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Probability Distribution of Decay Rate: A Novel Damage Identification Method in Time Domain

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ABSTRACT

Statistical time domain analysis is a rapidly growing field in Structural Health Monitoring (SHM), due to its practicality, efficacy and reliance on a well-established theoretical foundation. In the context of SHM, time domain analysis has an evident merit of providing direct means of estimating the underlying physical properties of the structure, particularly damping. This study presents a novel statistical damage identification model, which constructs a probability distribution of decay rate (PDDR) for transient vibration responses. Utilising this PDDR model, a damping estimate of the structure is created and subsequently reduced to a quantifiable parameter. With each change in structural health state, a parameter is established, which is then used for comparison. Based on this methodology, a five-step algorithm was created and tested against two sets of experimental vibration data. The first experiment involved a scale-model steel frame structure subjected to bolt-connection damages, while the second experiment focused on a steel pipe with support failures. Results obtained from both experiments strongly support the validity of proposed damage identification method.

1 INTRODUCTION

Damage detection and identification is an ongoing problem in SHM and impact damage verification cases (Fan & Qiao, 2011; Zhou et al., 2013). While a substantial amount of research has provided literature with innovative damage detection and identification schemes, a vast majority heavily rely on cumbersome numerical modelling, and/or linear system model assumptions (Carden & Fanning, 2004; Fan & Qiao, 2011; Lei et al., 2003). Thus, such damage identification methods are generally deemed infeasible in practical applications, due labour intensive numerical model tuning procedures against: (1) operational and environmental uncertainties; and (2) model limitations from simplification and/or assumptions (Lei et al., 2003). These two limitations are perhaps most prominent when dealing with estimates for structural damping. Since damping is the result of mechanical energy dissipation, dictated by the frictional forces and relative motion between a structure’s parts, analytical (predictive) models are notably difficult to design (de Silva, 2005).

Consequently, a majority of these analytical models are limited to establishing structural damage information relying exclusively on the structural stiffness physical property. Estimation of structural stiffness is usually made using only two out of three modal parameters; natural frequencies and mode shapes, while modal damping is often ignored (Curadelli et al., 2007; Frizzarin et al., 2010; Güemes, 2006; Kawiecki, 2001).

The difficulty in modelling structural damping is reflected in current literature's inattention to utilizing it as a damage-sensitive feature on real test data. Currently, the standard for a forward-problem approach in damage identification is to define a rudimentary estimate for the damping parameter (Curadelli et al., 2008; Güemes, 2006). Estimating a suitable damping parameter is usually achieved through modelling the test structure's geometry and characteristic material. The evolution of damping with respect to damage, is typically addressed using the Rayleigh damping method. This method, though the most popular, comes with a significant limitation of assuming linear system behaviour (Kinra & Wolfenden, 1992).

In contrast to developing an optimized numerical model for accurate damage identification, the inverse problem approach is noted as a much more effective methodology. In an early exploratory study, Kawiecki (2001) presents the potential use of modal damping characteristics as a damage detection method with surface-bonded piezo-elements, specifically suited for light-weight structures. Curadelli et al. (2007) present a study in which damping can be used a damage-sensitive property, whilst observing the changes in a model, made possible by combining natural frequencies and damping on test structures, via wavelet transform. Testing on both a (calibrated) numerical 2D model and an experimental reinforced concrete beam, authors support the notion that damping can be a robust damage-sensitive property, while stating that relying on shifts in natural frequencies exclusively can be limiting for damage identification. Frizzarin et al. (2010) takes a step further and develops a baseline-free nonlinear damage-sensitive model that employs the change in damping of a structure, analysed in time-domain with the use of random decrement signature technique. The proposed method is tested experimentally on a large-scale concrete bridge model subjected to different levels of seismic damage.

In the inverse problem, a trending methodology is statistical time domain analysis for damage identification. This trending direction fundamentally creates statistical models, which are implemented on raw vibration data in its original domain. Two significant advantages exist in using time domain analysis, these are: (1) provides a direct observation of the fundamental vibration response characteristics; and (2) eliminates the requirement of domain transformation.

This study aims to propose a novel damage identification model (PDDR) based on statistical time domain analysis. The developed PDDR model provides means of observing the overall decay rate (damping estimate) of a structure by specifically observing the change in local maxima/minima points of a time-response via a probability distribution representation. Two experiments presented in the following sections are used to test the effectiveness of this model in damage identification.

2 METHODOLOGY

2.1 Process Overview

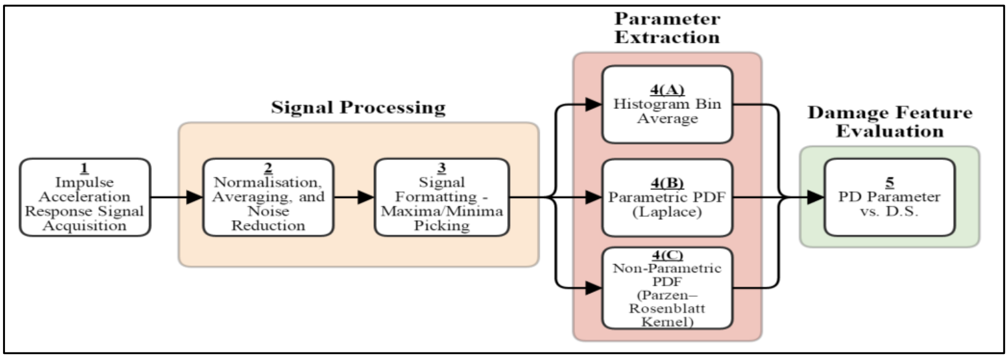


Figure 1. Proposed process overview

Figure 1 presents the five steps of the proposed damage identification method. Firstly, the input requires experimentally acquired impulse acceleration response data (transient vibration). Response acceleration data is then passed through signal processing steps to retain only the local maxima/minima points (one dimensional), acquired from the displacement over time function. Signal processing steps include strike averaging, noise reduction, windowing, and amplitude standardisation.

The following, step 4, is a key element of this proposed method, in which the retained one-dimensional vibration response set of local maxima/minima amplitudes are plotted on a histogram, in order to obtain a probability distribution. At this point, a probability distribution plot for each damage scenario is obtained. There are three possible approaches in extracting a probability density function (PDF) or parameter, considering the input set as a random variable (detailed in Figure 1). Due to paper limitations, the scope of this paper shall only cover option 4(A). Although, the most rudimentary route with no proper PDF fitting, option 4(A) still performs exceptionally well for damage identification procedures. With step 4(A), each damage scenario is reduced to a single quantitative parameter, which is the resultant weighted mean value of bins in the histogram. Lastly, in step 5, acquired quantitative values are tabulated to corresponding damage scenarios and severity, presented in the following results section.

The following section is to expand on the theory of step 4(A), i.e., creating a damage-sensitive feature based on the decay rate of local maxima/minima taken from the transient vibration response of a test structure.

2.2 Probability Distribution Parameter Extraction

Consider a simple linear system with an initial input force $f(t)$ for excitation, generating a transient response. Experimentally, this system's equivalent damping factor ζ_e can be estimated on the basis of two consecutive local maxima or minima, in a sinusoidal decay function, i.e. a logarithmic decrement (de Silva, 2005) .

Firstly, the second-order differential equation governing the system detailed above is (de Silva, 2005; Kavitha et al., 2009; Shabana, 1995):

$$M\ddot{x} + C\dot{x} + Kx = f(t) \quad (1)$$

with one of the solutions being as follows (general decaying sinusoid function):

$$x(t) = Ae^{-\omega_n \zeta t} sin(\omega_d t + \phi) \quad (2)$$

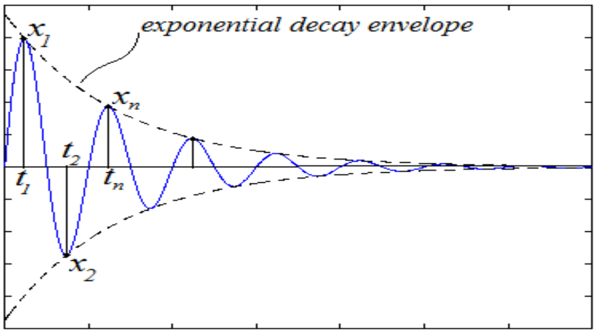


Figure 2. A general decaying sinusoid plot

where local maxima and minima are defined in this study as:

$$x_1 = Ae^{-\omega_n \zeta t_1} \sin(\omega_d t_1 + \phi) \quad (3)$$

...

$$x_n = Ae^{-\omega_n \zeta t_n} \sin(\omega_d t_n + \phi) \quad (4)$$

with

A: initial position; ω_d: damped natural frequency;

ζ: damping ratio; ω_n: undamped natural frequency, equal to zero;

ϕ: phase angle.

Now, the logarithmic decrement is defined as (using two consecutive points):

$$\delta = \ln\left(\frac{x_n}{x_{n+2}}\right). \quad (5)$$

It is noted that a potentially more accurate estimate of logarithmic decrement can be made using a pair of local maxima or minima, further apart in time, such that (de Silva, 2005):

$$\delta = \frac{1}{2m} \ln\left(\frac{x_n}{x_{n+2m}}\right), \quad (6)$$

where m, n are positive integers.

From this, equivalent damping factor ζ_e can be defined in relation to logarithmic decrement, as:

$$\zeta_e = \frac{\delta}{\sqrt{(2\pi)^2 + \delta^2}} \quad (7)$$

with the preceding equation, a structural damping estimate can be determined (Shabana, 1995). With this, let us define the following cumulative set:

$$X = \{x_1, x_2, \dots, x_n\} \quad (8)$$

Given a standard impact hammer test, with an impulse-excitation force $f(t)$ provided to the system, the resultant transient vibration can be picked up by the accelerometers and processed so that each damage scenario has a corresponding set $X_{DS(\alpha)}$, that is:

$$T = \{X_{DS0}, X_{DS1}, \dots, X_{DS\alpha}\} \quad (9)$$

where: $\alpha + 1$ is the total number of damage scenarios observed.

As per step 4(A) (Figure 1), the next procedure is to create histograms of each set of T. Given that, $\forall\, X$: $(-1.0 \leq x_n \leq 1.0)$, the histogram function β_i is defined as:

$$p = \sum_{i=1}^{k} \beta_i \quad (10)$$

where β_i is the number of observations that belong in each bin, p is number maxima/minima in X, and k is total number of bins, governed by Doane's formula.

Lastly, just prior to reducing each histogram plot to a quantitative estimate (bin frequency average), an exponential weighting factor is applied. The weighting is applied in order to improve the quality of probability distribution, as it mitigates for the erratic behaviour observed in experimental data, during the initial settling-in period of response vibration (start-up transient behaviour). The exponential weighting applied is set in favour of the centre mean region of the probability distributions. Accordingly, this weighting attenuates the tails of the probability distribution which correspond to maxima/minima recorded during the start-up transient period.

2.3 *Experiment 1: Steel Frame with Bolt-Connection Failures*

The first test structure is a simple scale-model steel frame with two columns and a single beam, comprised of members with identical cross-section (150UB18). Column-to-beam connections are made with two L-plates, positioned on top and bottom flanges of beam, which are bolted in place using a set of four bolts (⌀10 mm).

Figure 3. Steel Frame Structure Photograph (far-end accelerometer data used only) (Ay et al., 2013)

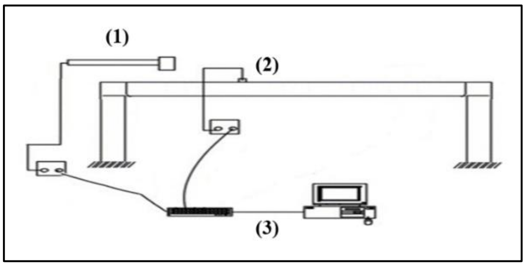
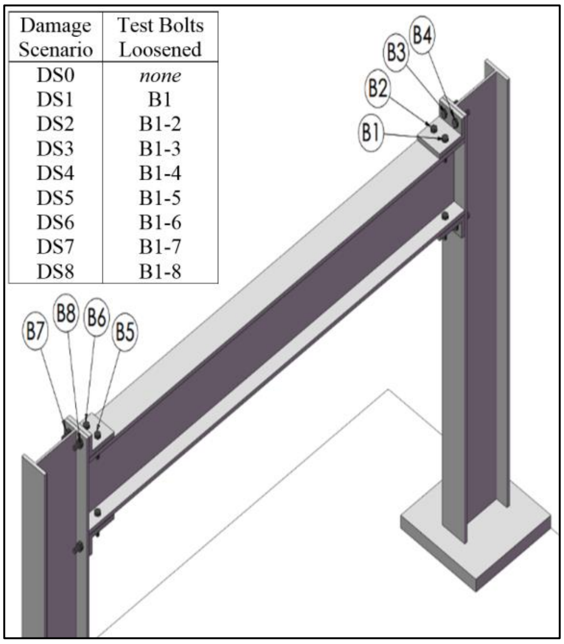


Figure 4. Steel frame experiment schematic; (1) Impact Hammer *Endevco 2304*, (2) Accelerometer *Endevco 61C13*, (3) CPU & HF-Data Acquisition Module *NI PXIe-4492* (Ay et al., 2013)



Damage Scenario	Test Bolts Loosened
DS0	*none*
DS1	B1
DS2	B1-2
DS3	B1-3
DS4	B1-4
DS5	B1-5
DS6	B1-6
DS7	B1-7
DS8	B1-8

Figure 5. Detailed View of Labelled Test Bolts Loosened for Damage Scenarios

A non-destructive impact hammer test was conducted in order to acquire response vibration data (Figure 4). The testing procedure involved a single impact and acceleration reference point (only far-end accelerometer used shown in Figure 3 photograph). Four strikes per damage scenario were conducted, as part of strike averaging in data processing step. A total of nine damage scenarios were tested with simulated bolt-connection damages. A bolt-connection was deemed 'damaged' when the connecting nut was rotated 720°, from a fully hand-tightened position. Damage scenarios (DS) were designed in an incrementally accumulating manner, starting from DS0, as all bolts fully tightened, up to DS8 with test bolts B1 to B8 loosened. Vibration data was acquired at a sampling rate of 20 kHz, for five seconds per strike, using experiment setup detailed in Figure 4.

2.4 *Experiment 2: Steel Pipe with Support Failures*

The second test structure is a simply supported steel pipe, with a total span of 2.4 m (Figure 6). The conducted experiment involved fully embedding the pipe in wet-sand and exposing segments of various lengths.

Figure 7 illustrates the four damage scenarios tested, in addition to accelerometer positioning. The scope of this study only required the vibration data from accelerometer 1 (A1). Point of strike by the impact hammer was set as the mid-point between accelerometers A1 and A2. Damage scenario 0 (DS0), was set as the intact structure, with full wet-sand support across the entire span of the steel pipe. Damage severity was then increased with each proceeding scenario, with the removal of segments of wet-sand with lengths detailed in Figure 7.

In regards to data acquisition setup and procedure, both experiments were virtually identical. Instrument kit seen in Figure 4 was used again, with the same number of strike averaging and signal acquisition settings. A significant difference between this experiment and previous one, was the location of testing. The first steel frame structure was tested indoors (mechanical laboratory), while the steel pipe was tested outdoors. Consequently, a substantial increase in noise contamination was observed (qualitatively) in steel pipe test data.

Figure 6. Steel pipe test structure photograph (damage scenario 3 shown)

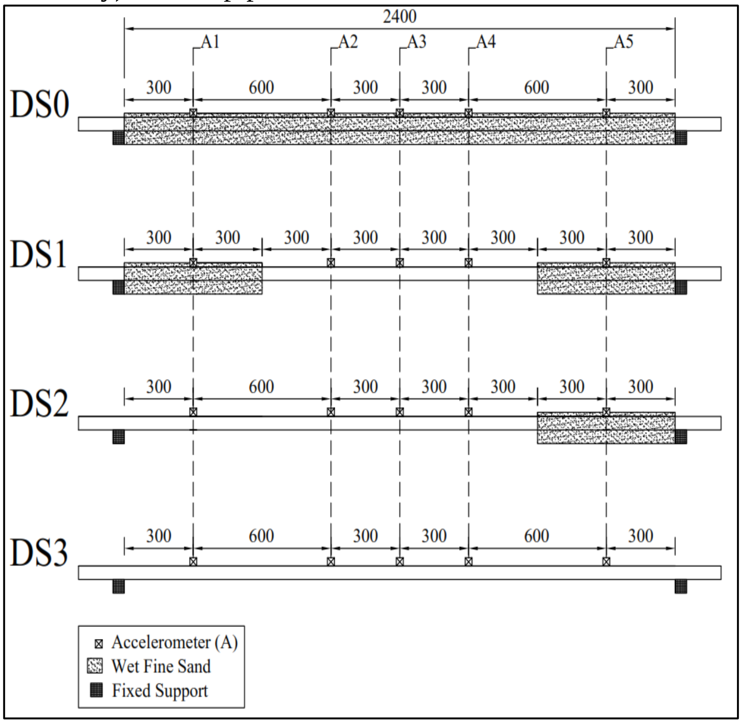


Figure 7. Steel pipe: damage scenario and accelerometer location details (this study accelerometer data A1 only)

3 RESULTS

The following set of results present the output data generated by the statistical model, after implementing the overall methodology, outlined in Figure 1. Tables 1 and 2 present the extracted damage-sensitive parameter against each damage scenario of the experiment. Additionally, a percentage change from the intact state of the structure (DS0) is provided, for each subsequent damage scenario.

Table 1. Experiment 1 steel frame results: change in bin mean for each damage scenario

Damage Scenario	Exponentially Weighted Bin Frequency Mean (μ)	Change from Intact or Damage Severity (%)
DS0	39.4013	0
DS1	34.6506	12.0573
DS2	31.6346	19.7119
DS3	26.1680	33.5860
DS4	15.4875	60.6930
DS5	14.5878	62.9764
DS6	11.9191	69.7496
DS7	10.0602	74.4674
DS8	9.9929	74.6381

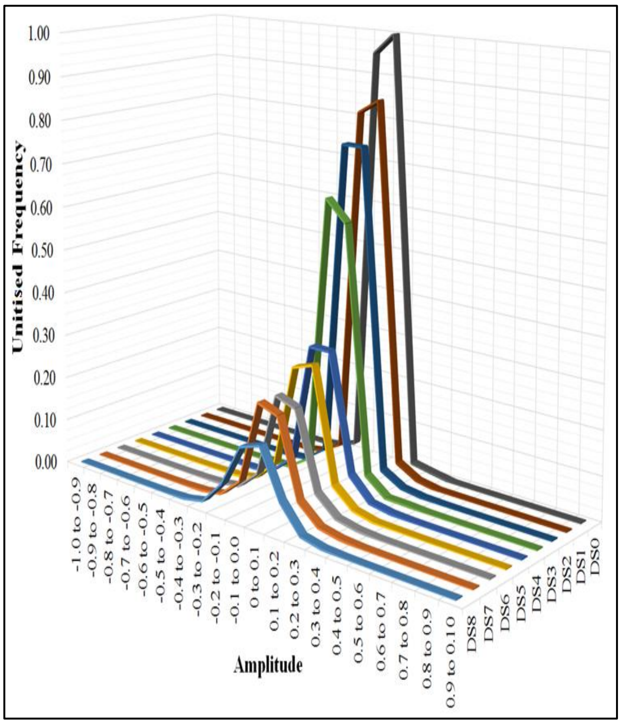


Figure 8. Experiment 1: exponentially weighted probability distributions for each damage scenario

Table 2. Experiment 2 steel pipe results: change in bin mean for each damage scenario

Damage Scenario	Exponentially Weighted Bin Frequency Mean (μ)	Change from Intact or Damage Severity (%)
DS0	18.0799	0
DS1	15.1681	16.1052
DS2	12.3732	31.5637
DS3	9.3732	48.1567

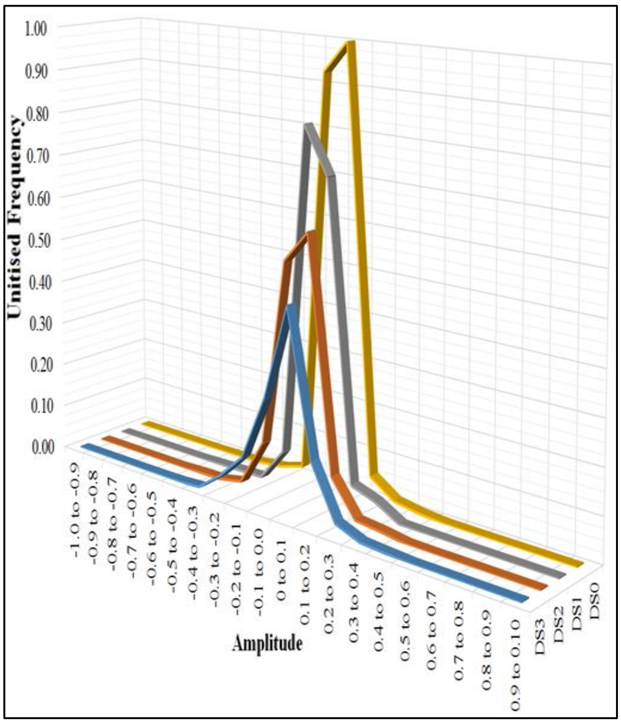


Figure 9. Experiment 2: exponentially weighted probability distributions for each damage scenario

4 SUMMARY AND DISCUSSIONS

A damage identification method based on statistical time domain analysis was presented in this paper. Results from both experiments strongly support the validity of the proposed model, particularly in the case of the second experiment, which was conducted in non-laboratory conditions, i.e., significant levels of noise contamination. Furthermore, the exponentially weighted probability distributions were in exact order to the incremental increase in simulated structural damage severity, for both set of results. Another notable observation was the sudden shift in probability distribution, seen in experiment 1 results (Figure 8), between damage scenarios DS3 and DS4. This significant change is correlated, from a physics-based perspective, to the complete loosening of the top right-end L-plate, fixed into position by four bolts, which are loosened by DS4 (Figure 5).

Lastly, two main limitations to this study have been identified: (1) outlined in Section 2.1, the probability distribution parameter extracted in this paper, was the most rudimentary and least sensitive one, compared to the parametric and non-parametric model approaches; and (2) experimental data acquisition was made on a single accelerometer, and single point of reference on relatively large test structures. This methodology could be greatly improved with multi-sensor data fusion or simply damage-sensitive parameter averaging.

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