Damage detection of base-isolated buildings using multi-inputs multi-outputs subspace identification

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**SUMMARY**

A damage detection algorithm of structural health monitoring systems for base-isolated buildings is proposed. The algorithm consists of the multiple-inputs multiple-outputs subspace identification method and the complex modal analysis. The algorithm is applicable to linear and nonlinear systems. The story stiffness and damping as damage indices of a shear structure are identified by the algorithm. The algorithm is further tuned for base-isolated buildings considering their unique dynamic characteristics by simplifying the systems to single-degree of freedom systems. The isolation layer and the superstructure of a base-isolated building are treated as separate substructures as they are distinctly different in their dynamic properties. The effectiveness of the algorithm is evaluated through the numerical analysis and experiment. Finally, the algorithm is applied to the existing 7-story base-isolated building that is equipped with an internet-based monitoring system.

**Keywords:** system identification; subspace identification; MIMO; health monitoring; base-isolation
1. INTRODUCTION

There is a growing interest in assessing structural integrity of buildings and infrastructures associated with their deterioration and natural hazards. To ensure the integrity and the safety of a building, an SHM (Structural Health Monitoring) system is one of solutions for prompt and quantitative evaluation.

For the purpose of damage detection, damage indices that are strongly correlated to the structural damages must be identified precisely. Many studies are still being conducted in this area [1]. The conventional damage indices such as modal frequencies [2], mode shapes [3], curvature mode shapes [4] and modal flexibilities [5] are considered not accurate enough for local and quantitative damage detection. When a damage occurs in some layers of the building due to, say, a large earthquake, the stiffness will be reduced. In this case, the story stiffness may be a good index. There are some studies, such as the method for online estimation of the stiffness matrix using extended Kalman filter [6], estimation of the story stiffness and viscous damping using transfer functions [7], parallel estimation of the story parameters [8] and so on. The accuracy of these methods highly depends on the noise level contained in the data. In this study, a new and stable algorithm to obtain story stiffness and damping using the subspace identification method is proposed.

The MIMO models are known to be suitable for representing behaviors in three-dimensional space. However, in civil engineering field single-input and single-output (SISO) models have been conventionally used. This is mainly due to the lack of tools to take care of multi-inputs and multi-output (MIMO) models and the difficulty to identify
the proper correlation between inputs and outputs for the specific mode. The proposed algorithm resolves these difficulties by using the subspace identification for MIMO models and by introducing participation factors.

The isolation devices are designed to absorb major components of energy input for a base-isolated building when subject to a large earthquake. However, there exists a certain probability to exceed the design capacity for the extreme earthquake. The structural integrity of the isolated building is no longer guaranteed in such a case. In the fear of the possibility of suffering from damages to the isolated building, incorporating an SHM system may have a good rationale for immediate diagnosis of the structural integrity as well as continuous observation of material deterioration. A conventional building absorbs the seismic energy mainly at beam-column joints of the supporting frames that have a high-degree of complexity; this implies that scenarios for structural damages vary depending on the characteristics of earthquakes. In addition, accurate simulation for each scenario is very difficult. The damage scenario for a base-isolated structure is much simpler and more accurate than the situation for a conventional building. Our strategy is to get the most out of this simplicity in the purpose of establishing the SHM system for base-isolated buildings.
2. FORMULATION

2.1. Model description

An N-story shear structure consisting of N masses, N springs and N dampers is considered as shown in Figure 1. Mass distribution is assumed given. The acceleration measured at the $i^{th}$ floor is described by $\ddot{X}_i$. The story stiffness indicated by the spring $k_i$ and the story damping indicated by the damper $c_i$ are unknown.

2.2. MOESP method

The MOESP method that is one of the subspace model identification methods is used as a basis of our algorithm for identifying story stiffness and damping. The subspace model identification is a method to obtain a state space model from input and output data using Hankel matrices. In this study, the subspace model identification method was employed because the method is easily applicable to MIMO models to improve the accuracy of the identification. As we are interested in state-space representation, we chose subspace model identification method among others. As an additional benefit, stability of identification can be evaluated by singular value decomposition in the course of this identification.

The linear state equations in a discrete form are given by:

$$\mathbf{x}_{k+1} = A\mathbf{x}_k + B\mathbf{u}_k$$ (1)

where $\mathbf{x} \in \mathbb{R}^n$ stands for the $n$-dimensional state vector. The vector $\mathbf{u} \in \mathbb{R}^m$ is the $m$-dimensional input vector. The corresponding output equations are:
\[ y_k = Cx_k + Du_k \] (2)

where the vector \( y \in \mathbb{R}^l \) is the \( l \)-dimensional output vector. Among many subspace identification methods, the MOESP algorithm [9] is utilized to realize system matrices \( A, B, C, D \) from measured inputs \( u \) and outputs \( y \) using QR-factorization and singular value decomposition (SVD). The MOESP algorithm is numerically stable and is suited for real time identification. Introducing Hankel matrices, the output equations become:

\[
\begin{bmatrix}
y_1 & y_2 & \cdots & y_j \\
y_2 & y_3 & \cdots & y_{j+1} \\
\vdots & \vdots & & \vdots \\
y_j & y_{i+1} & \cdots & y_{i+j-1}
\end{bmatrix} =
\begin{bmatrix}
C \\
CA \\
\vdots \\
CA^{i-1}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2 \\
\vdots \\
x_j
\end{bmatrix}
\]

\[
+ 
\begin{bmatrix}
D \\
CB & D & 0 \\
CAB & CB & \ddots \\
\vdots & \ddots & \ddots \\
CA^{i-2}B & CA^{i-3}B & \cdots & CB & D
\end{bmatrix}
\begin{bmatrix}
u_1 \\
u_2 \\
\vdots \\
u_j \\
u_{i+1} \\
\vdots \\
u_{i+j-1}
\end{bmatrix}
\] (3)

Equation (3) can be rewritten in a more compact form as:

\[ Y_j = O_iX_j + T_jU_{ij} \] (4)

where, \( O_i \) and \( T_i \) are called the extended observability matrix and the Toeplitz matrix, respectively. \( U_{ij} \in \mathbb{R}^{i \times \sigma} \) and \( Y_j \in \mathbb{R}^{j \times \sigma} \) are called block Hankel matrices (with \( i \) block rows, \( j \) columns). The whole Hankel matrix \( H \) containing the measured input-output data is then constructed. Applying the QR-factorization, the LQ decomposition of the matrix is given by:

\[
H = \begin{bmatrix}
U_{\bar{y}_j} \\
Y_{\bar{y}_j}
\end{bmatrix} = \begin{bmatrix}
L_{11} & 0 \\
L_{21} & L_{22}
\end{bmatrix}\begin{bmatrix}
Q_1^T \\
Q_2^T
\end{bmatrix} = \begin{bmatrix}
U_{\bar{y}_j} = L_{11}Q_1^T \\
Y_{\bar{y}_j} = L_{21}Q_1^T + L_{22}Q_2^T
\end{bmatrix}
\] (5)
where, \( Q_1^T \) and \( Q_2^T \) are orthonormal matrices which satisfy the conditions such that \( Q_1^T Q_1 = I \), \( Q_2^T Q_2 = I \) and \( Q_1^T Q_2 = 0 \). Considering Equations (4) and (5), the following equations are derived.

\[
Y_j = O_i X_j^T + T_j L_{11} Q_1^T = L_{21} Q_1^T + L_{22} Q_2^T
\]  
(6)

The row space of \( O_i \) is derived by multiplying \( Q_2 \) to Equation (6) from right-hand side. Considering the orthonormal conditions, the effect of the general input is eliminated to give a free response of the system as:

\[
Y_j Q_2 = O_i X_j Q_2 = R_{22}
\]  
(7)

Once the effect of input is eliminated, the procedure equivalent to the eigensystem realization algorithm (ERA [10], [11]) can be applied. The MOESP algorithm is equivalent to the ERA combined with the elimination process for the input to obtain free vibration. Following the procedure, the singular value decomposition is applied for \( L_{22} \) as:

\[
L_{22} = \begin{bmatrix} M_1 & M_2 \\ \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} N_1^T \\ \Sigma_1 \end{bmatrix} \approx M_1 \Sigma_1 \Sigma_1 \Sigma_1^T
\]

\[
\Sigma_1 = \text{diag}(\sigma_1, \ldots, \sigma_n), \Sigma_2 = \text{diag}(\sigma_{n+1}, \ldots, \sigma_q)
\]  
(8)

where \( M \) and \( N \) are orthonormal matrices, \( \Sigma \) is a diagonal matrix containing the singular values in descending order. Although the model order \( n \) is found as the rank of the matrix \( L_{22} \) under the idealized condition, a realistic structural system may have a model order that is larger than \( n \). We select \( n \) by searching the significant drop in the singular values such that \( \sigma_n >> \sigma_{n+1} \) to distinguish the subspace of the signal from the noise subspace. The extended observability matrix \( O_i \) can be approximated by:

\[
O_i = M_1 \Sigma_1^{1/2}
\]  
(9)
Once the extended observability matrix $O_i$ is obtained, the matrix $C$ is realized by extracting the top block. The matrix $A$ is computed based on the shift invariance of $O_i$ as:

$$
O_{i-1} \cdot A = O_{i-1}^\dagger \\
A = O_{i-1}^\dagger \cdot O_{i-1}^\dagger
$$

where, $O_{i-1}$ is the matrix obtained by deleting the last block row of $O_i$, $O_{i-1}^\dagger$ is the upper-shifted matrix by one block row, and $(\cdot)^\dagger$ represents the pseudo-inverse of a matrix. In this study, we don’t have to estimate the system matrices $B$ and $D$ because they contain no modal information.

From eigenvalue analysis of the matrix $A$, we obtain the $i^{th}$ pole $z_p_i$ and eigenvector $z\varphi_i$ in z-domain. Considering the relationship between z- and s-domain, $z_p_i$ is converted into $\lambda_i$, which is the pole in continuous-time system, i.e. in s-domain. In addition, by pre-multiplying the matrix $C$ to $z\varphi_i$, we can obtain a complex mode vector $\varphi_i$. Finally, the complex modal properties of the building are:

$$
\lambda_i = \frac{\log z_p_i}{\Delta t} \\
\varphi_i = C \cdot z\varphi_i
$$

To extend the algorithm to nonlinear systems, a step by step approach was employed. The Hankel matrix in this case is updated every time the new data is acquired as shown below (Please note that this is a possible example. Users can choose any number of rows and columns.):
2.3. Participation factors for identifying stabilized modes

When an MIMO modal analysis using the MOESP approach is conducted, the input-output relation is not automatically provided. In order to specify the relation, the participation factors are introduced. The participation factors are calculated based on the mode vectors as:

\[
\beta_{ip} = \frac{(\phi_i^*)^T \cdot M \cdot b_p}{(\phi_i^*)^T \cdot M \cdot \phi_i}
\]  

where, \(b_p\) is the column vector containing unit values in the corresponding elements where the input is applied as the \(p^{th}\) input component. The superscript * represents the complex conjugate. If a mode is associated with the \(p^{th}\) input component, the corresponding participation factor should be stable all the time during the response. In other words, by observing the stability of the participation factors we can find the proper input-output relationship associated with a certain mode. If the system is linear, the participation factors should be constant all the time. Thus, we recognize the IO relations unstable if the relevant participation factors are not constant. The unstable IO relations are rejected.

2.4. Identification of story parameters

After obtaining the modal parameters by the MOESP approach, the story stiffness and damping are obtained [12]. The procedure is explained below.
An inertia force at the $j^{th}$ mass $f_j$ is calculated as:

$$f_j = -\sum_{k=j}^{N} m_k \cdot \ddot{x}_k$$

(14)

where, $\ddot{x}_j$ is the acceleration at the $k^{th}$ mass. The inertia force should be equal to the spring and damping forces as:

$$f_j = k_j (X_j - X_{j-1}) + c_j (\dddot{X}_j - \dddot{X}_{j-1})$$

(15)

where, $k_j$ and $c_j$ are the story stiffness and damping, respectively. These parameters can be directly identified using acceleration time histories [8]. However, the identification procedure involves integrators in the course of deriving the relative displacement and velocity. The precision of the estimation, therefore, highly depends on the noise level and initial values taken for estimation. Instead of using acceleration time histories, we propose the use of modal parameters to estimate story stiffness and damping. The harmonic displacement response at the $j^{th}$ mass that vibrates in the $i^{th}$ mode can be expressed in the form:

$$X_{i(j)}(t) = \phi_{i(j)} \cdot e^{i\lambda t}$$

(16)

Therefore, the relative displacement and velocity are obtained by:

$$d_{i(j)}(t) = X_{i(j)}(t) - X_{i(j-1)}(t) = \{\phi_{i(j)} - \phi_{i(j-1)}\} \cdot e^{i\lambda t}$$

$$\dot{d}_{i(j)}(t) = \ddot{X}_{i(j)}(t) - \ddot{X}_{i(j-1)}(t) = \{\phi_{i(j)} - \phi_{i(j-1)}\} \cdot \lambda e^{i\lambda t}$$

(17)

The inertia force $f_{i(j)}$ associated with the $i^{th}$ mode at the $j^{th}$ story is given by:

$$f_{i(j)}(t) = -\sum_{k=j}^{N} m_k \cdot \dddot{x}_{i(k)}(t) = -\lambda_i^2 e^{i\lambda t} \cdot \sum_{k=j}^{N} m_k \phi_{i(k)}$$

(18)

Restricting $k_{i(j)}$ and $c_{i(j)}$ to be real numbers, the equation of equilibrium with respect the force acting on the $j^{th}$ story is derived as:

$$k_{i(j)} \cdot d_{i(j)}(t) + c_{i(j)} \cdot \dot{d}_{i(j)}(t) = f_{i(j)}(t)$$

(19)
Solving the above equation in least square manner, the stiffness and damping of the $j^{th}$ story should be obtained. It is noted that we do not use the $i^{th}$ modal mass. A free vibration with the shape of the $i^{th}$ mode is assumed to obtain the inertia force $f_{ii}(t)$ given by Eq. (18). Thus, $m_k$ in Eq. (18) is the true mass.

This algorithm requires only one mode, thus it is unnecessary to consider the superposition of multiple modes using the participation factors. In Eq. (19), a stable mode selected based upon the behavior of the participation factor is used. The moving window is used for the data extraction. The initial conditions for each window would not affect the identification as the MOESP approach generates the free vibration in the course of parameter identification. The algorithm requires short data length that is approximately equal to the first natural period of the object building. For each segment, the stiffness and damping values are obtained. Features and novelties of the proposed algorithm are:

1. Stable and precise identification using stable modal properties.
2. The input-output relationship is defined by the participation factor.
3. Online identification is possible using MIMO models.

Our proposed algorithm consists of two steps, modal parameter estimation by MOESP and story parameter identification.

2.5. Simplified models for base-isolated buildings

As stated in the introduction, the damage scenario of a base-isolated building is much simpler and more reliable than that for a conventional building. A typical base-isolated building can be separated into two structural systems, a superstructure and an isolation layer. The story stiffness of the superstructure is much higher than that of the isolation layer. The significant contrast in the story stiffness suggests us to treat two structural
systems separately. We focus ourselves on the isolation layer where the most seismic energy is dissipated. The base shear force at the isolation layer can be obtained by the inertia force calculated from acceleration data at each floor and the mass distribution. However, the direct integration of acceleration to obtain displacement response is usually erroneous so that a correct restoring behavior of the isolator is not easily obtained. Our proposed approach resolves this difficulty by employing more stable method. Direct application of our approach for identifying the stiffness and the damping of the isolation layer requires the response at every floor as expressed in Equation (18). However, installing many sensors may not be feasible for most structures. For the case where only a limited number of sensors is available, simple models for base-isolated buildings proposed here would be effective. As the superstructure vibrates in the very low frequency band compared to its lowest natural frequency, the motion of the superstructure should be quasi-static so that simple approximation may work well. Three models are explained below:

**Rigid body**

The simplest model is to treat the superstructure as a rigid body. Therefore, motion of the superstructure can be described by the response obtained by a sensor attached to the superstructure. For the system where the acceleration at the base and at the first floor of the superstructure is measured, the equation of motion is written as:

\[
\sum_{j=1}^{N} m_j \ddot{X}_j + c_i (\dot{X}_i - \dot{X}_0) + k_i (X_i - X_0) = 0
\]  

(21)

**Linear interpolation**
The second model is made by assuming the response of the superstructure to be linear. Therefore, the response is defined by the response at the top and the bottom of the superstructure.

**Cosine interpolation**

A slightly better model is available for a building that has uniform mass and stiffness distribution. For a structure consisting of identical mass and stiffness, the fundamental mode vector can be expressed by a cosine function as [13]:

\[
\phi_{1(h)} = \cos \left[ \frac{\pi}{2} \gamma \left( 1 - \frac{h}{H} \right) \right]
\]  

(22)

where, \( h \) is the height where the response is defined, \( H \) is the total height of the structure, and \( \gamma \) is the constant defining the 1\textsuperscript{st} natural frequency of the structure.

Schematics of three models are shown in Figure 2. Using a simple model, the required number of sensors is significantly reduced.

### 3. ANALITICAL VERIFICATION

3.1. Model description

A 4-story shear model is considered, as shown in Figure 3. It has uncoupled translational modes in X- and Y-direction. Each mass was assumed to be 1000ton. We chose the stiffness values and damping factors to realize the fundamental natural frequency of 1Hz and the damping ratio of 5% for X-direction and 2Hz and 5% for Y-direction. To consider nonstationary of the model, the stiffness of the 3\textsuperscript{rd} story in X-direction (underlined in Fig.4) is gradually reduced from the elapsed time of 5sec. With
the sampling frequency of 100Hz and the duration of 10sec, the response analysis was conducted using the Wilson’s θ method [14]. The inputs considered here were generated as white noises with 1% sensor noise added. X- and Y- inputs were simultaneously applied to the structure.

3.2. Damage detection using MIMO models

The MOESP algorithm is applied to MIMO models considering two inputs and eight outputs. Two inputs are X and Y components of the ground acceleration. Eight outputs are X and Y components of the acceleration response at four floors. For each segment for the MOESP, the data length of 0.99sec was chosen. The length results in the Hankel matrix of 20-rows 80-columns. As a result of singular value decomposition (SVD) in the first segment as shown in Figure 4(a), the model order was chosen to be 16. The cumulative contribution ratio (the percentage of the sum of the selected singular values to the whole singular values) of 16 singular values was retained more than 90% all the time. In addition, we verified that the cumulative contribution factor is significantly reduced when the sudden reduction of the story stiffness occurs in the model. This means that the cumulative contribution ratio can be an index for detecting the change of vibration characteristics due to the sudden destruction of the building. However, detailed discussion on this matter is not included here.

Fundamental modal frequencies were estimated based on the lowest 2 poles as shown in Figure 4(b). They correspond to the fundamental mode in X- and Y-direction, respectively. But it is not obvious when the prior knowledge about the modal information of the model was not available. To specify the input-output relationship in the MIMO model, the participation factors are used. The time histories of the
participation factors for the 1st mode are plotted in Figure 5. The participation factor of the (X-X) can be found stable, where (X-X) stands for the relationship between the input in X-direction and the output in X-direction. On the other hand, the participation factor of the (X-Y) is around zero. From this observation, the 1st mode can be concluded that it is associated with the X-component and has no correlation with the Y-component. For the participation factors of the 2nd mode, it is easily observed that the stable mode is only for the combination of (Y-Y). Hence, the second mode is the mode associated with the Y component. Consequently, the 1st and 2nd modes are suitable for the identification of the parameters in X- and Y-direction, respectively.

Using the first mode for identifying the stiffness and damping in X-direction, and the second mode for those in Y-direction, the estimated values are plotted in Figure 6 compared with true values. The identified values are confirmed excellent. Gradual reduction in the stiffness of the 3rd story was well estimated so that the proposed algorithm is applicable to nonstationary response.

Furthermore, we carried out an additional simulation assuming the 2nd and 4th layers were damaged simultaneously. The average of the identified stiffness in the 4th layer was $3.271 \times 10^5$ [kN/m] and $2.290 \times 10^5$ [kN/m], when the actual value was $3.273 \times 10^5$ [kN/m] and $2.291 \times 10^5$ [kN/m] (before and after damage, respectively). This simulation enhances effectiveness of the algorithm.

4. EXPERIMENTAL VERIFICATION

4.1. Experiment description
A 4-story shear structure model is used in the experiment as shown in Figure 7. Every floor in the test structure consists of 30cm×30cm×1cm aluminum plate supported by four plate springs made of phosphor bronze. The height of each story is 30cm. The weight of the mass is 3.5kg. The test structure represents base-isolation by using two types of plate springs. One is thin (t=1.5mm) for the isolation layer and the other is thick (t=2.5mm) for other stories. Response accelerations at every floor were recorded for 20sec with the sampling frequency 200Hz. The pulse input was applied to the base.

4.2. Spectrum analysis

At first, the spectrum analysis was carried out using the measured signals. The power spectral density functions, the coherence function and the transfer function are shown in Figure 8. They were calculated using the 2048 data points per a frame and the quarter-overlap window. Four peaks can be seen under 20Hz in the transfer function. In addition, the major power of the signals are under 20Hz as observed from the power spectrum density functions.

4.3. Application of proposed algorithm

We applied the MOESP algorithm to the 1-input and 4-outputs model, considering the base accelerations as the input and the acceleration response at each mass as outputs. The data was decimated to 50Hz before applying the MOESP. For each segment, the data length was set to be 0.98sec with the Hankel matrix of 10-rows 40-columns. As a result of SVD for the first segment, model order was chosen to be 9. The cumulative contribution ratio of 9 singular values was retained nearly 100% all the time. The modal frequencies were estimated based on all poles in the state space model as shown in
Figure 9(a). Comparing the participation factors as shown in Figure 9(b), the 1st mode was found dominant and stable. Therefore, the 1st mode was chosen for estimating story properties. The modal properties of the 1st mode are summarized in Figure 10.

Using the properties of the 1st mode, the stiffness and damping of the isolation layer were identified. The results using three simple models are compared with the results obtained by a whole model in Figure 11 and in Table 1. From the results, the cosine interpolation showed the most accurate results. This observation is reasonable as the mass and stiffness distribution for the model structure was uniform. In addition, the simple hand calculation was carried out to compare the identified parameters with the true parameters. Due to the simple hand calculation, the true stiffness in the isolation layer is about 2000[N/m]. This is consistent with the identified value.

5. APPLICATION TO THE EXISTING BASE-ISOLATED BUILDING

5.1. Description of building and monitoring system

The proposed algorithm is applied to the existing school building at Keio University in Japan. The monitoring target is the 7-story base-isolated building with the gross floor area of 18,606m² and with total height of 31m. It is equipped with the high-damping rubber bearings of 750 Ø 900 Ø diameter as the isolation devices between the base and the 1st floor. The basic frame system of the superstructure consists of CFT (Concrete Filled Tube) columns and steel beams.

The building is equipped with a monitoring system consisting of 16 accelerometers at 7 locations, 3 displacement meters at 2 locations. The sensor location is indicated in the elevation view as shown in Figure 12. Sensor measurements are recorded with sampling
frequency 100Hz in the monitoring server located on the 1st floor. The measured data can be retrieved via internet. The web-server has several signal analysis tools so that engineers can check the health of the building any time using his or her computer. For conducting detailed analyses such as the one explained here, the stored data can be easily downloaded to the local computer.

5.2. Analysis conditions

(1) The input-output data

In this analysis, 2-inputs and 6-outputs model was considered as summarized below:

Inputs: Translational acc. at the base ---- BF-Trans.X (#1-X) and BF-Trans.Y (#1-Y)

Outputs: Translational acc. in X-direction at the 1F and RF ---- RF-Trans.X (#5-X), 1F-Trans.X (#2-X)

Translational acc. in Y-direction at the 1F and RF ---- RF-Trans.Y (#5-Y), 1F-Trans.Y (#2-Y)

Torsional acc. at the 1F and RF ---- RF-Tors. [((#5-Y)-(#6-Y))/2], 1F-Tors. [((#2-Y)-(#3-Y))/2]

(2) Prescribed model properties

The building is modeled as a lumped shear system. The mass distribution is given in Figure 13.

(3) Input earthquake

The small earthquake occurred in the southern area of Ibaraki prefecture in June 14, 2002 is used for the analysis. The characteristics of the earthquake are listed in Table 2.
The time histories of the relative displacement of the isolation layer are presented in Figure 14 to show the level of the earthquake.

5.3 Evaluation of isolation layer

At first, data decimation to 20Hz was conducted. Then we estimated the modal properties considering the 2-inputs and 6-outputs model as described in the previous section. For each segment, the data length was set to be 3.95sec corresponding to the Hankel matrix of 10-rows and 70-columns. As a result of SVD for the first segment, model order was chosen to be 17. The cumulative contribution ratio of 17 singular values was retained more than 90% all the time. Considering the response level, we utilized data from 10 to 60sec in this analysis.

The lowest two modal frequencies were estimated as shown in Figure 15. Considering the participation factors, the first mode was identified to be the translational mode in Y-direction. Similarly, the second mode was identified to be the translational mode in X-direction.

Therefore, the 1st mode is appropriate for identification of the parameters associated with the Y-direction. The parameters in the isolation layer were identified using the cosine interpolation and are shown in Figure 16 compared with the values calculated from measured relative displacement data. Both results were found consistent, thus the validity of our proposed method was confirmed. The identified stiffness in the isolation layer, about $2\times10^6\,\text{kN/m}$, was in the same order of the story stiffness of the superstructure. This means that the isolation devices were not in the operation range for this small earthquake. The high-damping laminated rubber bearing is known that it exhibits large variation in the damping values in the small amplitude vibration. For the
segments in which the amplitudes of response are small, the precise identification of damping is difficult. Therefore, some values became negative.

6. CONCLUDING REMARKS

A damage detection algorithm for structural health monitoring systems based on the subspace identification and the complex modal analysis was proposed. The proposed algorithm is applicable to any shear structures. The algorithm utilizes the participation factors to identify the input-output relations for each mode obtained from the MIMO (Multi-Inputs and Multi-Outputs) models. Introducing the substructure approach, the algorithm was tuned for base-isolated buildings so that the required number of sensors would be significantly reduced. The effectiveness of the algorithm was examined through the simulations and the experiments. Furthermore, applying the algorithm to the existing 7-story base-isolated building that is equipped with an internet-based monitoring system, feasibility of the algorithm was verified.

REFERENCES


Figure 1. N-story shear structure.

Figure 2. Simplified models for base-isolated buildings.

Figure 3. 4-story shear model.

Mass:
\[m_1 \sim m_4 = 1000 \text{ [ton]}\]

Y-dir. Stiffness: \([\text{kN/m}]\)

Y-dir. Damping: \([\text{kN*}\text{s/m}]\)

\begin{align*}
\text{Gradual reduction} \\
\begin{aligned}
\text{X-dir. Stiffness: } [\text{kN/m}] \\
\text{X-dir. Damping: } [\text{kN*}\text{s/m}] \\
\end{aligned}
\end{align*}
(a) Singular values for the first segment.  
(b) Fundamental modal frequencies

Figure 4. Modal parameter estimation.

Figure 5. Participation factors of 1st mode.

(a) In X-direction using 1st mode  
(b) In Y-direction using 2nd mode

Figure 6. Identified stiffness.
Figure 7. Test model.

Figure 8. PSD, coherence and transfer function.

Figure 9. Modal parameter estimation.

(a) Estimated modal frequencies.  (b) Estimated participation factors.
Figure 10. Properties of 1st mode.

Figure 11. Identified parameters in the isolation layer.

Table 1. RMS errors for three simplified models.

<table>
<thead>
<tr>
<th>3-types of SSA</th>
<th>RMS Error to the whole model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Stiffness [N/m]</td>
</tr>
<tr>
<td>Rigid body</td>
<td>362.5</td>
</tr>
<tr>
<td>Linear interpolation</td>
<td>62.6</td>
</tr>
<tr>
<td>Cosine interpolation</td>
<td>59.9</td>
</tr>
</tbody>
</table>
Figure 12. Elevation view of 7-story base-isolated building.

Figure 13. Mass distribution of existing 7-story base-isolated building.
Table 2. Recorded earthquake response.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Date</strong></td>
<td>2002.06.14</td>
</tr>
<tr>
<td><strong>Time</strong></td>
<td>11:42</td>
</tr>
<tr>
<td><strong>Epicenter</strong></td>
<td>N36°12.7’ E139°58.8’</td>
</tr>
<tr>
<td><strong>Depth [km]</strong></td>
<td>57</td>
</tr>
<tr>
<td><strong>Magnitude</strong></td>
<td>4.9</td>
</tr>
<tr>
<td><strong>Maximum RF-Trans.X</strong></td>
<td>20.07</td>
</tr>
<tr>
<td><strong>Trans.Y</strong></td>
<td>19.58</td>
</tr>
<tr>
<td><strong>Maximum BF-Trans.X</strong></td>
<td>13.81</td>
</tr>
<tr>
<td><strong>Trans.Y</strong></td>
<td>9.08</td>
</tr>
<tr>
<td><strong>Maximum BF X-dir.</strong></td>
<td>0.63</td>
</tr>
<tr>
<td><strong>Y-dir.</strong></td>
<td>0.76</td>
</tr>
</tbody>
</table>

Figure 14. Relative displacement response of isolation layer.

Figure 15. Estimated modal frequencies.
Figure 16. Identified stiffness and damping of isolation layer in Y-direction.