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Blast Load Input Estimation of the Medium Girder Bridge using Inverse Method

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ABSTRACT

Innovative adaptive weighted input estimation inverse methodology for estimating the unknown time-varying blast loads on the truss structure system is presented. This method is based on the Kalman filter and the recursive least square estimator (RLSE). The filter models the system dynamics in a linear set of state equations. The state equations of the truss structure are constructed using the finite element method. The input blast loads of the truss structure system are inverse estimated from the system responses measured at two distinct nodes. This work presents an efficient weighting factor γ applied in the RLSE, which is capable of providing a reasonable estimation results. The results obtained from the simulations show that the method is effective in estimating input blast loads, so has great stability and precision.

Keywords: Input estimation, Kalman filter, blast loads, medium girder bridge, truss structure system, recursive least square estimator, RLSE, finite element method

NOMENCLATURE

A^e	Cross-sectional area of the element
$A,\ B$	Constant matrices
$B_s(k)$	Sensitivity matrices
C	Damping matrix
E	Elastic modulus
$F_b(k)$	Blast load vector
H	Measurement matrix
k	Time (discretised)
K	Stiffness matrix
K^e	Element stiffness matrix
$K_a(k)$	Kalman gain
$K_b(k)$	Correction gain
l	Length of the element
M	Mass matrix
M^e	Element mass matrix
P	Filter's error covariance matrix
ρ	Mass per unit length of the element
σ	Measurement standard deviation
Δt	Sampling time (interval)
$P_b(k)$	Error covariance matrix
Q	Process noise covariance matrix
Q_w	Scalar of process noise covariance
R	Measurement noise covariance matrix

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R_v	Measurement noise covariance
S	Innovation covariance
t	Time (continuous)
$v(k)$	Measurement noise vector
$w(k)$	Process noise vector
X	State vector
Y	Displacement vector
$\dot{Y}$	Velocity vector
$\ddot{Y}$	Acceleration vector
$Z(k)$	Observation vector
$\gamma(k)$	Weighting factor
Γ	Input matrix
δ	Kronecker delta
Φ	State transition matrix
Superscripts	
^	Estimated
-	Estimation value of the filter
T	Transpose of matrix
Subscripts	
i, j	Indices

1. INTRODUCTION

Rapid movement on the battlefield requires the existence of the road networks or natural high-speed avenues that cross an assortment of wet and dry gaps. The medium girder bridge (MGB) is a lightweight, hand-built, easily transportable bridge that can be erected in various configurations to cover a full range of military and emergency bridging requirements. The MGB could be damaged by the exceeding fluctuations due to the external blast loads. The external blast load determination is a very important task to ensure the readiness of MGB. Therefore, the dynamic blast loads on the structure must be determined using the estimation method or measurement techniques. One of the methods is to estimate the blast loads by applying the measured dynamic responses to the inverse estimation method.

Force input estimation is the process of determining the blast loads by applying the measurements, i.e., the responses of the system. Some techniques have handled the inverse problem during force estimation. The time domain approach models the structure and forces with a set of second-order differential equations by Law[1], *et al*. The forces are modelled as step functions in a small time interval. These equations of motion are then expressed in the *modal* coordinates, and they are solved using convolution in the time domain. The forces are then determined using the *modal* superposition principle. Druz[2], *et al*. formulated a nonlinear inverse problem and tried to find the location and magnitude of the external force. The *modal approach* by Chan[3], *et al*. determines the forces completely in the *modal* coordinates. Measured displacements are converted into *modal* displacements using an assumed shape function. The forces are then determined solving the uncoupled equations of motion in the *modal* coordinates.

Recently, Huang[4] used an algorithm based on the conjugate-gradient method to estimate the unknown external forces in the inverse nonlinear force vibration problem. Tuan[5,6] adopted the input estimation method to inversely solve the 1-D and 2-D heat conduction problems. Ma[7-9] and Deng[10] as well used this method to estimate the force input to the structure system. This method combines the Kalman filter without the input term and the adaptive recursive least square estimator (RLSE) to form a real-time online estimation method.

In the present work, the input estimation method uses the recursive form to process the data. As opposed to the batch process, using the recursive form is real-time and has higher effectiveness. This means that the presented algorithm can reduce both the requirement of storage space and the computation load of the computer. Conceptually, the blast loads acting on a structure can be found by taking the product of the inverse of the dynamic characteristics and the responses of the system. However, inverse processes generally tend to be ill-conditioned, because the estimation results of the load input are very sensitive to the effect induced by the noises.

To treat these ill-conditional problems, the adaptive input estimation method with the finite element scheme is used to determine the unknown excitation blast loads. The method is based on the Kalman filter and the recursive least square algorithm weighted by a fading factor, to determine the excitation blast loads acting on truss structures. The mathematical model of the truss structure is constructed using the finite element method (FEM)[11]. The practicability of the proposed method can be verified using numerical simulations of the blast load estimation of a simple truss bridge. In this study, the MGB is modelled as a truss structural system. The truss structure is subjected to decaying exponent blast loads. The blast loads can be estimated by applying the dynamic responses to the proposed input estimation algorithm. By comparing the results with the actual blast loads, the precision of the present inverse method can be demonstrated.

2. PROBLEM FORMULATION

To illustrate the practicability and precision of the presented approach in estimating the unknown blast load, the numerical simulations of the MGB structure are investigated. As shown in Fig. 1, the MGB is modelled as a truss structural system.

Input estimation is based on the state-space analysis method. In this study, the FEM to construct the state-space model of a truss structural system is used. The FEM of a truss structure is considered to be an n degrees-of-freedom (DOFs) system. Therefore, the differential equations of motion of the system in terms of mass, stiffness, and damping matrices are shown below:

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

where M is the n x n mass matrix; C is the damping coefficient matrix; K is the n x n stiffness matrix; $\ddot{Y}(t)$, $\dot{Y}(t)$, and $Y(t)$ are the n x 1 acceleration, speed, and displacement vectors, respectively. $F_b(t)$ is the n x 1 blast load vector. The matrices, M and K, can be obtained using the FEM. The matrix C was obtained by assembling the matrices M and K as a proportional damping model.

After converting to the state-space model, the state variables of the second-order dynamic system with n DOF are represented by a $2n$ x 1 state vector, i.e.

$$X = \begin{bmatrix} Y(t) & \dot{Y}(t) \end{bmatrix}^T .$$

From Eqn (1), the continuous-time state equation and measurement equation of the structure system can be formulated as follows:

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

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

where

$$A = \begin{bmatrix} 0_{n\times n} & I_{n\times n} \\ -M^{-1}K & -M^{-1}C \end{bmatrix}, \quad B = \begin{bmatrix} 0_{n\times n} \\ M^{-1} \end{bmatrix}, \quad H = \begin{bmatrix} I_{2n\times 2n} \end{bmatrix}$$

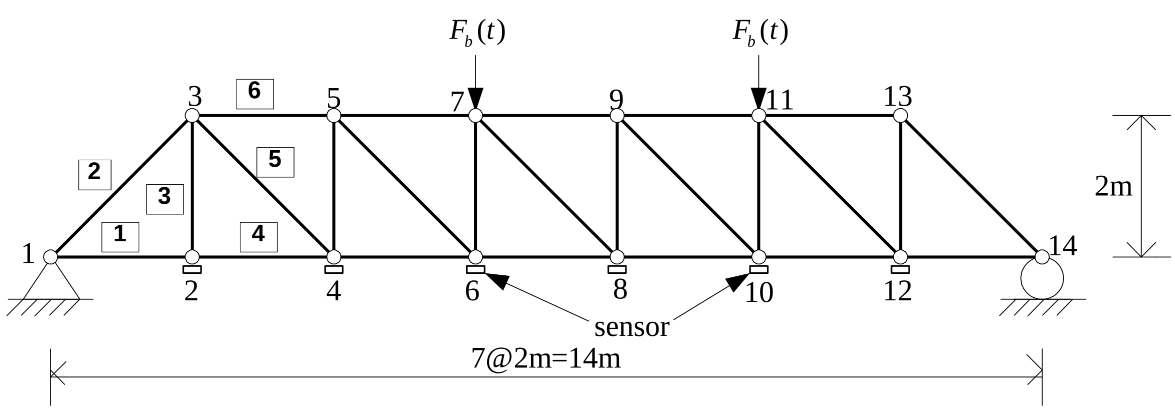

Figure 1. Finite element model of the truss structural system. (25 elements with 14 nodes).

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

where A and B are constant matrices composed of mass, damping, and stiffness of the beam structure system. $X(t)$ is the state vector, $Z(t)$ is the observation vector,and 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. Equations (2) and (3) do not take the noise turbulence into account. To construct the statistic model of the system state characteristics, a noise disturbance term, which can reflect these characteristics of the state, will need to be added 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 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[12].

Taking the above consideration into account, the continuous-time state equation is to be sampled with the sampling interval, Δt, to obtain the discrete-time statistic model of the state equation shown below[13]:

$$X(k+1) = \Phi X(k) + \Gamma \left[F_b(k) \quad w(k)\right] \tag{4}$$

where

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

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

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

$$F_b(k) = \left[F_{b1}(k) \quad F_{b2}(k) \quad \cdots \quad F_{bn-1}(k) \quad F_{bn}(k)\right]^T$$

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

where $X(k)$ 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.

$$E\left\{w(k)w^T(k)\right\} = Q\delta_{kj}, \text{ and } Q = Q_W \cdot I_{2n\times 2n}$$

where Q is the discrete-time processing noise covariance matrix. d_{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 the system state can be determined by measuring the output of the system. The measurement usually has a certain relationship with the system output. However, there is also the noise issue with the measurement. As a result, the discrete-time statistic model of the measurement vector can be:

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

where

$$Z(k) = \left[Z_1(k) \quad Z_2(k) \quad \ldots \quad Z_{2n}(k)\right]^T$$

$$v(k) = \left[v_1(k) \quad v_2(k) \quad \ldots \quad v_{2n}(k)\right]^T$$

$Z(k)$ is the observation vector, $v(k)$ represents the measurement noise vector and is assumed to be the Gaussian white noise with zero mean and the variance $E\left\{v(k)v^T(k)\right\} = R\delta_{kj}$, where $R = R_V \cdot I_{2n\times 2n}$. R is the discrete-time measurement noise covariance matrix, and H is the measurement matrix.

3. ADAPTIVE WEIGHTED RECURSIVE INPUT ESTIMATION METHOD

Adaptive weighted load input estimation is a process of determining the blast loads by applying the measurements of the responses of the system. The presented adaptive weighted load input estimation method consists of two parts: (a) Kalmam filter and (b) estimator. The Kalman filter is used to generate the residual innovation sequence. The residual innovation sequence connotes bias or systematic error from the unknown time-varying input item and variance or random error form the measurement. The estimator then computes the histories of the excitation blast loads by applying the residual innovation sequence to the adaptive weighted recursive least square algorithm. The detailed derivation of this technique can be found in the work by Tuan[14], *et al.* The equations of the Kalman filter are 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 Eqns (6)-(12), $\bar{X}(k/k-1)$ denotes state estimation, $P(k/k-1)$ is the state estimation error covariance, $\bar{Z}(k)$ is the bias innovation caused by measurement noise and input disturbance. $S(k)$ represents the innovation covariance, $\bar{X}(k/k)$ is the state estimate, $P(k/k)$ represents state error covariance. Q and R are the discrete-time process noise covariance matrix and measurement noise covariance matrix respectively.

The parameters of Kalman filter must be obtained at the beginning. The initial values of X_o and P_o are adopted. As the observation vector continues to be applied to the algorithm, the output of the Kalman filter can be obtained in real-time. The estimation value $\bar{X}(k/k-1)$ and the state estimation error covariance $P(k/k-1)$ of the structure system can be presented immediately. The formulation of the adaptive weighted recursive least square algorithm is:

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

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

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

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

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

where $\bar{Z}(k)$ denotes the innovation, $k_b(k)$ is the correction gain, P_b represents the error covariance of the estimated input vector, and $\hat{F}_b(k)$ is the estimated input vector. The weighting factor γ is employed to compromise between the upgrade of tracking capability and the loss of estimation precision. In this study, the adaptive weighting function is presented. The detailed derivation of this function are given by Tuan[15], *et al*.

The adaptive weighting function is shown below:

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

where σ is measurement standard deviation, the measurement noise covariance, $R = R_V \times I_{2n \times 2n}$. Set $R_V = \sigma^2$. In Eqns (13)-(17), the Kalman gain $K_a(k)$ is computed by the estimator, and the innovation covariance $S(k)$ and innovation $\bar{Z}(k)$ are produced from the Kalman filter. By substituting Eqn (18) in Eqns (15)-(16) for the weighting factor γ, the adaptive weighted recursive least square estimator is constructed.

4. RESULTS AND DISCUSSION

To verify the practicability and precision of the presented approach in estimating the unknown blast load, a two-dimensional example is applied to the input estimation method combined with the finite-element scheme. The element mass matrix M^e and the element stiffness matrix K^e of the truss are shown[11] as:

$$M^e = \frac{\rho A^e l}{6}\begin{bmatrix} 2c^2 & 2cs & c^2 & cs \\ & 2s^2 & cs & s^2 \\ & & 2c^2 & 2cs \\ SYM & & & 2s^2 \end{bmatrix}$$

and

$$K^e = \frac{A^e E}{l}\begin{bmatrix} c^2 & cs & -c^2 & cs \\ & s^2 & -cs & s^2 \\ & & c^2 & cs \\ SYM & & & s^2 \end{bmatrix}$$

where $c = \sin\theta$ and $s = \sin\theta$. θ is an arbitrary angle of the truss element oriented with respect to the horizontal axis. $\rho = 7860$ kg/m^3. $A^e = 2.5 \times 10^{-3}$m^2. The elastic modulus of all members, $E = 200$ GPa. The proportional damping coefficient, $C = \alpha M + \beta K$, where $\alpha = 0.002$ and $\beta = 0.00005$.

The initial conditions of the error covariance are given as $p(0/0) = \text{diag}[10^8]$ for the Kilman filter and $p_b(0) = 10^8$ for the adaptive weighted recursive least square estimator. The simulation parameters are set as follows.

Sampling interval, $\Delta t = 0.01$ s. The sensitivity matrix $M(0)$ is null. The weighting factor is an adaptive weighting function.

Example: Decaying exponential blast loads

The blast load produces a rapid release of the energy when the explosive detonates. In the meantime, a tremendous blast load is produced and spreads out along with the vibrational wave. This kind of blast load has the properties of decaying and transient existence. This is the reason that the blast load is often approximated in the form of decaying exponent. This simulation is adopting the decaying exponent blast loads with different values of amplitude on Nodes 7 and 11 of the truss structural system. The numerical model of the blast load inputs are shown as:

$$F_b 7(t) = \begin{cases} 2000000 \times \exp(-3(t-2)) & 2 \le t \le 7 \\ 0 & 0 \le t < 2 \end{cases} \ (N) \quad (19)$$

$$F_b 11(t) = \begin{cases} 1000000 \times \exp(-2(t-2)) & 2 \le t \le 7 \\ 0 & 0 \le t < 2 \end{cases} \ (N) \quad (20)$$

The processing noise covariance, $Q = Q_w \times I_{2nx2n}$. Set $Q_w = 10^3$. The measurement noise covariance, $R = R_v \times I_{2nx2n}$. Set $R_v = \sigma^2 = 10^{-12}$.

By applying the active reaction which contains noise to the input estimation algorithm, the estimates of the decaying exponent blast load inputs, $F_b 7(t)$ and $F_b 11(t)$, are produced and plotted in Figs 2 and 3. The result reveals the good estimation ability. The estimation values converge to actual values rapidly. Since $p(0/0)$ and $p_b(0)$ are initially unknown, the estimator was initialised with large values of $p(0/0)$ and $p_b(0)$, such as 10^8.

The influences produced using different sampling time on estimation results are shown in Fig. 4. The

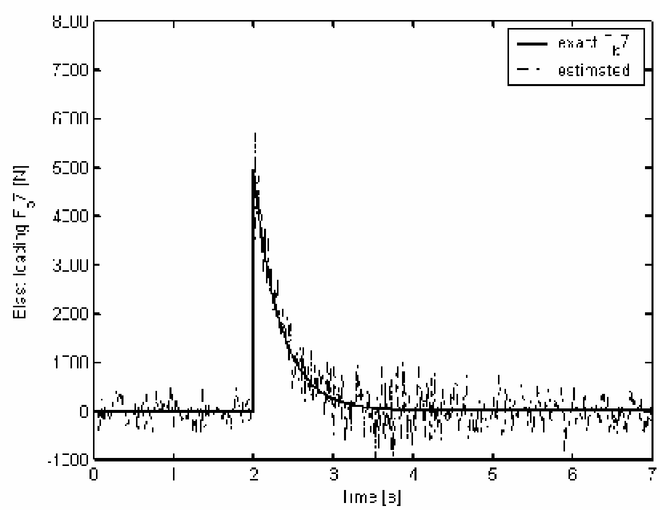

Figure 2. Inverse estimation of the blast load input, $F_b 7(t)$, with $Q_w=10^3$, $R_V=10^{-12}$, $\Delta t=0.01$.

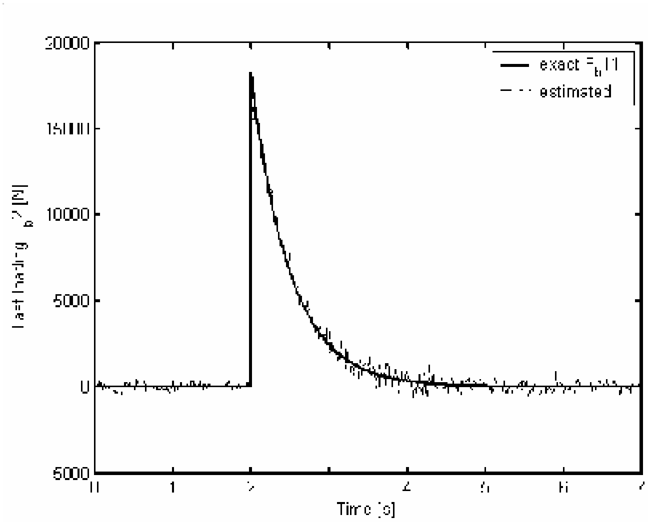

Figure 3. Inverse estimation of the blast load input, $F_b1(t)$, with Q_W=10^3, R_V=10^{-12}, Δt=0.01.

four sets of chosen sampling time, Δt = 0.1 s, 0.01 s, 0.001 s, and 0.0005 s. According to the figure, the estimation model has the best precision when the sampling time Δt is 0.01s. Figures 4(c) and 4(d) show that the severe fluctuation occurred from t = 2.5 s to 5.5 s. The estimation results are slightly better when Δt =0.001 s and 0.0005 s. In other words, the improvement is not significant. Besides, when Δt is < 0.0005 s, the computing time of the simulation will be longer.

The case has been compared using different process noise variances Q_w =10^{-3}, 10^{-1}, 10^1 and 10^3 as in Fig. 5. Figure 5 shows that if the process noise variance Q_w increases, it will influence the estimation resolution. A larger process noise variance will affect the capability of tracking the time-varying load input. Figure 6 shows the estimation results with the process noise variance fixed (Q_w = 10^3), and different measurement error variances (R_v = σ^2 =10^{-12}, 10^{-13}, 10^{-14} and 10^{-15}) from t = 0 s

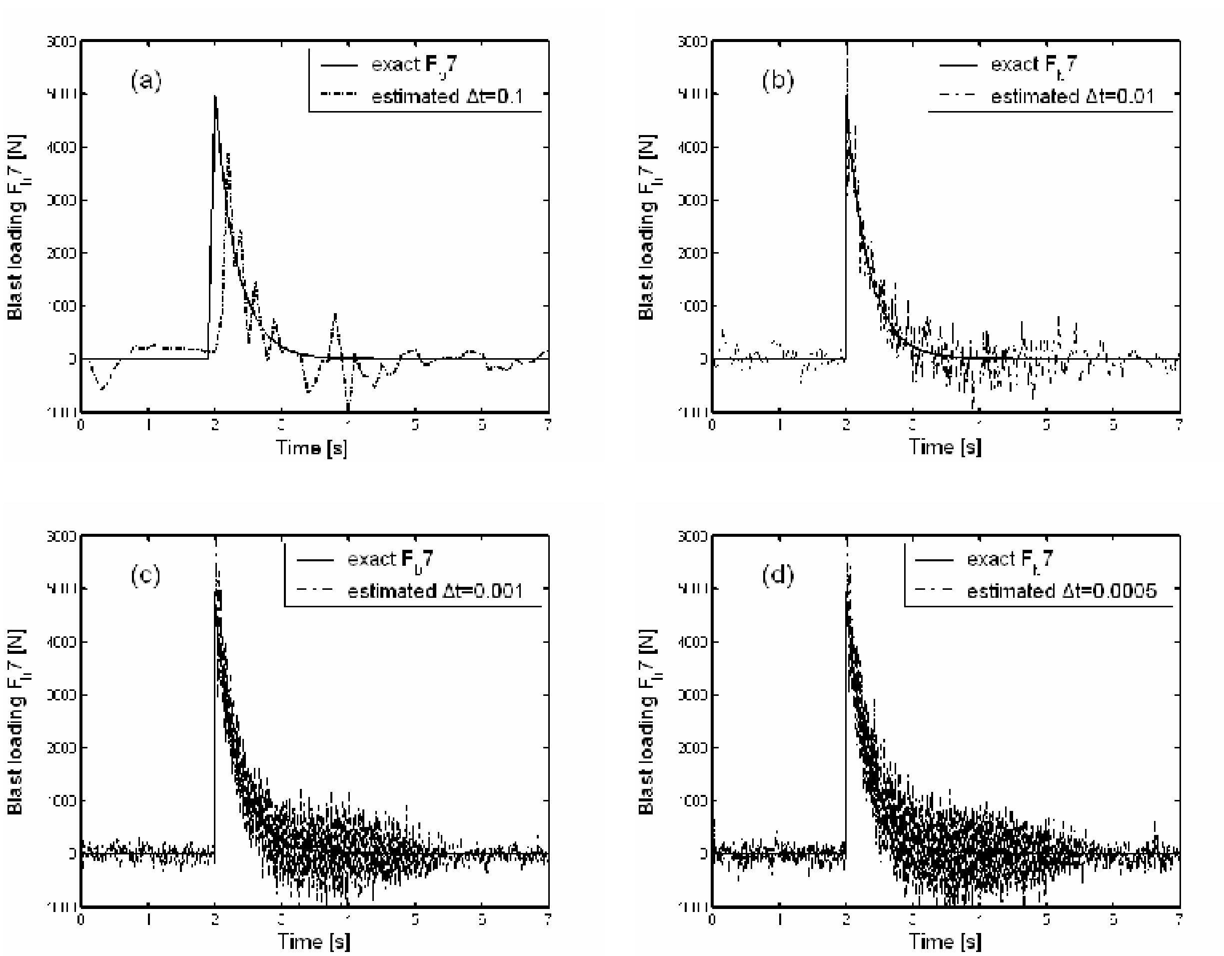

Figure 4. Inverse estimation of the blast load input, $F_b7(t)$, with Q_W=10^2, R_V=10^{-12}, Δt = 0.1, 0.01, 0.001 and 0.0005, respectively.

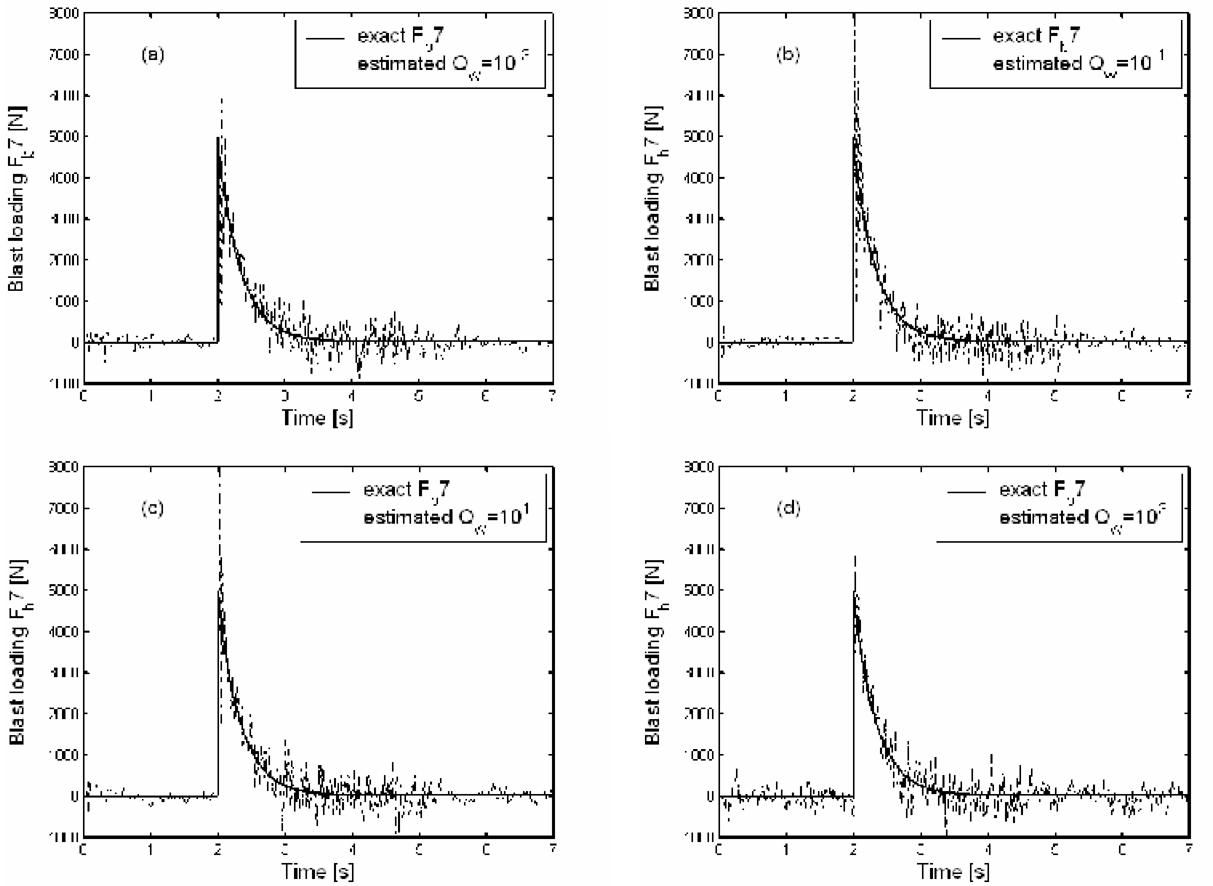

Figure 5. Inverse estimation of the blast load input, $F_b7(t)$, with R_V=10^{-12}, Δt = 0.01, Q_W=10^{-3}, 10^{-1}, 10^{1} and 10^{3} respectively.

to t = 7s. The result shows that when R_v is small, the filter transient performance will be faster with noise filtered out. On the contrary, the fluctuation will become severer when R_v increases. The filter transient performance will be slower with more influence induced by the noise. In other words, when the measurement variance R_v increases, the Kalman gain $[K_a(k)]$ in Eqn (10) will decrease. The reason is that the corrector uses the new measurement available at time step k. The correction in Eqn (11) will proportional increase, and the $K_a(k)$ will decrease, which causes the estimate closer to predicted value than the new measurement.

The estimation results of the proposed method are highly agreed with the actual values. The results

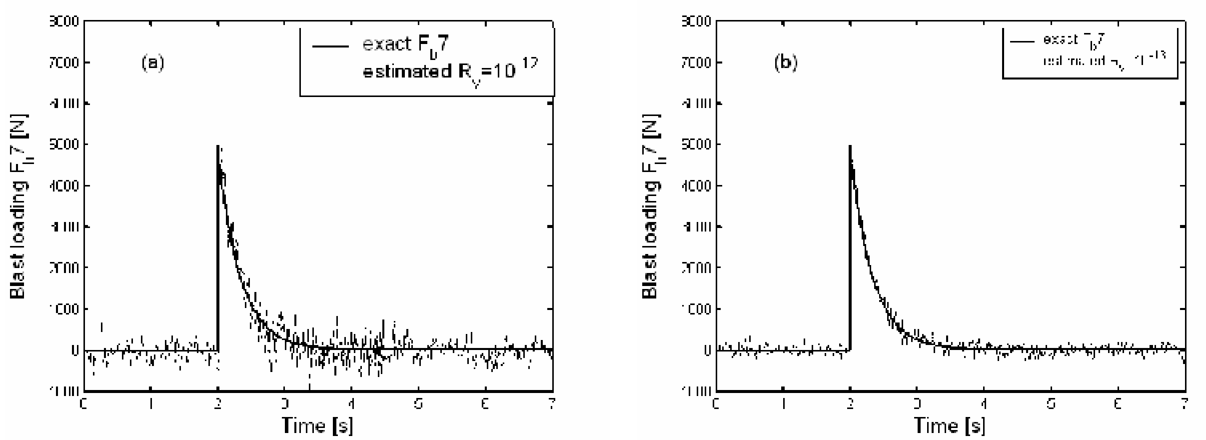

Figure 6. Inverse estimation of the blast load input, $F_b7(t)$, with Q_W=10^{3}, Δt = 0.01, R_V=10^{-12}, 10^{-13}, respectively.

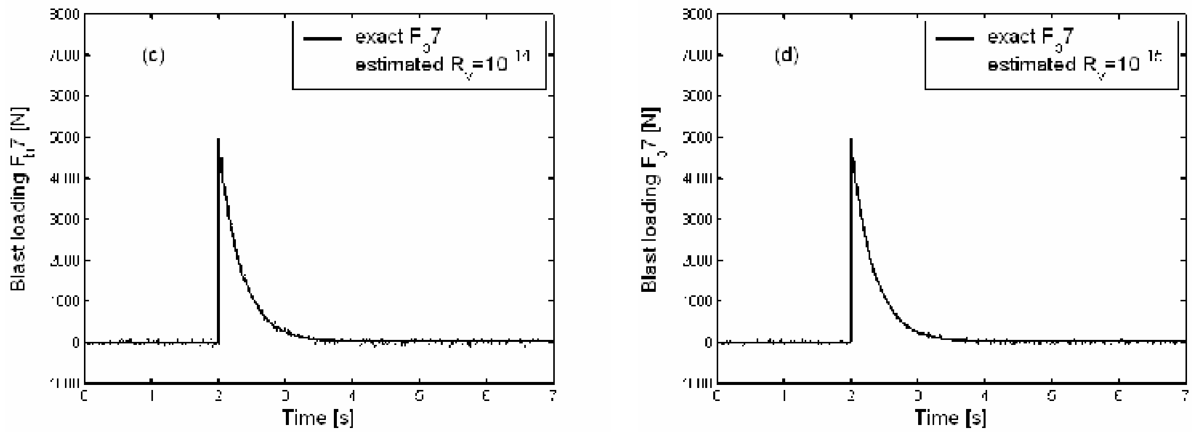

Figure 6. Inverse estimation of the blast load input, $F_b7(t)$, with $Q_w=10^3$, Δt = 0.01, $R_V=10^{-14}$, 10^{-15}, respectively.

show that a larger measurement error can cause estimation lag and estimate precision degradation when estimating the decaying exponent blast load.

Figure 7 shows the comparison between the constant weighting factor and the adaptive weighting function in affecting the estimation results with Q_w = 10^2, R_v = 10^{-12} and Δt = 0.01s. A smaller value of γ, despite its leading to a better tracking ability, involves the fluctuations due to the unwanted system noise. On the other hand, a larger value

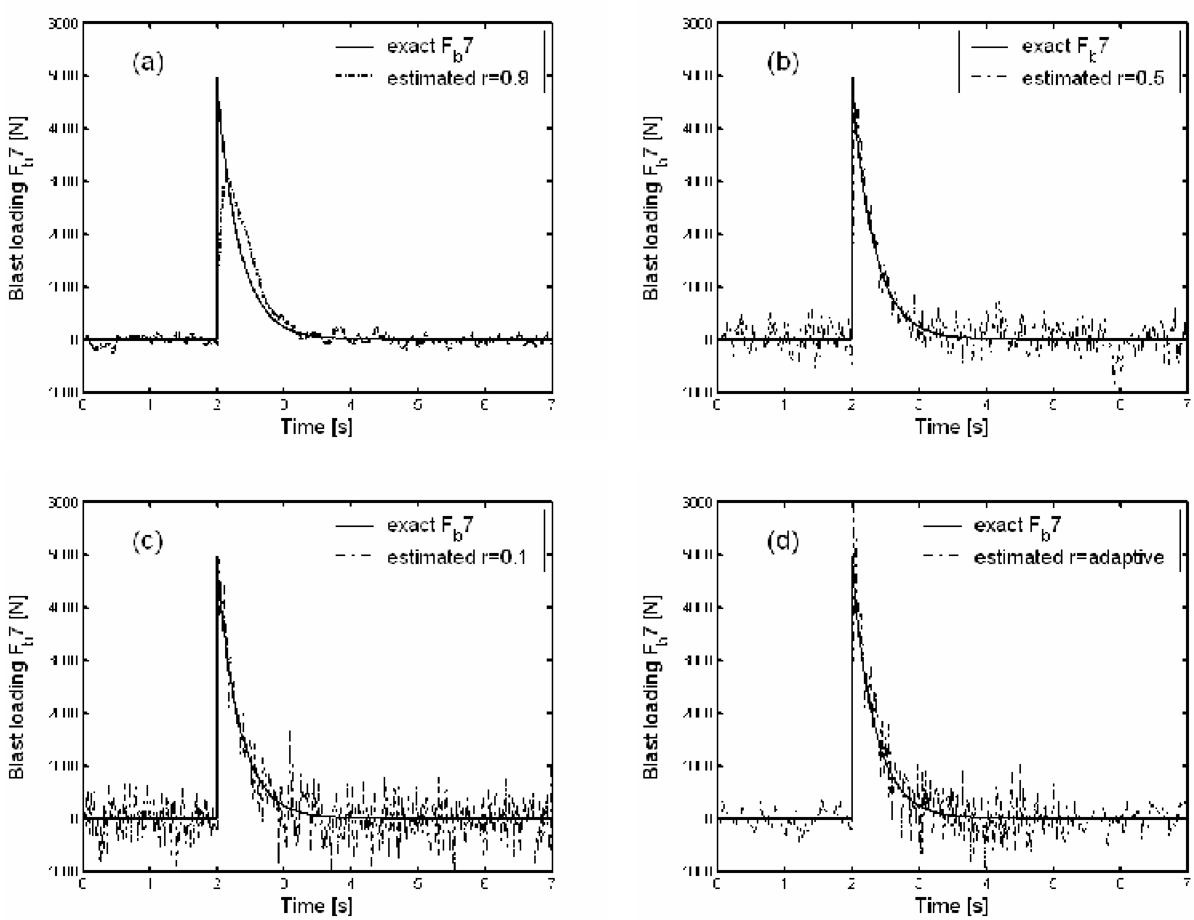

Figure 7. Inverse estimation of the blast load input, $F_b7(t)$, with $Q_w=10^2$, $R_V=10^{-12}$, Dt=0.01, g=0.9, 0.5, 0.1 and adaptive function, respectively.

of γ is less sensitive to disturbances, but has relatively poorer tracking ability. Therefore, the selection of γ is a compromise between the required tracking and acceptable noise sensitivity. Simulation results demonstrate that the adaptive weighted input estimation inverse methodology has good performance in tracking the time-varying unknown blast loads in the truss structural system.

5. CONCLUSIONS & FUTURE STUDY

In this paper, an adaptive weighted input estimation inverse methodology is applied to estimate the unknown time-varying blast loads in a truss structural system. The FEM is adopted to construct the state equation of the truss structure, and the Kalman filter is further combined with the adaptive weighted recursive least square estimator, which recursively estimates the unknown blast loads under a situation that the system involves the measurement and modelling errors. The algorithm is an efficient online recursive inverse method to estimate the blast loads. Under the situation that the sampling interval is shorter, the blast loads can still be precisely estimated using this method. The results also indicate that the presented technique will have higher estimation ability adopting the precise measurement instrument. The simulation results show the adaptive capability and high performance in tracking the unknown blast loads, by adopting the adaptive weighting factor, γ. Future study will address the issues of the force input estimation in the 3-D structure system and the applications in the optimal control scope.

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