Parameter Identification of Structures under Earthquake Excitations Using Adaptive Particle Filter and Ensemble Learning Method

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1. Introduction

After two major earthquakes in Gyeongju and Pohang, social interest and concerns about seismic disasters greatly increased. Furthermore, the need for the post-disaster evaluation of infrastructure using a Structural Health Monitoring (SHM) technique also increased. In particular, the estimation of system parameters through machine learning methods become popular. Among them, Particle Filter (PF), which is suitable for nonlinear systems, have been actively investigated to confirm high accuracy in the parameter estimation.

However, the system parameters of a structure can change significantly while experiencing extreme events, e.g. stiffness degradation. Existing parameter estimation methods could not detect these sudden changes. This problem makes it difficult to accurately detect damage in the system. Accordingly, this study aims at accurate estimation of sudden changes in parameters during an earthquake event by developing an Adaptive Particle Filter (APF) method. The variability in the estimation is further reduced through an ensemble learning method to facilitate more accurate estimation.

2. Methodology

2.1 Adaptive Particle Filter

PF is a machine learning method that estimates the system states or parameters based on the system equation and measurements by updating the values of randomly generated samples (particles) from the initial probability distribution. The main advantage of PF is its applicability to nonlinear and non-Gaussian systems. Estimation by PF consists of two main steps: the 'prediction' step of predicting the states at the next time step based on a given system equation, and the 'measurement update' step of estimating the posterior distribution from the weight of each particle based on the measurements.

However, the original PF is not effective in estimating parameters that change rapidly, such as stiffness degradation, caused by damage to the structure over a short period, such as an earthquake. To address this, APF [1] (see Figure 1) was proposed to adapt quickly to sudden change in the system. APF increases parameter estimation noise artificially by multiplying the noise vector by the adaptive coefficient λ_k, which is defined as the ratio of the trace of the actual residual covariance matrix $\mathbf{V}_k$ to that of theoretical residual covariance matrix $\mathbf{M}_k$, i.e.

$$\lambda_k = \frac{\mathrm{tr}\left[\mathbf{V}_k\right]}{\mathrm{tr}\left[\mathbf{M}_k\right]} \tag{1}$$

$$\mathbf{V}_k = \frac{\rho \mathbf{V}_{k-1} + \frac{1}{N_p}\sum_{i=1}^{N_p} \gamma_k^i \left(\gamma_k^i\right)^T}{1+\rho} \tag{2}$$

$$\mathbf{M}_k = \frac{1}{kN_p}\sum_{j=0}^{k-1}\sum_{i=1}^{N_p}\left(\hat{y}_{j+1|j} - y^i_{j+1|j}\right)\left(\hat{y}_{j+1|j} - y^i_{j+1|j}\right)^T \tag{3}$$

In this research, to improve the performance, an modified APF (mAPF) is proposed by adjusting individual elements of parameter estimation noise vector through adaptive coefficient *vector* $\boldsymbol{\lambda}_k$ instead of a single coefficient λ_k, i.e.

$$\boldsymbol{\lambda}_k = \left[\Lambda_{1,k} \quad \cdots \quad \Lambda_{N_\theta,k}\right]^T \tag{4}$$

where $\Lambda_{j,k}$ is defined as the geometric mean of all $\lambda_{k,i}$ related with the parameter θ_j at time step k.

$$\lambda_{k,i} = \frac{V_k(i,i)}{M_k(i,i)} \tag{5}$$

where $V_k(i,i)$ and $M_k(i,i)$ are the i^{th} diagonal element of $\mathbf{V}_k$ and $\mathbf{M}_k$.

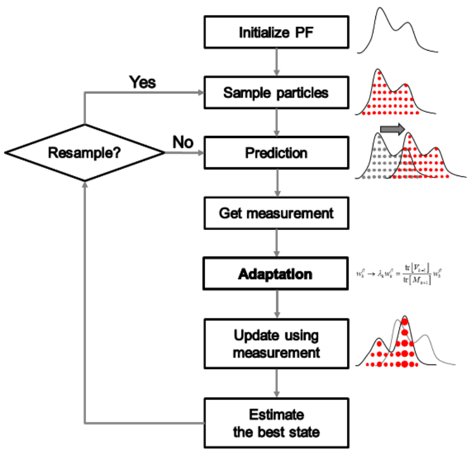

Fig. 1. Flow chart of an APF

2.2 Ensemble Learning Method

The ensemble learning method is a general learning technique that improves an estimation by weighting estimates from multiple models, rather than performing estimation with a single model. In general, the variance of estimation is reduced in this process as residuals cancel each other [2,3].

Among several ensemble learning methods, this paper uses one of the most simple and effective methods called

Bootstrap aggregating (or 'bagging') to obtain final estimates. The bagging method considers the average of the estimates obtained in each model as the final estimate. That is, the bagging method gives equal weight to the estimate from each model, so that all models are considered equally. The bagging method can reduce the variance of estimation and prevent the overfitting by improving unstable procedure [4].

Since mAPF increases the artificial noise to a detect sudden change, the bias of estimation is decreased but the variance can be increased. To reduce the variance, the bagging method is applied to every time step of mAPF. At the initial time point, multiple mAPF algorithms are initiated using different random noises. Then, the estimates are obtained from each algorithm through parallel computing each time step. Finally, the final estimate is obtained using the bagging method.

3. Numerical Examples and Results

A numerical example of 10 story shear building shown in Figure 2 is investigated to confirm the validity of the proposed methodologies. As a reference scenario, local failures in the target structure are assumed to occur during the earthquake event. A real ground acceleration time history is used as the input data.

3.1 Numerical Example: 10 Story Shear Building

The equation of motion describing a linear system subjected to the ground acceleration time history $\ddot{u}_g$ is given as

$$\mathbf{M}\ddot{\mathbf{u}}(t)+\mathbf{C}\dot{\mathbf{u}}(t)+\mathbf{K}\mathbf{u}(t)=-\mathbf{M}\ddot{u}_g \tag{6}$$

where $\mathbf{M}$, $\mathbf{C}$ and $\mathbf{K}$ are mass, damping and stiffness matrices respectively [5]; and $\mathbf{u}$, $\dot{\mathbf{u}}$ and $\ddot{\mathbf{u}}$ are respectively the displacement, velocity and acceleration vectors of the target structure. The structural properties of each degree of freedom, mass, damping coefficient, and stiffness are set to $m_1, \dots, m_{10} = 100$ kg, $c_1, \dots, c_{10} = 5\ \mathrm{N \cdot s/m}$, and $k_1, \dots, k_{10} = 180\ \mathrm{N/m}$ respectively.

To estimate the states of the system in Eq. (6) using the Particle Filter in the time domain, the state vector $\mathbf{z}(t)$ is defined to estimate $\mathbf{u}$ and $\dot{\mathbf{u}}$. In addition, every stiffness is considered as the system parameter to estimate. Therefore, the state vector $\mathbf{z}(t)$ is written as

$$\mathbf{z}(t)=\begin{bmatrix}\mathbf{u}(t) & \dot{\mathbf{u}}(t) & k_1, & \cdots, k_{10}\end{bmatrix}^T \tag{7}$$

Then, Eq. (6) is expressed as the nonlinear function in the state-space representation [5], i.e.

$$\dot{\mathbf{z}}_a = f\left(\mathbf{z}, \ddot{u}_g, \mathbf{w}\right) \tag{8}$$

where $\mathbf{w}$ is the system noise vector.

As the ground acceleration $\ddot{u}_g$, the N-S component of the El Centro earthquake that occurred in the Imperial Valley in 1940 is used. The El Centro earthquake recorded 0.3g of the Peak Ground Acceleration (PGA), and 6.9 of moment magnitude. The measurement frequency is 50 Hz.

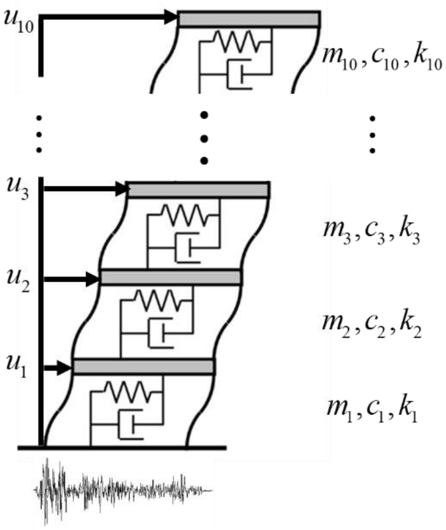

Fig. 2. Target system: 10 story shear building

3.2 Original Particle Filter

The result of the original PF is shown in Figure 3. As shown, the convergence rate of the estimation is low due to the small estimation noise. Because of this, PF cannot adapt to sudden changes in the system and there is a large difference between the theoretical and actual measurements. While trying to reduce this difference, the estimates of other parameters are also affected. In other words, small estimation noise results in estimation being caught on the local minima, which differs from the exact solution.

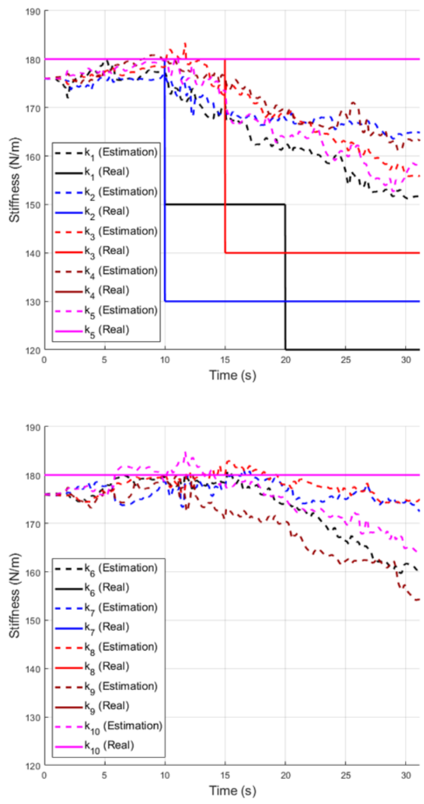

Fig. 3. Parameter estimation using original PF

3.3 Adaptive Particle Filter

The result of the mAPF proposed in this study is shown in Figure 4. Comparing the results with those by the original PF, a significant improvement in estimation accuracy is observed. In particular, mAPF adapts quickly at the moment of the stiffness degradation, and that parameter estimates converges to the exact solution.

While the bias in estimates is decreased significantly compared to the results of the original PF, the variance is increased significantly. In particular, estimates of parameters where stiffness degradation does not occur vary significantly. As mentioned, this is because mAPF increases parameter estimation noise for improved adaptibility.

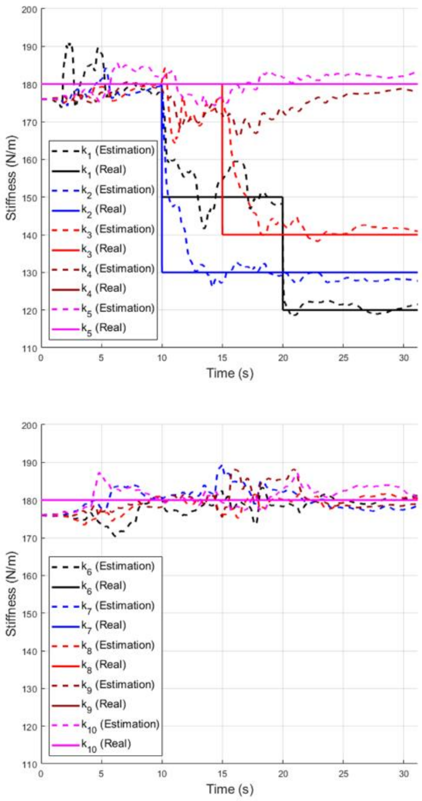

Fig. 4. Parameter estimation using mAPF

3.4 Adaptive Particle Filter with Bagging

Next, the result of parameter estimation for mAPF with the bagging method is shown in Figure 5. Comparing the results with those in Figure 4, it is confirmed that bagging significantly reduces the variance at all time steps with no significant changes in terms of bias. This verifies the validity of the mAPF combined with the bagging methodology.

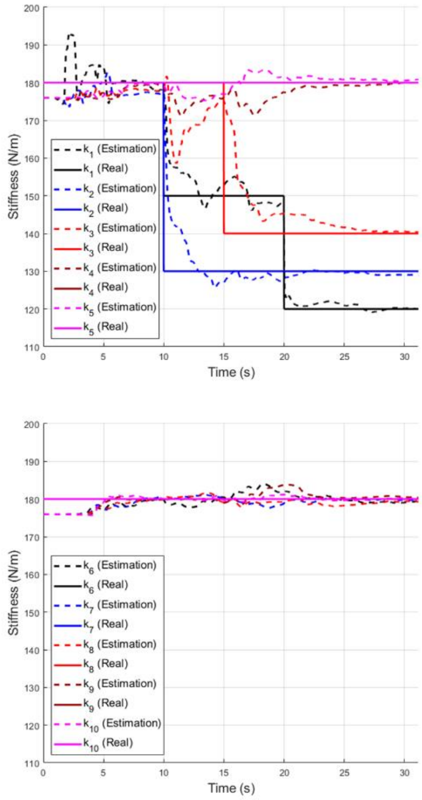

Fig. 5. Parameter estimation using mAPF with the bagging

4. Conclusions

Using the modified Adaptive Particle Filter (mAPF) with ensemble learning method as proposed in this study, it is possible to accurately detect sudden changes in the system parameters during disastrous dynamic actions over a short period of time only with a limited amount of measurement data and simple calculations. Based on these results, further studies are underway to capture changes in the system parameters in more complex nonlinear structures and to establish effective post-disaster evaluation and monitoring methodologies.

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