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Inverse active wind load inputs estimation of the multilayer shearing stress structure

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Abstract. This research investigates the adaptive input estimation method applied to the multilayer shearing stress structure. This method is to estimate the values of wind load inputs by analyzing the active reaction of the system. The Kalman filter without the input term and the adaptive weighted recursive least square estimator are two main portions of this method. The innovation vector can be produced by the Kalman filter, and be applied to the adaptive weighted recursive least square estimator to estimate the wind load input over time. This combined method can effectively estimate the wind loads to the structure system to enhance the reliability of the system active performance analysis. The forms of the simulated inputs (loads) in this paper include the periodic sinusoidal wave, the decaying exponent, the random combination of the sinusoidal wave and the decaying exponent, etc. The active reaction computed plus the simulation error is regard as the simulated measurement and is applied to the input estimation algorithm to implement the numerical simulation of the inverse input estimation process. The availability and the precision of the input estimation method proposed in this research can be verified by comparing the actual value and the one obtained by numerical simulation.

Keywords: adaptive input estimation method; shearing stress structure; wind load; Kalman filter.

1. Introduction

In the course of the anti-vibration design, the fatigue analysis, and the reliability assessment of the structure system, the most important procedure is to obtain the values of the active loads to the system. However, in the practical engineering problem, there are always difficulties in installing the load transducers used to measure the active loads to the structure system. Besides, the impact caused by the loads is sometimes overwhelming and transient so that the measurements will not be easy to obtain. In the design of high buildings, the loads caused by earthquakes and winds are both significant and need to be considered. Especially the strong wind causes severe vibration load to the building structure and makes the residents uncomfortable. This is the reason that the control in dealing with the influence due to the wind load on the buildings is worth researching. In the design of optimal control, the turbulence needs to be assumed as zero or the Gaussian white noise to formulate the Riccati equation, which can be solved to obtain the feedback gain matrix for the control effort. Because of the lack of

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consideration for the load inputs, which causes the loss of control effectiveness, this research explores the method to inversely estimate the actual load inputs of the structure system.

The input estimation is a type of active analysis of the structure system and is widely adopted to cope with the system with inputs that can not be measured directly. The input estimation of the structure system is the basis of the invention of load transducer. Generally speaking, the load estimation is based on that the active reaction of the structure system and its characteristics are known under an actual operating condition. The method does not need to directly use the load transducer to measure the active loads, but the result shows that the structure system has actually become a load sensor (Stevens 1987). There are various researches with regard to the input estimation of the structure system in recent years. For example, Bartlett and Flannelly (1979) and Giansante, *et al*. (1982) adopted the pseudo-inverse technique to estimate the vibration force on the hub structure of helicopters, by which the fatigue strength and the reliability of the helicopter structure can be assessed. Hillary and Ewins (1984) utilized the least square technique to estimate the sinusoidal forces acting on the both sides of the cantilever and used the experiment procedure to examine the estimation result. Furthermore, they applied the method to the impact load estimation of the airplane turbine blades. Okubo, *et al*. (1985) applied the least square method and the inverse technique to the input estimation of various structure systems. In order to cope with the numerical problem of the inverse convolution technique, Inoue, *et al.* (1995) used the least square method, which is based on the wiener filtering theory, the mean square error, and the singular value decomposition (SVD), to improve the estimation precision and to obtain the optimal estimates. Wang and Kreitinger (1994) used the weighted total acceleration method to detect the vibration force acting on the concentrated-massed nonlinear beam. Recently, Huang (2001) adopted the conjugate method (CGM) to estimate the force of the one-dimensional mass-spring-damper structure with the time-varying system parameters. The above researches used the batch form to process the measurement data. This method is time-consuming and is not a real-time procedure of the unknown input estimation.

The input estimation method adopted in this paper is combining the Kalman filter without input term and the adaptive recursive least square estimator to represent a real-time on-line estimation method. Tuan, *et al*. (1997) and Tuan and Hou (1998) adopted this method to inversely solve the 1-D and 2-D heat conduction problems. Liu, *et al*. (2000), Ma, *et al*. (2003), Ma and Ho. (2004), and Deng and Heh (2006) as well used this method to estimate the input force acting on the structure system. The input estimation method is using the recursive form to process the data. As opposed to the batch process, using the recursive form is real-time and has higher effectiveness. There is no need to store all the data to implement the process, and the quantity of memory used can be reduced when dealing with more complex systems.

In the present work, the input forces estimation method (Wang 2005) is applied in the nonlinear heat conduction problems. We first used the adaptive input estimation method to determine the unknown excitation loads. This research adopts this method to estimate the input wind loads of a five-layered shearing stress structure. The forms of the inputs include the periodic sinusoidal wave, the decaying exponent, the random combination of the sinusoidal wave and the decaying exponent, etc. The availability and precision of this method can be verified by using the numerical simulation presented in this paper.

2. Mathematical model

This paper is for the input estimation research with respect to the shearing stress structure. The structure system model is shown as in Fig. 1, which is the floor-slab structure that will not have the rotation phenomenon on the horizontal cross-section. Because the deformation caused by the horizontal wind load acting on the building structure has many similarities to that caused by only the shearing stress acting on the cantilever, there are several assumptions which make the deformation of the building structure have the similar characteristics: (1) The Mass of the structure is concentrated on the floor-slab layers. (2) The rigidity of the beams on the floor-slabs are assumed infinite as opposed to that of the pillars. (3) The deformation of the structure has no relation to the axial loads on the pillars.

This model can be constructed by connecting each spring and damper to the lumped mass to form a structure system with 5 degrees of freedom. By applying the free body diagram approach and the Newton theorem, the movement equation of the structure system (Chopra 1995) can be shown in the following equation:

$$M\ddot{Y}(t) + C\dot{Y}(t) + KY(t) = F(t) \tag{1}$$

M is the $n \times n$ mass matrix. C is the $n \times n$ damping coefficient matrix. K is the $n \times n$ stiffness matrix. $\ddot{Y}(t)$, $\dot{Y}(t)$, and $Y(t)$ are the $n \times 1$ acceleration, speed, and displacement vectors, respectively. $F(t)$ is the $n \times 1$ wind load vector.

The input estimation algorithm is a calculation method using the state space. Therefore, the state equation and the measurement equation have to be constructed before applying this method. In order to satisfy this situation, the equality, $X = [Y(t)\ \dot{Y}(t)]^T$, is used to transfer the movement equation to the state space form. The continuous-time state equation and measurement equation of the structure system can be presented as follows:

$$\dot{X}(t) = AX(t) + BF(t) \tag{2}$$

$$Z(t) = HX(t) \tag{3}$$

where

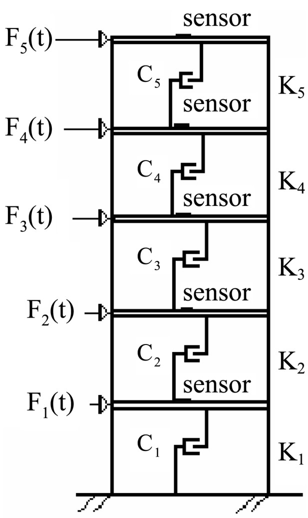

Fig. 1 Structure System Model with 5 degrees of freedom

$$A = \begin{bmatrix} 0_{n \times n} & I_{n \times n} \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$$

$$B = \begin{bmatrix} 0_{n \times n} \\ M^{-1} \end{bmatrix}$$

$$H = [I_{2n \times 2n}]$$

$$X(t) = [X_1(t)\ X_2(t)\ \cdots\ X_{2n-1}(t)\ X_{2n}(t)]^T$$

$$F(t) = [F_1(t)\ F_2(t)\ \cdots\ F_{n-1}(t)\ F_n(t)]^T$$

A and B are the constant matrices composed of the mass, damping coefficient, and stiffness of the structure system in all the dimensions. $X(t)$ is the state vector. $Z(t)$ is the observation vector. H is the measurement matrix.

There always exists the noise turbulence in the practical environment. This is the reason that any of the physical systems contains two portions: One is the deterministic portion, and the other is the random portion, which is distributed around the deterministic portion. Eqs. (2) and (3) do not take the noise turbulence into account. In order to construct the statistic model of the system state characteristics, a noise disturbance term, which can reflect these characteristics of the state, will be needed to add into these two equations. Up to now, one of the random noise disturbances that can be completely resolved is the Gaussian white noise, which has been statistically illustrated in full by using the probability distribution function and the probability density function. Practically, any function corresponding to the functions mentioned above has the same effect. The characteristic function of the random variable is one example. Two most important characteristic values are the mean and the variance, which represent the statistic properties of the random process (Chan, *et al.* (1979). Taking the above consideration into account, the continuous-time state equation is to be sampled using the sampling interval, Δt, to obtain the discrete-time statistic model of the state equation (Bogler 1987) shown below:

$$X(k+1) = \Phi X(t) + \Gamma[F(k) + w(k)] \tag{4}$$

were

$$X(k) = [X_1(k)\ X_2(k)\ \cdots\ X_{2n-1}(k)\ X_{2n}(k)]^T$$

$$\Phi = \exp(A\Delta t)$$

$$\Gamma = \int_{k\Delta t}^{(k+1)\Delta t} \exp\{A[(k+1)\Delta t - \tau]\} B d\tau$$

$$F(k) = [F_1(k)\ F_2(k)\ \cdots\ F_{n-1}(k)\ F_n(k)]^T$$

$$w(k) = [w_1(k)\ w_2(k)\ \cdots\ w_{n-1}(k)\ w_n(k)]^T$$

$X(k)$ is the state vector. Φ is the state transition matrix. Γ is the input matrix. Δt is the sampling interval. $w(k)$ is the processing error vector, which is assumed as the Gaussian white noise. Note that $E\{w(k)w^T(k)\} = Q\delta_{kj}$, and $Q = Q_W \times I_{2n \times 2n}$. Q is the discrete-time processing noise covariance matrix. δ_{kj} is the Kronecker delta function. When describing the active characteristics of the structure system, the additional term, $w(k)$, can be used to present the uncertainty in a numerical manner. The uncertainty could be the random disturbance, the uncertain parameters, or the error due to the over-simplified numerical model.

Generally speaking, the system state can be determined by measuring the output of the system. The measurement usually has a certain relationship with the output of the system. However, there is also the noise issue with the measurement. As a result, the discrete-time statistic model of the measurement vector can be presented below:

$$Z(k) = HX(k) + v(k) \tag{5}$$

where

$$Z(k) = [Z_1(k)\ Z_2(k)\ \cdots\ Z_{2n}(k)]^T$$

$$v(k) = [v_1(k)\ v_2(k)\ \cdots\ v_{2n}(k)]^T$$

$Z(k)$ is the observation vector. $v(k)$ is the measurement noise, which is assumed as the Gaussian white noise. Note that $E\{v(k)v^T(k)\} = R\delta_{kj}$, and $R = R_V \times I_{2n\times 2n}$. R is the discrete-time measurement noise covariance matrix. H is the measurement matrix.

3. Adaptive input estimation method

The adaptive input estimation method can inversely estimate the wind load inputs by applying the active reaction of the structure system. This method is composed of the Kalman filter without the input term and the adaptive weighted recursive least square estimator (RLSE). The Kalman filter can produce the residual innovation sequence, which contains the bias or systematic error caused by the unknown time-varying inputs, and the variance or random error caused by the measurement error. The further use of the least square theory can detect the system bias due to the unknown time-varying inputs. Therefore, the estimator utilizes the innovation sequence to estimate the loads over time by adopting the adaptive weighted recursive least square method. The Kalman filter without input term is shown as follows:

$$\bar{X}(k/k-1) = \Phi\bar{X}(k-1/k-1) \tag{6}$$

$$P(k/k-1) = \Phi P(k-1/k-1)\Phi^T + \Gamma Q\Gamma^T \tag{7}$$

$$\bar{Z}(k) = Z(k) - H\bar{X}(k/k-1) \tag{8}$$

$$S(k) = HP(k/k-1)H^T + R \tag{9}$$

$$K_a(k) = P(k/k-1)H^T S^{-1}(k) \tag{10}$$

$$\bar{X}(k/k) = \bar{X}(k/k-1) + K_a(k)\bar{Z}(k) \tag{11}$$

$$P(k/k) = [I - K_a(k)H]P(k/k-1) \tag{12}$$

In the above equations, the superscript, "-", represents the estimation value. $\bar{X}(k/k-1)$ is the state estimate. $P(k/k-1)$ is the state estimation error covariance. $\bar{Z}(k)$ is the residual sequence. $S(k)$ is the innovation covariance. $K_a(k)$ is the Kalman gain matrix. $\bar{X}(k/k)$ is the state filtering. $P(k/k)$ is the state filtering error covariance. Before implementing the filtering procedure, the state transition matrix Φ, the measurement matrix H, the processing noise covariance Q, and the measurement noise covariance R need to be determined. When further applying the initial values, X_0 and P_0, the output of the filter can be obtained in real-time as the observation vector is continuously inputted. The output of the filter contains the state estimate, $\bar{X}(k/k-1)$, and its relative estimation error covariance, $P(k/k-1)$. The adaptive weighted recursive least square algorithm of the input estimation method is shown as follows:

$$B_s(k) = H[\Phi M_s(k-1)+I]\Gamma \tag{13}$$

$$M_s(k) = [I-K_a(k)H][\Phi M_s(k-1)+I] \tag{14}$$

$$K_b(k) = \gamma^{-1}P_b(k-1)B_s^T(k)[B_s(k)\gamma^{-1}P_b(k-1)B_s^T(k)+S(k)]^{-1} \tag{15}$$

$$P_b(k) = [I-K_b(k)B_s(k)]\gamma^{-1}P_b(k-1) \tag{16}$$

$$\hat{F}(k) = \hat{F}(k-1)+K_b(k)[\bar{Z}(k)-B_s(k)\hat{F}(k-1)] \tag{17}$$

In the above equation, $\bar{Z}(k)$ is the innovation matrix, and $K_b(k)$ is the correction gain. $B_s(k)$ and $M_s(k)$ are the sensitivity matrices. γ is the weighting factor. $P_b(k)$ is the load estimation error covariance. $\hat{F}(k)$ is the vector of the load estimate. The input estimation method is an on-line inverse estimation algorithm. This method is composed of the Kalman filter without the input term and the adaptive weighted recursive least square estimator (RLSE). The Kalman filter can produce the residual innovation sequence, which contains the bias or systematic error caused by the unknown time-varying inputs, and the variance or random error caused by the measurement error. According to the error covariance matrix $P(k/k)$ in Eq. (12), in the meantime when the Kalman filter produces the state estimates, the error analysis is on going to determine if the error is a symmetric matrix greater or equal to zero, so that the precision of the estimation can be obtained. The measurement noise covariance R gets larger as the Kalman gain $K_a(k)$ gets smaller to decrease the influence of measurement error according to Eq. (9) and Eq. (10). Eq. (7) and Eq. (10) further show that the decrease of modeling error variance Q will reduce the error covariance $p(k/k)$, which will therefore reduce $K_a(k)$. This means that the new measurements produce lower influence of correction on state estimation. The further use of the least square theory can detect the system bias due to the unknown time-varying inputs. The estimated inputs can be converged rapidly to the exact value as the correction gain $K_b(k)$ gets smaller with the increased simulation time. Under the time-varying situation, this paper proposes an adaptive weighting function to prevent $K_b(k)$ from droping to zero and to matain the renewal capability of estimator. Therefore, the estimator utilizes the innovation sequence to estimate the loads over time by adopting the adaptive weighted recursive least square method.

The estimator is to apply the innovation quantity, $\bar{Z}(k)$, produced by the Kalman filter to the adaptive weighted recursive least square algorithm to estimate the load vector, $\hat{F}(k)$. $K_b(k)$, $S(k)$, and $\bar{Z}(k)$ are produced by the Kalman filter without the input term. The weighting factor used in this research is an adaptive weighted function, and the related formulation is in the Tuan and Hou (1998) by Tuan in 1998 with regard to the adaptive robust weighting factor, γ, which is as the following equation:

$$\gamma(k) = \begin{cases} 1 & |\bar{z}(k)| \le \sigma \\ \dfrac{\sigma}{|\bar{z}(k)|} & |\bar{z}(k)| > \sigma \end{cases} \tag{18}$$

By substitute Eq. (18) for the value of γ in Eq. (15) and (16), an adaptive weighted recursive least square estimator can be constructed.

The procedure for the input load estimation is as follows:

Step 1: Establish the system process model, Eq. (4), and also determine the simulated experimental displacement and velocity measurement, $Z(k)$, in Eq. (5), by adding an error term, $v(k)$.

Step 2: Set up the initial condition of the adaptive input estimator.

Step 3: Solve the system process model, Eq. (4), and the measurement model, Eq. (5), to determine the displacement of the measurement sensors.

Step 4: Use known values of $P(k-1/k-1)$, Φ, and Q to calculate $P(k/k-1)$ in Eq. (7).

Step 5: Use known value of $P(k/k-1)$ to calculate $K_a(k)$ in Eq. (10).

Step 6: Use known values of $K_a(k)$ and H to calculate $P(k/k)$ in Eq. (12).

Step 7: Use the recursive least square algorithm with an adaptive weighting factor (i.e., Eq. (13) to Eq. (17)) to estimate the unknown value of the input load, $F(k)$.

Step 8: Repeat the above procedures (Steps 3-7) until the final time step.

4. Results and discussion

This research investigates the applications of the adaptive input estimation method in estimating the wind load inputs of the 5-layered shearing stress structure system. Corresponding with Fig. 1, the properties of the shearing stress structure of the building with 5 floors are as follows. The mass of each floor, m = 345.6 kg. The stiffness, k, against the summation of the horizontal shear stresses on all the pillars in each floor is 34040 N/m. The damping coefficient of each floor, c = 2937 N s/m. The active reaction of the multilayer shearing stress structure system under various wind load inputs has to be determined first. The forms of inputs include the periodic sinusoidal wave, the decaying exponent, the random combination of the sinusoidal wave and the decaying exponent, etc. Furthermore, by applying the active reaction in the input estimation algorithm, the inverse load estimation of the structure system can be simulated numerically. This method is composed of the Kalman filter without the input term and an adaptive weighted recursive least square estimator. The initial conditions and other parameters of the simulation are shown as follows: $p(0/0) = diag[10^4]$. $F(0) = 0$. $p_b(0) = 10^6$. $M(0)$ is set to be a zero matrix. The sampling interval, $\Delta t = 0.001$ secs. The weighting factor, γ, is an adaptive weighted function. In order to verify the reliability of the model proposed in this research, the following algorithm is used to compute the percent RMS difference (PRD) (Genaro and Rade (1998) of the input estimate.

$$Error(\%) = \frac{\sqrt{\sum_{i=1}^{n}[F_{ex}(t_i) - F_{es}(t_i)]^2}}{\sqrt{\sum_{i=1}^{n}[F_{ex}(t_i)]^2}} \times 100\% \tag{19}$$

n is the total number of the time steps. $F_{ex}(t_i)$ and $F_{es}(t_i)$ are the actual value and the estimate at time, t_i, respectively.

Example 1: Periodic sinusoidal wind loads.

The periodic sinusoidal wind load with different amplitude is applied on each layer of the shearing stress structure. These sinusoidal waves are shown as follows:

$F_1(t) = 20 \times \sin((pi/3) \times (t-10)) / 5(N)$
$F_2(t) = 20 \times \sin((pi/3) \times (t-10)) / 4(N)$
$F_3(t) = 20 \times \sin((pi/3) \times (t-10)) / 3(N)$
$F_4(t) = 20 \times \sin((pi/3) \times (t-10)) / 2(N)$
$F_5(t) = 20 \times \sin((pi/3) \times (t-10)) (N)$

The active reaction of the structure system is determined by using the numerical approach when considering the influence due to the processing noise and the measurement noise of the system. The processing noise covariance, $Q = Q \times I_{2n\times 2n}$. Set $Q = 10^{-7}$. The measurement noise covariance, $R = R_w \times I_{2n\times 2n}$. Set $R = \sigma^2 = 10^{-14}$. By applying the active reaction which contains noise to the input estimation algorithm, the estimation result of the periodic load inputs can be obtained. According to Table 1, when the estimation parameters are fixed ($Q = 10^{-7}$, and $\sigma = 10^{-7}$), the transient performance of the estimator will be faster if the smaller value of the weighting factor, γ, is chosen. The tracking

Table 1 The values of error (%) when using different values of the weighting factor. (Set $Q = 10^{-7}$, and $\sigma = 10^{-7}$)

	$\gamma = 0.95$	$\gamma = 0.55$	$\gamma = 0.15$	$\gamma = adaptive$
$F_1(t)$	31.76	13.65	12.58	12.41
$F_2(t)$	32.58	14.50	13.42	13.24
$F_3(t)$	32.74	14.65	13.57	13.39
$F_4(t)$	32.25	14.14	13.06	12.88
$F_5(t)$	31.28	13.14	12.06	11.88

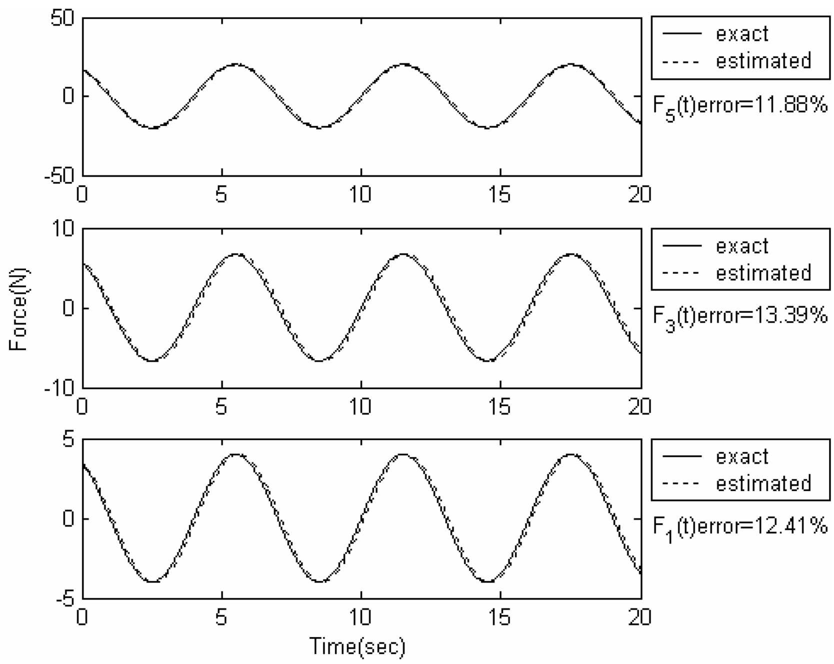

Fig. 2 Estimation result of the layers 1, 3, and 5 under the periodic sinusoidal load inputs. ($Q = 10^{-7}$, and $\sigma = 10^{-7}$)

capability is better, and the error of the estimation result is smaller. On the other hand, choosing a larger value of the weighting factor will obtain a slower transient performance. That is to say, the tracking capability is weaker, and the error of the estimation result is larger. If an adaptive weighting factor is adopted, the performance of the estimator will be much better than using constant values. This research adopted the adaptive weighting factor to implement all the simulation models.

Fig. 2 shows the comparison between the actual values of the inputs on layers 1, 3, and 5 with the estimates. The estimation performance is fine so that the estimates can converge toward the actual values rapidly. The reason is that larger values of the estimation error covariance, $p(0/0)$ and $p_b(0)$, are adopted to enlarge the initial error, and the estimator will neglect partial effects of the initial estimates. According to the result of the estimation, the input estimation method proposed in this research is capable of dealing with the multi-input and multi-output (MIMO) condition of the structure system.

Fig. 3 shows the comparison between the actual values of the inputs with the estimates on layers 1, 3, and 5 over time. By adjusting the estimation parameters, Q and σ, so that $Q=10^{-7}$ and $\sigma=10^{-8}$, and adopting the adaptive weighting factor, γ, to implement the simulation, the estimator can rapidly enhance the tracking capability to maintain higher estimation precision when the measurement noise covariance, R, is smaller. The error is apparently smaller in comparison with the result in Fig. 2.

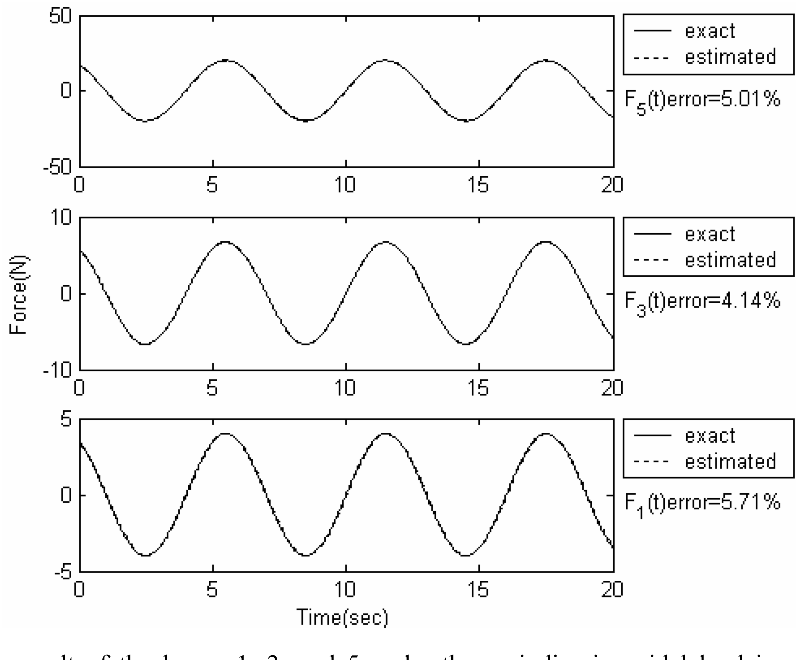

Fig. 3 Estimation result of the layers 1, 3, and 5 under the periodic sinusoidal load inputs. ($Q=10^{-7}$, and $\sigma=10^{-8}$)

Example 2: The combination of the sinusoidal and the decaying exponent wind loads.

The combination of the periodic sinusoidal load with different amplitude and the decaying exponent wind load is applied on each layer of the shearing stress structure. These loads are shown as follows:

$F_1(t) = 20\times\exp(-t/2)\times\sin(0.2\times t)$ (N)
$F_2(t) = 20\times\exp(-t/2)\times\sin(0.2\times t)$ (N)

$F_3(t) = 20 \times \exp(-t/2) \times \sin(0.2 \times t)$ (N)
$F_4(t) = 20 \times \exp(-t/2) \times \sin(0.2 \times t)$ (N)
$F_5(t) = 20 \times \exp(-t/2) \times \sin(0.2 \times t)$ (N)

The active reaction of the structure system is determined by using the numerical approach when considering the influence due to the processing noise and the measurement noise of the system. The processing noise covariance, $Q = Q_w \times I_{2n\times 2n}$. Set $Q = 10^{-2}$. The measurement noise covariance, $R = R_w \times I_{2n\times 2n}$. Set $R = \sigma^2 = 10^{-10}$. By applying the active reaction which contains noise to the input estimation algorithm, the estimation result of the periodic load inputs combined with the decaying exponent load inputs can be obtained as in Fig. 4. Fig. 4 shows the comparison between the actual values of the inputs with the estimates on layers 1, 3, and 5 over time. In the course of verifying the capability of the input estimation method numerically, this research takes the influence due to the system modeling noise and the measurement noise into account, and applies suitable random variables to the mathematical model of the structure system to simulate the practical situation. The availability of the overall estimation performance has been verified.

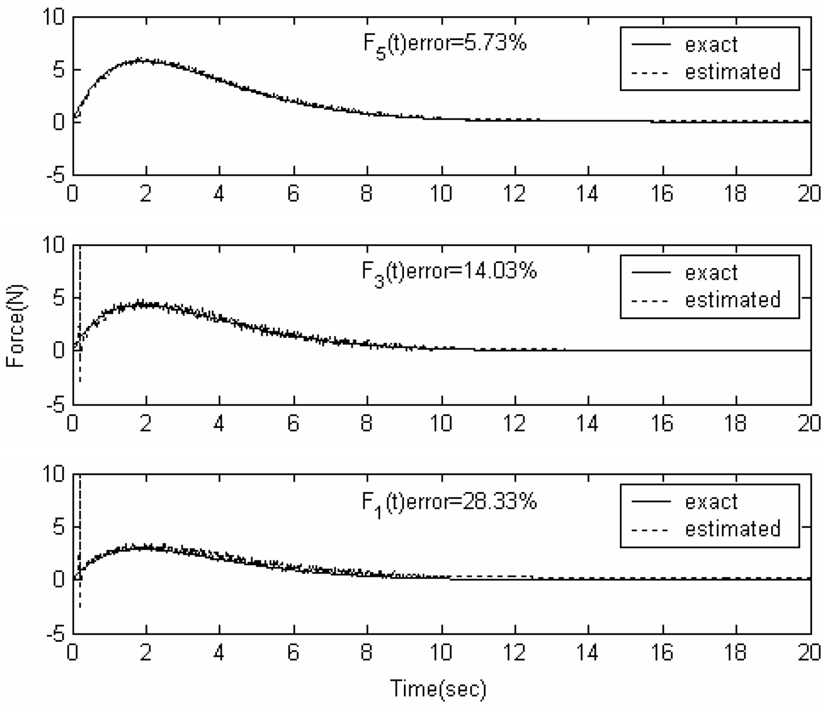

Fig. 4 Estimation result of layers 1, 3, and 5 under the combined load inputs of the sinusoidal and decaying exponent loads. ($Q = 10^{-2}$, and $\sigma = 10^{-5}$)

Fig. 5 shows the comparison between the actual values of the inputs on layers 1, 3, and 5 with the estimates. Note that $Q = 10^{-2}$, and $R = \sigma^2 = 10^{-14}$. When the measurement noise covariance, R, is smaller, the estimator can rapidly enhance the tracking capability to maintain higher estimation performance. The result of F1 simulation is close to the real value. However, with regard to the wind force inputs of other floors, F1 is smaller and the PRD is larger. The error is apparently smaller in comparison with that in Fig. 4.

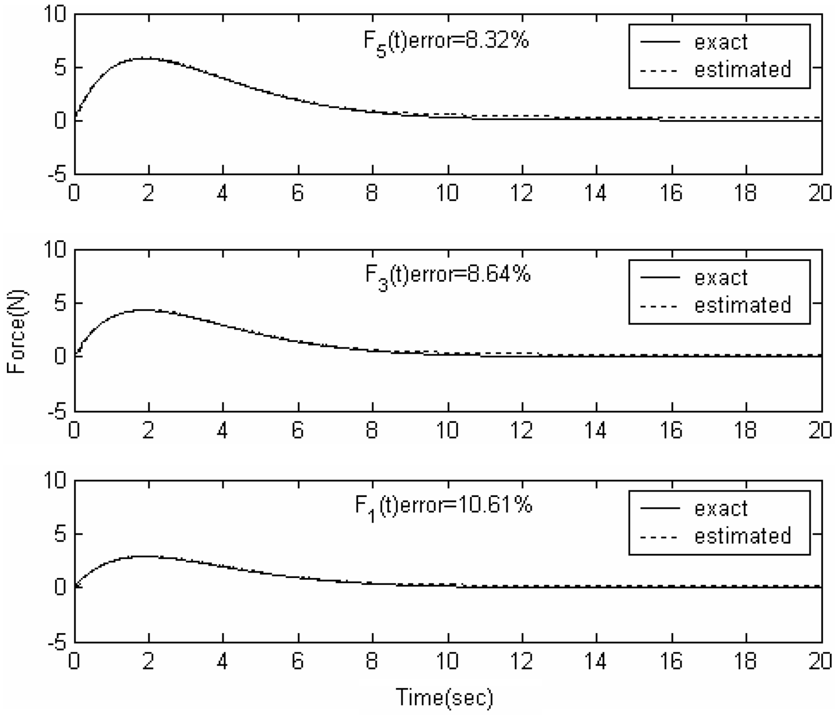

Fig. 5 Estimation result of layers 1, 3, and 5 under the combined load inputs of the sinusoidal and decaying exponent loads. ($Q=10^{-2}$, and $\sigma=10^{-7}$)

Example 3: Decaying exponent wind loads

This simulation is adopting the decaying exponent load with different value of amplitude for each layer. The numerical model of the wind load inputs are shown as follows:

$F_1(t)=400\times\exp(-t)$ (N)
$F_2(t)=450\times\exp(-t)$ (N)
$F_3(t)=500\times\exp(-t)$ (N)
$F_4(t)=550\times\exp(-t)$ (N)
$F_5(t)=600\times\exp(-t)$ (N)

The active reaction of the structure system is determined by using the numerical approach when considering the influence due to the processing noise and the measurement noise of the system. The processing noise covariance, $Q=Q_w\times I_{2n\times 2n}$. Set $Q=10^{-3}$. The measurement noise covariance, $R=R_w\times I_{2n\times 2n}$. Set $R=\sigma^2=10^{-10}$. By applying the active reaction which contains noise to the input estimation algorithm, the estimation result of the decaying exponent load inputs can be determined as in Fig. 6. Fig. 6 shows the estimation result on layers 1, 3, and 5. Under the initial condition, the estimate can converge toward the actual value rapidly, which is similar to the phenomenon in Fig. 5. The errors are larger at the turning point when the load inputs reach the maximum, which causes the tracking capability of the estimator to degrade. The values of the errors are 25.73%, 28.61%, and 26.29%. The overall estimation performance is just fine.

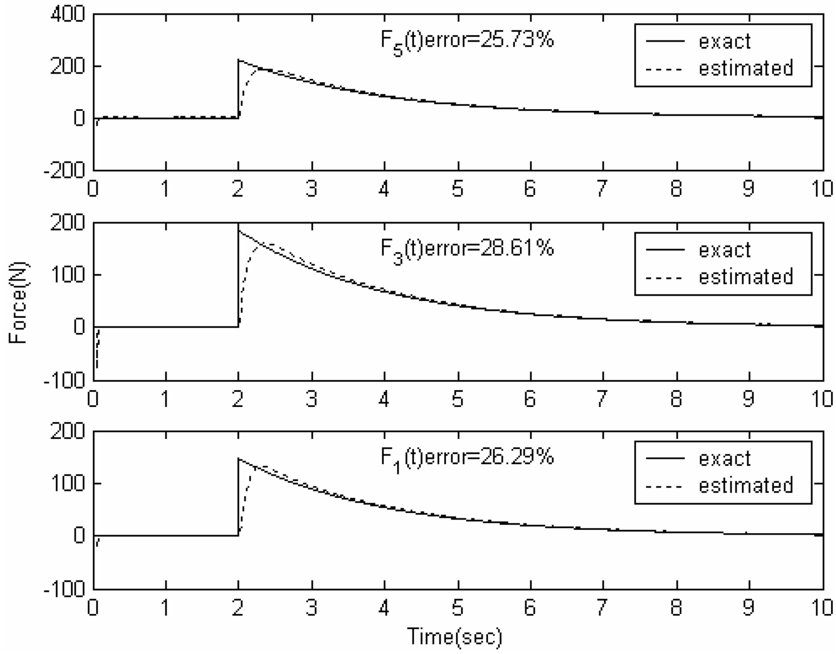

Fig. 6 Estimation result of layers 1, 3, and 5 under the decaying exponent load inputs. ($Q=10^{-3}$, and $\sigma=10^{-5}$)

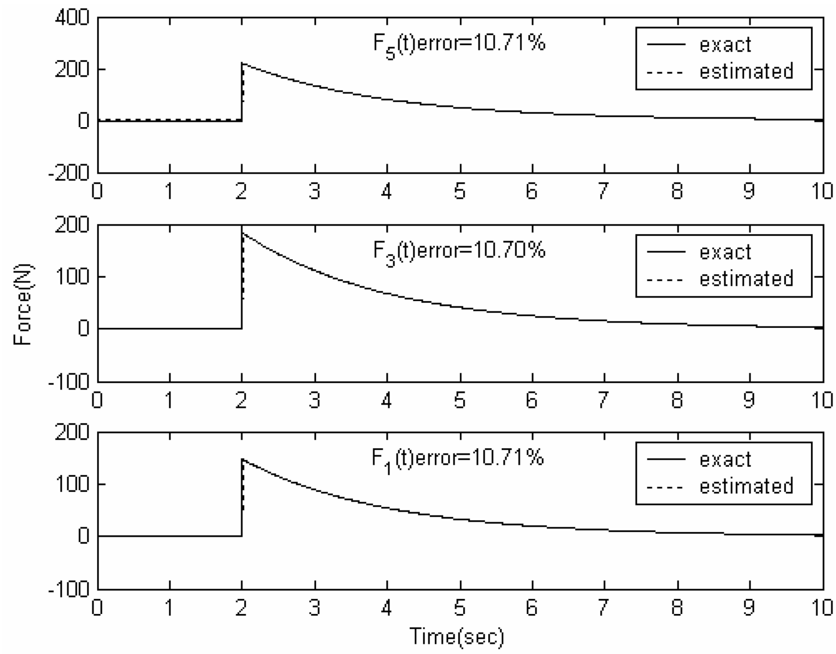

Fig. 7 Estimation result of layers 1, 3, and 5 under the decaying exponent load inputs. ($Q=10^{-3}$, and $\sigma=10^{-7}$)

By adjusting the estimation parameters, Q and σ, so that $Q=10^{-3}$, and $R=\sigma^2=10^{-14}$, the comparison between the actual load inputs and the estimates is shown in Fig. 7. According to the figure, if the processing noise covariance is fixed, a better estimation result will be obtained when the measurements are more precise. The errors are reduced down to 10.71%, 10.70%, and 10.71%. The overall estimation performance is good.

Example 4: Random wind loads.

In the practical processing environment, the loads, such as water, wind, and the earthquake loads, to the structure system are mostly irregular or random. Therefore, to explore the random load estimation is absolutely necessary. The mathematical formula of the random wind load inputs applied to all the layers of the shearing stress structure is shown below:

$$F_i(t) = random\ (N),\quad i = 1 \sim 5$$

The active reaction of the structure system is determined by using the numerical approach when considering the influence due to the processing noise and the measurement noise of the system. The related estimation parameters of the simulation are as follows: All the initial conditions are set to be zero. The sampling interval, $\Delta t = 0.01$sec. The processing noise covariance, $Q = Q_w \times I_{2n\times 2n}$. Set $Q = 10^{-3}$. The measurement noise covariance, $R = R_w \times I_{2n\times 2n}$. Set $R = 10^{-14}$. By applying the active reaction which contains noise to the input estimation algorithm, the estimation result of the random load inputs can be determined as in Fig. 8. The figure shows the comparison between the actual load values and the estimates on layers 2 and 4. The overall estimation performance is just fine. In the course of estimating the random load inputs, the tracking capability of the estimator is getting weak due to the severe variation of the load inputs, and the time delay is caused.

In order to effectively compute the errors of the load estimates, the shifting process of the time delay needs to be implemented. The cross correlation function is a kind of mechanism (Herlufsen

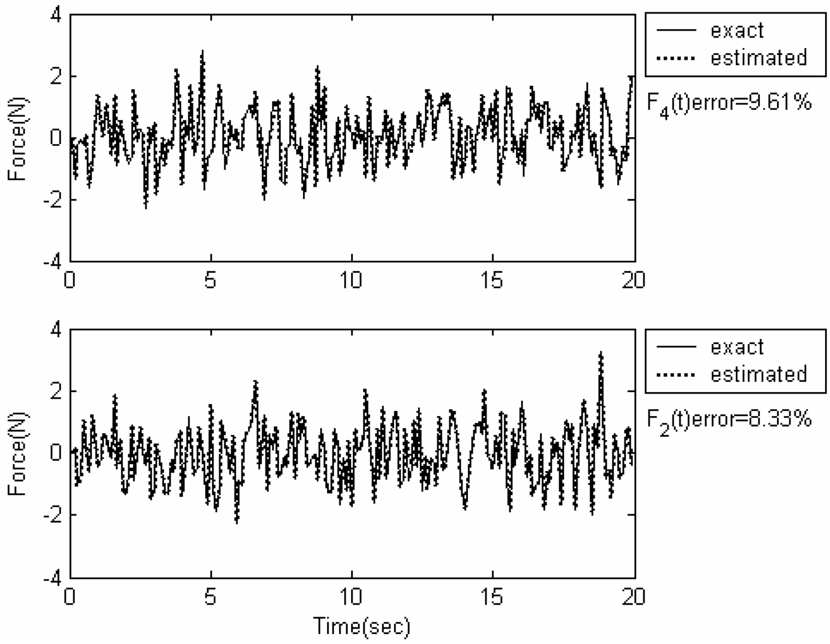

Fig. 8 Estimation results on layers 2 and 4 under the random load inputs. ($Q = 10^{-3}$, and $\sigma = 10^{-7}$)

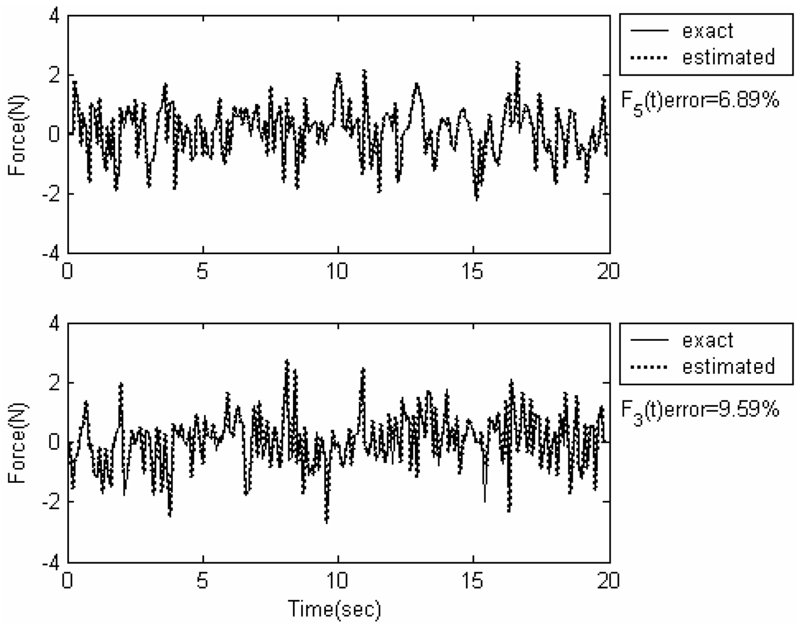

Fig. 9 Estimation results on layers 3 and 5 under the random load inputs. ($Q=10^{-4}$, and $\sigma=10^{-7}$)

1984) that measures the similarity between two signals with the time delay. The cross correlation function between the actual load values and the estimates shows that these two signals have 2 time steps in between. Therefore, a better estimation result can be obtained by implementing the time shifting process for 2 time steps. Fig. 9 shows the comparison between the actual load inputs and the estimates on layers 3 and 5. The estimation performance is just fine. Although the adaptive input estimation used in this paper is relatively less capable of dealing with the estimation of the random load inputs in the 1-D structure system with multiple degrees of freedom, the overall estimation capability of the estimation is sufficient. The estimation capability in dealing with the random load inputs will provide the applications in the practical processing environments.

Generally speaking, in the course of numerically verifying the capability of the input estimation method proposed in this research, the larger noise will certainly cause the larger vibration in the estimation of the load inputs. This situation has been realized by adding random variables in the mathematical model of the structure system to simulate the practical conditions. According to Fig. 2, 4, and 6, if the parameter, R, is larger, the estimation performance will be less effective. On the other hand, if R is smaller, the estimation performance will be better according to Fig. 3, 5, and 7.

5. Conclusions

This paper proposes the Kalman filter without the input term combined with the adaptive weighted recursive least square algorithm to develop the input estimation method, which can estimate the active loads of the structure system over time by applying the active reaction of the system to the algorithm. This method is effective in the use of estimating the transient or time-varying wind load inputs. Since this method adopts the recursive mode, which reduces the computational time and the memory storage as opposed to the batch mode, the on-line real-time estimation process can be implemented. According to the results of the simulation and the computation, the weighting factor, γ, is used in the input estimation method to offer a compromise between the requirement of tracking capability and the sensitivity tolerance of the noise input to maintain higher estimation effectiveness. Therefore, the suitable values of the measurement noise covariance and the adaptive weighting factor, γ, can be chosen to cope with the uncertain restricted conditions, such as the precision of actual measuring equipments, and the simplified or imprecise mathematical model, and to enhance the estimation performance. The future research can be focused on the 2-D or 3-D structure system to extend the applications of this combined method.

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