Data reduction for Structural Health Monitoring based on Chebyshev moments and wavelet transforms

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Abstract.
This work demonstrates the usage of a set of parameters to describe, compare and classify transient waveforms, such as those found in Acoustic Emission and Acousto Ultrasonics testing. While traditional AE parameters present a number of shortcomings, the set of parameters proposed aims to get a significant data reduction of transient signals while maintaining an adequate level of information on which to base data analysis and comparisons. These parameters are based on the computation of Chebyshev moments from a rectified wavelet transform of the original signal. The technique has been applied to different use cases, namely a stiffened composite panel under fatigue and impact, a gear tooth fatigue test and using a torque rate of change sensor to identify damage in gears. Results show the technique’s applicability to detecting changes in a variety of different structural health monitoring problems.

Introduction

The worldwide transportation industry is aiming to create cleaner, lighter and safer means of transport. Making transportation means lighter using lightweight materials can improve fuel efficiency directly; another way to reduce operative costs is reducing maintenance time. A common way to address the ability of providing maintenance on-demand is the adoption of Structural Health Monitoring (SHM) systems.

The most promising category of SHM utilizes ultrasonic surface waves, both in a passive or active way. These techniques include Acoustic Emission (AE) and Acousto-Ultrasonics (AU). AE is based on the passive recording of ultrasonic stress waves originated from damage development, while AU is based on the comparison of ultrasonic surface waves emitted from an actuator and recorded by a sensor. A third way, particularly useful in rotating machinery monitoring, is to monitor the torque Rate of Change (RoC). If a transmission shaft is magnetized in a particular way a transducer can measure it to pick up variations in torque which can be then linked to damage in the transmission chain.

All these techniques, however, demand high sampling rates and large amounts of data. In this work, a data reduction technique is proposed and its applications to SHM of engineering structures is presented; the technique can detecting and quantify the difference between two signals with limited processing and storage.

The signal processing technique, explained more in detail in [1] and inspired by [2], consists in first computing the discrete wavelet transform of a signal and reconstructing the wavelet details into a matrix; then, calculating the Chebyshev polynomial moments of the resulting matrix up to a degree $L$. This leads to the obtaining of $L^2$ parameters which can then be used as waveform descriptors.

Use cases and results

CFRP panel with stiffeners. A CFRP structure consisting of a flat panel and four stiffeners bonded to it was manufactured with an artificial defect (imperfect bonding) in one of the stiffeners (Figure 1). It was subjected to compressive fatigue and subsequent impacts with different energies on another stiffener. Four of the AE sensors used on the panel were used for AU tests. By comparing the baseline signal and the damage signals’ Chebyshev descriptors, and calculating the correlation coefficient across each test, the artificial debonding damage side (sensors 2, 3) indicated lower correlation during fatigue, while the impact (sensor 1) clearly marks the 30J impact. The extent of the damage was confirmed with an ultrasonic c-scan.

![Image of CFRP panel with sensors and annotations indicating debond and impact marks.]

![Graph showing Chebyshev moments correlation coefficient over test stages. Initial fatigue on left stiffener and evidence of impact damage on right stiffener are marked.]

![Caption: Evidence of impact damage on right stiffener. Initial fatigue on left stiffener is marked.]
Gear root crack monitoring. A tooth bending fatigue test was conducted using a bespoke test rig (Figure 2) [3]. An Acoustic Emission sensor was placed next to the contact tooth pair; AE waveforms were continuously recorded at one waveform per cycle. For each waveform, the Chebyshev moments were then calculated; the correlation coefficient using an early waveform as a baseline indicates early damage around 10000 cycles, while confirming damage also indicated by traditional AE signal processing around 22000 cycles. Traditional AE gave no discernible indication of early damage.

Torque Rate of Change (RoC). A series of spur gear pairs with varying levels of damage related to gear overloading were tested on a back-to-back power-recirculating test rig under a range of loads and torques. RoC [4] of torque was measured on the input to the rig (i.e. the torque losses in the system). For each RoC Torque dataset, corresponding to a shaft revolution, the Chebyshev moments were calculated and Figure 3 shows the correlation coefficient of the moments for each data file plotted against damage size. The technique clearly shows that the Chebyshev method is sensitive to gear tooth damage. It is anticipated that the method would show significant improvement if directly measuring RoC torque within the driveline rather than measuring rig frictional and windage torque losses.

Conclusions

A signal processing technique which is capable of reducing data while providing significant information about the change in status of a system was presented and demonstrated on different applications, including AE, AU and Torque RoC on aerospace and power transmissions applications. The technique equalled or outperformed the state-of-the-art processing methods usually utilized while also obtaining a large degree of data reduction.

References