(29) APPLICATION OF THE ADAPTIVE H_∞ FILTER TO STRUCTURAL IDENTIFICATION

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The adaptive H_∞ filter was established by adding a forgetting factor to the H_∞ filter in order to identify structural systems with time-varying dynamic characteristics. The Akaike-Bayes Information Criterion (ABIC) was used to determine the optimal forgetting factor. The behavior of the adaptive H_∞ filter in identifying time-varying structural systems was studied in detail by checking digital simulation results obtained using both the adaptive H_∞ and Kalman filters. These results show that the adaptive H_∞ filter efficiently tracks variation in the structural parameters and is more robust than the adaptive Kalman filter for identifying structural systems with time-varying dynamic characteristics.

Keywords: Identification, H_∞ filter, adaptive, structural systems

1. INTRODUCTION

Over the past several years, the H_∞ control has received much attention and has been used successfully in aerospace and mechanical engineering as a robust control approach. The H_∞ filtering problem, based on the H_∞ criterion, also has been solved [1), 2)]. The H_∞ filtering problem is a state estimation problem of minimizing the maximum energy in the estimation error over all the disturbance trajectories. The state estimation based on this criterion is valid when a significant uncertainty exists in the disturbance statistics. The H_∞ filter has been used to identify linear civil engineering structural systems [3)]. It has been shown to be very efficient for identifying the parameters of linear structural systems.

By adding the function of memory fading for past observation data, we have developed an adaptive H_∞ filter to identify structural systems with non-stationary dynamic characteristics. Identification algorithms are proposed for time-varying structural systems for which the velocity and displacement of each floor are available for identification. The Akaike-Bayes Information Criterion (ABIC) is used to determine the optimal forgetting factor. The identification algorithms that use the adaptive H_∞ and Kalman filters are applied to a 5 degree of freedom (DOF) linear system with non-stationary dynamic characteristics and to a 5 DOF nonlinear structural system. Digital simulation results show that the adaptive H_∞ filter efficiently traces the time-varying properties of structural systems. The behavior of the adaptive H_∞ filter is better than that of the adaptive Kalman filter for identifying a structural system with time-varying dynamic characteristics.

2. BACKGROUND OF THE H_∞ FILTER

Consider a system described by

$$x_{t+1} = A_t x_t + B_t w_t \tag{1}$$

$$y_t = C_t x_t + D_t v_t \tag{2}$$

$$u_t = L_t x_t \tag{3}$$

where x_t is the system state vector, y_t the measurement, and u_t the vector to be estimated. The respective exogenous signals w_t and v_t are the process and measurement noises, A_t the system transfer matrix, B_t, D_t and L_t the parameter matrices. Moreover, we assume that $R_t := D_t D_t^T > 0$ holds for any t.

The finite-horizon H_∞ filtering problem [1)] is to find estimates of u_t and x_t based on the measurement set $\{y_0, \cdots, y_t\}$ such that

$$\sup_{w,v,x_0} \frac{\sum_{k=0}^{N} \left\| u_t - \hat{u}_t \right\|^2}{\sum_{t=0}^{N} \left(\|w_t\|^2 + \|v_t\|^2 \right) + (x_0 - \bar{x}_0)^T \Pi^{-1} (x_0 - \bar{x}_0)} < \gamma^2 \tag{4}$$

where $\hat{u}_t$ is the estimate of u_t, and $\bar{x}_0$ the a priori estimate of the initial state, x_0. Π is the positive definite weighting matrix that represents the uncertainty of the initial state. γ is a positive constant that represents the magnitude of the penalty. The central H_∞ filter which satisfies the above H_∞ bound is given by [4)]

$$\hat{x}_t = \bar{x}_t + K_t (y_t - C_t \bar{x}_t) \tag{5}$$

$$\bar{x}_{t+1} = A_t \hat{x}_t, \quad \hat{x}_0 = \bar{x}_0 \tag{6}$$

$$\hat{u}_t = L_t \hat{x}_t \tag{7}$$

$$K_t = \bar{P}_t C_t^T R_t^{-1} \tag{8}$$

$$\bar{P}_t = \left(P_t^{-1} + C_t^T R_t^{-1} C_t \right)^{-1} \tag{9}$$

in which $\hat{x}_t$ is the estimate of the system state vector x_t; $\hat{u}_t$ the estimate to be obtained; and K_t the gain of the adaptive H_∞ filter at time t. $\bar{x}_{t+1}$ is the predicted value of the system state vector at time $t+1$. The covariance matrix P_t satisfies the Riccati difference equation

$$P_{t+1} = A_t P_t \left\{ I + \left(C_t^T R_t^{-1} C_t - \gamma^{-2} L_t^T L_t \right) P_t \right\}^{-1} A_t^T + B_t B_t^T, \quad P_0 = \Pi \quad (10)$$

and

$$V_t := \gamma^2 I - L_t P_t \left(I + C_t^T R_t^{-1} C_t P_t \right)^{-1} L_t^T > 0 \quad (11)$$

in which $\bullet^T$ is the transpose of a vector or matrix. I is an identical matrix.

If γ in Eq. (10) tends to the infinite, the covariance matrix P_t becomes

$$P_{t+1} = A_t \left\{ P_t^{-1} + C_t^T R_t^{-1} C_t \right\}^{-1} A_t^T + B_t B_t^T \quad (12)$$

Equation (12) is exactly the Riccati difference equation of the Kalman filter. Therefore, the H_∞ filter is a modified version of the Kalman filter.

3. THE ADAPTIVE H_∞ FILTER

One defect of the H_∞ filter is that the post-estimator of the state variable at the present time is a conditional estimator which puts equal weight on all past observation data. The H_∞ filter therefore can not track non-stationary variation of the state variable. The rate of modification of the pre-estimator of the state variable vector, $\bar{x}_t$, depends on the relative magnitude between the covariance matrices of the state variable and observation noise. The adaptability of the post-estimator to the non-stationary change of the state variable vector therefore is evaluated by placing the relative weight between them. This is done by replacing R_t and P_t with $a_t R_t$ and $b_t P_t$, in which a_t and b_t are arbitrary constants;

$$R_t \to a_t R_t, \quad P_t \to b_t P_t \quad (13)$$

By defining a new scalar parameter λ_t

$$\lambda_t = \frac{a_t}{b_t} \quad (14)$$

we can introduce the forgetting factor, λ_t, into Eq. (9) as

$$\bar{P}_t = \left(\lambda_t P_t^{-1} + C_t^T R_t^{-1} C_t \right)^{-1} \quad (15)$$

Substituting $\bar{x}_t = A_{t-1} \hat{x}_{t-1}$ into Eq. (5), we get

$$\hat{x}_t = \left(I - K_t C_t \right) A_{t-1} \hat{x}_{t-1} + K_t y_t \quad (16)$$

in which K_t is the H_∞ gain given by Eq. (8). The scalar parameter λ_t is called the forgetting factor because this value controls the fading away ratio of the effect of pre-information on the post-estimator of the state variable vector.

Expanding Eq. (16) back to the initial condition, the equation obtained is

$$\begin{aligned} \hat{x}_t &= \left(I - K_t C_t \right) A_{t-1} \hat{x}_{t-1} + K_t y_t \\ &= \left(I - K_t C_t \right) A_{t-1} \cdots \left(I - K_1 C_1 \right) A_0 \hat{x}_0 + \\ &\quad \left(I - K_t C_t \right) A_{t-1} \cdots \left(I - K_2 C_2 \right) A_1 K_1 y_1 + \\ &\quad \cdots\cdots + \left(I - K_t C_t \right) A_{t-1} K_{t-1} y_{t-1} + K_t y_t \end{aligned} \quad (17)$$

The term $I - K_i C_i$ in this equation is written using Eqs. (8) and (17) as

$$\begin{aligned} I - K_i C_i &= \bar{P}_i \left[\bar{P}_i^{-1} - \bar{P}_i^{-1} \left(\bar{P}_i C_i^T R_i^{-1} \right) C_i \right] \\ &= \bar{P}_i \left(\bar{P}_i^{-1} - C_i^T R_i^{-1} C_i \right) = \lambda_i \bar{P}_i P_i^{-1} \end{aligned} \quad (18)$$

Substituting Eq. (18), which is effective at each time step, into Eq. (17), gives

$$\begin{aligned} \hat{x}_t = \delta_{t;0} \bar{P}_t P_t^{-1} A_{t-1} \cdots \bar{P}_1 P_1^{-1} A_0 \hat{x}_0 + \delta_{t;1} \bar{P}_t P_t^{-1} A_{t-1} \\ \cdots \bar{P}_2 P_2^{-1} A_1 K_1 y_1 + \cdots\cdots \\ + \delta_{t;t-1} \bar{P}_t P_t^{-1} A_{t-1} K_{t-1} y_{t-1} + K_t y_t \end{aligned} \quad (19)$$

The scalar coefficient δ in front of each term in this equation is a weight multiplied to each observation vector that is given by

$$\delta_{t;i} = \prod_{j=i+1}^{t} \lambda_j, \quad \delta_{t;i} = \lambda_t \delta_{t-1;i}, \quad \delta_{t;t} = 1.0 \quad (20)$$

Therefore, if a positive but $\lambda_j < 1.0$ value is assigned, the effect of past observation data on the estimate of state variable vector can be reduced.

4. IDENTIFICATION ALGORITHM

4.1 Simulation of the structural system and observation data

Identification algorithms were developed to demonstrate the efficiency of the proposed adaptive H_∞ filter for identifying structural systems with time-varying characteristics. For a nonlinear structural system of n DOF, the equation of motion is

$$m \ddot{z}_t + c_t \dot{z}_t + f = -m \ddot{g}_t \quad (21)$$

in which m and c_t respectively are the mass and damping matrices, z the relative displacement vector to the ground, $\ddot{g}_t$ the ground motion acceleration, and f the nonlinear restoring force vector expressed by the Versatile model [5]. In this case, the component of vector f is expressed by

$$\dot{f}_i = k_i u_i - \alpha_i |\dot{u}_i| |f_i|^{n_i - 1} z_i - \beta_i \dot{u}_i |f_i|^{n_i} \quad (22)$$

in which u_i is the relative displacement between the i-1 th and i th mass point, k_i the stiffness, and α_i, β_i and n_i nonlinear parameters.

The seismic responses of the structural systems were simulated as observation data for identification. The El Centro NS (1940) earthquake record with a scaled peak value of 25.0 gal was the input excitation. The sampling interval of the structural responses to be used for identification is 0.01 second. As observation noise, we added pink noise with a frequency band from 0 to 25 Hz. The level of observation noise is defined by

$$\nu = \frac{\sigma_{noise}}{\sigma_{resp.}} \times 100\% \quad (23)$$

in which σ_{noise} and $\sigma_{resp.}$ respectively are the standard deviations of adding pink noise and the structural responses.

4.2 Algorithm for structural system identification

For a linear structural system with non-stationary dynamic characteristics, the parameters to be identified are non-stationary damping and stiffness. The mass matrix is assumed to be given. Instead of identifying damping and stiffness directly, we identified the natural frequency and damping constant of each floor of an n DOF structural system defined by

$$h_i(t)=\frac{c_i(t)}{2\sqrt{m_ik_i(t)}},\quad \omega_i(t)=\sqrt{\frac{k_i(t)}{m_i}},\quad i=1,\cdots,n \tag{24}$$

The state vector to be identified is defined by

$$x_t=\{\cdots z_i\ \dot{z}_i\ h_i\ \omega_i\ \cdots\}^T,\quad i=1,\cdots,n \tag{25}$$

in which z_i and $\dot{z}_i$ are the relative displacement and the velocity of mass point i with respect to the ground. The state transfer equation, derived from Eqs. (21) and (22), is expressed as the first order of the nonlinear differential equation of x_t;

$$\dot{x}_t=g(x_t)+B_t\omega_t \tag{26}$$

To apply the adaptive H_∞ filter to the system transfer equation defined by Eq. (26), the equation must be linearized and discretized using a proper linearization and discretization scheme such as[6].

$$x_t=A_{t-1}x_{t-1}+d_{t-1}+B_t\omega_t \tag{27}$$

The system transfer matrix in this equation is given by

$$A_{t-1}\approx I+F_{t-1}dt,\quad F_{t-1}=\left.\frac{\partial g_i}{\partial x_j}\right|_{x_{t-1}=\hat{x}_{t-1}} \tag{28}$$

in which dt is the integration time interval, and d_{t-1} a constant term developed by linearlization as

$$d_{t-1}=\left(e^{F_{t-1}dt}-I\right)F_{t-1}^{-1}\left\{g(\hat{x}_{t-1})-F_{t-1}\hat{x}_{t-1}\right\} \tag{29}$$

The pre-estimator of the state variable vector is

$$\bar{x}_t=A_{t-1}\hat{x}_{t-1}+d_{t-1} \tag{30}$$

When structural responses to the velocity and displacement of all the floors are available for identifying an n DOF structural system, the measurement equation is

$$y_t=C_tx_t+D_tv_t \tag{31}$$

in which y_t is the $2n$ observation vector defined by

$$y_t=\{\cdots\ z_i\ \ \dot{z}_i\ \ \cdots\}^T,\ i=1,\cdots,n \tag{32}$$

and C_t the $2n\times 4n$ measurement matrix given by

$$C_t=\begin{bmatrix}C_{1:t}\\C_{2:t}\\\vdots\\C_{n:t}\end{bmatrix}=\begin{bmatrix}C' & 0 & \cdots & 0\\0 & C' & \cdots & 0\\\vdots & \vdots & \ddots & \vdots\\0 & 0 & \cdots & C'\end{bmatrix} \tag{33}$$

in which

$$C'=\begin{bmatrix}1 & 0 & 0 & 0\\0 & 1 & 0 & 0\end{bmatrix} \tag{34}$$

5. ABIC: CRITERION FOR DEFINING THE FORGETTING FACTOR

The forgetting factor is determined by using the Akaike-Bayes Information Criterion (ABIC)[7]. The ABIC value is an index used to judge the adaptability of models to the estimated probability distribution function of the observed data. This value is calculated using

$$ABIC=-2(MLL)+2s \tag{35}$$

in which s is the number of hyper parameters. The MLL value is obtained by taking the logarithm of the probability distribution function of the observed data, which is the maximum likelihood function of the forgetting factor.

The mean value and variance of the system state vector is assumed to be

$$E(x_t)=\bar{x}_t \tag{36}$$

$$E\left[(x_t-\bar{x}_t)(x_t-\bar{x}_t)^T\right]=P_t \tag{37}$$

The probability distribution function of the state vector at time t then is given as follows if the stochastic characteristic of the state variable is defined by multi-degree normal distribution;

$$p(x_t)=\frac{1}{\sqrt{(2\pi)^n|P_t|}}exp\left\{-\frac{1}{2}(x_t-\bar{x}_t)^TP_t^{-1}(x_t-\bar{x}_t)\right\} \tag{38}$$

If we have the linear measurement equation as defined by Eq. (31), for the measurement set $\{y_0,\cdots,y_t\}$, the mean value of y_t is given by

$$E[y_t]=\bar{y}_t=C_t\bar{x}_t \tag{39}$$

The covariance matrix is given by

$$\begin{aligned}&E\left[(y_t-\bar{y}_t)(y_t-\bar{y}_t)^T\right]\\&=E\left[\{C_t(x_t-\bar{x}_t)+D_tv_t\}\{C_t(x_t-\bar{x}_t)+D_tv_t\}^T\right]\\&=C_tP_tC_t^T+R_t\end{aligned} \tag{40}$$

Assume that y_t is an independent random variable whose stochastic characteristic is expressed by a multi-dimensional normal distribution with the mean value given by Eq. (39) and the variance given by Eq. (40). The probability distribution of the observed data then is

$$p(y_t)=\frac{1}{\sqrt{(2\pi)^m\left|C_tP_tC_t^T+R_t\right|}}\exp\left\{-\frac{1}{2}(y_t-\bar{y}_t)^T\left(C_tP_tC_t^T+R_t\right)^{-1}(y_t-\bar{y}_t)\right\} \tag{41}$$

After introducing λ_t into the H_∞ filter, R_t and P_t in Eqs. (38) and (40) respectively should be replaced by a_tR_t and b_tP_t. The covariance matrix for measurement y_t is

$$\begin{aligned}&E\left[(y_t-\bar{y}_t)(y_t-\bar{y}_t)^T\right]\\&=E\left[\{C_t(x_t-\bar{x}_t)+D_tv_t\}\{C_t(x_t-\bar{x}_t)+D_tv_t\}^T\right]\\&=a_t\left(\lambda_t^{-1}C_tP_tC_t^T+R_t\right)\end{aligned} \tag{42}$$

and the distribution function

$$p(y_t)=\frac{1}{\sqrt{(2\pi a)^m\left|\lambda_t^{-1}C_tP_tC_t^T+R_t\right|}}exp\left\{-\frac{1}{2a_t}(y_t-\bar{y}_t)^T\left(\lambda_t^{-1}C_tP_tC_t^T+R_t\right)^{-1}(y_t-\bar{y}_t)\right\} \tag{43}$$

Then the ABIC value at time t is expressed as a function of the forgetting factor λ_t

$$\begin{aligned}ABIC(\lambda_t)=m\{\ln(2\pi)+\ln(a_t)+1\}-\ln\left|\lambda_tP_t^{-1}\right|\\+\ln|R_t|+\ln\left|\bar{P}_t^{-1}\right|+2s\end{aligned} \tag{44}$$

The value of the hyper parameter, a_t, is obtained by minimizing the logarithm for Eq. (44) with respect to a as

$$a_t = \frac{1}{m}\left(y_t - \bar{y}_t\right)^T\left(\lambda_t^{-1}C_tP_tC_t^T + R_t^{-1}\right)^{-1}\left(y_t - \bar{y}_t\right) \quad (45)$$

6. STRUCTURAL SYSTEM IDENTIFICATION

The identification algorithms developed were applied to a 5 DOF linear structural system with non-stationary damping constants or frequencies and to a 5 DOF nonlinear structural system. Identification results obtained with the adaptive H_∞ filter were compared to those obtained with the adaptive Kalman filter in order to show the performance of the adaptive H_∞ filter in the identification of structural systems with non-stationary dynamic characteristics.

6.1 Identification of a 5 DOF non-stationary linear structural system with velocity and displacement responses available

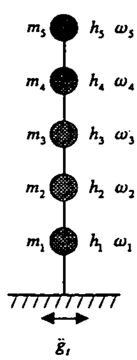

Fig. 1 5 DOF system model

Table 1. Parameters of the 5 DOF model

	damping constant h_i	frequency ω_i (Hz)
case 1	2% (at 0 second) 1% (at 10 seconds)	13.97 (constant)
case 2	2% (constant)	13.97 (at 0 second) 6.985 (at 10 seconds)
case 3	2% (at 0 second) 1% (at 10 seconds)	13.97 (at 0 second) 6.985 (at 10 seconds)

Assume that all the floor responses for velocity and displacement in the 5 DOF linear system are available for identification. Fig. 1 shows the 5 DOF model used to generate the observation time history (α and β in Eq. [22] are set as zero). The mass of each floor of the model is m_i=0.12553 kg (i = 1, ⋯, 5). El Centro NS with scaled peak acceleration 25 gal is used as input motion of simulation. Pink noise with the standard deviation set at 5% of the standard deviation of the structural response is used as the measurement noise. We treated the non-stationary dynamics characteristics of 5 DOF linear structural systems of the three cases listed in Table 1. Note that the damping constant and frequency are assumed to change linearly when non-stationary characteristics are considered.

The initial values of the system state vector, $\bar{x}_0$, are assumed to be given by $\{\cdots\ 0.0\ \ 0.0\ \ 0.03\ \ 3.0\ \cdots\}$. Pink noise with a standard deviation set at 5% of the standard deviation of the structural response is used as the measurement noise. The initial value of covariance, P_0, is defined as

$$P_0 = \left[\cdots\ \ qx_{0;i}^2\ \ \cdots\right],\ (i = 1,\cdots,5) \quad (46)$$

in which $x_{0;i}$ is the i th component of the initial value of $\bar{x}_0$, and q a positive scalar constant (q=1.0 in the simulation). In the digital simulation, the forgetting factor is set as a constant value between 0.9 and 1.0. To check the efficiency of identification, the mean square errors of the identified parameters also are calculated by the equation

$$rms = \frac{1}{G}\sum_{k=1}^{G}\sqrt{\frac{1}{H}\sum_{i=1}^{H}\left(\frac{\theta_{ex}^k - \theta_{id}^k}{\theta_{ex}^k}\right)^2} \quad (47)$$

in which θ_{ex} is the exact value of the parameter; θ_{id} the identified parameter; H the number of time steps used for identification; and G the number of identified parameters.

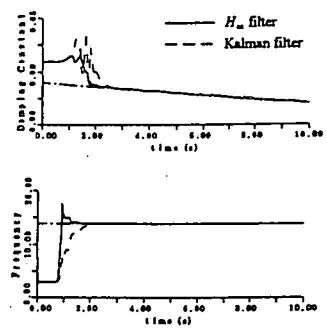

Fig. 2 Identified para. of the 5 DOF linear system with non-stationary characteristics (case 1)

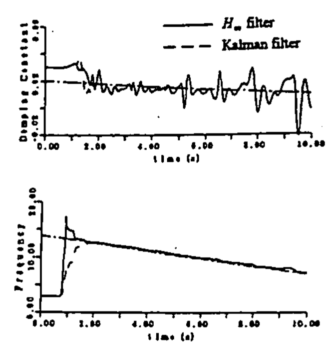

Fig. 3 Identified para. of the 5 DOF linear system with non-stationary characteristics (case 3)

Fig. 2 shows the identification results for the 1st floor obtained by the algorithms that use the adaptive H_∞ and Kalman filters for case 1 (R=1.0 and λ=0.95). The identified parameters effectively trace non-stationary damping. The parameters obtained using the H_∞ filter converge faster than those obtained using the Kalman filter because the H_∞ gain is more sensitive than the Kalman gain. Fig. 3 shows identification results for the 1st floor obtained by the algorithms using the adaptive H_∞ and Kalman filters for case 3 (R=1.0 and λ=0.95). The identified parameters also track the non-stationary characteristics well, but there is large fluctuation for the damping parameter. Again, the algorithm using the adaptive H_∞ filter works better than the adaptive Kalman filter.

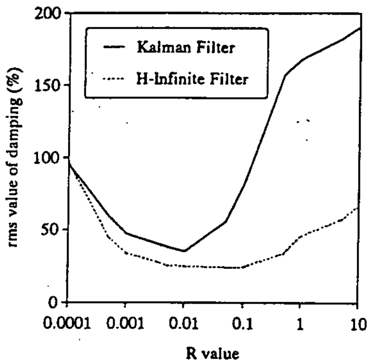

Fig. 4 rms of the identified para. of the 5 DOF linear system with non-stationary characteristics(case 1)

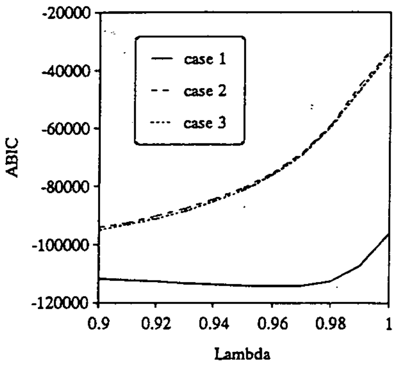

Fig. 5 ABIC value of the identified para. of the 5 DOF linear system with non-stationary characteristics

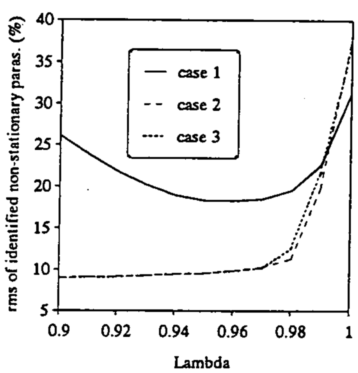

Fig. 6 rms of the identified para. of the 5 DOF linear system with non-stationary characteristics

Fig. 4 shows the rms values of the damping constants identified using the adaptive H_∞ and Kalman filters for case 1 (R=1.0 and λ=0.95). The parameters identified using the adaptive H_∞ filter have smaller rms values as compared to the identified results obtained using the adaptive Kalman filter. The adaptive H_∞ filter is less sensitive to the initial values of the state vector and the covariance matrix than is the adaptive Kalman filter. The adaptive H_∞ filter is more efficient and robust than the adaptive Kalman filter for identifying a structural system with non-stationary characteristics.

In the digital simulation, constant forgetting factors between 0.9 and 1.0 are used throughout the observation period to reduce the effect of past observation data on the identified results. Fig. 5 shows the relation between the ABIC value and constant forgetting factor for the three cases. For cases 2 and 3, the optimal forgetting factor is found at λ=0.90, whereas the optimal forgetting factor for case 1 is about 0.96. Fig. 6 shows the rms values of the identified non-stationary parameters for the three cases (rms values of the damping constants for case 1, rms values of the frequencies for cases 2 and 3) when the forgetting factor changes from 0.9 to 1.0. Use of the optimal forgetting factor gives the minimal rms values of the identified parameters with non-stationary characteristics.

6.2 Identification of a 5 DOF nonlinear structural system with available velocity and displacement responses for each floor

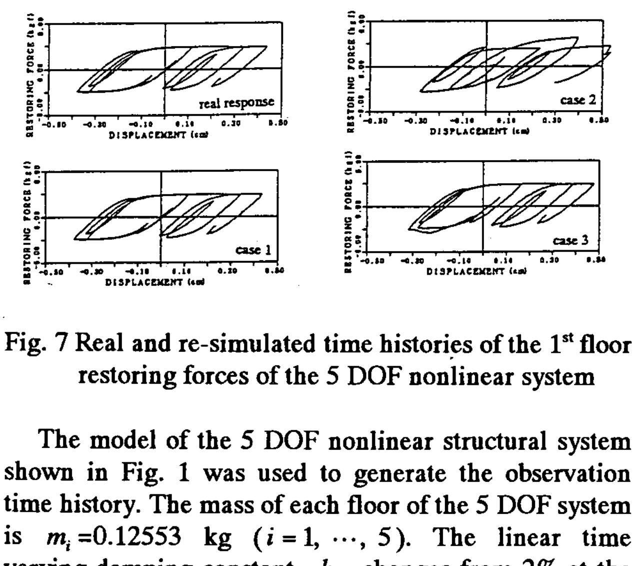

Fig. 7 Real and re-simulated time histories of the 1st floor restoring forces of the 5 DOF nonlinear system

The model of the 5 DOF nonlinear structural system shown in Fig. 1 was used to generate the observation time history. The mass of each floor of the 5 DOF system is m_i=0.12553 kg (i=1, ⋯, 5). The linear time varying damping constant, h_i, changes from 2% at the beginning to 1% at 10 seconds, and frequency is set as a constant, ω_i = 13.98 Hz. The parameters from Eq. (22) used to determine the restoring force are α_i = 2.0, β_i=1.0, and n_i=2.0. Assume that the all the floor responses of velocity and displacement of the nonlinear system are available for identification. The initial value of the system state vector, $\bar{x}_0$, is assumed to be given by 50% of the real value. Pink noise with the standard deviation set at 5% of the standard deviation of the structural response is used as the measurement noise. Assume that the mass of each floor of the system is known for identification. The parameters of the nonlinear system are identified for three different values of n_i in Eq. (22) and of λ, listed in Table 2. The re-simulated responses of acceleration, velocity, displacement and the restoring force obtained using the identified parameters are compared to the real responses of the nonlinear system in order to check the efficiency of identification.

Table2. Parameters for identification

	$n_i\ (i=1,\cdots,5)$	λ
case 1	2.0	0.95
case 2	2.0	1.0
case 3	1.0	0.95

Fig. 7 show the real and re-simulated (cases 1, 2, and 3) responses of 1st floor the restoring force. In case 1, the parameter n_i is set at the exact value. The identification algorithm using the adaptive H_∞ works well to track nonlinear variation of the structural parameters. The re-simulated responses using the identified parameters match the real responses very well. In case 2, the filter has lost its adaptive capacity because the forgetting factor is set at 1.0. Because the identified parameters can not track the nonlinear property, the re-simulated structural response does not match the real responses well, in particular the re-simulated restoring force.

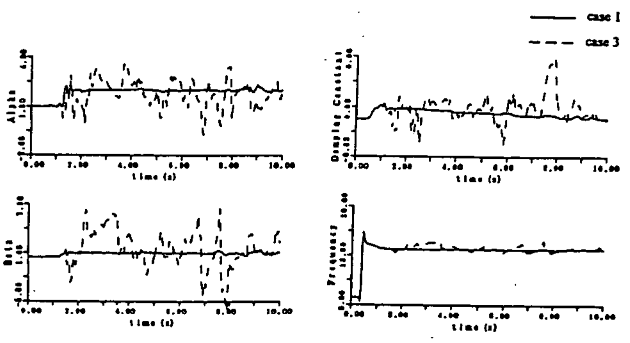

Fig. 8 Identified para. of the 5 DOF nonlinear system

In practical application, parameter n_i is an unknown. Therefore, the value of n_i is set at 1.0 in case 3 to check the efficiency of the identification algorithm when parameter n_i can be not set correctly. As shown in Fig. 7, the re-simulated responses in case 3 also match the real responses well. Fig. 8 shows the time history of the 1st floor identified parameters h_1, ω_1, α_1, and β_1 for cases 1 and 3. In case 1, because parameter n_i is set correctly, all the identified parameters tend to converge to the exact values. In case 3, in comparison, there is marked fluctuation of the identified parameters. Value n_i of case 3 is not set properly, as a result all the identified parameters are adjusted during the process of identification in order to track the nonlinear property of the system. This is the reason for the marked fluctuation.

From the above discussion, the proposed algorithm for identification of structural system using the adaptive H_∞ filter clearly is very efficient for identifying nonlinear structural systems.

7. CONCLUSIONS

The adaptive H_∞ filter was developed to identify structural systems with time-varying dynamic characteristics by introducing a forgetting factor to the H_∞ filter. Structural identification algorithms were proposed using the adaptive H_∞ filter to identify the parameters of structural systems with time-varying characteristics. The identification results of digital simulations show that the performance of the adaptive H_∞ filter for structural system identification is better than that of the adaptive Kalman filter. The conclusions of this study are

(1) The identified parameters of the structural system obtained using the adaptive H_∞ filter converge rapidly and effectively trace variation in the structural parameters.

(2) When value R is set large, convergence becomes slow, but large vibration is expected when R is set small.

(3) The optimal forgetting factor can be determined by using the minimal ABIC value.

(4) The adaptive H_∞ filter is more efficient and robust than the adaptive Kalman filter for identifying structural systems with non-stationary dynamic characteristics.

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