DEVELOPMENT AND APPLICATION OF A WIRELESS DATA ACQUISITION SYSTEM FOR STRUCTURAL IDENTIFICATION

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The purpose of this study is to develop a portable structural identification instrument combining a wireless data acquisition system and the developing structural identification application in our research group. The wireless data acquisition system is possible to transmit the digital signals of the observed structural responses. This instrument is set up to a five stories model building and the absolute acceleration at each story is measured. In this study, the Kalman filter and Monte Carlo filter techniques are applied to identify dynamic characteristics of a five stories model structure using observation data from shaking table test.

Key Words : *Wireless Data Acquisition System, Structural Identification, Kalman Filter, Monte Carlo filter, Shaking Table Test*

1. INTRODUCTION

In civil engineering, health monitoring of existing civil structures has been treated as an important subject because several bridges and buildings have been reported their collapses caused by fatigue loads or unexpected load such as earthquakes. To prevent the damage to structure continuous monitoring of structural deterioration and its repair are essential. After the event rapid detection of damage and its repair are also necessary to avoid the occurrence of secondary disaster.

For that purpose, health monitoring of large structure has been facilitated using by new technologies developed in the field of sensor, measurement, communications and computer. Actually, many research efforts have been conducted to develop health monitoring and damage detection techniques for existing civil structures[1), 2)]. The improvement of infrastructure system by applying developed techniques based on these efforts will support the high quality of our life. However, these methods are still in need of improvement for application to a real civil structure, more effectively.

In health monitoring, measurements such as strain, acceleration, velocity, displacement, rotation and other structural responses have been used for detecting damage or deterioration to structures. Wiring works of sensor connection to the data logger system is one of the most time consuming part of sensor deployment to the real structures. To overcome this problem in health monitoring of structure we develop a wireless data acquisition system.

Over the last few decades, structural identification techniques using Kalman filter[3), 4), 5)] and Monte Carlo filter[6), 7), 8)] have been developed in some useful forms for solving many practical problems in health monitoring of civil structures. Because the Kalman filter was firstly developed by the assumption of linear system with Gaussian uncertainty, its application to real system sometimes has not been work well. However, the Monte Carlo filter can be applied to nonlinear and non-Gaussian state space model, very widely. We therefore develop a package of computer programs to be able to use for structural system identification including not only above mentioned but existing efficient algorithms. This package is installed into the portable data processing system and combined with the wireless data acquisition system to develop portable structural identification instrument.

The validity of the developed structural identification instrument is verified by conducting shaking table test of a model structure.

2. IDENTIFICATION TECHNIQUES

(1) KALMAN FILTER

The state transfer and observation equations to be used in Kalman filter are defined as

$$x_n = \Phi_{n-1} x_{n-1} + \Gamma_{n-1} w_{n-1} \quad (1)$$

$$y_n = H_n x_n + v_n \quad (2)$$

in which, n is the time step, x_n is the state variable vector and y_n is the observation vector, w and v are system noise and observation noise vectors, respectively, Φ is the state transfer matrix, Γ is the state transfer matrix for system noise, and H is the observation matrix.

The Kalman filter algorithm is defined as follows,

Step 1. Define an initial value of the state vector $\hat{x}_0$ and its covariance matrix P_0 as well as the covariance matrix of the observation noise R_n.

Step 2. Calculate the pre-estimation value of the state variable vector $\bar{x}_n$ and its covariance matrix M_n as follows,

$$\bar{x}_n = \Phi_{n-1} \hat{x}_{n-1} + \Gamma_{n-1} \hat{w}_{n-1}$$

$$M_n = \Phi_{n-1} \hat{P}_{n-1} \Phi_{n-1}{}^T + \Gamma_{n-1} \Omega_{n-1} \Gamma_{n-1}{}^T$$

Step 3. Calculate the post-estimation value of the covariance matrix P_n of the state variable vector as follow,

$$P_n = (M_n{}^{-1} + H_n{}^T R_n{}^{-1} H_n)^{-1}$$

Step 4. Calculate the Kalman gain K_n as follow,

$$K_n = P_n H_n R_n{}^{-1}$$

Step 5. Calculate the most likelihood estimation value of the state vector $\hat{x}_n$ as follow,

$$\hat{x}_n = \bar{x}_n + K_n (y_n - H_n \bar{x}_n)$$

Step 6. Return to step 1 until the end of time step.

(2) MONTE CARLO FILTER

In Monte Carlo filter (MCF), the state transfer and observation equations are described as follows,

$$x_n = F(x_{n-1}, w_n) \quad (3)$$

$$y_n = H(x_n, v_n) \quad (4)$$

where, F and H are an arbitrary functions, w is the system noise vector defined by an arbitrary probability density function $q(w)$, and v is the observation noise vector defined by an arbitrary probability density function $r(v)$.

To introduce MCF, we need the following relationship between the observation noise vector v_n and state variable vector x_n as well as the observation vector y_n expressed by a function G that can be differentiable with respect to the observation vector y_n as follows,

$$v_n = H^{-1}(x_n, y_n) = G(x_n, y_n) \quad (5)$$

The state transfer and observation equations can be assigned any nonlinear functions.

MCF is an algorithm to approximate probability density functions by many of their realizations named as particles or samples. Thus, the state variable vector is described by many realizations instead of first and second moments of any distribution.

MCF consists of the following recursive algorithm to obtain one step-ahead prediction and filtering.

Step 1. Generate the initial distribution of state variable vector as k-dimensional random number assuming an arbitrary probability density function:

$$f_0^{(j)} \sim p_0(x) \qquad , j = 1, \cdots, m$$

Step 2. Repeat the following steps at each time step

(a) Generate the probability density function of system noise as random number:

$$w_n^{(j)} \sim q(w) \qquad , j = 1, \cdots, m$$

(b) Compute the particles to estimate predictor density using the state transfer equation:

$$b_n^{(j)} = F(f_{n-1}^{(j)}, w_n^{(j)}) \qquad , j = 1, \cdots, m$$

(c) Compute the likelihood of each particle by

$$\alpha_n^{(j)} = p(y_n \mid b_n^{(j)}) = r\left(\left(G(y_n, b_n^{(j)}\right)\right) \left| \frac{\partial G}{\partial y_n} \right|$$

(d) Generate m filtered particles $f_n^{(j)}$ by resampling of $b_n^{(j)}$ (j=1,...,m) as proportional to the likelihood of each particle:

$$f_n^{(j)} = \begin{cases} b_n^1 & \textit{with probability} \quad \alpha_n^{(1)} \Big/ \sum_{i=1}^m \alpha_n^i \\ \vdots & \\ b_n^m & \textit{with probability} \quad \alpha_n^{(m)} \Big/ \sum_{i=1}^m \alpha_n^i \end{cases}$$

Step 3. Return to step 1 until the end of time step

3. WIRELESS DATA ACQUISITION SYSTEM

A wireless data acquisition system is an instrument that transmits signals of observed structural responses using wireless transmission technique. This system has functions to convert the analog signals obtained from sensors to the digital signals and send these signals to the host computer through a signal processing unit. Structural identification is directly carried out at the host computer. Figure 1 shows the wireless data acquisition system. The main wireless signal processing unit uses LAN standard (IEEE802.11b) and each unit composes of the four wireless components. Because we have four units right now it is possible to process digital

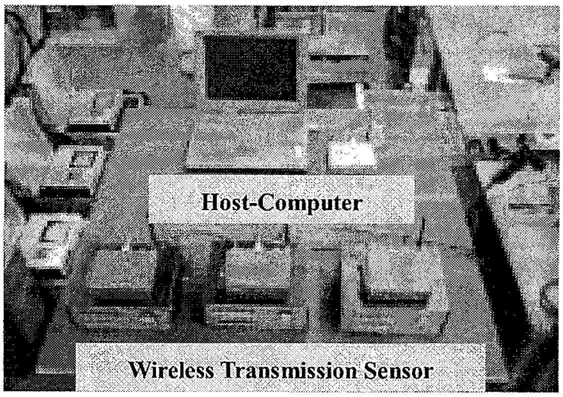

Figure 1. Wireless data acquisition system

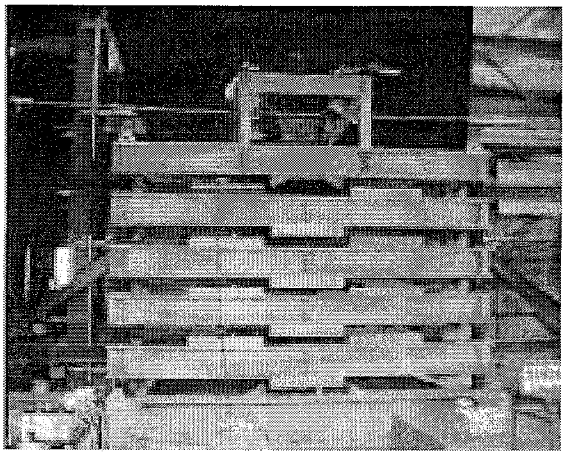

Figure 2. A five stories model structure

signals from 32 channels simultaneously.
The power of the wireless signal transmission system is possible to use both DC and AC sources. In this observation we use the AC100V20VA source because the shaking table system is well facilitated for experimental purpose. The distance limit of communication between the host and user wireless signal transmission system is restricted within 30m in-doors and 1km outdoors.

The processing unit carries out the sampling in the 100 Hz and its decomposability is 16-bit. The size of measurement unit is 200(W) x 190(D) x 145(H) mm. The communication protocols use UDP (User Datagram Protocol) and TCP (Transmission Control Protocol), and the command part and data part of two protocols are used simultaneously. The sampling precision is possible to maintain during 10 minutes within the range of 1 ms and the broadcast method defined in UDP is used for sampling of analog time histories.

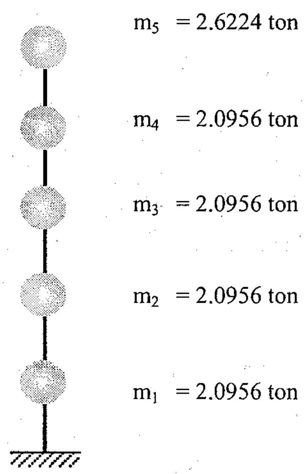

Figure 3. Shear building model

4. STRUCTURAL IDENTIFICATION

The dynamic responses of a five stories model with rubber bearings at the four edge corners of each layer as shown in Figure 2 are measured to identify for dynamic characteristics of this structure. Accelerometers are attached to each layer and the surface of shaking table. Each sensor is connected to the wireless data transmission systems. The servo-accelerometer (Akashi, JAE – 6A3) is used to measure the dynamic responses of the model structure.

The absolute accelerations at each layer and the surface of shaking table were observed and the observed data are processed using a band pass filter (BPF) with the frequency range of 0.5~10Hz by which the base-line correction for time integration is performed. The relative accelerations were obtained by subtracting the acceleration on surface of shaking table from the absolute acceleration of each layer. The relative velocity and displacement of each layer were obtained by time integration from the processed relative accelerations. Those time histories were used to identify dynamic characteristics of this model structure.

The shear building model of five degree of freedom system as shown in Figure 3 is used for identification of the five stories model structure. The input motion to this structure model is assumed to be the measured acceleration on surface of shaking table. The mass of each layer is given as shown in the figure. We identify the damping coefficient and stiffness of each layer under the condition that the relative acceleration and velocity of each mass are measured.

The frequency transfer functions between the ground and each layer are shown in Figure 4 that is calculated using the processed time history of observation data.

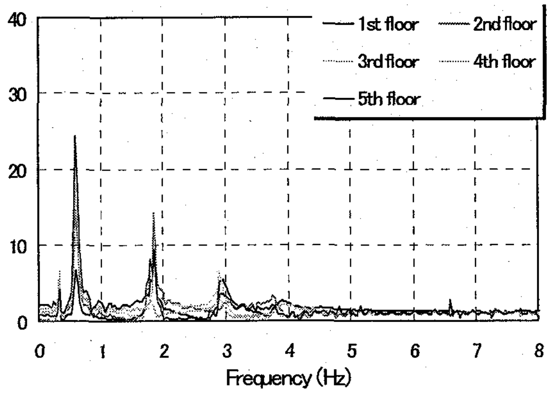

Figure 4. Transfer functions for each layer

Table 1 Natural frequencies of model structure

	1st Mode	2nd Mode	3rd Mode	4th Mode
1st floor	0.61	1.86	2.96	3.91
2nd floor	0.61	1.86	3.05	3.75
3rd floor	0.61	1.86	2.90	3.78
4th floor	0.61	1.80	2.90	3.91
5th floor	0.61	1.86	2.96	3.75
Average	0.61	1.85	2.95	3.82

(Unit : Hz)

The natural frequency of each layer is tabulated as shown in Table 1.

As shown in Table 1, the large amplitudes at 0.61Hz, 1.85Hz, 2.95Hz, and 3.82 Hz are correspond to the first, second, third and fourth vibration modes of the structural system, respectively.

(1) IDENTIFICATION USING KALMAN FILTER

The state variable vector at time step n is given by,

$$x_n = \{y_i, \dot{y}_i, c_i, k_i\}^T \quad (i = 1, \cdots, ndof)$$

in which, $ndof$ is the number of degree of freedom.

The reference values of the stiffness and damping coefficient of each layer are given in Table 2. The initial values of the state vector is defined as follows in which the initial values of stiffness and damping coefficient of each layer are equal to the reference values,

$$\hat{x}_0 = \{0.0, 0.0, c_i, k_i\}^T \quad (i = 1, \cdots, ndof)$$

The initial covariance matrix of the state vector is assumed as,

$$P_{0,i} = \{10^{-3}, 10^{-2}, 1.2^2, 100.0^2\}_i^T$$

The covariance matrix of the observation matrix (R_n) is a diagonal matrix with its component of 0.01.

Table 2 Reference values of stiffness and damping coefficient of each layer (Kalman filter)

	Stiffness (KN/m)	Damping Coefficient (KN·sec/m)
1st floor	400.0	1.158
2nd floor	300.0	1.003
3rd floor	600.0	1.418
4th floor	600.0	1.418
5th floor	200.0	0.916

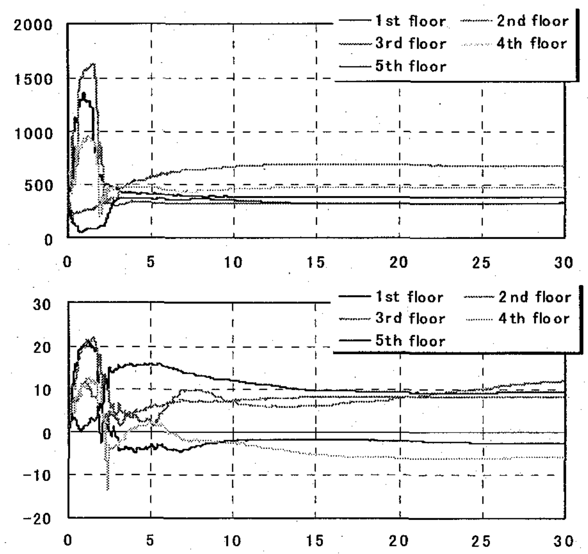

Figure 5. Time histories of identified stiffness (upper) and damping coefficient (lower) computed by Kalman filter technique

The identified time histories of the stiffness and damping coefficient of each layer are shown in Figure 5. The stiffness value of each layer is converged to a certain value whereas the damping value is fluctuated time to time. This means that the stiffness identification is more robust than that of damping coefficient. As general identification of damping coefficient is not stable comparing with stiffness identification because the sensitivity of damping is related to velocity response whereas that of stiffness is related to displacement response.

The identification values of stiffness and damping coefficient of each layer are estimated as mean value after 20 seconds from start of times histories as shown in Figure 5. These values are summarized in Table 3. Using the identified stiffness of each layer, the natural frequencies of the first, second, third and fourth modes are calculated as 0.61Hz, 1.77Hz, 2.89Hz, and 3.58Hz, respectively. The natural frequency of each mode has similar value with that obtained from the transfer function.

Table 3 Identified values of stiffness and damping coefficient of each layer (Kalman filter)

	Stiffness	Damping Coefficient
1st floor	385.69	-2.383
2nd floor	329.39	8.211
3rd floor	679.26	10.088
4th floor	479.09	-5.968
5th floor	327.95	9.206

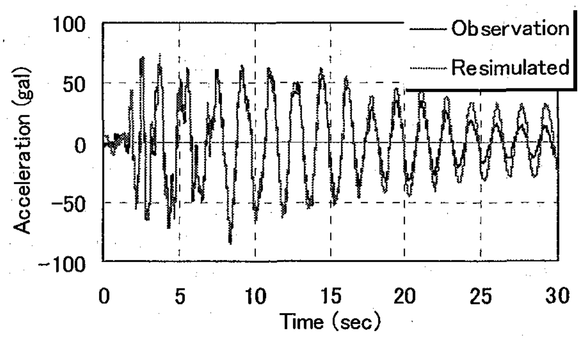

Figure 6. Comparison of observed response and re-simulated response computed by using dynamic characteristics obtained from Kalman filter technique

Using identified stiffness values and damping ratio of 0.02, we re-simulated the structural response of the fifth mass of the analytical model input band passed acceleration time history on shaking table as shown in Figure 6. Amplitudes of re-simulated response are slightly different from observed ones but both phases agree well.

(2) IDENTIFICATION USING MONTE CARLO FILTER

To conduct the structural identification using Monte Carlo filter, the distribution for initial state variables and system noise are defined as the Gaussian distributions as shown in Table 4. The reference values of stiffness and damping coefficient are given as shown in Table 5. The number of particles in Monte Carlo filter is 8000. The covariance matrix of observation matrix is a diagonal matrix with its component of 0.0001.

Time histories of mean stiffness and damping coefficient of each layer are shown in Figure 7. The identified values of stiffness and damping coefficient are fluctuated but almost have similar values in some interval. The stiffness identification is also more robust than that of damping coefficient like as the case of Kalman filter. The identified values of stiffness and damping coefficient are summarized in Table 6.

Table 4 Probability distribution of initial state vector and system noise

	Initial Distribution	Distribution of System Noise
Displacement	$N(0, (10^{-5})^2)$	$N(0, (10^{-8})^2)$
Velocity	$N(0, (10^{-4})^2)$	$N(0, (10^{-7})^2)$
Stiffness	$N(0, (c*0.03)^2)$	$N(0, (c*0.003)^2)$
Damping coefficient	$N(0, (k*0.03)^2)$	$N(0, (k*0.003)^2)$

Table 5 Reference values of stiffness and damping coefficient of each layer (Monte Carlo filter)

	Stiffness	Damping Coefficient
1st floor	400.0	1.158
2nd floor	400.0	1.158
3rd floor	400.0	1.158
4th floor	400.0	1.158
5th floor	600.0	1.587

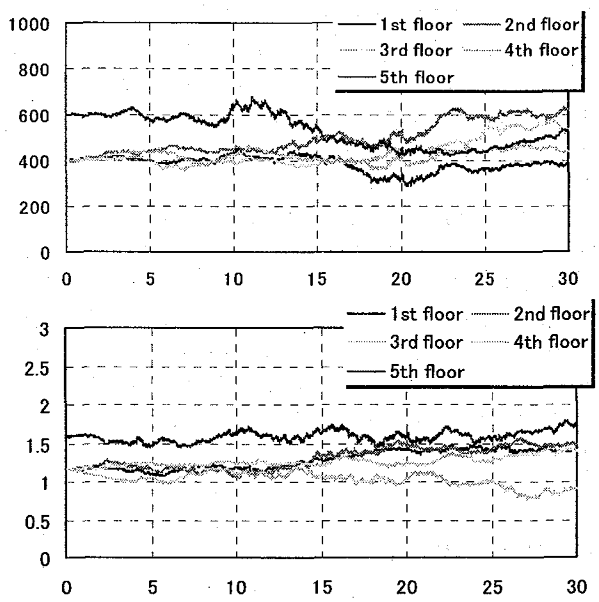

Figure 7. Time histories of identified stiffness (upper) and damping coefficient (lower) obtained by Monte Carlo filter technique

Table 6 Identified values of stiffness and damping coefficient of each layer (Monte Carlo filter)

	Stiffness	Damping Coefficient
1st floor	378.40	1.413
2nd floor	599.21	1.485
3rd floor	543.97	1.350
4th floor	453.15	0.865
5th floor	474.18	1.633

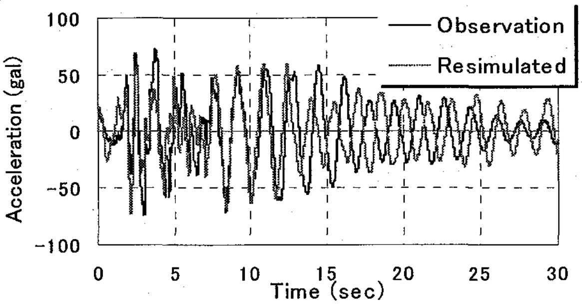

Figure 8. Comparison of observed response and re-simulated response computed by using dynamic characteristics obtained from Monte Carlo filter technique

These identification values of each layer are estimated as average value of the time history of mean value between 25 and 29 seconds from start of times histories as shown in Figure 7. Using the identified stiffness of each layer, the natural frequencies of the first, second, third and fourth modes are defined as 0.65Hz, 1.86Hz, 3.11 Hz, and 4.07Hz, respectively. The natural frequencies until third mode are similar with that obtained from the transfer function. The natural frequency of fourth mode has a little lager value.

Using identified stiffness and damping coefficient values, we re-simulated the structural response of the fifth mass of the analytical model with the input value as acceleration on the surface of shaking table as shown in Figure 8. The resimulated acceleration time history, especially amplitude, dose not agrees well with the observed one although the predominant period is almost same.

5. CONCLUDINGS

Using a wireless data acquisition technique, a portable structural identification instrument is developed. The dynamic characteristics of a five stories model structure are identified using by Kalman filter and Monte Carlo filter techniques.

In both techniques, the identification of stiffness is more robust than that of damping coefficient.

In Kalman filter, re-simulated responses were well agreed with observed responses. However re-simulated and observed responses are not agreed well in Monte Carlo filter.

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