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EXTRACTION OF DYNAMIC FEATURES FROM SHORT ACCELERATION DATA BURSTS: A REVIEW

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Abstract: It is well known that structural damage can lead to changes in dynamic features such as frequencies, mode shapes, damping, vibration intensity, etc. Signal processing tools available to extract these features include Wavelet analysis, Fourier and Hilbert-Huang transforms. Acceleration data is typically used as input to these tools, given that it is a type of response with a relatively high dynamic component (i.e., oscillations in the response due to inertial forces of the structure) in relation to the static component (i.e., derived from time-varying static deflections as a result of time/spatial-varying loads). Almost all traditional signal processing approaches require access to long-time data sets. For instance, long periods of acceleration and multiple measurement points allow engineers to accurately define the mode shapes of a structure. In this paper, a scenario is envisioned where drones are used to charge sensors placed on bridges as well as to acquire the data recorded by the sensors for processing. The novelty is the challenge of monitoring structural condition in the context of acquiring limited quantities of data. The latter requires being able to deal with a very significant impact of edge effects and the loss of resolution due to the short duration of the signal. This paper reviews attempts to obtain bridge dynamic features overcoming these limitations, i.e., via multi-stage measurements as in the case of the Short Time Frequency Domain Decomposition method.

1 INTRODUCTION

Nowadays, techniques and methodologies based on dynamic measurements aiming at detecting damage in a bridge or structure are very popular. Compared with static techniques, they offer the possibility of measuring the response of a bridge without controlling the loading while still being able to provide useful information about the condition of the structure. This approach, when loading is not controlled and often completely unknown, is called Operational Modal Analysis (OMA). In particular, the most general situation consists of measuring the response of the bridge through a number of accelerometers placed on the bridge (direct measurement). There are other approaches, still in development, that use accelerometers mounted in a vehicle crossing the structure (indirect measurement). Using the measurements from the structure or vehicle, several features of the bridge can be extracted and examined in order to evaluate the presence of damage. The three features that are usually targeted are natural frequencies, mode shapes and damping ratio, although other vibration-based parameters such as mean cumulative vibration intensity and distributed vibration intensity have proven to be of interest in some scenarios. Regarding the frequencies of the system, they can be extracted through several techniques; the more straightforward being the Fast Fourier Transform (FFT). However, the FFT only allows transforming the signal from time-domain to frequency-domain. Consequently, if the frequency were to vary in time, the FFT can simply provide an average of the frequency value along time. Thus, the FFT is only suitable for stationary, linear signals. This limitation is addressed through the use of Short-time FFT (SFFT) that consists of applying the FFT to small windows of a signal to obtain a solution in the time-frequency domain. The biggest constraint here is the impossibility of defining accurately a signal in the time and frequency domain at the same time. On the one hand, as the sampling frequency used to obtain a signal increases, so does the interval between frequency values in the frequency-domain. Therefore, a high sampling frequency, which should capture perfectly the signal being measured, results in higher inaccuracies in the detection of the fundamental frequencies of that same signal. On the other hand, if the signal is sampled using a low frequency, the risk is that the signal is not well defined and, hence, not all frequencies are captured. The best solution to this conundrum is increasing the number of samples in the signal; a sufficiently high number of samples ensures that, even using high sampling frequencies, the interval in the frequency-domain allows for a proper definition of the frequencies of the signal. However, it is not always possible to obtain long enough signals that provide a satisfactory resolution in the frequency-domain. The scenario in which only short amounts of data are available is addressed in this paper. Characterization of signals from a measured record is limited by other factors as well, such as the Nyquist rate and edge effects when using methodologies in the time-frequency domain.

Regarding the mode shapes and damping ratio, it should be noted that its extraction is more difficult than that of the frequencies. However, on the upside, they may be considered as better indicators of damage. The estimation of damping ratios often relies on many assumptions, which may be difficult to check in a real structure. In the case of mode shapes, many methodologies are available to characterize them once the frequencies of the system have been established. Mode shapes show potential as a damage indicator since they may be able to show localized damages in the structure while frequencies would only show an overall change in value, typically of small magnitude, that may be due to several causes. The paper first reviews a number of techniques commonly used to extract dynamic features from structures, i.e., Wavelet Transform (WT), Frequency Domain Decomposition (FDD) and Hilbert-Huang Transform (HHT) among others. Durations of the measurements reported in the literature are provided in order to stablish what can be understood as a short record of a signal. Then, a series of techniques directly aimed to deal with short signals are presented. Although the paper places more emphasis upon those signal processing techniques that use acceleration from a bridge, there are also a few references applied in a different context, when the principles behind them would also remain valid in bridge inspection. The paper ends with the conclusions drawn from this work.

2 TECHNIQUES TO EXTRACT DYNAMIC FEATURES

2.1 Wavelets

Taha et al. (2006) conduct a review on wavelet transform applied to Structural Health Monitoring (SHM) that covers many wavelet-based methods. Cantero et al. (2016) propose the use of the continuous wavelet transform (CWT) to evaluate the first flexural and torsional bridge frequencies and its variation due to moving trains. They carry out analysis to establish the Modified Littlewood-Paley base as ideal for detecting changes in frequencies for bridges subjected to moving loads. The methodology proposed is tested with experimental measurements from a 36 m long railway bridge. Different frequencies are obtained for forced and free vibration, with the former due to the train loading. A parametric study of the effect of train speed, distance between axles and other parameters is carried out, showing that the proposed method can determine non-stationary frequencies in different scenarios. Nonetheless, the two main limitations of the CWT can be seen in the results; first, the edge effects make the beginning and end of the time-frequency domain irrelevant; second, the CWTs offer a graphic representation very straightforward to analyze but from which it is difficult to obtain a clear value for the frequencies. The same bridge had been previously analyzed by Ulker-Kaustell and Karoumi (2011). In this case, the Morlet base is used instead and the viscous damping is characterized in addition to estimating the frequency of the system. For this purpose, the CWT is combined with the definition of viscous damping from a damped linear oscillator. The importance of edge effects is discussed in this paper, establishing a domain where they are negligible, i.e. between 5 s and 30 s in a 35 s long signal.

Regarding the wavelet basis, there are many options, some of them (Morlet, Cauchy, Harmonic) are discussed in Le and Argoul (2004). Le and Argoul discuss the concept of selecting wavelet parameters so that maximum efficiency in the detection of frequencies can be achieved. They also present the concepts of ridge and skeleton, which are used in latter applications of the CWTs. The ridge can be defined as the curve whose points correspond to the maximal values of the CWT modulus, whereas the skeleton refers to the values of the CWT modulus at the ridge points. In particular, Marchesiello et al. (2009) compare two methods for modal parameter estimation: one based on CWTs and another that uses Stochastic Subspace Identification (SSI). Focusing on the former, they determine the evolution of frequency and damping in time by extracting the ridge from the CWT by means of the crazy climber algorithm. The methodology is validated using experimental data from a lab test where the movement of a train over a bridge is simulated with a steel beam and scaled train model. Acceleration is measured, generating records of 7 s and 35 s depending on the vehicle speed, and the frequency and damping variation is obtained. Results are compared to those obtained with the SSI method and using the modal parameters calculated for stationary tests as reference.

Staszewski and Wallace (2014) use a CWT based methodology, with Morlet base, that seeks to extend the concept of Frequency Response Functions (FRFs) to time variant systems. The FRF is adapted by replacing the original Fourier Transforms with WTs. It is also proposed to use the average of several scenarios to improve the results. The methodology is tested both through numerical models of sprung masses and experimental data from a lab test involving a moving load. In both cases, the results with no average are difficult to interpret whereas, when many runs are averaged (i.e., 25 times), the results improve significantly. However, some limitations may arise for this methodology as it seems necessary to know the exact excitation of the structure at the same time than the measured response. This is not usually the case for dynamic tests in the field and it is certainly never the case for OMA. In addition, the authors include a remark in their work as to how the WTs show better resolution for low frequencies.

Naderpour and Fakharian (2016) propose a two-step algorithm for the determination of dynamic features (frequency and mode shapes). Instead of applying a CWT, the use a Wavelet Packet Transform (WPT) based on the Discrete WT in order to avoid redundancies and improve the resolution of high frequencies. The decomposition of the signal is then followed by implementation of the Peak Picking method (PP), which allows to identify the dynamic parameters in the decomposed signal most similar to the original one. The method is validated through a lab experiment where the mode shapes are evaluated by means of the Modal Assurance Criteria (MAC). The predicted and analytical 2nd mode shape are very similar but important differences can be found in the 1st and 3rd modes, specially when noise is introduced. In the case of Tomac et al. (2017), the authors propose a methodology for damping ratio identification that uses a CWT with Gabor base in combination with Morlet Wave damping identification. Emphasis is placed upon the edge effect, that limits the length of the signal that can be analyzed. The concept of ridges appears here again, and the methodology is tested with satisfactory results both through numerical simulations (16 s long signal) and lab experiments (8.2 s long signal). Prior to Tomac et al., Slavic and Boltezar (2011) develop a method for damping identification based exclusively on the Morlet Wave with simplified closed form solutions. In 2012, Hester and Gonzalez (2012) develop a damage detection method based on applying wavelets to the bridge acceleration signal from a simulated vehicle-bridge finite element interaction model. However, the proposed method does not rely on identifying specific parameters of the structure, but rather on analyzing the relative energy associated to the wavelet transform. It is found that the energy associated to scales that are far from the natural frequency of the bridge, show high concentrations of energy in the presence of damage. This is used to locate damage in different scenarios, including varying vehicle speeds, presence of noise, damping, multiple damage locations and road profile.

2.2 Frequency Domain Decomposition (FDD)

Zhang et al. (2005) include a brief but very illustrative compilation of the evolution of Frequency Domain techniques. All of them are based on the evaluation of the spectral matrix of the structural response, the first and simplest of them being the Pick Peaking method (PP). However, given the limitations of PP methods as discussed in Gentile and Saisi (2007), a more complex and advantageous technique labelled FDD is proposed. The difference lies on the calculation of the Singular Value Decomposition (SVD) of the spectral matrix in the case of FDD. Consequently, some limitations of the PP method are overcome, i.e. mode shapes are more easily extracted. Gentile and Saisi compare both methodologies using experimental data and they found that the results agree for both frequencies and mode shapes of the structure. Another example of the FDD is shown in Brincker et al. (2001) where the authors obtain the dynamic parameters (frequencies, mode shapes and damping ratio) of the numerical model of a 2-storey building using this technique. Here, the FDD is able to differentiate close modes of vibration in the presence of noise.

The next evolution of FDD would be Enhanced Frequency Domain Decomposition (EFDD), which is used by Magalhaes et al. (2010) and Rebelo et al. (2008). In both cases, the EFDD is used to estimate damping ratios of structures. Magalhães et al. apply this technique to numerical examples (2 DoF system) while Rebelo et al. analyse experimental data obtained from single-span ballasted railway bridges. In the latter case, non-linear behaviour of frequencies and damping ratios are observed depending on the amplitude of vibration. In the former case, it is mentioned that the Welch method (Welch 1967) is implemented to obtain the Power Spectral Density (PSD) matrix of the response. Another alternative mentioned by Pioldi et al. (2017) is the use of a correlation approach (Wiener-Kinchin method). The authors propose an enhancement of the FDD, called refined FDD (rFDD), aimed at scenarios with large damping ratios, focusing in particular on seismic signals (Pioldi and Rizzi 2017).

2.3 Hilbert-Huang Transform (HHT) and Empirical Mode Decomposition (EMD)

A full review of methods based on the HHT can be found on Chen et al. (2014). Recently, Xiao et al. (2017) have applied Ensemble Empirical Mode Decomposition (EEMD) to experimental measurements from tiltmeters installed in a steel bridge. The tests conducted consist of two heavy loaded trucks travelling at the same speed in the same direction. The authors are able to estimate the structural frequencies from rotations with enough accuracy, using a numerical model as comparison. Wu et al. (2013) embed the HHT algorithm into a wireless sensor network to obtain the dynamic features of structures. They test this technology in a scale lab model of a cable-stayed bridge and, although mode shape and frequency identification are successful, they also address the potential limitation of applying the methodology in a real structure, i.e. a large number of sensors is needed. Kunwar et al. (2013) propose a damage detection method based on applying HHT to the acceleration measurements from sensors on a bridge subjected to ambient vibration. They test the proposed methodology on a scaled model in the laboratory, for which different levels of damage are simulated. The results show the interest of looking at the marginal Hilbert spectrum as an indicator of damage, as well as analyzing instantaneous phases from the signal. Nonetheless, the authors note how the response of sensors away from the damage is barely altered in comparison with those closer to it.

Qin et al. (2015) propose a variation of the EMD, called Bandwidth Restricted EMD, that assumes EMD is a binary filter and it is aimed at dealing with the common problem of mode mixing. The authors then combine the improved EMD with two different techniques, namely SSI and Random Decrement Technique (RDT), to estimate the frequency and damping ratio of a railway bridge in China. The results obtained are in good agreement with standard EMD, SSI and PP methods. Finally, although not applied to bridge parameter identification, it is worth noting the work by Ji et al. (2012) as they use EMD to analyse the characteristics (frequency, phase, period) of sound radiation in double cylindrical shells. The authors are able to analyze the aforementioned features from a signal that is only 0.2 s long.

2.4 Others

Both Magalhães et al. and Marchesiello et al. use SSI methods and compare them to their proposed FDD and Wavelet methods, respectively. In the first case, the SSI outperforms the FDD-based methodology, as it provides better results with shorter acceleration records. In the second case, the authors develop a variation of the SSI method deemed Short-Time SSI (ST-SSI). The results, however, show no improvement compared to those obtained with the Wavelets, although it is noted that ST-SSI allows to use data from several sensors simultaneously for parameter extraction while Wavelets must analyse each sensor one at a time. Qin et al. combine SSI with Bandwidth Restricted EMD to detect frequencies and damping ratios. Another alternative approach from the same authors is RDT, which they use in combination with Bandwidth Restricted EMD.

An example of another technique, Time-Domain Decomposition (TDD) can be found in Kim et al. (2010). Frequencies and mode shapes are extracted for the case of a moving high-speed train. In addition, temporal parameters are obtained through algorithm for measured modal correlations. Masjedian and Keshmiri (2009) provide a review of other methods to extract dynamic features from the acceleration response of a structure, such as Short-Time Fast Fourier Transform, ARMA models and NExT methods amongst others.

3 DISCUSSION OF SIGNAL LENGTHS

An extensive number of methodologies can be found in the literature that use acceleration records as input and the duration varies vastly from one application to other. For instance, Benko and Juricic (2008) propose a method for short signals that is applied to a 20 s long signal. However, many other methods can be found that are applied to signals shorter than 20 s although they have not been specifically designed for short signals. Therefore, there is an ambivalence on which constitutes a short signal in the literature. In relative terms, the duration of a record can be thought of as short when it is not able to yield an expected accuracy for the frequency being sought. This section intends to discuss record lengths found in the literature according to the identification methods and to the targeted dynamic parameters.

3.1 Record durations according to the extracting technique

First, papers using WT based methods to extract dynamic features from acceleration signals are discussed in terms of duration of the signal. A novel method based on WT is proposed for estimation of modal parameters in Yu et al. (2014). A minimum signal duration of 0.45 s allows Yu et al. estimating the natural frequency from a five-degree-of-freedom mass-spring-damper system with a reasonable accuracy. Out of 15 reviewed papers, it is found that 5 s could be considered long enough to extract dynamic features through WT based method. Given that 66 % of these papers deal with signals longer than 5 s, this duration is adopted as reference to distinguish between short and long signals.

In the case of FDD, Gkoktsi and Giaralis (2017) extract frequencies and mode shapes from a 4.0 s acceleration signal accurately. For the specific problem of two quarter-cars travelling over a beam, Malekjafarian and Obrien (2014) use Short Time FDD to obtain the mode shapes to detect the location of damage from a set of 0.75 s long measurements. This is a very short length duration for an acceleration record, but it should be noted that the method is based on having 20 short signals; thus, it is equivalent to having a long one and splitting into segments. Based on the papers using FDD, again approximately 5 s or less are covered in one third of the publications.

The HHT and EMD applied to dynamic feature identification is a very common methodology. Ji et al. (2012) use the EMD based method to measure the natural frequencies within a very limited acceleration signal, 0.2 s, which is also the minimum signal length found through the reviewed papers. Regarding the methods that are based in HHT, EMD or any of its variations, one third of the reviewed papers use signals less than 5 s long, with a mean value of 2.1 s. In the 33% -- 66% range (number of papers), the mean length signal is 21.5 s, therefore ten times more than for the first third percentile. Cases in which the signal is greater than 60 s are not common, and more than half of the signals are less than 10 s long.

Blind Source Separation (BSS) has been proposed as a signal processing method capable of revealing features that are mixed together in the measured data (Amezquita-Sanchez and Adeli 2014) and Compressive Sensing (CS) theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use (Candes and Wakin 2008). Therefore, these two methodologies could be envisioned as ideal to be applied to short records of acceleration. Yang et al. (2013) develop a novel method based on BSS for extracting modal parameters in their study. By applying a BSS based method, the damping ratio can be directly extracted from 1.0 s acceleration signal. This is the lower limit found in the literature carried out for this kind of methods. However, the variability is high and the following lengths can be noted: 4 s (Gkoktsi and Giaralis 2017), 20 s (Bao et al. 2010), 40 s (Ghahari et al. 2017), 60 s (O'Connor et al. 2014), 500 s (Gkoktsi and Giaralis 2017).

3.2 Record durations according to dynamic feature being sought

The basic dynamic characteristics of the structure to be extracted from acceleration signal records are natural frequencies, damping ratio and mode shapes. A minimum duration of an acceleration signal of 0.3 s is used to extract structural natural frequencies in Yang et al. (2004). With such limited signal duration, Yang et al. use EMD and HHT based approach for determining the natural frequencies of the structure before and after damage from a benchmark building. The duration of the signals employed in 33% of reviewed papers with shorter signals has a mean value of 2 s, and for the 33% -- 66% range, the mean is 25 s. Moreover, all the signal durations in 33% of reviewed papers are less than 5 s.

When extracting damping ratios, the minimum signal duration is found to be 0.3 s in Yang et al. (2004). Yang et al. use an EMD and HHT-based approach to determine the damping ratio of the structure with an acceptable accuracy within limited signal length. Additionally, Yang et al. (2013) develop a novel method for extracting modal parameters, including mode shapes, natural frequencies and damping ratios. By applying Hilbert Transform (HT) and complex Independent Component Analysis (ICA) with reference for BSS, the damping ratio can be directly extracted from 1.0 s acceleration signal. Also, it is concluded that 5 s is enough to extract damping ratio from the statistical analysis. The minimum signal length to identify mode shapes of the structure is 1.0 s in Wu et al. (2013). Wu et al. present a new decentralized data processing approach for model shapes identification using the HHT algorithm with permissible error range 0.27 % from a real cable-stayed bridge and its laboratory bridge model. It is also observed that 10 s is sufficient to extract mode shapes as one third of the reviewed methods that extract this dynamic feature use a signal of that length or shorter.

4 TECHNIQUES SPECIFICALLY APPLIED TO SHORT RECORD LENGTHS

4.1 General techniques adapted for short signals

Among the Wavelet techniques that can offer specific advantages for short data bursts, the following can be of interest. First, combinations of synchrosqueezing and CWT show promising results in dealing with the edge effect. Synchrosquezzing seeks to improve the time-frequency representation of a signal by modifying the coordinates of points in the time-frequency plane according to local information around that point (Daubechies et al. 2011). Numerous papers can be found in this respect but the most recent ones include the next two. Mihalec et al. (2016) propose a variation of CWTs through synchrosqueezing to obtain damping ratios of a free vibration signal. At the same time, the modified wavelet (SWT) localises frequencies with higher accuracy than the standard technique. Two different procedures are analyzed: average and proportional SWT. It is shown by means of numerical applications that the frequency of the structure is more clearly identified with either of these techniques. From there, damping ratios are also evaluated and an improvement in detection is also obtained. In this case, a pure harmonic signal is used to illustrate the proposed methodology but experimental measurements from a steel beam are used to further validate the analysis. Similarly, Wang et al. (2013) apply synchrosqueezing in combination with WT to improve the results of CWT. They combine SWT with extended analytical mode decomposition to obtain instantaneous frequencies in forced vibration. The signals analysed in this case are 30 s long and indices of accuracy smaller than 6% are obtained (the smallest the index, the more accurate the signal is reconstructed). Another variation from the same authors as Mihalec et al. can be found in Boltezar and Slavic (2004) where they propose three techniques to mitigate the edge effect by modifying the wavelet instead of extending the signal. Of the three proposed techniques, two of them (reflected-window and equal-window-area) show promising results as they identify damping ratios using signals three time shorter than in the traditional approach.

Other examples that can be of interest, although they have not been applied to bridges, include Yan et al. (2017) where the authors propose a modification of the Frequency Slice Wavelet Transform (SFWT) called DSFWT, the D standing for Discrete. Similarly, Klepka and Uhl (2014) investigate the use of wavelet filtering to evaluate non stationary stiffness systems such as a turbine of an airplane. They propose an adaptive approach to wavelet filtering and create an algorithm combining this idea with modal parameter estimation based on Recursive Least Squares (RLS). They conclude that the algorithm is fit to be applied to very short signals due to its adaptive nature.

A variation of the FDD for short signals is the Short Time FDD (STFDD) that Malekjafarian and Obrien (2014) apply to the acceleration measurements from two linked axles of a vehicle travelling over a bridge. By calculating the FDD of short signals corresponding to the axles travelling over predefined segments of the bridge, they are able to calculate the mode shapes of the structure with high accuracy once the vehicle drives at a very low speed. In addition to the analysis with one vehicle, the possibility of multiple vehicles and the presence of road profiles are also evaluated. The method is extended in OBrien and Malekjafarian (2016) to explore damage identification in bridges.

4.2 Techniques aimed at dealing with short signals

Compressive Sensing (CS) and Blind Source Separation (BSS) are two techniques specifically designed to deal with short signals and sparse data. A description of the basic principles behind CS can be found in Candes and Wakin (2008). The aim of this technique is to evaluate the possibility of sampling signals at a sub-Nyquist rate, thus resulting on sparse data records. Two assumptions regarding the measured signal are highlighted for this to be possible: sparsity and incoherence. The first one assumes that a signal depends on number of degrees of freedom considerably smaller than its length. The second assumption makes reference to the fact that a signal sparse in time domain should be spread in the frequency domain. Bao et al. (2010) simulate CS with real data from accelerometers placed in the Shandong Binzhou Yellow River Highway Bridge. Although the compression ratios they achieve are limited, the authors conclude that the technique has interest in the future. Similarly, O'Connor et al. (2014) find that the compression ratios that can be achieved with accelerations signals from structures are limited by the lack of sparsity on the signals. Nonetheless, they insist in its potential as a method to reduce energy consumption in wireless sensors. A maximum of 20 % compression sampling is found as the limit for modal reconstruction (modal assurance criterion, MAC, over 0.9) for the numerical simulations in the paper.

Gkoktsi and Giaralis (2017) compare two different methodologies, both sampling at sub-Nyquist rates. The first approach is based on CS while the second one consists of a power spectrum blind sampling (PSBS) technique. The main difference between the two methodologies lies on the sampling pattern and the basic assumptions. While CS assumes a sparse signal, the PSBS method treats the acceleration as a wide-sense stationary stochastic process. As for the sampling pattern, CS relies on a completely random sampling whereas PSBS proposes a deterministic sampling pattern based on multi-coset sampling. In both methodologies, FDD is applied as a final step to extract the dynamic features. The authors apply both methodologies to numerical simulations (simply supported beam) and real data (Baarenbohlstrasse overpass, Zurich) to obtain mode shapes of the structures. Two compression rates of 11 % and 31 % are assumed for both methodologies and the authors conclude that the PSBS method outperforms the CS one, specially for highly under-sampled signals.

Blind source separation (BSS) is a technique that assumes that the recorded signal is the result of the sum of different components due to several excitation forces that are usually unknown. Basic principles for BSS can be found in Zibulevsky and Pearlmutter (2001) and Antoni (2005). Sadhu et al. (2013) propose a decentralised modal identification method based on BSS and parallel factor decomposition. The method is tested both numerically and with real data from a building, allowing the identification of frequencies and mode shapes. It is noticed that one advantage is the small number of sensors needed; however, the method is limited when dealing with highly damped structures. Ghahari et al. (2017) develop a complete methodology for obtaining frequencies, mode shapes and damping ratios, which extends the application of BSS to non-classically damped structures with complex mode shapes. Given that the traditional BSS methodology assumes stationary signals, Guo and Kareem (2016) propose a modification of BSS methods that is intended for non-stationary signals, called Time-Frequency Blind Source Separation. The approach in this method is selecting specific regions in the time-frequency plane where only one mode contributes significantly. The methodology is tested using numerical examples and full-scale data from an earthquake to characterize the main dynamic features.

Finally, Benko and Juricic (2008) develop a different approach specific for short signals based on Filter Diagonalization (FD). There are two main steps in this methodology; first, the frequencies outside the desired range are filtered and, second, frequencies are extracted using diagonalization of small matrices.

One advantage of the proposed methodology is its ability to perform when high levels of noise are present in the signal.

5 CONCLUSIONS

This paper has reviewed methods to extract dynamic features of an acceleration record. A high variability in terms of the duration of the signal used by the different authors, even when applying similar techniques, has been observed. It has been found that around one third of the literature operate with signals shorter than 5 s, where edge effects and lack of resolution may become troublesome.

Techniques that work in the time-frequency domain, such as wavelets and HHT, have the advantage of evaluating the variation of frequency with time; therefore, allowing to detect changes due to damage. However, they usually present edge effects that complicate its use with short signals. In the case of wavelets, procedures to mitigate these effects have been proposed, namely synchrosqueezing. Regarding the HHT, mode-mixing is a common limitation of this technique when applied in combination with EMD. Nonetheless, variations of the EMD such as EEMD, Bandwidth Restricted EMD and others can help overcome mode-mixing. In addition, if the range of frequencies of interest is previously known, band-pass filters could be applied to the original signal. On the other hand, techniques that work in the frequency domain, i.e., FDD, are not able to capture the variation of frequencies within a signal. However, they do not show the limitations related to edge effects and they prove to be extremely useful to evaluate the mode shapes and damping ratio of a structure. In particular, mode shapes show high potential as damage indicators and examples have been found where the FDD is applied to multiple short records.

Finally, this paper has analyzed a variety of specific techniques for short data bursts. Compressive Sensing seems to be an option at the level of sensor design, allowing to obtain short signals that are at the same time representative of the behaviour of the structure. The upside of applying these techniques to pre-recorded signals appears to be nonetheless limited. As for Blind Source Separation, it has been found that this is an interesting technique to be applied to short data burst of acceleration signals. In general, it should be noted that these methodologies assume that multiple sensors can be placed on the structure and register the response from different points of the structure at the same time.

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