SEISMIC TRANSIENT CHANGE OF NATURAL FREQUENCY ESTIMATION BY ADAPTIVE FILTERING SCHEME

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ABSTRACT:

A new system identification procedure, named as "Adaptive Forward-Backward Kalman Filter (AFB-KF)", is developed to estimate natural frequency transition of a building that exhibits time-varying nonlinear behavior during a strong earthquake. Such natural frequency transition changes with seismic damage level of a building; therefore the natural frequency estimation by the AFB-KF is useful to detect the occurrence of seismic damage of the building. This paper presents theoretical background of the system identification procedures proposed herein, and discusses its effectiveness based on numerical simulations and two real lives monitoring of existing buildings. According to the system identification, it is shown that the first natural frequency of the building clearly decreased during the main shock of the earthquake. Therefore it is expected that structural health monitoring is possible by evaluating natural frequency transition during an earthquake based on the AFB-KF.

KEYWORDS: Kalman Filter, System Identification, Time-Varying System, Structural Health Monitoring, Time-Backward Estimation, Time Series Renewal Algorithm

1. INTRODUCTION

The vibration characteristic of a building, such as natural frequency and modal participation factor, is utilized the evaluation index of structural health monitoring, because vibration characteristic must change against the huge load of a strong ground motion. It is well-known that the change of vibration characteristic of a building is detected from vibration observations before and after earthquake. On the other hand, there are few studies focused on the fluctuation of vibration characteristic during an earthquake. The reason why few study exists is the difficulties of treating as earthquake records, the measurement data of a building during an earthquake is included the nonstationary behaviors, and it is difficult to deal with the data in comparison to the stationary data, such as ambient vibration or force-induced vibration. If the transition of vibration characteristic of a building during an earthquake can be evaluated accurately, the evaluation is expected to utilize for structural health monitoring. The application for structural health monitoring, the authors think, is shown in Figure 1.

In order to trace the transition of vibration characteristic, such as natural frequency changing, the system identification procedure which can be traced on the nonstationary changes of natural frequency, named as Adaptive Forward-Backward Kalman Filter (AFB-KF), is proposed in this paper (F.Kirita,2007). The AFB-KF is compared to the conventional Kalman Filter in terms of the following three development points: (1) Forgetting factor for covariance functions is introduced to track time-varying structural parameters rapidly; (2)

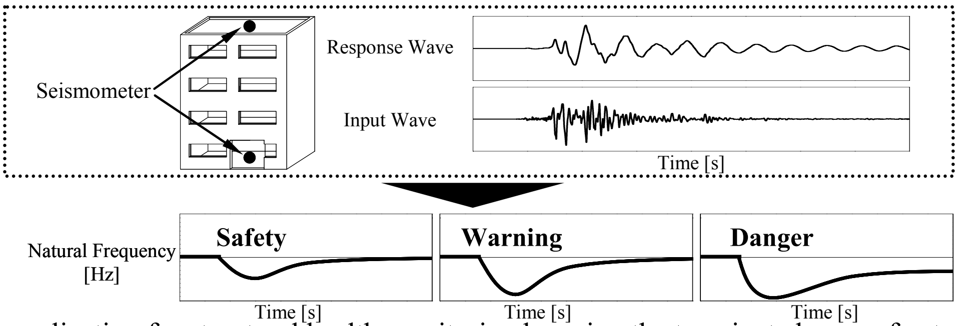


Figure 1 The application for structural health monitoring by using the transient change of natural frequency.

Time-backward estimation scheme and global iteration scheme of the forward and backward processes are added to estimate unknown initial value of structural parameters; (3) Time-varying structural parameters are treated as sequence variable on time to identify the time-varying system with higher accuracy; i.e., time sequences of the time-varying structural parameters are gradually optimized through global iteration scheme. This paper presents theoretical background of the system identification procedures proposed herein, and discusses its effectiveness based on numerical simulations and two real lives monitoring of existing buildings.

2. CONVENTIONAL KALMAN FILTER

2.1 Summary of Kalman Filter

The Kalman Filter (KF) is a filtering approach for linear stochastic system represented by state-space model (R.E.Kalman,1961; C.B.Yun,1980). It consists of state-space form which put two equations together, "Transition Equation" in Eq.(2.1) and "Measurement Equation" in Eq.(2.2). The transition equation describes a transition of the states of system, and the measurement equation shows the relationship between the state of system and the observation data. The mathematical models which described behavior of a dynamical system are shown as following equations.

$$\mathbf{x}_t = \mathbf{\Phi}_{t-1}\mathbf{x}_{t-1} + \mathbf{\Gamma}_{t-1}\mathbf{w}_{t-1}, \tag{2.1}$$

$$\mathbf{y}_t = \mathbf{H}_t\mathbf{x}_t + \mathbf{v}_t, \tag{2.2}$$

where $\mathbf{x}_t$: the state vectors of system; $\mathbf{y}_t$: the measurement vectors; $\mathbf{\Phi}_t$: the state transition matrix; $\mathbf{\Gamma}_t$: the transform matrix; $\mathbf{H}_t$: the observation matrix. The exogenous signals $\mathbf{w}_t$ and $\mathbf{v}_t$ respectively are the process and measurement noise vectors, which are Gaussian white noise as follows:

$$\mathrm{E}[\mathbf{w}_t] = 0, \quad \mathrm{E}[\mathbf{v}_t] = 0, \tag{2.3}$$

$$\mathrm{E}[\mathbf{w}_t\mathbf{w}_t^{\mathrm{T}}] = \mathrm{Diag}[\mathbf{Q}_t], \quad \mathrm{E}[\mathbf{v}_t\mathbf{v}_t^{\mathrm{T}}] = \mathrm{Diag}[\mathbf{R}_t], \tag{2.4}$$

where $\mathbf{Q}_t$ and $\mathbf{R}_t$ are the statistical properties of each noise vectors. $\mathrm{E}[\cdot]$ is the operator of the mean and $\mathrm{Diag}[\cdot]$ denotes a diagonal matrix. The fundamental equations of the KF are described as the forward prediction equations in Eqs.(2.5) and (2.6), the filter equations in Eqs.(2.7) and (2.8), and the Kalman gain in Eq.(2.9).

Forward Prediction Equations

$$\overline{\mathbf{x}}_{t|t-1} = \mathbf{\Phi}_{t-1}\hat{\mathbf{x}}_{t-1|t-1}, \tag{2.5}$$

$$\overline{\mathbf{P}}_{t|t-1} = \mathbf{\Phi}_{t-1}\hat{\mathbf{P}}_{t-1|t-1}\mathbf{\Phi}_{t-1}^{\mathrm{T}} + \mathbf{\Gamma}_{t-1}\mathbf{Q}_{t-1}\mathbf{\Gamma}_{t-1}^{\mathrm{T}}, \tag{2.6}$$

Filter Equations

$$\hat{\mathbf{x}}_{t|t} = \overline{\mathbf{x}}_{t|t-1} + \mathbf{K}_t[\mathbf{y}_t - \mathbf{H}_t\overline{\mathbf{x}}_{t|t-1}], \tag{2.7}$$

$$\hat{\mathbf{P}}_{t|t} = [\mathbf{I} - \mathbf{K}_t\mathbf{H}_t]\overline{\mathbf{P}}_{t|t-1}[\mathbf{I} - \mathbf{K}_t\mathbf{H}_t]^{\mathrm{T}} + \mathbf{K}_t\mathbf{R}_t\mathbf{K}_t^{\mathrm{T}}, \tag{2.8}$$

Kalman Gain

$$\mathbf{K}_t = \overline{\mathbf{P}}_{t|t-1}\mathbf{H}_t^{\mathrm{T}}[\mathbf{H}_t\overline{\mathbf{P}}_{t|t-1}\mathbf{H}_t^{\mathrm{T}} + \mathbf{R}_t]^{-1}, \tag{2.9}$$

where $\overline{\mathbf{x}}_{t|t-1}$ and $\hat{\mathbf{x}}_{t|t}$: the mean vectors of the state; $\overline{\mathbf{P}}_{t|t-1}$ and $\hat{\mathbf{P}}_{t|t}$: the covariance matrix of the state vectors; $\mathbf{K}_t$: the kalman gain. $\bar{\ }$ and $\hat{\ }$ denote the predicted value and the filtered value.

Calculation on the KF performs by the two steps. In the first step, $\overline{\mathbf{x}}_{t|t-1}$ and $\overline{\mathbf{P}}_{t|t-1}$ at time t are predicted from Eqs.(2.5) and (2.6) under the requirement that $\hat{\mathbf{x}}_{t-1|t-1}$ and $\hat{\mathbf{P}}_{t-1|t-1}$ at time $t-1$ are known. In the second step, the Kalman gain is calculated from Eq.(2.9) with employing predicted $\overline{\mathbf{x}}_{t|t-1}$ and $\overline{\mathbf{P}}_{t|t-1}$, and $\hat{\mathbf{x}}_{t|t}$ and $\hat{\mathbf{P}}_{t|t}$ at time t are calculated from Eqs.(2.7) and (2.8). In the two steps, $\hat{\mathbf{x}}_{t|t}$ is not measured, thus $\hat{\mathbf{x}}_{t|t}$ is estimated for recursion at time t by giving measurement $\mathbf{y}_t$ and the arbitrary initial value of $\hat{\mathbf{x}}_{0|0}$ and $\hat{\mathbf{P}}_{0|0}$. Here, the process estimated the state of the system in forward direction on time t base is called here as "Time-Forward Estimation scheme".

2.2 Adaptive Kalman Filter

The KF is one of the system identifications on stationary theory. However, vibration characteristic of a building is not constant during an earthquake. In such a case, the KF cannot be employed any more, therefore, it is necessary to improve the KF in order to trace the accurate state changing rapidly. For this purpose, the Adaptive Kalman Filter (A-KF) has been proposed (L.Ljung,1983; M.Hoshiya,1984; T.Sato,1998). In this method by employing a forgetting factor which is multiplied to the covariance matrix as a magnification factor, the influence of the past measurement is decreasing whereas the influence of the present is increasing.

In practice, we multiply the covariance $\hat{\mathbf{P}}_{t|t}$ the forgetting factor λ $[0 \le \lambda \le 1]$ at every time step. Thus, we employ Eq.(2.10) instead of Eq.(2.6).

$$\overline{\mathbf{P}}_{t|t-1} = \mathbf{\Phi}_{t-1}[\frac{1}{\lambda}\hat{\mathbf{P}}_{t-1|t-1}]\mathbf{\Phi}_{t-1}^{\mathrm{T}} + \mathbf{\Gamma}_{t-1}\mathbf{Q}_{t-1}\mathbf{\Gamma}_{t-1}^{\mathrm{T}} \quad (2.10)$$

3. ADAPTIVE FORWARD-BACKWARD KALMAN FILTER

3.1 Use of Time-Backward Estimation Scheme

The A-KF is one of the online identification methods estimating the state vectors of system from the observable measurement. In the A-KF, the state vectors near the initial time cannot be well-estimated, because the state vectors cannot converge to the true value around the initial time if the given initial value of the state vectors is different from the true value, and one cannot give the initial value as true. However, the state vectors around the initial time are very useful, because this information is considered as the healthy condition of the building.

In this paper, a global iteration scheme is employed where the calculation procedure of the A-KF is repetitively performed with referring the observable records from the initial to the end. Then, if we employ only the time-forward estimation scheme, we cannot estimate the true initial state vectors, because the state vectors at the last time is usually different from those at initial time. To avoid the problem, “Time-Backward Estimation scheme” is introduced, that is, both the time-forward and backward estimations are repetitively performed. By performing both estimations repeatedly, the state vectors near the initial time can gradually converge to the true value. For the time-backward estimation, the fixed-interval smoothing method is employed in this study (J.B.Moore,1973; T.Katayama,1983). That is described as “Smoothing Gain” in Eq.(3.1), “Smoothing Estimation Value” in Eq.(3.2) and “Smoothing Covariance Matrix of Estimation Error” in Eq.(3.3), as follows:

<u>Smoothing Gain</u>

$$\mathbf{C}_{t-1} = \hat{\mathbf{P}}_{t-1|t-1}\mathbf{\Phi}_{t-1}^{\mathrm{T}}\overline{\mathbf{P}}_{t|t-1}^{-1}, \quad (3.1)$$

<u>Smoothing Estimation Value</u>

$$\breve{\mathbf{x}}_{t-1|N} = \hat{\mathbf{x}}_{t-1|t-1} + \mathbf{C}_{t-1}[\breve{\mathbf{x}}_{t|N} - \overline{\mathbf{x}}_{t|t-1}], \quad (3.2)$$

<u>Smoothing Covariance Matrix of Estimation Error</u>

$$\breve{\mathbf{P}}_{t-1|N} = \hat{\mathbf{P}}_{t-1|t-1} + \mathbf{C}_{t-1}[\breve{\mathbf{P}}_{t|N} - \overline{\mathbf{P}}_{t|t-1}]\mathbf{C}_{t-1}^{\mathrm{T}}. \quad (3.3)$$

In time-backward estimation scheme, the mean of the state vectors $\hat{\mathbf{x}}_{t|t}$ and $\overline{\mathbf{x}}_{t|t-1}$ and covariance matrix $\hat{\mathbf{P}}_{t|t}$ and $\overline{\mathbf{P}}_{t|t-1}$, are calculated from the time-forward estimation, are used in Eqs.(3.1) to (3.3).

3.2 Proposal on Time Series Renewal Algorithm

In the A-KF with time-backward estimation scheme, described in the previous section 3.1, the both state vectors at the first and last time are transferred at the ends of the two schemes. In other words, the two estimates by the forward and backward scheme are connected only at the both ends, as described solid arrows in Figure 2. In order to estimate the state vectors more accurately, identification procedure is improved to connect the state vectors at all time, as described dashed arrows in Figure 2.

To realize this idea, “Time Series Renewal Algorithm” is proposed to estimate state vectors more accurately. All data of the state vectors, which are calculated in time-backward estimation, is considered a time constant sequence. And, the mean and covariance of the state vectors is renewed with treating as the time constant sequence in time-forward estimation at the next global analysis step. In this algorithm, the state vectors are divided into “stationary parameter” and “nonstationary parameter” as follows:

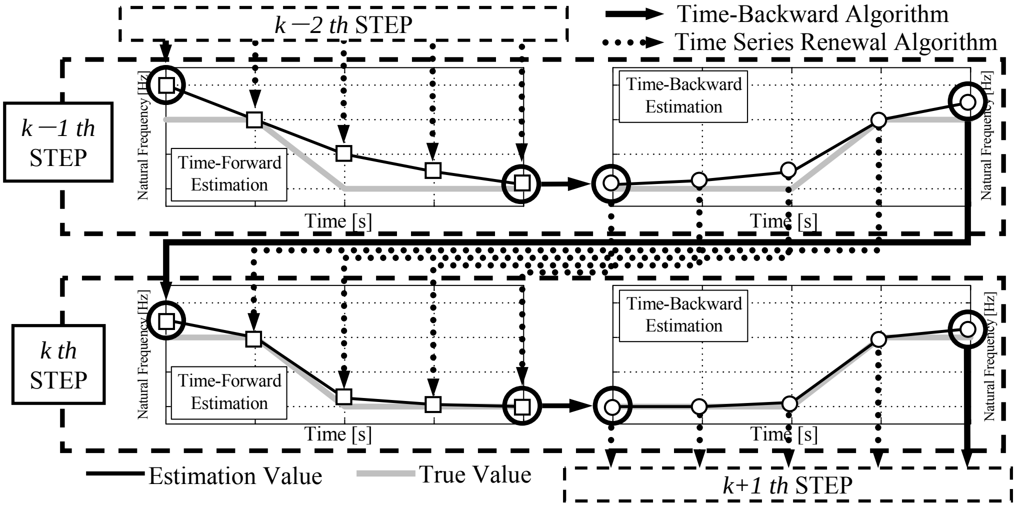


Figure 2 The flow of system identification by using th AFB-KF.

Mean Vectors and Covariance Matrix of the State Vectors at time *k*-1th analysis step

$$\overleftarrow{\mathbf{x}}_{t|N}^{(k-1)} = \begin{Bmatrix} \overleftarrow{\mathbf{x}}_{\mathrm{S}\,t|N}^{(k-1)} \\ \overleftarrow{\mathbf{x}}_{\mathrm{T}\,t|N}^{(k-1)} \end{Bmatrix}, \quad \overleftarrow{\mathbf{P}}_{t|N}^{(k-1)} = \begin{bmatrix} \overleftarrow{\mathbf{P}}_{\mathrm{SS}\,t|N}^{(k-1)} & \overleftarrow{\mathbf{P}}_{\mathrm{ST}\,t|N}^{(k-1)} \\ \overleftarrow{\mathbf{P}}_{\mathrm{TS}\,t|N}^{(k-1)} & \overleftarrow{\mathbf{P}}_{\mathrm{TT}\,t|N}^{(k-1)} \end{bmatrix}, \tag{3.4}$$

Mean Vectors and Covariance Matrix of the State Vectors at time *k*th analysis step

$$\overline{\mathbf{x}}_{t|t-1}^{(k)} = \begin{Bmatrix} \overline{\mathbf{x}}_{\mathrm{S}\,t|t-1}^{(k)} \\ \overline{\mathbf{x}}_{\mathrm{T}\,t|t-1}^{(k)} \end{Bmatrix}, \quad \overline{\mathbf{P}}_{t|t-1}^{(k)} = \begin{bmatrix} \overline{\mathbf{P}}_{\mathrm{SS}\,t|t-1}^{(k)} & \overline{\mathbf{P}}_{\mathrm{ST}\,t|t-1}^{(k)} \\ \overline{\mathbf{P}}_{\mathrm{TS}\,t|t-1}^{(k)} & \overline{\mathbf{P}}_{\mathrm{TT}\,t|t-1}^{(k)} \end{bmatrix}, \tag{3.5}$$

where $\mathbf{x}_{\mathrm{S}}$ is the stationary parameter and $\mathbf{x}_{\mathrm{T}}$ the nonstationary parameter.

The new state vectors are calculated from the both results by the *k*-1th global iteration and by the previous time step of the same global iteration, by taking weighted average with the reflection coefficient *p*. The new mean vectors and covariance matrix is described as follows:

$$\widetilde{\mathbf{x}}_{t|t-1} = \begin{Bmatrix} \overline{\mathbf{x}}_{\mathrm{S}\,t|t-1}^{(k)} \\ p\overleftarrow{\mathbf{x}}_{\mathrm{T}\,t|N}^{(k-1)} + (1-p)\overline{\mathbf{x}}_{\mathrm{T}\,t|t-1}^{(k)} \end{Bmatrix} \left(\equiv \begin{Bmatrix} \widetilde{\mathbf{X}}_{\mathrm{S}} \\ \widetilde{\mathbf{X}}_{\mathrm{T}} \end{Bmatrix} \right), \quad \widetilde{\mathbf{P}}_{t|t-1} = \begin{bmatrix} \overline{\mathbf{P}}_{\mathrm{SS}\,t|t-1}^{(k)} & \mathbf{\Lambda}_{\mathrm{ST}} \\ \mathbf{\Lambda}_{\mathrm{TS}} & \mathbf{\Lambda}_{\mathrm{TT}} \end{bmatrix}, \tag{3.6}$$

$$\begin{aligned} \mathbf{\Lambda}_{ij} = p\{&\overleftarrow{\mathbf{P}}_{ij\,t|N}^{(k-1)} + (\widetilde{\mathbf{X}}_i - \overleftarrow{\mathbf{x}}_{i\,t|N}^{(k-1)})(\widetilde{\mathbf{X}}_j - \overleftarrow{\mathbf{x}}_{j\,t|N}^{(k-1)})^{\mathrm{T}}\} \\ &+ (1-p)\{\overline{\mathbf{P}}_{ij\,t|t-1}^{(k)} + (\widetilde{\mathbf{X}}_i - \overline{\mathbf{x}}_{i\,t|t-1}^{(k)})(\widetilde{\mathbf{X}}_j - \overline{\mathbf{x}}_{j\,t|t-1}^{(k)})^{\mathrm{T}}\} \end{aligned} \qquad \begin{matrix} i, j = \mathrm{S}, \mathrm{T} \\ i = j \neq \mathrm{S} \end{matrix}. \tag{3.7}$$

By considering Eq.(3.8) to Eq.(3.10), the filter equation in Eq.(2.6), the covariance matrix of estimation error in Eq.(2.7) and the Kalman gain in Eq.(2.9) are renewed as follows:

Filter Equation

$$\hat{\mathbf{x}}_{t|t} = \widetilde{\mathbf{x}}_{t|t-1} + \mathbf{K}_t[\mathbf{y}_t - \mathbf{H}_t\widetilde{\mathbf{x}}_{t|t-1}], \tag{3.8}$$

Covariance Matrix of Estimation Error

$$\hat{\mathbf{P}}_{t|t} = [\mathbf{I} - \mathbf{K}_t\mathbf{H}_t]\widetilde{\mathbf{P}}_{t|t-1}[\mathbf{I} - \mathbf{K}_t\mathbf{H}_t]^{\mathrm{T}} + \mathbf{K}_t\mathbf{R}_t\mathbf{K}_t^{\mathrm{T}}, \tag{3.9}$$

Kalman Gain

$$\mathbf{K}_t = \widetilde{\mathbf{P}}_{t|t-1}\mathbf{H}_t^{\mathrm{T}}[\mathbf{H}_t\widetilde{\mathbf{P}}_{t|t-1}\mathbf{H}_t^{\mathrm{T}} + \mathbf{R}_t]^{-1}. \tag{3.10}$$

The above proposed procedure which is innovated time-backward estimation scheme and time series renewal algorithm to the A-KF is named as "Adaptive Forward-Backward Kalman Filter (AFB-KF)".

4. NUMERICAL SIMULATION

4.1 Summary of Numerical Simulation

To illustrate the application on the proposed identification scheme, numerical simulations of a single degree of freedom (SDOF) are conducted, shown in Figure 3. A input wave to the numerical model is given as white noise, whose amplitude characteristic is constant from 0.2Hz to 50.0Hz and phase characteristic is uniform random. In addition, two kinds of transition of natural frequency are set to the SIN type or the STEP type. The SIN type is a pattern as natural frequency gently changing, and it is modeled such that restoring forces of a building varied smoothly in weak nonlinear behavior during an earthquake. On the other hand, the STEP type is a pattern as natural frequency rapidly changing, and it is modeled such that a permanent damage occurs in main structural members by a strong earthquake. Damping factor is given as 2 percent in constant. Response waves are calculated by the Runge-Kutta method to use the white noise and the numerical models in case of the SIN or STEP types. The sampling frequency of input or response wave is set to 200Hz.

4.2 Application of the AFB-KF

In the numerical simulation, parameters of the state vectors $\mathbf{x}_t$ are consisted of displacement, velocity and natural circular frequency, whereas the damping factor is set to 0.02 in constant. The natural frequency is shown by dividing natural circular frequency by 2π. Parameters of displacement or velocity are assumed as stationary parameter, which are not applied for the time series renewal algorithm. On the other hand, a parameter of natural circular frequency is assumed as nonstationary parameter, which is applied for that algorithm.

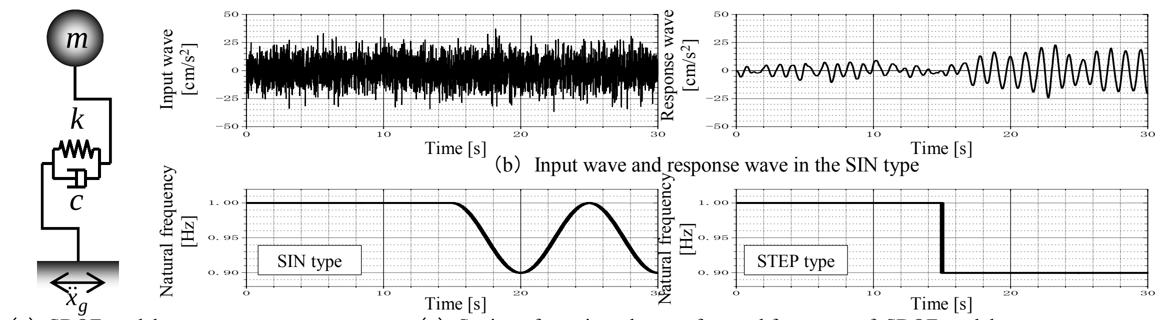
4.3 Identification Result by the A-KF

To evaluate to the identification result by proposed procedure, the identified natural frequency in case of using the A-KF for the numerical simulation of the SIN type is shown in Figure 4. In the analysis, arbitrarily initial value of natural frequency is set to 1.1Hz, where the initial value is largely given by 10 percent. And, the forgetting factor is set to 0.97 which is the optimal value by the preliminary parameter study. To clarify the effectiveness of the A-KF which is only added with the manipulation of the forgetting factor, the identification result of the KF is also shown in Figure 4.

As shown in Figure 4, the identification result of the KF described as the dash line is not traced on the true transition of natural frequency. On the other hand, the identification result by the A-KF can be roughly traced on the true value, but the result is also shown the periodic vibration. We call the appearance of the periodic vibration “the ruffling error”. In use of the A-KF, the larger forgetting factor is chosen, the more accurate the tracing capability for nonstationary state changing. Then, however, the ruffling error also appears strongly. Moreover, another error is found in the result of the A-KF, that is, the transition curve of the A-KF varies later than the true trajectory. This time-lag error might be caused by poor convergence performance of the A-KF.

4.4 Result of Time-Backward Estimation Scheme

Applying the A-KF with time-backward estimation scheme to the numerical model with the SIN type, the transition of initial value estimates of natural frequency at each iteration step is shown in Figure 5, where the initial value of natural frequency is given to 1.1Hz whereas the true value equals to 1.0Hz, and the forgetting factor is set to 0.97. In addition, identification result of natural frequency is shown in Figure 6(a). The identification results of the first and the 50th time-backward estimations are shown.



(a) SDOF model (b) Input wave and response wave in the SIN type (c) Setting of transient change of natural frequency of SDOF model

Figure 3 The SDOF model, input and response wave, and setting of natural frequency at numerical simulation.

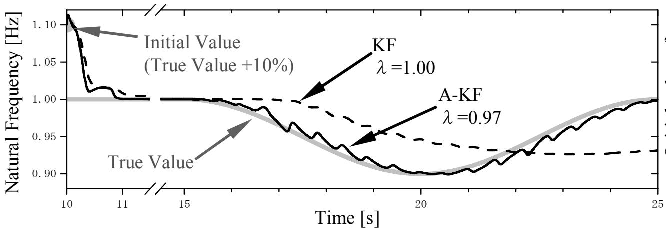


Figure 4 Comparison between the KF and the A-KF.

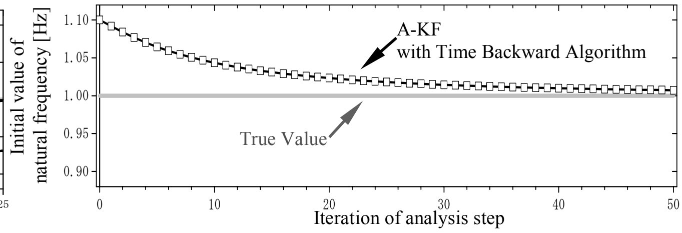
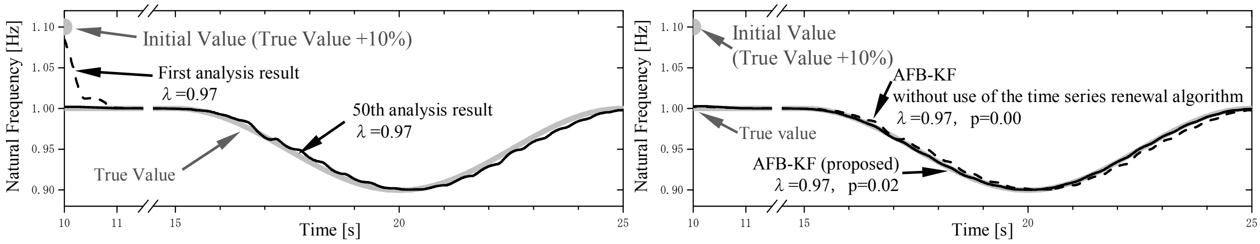


Figure 5 Convergence of the initial value estimate.



(a) AFB-KF except time series renewal algorithm

(b) The AFB-KF proposed here

Figure 6 Comparison between the AFB-KF and its except time series renewal algorithm.

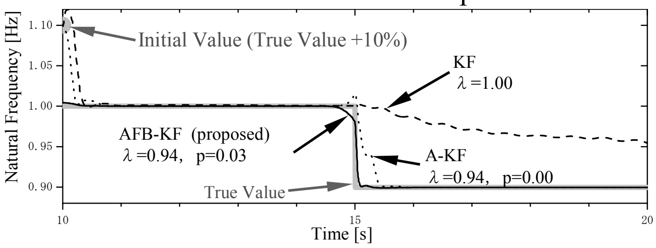


Figure 7 Comparison between the KF, the A-KF and the AFB-KF in the STEP type.

As shown in Figure 5, it is confirmed the initial value estimates gradually converge to the true value, and the estimate after 50th iteration can almost reach at the true value. This iteration effects are found in Figure 6(a). By compared between figure 6(a) and figure 4, the ruffling error and the time-lag error is slightly reduced in the use of the time-backward estimation scheme, but these errors cannot perfectly vanished.

4.5 Result of Time Series Renewal Algorithm

By using the AFB-KF proposed here, the effect of the time series renewal algorithm is examined. The result of applying the proposed procedure to the numerical model with the SIN type is shown in Figure 6(b). In the analysis, the forgetting factor and the reflection factor are set to 0.97 and 0.02 respectively, which are the optimal values by the preliminary parameter study. The initial value of natural frequency is set to 1.1Hz and the number of the iteration analysis is 50 times. To show the effectiveness of the proposed procedure, the result by the AFB-KF without use of the time series renewal algorithm are also described as dash line in Figure 6(b).

By using the AFB-KF, the natural frequency estimate agrees completely with the true value, the ruffling error and the time-lag error of natural frequency are perfectly vanish.

4.6 Application to Numerical Simulation with the STEP type Changing

To show the further effectiveness of the AFB-KF, the identification result of natural frequency by applying the AFB-KF to the numerical simulation with the STEP type is shown in Figure 7. In the analysis, the forgetting factor and the reflection factor are set to 0.94 and 0.03 respectively, which are the best result in the preliminary parameter study. On the other hand, the initial value of natural frequency is set to 1.1Hz. For comparison, the identification results of the A-KF ($\lambda = 0.94$, $p = 0.00$) and the KF ($\lambda = 1.00$) are also shown in Figure 7.

According to Figure 7, the result of the AFB-KF shows the best agreement with the true natural frequency especially, when the natural frequency suddenly decrease at 15 second. On the other hand, the identification results by the KF or A-KF are not agreed with the true natural frequency after the sudden decreasing. In this way, the AFB-KF gives an accurate transition of natural frequency even when the natural frequency varies suddenly.

5. APPLICATION OF AFB-KF FOR EXISTING BUILDING

To demonstrate the practicality of the proposed AFB-KF in the real-life, the natural frequencies of two existing buildings are identified. The first example is a real seismic observation record on a seismic base-isolated building. Although the amplitude of the seismic record is relatively small, the natural frequency is easily changing in case of the base-isolated building even when the observed earthquake motion is small. The second example is acceleration records on a shaking table test of a 4-story steel building specimen. During the test, the specimen suffers some damage from the huge input given by the shaking table.

5.1 Base-Isolated Building

The base-isolated building, measured on the seismic response data, is the lecture building in Tokyo University of Science, JAPAN. The appearance, floor plan and cross-section diagram of this building are shown in Figure 8(a). The superstructure is a reinforced concrete 7-story structure of 36.5 by 70.4 meters in floor plan. Under the superstructure, natural rubber bearings with steel damper, lead rubber bearings and elastic sliding bearing are installed as seismic isolation devices. The seismometers are installed on the foundation, the first floor and top floor (K.Kanazawa,2006). Of these seismometers, we used here the record of the two seismometers on the foundation and the first floor as input and response respectively. The seismic observation record was observed in February 16th, 2004, as shown in Figure 9(a). The acceleration records are band-pass-filtered such that only the first model component is dominant.

As shown in the lowest graph of Figure 9(a), the result of the natural frequency is identified by the AFB-KF. The natural frequency of the lecture building gradually decreased while the primary wave of the earthquake was measured. After the main shock, the natural frequency is recovered gradually, and at the end of earthquake the natural frequency was recovering the original value before the earthquake. According to the record, it can be shown that the superstructure and seismic isolators are not damaged because the natural frequency did not vary before and after the earthquake.

5.2 Four-Story Steel Building Specimen

The second building is the 4-story steel moment frame building specimen in “E-Defense Experimental Projects for Steel Buildings” constructed by the E-Defense of the National Research Institute for Earth Science and Disaster Prevention (NIED) (K.Kasai,2007; K.Suita,2007; K.Suita,2008). The specimen is modeled as possibly a real existing building with concrete slabs, fire proof covers, exterior panels, ceiling, and partitions. The appearance, floor plan and cross-section diagram of this building are shown in Figure 8(b). In addition, the installation of seismometers is also shown.

The AFB-KF is applied to the acceleration response record on the shaking table test, when some of the main structural members behaved plastically. In the identification analysis, the acceleration response records on the shaking table and roof are treated as input and response respectively. The identification result calculated by the AFB-KF, is shown in Figure 9(b). In addition, response and input records, which are used for identification analysis, is also shown. Moreover, to investigate the accuracy of the identification result, the experimental value is calculated by using the response records measured at every story in shaking table test. In detail, the

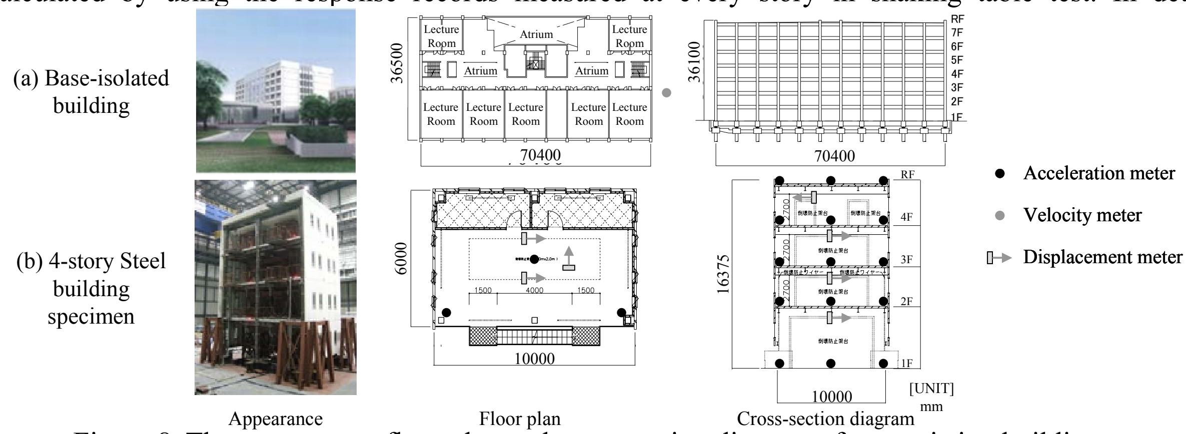
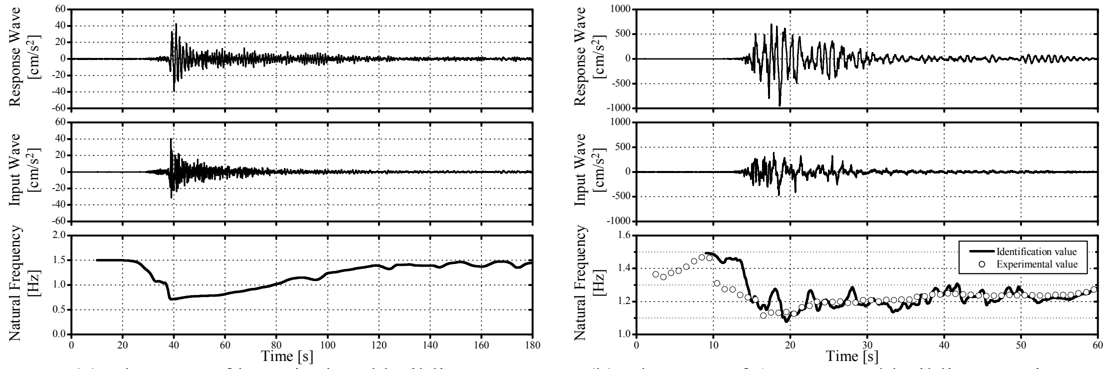


Figure 8 The appearance, floor plan and cross section diagram of two existing buildings.



(a) The case of base-isolated building (b) The case of 4-story steel building specimen

Figure 9 The application of the AFB-KF for existing buildings.

load-displacement relationship is calculated from the records of both absolute acceleration and relative story displacement on every story, and the transit change of natural frequency of experimental building during shaking test is calculated by performing eigenvalue analysis from the load-displacement relationship and weight of every story. In Figure 9(b), the experimental value of natural frequency calculated by this way is also shown.

According to Figure 9(b), the identification result of natural frequency is agreed well with the experimental value. This fact means the result by the proposed method is accurate. In addition, there is a difference of the natural frequency estimates between the initial time and the last time. This difference can be caused by some damage of the main structural members of the specimen due to the strong shaking.

6. CONCLUSION

In this paper, to estimate a natural frequency transition even when the building behave in time-varying nonlinear response during a strong earthquake, a new system identification procedure is developed, named as "Adaptive Forward-Backward Kalman Filter (AFB-KF)". We present the theoretical background of the system identification procedures, and discusses on the effectiveness throughout the numerical simulations. As a result, the AFB-KF is very effective in comparison of conventional Kalman Filter even when the natural frequency is suddenly changing. In addition, to apply the AFB-KF to the response record of two existing buildings, which are base-isolated building and 4-story steel building specimen, the change of natural frequencies of a building during an earthquake clearly detected, and the accuracy of the AFB-KF is confirmed.

REFERENCES

F.Kirita, K.Kanazawa, N.Morikiyo and H.Kitamura (2007), Adaptive forward-backward system identification for seismic damage detection of building, *Journal of Structure and Construction Engineering*, AIJ, No.619, 65-72. (in Japanese)

R.E.Kalman and R.S.Busy (1961), New results in linear filtering and prediction theory, Transaction of the ASCE, *Journal of Basic Engineering*, Series D, **83**, 95-108.

C.B.Yun and M.Shinozuka (1980), Identification of nonlinear structural dynamics system, *Journal of Structural Mechanics*, ASCE, Vol.**8**, No.2, 187-203.

L.Ljung and T.Soderstrom (1983), Theory and practice of recursive identification, *MIT press*, 368-369.

M.Hoshiya and E.Saito (1984), Structural identification by extended kalman filter, *Journal of Engineering Mechanics*, ASCE, Vol.**110**, No.12, 1757-1770.

T. Sato and K. Takei (1998), Development of an adaptive kalman filter and its application, *Journal of Structural Mechanics and Earthquake Engineering*, JSCE, 584/I-42, 163-173.

J.B.Moore (1973), Discrete-time fixed-lag smoothing algorithms, *Automatica*, Vol.**9**, No.2, 163-173.

T.Katayama (1983), Applied kalman filter, 124-127. (in Japanese)

K.Kanazawa, H.Kitamura and N.Morikiyo (2006), Dual vibrational observation system for structural health monitoring, *Proc. of the 8th US-National Conference on Earthquake Engineering*, paper No.831.

K.Kasai, Y.Ooki, S.Motoyui, T.Takeuchi and E.Sato (2007), E-Defense tests on full-scale steel buildings: Part 1 – Experiments using dampers and isolators, *Proc. Structure Congress 2007*, ASCE, Long Beach, 247-17.

K.Suita, S.Yamada, M.Tada, K.Kasai, Y.Matsuoka and E.Sato (2007), E-Defense tests on full-scale steel building: Part 2 – Collapse experiments on moment frames, *Proc. Structure Congress 2007*, ASCE, Long Beach, 247-18.

K.Suita, S.Yamada, M.Tada, K.Kasai, Y.Matsuoka and E.Sato (2008), Results of Recent E-Defense tests on full-scale steel buildings: Part 1 – Collapse experiments on 4-story moment frames, *Proc. Structure Congress 2008*, ASCE, Vancouver.