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A random demodulation architecture for sub-sampling acoustic emission signals in structural health monitoring

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ABSTRACT

Structural health monitoring (SHM) has received increasing attention due to its low cost and high performance in the field of non-destructive testing. However, the data acquisition step of SHM, especially in acoustic emission (AE) applications, often encounters a sampling rate barrier because of limited energy and storage resources. In this paper, we propose and evaluate a compressed sensing AE signal acquisition system to solve this problem. Our sampling framework is based on the existing random demodulation (RD) architecture, which is easy to implement in AE monitoring systems. Our sparse recovery algorithm is based on ℓ_1-homotopy with a learned dictionary, which compared to alternative techniques/dictionaries is more accurate, fast, and easily-implemented for dynamic, non-stationary, streaming AE signals. Finally, we apply the proposed method to actual signals to verify its validity and efficiency. The results confirm that the proposed sampling model, dictionary, and algorithm can realize the goal of under-sampling and reconstructing AE signals with high accuracy and speed.

1. Introduction

To ensure the safety of structures such as in aerospace, civil, and mechanical engineering infrastructure, traditional maintenance is usually done in a time-based model wherein decisions (e.g., preventive repair times/intervals) are determined based on failure time analyses with non-destructive testing (NDT) techniques. As an example, aircraft are periodically inspected on the ground and missiles are retired after a set amount of captive-carry hours [1]. However, time-based maintenance requires downtime for inspection which may be very costly. In addition, periodic inspection is not sensitive to emergencies and may not yield enough structural information in time [1,2]. These drawbacks are amplified with the increasing size and complexity of structures, especially in the fields of aerospace and civil engineering.

To address these types of challenges, structural health monitoring (SHM) has been proposed as an alternative to the conventional monitoring paradigm. SHM involves integrating sensors into the structure as a whole to collect first-hand information that can be used to assess a structure's integrity and durability in real time, and it can also provide early warnings regarding the safety of the structure [3–5]. SHM systems have two main characteristics: they are *online*, which means that the health of a structure can be assessed immediately during the complete life cycle process, and they are *integral*, which means that the

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loads, damage monitoring, sensing and assessment algorithms are all embedded in the structure as a whole [6,7]. These two characteristics of SHM allow traditional time-based maintenance to be replaced with a more cost-effective condition-based maintenance wherein recommendations are made based on the information collected through a continual monitoring process [1,2]. One should take these two features into consideration when building new SHM systems.

Acoustic emission (AE) is an important technique studied in SHM. AE signals correspond to certain stress waves in solids caused by changes such as crack formation or plastic deformation in the internal structure, which may be introduced by aging, temperature gradients, or external mechanical forces [8,9]. Consequently, the information contained in an AE signal is closely related to the damage; for example, AE can help in finding the position of developing cracks. AE signal features such as amplitude, duration, rise time, decay time, energy, and frequency content can be used to identify and evaluate damage in a structure [10]. However, because AE signals are susceptible to environmental noise and because the AE theory is not yet mature, the practical application of AE techniques is currently limited to isolated cases such as concrete bridges [11–13]. Still, as a passive NDT method, AE has some advantages such as the fact that AE sources come from the material itself, meaning that no additional excitation device is needed for inspection, and it can provide real-time continuous monitoring of the structure [14]. These advantages make AE technology a very promising method in SHM, and AE is widely studied and used in the lab to test the materials like concrete structures [10] and fibre composites [15]. One may expect that with the improvement of AE theory and the progress of signal acquisition and processing technology, AE will become more widely used in SHM outside of laboratory settings.

The signal acquisition component is an important consideration in an AE system. One can obtain accurate material health assessments by monitoring AE signals, and more detailed damage information can be extracted if one can precisely collect and analyze AE signals. The frequency range of AE signals is typically from 10 Hz to 500 kHz, and different frequency bands contain different information [14,16–18]. Unfortunately, it is difficult to support such a high bandwidth in real-time SHM sampling systems, where energy and storage may be limited. The Fiber Bragg Grating (FBG) sensor, which has many advantages such as anti-electromagnetic interference, small size, and ease of integration, is considered an alternative for the next generation of SHM systems [19]. Unfortunately, the sampling rate of SHM systems based on FBG sensors is relatively low and cannot support the bandwidths of AE signals [20]. Therefore, it is worthwhile to study the problem of sampling AE signals at a low rate while retaining as much information as possible.

Several researchers have explored the use of compressed sensing (CS) in SHM systems to efficiently capture high-bandwidth signals. CS makes use of sparse signal structure to break the conventional Nyquist sampling limit [21–23]. By capturing a signal directly in compressed form, CS allows for a potentially significant reduction in a signal's sampling rate. From the compressed samples, one can later use the sparse model to recover the signal fully. By introducing CS into an SHM system, one can not only greatly reduce the required energy and storage, but also increase the reliability and extend the lifetime of the SHM system.

Current investigations of CS for SHM can be divided into two categories. One category involves applying CS compression after data has first been acquired in a conventional fashion. In this vein, Cortial et al. [24] applied CS as a means of data compression in SHM sensor networks, Haile and Ghoshal [25] used CS for full-field strain image reconstruction, Huang et al. [26] utilized CS to recover spike signals in SHM and tested on data from bridge monitoring, and Yang and Nagarajaiah [27] incorporated sparsity into a framework for damage classification. In various contexts, these works allowed for reduced transmission, calculation, and storage requirements while improving the information extracted from the signals in SHM systems. However, all of these works of data compression and reconstruction involved *offline* application of CS, where compression/subsampling was performed in software after an initial high-rate acquisition of Nyquist-rate samples. Indeed, much of the original CS literature focused on discrete and finite-dimensional signals and could not be directly applied to analog signals.

The second category involves integrating CS directly into the analog SHM front end, after which signal features (or the complete signal itself) may be extracted/reconstructed from the low-rate compressed measurements. While some of the CS literature has since expanded to consider compressive sampling and reconstruction architectures for analog signals, relatively little work in SHM has considered these architectures explicitly. Li et al. [28] focused on extraction of mode shapes and frequencies from vibrational data. This work considered various randomized sampling and compression protocols, some of which can be applied directly to an incoming analog signal. However, specific hardware implementations and performance on actual data were not provided. Along similar lines, Yang and Nagarajaiah [29] proposed a sparsity-based technique for output-only modal identification. That work potentially allows for fewer sensors to be used in multi-sensor settings, but did not consider the problem of compression at each individual sensor. A subsequent paper [30], which included experimental results, extended the authors' work in output-only modal identification and incorporated non-uniform, sub-Nyquist sampling as a front-end CS acquisition protocol. Finally, Yang et al. [31] considered the problem of output-only modal identification from video cameras with a sub-Nyquist temporal sampling rate.

This paper proposes a CS-based SHM sub-sampling architecture for analog AE signals and simulates its performance on actual AE data. The signal acquisition protocol is based on random demodulation (RD) [32–34], which is one of the CS techniques that can permit low-rate sampling in an analog front-end. To dynamically reconstruct the high-rate sample stream from the low-rate compressive samples, we adopt the ℓ_1-homotopy method [35] in an online fashion. To boost the performance of this algorithm, we incorporate a sparse dictionary learned from AE training data. It should be noted that this paper only proposes a hardware-level sub-sampling system architecture, and does not provide a specific hardware implementation. However, through simulations on real (previously recorded) signals, the proposed architecture is proved to be efficient and feasible, and could be naturally extended to an actual hardware system.