Structural Engineering and Mechanics, Vol. 38, No. 4 (2011) 417-428
DOI: http://dx.doi.org/10.12989/sem.2011.38.4.417

Recovering missing data transmitted from a wireless sensor node for vibration-based bridge health monitoring

C.W. Kim[1]*, M. Kawatani[2], R. Ozaki[2] and N. Makihata[3]

[1]*Department of Civil & Earth Resources Engineering, Graduate School of Engineering, Kyoto University, Kyoto 615-8540, Kyoto, Japan*
[2]*Department of Civil Engineering, Graduate School of Engineering, Kobe University, Kobe 657-8501, Japan*
[3]*JIP Techno Science Corporation, Osaka 532-0011, Japan*

(Received April 27, 2010, Accepted January 15, 2011)

Abstract. This paper presents recovering of missing vibration data of a bridge transmitted from wireless sensors. Kalman filter algorithm is adopted to reconstruct the missing data analytically. Validity of the analytical approach is examined through a field experiment of a bridge. Observations demonstrate that, even a part of recovered acceleration responses is underestimated in comparison with those responses taken from cabled sensors, dominant frequencies taken from the reconstructed data are comparable with those from cabled sensors.

Keywords: AR process; bridge health monitoring; Kalman filter; missing data recovery; wireless sensor node.

1. Introduction

This study is intended to investigate the feasibility of reconstructing missing data or incomplete observations in a wireless sensing system which is developed for vibration-based bridge health monitoring (BHM). The Kalman filter algorithm is applied to recover missing data transmitted from wireless sensor nodes. Feasibility of the method is investigated by comparing reconstructed data with the data measured by wired accelerometers. Brief explanation about the wireless sensor node developing for BHM is also described.

Maintaining and improving condition of bridges is critical to the structural integrity and cost effectiveness of the transportation system. The majority of bridges are small and medium span structures, and large portions of those small and medium span bridges are located on local and rural areas. Attention also must be paid to their health condition (e.g., Doebling *et al.* 1996). Actual situation, however, reveals that most of monitoring concerns focus on bridges in urban area and monumental bridges such as long span bridges because of budgetary problems of bridge owners.

System identification of bridge structures based on the system output such as vibration data of the bridge is a useful technique for BHM (e.g., Hoshiya and Saito 1984, He and De Roeck 1997). An

*Corresponding author, Professor, E-mail: kim.chulwoo.5u@kyoto-u.ac.jp

important problem that must be solved in health monitoring for the small and medium span bridges of rural areas using vibration measurements is in developing a cost-effective sensor system.

There are a wide range of commercially available wired sensor systems, some of which have been developed for general purpose data acquisition and others which have been specifically developed for structural health monitoring (SHM) applications. The majority of these systems work by AC power. It means there are very limited numbers of those designed to run off of batteries. Furthermore, experience with field-deployed systems has shown that the wires can be costly to maintain because of environmental degradation (Lynch 2004). In addition, the deployment of such system can be challenging with a great portion of the installation time attributed to the installation of system wires and cables for large scale structures (Farrar *et al.* 2006). The integration of wireless communication technologies into SHM methods has been widely investigated in order to overcome the limitations of wired sensing networks (e.g., Straser *et al*. 1998, Castaneda *et al*. 2009). Wireless communication can remedy the cabling problems of the traditional monitoring system and significantly reduce the maintenance cost. Detail summaries of the wireless sensor systems for structural health monitoring are available from references (e.g., Farrar 2006, Spencer *et al*. 2004).

To realize a method which focuses on the health monitoring of small and medium span bridges even in rural areas, it needs a wireless sensor system which provides a cost-effectiveness and real-time communication of vibration data. The authors have been developed a novel sensor node equipped a wireless device for data transmitting and MEMS accelerometer (Kim *et al*. 2008). The design of wireless sensors is done with commercially off-the-shelf components to keep costs down. The sensor node is also designed to minimize the memory space and energy consuming. The performance of a trial piece of the sensor node is examined through bridge vibration experiments. The results indicate that acceleration responses taken from the wireless sensor node are comparable with those from the conventional sensing device with cabled acceleration transducers. However data missing is observed in time series data from the wireless sensor node (Kim *et al*. 2008, Kim *et al*. 2009).

The multi-packet transmission is an option to solve the data missing problem. The way of recovering missing data using multi-packet transmission (or repeated broadcasting) is as follows (Kim *et al*. 2007): in response to the request of the receiver, the sender sends the entire data and the receiver identifies missing packets, and then sends a list of those packets back to the sender; the sender resends those missing packets, and repeats until no data loss is found. However the repeated broadcasting requires large memory space and consumes much power.

Another option is the reconstruction of missing data. Kalman filter and state space model formulation together provide a powerful tool for the recursive treatment of dynamic systems (Anderson and Moore 1979, Kitagawa and Gersh 1984, 1996, Lee and Yun 2008). Many standard statistical examples arise from estimation, interpolation and prediction procedures for autoregressive time series (e.g., Akaike 1978). Numerous real data examples show that there are suitable modifications of the Kalman filter which allows the treatment of incomplete data (e.g., Cipra and Romera 1997).

2. Methodology for recovering missing data

The discrete state equation for time history data can be described as (Ljung 1999)

$$\mathbf{x}(k+1) = \mathbf{F}x(k) + \mathbf{G}v(k), \quad \mathbf{y}(k) = \mathbf{H}\mathbf{x}(k) \tag{1}$$

where **x** is the state vector of a system. **F** indicates the system matrix. **G** and **H** denote the input and output influence matrices respectively. **y** indicates the output vector which links to observed physical outputs.

The output signal is modeled as the output of an autoregressive (AR) model, because such AR model may be easily and effectively computed from covariance data using least squares method (LSM), Yule-Walker equation or Levinson algorithm (e.g., Ljung 1999). Through numerical manipulations the state equation is described in the form of AR model subjected to a white-noise input.

$$y(k)+\sum_{i=1}^{m}a_i y(k-i) = e(k) \tag{2}$$

Therein $e(k)$ denotes a white noise with zero mean and covariance as

$$E[e(k+q)e^T(k)] = \begin{cases} \sigma^2, q = 0 \\ 0, q \neq 0 \end{cases} \tag{3}$$

where, $E[\ ]$ indicates the operator for mathematical expectation.

The AR parameter in Eq. (2) can be estimated by means of the maximum likelihood estimate (MLE) as an exact solution. In this study an approximate solution based on the Levinson algorithm is adopted instead of the MLE.

If $\hat{y}(k)$ signifies a predicted estimate which is definable as

$$\hat{y}(k) = \sum_{i=1}^{m}a_i y(k-i) \tag{4}$$

Then the AR parameter is the solution taken from minimizing a prediction error, which is obtainable from the following relationship.

$$\frac{\partial J}{\partial a_i} = 0 \tag{5}$$

where, $J = E[\varepsilon(k)^2]$ and $\varepsilon(k) = y(k)-\hat{y}(k)$ which denotes a prediction error.

Finally Eq. (5) results the Yule-Walker equation as shown in Eq. (6).

$$\mathbf{Ra} = \mathbf{r} \tag{6}$$

where

$$\mathbf{R} = \begin{bmatrix} R(0) & R(1) & \dots & R(m-1) \\ \vdots & \vdots & \ddots & \vdots \\ R(m-1) & R(m-2) & \dots & R(0) \end{bmatrix} \tag{7}$$

$$R(m-1) = E[y(k)y(k-m+1)] \tag{8}$$

$$\mathbf{a} = [a_1;\ a_2;\ \dots\ a_m] \tag{9}$$

$$\mathbf{r} = [R(1);\ R(2);\ \dots\ R(m)] \tag{10}$$

The Levinson algorithm is used to solve the linear equation in Eq. (6), which gives AR parameters.

The state space equation of Eq. (1) is now re-definable in the AR model using following definition for the system matrix **F**, input influence matrix **G** and output influence matrix **H**.

$$\mathbf{F} = \begin{bmatrix} a_i & a_2 & \dots & a_m \\ 1 & & & \\ & \ddots & & \\ & & 1 & 0 \end{bmatrix} \tag{11}$$

$$\mathbf{G} = [1;\ 0;\ \dots\ 0] \tag{12}$$

$$\mathbf{H} = (1\ \ 0\ \ \dots\ \ 0) \tag{13}$$

Therein, m is the optimal order of the AR model, which is selected by means of the Akaike Information Criteria (AIC). The AIC is a way of selecting a model from a set of models. The chosen model is the one that minimizes the Kullback-Leibler distance between the model and the truth. The AIC is defined as

$$AIC = N\{\log(2\pi\sigma^2) + 1\} + 2(m+1) \tag{14}$$

where $\sigma^2 = R(0) - \sum_{i=1}^{m} a_i R(i)$.

The aim of time history analysis is to identify the state vector **x** appropriately. The Kalman filter algorithm provides a good step-by-step method for identifying the state of a system such as prediction, filtering and smoothing the state (e.g., Kitagawa 1984).

If a time series model is given, a future state can be predicted in terms of the Kalman filter algorithm as

$$\begin{cases} \mathbf{x}(n|n-1) = \mathbf{F}\mathbf{x}(n-1|n-1) \\ \mathbf{V}(n|n-1) = \mathbf{F}\mathbf{V}(n-1|n-1)\mathbf{F}^T + \mathbf{G}\mathbf{Q}\mathbf{G}^T \end{cases},\quad (0 < n \le L) \tag{15}$$

where, $\mathbf{x}(n|n-1)$ and $\mathbf{V}(n|n-1)$ stand for the predicted conditional mean vector and covariance matrix at a time (n) under the condition of the state at a time ($n-1$), respectively. **Q** denotes covariance matrix of the system noise v, which is set to be σ^2. L denotes the number of data including missing part. Moreover an initial state can be described as

$$\mathbf{x}_{0|0} = \begin{Bmatrix} 0 \\ \vdots \\ 0 \end{Bmatrix},\quad \mathbf{V}_{0|0} = \sigma^2 \mathbf{I}_m \tag{16}$$

where $\mathbf{I}_m$ denotes the unit matrix.

Filtering problem is also solved by the step-by-step algorithm as

$$\begin{cases} \mathbf{K}(n) = \mathbf{V}(n|n-1)\mathbf{H}^T(\mathbf{H}\mathbf{V}(n|n-1)\mathbf{H}^T)^{-1} \\ \mathbf{x}(n|n) = \mathbf{x}(n|n-1) + \mathbf{K}(n)(y(n) - \mathbf{H}\mathbf{x}(n|n-1)),\ (0 < n \le N) \\ \mathbf{V}(n|n) = (\mathbf{I} - \mathbf{K}(n)\mathbf{H}(n))(\mathbf{V}(n|n-1)) \end{cases} \tag{17}$$

where $\mathbf{K}(n)$ is the Kalman gain computed from the solution to the Ricatti difference equation. N denotes the number of un-missing data.

In recovering missing data the smoothing by Kalman filter algorithm is very useful. The smoothing algorithm is a kind of backward step-by-step state identification algorithm. In other words, using all the observations a state at a past time is estimated as following procedure.

$$\begin{cases} \mathbf{A}(n) = \mathbf{V}(n|n)\mathbf{F}^T\mathbf{V}(n+1|n)^{-1} \\ \mathbf{x}(n|L) = \mathbf{x}(n|n) + \mathbf{A}(n)(\mathbf{x}(n+1|L) - \mathbf{x}(n+1|n)) \\ \mathbf{V}(n|L) = \mathbf{V}(n|n) + \mathbf{A}(n)(\mathbf{V}(n+1|L) - \mathbf{V}((n|+1)n))\mathbf{A}(n)^T \end{cases}, (0 \le n < L) \tag{18}$$

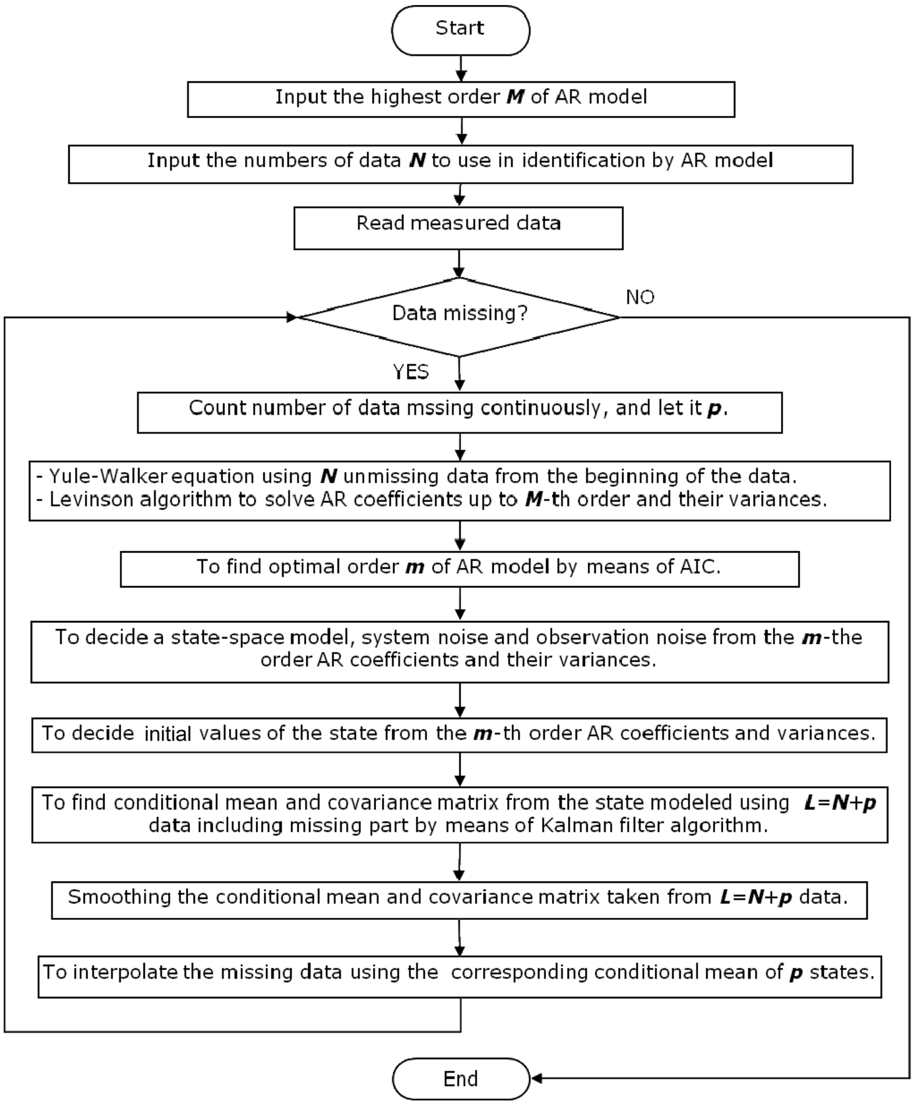


Fig. 1 Flow chart of recovering missing data

In estimating parameters in Eq. (18) following assumptions are used for missing part.

$$\begin{cases} \mathbf{x}(n|n) = \mathbf{x}(n|n-1) \\ \mathbf{V}(n|n) = \mathbf{V}(n|n-1) \end{cases}, \ (N < n \leq L) \tag{19}$$

Finally $y(n|L) = \mathbf{Hx}(n|L)$ gives $y(n)$ which is the recovered missing data under N observations. It is noteworthy, however, that the raw data is not smoothed in this study. The flowchart of the recovering missing data is shown in Fig. 1.

3. Wireless sensor node

The developed prototype wireless sensor module is shown in Fig. 2 (Kim *et al*. 2008). It comprises commercially available off-the-shelf components: a 2.4 GHz radio transceiver with an embedded 8051 compatible microcontroller of Nordic Semiconductor ASA (nRF2401) and the LIS3LV02DQ of STMicroelectronics which is a three axes MEMS accelerometer. A schematic block diagram of the sensor node is appeared in Fig. 2(b). The dimension of the module exclusive of the battery pack is 20 mm (width) × 20 mm (depth) × 3.9 mm (thickness). The module works on two AA batteries.

The microcontroller is an instruction set compatible with the industry standard 8051, and has a 256 byte data RAM. A small ROM of 512 bytes, contains a bootstrap loader that is executed automatically after power on reset or if initiated by software later. The user program is normally loaded into a 4k byte RAM from an external serial EEPROM by the bootstrap loader. The 4k byte RAM may also partially be used for data storage in some applications. The AD converter can be configured by software to perform 6, 8 or 12 bits conversions.

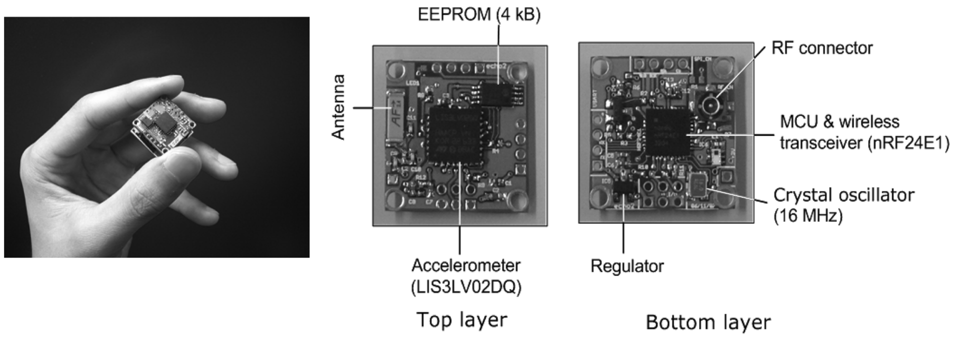
The transceiver part of the circuit has single chip RF transceiver for the world wide 2.4 - 2.5 GHz ISM band (Industrial, Scientific and Medical band). The maximum data transmission rate is 1 Mbps. The typical current consumption in data transmitting phase is 20 mA. In sleep mode it needs 4 μA. The data communication adopted is the infrastructure mode.

The MEMS accelerometer, LIS3LV02DQ, has a user selectable full scale of ±2 g, ±6 g and it is capable of measuring acceleration over a bandwidth of up to 640 Hz for all axes. The sampling frequency is also adjustable according to the user's needs. The sensitivity of the sensor under the conditions of ±2 g and 12 bit representation is 0.957 Gal. The effective range of data transmission was up to 40 m in indoor test. However, in outdoor test the limit transmission distance was about 10 m.

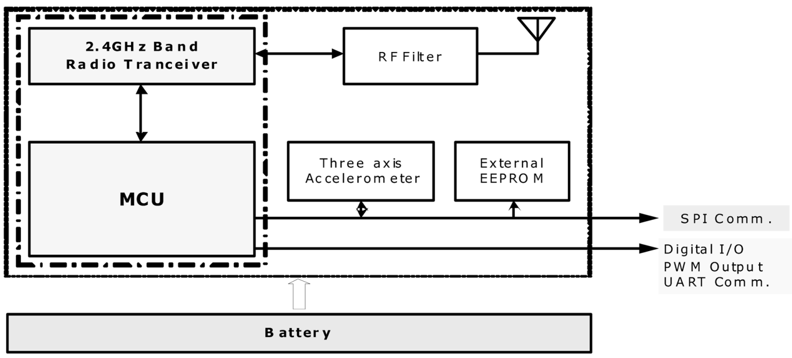
To control functions of the sensor nodes, it is designed to be changeable by adding and deleting rules (Kodama *et al*. 2007, Kim *et al*. 2009). According to the hardware control rule, for example, the sampling frequency, range of maximum acceleration to be measured, etc. are easily changeable, which is a distinguishing point of the sensor node.

4. Field experiment using wireless and cabled sensor

Field experiments on a bridge are conducted to examine performance of the wireless sensor node. The observation bridge is shown in Fig. 3, which is a seven-span continuous steel box girder bridge.



(a) Sensor node



(b) Block diagram of sensor node

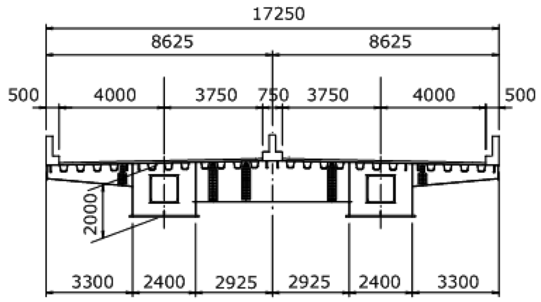
Fig. 2 Wireless sensor node

The observation points are summarized in Fig. 4, in which four points denoted as S-0.25L-G1, S-0.5L-G1, S-0.75L-G1 and S-0.5L-G2 are the locations of both wireless and cabled sensors. A relay node is also used because of the limitation of transmission distance especially for the sensor at S-0.25L-G1. The sampling rates of signals of wireless and cabled sensors are 100 Hz and 200 Hz, respectively. The measurement period is 10 minutes.

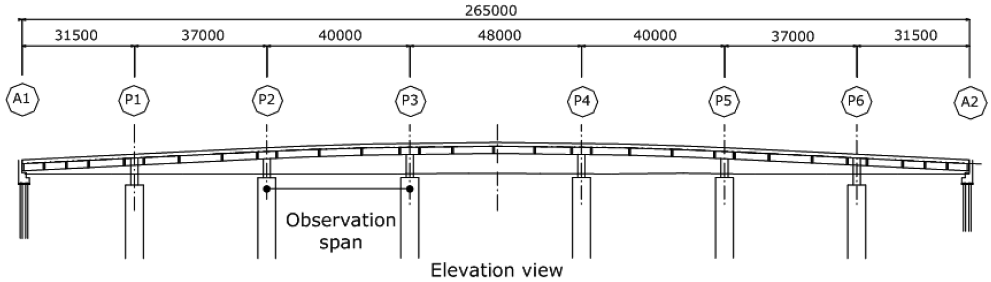
Data missing is observed in the data measured by the wireless sensor. The rate of data missing is summarized in Table 1. Table 1 shows that the rate of data missing changes even in the same sensor. It signifies that the performance of radio data transmission of the wireless sensor is easily affected by nearby environmental conditions of the bridge. The rate of missing data goes up to 7.06%.

Fig. 5 shows examples of burst data missing: for S-0.5L-G2 the data missing occurs between 580 s and 590 s; and for S-0.25L-G1 incomplete observations are concentrated between 450 s and 550 s. The vertical scale of Fig. 5 indicates the existence of data missing: "0" means no data missing occurs; and "1" indicates data missing.

Those missing data are recovered using the Kalman filter algorithm. Fig. 6(a) shows the acceleration time history from 560 s to 600 s of S-0.5L-G2 which shows burst data missing between 580 s and 590 s. It is noteworthy that the Fourier amplitude spectrum shown in Fig. 6(a) is estimated by using zero padding on data missing parts. These missing data are reconstructed as shown in Fig. 6(b), and the time history taken from the cabled sensor is shown in Fig. 6(c).



(a) Cross sectional view



(b) Elevation view

Fig. 3 Observation bridge

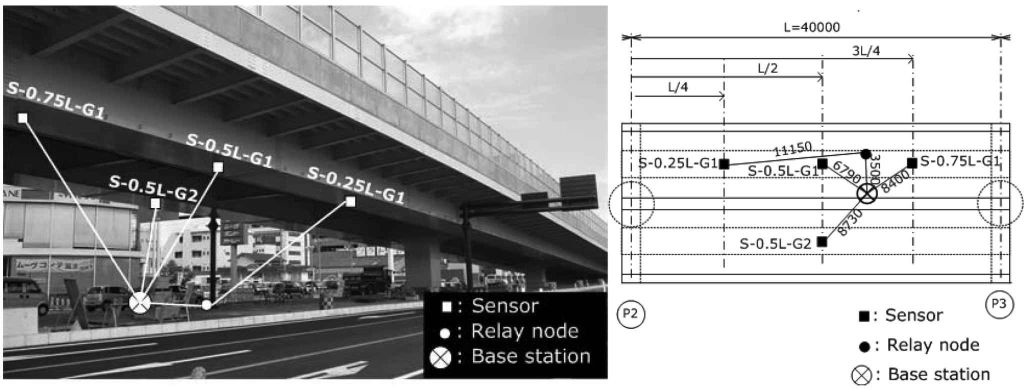


Fig. 4 Observation points and sensor location

Table 1 Data missing rate (%)

	S-0.25L-G1	S-0.5L-G1	S-0.75L-G1	S-0.5L-G2
First	1.37	1/6000	0.28	4.12
Second	0.01	0.01	0.01	0.93
Third	7.06	0.00	1.50	0.16

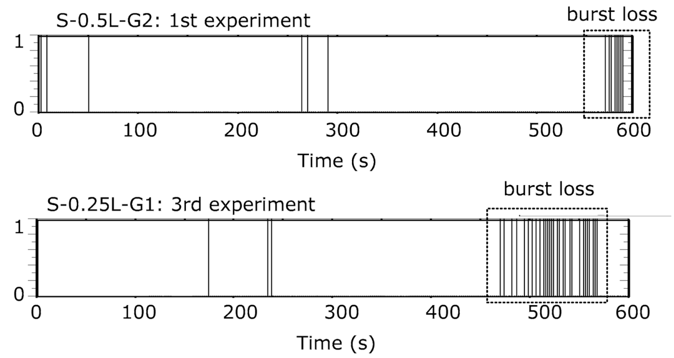
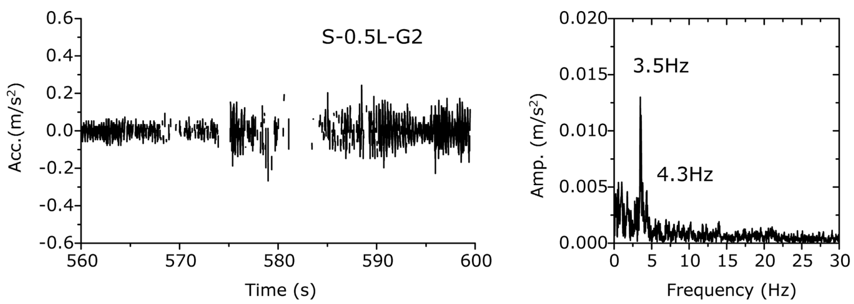
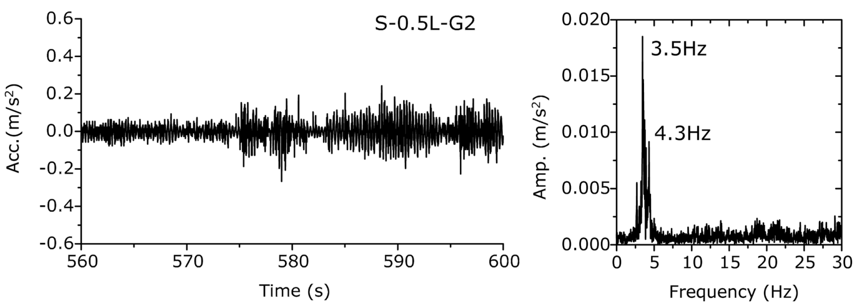


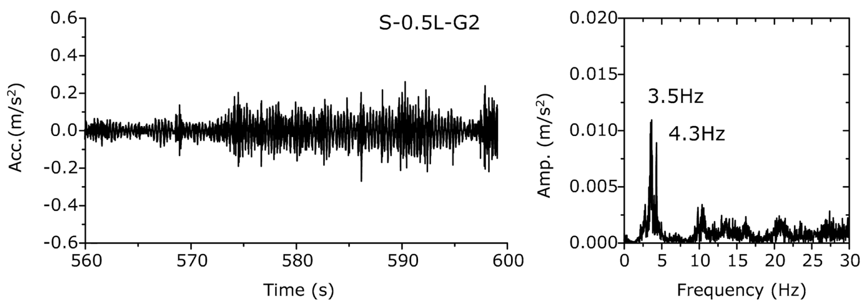
Fig. 5 Examples of data loss



(a) Acceleration response with incomplete observations transmitted from wireless sensor



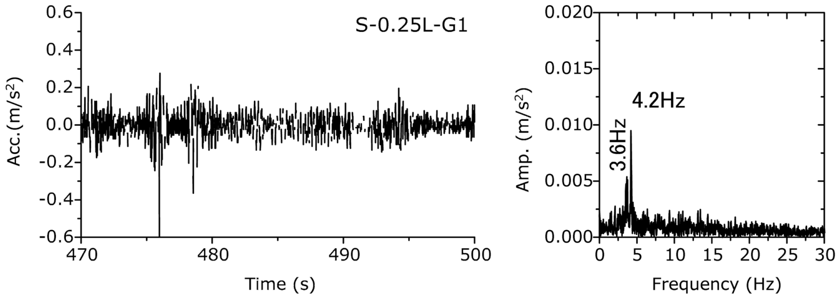
(b) Reconstructed acceleration response



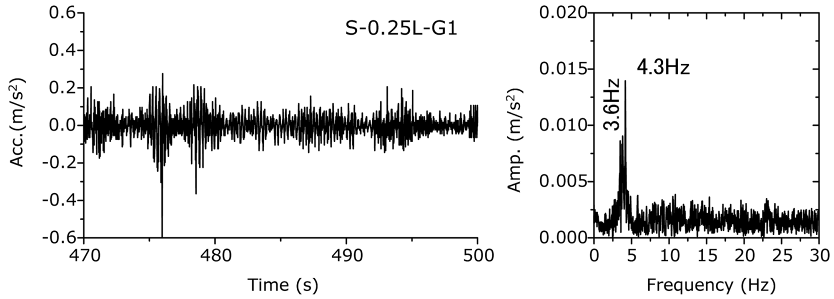
(c) Acceleration response taken from cabled sensor

Fig. 6 Acceleration response and Fourier amplitude spectra of observation point S-0.5L-G2 with 4.12% of data missing rate

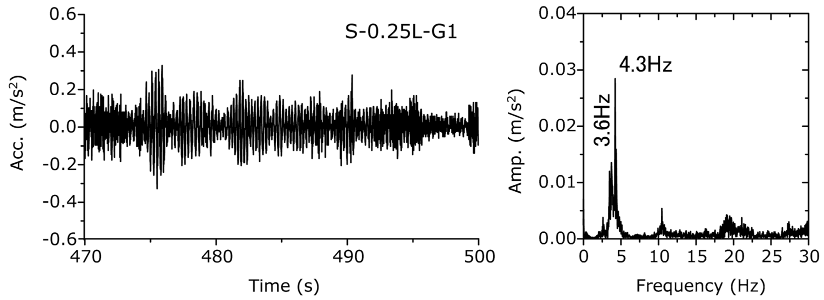
Observations show that amplitude of the recovered acceleration is small in comparison with that of the cabled sensor. However dominant frequencies of the reconstructed signal are comparable with those of cabled sensors. Another recovered acceleration response is appeared in Fig. 7 which is observed at S-0.25L-G1. The Fourier amplitude spectrum shown in Fig. 7(a) is also estimated by using zero padding on data missing parts. It demonstrates that the missing data measured using wireless sensors is recovered using the method and comparable results between cabled and wireless sensor such as acceleration and Fourier amplitude spectra are obtained, even though some noises and peak responses on the time history measured by wireless sensors are appeared.



(a) Acceleration response with incomplete observations transmitted from wireless sensor



(b) Reconstructed acceleration response



(c) Acceleration response taken from cabled sensor

Fig. 7 Acceleration response and Fourier amplitude spectra of observation point S-0.25L-G1 with 7.06% of data missing rate

5. Conclusions

This study investigates the feasibility of reconstructing missing data or incomplete observations in a wireless sensing system which is developed for vibration-based bridge health monitoring. The Kalman filter algorithm is applied to recover missing data transmitted from wireless sensor nodes because the wireless sensor node is designed to minimize the memory space and energy consuming.

Field experiments on a seven-span continuous steel box girder bridge are conducted. Observations from the field experiment demonstrate that the rate of data missing changes even in the same sensor. It signifies that the performance of radio data transmission of the wireless sensor is easily affected by nearby environmental conditions of the bridge.

Those missing acceleration data transmitted from the wireless sensors are reconstructed by the Kalman filter algorithm. Comparable results between data taken from cabled and wireless sensors such as acceleration and Fourier amplitude spectra are obtained, even though some noises and peak responses on the time history measured by wireless sensor are observed. A part of recovered acceleration amplitude, however, is small in comparison with cabled sensor, which is one of the next tasks of this study.

Acknowledgements

This study is supported by the Japan Society for the Promotion of Science (Grant-in-Aid for Exploratory Research under project No.19656112 and Scientific Research (C) under project No.20560443), which is gratefully acknowledged.

References

Akaike, H. (1978), "Covariance matrix computation of the state variable of a stationary Gaussian process", *Ann. I. Stat. Math., Part B,* **30**, 499-504.

Anderson, B.D.O. and Moore, J.B. (1979), *Optimal Filtering*, Englewood Cliffs, Prentice-Hall, New Jersey.

Castaneda, N.E., Dyke, S., Lu, C., Sun, F. and Hackmann, G. (2009), "Experimental deployment and validation of a distributed SHM system using wireless sensor networks", *Struct. Eng. Mech.*, **32**(6), 787-809.

Cipra, T. and Romera, R. (1997), "Kalman filter with outliers and missing observations", *Test, Sociedad de Estadística e Investigación Operativa*, **6**(2), 379-395.

Doebling, S.W., Farrar, C.R., Prime, M.B. and Shevitz, D.W. (1996), "Damage identification and health monitoring of structural and mechanical systems from changes in their vibration characteristics: A literature review", Los Alamos National Laboratory Report LA-3070-MS.

Farrar, C.R., Park, G., Allen, D.W. and Todd, M.D. (2006), "Sensor network paradigms for structural health monitoring", *Struct. Control Health Monit*., **13**(1), 210-225.

He, X. and De Roeck, G. (1997), "System identification of mechanical structures by a high-order multivariate autoregressive model", *Comput. Struct.*, **64**(1-4), 341-351.

Hoshiya, M. and Saito, E. (1984), "Structural identification by extended Kalman filter", *J. Eng. Mech.-ASCE*, **110**(12), 1757-1770.

Kim, C.W., Kawatani, M., Tsukamoto, M. and Fujita, N. (2008), "Wireless sensor node development for bridge condition assessment", *Adv. Sci. Tech.,* Trans Tech Publications, **56**, 573-578.

Kim, C.W., Kawatani, M., Tsukamoto, M. and Fujita, N. (2009), "A novel wireless sensor node for monitoring of civil structures", *Proceeding of the 5th International Symposium on Steel Structures*, Seoul, March.

Kim, S., Pakzad, S., Culler, D., Demmel, J., Fenves, G., Glaser, S. and Turon, M. (2007), "Health monitoring of

civil infrastructures using wireless sensor networks", *Proceeding of Information Processing in Sensor Networks (IPSN 2007)*, Cambridge, Massachusetts, April.
Kitagawa, G. and Gersh, W. (1984), "A smoothness priors-state space modeling of time series with trend and seasonality", *J. Am. Stat. Assoc.*, **78**, 378-389.
Kitagawa, G. and Gersh, W. (1996), *Smoothness Priors Analysis of Time Series*, Lecture Notes in Statistics, No.116. Springer-Verlag.
Kodama, K., Fujita, N., Yoshihisa, T., Tsukamoto, M. and Tagawa, S. (2007), "Development of a small motion sensor node with rule base control", *Proceeding of Multimedia, Distributed, Cooperative and Mobile Symposium (DICOMO2007)*, 569-576. (in Japanese)
Lee, K.J. and Yun, C.B. (2008), "Parameter identification for nonlinear behavior of RC bridge piers using sequential modified extended Kalman filter", *Smart Struct. Syst.*, **4**(3), 319-342.
Ljung, L. (1999), *System Identification- Theory for the User*, 2nd Edition, PTR Prentice Hall.
Lynch, J.P. (2004), "Overview of wireless sensors for real-time health monitoring of civil structures", *Proceeding of the 4th International Workshop on Structural Control and Monitoring*, New York, NY, June.
Spencer Jr., B.F., Ruiz-Sandoval, M. and Kurata, N. (2004), "Smart sensing technology: Opportunities and challenges", *Struct. Control Health Monit.*, **11**, 349-368.
Straser, E.G., Kiremidjian, A.S., Meng, T.H. and Redlefsen, L. (1998), "A modular, wireless damage monitoring system for structures", *SPIE Proceedings*, **3243**(1), 450-456.