# Inverse Dynamic Active Ground Motion Acceleration Inputs Estimation of the Retaining Structure

Ming-Hui Lee, Iau-Teh Wang

*Abstract*—The innovative fuzzy estimator is used to estimate the ground motion acceleration of the retaining structure in this study. The Kalman filter without the input term and the fuzzy weighting 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 fuzzy weighting recursive least square estimator to estimate the acceleration input over time. The excellent performance of this estimator is demonstrated by comparing it with the use of difference weighting function, the distinct levels of the measurement noise covariance and the initial process noise covariance. The availability and the precision of the proposed method proposed in this study can be verified by comparing the actual value and the one obtained by numerical simulation.

*Keywords*—Earthquake, Fuzzy Estimator, Kalman Filter, Recursive Least Square Estimator.

## I. INTRODUCTION

IN the past few years, there were many horrible earthquakes occurred in the seismic zones around the world, e.g., the Southern Sumatra earthquake in Indonesia (2009), the Wenchuan earthquake in China (2008), the Jawa earthquake in Indonesia (2007), the Chi-Chi earthquake in Taiwan (1999), the Kobe earthquake in Japan (1995), and the Northridge earthquake in California (1994). The probability of occurring earthquakes increases on account that Taiwan is located on the seismic belt of the Pacific Ocean. The Taiwan area was destroyed by the serious Chi-Chi (921) earthquake event in the twentieth century. Owing to the strong shaking and widespread surface damage, more than 2500 people lost their lives and more than 100,000 buildings were destroyed in this significant event [1]. Earth-retaining structures constitute an important topic of research in the civil engineering under earthquake conditions. In the course of design, analysis, and reliability assessment of the retaining wall structure system, the most important procedure is to obtain the values of active input to the system. Estimation of the responses of structural systems based on dynamic analysis is essential for the seismic design of civil structures on the seismic belt. According to the dynamic characteristics of building structure, the security of building structure can be evaluated. The reliability of structure security depends on the earthquake resistance design. It will influence the safety of civilian lives and properties directly.

In recent years, the utilization of time histories of earthquake ground motion has grown considerably in the field of earthquake engineering. For example, the ground motion time histories are used in the design and analysis of civil structures. Hence, there is a need for efficient and accurate methods for the simulation of earthquake ground motion throughout a region that utilize ground motions from previous earthquakes and recorded motions from the earthquake that just occurred. The strong motion prediction model, EMPR (Earthquake Motion Prediction model on Rock surface), was developed by Sugito et al. [2]. A simple off-line correction procedure is an adequate application for producing reasonable reproductions of historical earthquakes [3]. Sato et al. developed a method based on the concept of wavelet transformation to simulate earthquake motion that uses phase spectra of earthquake motions [4]. The stochastic method for simulating ground motions is to combine parametric or functional descriptions of the ground motion's amplitude spectrum with a random phase spectrum modified such that the motion is distributed over a duration related to the earthquake magnitude and to the distance from the source [5]. The simulated ground motion by the EMPR is adopted as the Green's function for the inversion of the fault process [6]. The above researches used the off-line form to process the measurement data. The method is not an on-line procedure to estimate the unknown input.

Reliable ground motions are essential for regional hazard and risk assessment and management purposes. However, in the practical engineering problem, there are always difficulties in installing the force transducers used to measure the input forces from the structure system. Besides, the ground motion accelerations caused by the earthquake is sometimes overwhelming and transient so that the measurements will not be easy to obtain. Hence, an on-line, inverse input estimation method is frequently employed to the structural dynamic problems. Ji et al.[7] used the Kalman filter with the recursive

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least square method to estimate the input force of a plate. Liu and Ma [8-10] and Deng [11] as well used this method to estimate the force input to the structure system. Lee et al. [12] utilized the adaptive weighted input estimation method to inversely solve the burst load of the truss structure system. Chen et al. [13,14] investigated the adaptive input estimation method applied to the inverse estimation of load input in the multi-layer shearing stress structure and the identification of moving load in the bridge structure system. This method combines the Kalman Filter without the input term and the adaptive recursive least square estimator to form a real-time on-line estimation method. The input estimation method is using the recursive form to process the measurement data. As opposed to the batch process, using the recursive form is an on-line process and has higher efficiency.

In this study, an efficient estimator to estimate the ground motion acceleration of the retaining structure system is presented. The estimator is weighted by the fuzzy weighting factor proposed based on the fuzzy logic inference system. By comparing the results with the actual Chi-Chi earthquake ground motion data, the precision of the present inverse method can be demonstrated. The rapider target tracking and more effective noise reduction capabilities of this method will be demonstrated through the simulation case study.

## II. PROBLEM FORMULATION

The geometry and coordinates of a soil-wall system are shown in figure 1(a). The semi-infinite, homogeneous and viscoelastic medium of soil is retained by a vertical rigid retaining wall along one of its vertical boundaries, connected to a rigid base. The base of the soil layer is excited by the ground motion accelerations of the 921 Chi-Chi earthquake in Taiwan. The soil-wall system is modeled by a simple two-degree freedom (2-DOF) mass spring dashpot dynamic model as shown in figure 1(b). Considering the dynamic equilibrium of these two masses by using D'Alembert's principle, the basic dynamic equation can be written in matrix form [15]:

$$M\ddot{U} + C\dot{U} + KU = M\ddot{x}_g(t) \qquad (1)$$

where $M = \begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix}$ is the diagonal mass matrix,

$C = \begin{bmatrix} (c_1 + c_2) & -c_2 \\ -c_2 & c_2 \end{bmatrix}$ is the damping matrix and

$K = \begin{bmatrix} (k_1 + k_2) & -k_2 \\ -k_2 & k_2 \end{bmatrix}$ is the restoring force vector.

$U = \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T$ represents the displacements of the masses $m_1$ and $m_2$. $\dot{U} = \begin{bmatrix} \dot{x}_1 & \dot{x}_2 \end{bmatrix}^T$ is the velocities of the masses $m_1$ and $m_2$. $\ddot{U} = \begin{bmatrix} \ddot{x}_1 & \ddot{x}_2 \end{bmatrix}^T$ is the accelerations of the masses $m_1$ and $m_2$. $\ddot{x}_g(t)$ is the ground motion acceleration.

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, $X(t) = \begin{bmatrix} U & \dot{U} \end{bmatrix}^T$ 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 [16]:

$$\dot{X}(t) = AX(t) + BG(t), \qquad (2)$$

$$Z(t) = HX(t), \qquad (3)$$

where $G(t) = \begin{bmatrix} \ddot{x}_g(t) & \ddot{x}_g(t) \end{bmatrix}^T$,

$A = \begin{bmatrix} 0 & I \\ -M^{-1}K & -M^{-1}C \end{bmatrix}$,

$B = \begin{bmatrix} 0 \\ M^{-1}M \end{bmatrix}$,

$H = \begin{bmatrix} 1 & 0 \end{bmatrix}$

$A$ and $B$ are both constant matrices composed of the $n$th natural frequency and the inertia moment of the structure system. $X(t)$ is the modal state vector. $U(t)$ is the input dynamic loading. $Z(t)$ is the observation vector, and $H$ is the measurement matrix. Generally speaking, there always exists the noise turbulence in the practical engineering environment. Nevertheless, equations (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 statistical characteristics of the state, will need to be added into these two equations. For this reason, the continuous-time state equation (2) can be sampled with the sampling interval, $\Delta t$, to obtain the discrete-time statistic model of the state equation shown as the following [16]:

$$X(k+1) = \Phi X(k) + \Gamma[G(k) + w(k)] \qquad (4)$$

where

$X(k) = \begin{bmatrix} x_1(k) & x_2(k) \end{bmatrix}^T$

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

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

$X(k)$ is the discrete state vector. $\Phi$ is the state transition matrix. $\Gamma$ is the input matrix. $\Delta t$ is the sampling interval. $G(k)$ is the sequence of deterministic acceleration input, and $w(k)$ is the processing error vector, which is assumed as the Gaussian white noise. In the equation (8), when describing the active characteristics of the structure system, the additional term, $w(k)$, can be used to represent the uncertainty in a numerical manner. The uncertainty could be the random disturbance, the uncertain parameters, or the error due to the over-simplified assumption of numerical models. Note that $E\{w(k)w^T(k)\} = Q\delta_{kj}$, $Q = Q_w \times I_{2n \times 2n}$, $Q$ is the discrete-time processing noise covariance matrix. $\delta_{kj}$ is the Kronecker delta function.

In order to additionally consider the measurement noise, Equation (3) is then expressed as

$$Z(k) = HX(k) + v(k) \qquad (5)$$

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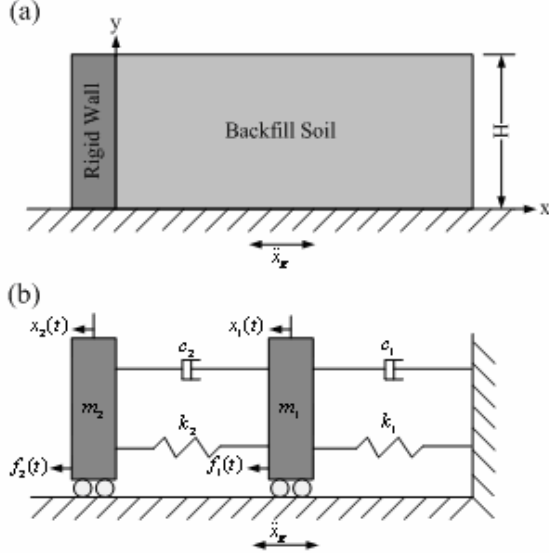


Fig. 1:(a) Considered soil-wall system. (b) Proposed 2-DOF mathematical model [15].

## III. THE INTELLIGENT FUZZY WEIGHTING FUNCTION IN THE RLS INPUT ESTIMATION METHOD

This method is composed of the Kalman filter without the input term and the fuzzy weighting recursive least square estimator. Using the Kalman filter requires an exact knowledge of the process noise variance $Q$ and measurement noise variance $R$, where $R$ depends on the sensor measurements. The Kalmen filter is used to generate the residual innovation sequence. Meanwhile, the real-time recursive least square algorithm is derived by the residual sequence to compute the value of ground motion acceleration. The detailed formulation of this technique can be found in the research by Tuan *et al* [16].

The equations of the Kalman filter are as follows:

The state prediction is

$$\overline{X}(k/k-1) = \Phi \overline{X}(k-1/k-1) \qquad (6)$$

The prediction error covariance matrix is

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

The covariance of residual is $S(k)$

$$S(k) = HP(k/k-1)H^T + R \qquad (8)$$

The Kalman gain is

$$K(k) = P(k/k-1)H^T S^{-1}(k) \qquad (9)$$

The filter error covariance matrix is expressed by

$$P(k/k) = [I - K(k)H]P(k/k-1) \qquad (10)$$

The bias innovation produced by the measurement noise and input disturbance is expressed by

$$\overline{Z}(k) = Z(k) - H\overline{X}(k/k-1) \qquad (11)$$

And the state filter value is expressed as

$$\overline{X}(k/k) = \overline{X}(k/k-1) + K(k)\overline{Z}(k). \qquad (12)$$

The equations of the recursive least square estimator are as follows:

The sensitivity matrices are $B(k)$ and $M(k)$

$$B(k) = H[\Phi M(k-1) + I]\Gamma \qquad (13)$$

$$M(k) = [I - K(k)H][\Phi M(k-1) + I] \qquad (14)$$

The correction gain is expressed as

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

where $\gamma$ is the weighting factor. The error covariance of the input estimation process is

$$P_b(k) = \left[I - K_b(k)B(k)\right]\gamma^{-1}P_b(k-1) \qquad (16)$$

The estimated earth motion acceleration is

$$\hat{G}(k) = \hat{G}(k-1) + K_b(k)\left[\overline{Z}(k) - B(k)\hat{G}(k-1)\right] \qquad (17)$$

The weighting factor can operate at each step based on the innovation produced from the Kalman filter. It also plays the role as an adjustable parameter to control the bandwidth of estimator or the gain magnitude of recursive least square estimator. Furthermore, the weighting factor $\gamma(k)$ is employed to compromise between the tracking capability and the loss of estimation precision. The relation has been derived as follows by Tuan *et al*. in 1996 [17]:

$$\gamma(k) = \begin{cases} 1 & \left|\overline{Z}(k)\right| \le \sigma \\ \dfrac{\sigma}{\left|\overline{Z}(k)\right|} & \left|\overline{Z}(k)\right| > \sigma \end{cases} \qquad (18)$$

According to Equation (18), the weighting factor can be adjusted according to the measurement noise and input bias. The error covariance of input estimation is increased by the weighting factor, $\gamma(k)$, which is chosen in the interval, $[0,1]$. In the industrial applications, the standard deviation $\sigma$ is assumed as a constant value. The magnitude of weighting factor is determined according to the modulus of bias innovation, $\left|\overline{Z}(k)\right|$. The unknown input prompt variation will cause the large modulus of bias innovation. In the meantime, the smaller weighting factor is obtained when the modulus of bias innovation is larger. Therefore, the estimator accelerates the tracking speed and produces larger vibration in the estimation process. On the contrary, the smaller variation of unknown input causes the smaller modulus of bias innovation. Meanwhile, the larger weighting factor is obtained according to the smaller modulus of bias innovation. The estimator is unable to estimate the unknown input effectively. For this reason, the intelligent fuzzy weighting factor for the inverse estimation method which efficiently and robustly estimates the time-varying unknown input will be constructed in this study to cope with this issue. The intelligent fuzzy weighting factor is

proposed based on the fuzzy logic inference system in this search.

The Pythagorean theorem with the transverse axle (time, t) and the vertical axle (residual of predictor, $\bar{z}$) can be used to solve the length of the hypotenuse. In other words, the length of the hypotenuse is the variation rate of the residual in the sampling interval. The dimensionless input variable, $\theta(k)$, is defined as the following:

$$\theta(k) = \frac{\left|\frac{\Delta\bar{Z}(k)}{\bar{Z}(k)}\right|}{\sqrt{\left(\frac{\Delta\bar{Z}(k)}{\bar{Z}(k)}\right)^2 + \left(\frac{\Delta t}{t_f}\right)^2}} \tag{19}$$

The basic configuration of the fuzzy logic system considered in this paper is illustrated as follows. The fuzzy logic system includes four basic components, which are the fuzzy rule base, fuzzy inference engine, fuzzier, and defuzzier. The proposed intelligent fuzzy weighting factor uses the input variable $\theta(k)$ to self-adjust the factor $\gamma(k)$ of the recursive least square estimator. Therefore, the fuzzy logic system consists of one input and one output variables. The range of input, $\theta(k)$, and output, $\gamma(k)$, can be chosen in the interval, $[0,1]$. The fuzzy sets for $\theta(k)$ and $\gamma(k)$ are labeled in the linguistic terms of EP (extremely large positive), VP (very large positive), LP (large positive), MP (medium positive), SP (small positive), VS (very small positive), and ZE (zero). A fuzzy rule base is a collection of fuzzy IF-THEN rules:

IF $\theta(k)$ is zero (ZE) THEN $\gamma(k)$ is an extremely large positive (EP);

IF $\theta(k)$ is a very small positive (VS) THEN $\gamma(k)$ is a very large positive (VP);

IF $\theta(k)$ is a small positive (SP) THEN $\gamma(k)$ is a large positive (LP);

IF $\theta(k)$ is a medium positive (MP) THEN $\gamma(k)$ is a medium positive (MP);

IF $\theta(k)$ is a large positive (LP) THEN $\gamma(k)$ is a small positive (SP);

IF $\theta(k)$ is a very large positive (VP) THEN $\gamma(k)$ is a very small positive (VS);

IF $\theta(k)$ is an extremely large positive (EP) THEN $\gamma(k)$ is zero (ZE).

In the above rules, $\theta(k) \in U$ and $\gamma(k) \in V \subset R$ are the input and output of the fuzzy logic system, respectively. The fuzzier maps a crisp point $\theta(k) \in U$ into a fuzzy set $A$ in $U$. Therefore, the nonsingleton fuzzier can be expressed as in Reference [18]:

$$\mu_A(\theta(k)) = \exp\left(-\frac{\left(\theta(k) - \bar{x}_i^l\right)^2}{2\left(\sigma_i^l\right)^2}\right) \tag{20}$$

$\mu_A(\theta(k))$ decreases from 1 as $\theta(k)$ moves away from $\bar{x}_i^l$. $\left(\sigma_i^l\right)^2$ is a parameter characterizing the shape of $\mu_A(\theta(k))$.

The Mamdani maximum-minimum inference engine is used in this study. The max-min-operation rule of fuzzy implication is shown in Reference [18]:

$$\mu_B(\gamma(k)) = \max_{j=1}^c \left\{\min_{i=1}^d\left[\mu_{A_i^j}(\theta(k)), \mu_{A_i^j \to B^j}(\theta(k), \gamma(k))\right]\right\} \tag{21}$$

where $c$ is the fuzzy rule, and $d$ is the dimension of input variables.

The defuzzier maps a fuzzy set $B$ in $V$ to a crisp point $\gamma \in V$. The fuzzy logic system with the center of gravity is defined in Reference [18]:

$$\gamma^*(k) = \frac{\sum_{l=1}^n \bar{y}^l \mu_B(\gamma^l(k))}{\sum_{l=1}^n \mu_B(\gamma^l(k))} \tag{22}$$

$n$ is the number of outputs. $\bar{y}^l$ is the value of the $lth$ output. $\mu_B(\gamma^l(k))$ represents the membership of $\gamma^l(k)$ in the fuzzy set $B$. Using $\gamma^*(k)$ in Equation (22) to replace $\gamma$ in Equations (15) and (16) allows us to configure an adaptive fuzzy weighting function for the recursive least square estimator (RLSE). A flow chart of the computation for the application of the proposed input estimation algorithm is shown in Figure 2.

## IV. RESULTS AND DISCUSSION

In order to demonstrate the accuracy and efficiency of the presented method in estimating the unknown active earth acceleration, several numerical simulations of the retaining structure are investigated. The soil-wall system considered is shown in figure 1(a). The system is modeled by a simple two-degree freedom (2-DOF) mass spring dashpot dynamic model as shown in figure 1(b) [15]. The material of the wall and the soil layer is defined by the mass density, $\rho$, shear modulus of elasticity, $G$, Poisson's ratio, $\mu$, and the material damping factor $\eta$ of concrete and dense sand respectively. The material data and dimensions of the soil-wall system are shown in Table 1.

For the estimation of the stiffness value for both soil and wall, the method was described by Veletsos and Younan [19]. It is determined such that the undamped natural frequency of the model equals the fundamental natural frequency of the medium idealized as a series of vertical shear-beams. The stiffness, $k$ of a particular system can be estimated as

$$k = m\left(\pi^2 / 4H^2\right)(G/\rho) \tag{23}$$

where $m$ is the mass of the system considered. This method is composed of the Kalman filter without the input term and the intelligent fuzzy weighted recursive least square estimator. The initial conditions and other parameters of simulation are shown as follows: $p(0/0) = diag\left[10^4\right]$. $\hat{G}(0) = 0$. $p_b(0) = 10^8$. $M(0)$ is set as a zero matrix. The weighting factor, $\gamma$, is an intelligent fuzzy weighting function. The sampling interval, $\Delta t = 0.005$ s, and the total simulation time, $t_f = 70s$. The earth motion accelerations of the 921 Chi-Chi earthquake in Taiwan was measured from the seismological station (TCU 056) in the Li-Ming elementary school [20]. The unknown earth motion acceleration can also be estimated from the dynamic responses of the wall. In this study, the precision of the estimation model was verified by the root mean square error (RMSE). The definition of the RMSE is described as Equation (23).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left[\left(G_{real}\right)_i - \left(\hat{G}_{estimated}\right)_i\right]^2}{n}} \qquad (24)$$

where $n$ is the total number of time steps. $G_{real}$ is the real earth acceleration. $\hat{G}_{estimated}$ is the estimated earth acceleration. The process noise and measurement noise are both considered in the simulation process. The process noise covariance matrix, $Q = Q_w \times I_{2n \times 2n}$, where $Q_w = 10^{-2}$. The measurement noise covariance matrix, $R = R_v \times I_{2n \times 2n}$, where $R_v = \sigma^2 = 10^{-12}$. $\sigma$ is the standard deviation of noise. Figure 3 shows the displacement, velocity and acceleration-time history responses of wall structure to the earth motion acceleration. Figure 4 shows that the smaller weighting factor can be chosen in the fuzzy recursive least square method when the unknown system input is larger. Figure 5 shows the comparison between the intelligent fuzzy weighting and adaptive weighting estimation results of the earth motion acceleration with $Q_w = 10^{-2}$, and $R_v = 10^{-12}$. The simulation results in Figures 5~7 demonstrate that if the process noise variance $Q_w$ decreases and the measurement error variance $R_v$ increases, it will influence the estimation resolution. A smaller process noise variance and a larger measurement error variance will affect the capability of tracking the earth motion acceleration input. As a result, it will not be capable of reducing the effect caused by the measurement noise. The overall estimation efficiency will therefore degrade. The estimates of earth motion acceleration using the fuzzy weighting function and the constant weighting factor, $\gamma = 0.15$, are plotted in Figure 8. The similar simulation results of the earth motion acceleration with the fuzzy weighting function and the constant weighting factor, $\gamma = 0.95$, are shown in Figures 9. The estimation results show that the tracking performance of estimators is not good enough, and they are not suitable in reducing the effect of the noise.

In order to obtain a better estimation result, the constant weighting factor is chosen by the trial-and-error method. The adaptive weighted input estimator has better target tracking capability when the input variation is severe. However, the capability to reduce the effect caused by the noise is not sufficient. To resolve this situation, the method proposed in this research will be more efficient in tracking the unknown inputs and reducing the influence due to the measurement noise. The comparison of estimation results in terms of RMSEs using several different weighting functions are shown in Table 2. The RMSE is smaller when adopting the fuzzy weighted estimators.
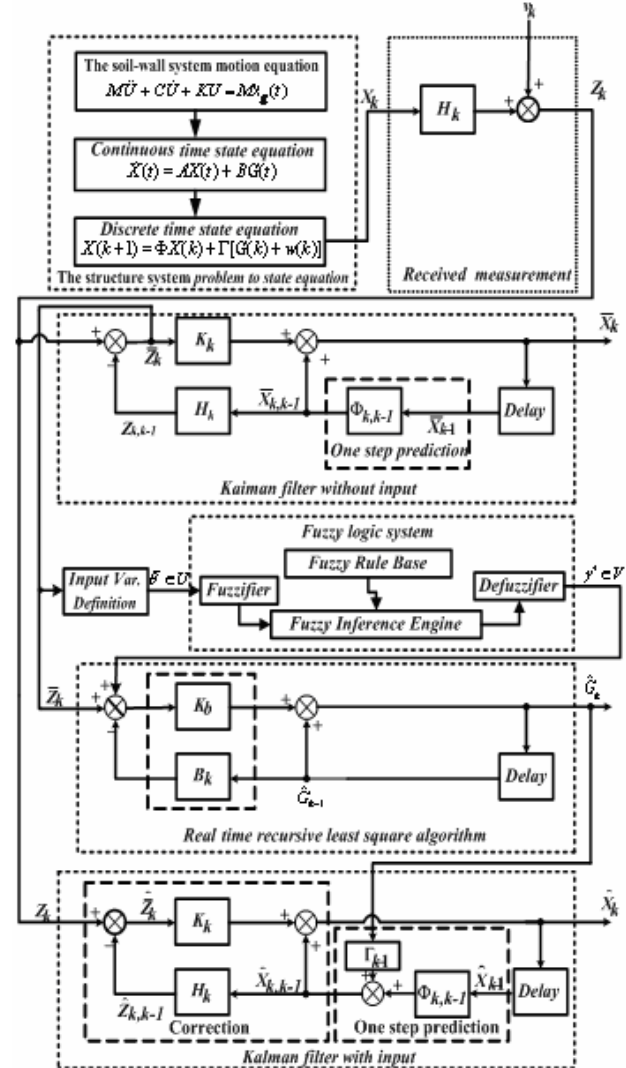


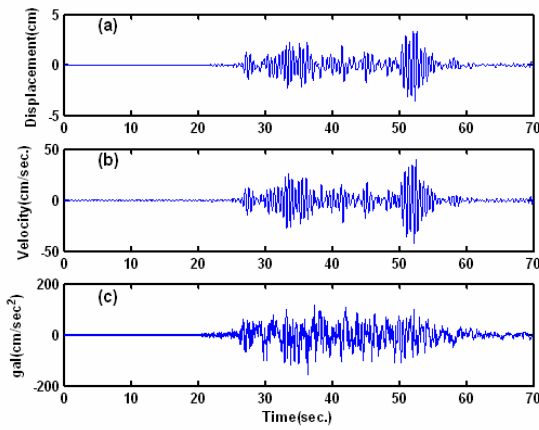Fig. 2: Flowchart of the intelligent fuzzy weighted input estimation algorithm.

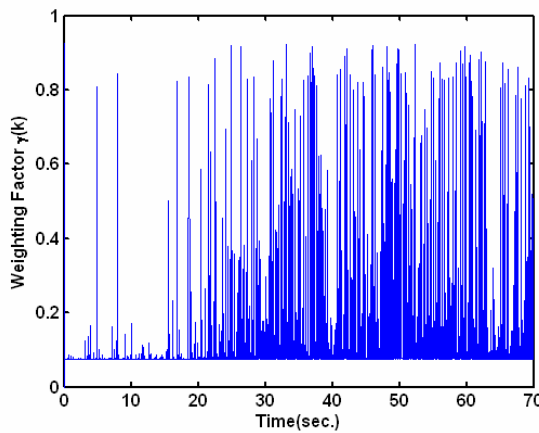Fig. 3: The displacement, velocity and acceleration of the wall caused by the seismic force.



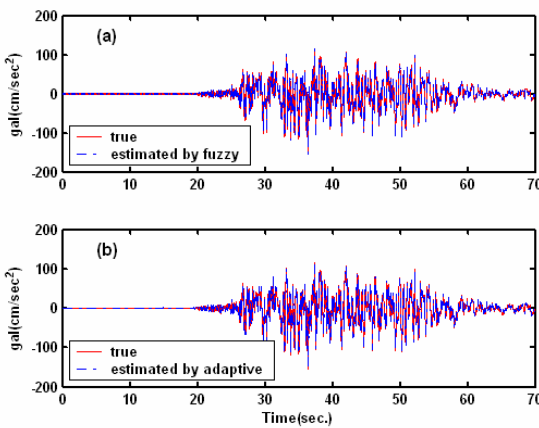Fig. 4: The variance of the fuzzy weighting factor $\gamma(k)$.



Fig. 5: Comparison of the estimation results using the fuzzy and adaptive weighting functions. ( $Q_w = 10^{-2}$ , $R_v = 10^{-12}$ , (a)RMSE=3.18, (b)RMSE=3.71)
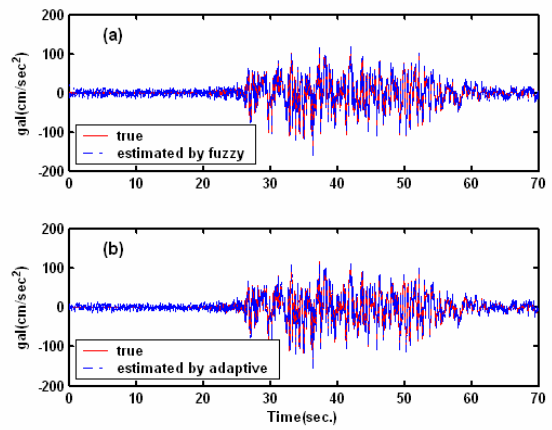


Fig. 6: Comparison of the estimation results using the fuzzy and adaptive weighting functions. ( $Q_w = 10^{-4}$ , $R_v = 10^{-10}$ , (a)RMSE=5.43, (b)RMSE=5.78)
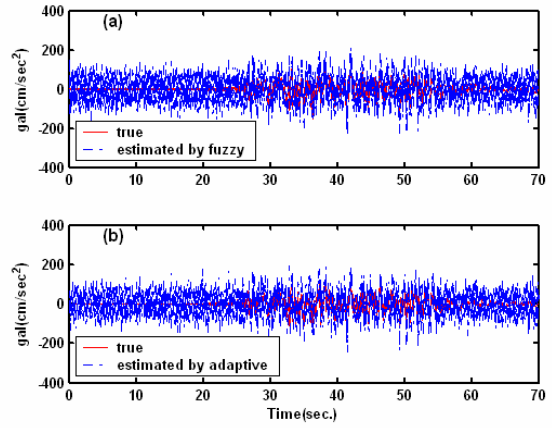


Fig. 7: Comparison of the estimation results using the fuzzy and adaptive weighting functions. ( $Q_w = 10^{-6}$ , $R_v = 10^{-8}$ , (a)RMSE=45.58, (b)RMSE=48.63)
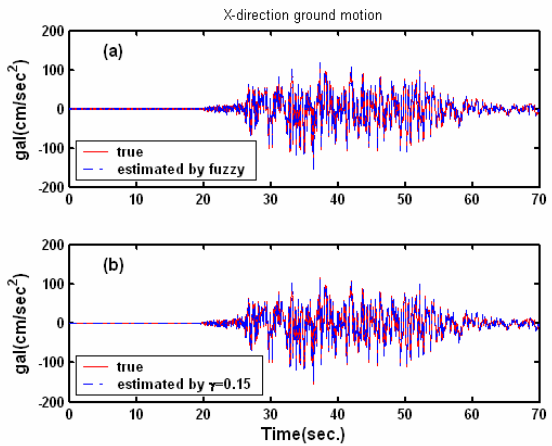


Fig. 8: Comparison of the estimation results using the fuzzy weighting function and the constant weighting factor ( $\gamma = 0.15$ ). ( $Q_w = 10^{-2}$ , $R_v = 10^{-12}$ , (a)RMSE=3.18, (b)RMSE=3.41)
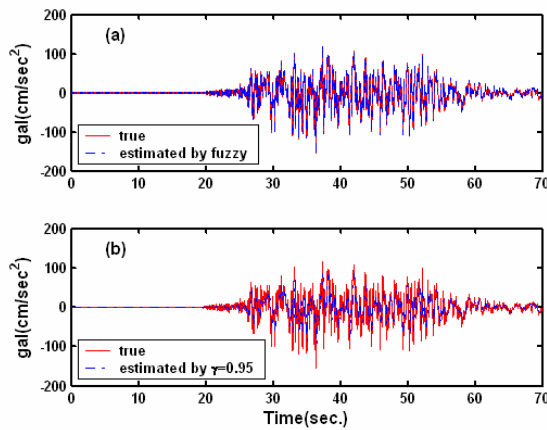
Fig. 9: Comparison of the estimation results using the fuzzy weighting function and the constant weighting factor ( $\gamma = 0.95$ ). ( $Q_w = 10^{-2}$, $R_v = 10^{-12}$, (a)RMSE=3.18, (b)RMSE=20.13)

TABLE I THE MATERIAL DATA AND DIMENSIONS OF THE SOIL-WALL SYSTEM [15]

| Wall height, $H$ | 5 ( $m$ ) |
|---|---|
| Unit weight of the concrete wall, $\gamma_{conc}$ | 24 ( $KN/m^3$ ) |
| Shear modulus of the concrete wall, $G_{conc}$ | $9921 \times 10^3 (KN/m^2)$ |
| Unit weight of the backfill soil, $\gamma_{soil}$ | 18 ( $KN/m^3$ ) |
| Shear modulus of the backfill soil, $G_{soil}$ | $5769(KN/m^2)$ |

TABLE II COMPARISON OF THE ESTIMATION RESULTS (RMSE) USING 4 DIFFERENT WEIGHTING FUNCTIONS

| $Q_w$ | $R_v$ | $\gamma = 0.15$ | $\gamma = 0.95$ | $\gamma = adaptive$ | $\gamma = Fuzzy$ |
|---|---|---|---|---|---|
| $10^{-2}$ | $10^{-12}$ | 3.41 | 20.13 | 3.71 | 3.18 |
| $10^{-4}$ | $10^{-10}$ | 5.46 | 20.23 | 5.78 | 5.43 |
| $10^{-6}$ | $10^{-8}$ | 46.19 | 30.03 | 48.63 | 45.58 |

## V. CONCLUSIONS

This study presents the Kalman filter technology combined with the fuzzy weighting recursive least square method to estimate the active ground motion acceleration input of the retaining structure with the modeling and measurement noises. The fuzzy estimator has the properties of fast tracking capability and the efficiency against noises since it is weighted by the weighting factor, $\gamma(k)$ of the presented method based on the fuzzy logic inference system. The excellent performance of this inverse method is demonstrated by solving the earthquake-excitation estimation problem, and the proposed algorithm is compared by alternating between the constant and adaptive weighting factors. The results reveal that this method has the properties of better target tracking capability and more effective noise reduction.

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