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Structural Condition Assessment by Reliability Index

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Abstract

The failure and deterioration of civil engineering systems due to structural damage have important societal and human consequences. Therefore, there is a vital motivation to assess the global condition of structures to detect and identify the existing damage. The objective of this article is to introduce two kinds of reliability indices for structural condition assessment using the dynamic responses in time domain. Initially, a relative reliability index (RRI) based on statistical features of both damaged and undamaged structures is proposed to specify the structural conditions. Next, a general relative index (GRI) based on distance theory is applied to identify the location of damage. In both techniques, the dynamic responses are divided into several subgroups that assist to have more obvious perspective for the structural condition assessment. In order to demonstrate the efficiency and accuracy of the proposed algorithms, acceleration time histories of a laboratory frame are used. Results show that the relative reliability index adequately enables to discriminate the condition of structure by evaluating the reliability of subgroups and exploiting the reliability charts. In addition, the distances gained by the general reliability index one can identify the location of damage in such a way that the damage area has most reliability distance value.

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Abstract

The failure and deterioration of civil engineering systems due to structural damage have important societal and human consequences. Therefore, there is a vital motivation to assess the global condition of structures to detect and identify the existing damage. The objective of this article is to introduce two kinds of reliability indices for structural condition assessment using the dynamic responses in time domain. Initially, a relative reliability index (RRI) based on statistical features of both damaged and undamaged structures is proposed to specify the structural conditions. Next, a general relative index (GRI) based on distance theory is applied to identify the location of damage. In both techniques, the dynamic responses are divided into several subgroups that assist to have more obvious perspective for the structural condition assessment. In order to demonstrate the efficiency and accuracy of the proposed algorithms, acceleration time histories of a laboratory frame are used. Results show that the relative reliability index adequately enables to discriminate the condition of structure by evaluating the reliability of subgroups and exploiting the reliability charts. In addition, the distances gained by the general reliability index one can identify the location of damage in such a way that the damage area has most reliability distance value.

Keywords: Structural condition assessment; Reliability index; Statistical features; Vibration-time data.

1. Introduction

Damage occurrence in the civil infrastructures has significant effect on serviceability, safety levels, economic conditions, and human life style. A damaged structure accounts for a dangerous threat for its performance, human health, and social economic. Some important structures such as bridges, buildings, and dams play crucial roles in the society and it is essential to ensure their health and global structural conditions. Other types of structures have got historical, national, and ancient importance that should be maintained because they are valuable heritages of our predecessors and should be stable for future generations.

Structural condition assessment is a process for evaluating the global condition of structure and damage identification that includes identification of any defects, deterioration, and any type of damage (structural and non-structural). This process mainly focuses on the evaluation of global condition of structure, and the detection of local damage. Structural health monitoring (SHM) takes into account a portion of the condition assessment in which the vibration data extracted from the structure are applied to identify the structural damage [1]. Some of the critical steps in structural condition assessment associated with the damage detection may be summarized as (1) setting up the parameters limits which categorises the condition status; (2) diagnosing the presence of damage; (3) damage localization; (4) detection of damage type; (5) damage quantification; (6) assessing the effects of damage on structural reliability [2].

Assessment techniques can generally be classified as either physics-based or data-based methods. The physics-based approaches utilize the inherent properties along with numerical models of the structure; however, intensive computation efforts are their main limitations in the procedure of novel condition assessment. Data-based techniques, on the other hand, rely on measurements from the structure to assess the current condition of structure and identify the damage state, typically by means of some vibration signals as well as several statistical approaches.

Xia and Brownjohn [3] presented a structural condition assessment procedure based on updating and validating the dynamic parameters of the damaged structure. The stiffness variation (flexural rigidity reduction) of a short-span pedestrian concrete bridge deck was chosen as the damage criterion to identify the cracks location and their severity. Yang et al. [4] developed an online structural condition assessment technique using long-term monitoring data measured by a structural health monitoring system. They applied the seasonal correlations of frequency-temperature and displacement-temperature and further formulated a statistical modelling technique by these data from which abnormal changes of measured frequencies and displacements are detected using the mean value control chart. Halling et al. [5] presented a condition assessment algorithm based on using vibration data to identify the condition of the structure and detect damage on an isolated single span of a freeway overpass structure. By constructing finite element model of the structure and optimizing its parameters, the structural condition assessment was conducted. Catbas and Aktan [6] discussed the distinction between global and local state properties, linearized and nonlinear condition indices and experimental constraints along with a classification of condition assessment techniques. They applied the results of research on steel stringer highway bridges and a long span bridge to exemplify the interrelation between structural conditions, damage, and some of the promising damage indices. Gul and Catbas [7] presented a conceptual and reliable method for system identification and structural condition assessment using ambient vibration data. For system identification, they used complex mode indicator functions after averaging the vibration data by the random decrement technique. For condition assessment, the deflection profiles obtained from unscaled flexibility were compared for undamaged and damaged structures.

The objective of this article is to use reliability index for the structural condition assessment and the damage diagnosis based on using vibration data in the time domain. A relative reliability index (RRI) is proposed to assess the global structural condition. To locate the damage, a general reliability index (GRI) on the basis of distance theory is applied, in which most distance value relies on the location of damage. In both methods, the dynamic responses in the time domain are divided into given subgroups. The acceleration time histories of a three-story laboratory frame are applied in order to provide experimental validation of the proposed algorithms. Results indicate that the RRI enables to find abnormal conditions of structure and the measured distance of the GRI is an appropriate criterion for the process of damage localization.

2. Theoretical background

2.1 Reliability index

The reliability index is a useful indicator to compute the failure probability, which widely used in the structural reliability analysis [8]. In this study, the basic concept of this index is applied to assess the structural condition, particularly the process of damage identification. Suppose a random distribution such as $A = [a_1,a_2,\ldots,a_p]$ with p observations, which has the mean μ, the variance σ^2, and the standard deviation σ. The reliability index of the distribution is simply determined using its mean and standard deviation. In general, this indicator is identical to the inverse of coefficient of variation (CV), which is known as a standardized measure of dispersion of a probability distribution [8]. It is defined as the ratio of the standard deviation and mean from the following form:

$$CV_a = \frac{\sigma_a}{\mu_a} \tag{1}$$

Accordingly, the reliability index formulation is given by:

$$\beta = \frac{1}{CV_a} = \frac{\mu_a}{\sigma_a} \tag{2}$$

If the distribution X becomes a normal distribution, the reliability index in Eq. (2) is rewritten as follows:

$$\beta = \frac{\mu_a - 1}{\sigma_a} \tag{3}$$

Even though Eqs. (1)-(3) are current expressions used in the structural reliability and probabilistic analysis, the results of these equations cannot be used for evaluating the structural conditions in a comprehensive manner. To put it another way, the statistical features such as mean, standard deviation, and variance are scalar values and these quantities may not be able to provide thorough viewpoint about the situation of structure. In order to make a realistic and applicable tool for the structural condition assessment, the dynamic responses are divided into some subgroups with same segments. This process efficiently assists to have more complete and better observations of structural variability. The subgrouping of data takes into account a common method in the quality control that is widely utilized in the context of SHM [9, 10]. In this regard, assume that the random distribution A is divided into m subgroups with n observations. Under this assumption, the reliability index for each subgroup is given by:

$$\beta_i = \frac{\{\mu_a\}_i - 1}{\{\sigma_a\}_i}, \quad i = 1,2,\ldots,m \tag{4}$$

where μ_i and σ_i denote the mean and standard deviation of i^{th} subgroup. In such circumstance, there is m reliability indices obtained from m subgroups with n observations that are able to supply more reasonable and useful information about variability of structural conditions caused by probable damage.

2.2 Relative reliability index

One great limitation of the reliability index, even with producing the subgroups, is the presence of an irregular dispersion on reliability charts in both the baseline and damaged structural conditions. Due to lack of any physical meaning about the irregular dispersions, it is essential to make a new indicator in association with the concept of reliability index. Thus, a relative reliability index (RRI) is proposed that computes the relative difference between the reliability indices of both undamaged and damaged states.

It is assumed that the random vectors X and Y represent the vibration time series data of the undamaged and damaged structures, respectively. According to Eq. (4), the reliability indices for these data are β_x and β_y, respectively. Thus, the RRI is expressed in the following form:

$$RRI(\%) = \left| \frac{\{\beta_y\}_i - \{\beta_x\}_i}{\{\beta_x\}_i} \right| \times 100, \quad i = 1,2,\ldots,m \tag{5}$$

On the basis of this equation, the relative reliability index obtained from only the healthy structure is introduced as a reference level that is always equal to zero. In this case, a straight line named as a threshold line one can draw in the charts of relative reliability indices so that any deviation of this line is indicative of an abnormal state occurred on the structure. In fact, the deviation from the threshold line relies on this fact that the reliability of structure has been reduced and there is no longer any trustworthiness in the structure. As a consequence, the condition of structure represents a damaged or critical state.

An important note is that it is essential to distinguish any noise from vibration time series data. In other words, some operational and environmental variability alter the content of vibration data that affect the dynamic properties of structure. Hence, it is assumed that the vibration time series data divided into the subgroups are not contaminated by noise and there is no influence of operational and environmental conditions over these data.

2.3 General reliability index

In previous sections, the common version of reliability index along with the relative reliability index have been described based on using the statistical properties of the undamaged and damaged structures. There is another version of the reliability index named as the general reliability index (GRI)that is based on computing a distance from the threshold line [8]. Furthermore, it is worth remarking that the previous reliability indices could not identify the location of damage; however, the distance value gained by the GRI one can found the damage areas. The general reliability index is written as follows:

$$\beta_r = \frac{\mu_y - \mu_x}{\sqrt{\sigma_y^2 + \sigma_x^2}} \tag{6}$$

where subscriptions x and y belong to the undamaged and damaged structures, respectively. Since the vibration data are divided into the subgroups, the reliability index in Eq. (6) should be computed based on the mean and variance of each subgroup. Eventually, the general reliability index of r^{th} sensor, one can obtain as: in the following form:

$$\beta_r = \frac{\sum_{i=1}^{m}(\mu_y)_i - \sum_{i=1}^{m}(\mu_x)_i}{\sqrt{\sum_{i=1}^{m}(\sigma_y^2)_i + \sum_{i=1}^{m}(\sigma_y^2)_i}}, \qquad r = 1,2,\ldots,s \tag{7}$$

In this equation, s is the number of sensors that have been mounted on the structure. Based on Eq. (7), a shortest distance from the threshold line demonstrates the structural safety state in the sense that there is no damage in the structure. In contrast, the largest distance values among all mounted sensors indicate the locations of damage.

3. Experimental validation

In order to demonstrate the efficiency and correctness of proposed methods for structural condition assessment and damage diagnosis process, the acceleration time series data of a three-story laboratory frame are applied as shown in Fig. 1. This structure is a public reference model that the test measurements can be downloaded from http://institute.lanl.gov/ei/software-and-data/data. A comprehensive details of descriptions of the structure are given in [11]. An electrodynamic shaker provides a lateral excitation to the base floor along the centerline of the structure. The structure was instrumented with four accelerometers mounted at the centre line of each floor on the opposite side from the excitation source to measure the acceleration time history response. The shaker and frame were mounted together on an aluminium baseplate and the entire system rests on rigid foam. The analog sensor signals were discretized into 8192 data points sampled at 3.125 microsecond intervals corresponding to a sampling frequency of 320 Hz. These sampling parameters yield time series 25.6 seconds in duration.

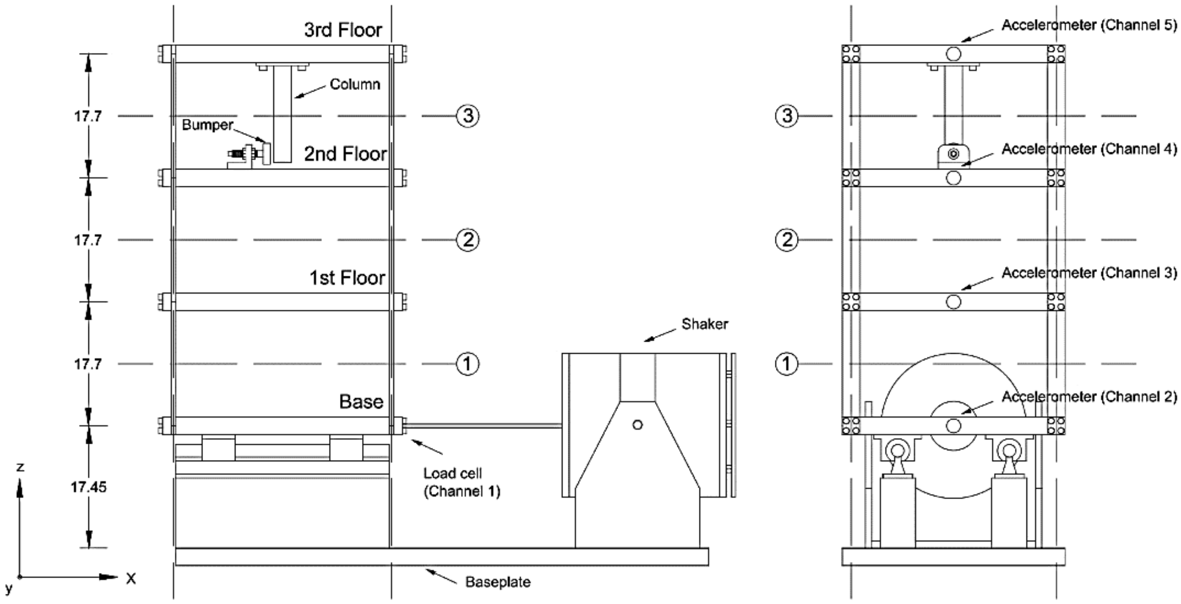

Figure 1. The three-story laboratory frame [11]

To induce the structural damage, a centre column was suspended from the third floor. This column was contacted a bumper mounted on the second floor so that the position of the bumper can be adjusted to define diverse structural damages. Force and acceleration time series data for a variety of different structural conditions were collected that can be categorized into four main groups including: (1) baseline condition, (2) structural condition with simulated operational and environmental variability, (3) damaged structural conditions, and (4) the damaged structural conditions in addition to operational and environmental variability. The complete details of the structural conditions can be found in [11]. Table 1 shows the structural state #1 as the baseline condition and the state #14 as the damaged structural condition in order to verify the proposed methodology in this study.

Table 1. The structural conditions in the laboratory frame

State No.	Condition	Description
1	Undamaged	Baseline or healthy condition
14	Damaged	Distance between bumper and column tip 0.05 mm

Figs. 2(a) and 2(b) indicate the acceleration time series data at the channel 5 in the states #1 and #14, respectively. As can be seen, it is difficult and roughly impossible to discriminate the damaged from the undamaged conditions based on the raw acceleration time histories. It should be mentioned that prior to constituting subgroups, the measurements should be normalized by subtracting the mean and dividing by the standard deviation from the baseline condition.

$$\hat{X}_j = \frac{\{X\}_j - \{\mu_x\}_j}{\{\sigma_x\}_j}, \qquad j = 1,2,\ldots,p \tag{8}$$

where p denotes the number of data points in the acceleration measurements. In addition, this normalization procedure based on the baseline condition is applied to all acceleration measurements in the damaged state.

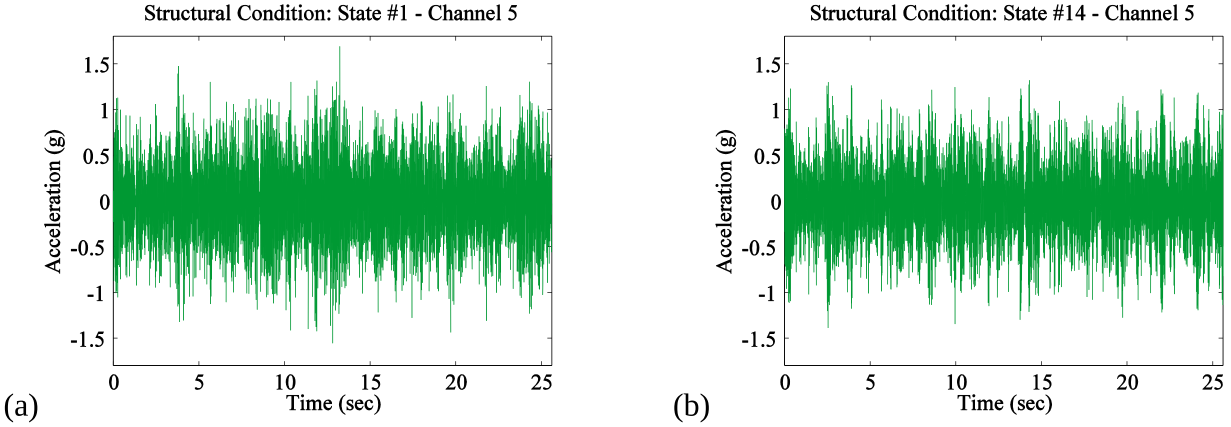

Figure 2. Acceleration time series data at the channel #5: (a) state #1, (b) state #14

The acceleration time histories at all channels of the baseline condition (state #1) are chosen as reference points to determine the baseline reliability index β_x. In contrast, the corresponding acceleration measurements for all channels of the state #14 are used to calculate the reliability index β_y. To create subgroups for both states, 32 observations are arbitrarily selected for each subgroup and thus, there are 256 subgroups in each time series data at each channel.

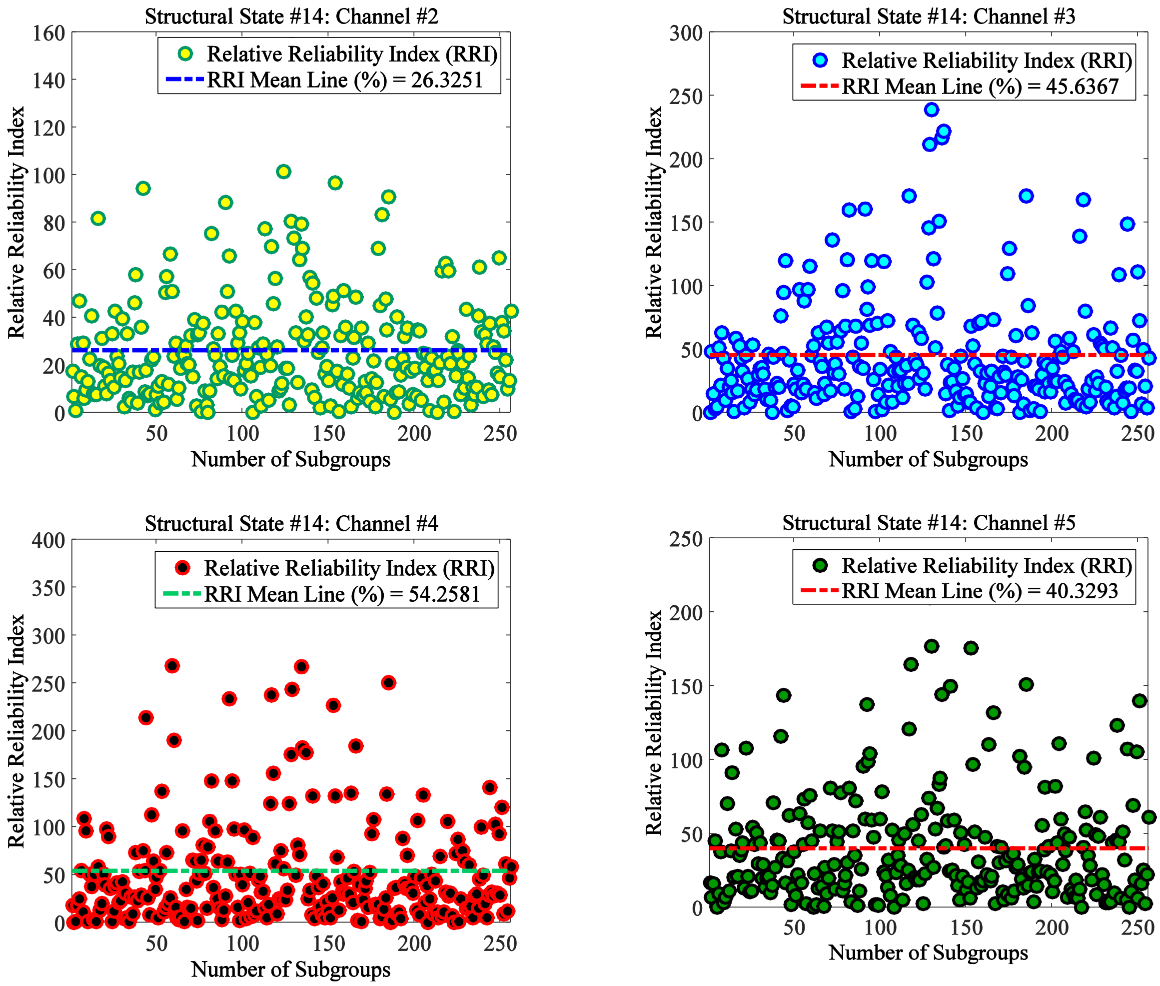

Figure 3. Relative reliability index (RRI) between states #1 and #14 for all channels

Figs. 3(a)-3(d) show the dispersion of RRI values associated with the subgroups of state #14 with respect to the threshold line. In all the charts, considerable dispersions one can observe in the RRIs that verify demonstrate the damaged condition of laboratory frame. Each of the points (circles) plotted in the charts belongs to the relative reliability index calculated in each subgroup; thus, there are 256 points at each chart. As explained earlier, the threshold line is a strength line, which is always equal to zero. Therefore, any deviation from this line indicates that a damage or abnormal situation is available in the structure.

Furthermore, the red line displays the RRI mean value of each channel in all the subgroups of the damaged structural condition (state #14). The distance between the RRI mean lines with the threshold line is a convenient criterion to describe the damage severity. For instance, Fig. 3(c) illustrates that the distance of RRI mean line at the channel #4 with respect to threshold line is most distance value (54.26%). This means that the most intensive damage quantity has occurred in this position. Thus, by increasing the damage severity, the RRI mean line becomes far away from the threshold line.

The variation of relative reliability index is another criterion to assess the condition of structure. As can be seen from Figs. 3(a)-3(d), the compression of RRIs are on the range of 50-100% for all channels. This means that there is an abnormal condition in the laboratory frame since the variations of RRIs are much more than 0%, which indicates the safety condition of structure.

Another important result of the structural condition assessment can be obtained by the concept of the distance of the general reliability index for each signal. Table 2 shows the distances for channels 2-5 in the state #14 computed by general reliability index β_r.

Table 2. Damage localization by computing distance in the general reliability index

Channel No.	Channel 2	Channel 3	Channel 4	Channel 5
β_r	0.01	0.34	0.9	0.41

As can be observed, the channel #4 has most quantity of the general reliability index, that is, the location of damage has occurred in that position. As illustrated in Fig. 1, the bumper was mounted at the 2nd story, where the channel #4 has been installed there. Therefore, most distance quantity in the general reliability index demonstrates the location of damage. It is worth remarking that both the relative and general reliability indices evaluate the structural conditions by pair sensor location in both the undamaged and damaged structures. In other words, it is important to compute the reliability indices of two signals installed at one place.

4. Conclusions

The main aim of this work is to provide a trustworthy, powerful, and efficient approach for the structural condition assessment using the raw dynamic responses in the time domain. For this purpose, two kinds of reliability indices were used to specify the condition of structure and then identify the location of damage. At the first step, the relative reliability index (RRI) was proposed through applying the statistical properties such as the mean and standard deviation of the undamaged and damaged structures. Then, the general reliability index (GRI) based on distance theory was utilized in such a way that most distance value relies on the location of damage. In both methods, the vibration time series data were divided into given and arbitrary subgroups. The main intention for using subgroups was that they could assist to have more obvious perspective of structural condition so that the more data points in the subgroups provided better consequences. In order to validate the efficiency of methods, the acceleration time series data of a three-story laboratory frame were applied. The results of this study can be summarized as follows. The relative reliability index potentially enables to distinguish between conditions of the damaged and healthy structures. In this approach, any deviation of the subgroups' relative reliability index from the threshold line indicates the abnormal condition. Accordingly, the RRI's charts for all the channels in the damaged state show the adverse dispersion from the baseline condition. Furthermore, the distance of RRI mean line from the threshold line is an appropriate damage quantification criterion. In this regard, the most intensive damage severity has the largest distance value. The general reliability index also provide a convenient damage localization algorithm so that the sensor location with the maximum distance measure is indicative of the location of damage.

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