

Near-Real Time Evaluation Method of Seismic Damage Based on Structural Health Monitoring Data

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Abstract. Most modern seismic design codes build upon the concept of performance-based earthquake engineering that allows structures to sustain repairable damage during moderate and large earthquakes. Therefore, accurate and quantitative post-earthquake damage evaluation of real-world structures is crucial for safe operation of buildings. Structural-health monitoring provides sensor-based information regarding the structural state and informs post-earthquake building assessment. With the utilization of monitoring data, which is recorded during earthquake excitation, damage-sensitive features (DSFs) can be extracted in both purely data-driven or hybrid forms; with the latter term referring to damage indicators (DIs) that fuse data with dynamic models. In this paper, data-driven and hybrid damage identification methods are introduced and compared with respect to their performance and robustness in detecting and quantifying structural damage. The damage localization and quantification performance are discussed for varying number of building floors. Moreover, numerical models are used to enable the comparison of DSFs with metrics of nonlinearity, such as maximum drift, and with response metrics that are traditionally used to quantify damage, such as maximum inter-story drifts. Finally, uncertainties in DSFs and their sensitivity to sensor noise, prior knowledge of mass and the spectral content of earthquake excitation are assessed to explore the robustness of the hybrid DI.

Keywords: Structural health monitoring \cdot Damage identification \cdot Hybrid damage indicators \cdot Damage-sensitive features \cdot Post-earthquake damage assessment

1 Introduction

Most modern seismic design codes build upon the concept of performance-based earthquake engineering [1] that allows buildings to sustain repairable damage during moderate and large earthquakes [2]. Yet, structural damage negatively affects structural safety and future seismic performance of buildings, thereby exposing residents to a significant risk [3]. Hence, rapid and accurate assessment of the structural performance and the damage state of buildings during strong earthquakes is crucial for post-earthquake decision making [4]. Assessing the structural performance after an earthquake commonly involves engineering demand parameter (EDPs), such as drift values that are widely used [5]. Based on EDPs, structural deterioration and damage can be inferred using predefined limit values, such as those proposed in current guidelines [6]. However, direct measurement of EDPs often poses challenges, as the measurement precision that is required for decisionmaking on residential buildings after an earthquake cannot be achieved at reasonable cost. In addition, the limited application of pre-defined threshold values to an individual building at hand results in an extensive reliance on expert-conducted visual inspections, despite the time-consuming, labor-intensive, and subjective outcomes [7].

Continuous structural health monitoring (SHM) of buildings under seismic risk may provide accurate and objective information on structural damage [8]. Availability of affordable and sensitive sensing solutions make SHM based on measured accelerations a viable solution to record structural responses and to extract damage-sensitive features (DSFs) that enable conclusions regarding the safety condition of structures [9]. Thus, SHM offers opportunities to correlate measured structural responses with damage [10].

Currently, many DSF formulations involve changes in vibration response and structural dynamic characteristics, such as natural frequency and mode shapes [11–14]. On the other hand, a series of damage models based on EDPs have also been proposed and utilized for decades, such as the Park-Ang model [15], and the energy based damage indicators [16]. Although most of them have been proven to be theoretically efficient, limitations of available sensing solutions often hinder their real-world application within a SHM framework.

In this paper, a hybrid damage indicator, based on the model-reference concept, is briefly introduced in Sect. 2. The formulation and key characteristics are presented for a simulated case study: a five-story shear spring-mass model with stiffness deterioration. With the utilization of the simulation cases, the damage quantification and localization results of the proposed method are illustrated in Sect. 3. Subsequently, the performance of the proposed method to detect and quantify damage is compared with other DSFs with respect to their robustness to changing ground-motion excitation and building floor numbers (Sect. 4). Finally, the sensitivity to sensor noise and the requirement of prior mass knowledge for the linear reference model used in the hybrid damage indicator are discussed to investigate potential real-world applications.

2 Damage Evaluation Method

For structural damage evaluation, a hybrid damage index (DI) was previously proposed by Shan et al. [17] based on the model-reference concept, characterized by (i) the absence of knowledge regarding the nonlinear behavior; (ii) full utilization of SHM measurements; and (iii) accounting for both: peak and cumulative damage effects. Generally, the DI, ξ , is formulated in a normalized form as follows:

$$\xi = \left[\alpha_d \left(1 - \frac{K_{\text{eff}}}{K_{\text{linear}}}\right)^{R^2} + \beta_d \left(\frac{r_{\text{RMS}}}{x_{RMS}^r}\right)^{R^2}\right]^{n_d} \tag{1}$$

where K_{eff} is the minimum stiffness observed during the earthquake response (defined by the maximum absolute displacement and the corresponding force); K_{linear} is the stiffness of the identified linear reference model; R^2 captures the correlation between instantaneous displacement and force values for the hysteretic loop that contains the maximum absolute displacement; r_{RMS} is the root-mean-square (RMS) value of the acceleration tracking error, e_{acc} ; x_{RMS}^r is the RMS of the linear reference acceleration response; and α_d , β_d and n_d are three weighting parameters controlling the balance between the peak and cumulative effects with a suggested relationship of $\alpha_d + \beta_d = 1$. The acceleration tracking error, e_{acc} , is defined as the difference between the measured acceleration and the acceleration response predicted with the linear reference model excited by the measured ground-motion. A brief introduction of the components of the hybrid DI, ξ , are presented in Table 1.

Several assumptions are required to derive the DI, ξ , using Eq. 1. Given that this particular formulation requires displacement estimates for evaluating R^2 , accelerations need to be integrated, in case no displacement measurement is available. In addition, assumptions regarding the floor mass are required for inferring stiffness estimates, as described in Sect. 3.1, which implies that engineering knowledge needs to be exploited.

No	Variable	Definition and characteristics	Classification
1	K _{eff}	 Effective stiffness Correlates to the peak displacement point x_{max} 	Peak effect
2	K _{linear}	• Prior-identified linear stiffness of the target structure under health condition	
3	<i>R</i> ²	 Increase the reliability of quantification to avoid the monitoring uncertainty caused by the instantaneous single data point of <i>x</i>_{max} Linear regression analysis of the hysteresis loop containing the peak deformation point <i>x</i>_{max} 	
4	x _{RMS}	• The root mean square (RMS) value of the measured structural response	Cumulative effect
5	r _{RMS}	 The RMS value of the tracking error of selected structural responses Tracking error signal is directly related to the development of structural hysteresis 	
6	α_d, β_d, n_d	• Parameters controlling the weighting balance between the peak and cumulative terms	Model parameters

 Table 1. Theoretical basis of variables contributing to the DI model.

3 Application to Simulated Seismic Responses

To evaluate the performance of the proposed DI, a five-story spring-mass shear model with nonlinear hysteretic Bouc-Wen springs with stiffness degradation is employed. The model is used to predict acceleration measurements, contaminated with a random white noise of 0.5 mm/s^2 . As localization of damage is attempted, sensors are supposed to be installed on all degrees of freedom (DOFs).

3.1 Model Identification

To adopt the proposed damage evaluation method, outlined in Sect. 2, a linear elastic reference model of the structure is required. For system identification, simulated acceleration measurements under white-noise excitation are used to find the optimal fit of inter-story stiffness and damping coefficients.

As a result, the viscous damping coefficient for the equivalent lumped mass model is identified as $\zeta = 0.0301$, and the inter-story stiffnesses $[k_1, k_2, k_3, k_4, k_5]$ are estimated as $[2.661, 2.528, 2.342, 2.125, 1.781] \times 10^8 N/m$. Compared against the ground-truth stiffness values, of the reference model, this corresponds to an error of [14.4, 10.4, 15.6, 9.3, 24.1] %, respectively. The acceleration responses and the corresponding power spectrum from the identified model and the simulated structure are illustrated in Fig. 1.



Fig. 1. Comparison of seismic responses between the simulated structure and the identified model.

3.2 Damage Quantification and Localization Performance

In this section, the structural response to the 2009 L'Aquila (LAQ) earthquake excitation is employed to the base of the assumed structure to explore damage localization and quantification performance. To evaluate the damage state, the hysteresis curves of each floor are first approximated from simulated acceleration measurements, to determine the effective stiffness corresponding to the peak damage effect. To present the best quantification ability, the displacement data are adopted directly for the illustrated case since it is obviously difficult to obtain residual drift by integration. With the utilization of the identified linear baseline model, the reference linear response is computed adopting

the monitored data for all floors and thus, the tracking error can be calculated to derive the cumulative error term, x_{RMS}^r . The DI is subsequently derived according to Eq. (1); the weighting terms of which are set to $\alpha_d = \beta_d = 0.5$. Figure 2 illustrates the response difference of inter-story drift between the linear reference model and the true building behavior. Also, the critical damage quantification variables composing the DI (see Table 1) are represented for the five floors.

The inter-story drift response of the five DOFs in time domain, shown in Fig. 2a to e, indicates a noticeable tracking error between real drift and drift predicted with the linear reference model. Significant residual drifts can be observed for the first and second floor, indicating occurrence of nonlinearity for this DOFs, as picked by the DI shown in Fig. 2k. As illustrated in Fig. 2k, the peak term corresponding to stiffness degradation decreases from Floor 1 to Floor 4, yet increases for the top floor, which is correlated to stiffness degradation, as shown in Fig. 2f to j. The combined DI value accounts for the R^2 value and thus, eliminates the uncertainty caused by the peak term (i.e., maximum displacement) for floor 5. The decrease in DI values between the bottom to the top floor is in agreement with the occurrence and extent of structural damage, which is concentrated on the first and second floor. Thus, the hybrid DI can provide crucial damage quantification and localization information.



Fig. 2. Structural nonlinear response and sublevel damage quantification variables for different floors under an earthquake excitation.

4 Sensitivity of the Damage Indicator

4.1 Earthquake Signal and Floor Numbers

The robustness of the DI with respect to changing earthquake signals and number of floors is assessed and compared with data-driven DSFs. In this section, three DSFs,

summarized in Table 2, are used. The transmissibility assurance criterion (TAC) tracks structural stiffness reduction through lack of collinearity between the transmissibility of a healthy reference measurement and the earthquake excitation [18, 19]. In addition, local changes in mode-shape curvatures (Δ MSC) derived under ambient vibrations are used as indicator of damage [14]. Given this indicator is based on the mode shape, a dense instrumentation of DOFs is recommended. Finally, the duration of relative energy accumulation (DREA) between the wavelet-decomposed input and output signal is considered [20].

Their performance of these data-driven DSFs and the presented DI are compared with respect to their correlation with 2 selected EDPs: maximum average roof drift of the building and maximum inter-story drift normalized with respect to the yield drift.

DSF	Definition and characteristics	Requirements
TAC	Change in the transmissibility between a linear reference measurement and the building response under an earthquake	Reference linear signalInput and output signal
ΔMSC	Difference in mode-shape curvature derived from ambient measurement before and after an earthquake	Reference linear signalMeasurement signal at multiple DOFs
DREA	Duration of relative energy accumulation between an input and an output signal	- Input and output signal

Table 2. Brief introduction of three selected DSFs. Input and output signals may be for instance ground motion and roof acceleration, respectively.

Figures 3 and 4 illustrate the behavior of four methods under different excitations and floor numbers, respectively. To investigate the impact of earthquake characteristics, the building response to over 50 ground motions is derived: eight earthquake signals, corresponding to L'Aquila (LAQ) 2009, Montenegro (MNG) 1979, Northridge (NRG) 1994, Christchurch (CRC) 2011, Imperial Valley (IMP) 1979, Gilroy (GIL) 2002, Marche (MAR) 1997, and Kozani (KOZ) 1995, are scaled to seven levels of shaking. In Fig. 3, different markers represent the eight earthquake records and the color saturation encodes the peak-ground acceleration of the earthquake, scaled to seven amplitudes. In Fig. 3a, TAC shows good correlation with inter-story drift. The DREA and the proposed DI also correlated well with the EDP, as demonstrated in Fig. 3c and 3d.

Furthermore, the influence of the number of floors is evaluated. Figure 4 shows the correlation between DSFs and the selected EDP, maximum inter-story drift normalized with the drift at yield, of spring-mass models with three, five, and eight DOFs. As illustrated in Fig. 4a and 4d, both the proposed damage model and the TAC behave effectively for structures with varying number of floors, showing good correlation between DSFs and EDP. While the TAC is most sensitive for low-rise buildings, the proposed DI is more sensitive for high-rise buildings, pointing to the conclusion that combining DSFs may increase their potential to identify damage. The changes in mode-shape curvatures, Δ MSC, is very sensitive and therefore, represented in log-normal scale. For high-rise



Fig. 3. Correlation between four DSFs and the selected EDP with different excitations. (maximum average roof drift of the building) with changing ground-motion characteristics. Markers differentiate ground motion signals and saturation indicates the amplitude of peak ground acceleration.

structures, with more measured DOFs and a more flexible behavior, mode-shape curvature is a very efficient indicator of damage, while the lack of measurable DOFs reduces the sensitivity for low-rise buildings. The DREA is the least sensitive with respect to building height, yet has a large scatter for various ground motions, which may undermine successful damage identification.



Fig. 4. Comparison of the correlation between four DSFs and the selected EDP (maximum interstory drift normalized with respect to the yield drift) for changing number of floors.

4.2 Mass Uncertainty and Noise Sensitivity

The hybrid DI requires an initial identification of a linear reference model. In this step, the mass of each DOF is assumed to be known in order to enable identification of stiffness and damping parameters. However, an accurate information of mass for each substructure is rarely available in reality. Meanwhile, sensor noise is inevitable when monitoring, especially with low-cost sensors. In this section, the effects of unknown mass and measurement noise are evaluated.

To assess the influence of mass assumptions, the model outcomes for a correctly estimated mass matrix is compared with the outcome of the mass being assumed at the mean value of all DOFs, and finally, a third scenario assumes the masses at the mean value with a bias of 15%. The influence of noise is tested by increasing the level of Gaussian white noise added to the signal to simulate measurements.

As shown in Fig. 5, for undamaged structures, the affect caused by either mass uncertainty or sensor noise remains very low. For seriously damaged structures, the mass uncertainty has no significant effect, as observed when comparing Fig. 5a to c. The noise renders damage identification impossible only at high levels (> 10^{-2} m/s²), which is rarely encountered in practice. Little sensitivity to noise level in the range of usual sensing devices, demonstrates the promising outlook of damage indicators for real-world applications.



Fig. 5. Influence of mass uncertainty and noise level for the proposed DI corresponding to seriously and lightly damaged structures.

5 Conclusion

In this paper, a hybrid data-driven damage index (DI) is introduced and applied to a simulated shear model to illustrate its damage evaluation performance. The influence of different excitations, floor numbers and sensor noise are also assessed to show the robustness of the DI. The following conclusions are drawn:

- The hybrid DI tracks the peak and cumulative effects of nonlinearity in acceleration response data. Thus, the structural seismic damage, due to post-yield drift and residual drift may be detected and quantified.
- Deriving the DI at floor level, shows potential to localize the damage and scale with the amount of damage within the structure. In addition, the DI correlates with a widely-used EDP: maximum drift, in a similar manner than data-driven damage-sensitive features.
- Modelling assumptions that are required to derive the hybrid DI, such as floor mass, and numerical imprecisions in integrating acceleration and computing reaction forces do not alter the damage identification performance significantly.

Despite the promising capabilities of the DI to quantify seismic damage, several aspects of the DI need further testing, such as the application to three-dimensional structures; influence of acceleration sensors that do not have a flat response in the frequency

domain; correlation with other EDPs, such as residual drift; and nonlinearities in the equivalent elastic domain of real-world structures [21].

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