# The Effect of Acceleration Signal Length on the Outputs from Modal Identification Methods

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***Abstract*—The damping ratio is a significant factor influencing the dynamic behaviour of a structure. The safety, serviceability and habitability of a structure are all impacted by the damping ratio. Damping ratio does not relate to a unique physical phenomenon like mass or stiffness and in practice, design analysis relies on estimates of damping ratios from empirical measurements of similar structures. Overestimates of the damping ratio arising from uncertainty in estimates can lead to structures experiencing acceleration responses during wind and seismic events that could potentially cause human discomfort. Full-scale testing provides the most accurate insight into the actual damping ratio of a structure. Where full scale testing is performed, acceleration signals are recorded and assessed using modal identification techniques to identify the characteristic modal parameters such as natural frequency and damping ratio. However, this form of testing is not without errors which may arise as a result of response conditions during monitoring, the modal identification methods applied, the duration of acceleration signal processed and the sampling frequency of the acceleration signal.**

**This paper considers real ambient acceleration response signals of different lengths and sampling frequencies obtained from a full-scale monitoring campaign. The influences of signal length and sampling frequency on the natural frequencies and the damping ratios calculated using two different modal identification methods are investigated. Outputs from signal lengths of 12 hours, 1 hour, and 10 minutes are compared as well as sampling frequencies of 20Hz, 10 Hz and 5Hz. The two modal identification methods used are the Bayesian Fast Fourier Transform (BFFT) and a composite method of Analytical Mode Decomposition (AMD) and the Random Decrement Technique (RDT) in which bootstrapping is also performed to identify error in the estimates.**

***Index Terms*—Modal Identification Methods, Damping Ratio, Ambient Vibration Monitoring, Signal Processing**

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## I. Introduction

Advancements in structural engineering including new materials, construction methods and computational power are enabling more tall, slender and often unconventional structures to be built. With this comes the responsibility of designers to better understand modal parameters and hence the dynamic behaviour of structures in order to mitigate serviceability issues which may arise as a result of wind induced motion. The damping ratio is a significant factor governing the dynamic response of a structure [1], [2]. Uncertainty in estimates of the damping ratio can result in excessive dynamic responses negatively affecting the habitability of a structure with potential to cause human discomfort.

Empirical values for the damping ratio of different materials including steel, concrete and composite structures are provided by design codes and literature [3]–[5]. These values are typically a result of extensive studies of full-scale acceleration monitoring carried out on in-situ structures. However, uncertainty still exists in these values due to inter structure variation and the modal identification techniques employed in evaluating the damping ratio. Additionally, the different lengths of signal and sampling frequencies of the acceleration response which were recorded and processed have found to impact the estimates of the modal properties [6]–[8]. In reality, constraints such as cost of monitoring, data storage and computational effort will likely govern the length and sampling frequency of a signal used. However, the full influence of these constraints must be better understood in order to make decisions on monitoring accuracy, cost and time efficiency that are compatible with the characteristics of the structural system being investigated.

The Bayesian Fast Fourier Transform (BFFT) is a modal identification technique frequently employed for assessing damping ratios. This method uses Bayesian theory to identify natural frequencies, damping ratios and the associated coefficient of variation (CV) from a structure's acceleration response. Another common method for estimating the damping ratio is the Random Decrement Technique (RDT). The RDT is often combined with a modal decomposition method such as Analytical Mode Decomposition (AMD) in order to better identify closely spaced modes [9]. Here, the AMD and RDT are combined with a statistical procedure known as bootstrapping in order to identify the error associated with the estimates of this method. This composite method is herein referred to as the bootstrapping AMD-RDT.

This paper compares the damping ratio and standard error estimates obtained through applying these two methods, bootstrapping AMD-RDT and BFFT, to ambient acceleration response data recorded by in-situ monitoring of two tall structures with closely spaced modes. Both methods are applied to 12 hour, 1 hour, and 10 minute samples from 10 different signals with a sampling frequency of 5 Hz. 10 minute samples from 5 different acceleration signals are also compared for a sampling frequency of 5Hz, 10 Hz and 20 Hz.

## II. Modal Identification Methods

Signal processing of ambient acceleration data is performed using two modal identification methods in order to identify modal properties and the respective coefficient of variation (CV). The two methods are the BFFT which operates in the frequency-domain and the RDT which operates in the time-domain. A variation of the RDT which combines the original method with signal decomposition using Analytical Mode Decomposition (AMD) and bootstrapping of the signal is used in order to better identify closely spaced modes and provide information on the error of the estimates of the RDT [10], [11].

### A. Bayesian Fast Fourier Transform

The BFFT is a common modal identification technique used to predict the modal properties of a structure from ambient data and has been investigated extensively [12]–[14]. The BFFT assumes that both the real and imaginary parts of the FFT of the acceleration response of a structure experiencing broad-band excitation will have a Gaussian distribution that can be described analytically by a set of modal parameters, $\theta$. The modal parameters contained in $\theta$ are the natural frequency $f$, damping ratio $\zeta$, mode shape $\Phi$, entries of the force spectral density matrix $\{S_{ij}\}$ and the spectral density of the prediction error $\sigma^2$, for any given mode.

This paper considers the BFFT as set out by Au et al. [12]. The FFT data obtained from ambient vibrations is used to maximise the posterior probability density function (PDF) of the modal parameters in order to find the most probable value (MPV) of each of the modal properties.

It is appropriate to approximate the posterior PDF using a Gaussian PDF for a sufficiently large data set [12]. This is achieved by letting $\hat{\theta}$ be the MPV that minimises the second order approximation of the log-likelihood function, $L(\theta)$. $L(\theta)$ is then treated as a second order Taylor series about $\hat{\theta}$ with the first-order term vanishing to optimality of $\hat{\theta}$. The posterior PDF becomes a Gaussian PDF as shown in Equation (1).

$$p(\theta|\{\mathbf{Z}_k\}) \propto exp\Bigg[-(\frac{1}{2})(\theta-\hat{\theta})^T\hat{\mathbf{C}}^{-1}(\theta-\hat{\theta})\Bigg] \quad (1)$$

Where $\mathbf{Z}_k$ is the joint PDF of the augmented FFT vectors of the ambient data and is considered a zero-mean Gaussian vector; $\hat{\mathbf{C}}$ is the posterior covariance matrix of $\mathbf{Z}_k$ defined as

$$\hat{\mathbf{C}} = H_L(\hat{\theta})^{-1} \quad (2)$$

where the Hessian of L at the MPV is $H_L(\hat{\theta})$.

The MPV and covariance matrix are the focus of the main computational effort in Bayesian Identification as they are critical to the calculation of the Gaussian PDF.

The BFFT enables both a damping ratio and the associated posterior CV to be identified from an acceleration response. This enables a better understanding of the uncertainty of the damping estimate in design processes. However, the BFFT can be inaccurate when closely spaced modes influence the measured acceleration response.

### B. Random Decrement Technique

The RDT is based on the theory that an ambient, white noise excitation of a structure will result in an acceleration response at the nth DOF in the $i$ th mode, $x_{ni}(t)$, which consists of response components due to iinitial displacement $x_{x_0ni}$, the response due to the initial velocity $x_{\dot{x}_0ni}$ and forced response due to random excitation $x_{Fni}$ such that

$$x_{ni}(t) = x_{x_0ni} + x_{\dot{x}_0ni} + x_{Fni} \quad (3)$$

The RDT estimates the damping experienced by a linear structural system by using the resulting signature from combining averaged segments of its response [11], [15]. The response segments are those from the time history of the acceleration response which satisfy a threshold condition, $X_{pni}$ [11], [16]. In theory, by averaging a large number of random decrement response segments with identical triggering conditions, the initial velocity and forced vibration responses reduce to zero, leaving only the response due to the initial displacement. Essentially the random component of the response is removed leaving a signal comprised of only the free decay response of the structure. The RDT was applied in this paper as described by Ibrahim [13] to obtain the random decrement signatures defined as

$$\delta_{ni}(t) = \frac{1}{N}\sum_{k=1}^{N} X_{pni}(t_k+\tau) \quad (4)$$

where N = number of subsamples and $\tau = t - t_i$.

The triggering condition, $X_{pni}$, is set as the standard deviation of the acceleration response as suggested by Tamura et al. [14]. A "level-crossing, overlapping criterion" is set as suggested by Zhou et al. [11].

The Hilbert transform is applied to each random decrement signature $\delta(t)$ to approximate the free decay response and determine the modal damping ratio $\zeta_i$ [17], [18].

### *C. Analytical Mode Decomposition*

The Random Decrement Technique can be inaccurate when modes are closely spaced together. Hence, it is often combined with an anterior signal decomposition method [10], [18] Analytical Mode Decomposition has been found to be effective for signals with highly coupled modes [9]. This paper combines AMD with the RDT for modal identification from ambient data.

AMD decomposes a subsignal into multiple components, each with Fourier spectra that are non-vanishing over mutually exclusive frequency ranges separated by a bisecting frequency $\omega$. Each subsignal is then analysed using the RDT outlined in Section II-B to extract the free decay response of the structure and determine its damping ratio. The AMD is applied in this paper as described by Wen et al. [10]. A brief description of the method is given here.

Let $\mathbf{x}(t)$ ) denote the measured acceleration data containing a number of frequency components $(\omega_1, \omega_2, \ldots, \omega_n)$ where $n$ is the number of subsignals into which the data is to be decomposed. The subsignals, $\mathbf{x}_i(t)(i = 1, 2, \ldots, n)$ have Fourier Spectra $\hat{\mathbf{X}}(\omega)$ which cover $n$ mutually exclusive frequency ranges such that $(|\omega| < \omega_{b1}), (\omega_{b1} < |\omega| < \omega_b 2), \ldots, (\omega_{(bn-2)} < |\omega| < \omega_{(bn-1)})$ and $(\omega_{(bn-1)} < |\omega|)$. $\omega_{bi} \in (\omega_i, \omega_{i+1})(i = 1, 2, \ldots, n-1)$ are the bisecting frequencies. Therefore,

$$\mathbf{x}(t) = \sum_{i=1}^{n} \mathbf{x}_i(t) \tag{5}$$

Each of the modal responses has a narrow bandwidth in the frequency domain and can be determined by

$$\mathbf{x}_i(t) = \mathbf{s}_i(t) - \mathbf{s}_{i-t}, \ldots, \mathbf{x}_n(t) = \mathbf{x}(t) - \mathbf{s}_{n-1}(t) \tag{6}$$

$$\mathbf{s}_i(t) = sin(\omega_{bi} t H[\mathbf{x}(t) cos(\omega_{bi} t)] - cos(\omega_{bi} t H[\mathbf{x}(t) sin(\omega_{bi} t)] \tag{7}$$

where $H[.]$ represents the Hilbert Transform. After application of the AMD method to create subsignals of the response signal, the RDT is applied to obtain the free vibrational response of the structural system and identify its damping ratio.

### *D. Bootstrapping*

Whilst use of the RDT is prominent in the literature on modal identification [11], previous applications of the method have not provided any measure of the uncertainty in its damping estimates. To address this deficiency, this paper incorporates the statistical procedure known as Bootstrapping within the combined AMD-RDT method to obtain a statistical measure of the error in the calculated damping ratio values, and hence, an understanding of the uncertainty of damping estimates obtained using the AMD-RDT. Bootstrapping is a computationally expensive statistical procedure which enables descriptive features of a sample to be assessed. The principle of bootstrapping is to treat a sample as though it is the population and randomly sample from this to produce an empirical estimate of the statistic's sampling distribution [11], [19], [20]. The bootstrap procedure is applied in this paper as first presented by Efron et al. [19] and involves the following steps:

1) A random independent sample, $X = (x_1, x_2, ..., x_n)$ with a statistic of interest $\hat{\theta} = s_X$ is drawn from an unknown identical distribution F.
2) The original data is sampled with replacement to create a bootstrap sample $X^* = (x_1^*, x_2^*, ..., x_n^*)$ with a corresponding estimator $\hat{\theta}^* = s(X^*)$.
3) The bootstrap operation in step 2 is repeated B times to create a bootstrap ensemble containing B number of replicates $(\hat{\theta}_1^*, \hat{\theta}_2^*, ..., \hat{\theta}_B^*)$.
4) The histogram of the bootstrap ensemble can be produced in order to identify the probability density function and hence calculate the bootstrap mean, $\bar{\theta}^*$, considered the optimal estimate by the bootstrap method using Equation (8), assuming a normal distribution. The standard deviation $s_\theta^*$, which can be regarded as an estimate of the standard error of $\hat{\theta}$ can also be found using Equation (9) for a normal distribution. The coefficient of variation can be found using Eq. 10.

$$\bar{\theta}^* = \mu(\hat{\theta}_b^*) = \frac{1}{B} \sum_{b=1}^{B} \hat{\theta}_b^* \tag{8}$$

$$s_\theta^* = \sigma(\hat{\theta}_b^*) = \sqrt{\frac{1}{B-1} \sum_{b=1}^{B} (\hat{\theta}_b^* - \bar{\theta}^*)^2} \tag{9}$$

$$CV = \frac{s_\theta^*}{\bar{\theta}^*} \tag{10}$$

## III. Results

Table I shows the different signals processed by both modal identification methods. Two structures of similar height and construction method were monitored. The two structures in which the signals being analysed were obtained have a natural frequency of approximately 0.30 Hz. The Nyquist criterion requires that the sampling frequency be at least two times the natural frequency of the highest mode being considered. Therefore, the minimum sampling frequency considered is 5 Hz. The length of data recorded and sampling rates shown in Table I were all controlled as part of the in-situ monitoring of the structures which took place in 2018 for Structure A and 2022 for Structure B.

For structure A, two triaxial accelerometers were in place at the top of the structure. 12 hours of data sampled at a frequency of 5 Hz was recorded for 10 different measurements. This resulted in 40 12 hour long signals. Both one hour and 10 minutes of data were sampled from the middle of the signal for each measurement. This resulted in a total of 120 signals for structure one.

Structure B had one triaxial accelerometer recording continuous data at a sampling rate of 20 Hz for a six month monitoring duration. From this data, five measurements of length 10 minutes were chosen where RMS accelerations were similar to those experienced by Structure A. The five 10 minute long acceleration signals were sampled at 10 Hz and 5 Hz to create a total of 30 signals from Structure B. In total, 150 signals were processed using both modal identification methods.

TABLE I
SIGNAL LENGTHS AND SAMPLING FREQUENCIES PROCESSED BY BOTH MODAL IDENTIFICATION METHODS

| Structure | Number of Measurements | Number of Accelerometers | Number of Modes | Signal Length | Sampling Frequency |
|---|---|---|---|---|---|
| 1 | 10 | 2 | 2 | 12 Hours | 5 Hz |
| 1 | 10 | 2 | 2 | 1 Hour | 5 Hz |
| 1 | 10 | 2 | 2 | 10 Minutes | 5 Hz |
| 2 | 5 | 1 | 2 | 10 Minutes | 5 Hz |
| 2 | 5 | 1 | 2 | 10 Minutes | 10 Hz |
| 2 | 5 | 1 | 2 | 10 Minutes | 20 Hz |

Tables II and III display the results from Accelerometer 1 in the East-West Direction for 12 hours, 1 hour and 10 minutes of acceleration signal obtained from the ambient excitation of Structure A processed by the BFFT and Bootstrapping AMD-RDT respectively. It is worth noting that the measurements were recorded while Structure A was still under construction. The structure was fully completed for Measurements 6-10. Measurement 4 is corrupted by significant noise due to the on-going construction within the structure.

It can be seen that for both methods, the CV increases as the duration of the signal is shortened. This effect is more significant for the BFFT method than the bootstrapped AMD-RDT. As well as higher CV values, more variation in the damping estimates from the different measurements is observed as the signal duration reduces. It is also worth noting that for the 10 minute length signal the estimates of damping ratio are on average smaller. Considering fig. 1 and 2 the increase in error and lower damping estimate as duration is shortened and becomes more apparent. Where error ribbons are excluded it is due to their exceedance of the y axis limits.

Tables IV and V display the results from Accelerometer 1 in the East-West Direction for acceleration signals with sampling frequencies of 20 Hz, 10 Hz and 5 Hz obtained from the ambient excitation of Structure B processed by the BFFT and Bootstrapping AMD-RDT respectively. It can be seen that for the bootstrapped AMD-RDT method, error increases as sampling frequency decreases. However, for the BFFT method it appears that a sampling frequency of 5 Hz is more accurate than for 20 or 10 Hz. In reality, results from analysing only a 10 minute signal using the BFFT method appear unreliable regardless of sampling frequency used. Figure 3 shows how

TABLE II
DAMPING RATIO ESTIMATE AND RELATIVE CV FOR ACCELERATION SIGNALS OF DECREASING LENGTH PROCESSED BY BFFT METHOD (STRUCTURE A, ACCELEROMETER 1, EAST-WEST DIRECTION)

| | 12 Hours | | 1 Hour | | 10 Minutes | |
|---|---|---|---|---|---|---|
| Measurement | Damping (%) | CV | Damping (%) | CV | Damping (%) | CV |
| 1 | 1.28 | 5.4016 | 0.98 | 16.0520 | 2.63 | 192.6306 |
| 2 | 1.27 | 5.2950 | 1.46 | 25.4000 | 1.68 | 64.6500 |
| 3 | 1.31 | 5.5431 | 1.48 | 20.2549 | 1.12 | 44.1156 |
| 4 | 1.84 | 7.9068 | 2.44 | 47.2153 | 4.47 | 261.4259 |
| 5 | 1.25 | 6.0806 | 1.19 | 17.2040 | 0.60 | 26.4774 |
| 6 | 1.25 | 2.0829 | 1.51 | 24.7551 | 2.54 | 104.7200 |
| 7 | 1.23 | 5.2221 | 1.31 | 10.3512 | 1.45 | 38.8289 |
| 8 | 1.04 | 5.1723 | 1.1 | 18.6407 | 0.46 | 22.4415 |
| 9 | 1.16 | 5.5173 | 1.39 | 22.7803 | 0.88 | 36.2479 |
| 10 | 1.12 | 5.3822 | 0.96 | 11.3940 | 0.87 | 36.1970 |

TABLE III
DAMPING RATIO ESTIMATE AND RELATIVE CV FOR ACCELERATION SIGNALS OF DECREASING LENGTH PROCESSED BY BOOTSTRAPPED AMD-RDT METHOD (STRUCTURE A, ACCELEROMETER 1, EAST-WEST DIRECTION)

| | 12 Hours | | 1 Hour | | 10 Minutes | |
|---|---|---|---|---|---|---|
| Measurement | Damping (%) | CV | Damping (%) | CV | Damping (%) | CV |
| 1 | 1.23 | 3.8171 | 1.11 | 6.3820 | 0.43 | 21.8252 |
| 2 | 2.06 | 2.2819 | 1.52 | 2.8785 | 0.38 | 15.2839 |
| 3 | 1.84 | 5.0447 | 1.41 | 9.3000 | 0.38 | 18.9790 |
| 4 | 16.68 | 6.1771 | 3.26 | 59.7624 | 0.9 | 41.3685 |
| 5 | 1.56 | 3.1257 | 1.29 | 5.1697 | 0.43 | 16.5020 |
| 6 | 1.09 | 2.5871 | 0.79 | 7.7255 | 0.76 | 14.0143 |
| 7 | 1.07 | 2.2722 | 1.07 | 6.7782 | 0.25 | 24.7050 |
| 8 | 1.09 | 1.9229 | 1.16 | 6.9070 | 0.4 | 17.3729 |
| 9 | 1.03 | 2.3142 | 1.02 | 8.2471 | 0.78 | 13.3704 |
| 10 | 1.14 | 2.1688 | 1.16 | 7.0772 | 1.15 | 25.9714 |

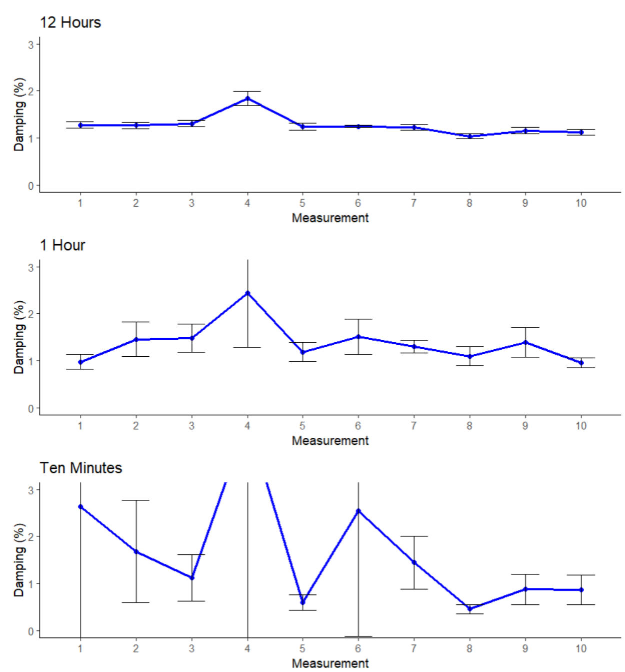


Fig. 1. BFFT estimated damping ratio and error for varying signal length

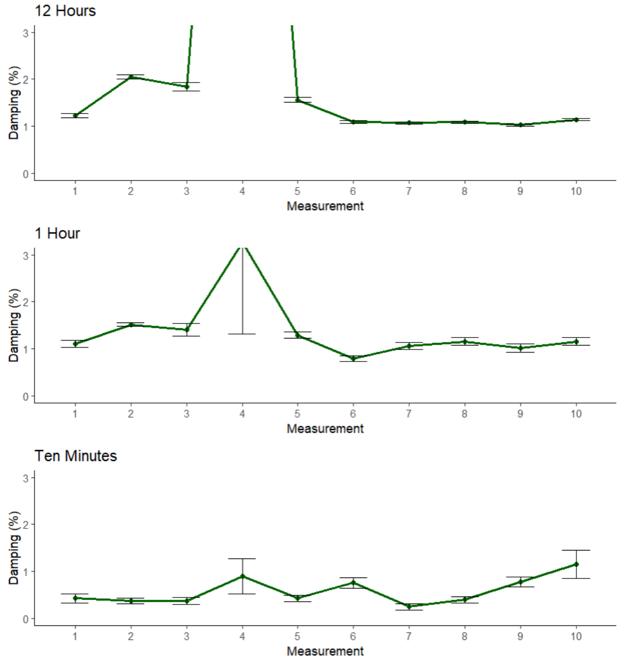


Fig. 2. Bootstrapping AMD-RDT estimated damping ratio and error for varying signal length

TABLE IV
DAMPING RATIO ESTIMATE AND RELATIVE CV FOR ACCELERATION SIGNALS OF DECREASING SAMPLING FREQUENCY PROCESSED BY BFFT METHOD (STRUCTURE A, ACCELEROMETER 1, EAST-WEST DIRECTION)

| | 20 Hz | | 10 Hz | | 5 Hz | |
|---|---|---|---|---|---|---|
| Measu-rement | Damping (%) | CV | Damping (%) | CV | Damping (%) | CV |
| 1 | 54.57 | 11628.5900 | 22.37 | 7576.2810 | 3.65 | 82.5249 |
| 2 | 18.34 | 257.8367 | 29.19 | 931.3229 | 2.2 | 55.1128 |
| 3 | 9.58 | 122.0319 | 40.51 | 1486.2700 | 2.71 | 64.1948 |
| 4 | 21.28 | 331.2505 | 35.82 | 1240.8010 | 12.81 | 774.4459 |
| 5 | 10.67 | 83.7595 | 19.76 | 1849.0980 | 2.15 | 47.6114 |

TABLE V
DAMPING RATIO ESTIMATE AND RELATIVE CV FOR ACCELERATION SIGNALS OF DECREASING SAMPLING FREQUENCY PROCESSED BY BOOTSTRAPPED AMD-RDT METHOD (STRUCTURE A, ACCELEROMETER 1, EAST-WEST DIRECTION)

| | 20 Hz | | 10 Hz | | 5 Hz | |
|---|---|---|---|---|---|---|
| Measu-rement | Damping (%) | CV | Damping (%) | CV | Damping (%) | CV |
| 1 | 0.58 | 8.3047 | 0.81 | 6.6526 | 0.58 | 9.3936 |
| 2 | 0.2 | 13.0829 | 0.29 | 13.0693 | 0.27 | 18.0217 |
| 3 | 0.35 | 8.8420 | 0.72 | 12.7818 | 0.64 | 14.1042 |
| 4 | 0.35 | 9.6616 | 0.42 | 8.7910 | 0.32 | 14.3642 |
| 5 | 0.34 | 10.2591 | 0.37 | 11.1355 | 0.34 | 14.7228 |

significant the error on some estimates is. In comparison, fig. 4 appears to show that the bootstrapped AMD-RDT method can provide consistent estimates of damping and error for 10 minutes of a signal at all sampling frequencies. A significant advantage of this finding is that the bootstrapped AMD-RDT is a suitable modal identification method for processing signals which are shorter, enabling effective identification of damping ratios of structures where data acquisition is limited by time, noise or sampling frequency constraints. The implications of this are far-reaching with possible application of the AMD-RDT method throughout structural health monitoring of buildings, bridges and mechanical systems alike.

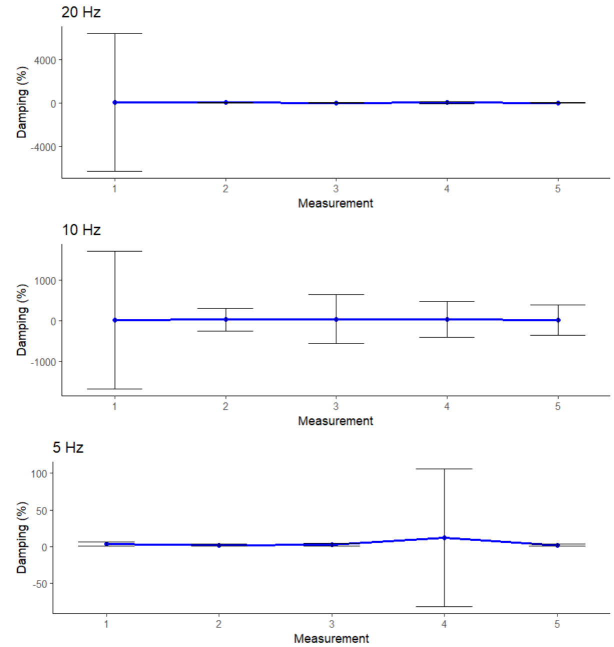


Fig. 3. BFFT estimated damping ratio and error for varying sampling frequencies

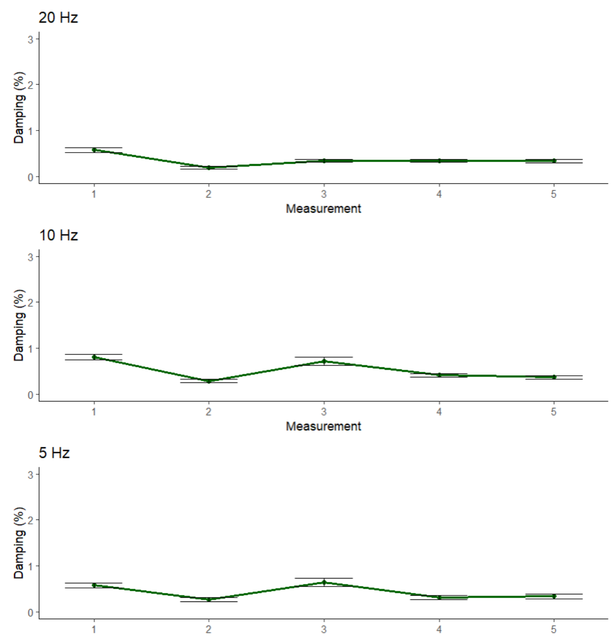


Fig. 4. Bootstrapping AMD-RDT estimated damping ratio and error for varying sampling frequencies

## IV. Conclusion

This paper compared damping ratio estimates from 150 different ambient acceleration response signals. The signals were obtained from in-situ ambient vibration monitoring of two structures of similar construction materials and heights using triaxial accelerometers. The signals varied in length and sampling frequencies. Two different modal identification methods, the BFFT and bootstrapping AMD-RDT were used to estimate the damping ratio from each signal.

It was found that the error in damping ratio increased as signal length decreased. This was more pronounced for the BFFT method. The Bootstrapped AMD-RDT method showed a slight increase in error as sampling frequency was reduced but was capable of producing reliable results. The BFFT method was not well suited to a low-sampling frequency or short signal length.

It is clear that using the bootstrapped AMD-RDT method, consistent estimates of damping ratio can be obtained for a shorter signal length (10 minutes) and lower sampling frequency (5 Hz). This is beneficial as the bootstrapped AMD-RDT method can be computationally expensive. Comparatively, the BFFT method is not reliable for small amounts of data, but is more efficient and it is not difficult to apply this method to long signals. Results are more accurate when a longer signal and higher sampling frequency are used, regardless of method.

In practice, the length and sampling frequency of a signal used will be influenced by constraints such as cost of monitoring, data storage and computational effort balanced against the modal parameter accuracy required for specific structural design or analysis activities. The AMD-RDT has been shown to provide accurate modal identification where signal length i.e. time and sampling frequency, are limited. This finding enables more confident application of the AMD-RDT to a range of signals obtained through Structural Health Monitoring which have been constrained. Further sensitivity analyses will enhance this research and enable better informed decisions on the balance of these constraints for optimised accuracy.

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[11] Kang Zhou and Qiu-Sheng Li. Reliability analysis of damping estimation by random decrement technique for high-rise buildings. 2020. Compilation and indexing terms, Copyright 2020 Elsevier Inc. 20204809555275 Acceleration response Confidence interval Damping estimations Field measurement Free-vibration tests High rise building Inherent limitations Random decrement technique.

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