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DEVELOPMENT OF FRAGILITY FUNCTIONS FOR STEEL MOMENT FRAMES USING WAVELET BASED DAMAGE SENSITIVE FEATURES FROM STRUCTURAL HEALTH MONITORING

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ABSTRACT

In this paper, a new framework to construct fragility functions for steel structures based on damage sensitive features (*DSF*'s) obtained from the field of structural health monitoring (*SHM*) is developed. Using an analytical model of the structure that is subjected to a set of selected ground motions at various intensities, and the time-histories of the structural responses and the damage states are recorded through the data collection scheme of *SHM*. The wavelet based damage sensitive features, which include the information, regarding the damage state of the structure are extracted from those signals using statistical signal processing techniques. Finally the fragility function defined as the probability of being in each damage state given the value of *DSF* is constructed using a kernel smoother and a conventional distribution function. The proposed framework combines the concept and technology from two different fields, *SHM* and performance-based earthquake engineering (*PBEE*). These fragility functions can be used as the classification scheme for damage diagnosis in *SHM* and also the prediction model of structural behavior in *PBEE*. In order to demonstrate and validate the procedure, the framework is applied to the acceleration response data obtained from the experimentally validated analytical model of a four-story steel moment resisting frame. The results demonstrate that the proposed fragility functions can represent the damage state of the steel frame probabilistically based on the value of *DSF*, and have smaller variance than the conventional ones. but with smaller damage variances of majority of intensity measures and thus improved confidence of level of prediction of damage.

Introduction

Structural safety is one of the most fundamental issues in the design and the maintenance of structures in order to protect life safety and facilitate their operations. Over their lifetimes structures are exposed to various sources of damage, and it is essential to accurately predict the

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potential hazard and risk of the structures. Many restrictions have been enforced by building codes in the design and the maintenance process of civil structures to ensure the minimum safety, but as structural design becomes diverse and new construction technologies emerge it has become difficult to apply a consistent design code to all cases. Also, as the structure deteriorates or gets damaged with time the potential risk changes. Performance-based design (*PBD*) has been receiving increasing attention among researchers and practitioners in the structural engineering community. At the same time, extensive research has been focused on developing reliable and efficient damage diagnosis and prognosis methods for structural health monitoring (*SHM*) to provide accurate information of the current state of the structure.

The main goal of the *PBD* is to predict the probabilistic performance of the structure subjected to extreme earthquake events and to design accordingly to achieve the performance objectives (SEAOC 1995, Ghobarah 2001, Porter 2007). According to Ghobarah (2001), *PBD* is a methodology in which the design criteria are expressed in terms of achieving performance objectives when the structure is subjected to various levels of seismic hazard. In the conventional *PBD* framework, the fragility function maps the intensity measure (*IM*) of the ground motion or the engineering demand parameter (*EDP*) of the structure to the damage measure (*DM*) in order to predict the probability of the future damage of structures. Frequently used *IM*'s and *EDP*'s are peak ground acceleration, spectral acceleration, and peak floor acceleration (Ibarra et al. 2002, 2005, Medina and Krawinkler 2003, Zareian and Krawinkler, 2007, Porter 2007). There are many uncertainties involved, the most prevalent being the modeling of inelastic structural behavior and ground motion.

SHM consists of (a) damage diagnosis where structural damage is detected, localized, and quantified, and (b) damage prognosis where residual strength and life is forecasted (Rytter 1993). By automatically diagnosing damage and estimating future performance, *SHM* can make the maintenance process more efficient, less expensive, and safer than visual inspection by professionals. *SHM* provides accurate estimates of the current state of the structure and expedites and provides an appropriate response such as limiting access or sending emergency crews after extreme events such as an earthquake or planning repairs and replacements. Damage diagnosis methods using statistical pattern recognition methods extract the *DSF*'s from structural response signals using signal processing techniques. The *DSF*'s contain information on the damage state of the structure and migrate as the damage progresses, and are mapped to different damage states using statistical classification methods. Extensive literature reviews on damage diagnosis methods are provided in Doebling et al. (1996) and Sohn et al. (2003). With the recent development of autonomous sensing units and wireless communications, structures can be densely instrumented to monitor their response before and after and/or during an earthquake event (Straser 1998, Lynch 2004). The statistical pattern recognition methods can be embedded in the sensor units and the results can be transmitted wirelessly in order to reduce the installation and maintenance cost.

The main purpose of this paper is to develop a novel framework to build fragility functions that integrate wireless sensing technology, numerical model development and its validation techniques, damage diagnosis algorithms using statistical signal processing methods, the *PBD* framework, and statistical parameter estimation tools. Structural response and the resulting *DM* are obtained from the analysis of a validated model. Using the signal processing methods of damage diagnosis in *SHM*, the *DSF* is extracted from each signal, and the probabilistic mapping between the *DSF* and the *DM* is defined using a kernel smoother and distribution function fitting. The *DSF* combines information from the whole structural response signal and is physically related to the structural parameters (Nair 2007). Thus, it contains more information about the structure than conventionally used measures such as spectral acceleration and peak floor acceleration. The proposed fragility functions can be utilized in two ways. From the *PBD* perspective, they can be used to predict potential structural damage at the design stage like other conventional fragility functions. The proposed fragility functions can be part of the *PBD* process and can be used to compute the annual loss rate of the structure. On the other hand, they can also be used as a classification method for *DSF*'s to estimate damage in *SHM* when a new earthquake occurs.

Framework for Creating Fragility Functions Based on Damage Sensitive Feature

The framework consists of three parts: (i) data collection; (ii) feature extraction; and (iii) development of fragility functions. This framework can be applied to any structure. It is assumed that a numerical model for the structure is available. In part (i) the structure is subject to a suite of ground motions and corresponding structural responses time-histories are collected at various damage states keeping track of the damage state corresponding to each signal. In part (ii), the *DSF* that contains the damage information of the structure is extracted from each signal using signal processing techniques in *SHM*. Finally in part (iii), the fragility functions are computed based on the results of part (ii) using a kernel smoother and by fitting a conventional distribution function through the final damage functions.

Data Collection

Structural responses at various levels of damage are collected in order to populate the database. Since the statistical tools are used to build the framework, it is important to have a large pool of data with minimum bias. The responses can be obtained from a validated numerical model or from an instrumented structure depending on the availability. The measurements can be ambient vibration or strong motion responses depending on the damage diagnosis algorithm to be used. Acceleration and strain measurements are typically used since they are easy to measure in the *SHM* system. The corresponding *DM* is also recorded along with the structural response.

Feature Extraction

Damage diagnosis algorithms using statistical pattern recognition methods are applied to the structural response data to extract *DSF*. The algorithms can be categorized into two types according to ambient vibration responses before and after the damage, or strong motion responses. The algorithms using ambient vibration responses include time-series based analysis developed by Sohn et al. (2001) and Nair et al. (2006). On the other hand, Hou et al. (2000), Hera and Hou (2004), Nair and Kiremidjian (2007), and Noh et al. (2009) used the wavelet analysis for strong motion responses. An appropriate method for damage diagnosis is chosen according to the collected data and the damage of interest, and the *DSF* is computed for each signal at every sensor locations. For the application given in this paper wavelet based *DSF* developed by Noh et al. (2009) is used since the collected signals are non-stationary strong motion responses.

Fragility Function Development

In order to estimate the damage state of the structure based on the *DSF*, the probabilistic relationship between *DSF* and a measure of damage level (*DM*) is developed. The conditional probability of *DM* given *DSF* value, commonly referred to as the fragility function is obtained by using a kernel smoother and fitting a conventional cumulative distribution function (*CDF*).

DM can be a continuous numeric value such as dollar loss and downtime or a discrete damage state such as 'no damage', 'slight damage', and 'severe damage'. When the *DM* is continuous it can be divided for simplicity into a few mutually exclusive and collectively exhaustive sets each of which defines a damage state (*DS*). The *DS*'s are defined as follows:

$$DS_i = \{DM | ds_{i-1} \le DM < ds_i\} \text{ for } i = 1, 2, 3, \ldots, n \quad (1)$$

where DS_i is the i^{th} *DS*, ds_i's are monotonically increasing limit values for increasing i's and n is the number of *DS*'s. For example, each DS_i can correspond to fully operational, operational, life safe, and near collapse (SEAOC 1995). When the *DM* is discrete, either (i) each levels of *DM* can be used for a *DS*, or (ii) a set of *DM* can be defined as a *DS* following the similar procedure as the continuous *DM* case.

From the numerical simulation and the structural damage diagnosis a pair of *DM* and *DSF*, $\{dm_i, dsf_i\}$, is computed for each signal at each sensor location. All the *DM* and *DSF* pairs are sorted in the descending order of *DSF* in order to compute the fragility function, the conditional probability that *DM* is greater than or equal to ds_i given the value of *DSF*. One method is to use data binning to quantize *DSF* and count the number of *DM*'s that satisfies the condition within the bin (Porter et al., 2007). Instead, the kernel smoother is applied to compute the conditional probability in this framework. The fragility function is given as:

$$F_i(dsf_j) = \Pr ob\{DM \ge ds_i | DSF = dsf_j\} = \frac{\sum_m I(dm_m \ge ds_i) \times K_j(dsf_m)}{\sum_n K(dsf_n)} \quad (2)$$

where $I(x)$ is an indicator function that is 1 if x is true and 0 otherwise, and K_j is a kernel. The kernel assigns a different weight for each pair of *DM* and *DSF*. Using a rectangular kernel with height 1 is equivalent to the data binning methods. The advantages of using the kernel smoother instead of the data binning are:

1. All the data are used to estimate the conditional probability. Thus, there is no problem regarding lack of data such as bins with no elements.
2. The conditional probability can be computed for all the dsf_j, not per bin.
3. The resulting fragility function is a smooth curve.

This conditional probability as a function of dsf_i is the fragility function. The conditional probability that *DM* is in a particular *DS* can be computed by taking the difference between F_i and F_{i+1}. The fragility function is computed for each sensor location separately.

For convenience, the conventional *CDF* is fitted to the fragility function. The benefits of fitting the *CDF* are:

1. The function is completely described by a few parameters.
2. The function is continuous, thus defined for all possible *DSF* values (no interpolation is necessary).
3. The function is monotonically increasing.

The lognormal *CDF* is used in the conventional fragility functions, but other functions such as beta *CDF* and normal *CDF* can be also used depending on distribution of the data. In general, the function should be chosen to minimize the fitting error.

Application

The framework for developing fragility functions for steel buildings based on *DSF* is applied to acceleration data obtained from a numerical model of a 4-story steel moment resisting frame designed based on current seismic provisions in United States. Details about the prototype structure can be found in Lignos and Krawinkler (2009). The analytical model of the 4-story frame is modeled in DRAIN-2DX (Prakash et al. 1993) with elastic beam column elements and deteriorating springs at their ends. Deterioration parameters for the components are extracted from a recently developed steel database for deterioration modeling (Lignos and Krawinkler, 2007, 2009). The analytical model of the building is subjected to a set of 40 earthquake ground motions utilizing incremental dynamic analysis (Vamvatsikos and Cornell, 2002) scaled to provide behavior from elastic response through collapse. A scale model of the 4-story steel moment frame was tested experimentally on a shaking table through collapse to validate the analytical models (Lignos and Krawinkler, 2009). The acceleration responses during the strong motion are collected after each excitation. A wavelet based damage diagnosis algorithm developed by Noh et al. (2009) is applied to the data to extract the *DSF* and is used to compute the fragility functions.

Methodology

Acceleration time histories at all the floors including the ground floor and the roof during the earthquake excitations and the maximum story drift ratio (*SDR*) are obtained from the numerical model. For feature extraction, the wavelet based *DSF* developed by Noh et al. (2009) is used since the non-stationary character of both earthquake ground motions and structural responses can be captured using the wavelet transform. This *DSF* varies between 0 (when there is no damage) and 1 (when the structure is severely damaged) and quantifies the damage of the structure after each ground motion. An example of the values of the *DSF* for different intensities of input ground motions, referred as damage patterns (*DP*'s) is shown in Fig 1. The details of the procedure to calculate the *DSF* is given in Noh et al. (2009). *SDR* is used to define the four damage states (*DS*'s) of the structure - no damage, slight damage, severe damage, and collapse with ds_i's 0 %, 1.5 %, 4 %, 8 %, and ∞ for i = 0, 1, …, 4 respectively. Although *SDR* is an *EDP*, it is often directly used to describe the damage state of the structure (BSS Council 1997, Ghobarah 2001, Liu 2004) since it is strongly correlated with the structural damage and can easily quantify the damage. While it is relatively easy to compute *SDR* in numerical analysis compared to other *DM*'s, it is expensive to measure displacements accurately in practice. Thus, it is useful to estimate *SDR* from the easily measurable *DSF*. The fragility functions between *DS* and DSF are computed using Gaussian kernel and beta *CDF*.

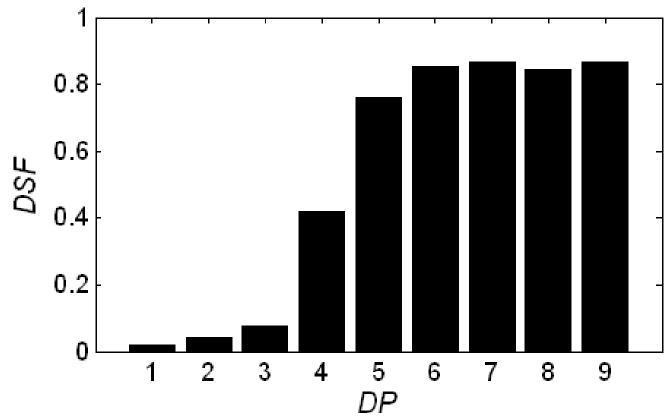

Figure 1. *DSF* for increasing intensities (*DP*) of the input ground motion.

Results

Figure 2 shows the fragility functions at the roof created using the beta *CDF*'s. The fragility functions for more severe *DS*'s are smaller in magnitude than those for smaller *DS*'s at all *DSF* values. The probability of being in a *DS* is computed as the difference between two adjacent fragility functions, and the results are shown in Figure 3. When these fragility functions are used for *SHM* in practice, all the floor acceleration time histories are measured from the physical structure while subjected to a real earthquake. The *DSF* is computed afterwards based on this acceleration record. Finally the damage state of the structure is determined probabilistically based on the *DSF* using the fragility functions developed from the numerical model prior to the occurrence of the earthquake. Note that the fragility functions are structure specific, thus they can be used for damage diagnosis of only the structure whose model is used to build the fragility functions. The *DS* of the structure can be determined as the *DS* that occurs with the maximum probability or the mean *DS* value over all damage states.

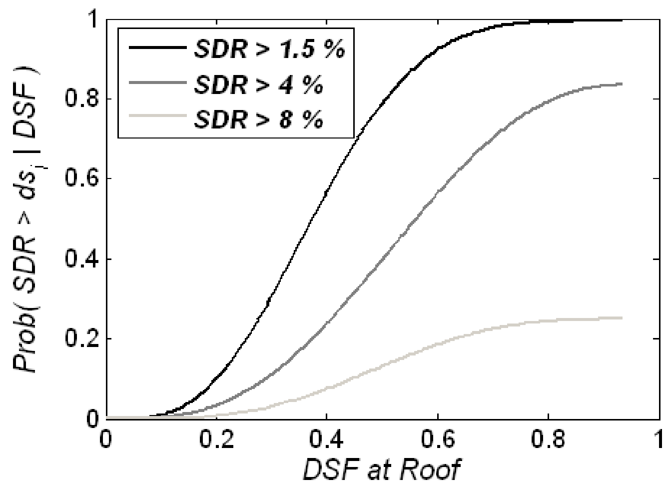

Figure 2. Fragility functions using Beta *CDF* at the roof

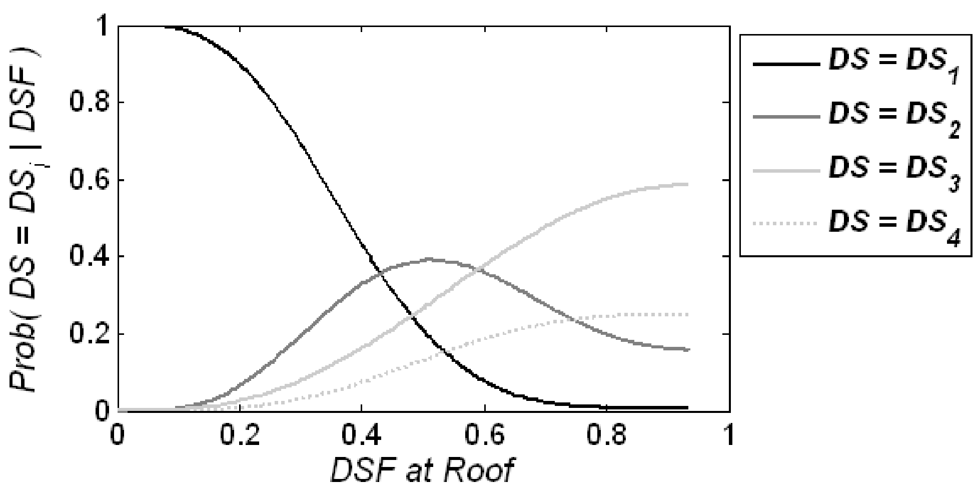

Figure 3. Probability of each damage state at the roof

The performance of the wavelet based *DSF* and other conventional *EDP* or *IM* measures (spectral acceleration (*Sa*) and peak roof acceleration) for damage diagnosis are compared to check the efficiency of each measure. The scatter plots of *SDR* versus these measures are presented in Fig. 4 that Figs. 4 (a), (b) and (c) show *SDR* vs. *Sa*, peak roof acceleration, and the *DSF*, respectively. The correlation coefficient between the *DSF* and the *SDR* has the largest value 0.877 followed by that of the peak roof acceleration (0.8621) and that of the *Sa* (0.8295). The correlation coefficient represents the strength of the linear relationship between two parameters, but what we are more interested in is the dispersion of the *SDR* given the value of *EDP* or *IM*. It is observed from these figures that the dispersion of the *SDR* given the *DSF* is smaller than that given the *Sa* or the peak roof acceleration. This implies that the *DSF* can estimate the *DS* with smaller variance, thus demonstrating that *DSF* based fragility functions are more effective in prediction in this example than the *Sa* or the peak roof acceleration. Further investigation, however, is necessary with various types of structures and loadings in order to validate the performance of the *DSF*.

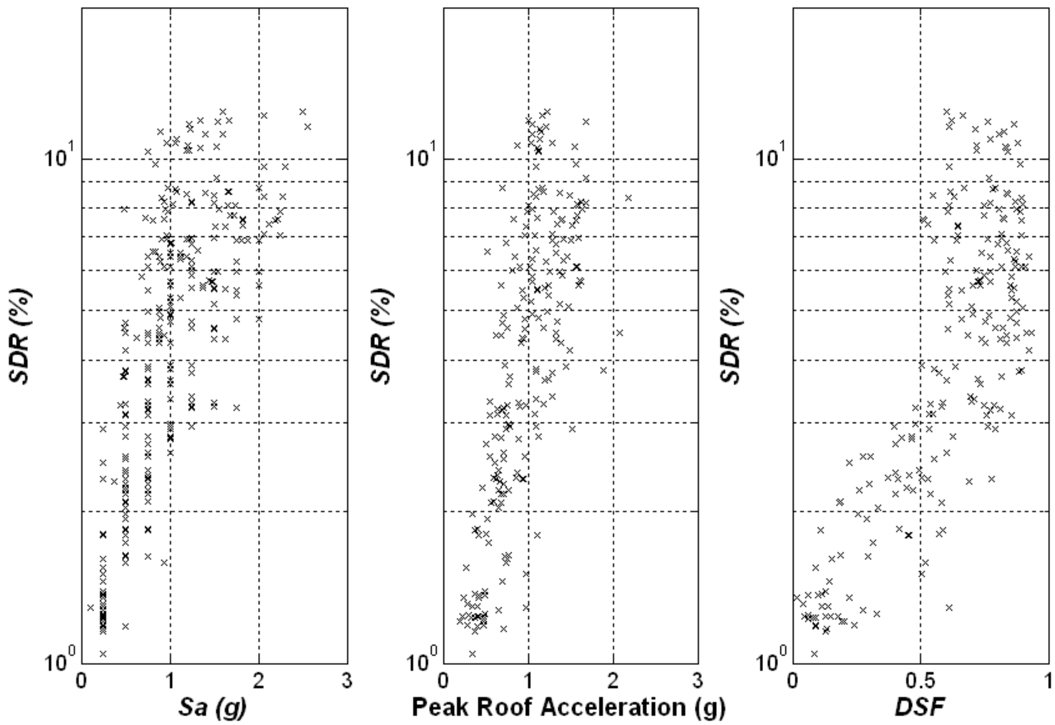

Figure 4. Scatter plots: (a) spectral acceleration vs. *SDR*; (b) peak roof acceleration vs. *SDR*; (c) *DSF* vs. *SDR*

Conclusions

A new framework is developed to create fragility functions for steel structures based on the damage sensitive feature from damage diagnosis algorithms in structural health monitoring using statistical pattern recognition methods. The framework is based on an extensive database of structural responses created from a numerical model and the *DSF* that contains information on the damage state of the structure extracted from the data using the damage diagnosis algorithms. Finally, the probabilistic relationship between the damage state and the *DSF* is computed using a kernel smoother and a conventional distribution function. Thus, the newly developed fragility functions provide the probability of the structure being in a particular damage state given the *DSF* computed from the structural response. The procedure is demonstrated through an example of a 4-story steel moment resisting frame subject to various intensities of 40 different ground motions. In the example a wavelet based *DSF* developed by Noh et al. (2009) is used for feature extraction, and *SDR* is used to describe the damage state of the structure. The fragility functions that map the *DSF* to *SDR* in the probabilistic frame are defined using Gaussian kernel smoothers and beta *CDF* fitting. The results show that the newly developed fragility functions can predict the damage state defined by *SDR* with smaller variance than the conventional ones. These fragility functions can be used as the classification scheme for damage diagnosis in *SHM* and the prediction model of the future structural risk in *PBEE*.

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