Structural Identification using Adaptive Monte Carlo Filter

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Adaptive Monte Carlo filter was developed to identify structural parameters of systems with non-stationary dynamic characteristics. The concept of the forgetting factor multiplying to the process and observation noises is applied to Monte Carlo filter. The forgetting factor is defined as the ratio between two probability density functions. The advantage of this algorithm is that the identification can be conducted by the different combinations of two forgetting factor for adaptive Monte Carlo filter. The validity and effectiveness of the proposed approach has been verified by three cases using by the adaptive process and adaptive observation noises. The Monte Carlo filter and the adaptive Monte Carlo filter are applied to identify dynamic characteristics of a single degree of freedom system.

Key Words: Monte Carlo filter, Adaptive Monte Carlo filter, Forgetting Factor

1. Introduction

System identification refers to determination of the analytical models of systems from the observation or experimental data[1),2)] . Structural identification of dynamic system subjected to the earthquake motion has been focused on the accurate prediction of structural response as well as damage assessment. Especially, the stochastic methods have generally been used to predict the unknown parameters of any dynamical structure systems.

Over the last few decades, structural identification techniques using Kalman filter[3)] and Monte Carlo filter[4)] have been developed in some useful forms for solving many practical problems in 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 working well. On the other hand, the Monte Carlo filter can be applied to nonlinear and non-Gaussian state space models widely.

Because the identification for the system with non-stationary dynamic characteristics depends upon the past observation data, these recursive filters do not have a sufficient time tracking ability for non-stationary change of structural parameters. Thus, results from identification appear low accuracy for structural parameters. To overcome this problem, adaptive H infinity filter[5)], adaptive Kalman filter[6)], and adaptive Monte Carlo filter[7),8)] were suggested by the adaptive model identification techniques[1)].

In this study, the new adaptive technique is applied to Monte Carlo filter using the concept of the adaptive process noise and adaptive observation noise. The developed algorithm is applied to identify dynamic characteristics of a single degree of freedom system. The identified values are compared with the values obtained from Monte Carlo filter.

2. Monte Carlo Filter

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

$$x_k = F(x_{k-1}, w_k) \tag{1}$$

$$y_k = H(x_k, v_k) \tag{2}$$

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

MCF is an algorithm to approximate probability density functions by the large number of their realizations named as particles or samples. And, the state variable vector is defined by many realizations.

Thus, in the MCF, we can approximate a probability density function $p(x)$ using samples $x^{(i)}$ $(i=1,2,\cdots n)$ as defined by

$$p(x)=\frac{1}{n}\sum_{i=1}^{n}\delta\left(x-x^{(i)}\right) \tag{3}$$

in which δ is the Kronecker's delta. Samples, $x_{k|k}^{(i)}$, are generated based on $p(x_k \mid Y_k)$ which is the probability density function of sate vector x_k under the condition that the observation data $Y_k=(y_1,y_2,\cdots,y_k)$ is given.

If we have samples, $x_{k-1|k-1}^{(i)}$, the one step forward prediction of samples, $x_{k|k-1}^{(i)}$, are obtained using the state transfer function,

$$x_{k|k-1}^{(i)}=F(x_{k-1|k-1}^{(i)},w_k^{(i)}) \tag{4}$$

The above Eq.(4) is called the time updating process in MCF.

Substituting the formula given by Eq.(4) into Eq.(3), the approximation of probability density function, $p(x_k \mid Y_{k-1})$,can be obtained. This is named as prediction process and proved as follows:

$$\begin{aligned}
p(x_k \mid Y_{k-1}) &= \iint p(x_k,x_{k-1},w_k \mid Y_{k-1})dx_{k-1}dw_k \\
&= \iint p(x_k \mid x_{k-1},w_k,Y_{k-1})p(x_{k-1},w_k \mid Y_{k-1})\cdot \\
&\quad dx_{k-1}dw_k \\
&= \iint \delta(x_k-F(x_{k-1},w_k))\frac{1}{n}\sum_{i=1}^{n}\delta\left(x_{k-1}-x_{k-1|k-1}^{(i)}\right)\cdot \\
&\quad \delta\left(w_k-w_k^{(i)}\right)dx_{k-1}dw_k \\
&= \frac{1}{n}\sum_{i=1}^{n}\delta\left(x_k-x_{k|k-1}^{(i)}\right)
\end{aligned} \tag{5}$$

After obtaining the observation y_k at time k, the process to obtain the probability density function $p(x_k \mid Y_k)$ is called the filtering which is obtained by,

$$\begin{aligned}
p(x_k \mid Y_k) = p(x_k \mid y_k,Y_{k-1}) &= \frac{p(x_k,y_k \mid Y_{k-1})}{p(y_k \mid Y_{k-1})} \\
&= \frac{p(y_k \mid x_k,Y_{k-1})\,p(x_k \mid Y_{k-1})}{\int p(y_k \mid x_k,Y_{k-1})\,p(x_k \mid Y_{k-1})\,dx_k}
\end{aligned} \tag{6}$$

Substituting Eq.(5) into Eq.(6) we obtain

$$p(x_k \mid Y_k)=\frac{p(y_k \mid x_k,Y_{k-1})\frac{1}{n}\sum_{i=1}^{n}\delta\left(x_k-x_{k|k-1}^{(i)}\right)}{\int p(y_k \mid x_k,Y_{k-1})\frac{1}{n}\sum_{i=1}^{n}\delta\left(x_k-x_{k|k-1}^{(i)}\right)dx_k} \tag{7}$$

The term $p(y_k \mid x_k,Y_{k-1})$ is the probability density function of observed vector y_k provided the state vector x_k is given. Because this distribution function is defined by the observation error distribution this can be expressed the simple form of $p(y_k \mid x_k)$. If we evaluate this probability distribution function for a fixed y_k, this expresses the likelihood of the state vector x_k. If we define the likelihood for a sample $x_{k|k-1}^{(i)}$ as $q_k^{(i)}=p\left(y_k \mid x_{k|k-1}^{(i)}\right)$, Eq.(7) yields,

$$\begin{aligned}
p(x_k \mid Y_k) &= \sum_{i=1}^{n}\left(\frac{q_k^{(i)}}{\sum_{i=1}^{n}q_k^{(i)}}\right)\delta\left(x_k-x_{k|k-1}^{(i)}\right) \\
&= \sum_{i=1}^{n}\alpha_k^{(i)}\,\delta\left(x_k-x_{k|k-1}^{(i)}\right),\ \alpha_k^{(i)}=\left(\frac{q_k^{(i)}}{\sum_{i=1}^{n}q_k^{(i)}}\right)
\end{aligned} \tag{8}$$

To calculate $q_k^{(i)}=p\left(y_k \mid x_{k|k-1}^{(i)}\right)$ in MCF, we need the following relationship between the observation noise vector v_k and state variable vector x_k as well as the observation vector y_k expressed by a function G that is differentiable with respect to the observation vector y_n as follows,

$$v_k=H^{-1}(x_k,y_k)=G(x_k,y_k) \tag{9}$$

Then, the likelihood for each sample, $q_k^{(i)}=p\left(y_k \mid x_{k|k-1}^{(i)}\right)$ is obtained by,

$$q_k^{(i)}=p\left(y_k \mid x_{k|k-1}^{(i)}\right)=r\left(G\left(y_k,x_{k|k-1}^{(i)}\right)\right)\left|\frac{\partial G}{\partial y_k}\right| \tag{10}$$

This is called the observation updating process in MCF.

Based on the above derivation 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:

$$x_{0|0}^{(i)} \sim p_0(x), \qquad i=1,\cdots,n$$

Step 2. Repeat the following steps at each time step

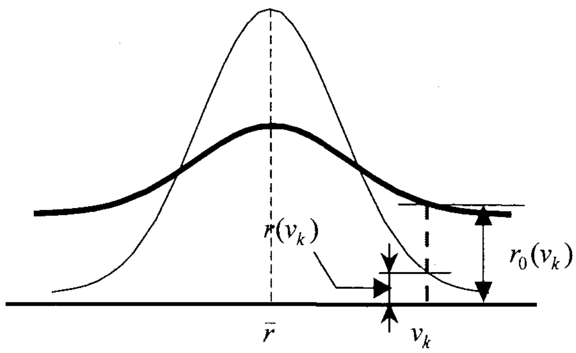

Fig.1 Adaptive observation noise distribution

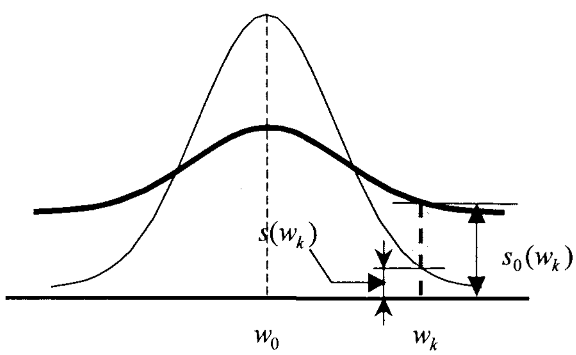

Fig.2 Adaptive process noise distribution

(a) Generate samples obeying the probability density function of system (process) noise:

$$w_k^{(i)} \sim s(w), \qquad i = 1, \cdots, n$$

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

$$x_{k|k-1}^{(i)} = F(x_{k-1|k-1}^{(i)}, w_k^{(i)}), \qquad i = 1, \cdots, n$$

(c) Compute the likelihood of each particle by

$$q_k^{(i)} = p(y_k \mid x_{k|k-1}^{(i)}) = r\left(G\left(y_k, x_{k|k-1}^{(i)}\right)\right)\left|\frac{\partial G}{\partial y_k}\right|$$

(d) Generate n filtered samples $x_{k|k}^{(i)}$ by resampling of $x_{k|k-1}^{(i)}$ (i=1,...,n) as proportional to the likelihood of each sample:

$$x_{k|k}^{(i)} = \begin{cases} x_{k|k-1}^{(1)} & with\ probability \quad q_k^{(1)} \Big/ \sum_{j=1}^{n} q_k^{(j)} \\ \vdots & \\ x_{k|k-1}^{(m)} & with\ probability \quad q_k^{(n)} \Big/ \sum_{j=1}^{n} q_k^{(ji)} \end{cases}$$

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

3. Adaptive Monte Carlo Filter

The basic concept of adaptive MCF is to increase the width of distribution characteristic of particles (samples) so that the re-sampled particles in MCF algorithm can well track the changes of dynamic characteristics of a system by using some hypothetical distribution.

In order to increase the width of the distribution characteristic, the weighting as forgetting factor is multiplied to the observation noise and process noise. The forgetting factor is defined as the ratio of probability density functions between the hypothetical distribution and the baseline distribution of observation noise or process noise. This hypothetical distribution, which is generated by multiplying the forgetting factor to the baseline distribution, can be named as the adaptive observation noise distribution or adaptive process noise distribution. The basic concepts of adaptive observation noise and adaptive process noise are shown in Fig.1 and Fig.2, respectively. In these Figures, the bold solid lines indicate the distributions of the adaptive observation noise and adaptive process noise, and the solid lines indicate the baseline distribution of the observation noise and process noise. And, $r_0(v_k)$ and $s_0(w_k)$ represent the probability density functions of adaptive observation noise and adaptive process noise, respectively.

3.1 Adaptive Observation Noise

The probability density function $p(y_k \mid x_k, Y_{k-1})$ in the filtering process plays an important role to generate filtered samples. If the likelihood is evaluated by $p_0(y_k \mid x_k, Y_{k-1})$ instead of $p(y_k \mid x_k, Y_{k-1})$ we have the following relationship to evaluate the likelihood of each sample,

$$\begin{aligned} p(y_k \mid x_k, Y_{k-1}) &= \frac{p(y_k \mid x_k, Y_{k-1})}{p_0(y_k \mid x_k, Y_{k-1})} p_0(y_k \mid x_k, Y_{k-1}) \\ &= d_k p_0(y_k \mid x_k, Y_{k-1}) \end{aligned} \tag{11}$$

in which, $d_k = p(y_k \mid x_k, Y_{k-1}) / p_0(y_k \mid x_k, Y_{k-1})$. This value is a correction term for evaluating the likelihood of particle by the distribution $p_0(y_k \mid x_k, Y_{k-1})$.

Substituting Eq.(11) into Eq.(6) we obtain a new expression of the probability density function $p(x_k \mid Y_k)$ as follows:

$$\begin{aligned} p(x_k \mid Y_k) &= \frac{p(y_k \mid x_k, Y_{k-1}) \frac{1}{n} \sum_{i=1}^{n} \delta(x_k - x_{k|k-1}^{(i)})}{\int p(y_k \mid x_k, Y_{k-1}) \frac{1}{n} \sum_{i=1}^{n} \delta(x_k - x_{k|k-1}^{(i)}) dx_k} \\ &= \frac{d_k p_0(y_k \mid x_k, Y_{k-1}) p(x_k \mid Y_{k-1})}{\int d_k p_0(y_k \mid x_k, Y_{k-1}) p(x_k \mid Y_{k-1}) dx_k} \\ &= \sum_{i=1}^{n} \left(\frac{d_k^{(i)} \bar{q}_k^{(i)}}{\sum_{l=1}^{n} d_k^{(l)} \bar{q}_k^{(l)}} \right) \delta(x_k - x_{k|k-1}^{(i)}) \\ &= \sum_{i=1}^{n} \alpha_k^{(i)} \delta(x_k - x_{k|k-1}^{(i)}) \end{aligned} \tag{12}$$

in which, $\alpha_k^{(i)} = (d_k^{(i)}\bar{q}_k^{(i)}) / \sum_{l=1}^{n} d_k^{(l)}\bar{q}_k^{(l)}$, and $\bar{q}_k^{(i)}$ is the likelihood of the state vector evaluated by $p_0(y_k \mid x_{k|k-1}^{(i)})$ which is defined by a new observation error density distribution $r_0(v)$.

3.2 Adaptive Process Noise

In the prediction process defined by Eq.(5) the probability density function, $p(x_k, w_k \mid Y_{k-1})$ plays an important role and the probability density function of the process noise, $s(w_k)$, is essential to calculate this probability. If we select a proper process noise denoted by $s_0(w_k)$ to evaluate process noise. $p(x_k, w_k \mid Y_{k-1})$ is obtained by,

$$\begin{aligned} p(x_{k-1}, w_k \mid Y_{k-1}) &= p(x_{k-1} \mid Y_{k-1}) s(w_k) \\ &= p(x_{k-1} \mid Y_{k-1}) \frac{s(w_k)}{s_0(w_k)} s_0(w_k) \\ &= \frac{1}{n}\sum_{i=1}^{n} \delta(x_k - x_{k-1|k-1}^{(i)}) \frac{s(w_{0,k}^{(i)})}{s_0(w_{0,k}^{(i)})} \delta(w_k - w_{0,k}^{(i)}) \\ &= \frac{1}{n}\sum_{i=1}^{n} \delta(x_k - x_{k-1|k-1}^{(i)}) c_k^{(i)} \delta(w_k - w_{0,k}^{(i)}) \end{aligned} \tag{13}$$

in which, $c_k^{(i)} = s(w_{0,k}^{(i)}) / s_0(w_{0s,k}^{(i)})$,and $w_{0,k}^{(i)}$ is the adaptive process noise vector of each particle.

Substituting Eq. (13) into Eq. (5), the time updating process for the case of using process noise $s_0(w_k)$ is obtained by,

$$\begin{aligned} p(x_k \mid Y_{k-1}) &= \frac{1}{n}\sum_{i=1}^{n} \delta(x_k - F(x_{k-1|k-1}^{(i)}, w_{0,k}^{(i)})) c_k^{(i)} \\ &= \frac{1}{n}\sum_{i=1}^{n} c_k^{(i)} \delta(x_k - x_{k|k-1}^{(i)}) \end{aligned} \tag{14}$$

The Eq.(14) expresses the time updating process for adaptive process noise.

Conducting same calculation given through Eqs.(7) to (8) on $P(x_k \mid Y_k)$ we can obtain,

$$\begin{aligned} p(x_k \mid Y_k) &= \frac{p(y_k \mid x_k, Y_{k-1}) \frac{1}{n}\sum_{i=1}^{n} \delta(x_k - x_{k|k-1}^{(i)})}{\int p(y_k \mid x_k, Y_{k-1}) \frac{1}{n}\sum_{i=1}^{n} \delta(x_k - x_{k|k-1}^{(i)}) dx_k} \\ &= \sum_{i=1}^{n} \left(\frac{c_k^{(i)} q_k^{(i)}}{\sum_{l=1}^{n} c_k^{(l)} q_k^{(l)}} \right) \delta(x_k - x_{k|k-1}^{(i)}) \end{aligned} \tag{15}$$

To combine adaptivity in the filtering process with the adaptivity in prediction process we use Eq.(11) to evaluate the function, $p(y_k \mid x_k, Y_{k-1})$ in Eq.(15), then the final result to approximate the probability density function, $p(x_k \mid Y_k)$, is expressed as follows:

$$\begin{aligned} p(x_k \mid Y_k) &= \frac{p(y_k \mid x_k, Y_{k-1}) p(x_k \mid Y_{k-1})}{\int p(y_k \mid x_k, Y_{k-1}) p(x_k \mid Y_{k-1}) dx_k} \\ &= \frac{d_k p_0(y_k \mid x_k, Y_{k-1}) \frac{1}{n}\sum_{i=1}^{n} c_k^{(i)} \delta(x_k - x_{k|k-1}^{(i)})}{\int d_k p_0(y_k \mid x_k, Y_{k-1}) \frac{1}{n}\sum_{i=1}^{n} c_k^{(i)} \delta(x_k - x_{k|k-1}^{(i)}) dx_k} \\ &= \sum_{i=1}^{n} \left(\frac{d_k^{(i)} c_k^{(i)} \bar{q}_k^{(i)}}{\sum_{l=1}^{n} d_k^{(l)} c_k^{(l)} \bar{q}_k^{(l)}} \right) \delta(x_k - x_{k|k-1}^{(i)}) \\ &= \sum_{i=1}^{n} \beta_k^{(i)} \delta(x_k - x_{k|k-1}^{(i)}) \end{aligned} \tag{16}$$

in which, $\beta_k^{(i)} = (d_k^{(i)} c_k^{(i)} \bar{q}_k^{(i)}) / \sum_{l=1}^{n} d_k^{(l)} c_k^{l} \bar{q}_k^{(l)}$.

Consequently, the adaptive Monte Carlo filter (MCF) is an algorithm to constraint the effect of the past observation data by controlling the adaptive process noise and observation noise. Controlling both or one of forgetting factors $c_k^{(i)}$ and $d_k^{(i)}$ for time updating and observation updating processes, we can obtain the identified structural parameters that do not depend on the past observation but depend on the observed data at the nearest time.

For the adaptive MCF, the three cases can be considered.

Table 1 Dynamic structural property

Mass	1.0 (ton)
Stiffness	157.75 (KN/m)
Damping Coefficient	1.256 (KN·sec/m)
Damping Ratio	0.05
Damped Natural Period	0.5 (sec)

Table 2 Initial and process noise distributions

	Initial Distribution	Process Noise Distribution
Displacement	$N(0, (1.0)^2)$	$N(0, (10^{-3})^2)$
Velocity	$N(0, (10.0)^2)$	$N(0, (10^{-2})^2)$
Damping coefficient	$N(c, (c*0.03)^2)$	$N(0, (c*0.003)^2)$
Stiffness	$N(k, (k*0.03)^2)$	$N(0, (k*0.003)^2)$

First case is the case that the forgetting factor $c_k^{(i)}$ is only applied to the time updating process and resampling process of MCF. The second case is to apply the forgetting factor $d_k^{(i)}$ for the observation updating process and resampling of MCF. And, the third case is to consider the factor $c_k^{(i)}$ for the time updating process and the factor $d_k^{(i)}$ for the observation updating process of MCF, simultaneously.

4. Numerical Simulations

Consider a single degree of freedom (SDOF) system of a shear building model subjected to earthquakes. The responses of structure system are firstly simulated by decreasing the initial stiffness 20% and by increasing the initial damping coefficient 15%, at 5 seconds after the excitation starts. El Centro (NS, 1940) earthquake motion is inputted. Then, the observational structural responses, which consist of relative displacement and relative velocity, are obtained by adding a white noise with 3% of standard deviation to the simulated structural responses. These structural responses are used to identify the unknown parameters using MCF and adaptive MCF. The dynamic structural properties are tabulated in Table 1. The damage is assumed that the stiffness decreases from 157.75 to 126.2 KN/m and the damping coefficient increases from 1.256 to 1.444 KN·sec/m.

4.1 Identification using Monte Carlo Filter

To conduct the identification for the stiffness and damping coefficient using MCF, the initial distribution and process noise distribution are defined by the Gaussian distributions as shown in Table 2. The state variable vector consists of relative displacement, relative velocity, damping coefficient, and stiffness. The number of particles is 2000.

The sub-covariance matrix of observation noise for MDOF system can be defined by,

$$R_{sub} = \begin{bmatrix} r1 & \\ & r2 \end{bmatrix} \tag{17}$$

where, $r1$ and $r2$ are the components corresponding to displacement and velocity of the system, respectively. Thus, the covariance matrix of observation noise is defined as a diagonal matrix of sub-covariance matrix as following,

$$R = diag\,[R_{sub,i}] \quad , i = 1, \cdots, \text{ndof} \tag{18}$$

where, ndof is the number of degree of freedom system. In the case of SDOF system, the covariance matrix is equal to the sub-covariance matrix. In this study, $r1$=10000 and $r2$ =100 are used.

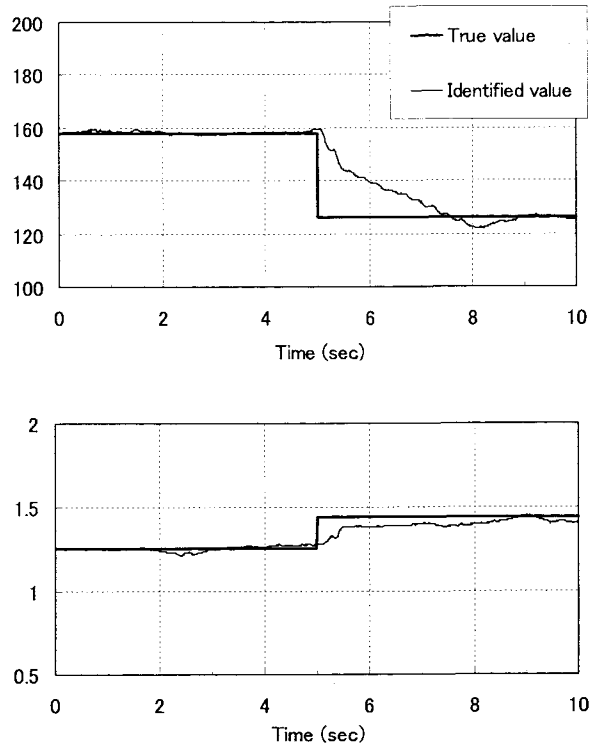

Fig.3 Time histories of identified stiffness (upper) and damping coefficient (lower) obtained by MCF

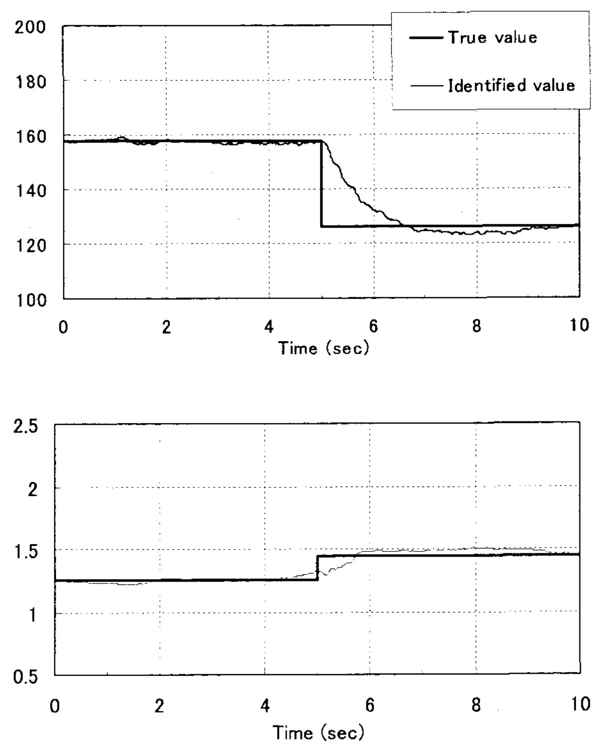

Fig.4 Time histories of identified stiffness (upper) and damping coefficient (lower) obtained by adaptive process noise (forgetting factor = 0.99)

Time histories of mean stiffness and damping coefficient are shown in Fig. 3. The stiffness value is converged to the true value in some interval whereas, the damping coefficient is converged any constant value but somewhat fluctuated time to time.

This means that the stiffness identification is more robust than that of damping coefficient. In 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.

As shown in Fig.3, the tracking ability is not enough to trace the sudden changes of stiffness and damping coefficient.

4.2 Identification using Adaptive Monte Carlo Filter

(1) Adaptive Process Noise

In this case, the forgetting factor is applied to the process noise distribution as shown in Table 2, and it is fixed to a constant value with time progresses. In order to apply the forgetting factor, we consider two standard deviations, ***A*** and ***B*** that indicate the standard deviations of the adaptive process noise and the baseline process noise, respectively. The relation of ***A*** and ***B*** can be represented by the forgetting factor as following,

$$A = \frac{1}{c_k} B = \lambda B \ , c_k = c_k^{(i)} \tag{19}$$

Generally, the forgetting factor exists the range of between the value of 0 and 1. In this case, we obtained the good result when the forgetting factor is close to 1, such as 0.9 or 0.99.

Fig.4 shows the time histories of stiffness and damping coefficient when the forgetting factor is 0.83. Comparing with the general MCF, the stiffness and damping coefficient quickly trace their abrupt change. And, their identified values are converged their true values but the convergences of unknown parameters are somewhat slow.

(2) Adaptive Observation Noise

The forgetting factor is also a constant value that does not change with time. In this case, we can expect better result than the previous cases by changing directly the magnitude of the given covariance matrix that is regarded as the covariance of the observation data.

Let us consider a new covariance matrix of adaptive observation noise, R'. The new covariance matrix can be represented by,

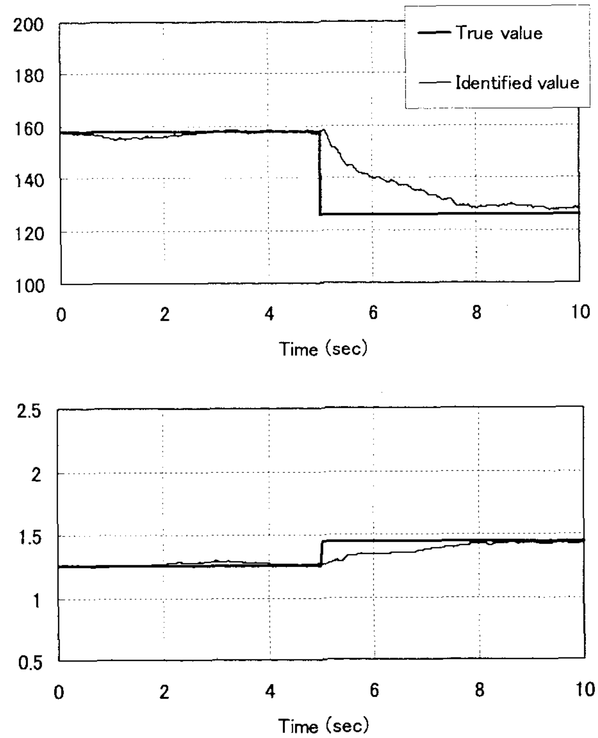

Fig.5 Time histories of identified stiffness (upper) and damping coefficient (lower) obtained by adaptive observation noise (forgetting factor = 0.9)

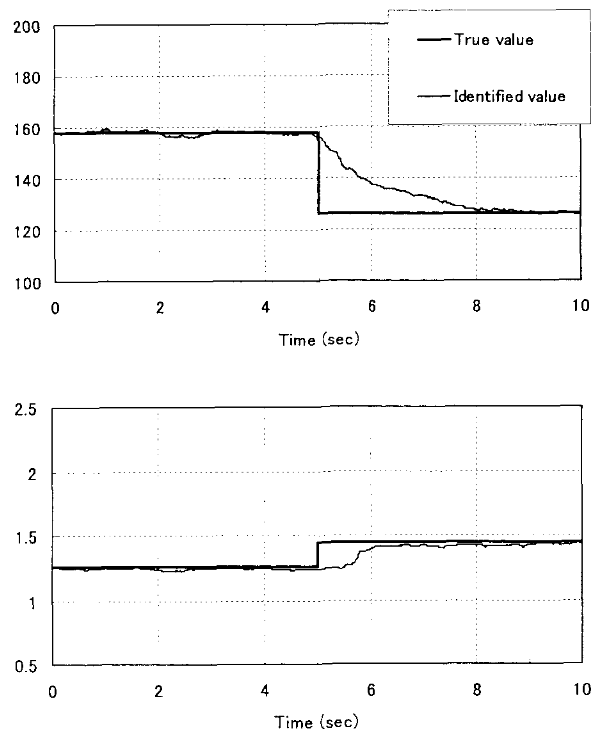

Fig.6 Time histories of identified stiffness (upper) and damping coefficient (lower) obtained by adaptive observation noise (forgetting factor = 0.5) and adaptive process noise (forgetting factor =0.5)

$$R' = \alpha R = (\alpha - 1)R + R = (d_k + 1)R \tag{20}$$

where α is a constant; $\alpha = (1 + d_k)$.

Since the stochastic characteristics of the observation data have mean Hx_k and its covariance R under the condition of a constant x_k, the likelihood of each particle of predictor is calculated by applying the new covariance matrix,

$$\bar{q}_k^{(i)} = \frac{1}{\sqrt{(2\pi\alpha)^m |R|}} \exp\left\{ -\frac{1}{2\alpha} J_k \right\}$$
$$J_k = (y_k - Hx_{k|k-1}^{(i)})^T R^{-1} (y_k - Hx_{k|k-1}^{(i)}) \tag{21}$$

Using Eqs. (20) and (21), we conducted the identification for different forgetting factors. We obtained a good result when the forgetting factor is close to 1.

The time histories of the stiffness and damping coefficient are shown in Fig.5 when the forgetting factor is 0.9. Comparing with the ordinary MCF, we can see the better tracking ability for the stiffness and damping coefficient. Both of the stiffness and damping coefficient are well converged to the true values.

(3) Using Adaptive Observation Noise and Adaptive Process Noise

In previous two sections, the identification is performed by two different techniques. The result using an adaptive observation noise is better than those of the ordinary MCF and adaptive process noise.

In this case, two forgetting factors are applied to verify the effectiveness the developed adaptive MCF. In the case of using two forgetting factors which used in previous two cases, the number of resampling may be decreased due to samples of small likelihood [8]. Thus, the identification is conducted by two forgetting factors equal to 0.5. The identified time histories of the stiffness and damping coefficient are shown in Fig.6. As shown in Fig.6, the identification of stiffness follows the abrupt change and converges to the true value quickly.

5. Conclusion

The adaptive Monte Carlo filter (MCF) was developed to identify parameters of the system with non-stationary dynamic characteristics using the adaptive process noise and adaptive observation noise. The validity and effectiveness of the developed adaptive MCF was verified by using three cases defined by two different forgetting factors.

As the results of three cases, the identifications of stiffness and damping coefficient obtained using the adaptive MCF converged rapidly and effectively trace the abrupt change. And, in the three cases of adaptive MCF, the identified values of unknown parameters obtained from using case 3 were better converged than other cases.

The proposed algorithm can be used to identify the characteristics damaged by external excitation. With comparing the results from MCF and three cases of adaptive MCF, the identified stiffness values obtained from the both techniques were well converged. For the identified damping coefficient, it was not converged to its true value at all in MCF, whereas it was converged its true value but somewhat slow in case 2 of developed adaptive MCF. Thus we can conclude that the adaptive MCF is more efficient than MCF for identifying the system with time-varying stochastic characteristics.

In general, the changes of dynamic responses of a damaged structure may be certainly seen at the time that system parameters of the structure undergo their sudden or abrupt change. Thus, it needs to develop an algorithm that the forgetting factor activates when the abrupt changes of system parameters of the structure are occurred, with time progresses.

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(Received September 17, 2004)