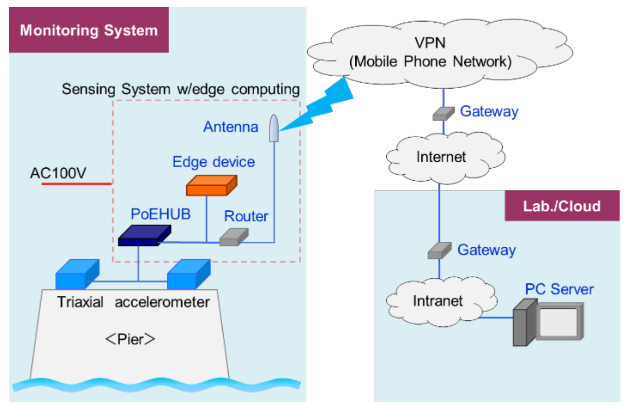

Figure 3: Remote scour monitoring system.

Figure 4. Monitoring bridge.

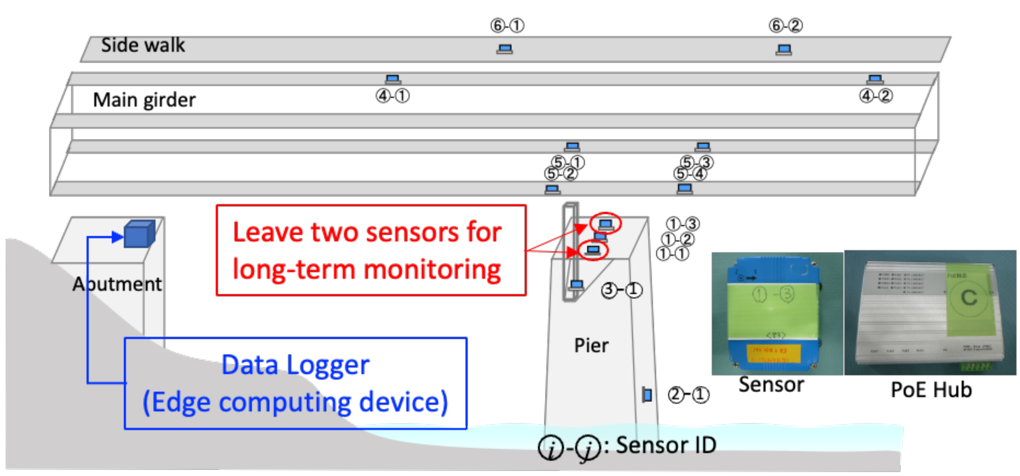

Figure 5: Sensor deploying map.

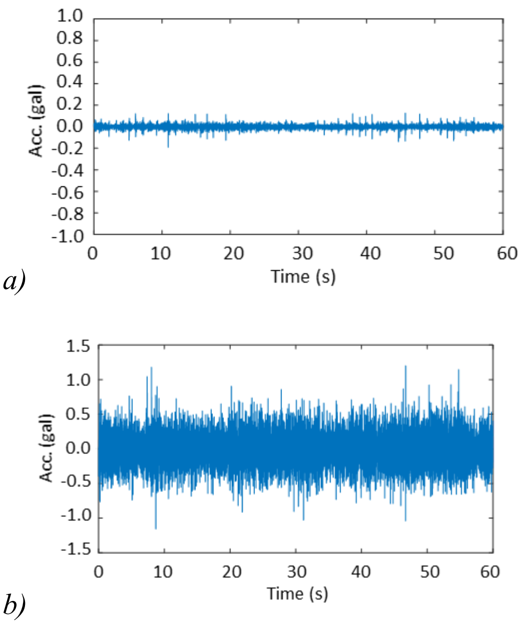

Figure 6: Measured microtremors: a) during normal river water period, b) during swollen river water period.

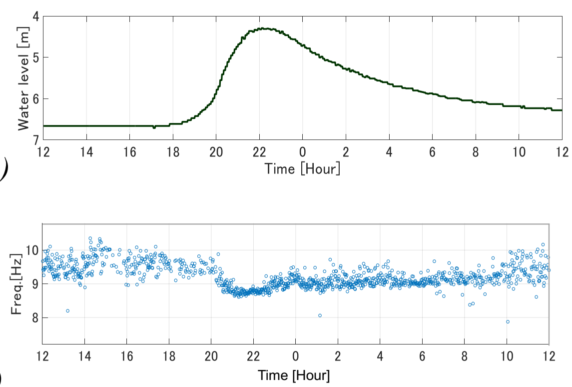

Figure 7: Observed water level and identified frequency from noon September 30 to noon October 1; a) water level per five minutes; b) identification frequency.

on October 1. The "water level" represents the distance between the water surface and the lower flange of the bridge girder. The "swollen condition" is defined as the period the water level is lower than 6m and the other period is defined as the "normal condition". Figure 7b) shows the identified target frequency by means of the fast Bayesian FFT in which the horizontal axis shows the observation time.

Table 3: Relationship between soundness index and stochastic warning index.

Frequency	Category	SWI (Ψ_c)
$X \leqq 6.4$Hz	A1	$\Psi_c \leqq 0.0016$
6.4Hz $< X \leqq 7.8$Hz	A2	$0.0016 < \Psi_c \leqq 0.0053$
7.8Hz $< X \leqq 9.1$Hz	B	$0.0053 < \Psi_c \leqq 0.46$
9.1Hz $< X$	S	$0.46 < \Psi_c$

5. REAL-TIME SCOUR ASSESSMENT

5.1. Batch processing for scour detection

5.1.1. Batch scour assessment using mean frequency during the swollen period

Assuming the PDF of the estimated reference frequency of the pier during the normal period is given by $S_N(\alpha_N, \beta_N, \gamma_N, d_N, X)$, the stochastic warning index (SWI), Ψ_c, is estimated as follows.

$$\Psi_c = \Psi(\alpha_N, \beta_N, \gamma_N, d_N, Z_m) \tag{2}$$

where, $\Psi(\alpha_N, \beta_N, \gamma_N, d_N, Z_m)$ is the CDF of S_N and Z_m denotes the mean natural frequency during the swollen period. The SWI estimated using Eq. (2) is called *Batch Method A*.

Here, a concept of marginal indicator of stochastic warning index (MISWI), Ψ_s, is proposed to assess scour occurrence. If SWI during the swollen period reaches the MISWI, it indicates a possible occurrence of scour. The MISWI can be defined considering relationships with the soundness index in Table 1. The soundness indices 0.70, 0.85, and 1.00 correspond to frequencies of 6.4Hz, 7.7Hz, and 9.1Hz respectively if the frequency in healthy condition is 9.1Hz.

The relationship between the soundness index κ and the SWI, Ψ_c, is summarized in Table 3. When the soundness index κ is 0.70, the corresponding frequency $Z_m = 6.4$Hz and the corresponding SWI is $\Psi_c = 0.0016$. Indeed, category A1 shows extremely low probability as SWI = 0.0016, and the stochastic approach can link to risk analysis.

In order to obtain the higher probability of the Type I error (occurrence of scour is determined even under health condition) and lower probability of the Type II error (scour is occurred while health condition is determined), the MISWI is set to be $\Psi_S = 0.05$ as an example, which is larger than the threshold value ($\Psi_c = 0.0053$). It is noted that how to decide MISWI depends on the risk sensitivity of bridge authorities.

5.1.2. Batch scour assessment using PDF of frequency during the swollen period

Assuming that the PDF for the target frequency during the swollen period can be represented by S_F , the SWI during the swollen period is estimated utilizing Eq. (3) which is called *Batch Method B*.

$$\Psi_c = \int_{-\infty}^{\infty} S_F \int_{-\infty}^{X} S_N dZ dX \tag{3}$$

5.2. Real-time processing for scour detection

Although the batch processing for the scour assessment taking into account the uncertainty of the frequency during the swollen period was discussed, one needs to wait until the water level return to the normal period to identify the PDF characteristic of the target frequency using Eqs. (2) and (3) during the swollen period. Thus, considering the time series on the identified frequency of the target pier during the swollen period, three different methods for calculating the real-time stochastic warning index (RWI) are proposed.

5.2.1. Real-time scour assessment using likelihood function of frequency during the swollen period

Assuming that the empirical PDF parameters of α_F, and γ_F are given beforehand from the past observations, and the frequency, X_t, during the current swollen period is observed, the likelihood function during the swollen period is given as Equation 4.

$$L_F(X) = S_F(\alpha_F, \beta_F, \gamma_F, X_t, X) \tag{4}$$

where X_t is the identified frequency from a data sample measured at a time span, *e.g.,* identified frequency from every 1-minute data sample.

Replace $S_F(\alpha_F, \beta_F, \gamma_F, X_t, X)$ in Eq. (3) to the likelihood function $L_F(X)$ in Eq. (4), the RWI is given as Eq. (5) that is called *Real-time Method A*.

$$\Psi_c(t) = \int_{-\infty}^{\infty} L_F(X) \int_{-\infty}^{X} S_N dZ\, dX \tag{5}$$

5.2.2. Real-time scour assessment using time series of frequency during the swollen period

In real-time scour detection, it is crucially important to reduce computation time. Therefore, instead of applying Eq. (5), as a simplified method the time series of frequency, Z_t, during the swollen period is considered in estimating RWI using Eq. (6) which is called *Real-time Method B*.

$$\Psi_c(t) = \Psi(\alpha_N, \beta_N, \gamma_N, d_N, Z_t) \tag{6}$$

5.2.3. Real-time scour assessment assuming a normal distribution for frequency during the swollen period

Considering each frequency of swollen river water period as a normal distribution by using the identified frequency and standard deviation obtained from the fast Bayesian FFT, RWI can be given as Eq. (7) which is called *Real-time Method C*.

$$\Psi_c(t) = \int_{-\infty}^{\infty} N(X_t, \sigma_t) \int_{-\infty}^{X} S_N dZ dX \tag{7}$$

where, X_t and σ_t denote mean and standard deviation of the identified frequency during the swollen river water period, which are obtained by means of the fast Bayesian FFT.

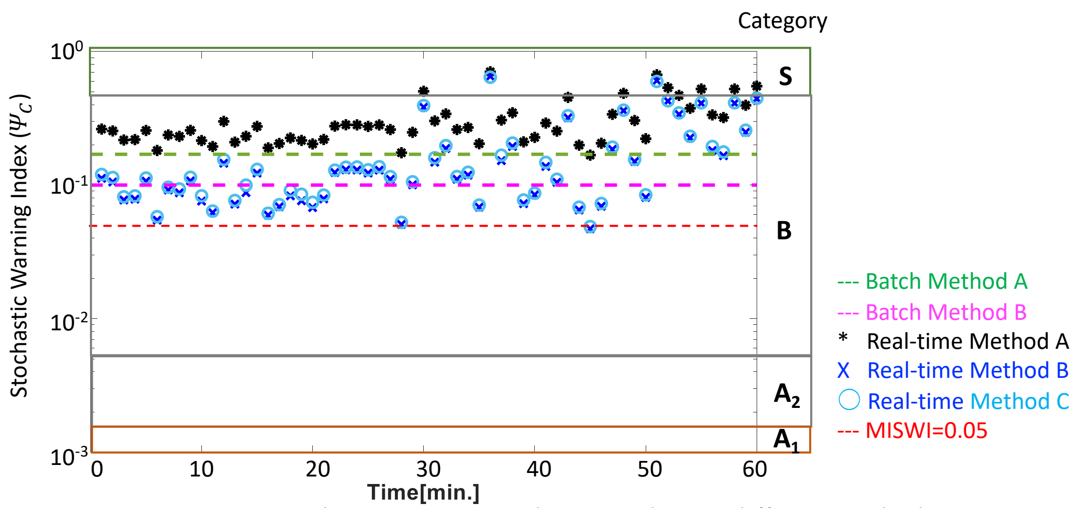

Figure 8: Stochastic warning index according to different methods.

5.3. Discussions on scour detection

Ambient vibration data from 22:00 to 23:00 on 30th September 30 in 2018 is again considered an example the ambient vibration data. Assume every identified frequency at a time as real-time data X_t and estimate the RWI at each time, time series of the RWI during the swollen river water period is shown in Figure 8, where the vertical axis indicates the RWI and the horizontal axis indicates the monitoring time. The horizontal red dotted line denotes the assumed MISWI, $\Psi_S = 0.05 = 5\%$. It can be seen that a warning is not announced during the swollen river water period.

Figure 8 shows that SWI is in the range of $0.0053 < \Psi_c \leqq 0.46$ which corresponds with category B, which means that there is a low possibility of scour during the target period. It can also be seen that *Real-time Method B*, which estimates the RWI using the CDF of the normal period and time series of frequency during the swollen period, resulted in a decision on the safe side among three real-time methods, from *Real-time Method A* to *Method C*. In other words, *Real-time Method B* would provide a safe-side scour assessment with fewer computation efforts.

6. CONCLUSIONS

This study proposes a remote scour monitoring system using ambient vibration monitoring of the bridge pier during swollen river water period. The natural frequency of the bridge pier was identified with high accuracy from the ambient vibration during the swollen river water period.

Reliability-based scour assessment, parameters of the PDF of the Levy flight distribution are identified by means of the maximum likelihood method using the frequency of the pier during normal and swollen river water periods, and the stochastic warning index is proposed and data collected from real swollen river water period is used as a case study. A real-time reliability-based scour assessment is also investigated.

This study demonstrated the effectiveness of the proposed remote scour monitoring system. It is possible to assess probabilistic scour occurrence by using the ambient vibration data during swollen river water period. Moreover, the feasibility of the real-time stochastic scour assessment was observed.

7. ACKNOWLEDGMENTS

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