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INFORMATION THEORETIC APPROACH FOR EARTHQUAKE-INDUCED BUILDING STRUCTURAL DAMAGE DIAGNOSIS

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Abstract

This paper introduces a damage diagnosis algorithm using an information-theoretic approach to localize building structural damage due to earthquakes. Accurate and timely post-earthquake diagnosis of building structural damage is important for facilitating emergency responses and rehabilitations. Many prior works have focused on structural health monitoring methods to automate damage diagnosis. Among the approaches, structural vibration-based methods have been widely adopted; however most of them 1) require detailed prior information about the structure (model-based), which may not be available in reality; 2) consider each location measurement separately (signal-based), which requires dense deployment of sensors (costly to install); or 3) require post-earthquake sensing data, which is often impossible due to broken sensing/communication systems and limited availability personnel These constraints limit the applicability of existing approaches in real scenarios.

This paper presents a method that localizes seismic damage in building structures by representing the wave propagation process as information exchanges between vibration signals. When a seismic wave is propagated inside building, the form of the wave changes depending on the dynamic characteristics of the structure (i.e., carries information about structural properties). Thus, the relationship between such information (i.e., information exchange) measured from different locations in the building represents the state of structure at corresponding areas. This method consists of three steps: 1) Structural vibration at each floor is recorded during an earthquake from an instrumented building. 2) A feature based on the 'directed information' metric from information theory is extracted to quantify the information exchange between two vibration sensor signals. 3) By detecting the changes of the information exchange feature, the evolution of seismic structural damage state is estimated. This information theoretic approach eliminates simplifying assumptions about the vibration process, such as linearity or specific distribution, which contributes to improving the damage diagnosis accuracy. The advantages of the proposed method are that it1) is accurate across different structures 2) is robust to noisy measurements 3) requires only sparse deployment of sensors and 4) does not need post-earthquake data. The algorithm is validated using experimental data from a 4-story steel moment resisting frame subjected to a series of earthquake excitations. As a result, the damage is localized with up to mean square error 4X improvement compared with the baseline method.

Keywords: Seismic Damage Diagnosis, Information Theory, Building Vibration Analysis, Damage Localization

1. Introduction

Accurate and timely diagnosis of seismic damage in a structure is critical for determining buildings' safety and facilitating emergency responses. Such damage diagnosis can reduce economic losses and ensure that people avoid dangerous structures. This is especially important for initial earthquake response in identification of safety for critical structures. Earthquake-induced building damage is one of the most critical threats to cities [1, 2, 3]. In particular, the locations and levels of damage in a building are essential pieces of information for successful rescue and reconstruction in disaster areas. Therefore, there is a clear and critical need for methodology that can rapidly assess earthquake-induced damage of buildings and localize damage for repair.

Current practices of evaluating damage to buildings after earthquake events mainly involve visual inspection. However, these approaches are labor intensive, time consuming, and error prone [4, 5]. To address these challenges, previous research takes one of two main categories: remote sensing image-based techniques and vibration-based techniques [6, 7, 8, 9, 10, 11, 12, 13]. The former requires high resolution and good weather conditions, which limit their applications in damage diagnosis and detection. Vibration-based technology can provide the accuracy and speed needed to quickly evaluate the structural health. However, vibration-based method are often challenging in practical post-earthquake scenarios due to three main factors. 1) These methods are often sensitive to non-stationary noise, which is often difficult to characterize in extreme events such as earthquakes. 2) These methods tend to require high-density sensor systems that are expensive to both deploy and maintain. 3) Many methods require post-disaster sensor data, which are often damaged post-earthquakes.

This paper introduces a method to localize story-level damage using a sparse deployment of acceleration sensors. The method is based on the premise that the structural damage will induce changes in wave propagation patterns between two points, which can be viewed as information exchanges between these two point. Recently, the advances in information theory succeeded to quantify the causality and determine real-time causal relationship [14, 15, 16]. Through detecting changes in exchanges of information between a pair of sensors, the algorithm can determine the damage situation in the physical interval between locations of two vibration sensors with little prior knowledge. This approach allows improved performance of damage diagnosis by eliminating assumptions on linearity and probability distribution of the stochastic processes. To collect this information, the proposed method only requires an accelerometer to be installed on each floor before an earthquake event. Structural vibration signals from each floor are then collected during earthquake excitations. This also means that there is no need for collecting data after earthquakes, when damage to roads, power lines and other infrastructure may prevent access to the building or disrupt data collection. The algorithm extracts the information exchanges between vibrations of the floor and the ceiling of each story, and uses them as damage-sensitive features to estimate the structural damage. The estimation is achieved by detecting the changes in the information exchange pattern during earthquake using machine learning techniques. This paper has three key contributions:

1) This paper proposed a method to localize post-earthquake damage in the building using sparsely implemented sensors.

2) This paper represented wave propagations in building structure as information exchange, which allows the analysis of noisy data with less prior structural knowledge.

3) This paper evaluated the algorithm using experimental data on a 4-story moment resisting frame subjected to a series of earthquake excitations.

In this paper, the physical insights of representing vibration responses as information flow are firstly explained in Section 2. Then the damage localization algorithm is introduced in Section 3 and evaluated in Section 4. Finally, Section 5 concludes the paper.

2. Physical Insights for Information Exchanges with Structural Vibration

Information exchange is a concept typically used in signal processing and related areas. This section provides the physical insights linking this concept with the physical earthquake induced vibrations. When an earthquake happens, the seismic waves propagate from the ground into the building. These waves then propagate throughout the building. In each story of the building, these waves can be separated into two parts: up-going and down-going components [17]. Whenever the up-going and down-going waves cross a floor interface, they are partly reflected and partly transmitted into the next floor. As waves propagate, their amplitudes, phases and other identical features are changed by the structural characteristics because of the reflections and transmissions at the floor interface. Thus it can be viewed as that the information about the structure is captured in the wave as it propagates. Therefore, when a wave propagates between two locations, information about structures along the propagation path, and the earthquake excitations that generated the wave, can be viewed as being exchanged between the locations.

At each story in the building, the information (i.e. wave deformation) at that location is affected by the vibration coming from above and below it. So for two neighboring floors the shared information is the connecting structures between them. For example, the waves at the ceiling of the 2nd story are affected by the 2nd story and 3rd story, and the wave at the celling of 3rd story is affected by the 3rd story and the 4th story. The shared information between these two waves will then be the information from the 3rd story. Thus, if we have a sensor on each floor, the shared information between neighboring sensors will reflect the structure for the story between the sensors.

Wave propagation patterns inside building will be altered if structural state changes during an earthquake (e.g. due to damages). If there is damage in the propagation path, structural properties change, and the characteristics of the shear waves will be altered. Assuming at the start of the earthquake, the building is not damaged, then these alterations can be extracted to identify and localize corresponding damage inside the building.

Since structural damages will induce changes in the information exchange patterns inside the building, the algorithm can detect such changes to diagnose the damage state of structure. Here, the concepts of directed information are introduced to represent information exchanges between vibration signals [14, 15, 16]. The vibration signals are collected from the floor and ceiling of one story. The directed information inferred from vibration signals contains damage state in the physical area between the two measurement locations, including the sensor locations themselves. In addition, the algorithm estimates the damage of the target area by detecting the changes of structural state at different time intervals. Some material difference in the structural components or existing void, like a pipe into a masonry wall, will not affect the performance, since they are existing parts of structure and will not change with time.

3. Description of Damage Algorithm

Base on the physical intuition described above, the proposed algorithm aims to localize structural damage using its acceleration responses to earthquake excitations. In this paper, the algorithm is explained for story-level localization for simplicity, and can be expanded to finer/coarser-grained localization, depending on the sensor density. The algorithm first collects acceleration responses from each floor and then bi-directional information exchanges between two adjacent floors are extracted as a damage sensitive feature of the corresponding story. With these features as input, ridge regression is applied to estimate the structural damage of each story and thus localize damages in story level. We describe the algorithm in greater details bellow.

3.1 Data collection: structural response

In the proposed algorithm, the absolute vertical acceleration response of each floor is respectively collected during each earthquake excitation for N data points. These vibration signals are quantized into S levels for computational efficiency. The exchanged information in each story is extracted from pairs of pre-processed vibration data collected from two adjacent floors. For example, vertical accelerations of the floor and the ceiling of the ith story, namely X^i and X^{i+1}, are used to extract the information exchanges in ith story. In our experiments (described in Section 4.1), we collect single-axis horizontal information, this can be easily extended to multiple axis given matching axis between sensors.

3.2 Directed information as a feature

Given vibrations collected from each floor, the algorithm uses directed information as a feature to quantify the information exchanges in each story. To describe the approach and overview of directed information is first provided (Section 3.2.1), and then it is shown how to extract directed information as features from the collected data (Section 3.2.2). This feature is used for estimation of structural damage (Section 3.3).

3.2.1 Directed information overview

To better describe the proposed approach, an overview of directed information is firstly provided. Directed information is a measurement, which represents the overall information exchange in one direction between two signals. Suppose there are two stochastic processes, X^i and X^{i+1}, which are vibration signals from two sensors installed in the floor and ceiling of ith story. Information theory helps quantify information exchanges between X^i and X^{i+1}. In information theory, the entropy measures the information contained in each random variable or process. When two stochastic processes, X^i and X^{i+1}, are mutually dependent, it means X^i and X^{i+1} share some information (i.e. entropy reduction of $X^{i+1}$by knowing X^ior vis versa). Mutual information is used to quantify this shared information (i.e., mutually dependent relationship) between X^i and X^{i+1}. Suppose time-series sequence X^i and X^{i+1} are collected for t time points from $1,\cdots,t$. Here, the mutual information shared by X^i and X^{i+1} is the information gain when changing the hypothesis from that X^i and X^{i+1} are independent to that X^i and X^{i+1} are dependent. The Kullback-Leibler (K-L) divergence is applied to measure this information gain. For independent processes, the joint probability density function will be $P(X_1^i,\cdots,X_t^i)\times P(X_1^{i+1},\cdots,X_t^{i+1})$. For dependent processes, the joint probability distribution of X^i and X^{i+1} will be $P\left(X_1^i,\cdots,X_t^i;\ X_1^{i+1},\cdots,X_t^{i+1}\right)$. With the mathematical definition of $D_{KL}(f \parallel g) = E_f[\log\left(f(x)/g(x)\right)]$, the Kullback-Leibler (K-L) divergence measures the information gain when changing the assumption about the distribution of a random variable from a probability distribution g into a probability distribution f. In the case of calculating mutual information, the prior distribution g is based on the assumption that X^i and X^{i+1} are independent, and posterior distribution f is based on that X^i and X^{i+1} are dependent. And the mutual information can be expressed using K-L divergence as:

$$I(X_{1:t}^i; X_{1:t}^{i+1}) = E[log\frac{P(X_{1:t}^i;X_{1:t}^{i+1})}{P(X_{1:t}^i)P(X_{1:t}^{i+1})}] \quad (1)$$

However, mutual information only describes how much information is shared (i.e. how similar two floors vibrate), but does not contain *how* the information is shared (i.e. which direction the wave propagates). To include the directivity of shared information, Massey [14] proposes the concept of directed information. Directed information builds on mutual information by describing how information flows from one time series to another. For example, directed information from X^i to X^{i+1} represents the how much current information from X^i can be used to predict the future vibration value of X^{i+1}. Similarly, to quantify the directed information using K-L divergence, the prior assumption needs to be changed from that X^i and X^{i+1} are independent into assumption that X^i and X^{i+1} are partially dependent. For example, to obtain the directed information from X^i to X^{i+1}, the new prior distribution corresponds to the assumption that X^i is dependent on X^{i+1} but X^{i+1} is not dependent on X^i. The prior distribution g, which is based on that X^i and X^{i+1} are partially dependent, will become $\bar{P}(X_{1:t}^i|X_{1:t}^{i+1})P(X_{1:t}^{i+1})$, where $\bar{P}\left(X_{1:t}^i|X_{1:t}^{i+1}\right) = \prod_{k=1}^N p(X_k^i|X_{1:k}^{i+1}, X_{1:(k-1)}^i)$. And the directed information is defined as:

$$I(X_{1:t}^i \rightarrow X_{1:t}^{i+1}) = E[log\frac{P(X_{1:t}^i;X_{1:t}^{i+1})}{\bar{P}(X_{1:t}^i|X_{1:t}^{i+1})P(X_{1:t}^{i+1})}] \quad (2)$$

By separately looking at the information conveyed from X^i to X^{i+1} and from X^{i+1} to X^i, the directed information quantifies the causality between X^i and X^{i+1} [15]. Based on above definition, Jiao et.al has developed directed information estimator based on minimax estimation of discrete distributions [15, 16].

3.2.2 Extraction of directed information as feature

In the proposed approach, directed information from floor to ceiling/from ceiling to floor of each story is extracted as feature of the corresponding story. Given a l-story building, the causality between two vibration signals, quantified as directed information, reflects the situation of vibration propagation in the physical interval between locations of the sensor pair as explained in Section 2. Thus, the causality can be used to infer the structural condition of this physical interval and make the evaluation of its damage state.

In the proposed method, the vibration signals of each floor are first discretized for computational efficiency. Each sensor pair here includes the two sensors at floor of the ith story, which is X^{i}, and the ceiling of the ith story, which is X^{i+1}. To estimate directed information by looking at the difference between two sequences, the signals need to be quantized into S level with the principle of $n \approx \frac{S^{D+1}}{lnS}$ [16], where n is the least number of samples necessary to estimate DI at each time point with statistical stability and D is the maximum value of estimated delayed time between two processes. Then X_i and X_{i+1} are reorganized into two $\mathrm{m}\times(\mathrm{N}-\mathrm{m})$ matrix M_i and M_{i+1} as input for the minimax estimation with the principle that $m \geq n$ [16], where N is the total number of samples in the signal. As a result, directed information from X_i to X_{i+1} (denoted $\mathrm{I}(X_i \rightarrow X_{i+1})$) and from X_{i+1} to X_i (denoted $\mathrm{I}(X_{i+1} \rightarrow X_i)$) are extracted. To differentiate these two directions ($X_i \rightarrow X_{i+1}$ and $X_{i+1} \rightarrow X_i$), directed information (DI) is used to represent the information from floor to ceiling of the ith story, and inverse directed information (inverse DI) is used to refer to the information from the ceiling to floor of the ith story. The extracted directed information and inverse directed information between the floor and the ceiling is the feature for the ith story.

3.3 Damage localization

Using the directed information features extracted above, kernel regression is applied to estimate the actual value of damage in each story, which is represented through story drift ratio (SDR) in our case. While there are many data-driven approaches for determining damage state in each story, accurately predicting the value of structural damage is still difficult [20, 21, 22, 23, 24]. SDR is a commonly used index for identifying structural damage and to relate ground motion intensity to structural damage [25, 26, 27]. In practice, it is difficult and expensive to automate a direct and accurate evaluation of structural drift. In contrast, the directed information is computed from the acceleration response of a structure, which is relatively easier to measure than displacement. Here, with quantified information flows propagating with waves, the aim is to estimate the final value of SDR when the earthquake ends (i.e., SDR due to permanent displacement in the building).

A supervised-learning method is used in this paper for SDR estimation with the DI features. In particular, Kernel ridge regression (KRR) models and cross validation are applied to train the model. KRR is one of ridge regression method combining with kernel trick [28, 29]. Ridge Regression addresses the overfitting problem of Ordinary Least Squares by imposing a penalty on the size of coefficients. Given a set of n samples $(\mathrm{A_1}, \mathrm{B_1})$, $(\mathrm{A_2}, \mathrm{B_2}), \cdots, (\mathrm{A_n}, \mathrm{B_n})$, where $\mathrm{A_i} \in \mathbb{R}^t$ is a vector of features belonging to the ith sample, and $\mathrm{B_i} \in \mathbb{R}$ is outcome of the ith sample, the solution of the ridge regression problem is to minimize the penalized square error as follows:

$$L_{RR}(w) = \sum_{i=1}^{n}(w^T A_i - B_i)^2 + \lambda||w||^2 \tag{4}$$

In our case, during-earthquake data are used to predict the value of final SDR at the end of an earthquake, which means high-dimensional feature space. Since the regression problem with high-dimensional feature space tends to be a non-linear problem and thus difficult to be solved, the kernel function $K(X, X_i)$ is applied for reducing the feature dimension to make the problem solvable in new feature space [28, 29]. The new features are:

$$Z = [K(A, A_1), \cdots, K(A, A_n)]^T \tag{5}$$

In particular, $(\mathrm{Z_1}, \mathrm{B_1}), (\mathrm{Z_2}, \mathrm{B_2}), \cdots, (\mathrm{Z_t}, \mathrm{B_n})$ are empirical samples in new low-dimensional feature space. Substituting $\mathrm{Z_i}$ for $\mathrm{A_i}$, KRR solution is obtained as:

$$\widehat{w} = arg\min_{w} \sum_{i=1}^{n}(w^T Z_i - B_i)^2 + \lambda||w||^2 \tag{6}$$

The main benefit of KRR is that it is computationally more efficient and better applicable to non-linear problem. While there are multiple kernel functions, the most widely used kernel is the Gaussian radial basis function (RBF) kernel [28], which is also selected for the proposed approach:

$$K(A,Z) = exp(-\frac{||A-Z||^2}{2d^2}) \quad (7)$$

where d is the kernel bandwith and controls the smoothness of the kernel function. In our case, the input feature A_i is the extracted information exchanges in the ith story, the output B_i is the SDR value to estimate. The parameter and optimization method selection are described in Section 4.3.

4. Evaluation

The algorithm is evaluated using experimental data collected from shake-table tests of a 4 story moment-resisting frame. The data is used to 1) analyze the response of directed information and inverse directed information of each story to various earthquake intensities and 2) compare performances (damage localization accuracy, SDR estimation error) between the proposed information-based model and baseline models.

4.1 Experiment setup

To evaluate the proposed algorithm, a four-story steel moment-resisting frame is used with sparse sensor implementation (one sensor in each floor). As shown in Fig. 1, based on current seismic criterion, the steel frame is installed with reduced beam moment connections, which can simulate various earthquake excitations [30, 31, 32]. A single-axis accelerometer sensor is installed in the middle of each floor to detect the accelerations in horizontal direction with sampling frequency of 128Hz. A series of single-axis shake-table tests with 4 different intensities of earthquake excitations were conducted at the NEES facility at the State University of New York at Buffalo [27, 33, 34]. The single-axis accelerometers are aligned with the direction of the single-axis shake table. The structure was subjected to the ground motion of 1994 Northridge earthquake recorded at Canoga Park Station.

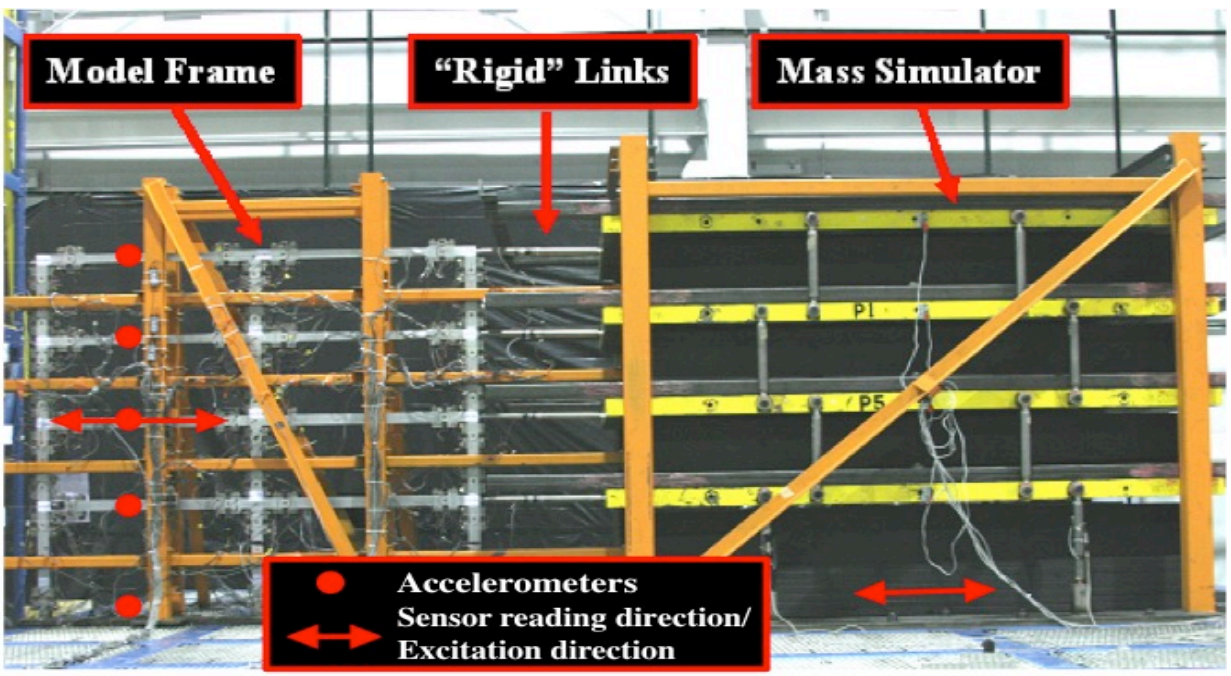

Fig. 1 Four-story steel moment-resisting frame with accelerometers implementation. Red points show the location of accelerometers. The accelerometers on each floor collect floor vibration in horizontal direction.

The testing sequence was designed using incremental dynamic analysis (IDA)[33]. The excitation pattern that was executed for the structure included a service level earthquake (SLE, 40% of the ground motion record), a design level earthquake (DLE, 100% of the ground motion record), a maximum considered earthquake (MCE, 150% of the ground motion record), and a collapse level earthquake (CLE, 190% of the ground motion record).

The excitations of above earthquake excitations are calculated by multiplying the factors of 0.4, 1.0, 1.5, and 1.9 to the amplitude of the original ground motions of the 1994 Northridge earthquake recorded at Cango Park Station. During each scaled intensity of the ground motion, accelerations at each floor, including the ground motion and the roof response, were measured. Meanwhile, there are five damage states defined for the structure in terms of SDR at each story, which are no damage (0% ≤ SDR < 1%), slight damage (1% ≤ SDR < 2%), moderate damage (2% ≤ SDR < 3%), severe damage (3% ≤ SDR < 6%), and collapse (6% ≤ SDR). These thresholds of SDR are selected to describe various damage states based on current practice [35, 36, 37]. Fig. 2 shows how the SDR of 1st and 2nd story change with varying intensities of earthquake. Based on the measured accelerations at each floor, features are extracted for damage detection and localization.

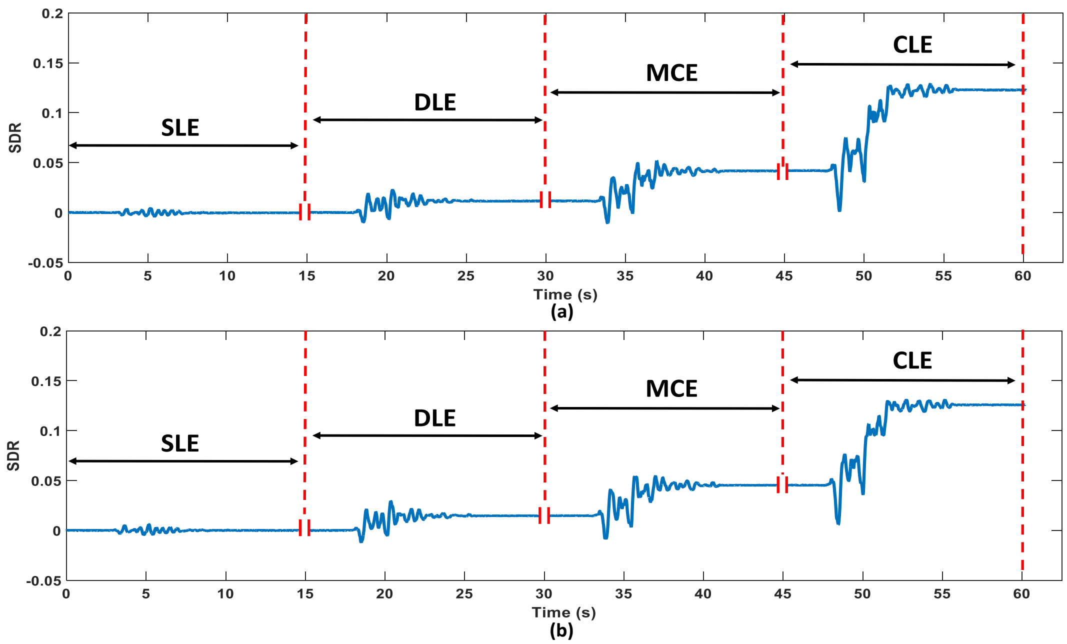

Fig. 2 (a) Story Drift Ratio of the 1st story during four earthquakes with different intensities; (b) Story Drift Ratio of the 2nd story during four earthquakes with different intensities.

4.2 Feature characterization

Using collected vibration signals, the information exchanges in each story are extracted as features. Each sensor pair here includes the two sensors at floor of the ith story and the floor above ($i \in \{1, \cdots, 4\}$). Based on the algorithm described in Section 3, the vibration signals of the two sensors are collected during each earthquake excitation for 10 seconds. Here quantization level is chosen as $\mathrm{S} = 10$, and X_i and X_{i+1} are reorganized into new matrix M_i and M_{i+1} with size of 40×1240 as inputs for the minimax estimation. As a result, there are 4 pairs of directed information from X_i to X_{i+1} and inverse directed information from X_{i+1} to X_i, where $i \in \{1, \cdots, 4\}$. Combining corresponding directed information and inverse directed information in each pair, a 2×1240 vector is obtained as feature for each story.

The extracted directed information and inverse directed information are analyzed. Figs. 3a and 3b show the time-series of directed information (red line) and inverse directed information (blue line) for the 1st story and the 2nd story under 4 increasing intensities of earthquake excitations (SLE, DLE, MCE, CLE), respectively. Comparing Fig. 3a and Fig. 3b, we can find that 1) for different stories under the same earthquake excitation, the value of directed information and inverse directed information decreases with the increasing of story number, which is due to the energy gradually dissipating as the wave propagates to the top story; 2) for the same story with different earthquake intensities, the relative value of directed information and inverse directed information changes corresponding to various structural damage states shown in Fig. 2. These characteristics of directed information and inverse directed information show that correlations exist between information exchange and structural damage in each story.

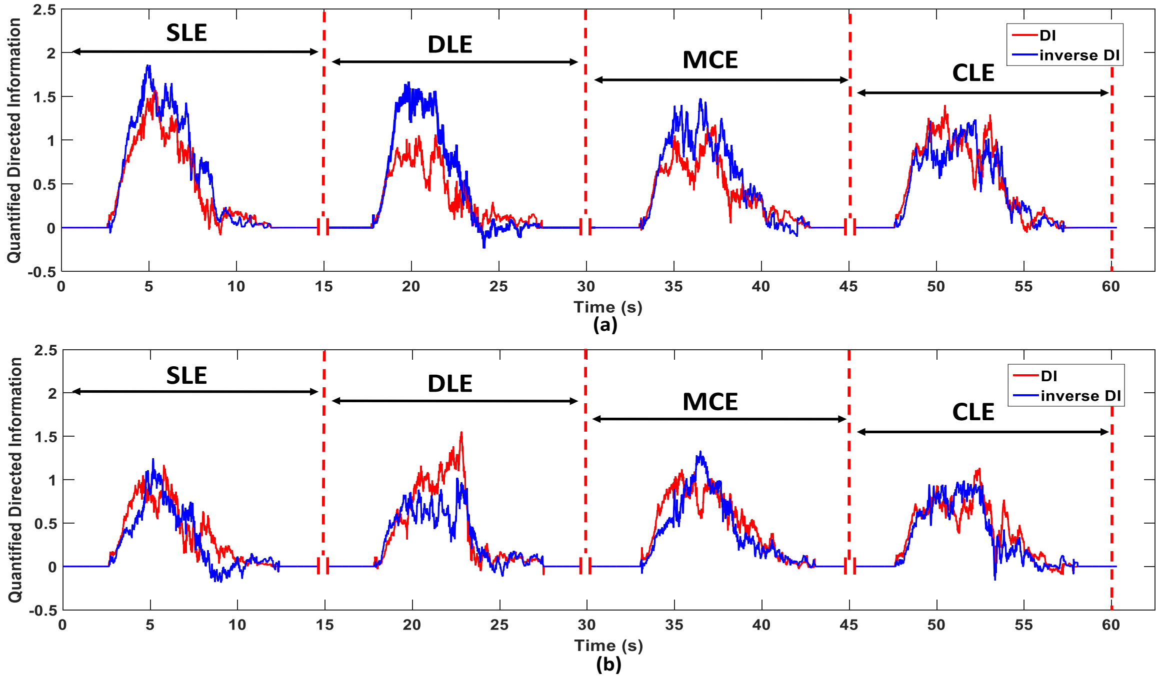

Fig. 3 (a) Directed information (red) and inverse directed information (blue) in 1st story (between 1st floor and 2nd floor); (b) Directed information (red) and inverse directed information (blue) in 2nd story (between 2nd floor and 3rd floor).

4.3 Damage localization results and discussion

To explore the floor-level structural damages under earthquakes' effects, a regression method is applied to estimate the value of the SDR when the earthquake ends. The directed information and inverse directed information are extracted as time sequences. Each example uses a ~1280 dimensional vector of features. The regression problem with high dimensional features is often difficult to solve in the original feature space due to possibility of the "curse of dimensionality" [28]. The kernel trick is applied to reduce the dimensions of feature space and convert the non-linear problem into a linear regression problem to solve it efficiently [28].

The training set is prepared with extracted directed information features for each measurement sample, and story drift ratio (SDR) as the corresponding output. The vibration signals for each story under 4 intensities of earthquake are collected as a time-series sample. For each time-series sample, the feature will be all extracted directed information and inverse directed information during earthquake. The outcomes are labeled using the average SDR after the earthquake ends; the average value is calculated using 50 samples to reduce the effects of noise. Using this dataset, a regression model is trained and the model's performance is evaluated in estimating the SDR value of different stories under various earthquake intensities.

When training the model, cross validation is used to evaluate the performance of the model. Both stochastic gradient descent (SGD) and limited-memory (LBFGS) Newton algorithms are applied for computational efficiency. For the bandwidth h and coefficient of regularization term λ, the optimal values 5 and 0.02 are selected respectively using cross-validation. By using leave-one-out cross validation, the mean square error is calculated to evaluate the accuracy of estimation. The mean square error between final estimation value and ground truth is 5.12×10^{-4}. The similarity test between sequences of estimation and ground truth shows the similarity is significant (with P-value of 0.0005).

As a comparison, the difference of raw vibration signals between the floor and the ceiling of the ith story as well as the autoregressive model coefficients are extracted as features. For the raw signal features, using the same training methods shown above, the best performance of alternative models resulted in the mean square error of 0.0021, which is 4.0X higher than the results of DI-based model. For the features based on autoregressive time series modeling of structure's acceleration response, there are several conventional methods for damage sensitive feature extraction [38, 39, 40, 41]. Here, the autoregressive coefficients are extracted by fitting vibration signals in each floor to the AR (3) model, and the coefficients extracted from accelerations in the floor and the ceiling of the ith story are combined as features for damage estimation in the ith story (AR coefficients-based features). The mean square error for regression model based on AR coefficients is 9.03×10^{-4}, which is 1.7X higher than the mean square error of DI-based model.

More detailed analysis results comparing the performance of the three approaches are shown in Fig. 4. It can be found that DI-based model can estimate the SDR value with lowest mean square error in most stories (1st, 3rd and 4th) and its overall performance is the best among three models. In particular DI-based model performs best in the top (4th) story of experimental frame due to less sensor noise on the higher floors.

For damage localization, we conducted hypothesis tests with the null hypotheses H_0: the story is undamaged (0% < SDR < 1%), and alternative hypotheses H_1: the story is damaged (SDR > 1%). The proposed algorithm localized the damage with type I error (false damage alarm) of 0%, and type II (false negative) error of 8.3%. The algorithm localized the damage with total accuracy of 93.75%, which is 12.5% higher than AR coefficients-based model and 18.75% higher than signal-based model.

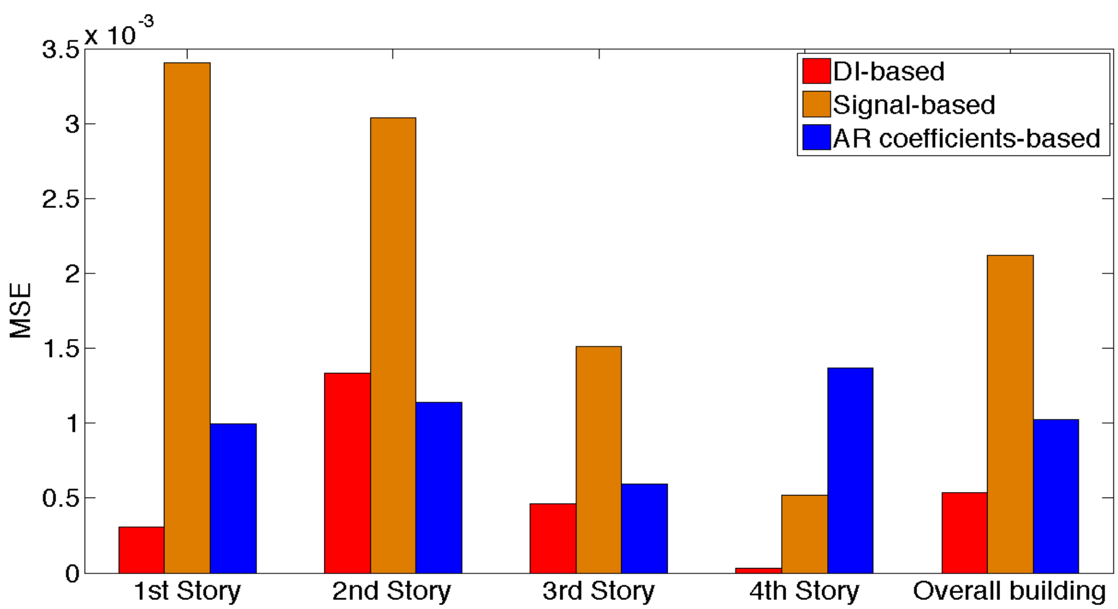

Fig. 4 Mean square error for estimating SDR value of each story and overall building under various earthquake excitations using DI-based model, raw signal-based model and AR coefficients-based model.

5. Conclusion

This paper presents a new approach to diagnosing earthquake-induced structural damage by examining changes in in-buildings wave propagation during an earthquake. Using information theory approaches, the wave propagation is modeled as a series of information exchanges (related to structural dynamic characteristics) between sparsely deployed sensing points in a building. Using sets of vibration signals collected from an experimental frame, the results show that, when using directed information based features, damage state of each story is classified with accuracy of up to 93.75%. In addition, estimation error for story drift ratio improved by factors of 1.7X and 4.0X when compared with using conventional autoregressive coefficients-based model and direct time-series vibration signals as features, respectively.

This information-theoretic method does not need to assume a particular structural model, or probability distribution of the vibration data. Furthermore, the algorithm uses only during-earthquake data from sparsely deployed sensors for detecting the existence of damage and estimating the actual story drift ratio at each story in a computationally efficient way. Hence, this approach is more robust than prior approaches in many practical earthquake scenarios.

6. Acknowledgement

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7. Copyrights

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