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Compressive Sensing for Operational Modal Analysis of wind-excited slender structures

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SUMMARY
This work investigates the application of Compressive Sensing (CS) techniques to Structural Health Monitoring (SHM). Structural response signals often exhibit sparsity in the frequency domain, enabling their reconstruction from a reduced number of samples compared to the Nyquist–Shannon requirement. An experimental campaign was conducted using acceleration measurements of three real steel towers. The recorded responses, dominated by wind-induced vibrations, were compressed and subsequently reconstructed at sampling rates significantly lower than those typically adopted in SHM practice. Modal parameters were then identified from both original and reconstructed signals using established output-only operational modal analysis (OMA) techniques. The results highlight the potential of the proposed approach to reliably extract meaningful modal information from compressed measurements, even under the low-amplitude and broadband excitation induced by wind. Overall, the study suggests that CS can effectively reduce data acquisition and transmission requirements, supporting the development of efficient and cost-effective IoT-based monitoring strategies for slender structures.

Keywords: Compressive Sensing, Structural Health Monitoring, Operational Modal Analysis

1. INTRODUCTION

Structural Health Monitoring (SHM) is essential for ensuring the safety, durability, and serviceability of civil infrastructure. Continuous monitoring provides valuable information about structural behavior, enabling early damage detection and optimized maintenance strategies. However, SHM systems generate large volumes of data, creating challenges related to transmission, storage, and energy consumption. These challenges become critical when monitoring structures located in remote areas or when using low-cost wireless systems. Even in well-connected environments, reducing data flow is beneficial for improving system efficiency and scalability. In this context, Compressive Sensing (CS) offers a promising solution. CS exploits the sparsity of signals in a transformed domain, typically the frequency domain, to reconstruct them from a reduced number of samples (Foucart and Rauhut, 2013).

In structural applications, vibration signals are often sparse in the frequency domain due to the dominance of a limited number of modal contributions, making Compressive Sensing (CS) particularly suitable for SHM purposes. This characteristic is even more pronounced in wind-sensitive structures—typically slender and flexible systems—where the dynamic response is largely concentrated around a few dominant frequencies.

While the theory of CS is well established (Candes and Wakin, 2008), its application to structural dynamic identification is still limited (Zhou et al., 2018; Bao et al., 2020). In particular, the impact of reduced sampling on modal parameter estimation requires further investigation, particularly for damping, due to its sensitivity and the potential for error propagation in wind-induced response predictions (Pagnini, 1996). This study aims to evaluate the applicability of CS for structural dynamic identification using real data from three different slender structures subjected to wind loading, monitored through accelerometers.

2. METHODS

2.1. Compressive Sensing framework

Compressive Sensing enables the reconstruction of a signal from a subset of its samples. It leverages on the property of sparsity: a vector is sparse if most of its entries are very close to zero while only few are significantly larger. The more a signal is sparse, the more CS can reduce the number of necessary samples, possibly allowing sub-Nyquist sampling without notable information loss. Applying CS means solving an optimization problem:

$$min\|\boldsymbol{x}\|_1 \quad subject\ to \quad \boldsymbol{Ax} = \boldsymbol{y} \tag{1}$$

where the L_1-norm of the target vector $\boldsymbol{x}$ is minimized, $\boldsymbol{y}$ being the subset of measures used and $\boldsymbol{A}$ a modified version of the transformation matrix relative to the sparsity domain.

2.2. Modal identification techniques

Modal parameters are extracted using two well-established operational modal analysis (OMA) techniques: Enhanced Frequency Domain Decomposition (EFDD), which operates in the frequency domain (Brincker et al., 2001) and Stochastic Subspace Identification (SSI), an advanced time-domain method (Peeters and De Roeck, 2001).

These techniques are applied both to the original signals and to the CS-reconstructed signals to evaluate the impact of data reduction.

3. EXPERIMENTAL SETUP

The performance of CS is investigated with respect to its application in the dynamic monitoring of three slender steel towers (Fig.1). The monitored structures include two lighting towers, with heights of 16.6 m and 35 m, located in the harbours of La Spezia and Genoa (Italy), respectively, and a 30 m high lightning rod installed in Latina (Italy).

Each structure is instrumented with two biaxial accelerometers, positioned at the top and approximately at two-thirds of the total height, recording the structural response at a sampling frequency of 200 Hz. Continuous measurements have been acquired over several months for the lighting towers, whereas only a limited dataset comprising a few hours of ambient vibration recordings is available for the lightning rod.

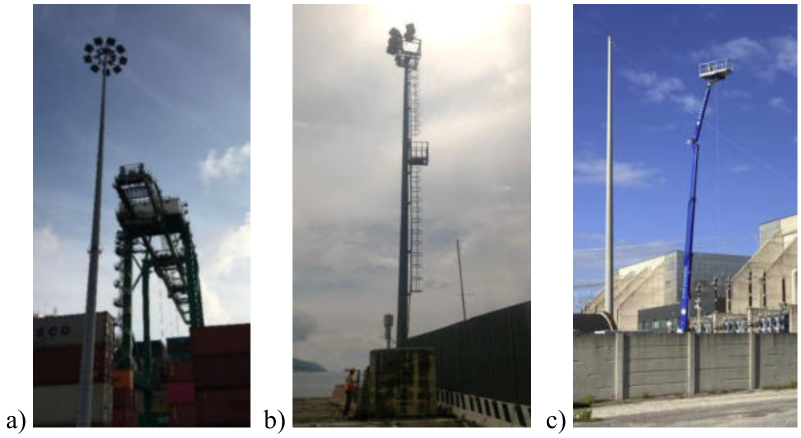

Figure 1. The monitored towers in Genoa (a), La Spezia (b) and Latina (c)

The full-scale datasets exhibit varying degrees of sparsity in the structural response signals across the three case studies. This characteristic, primarily arising from differences in the distribution of appendages and ancillary components along the height of the structures, provides a valuable opportunity to assess how signal sparsity influences the impact of data reduction on the identification of modal parameters.

4. RESULTS

CS was implemented in MATLAB using the packages *CVX* for convex optimization and *ASP* for sparse signal reconstruction. The terms "pseudofrequency" and "pseudo-Hz" (psHz) are introduced to represent the average number of random measurements acquired per second during the initial CS reconstruction stage. The methodology is evaluated at several pseudofrequencies, all markedly lower than the sampling rates typically employed in structural monitoring applications.

As an illustrative case, Fig. 2 compares the power spectral density (PSD) of the reconstructed compressed signals (2, 4, and 6 psHz) and the original top acceleration record of the lightning rod. Although the reconstructed signals exhibit a certain level of background noise, its amplitude remains negligible when compared to the dominant spectral peaks associated with the structure's natural frequencies.

The final paper reports, for each monitored structure, a comparison between the modal parameters, specifically natural frequencies and damping ratios, estimated from the original response data and those obtained from the compressed signals, using the outlined OMA techniques.

5. CONCLUSIONS

This study demonstrates the feasibility of applying Compressive Sensing to operational modal analysis of slender structures subjected to wind loading. The findings demonstrate that, for the considered case studies, CS can significantly reduce the amount of data required for structural monitoring without compromising the accuracy of key modal parameters.

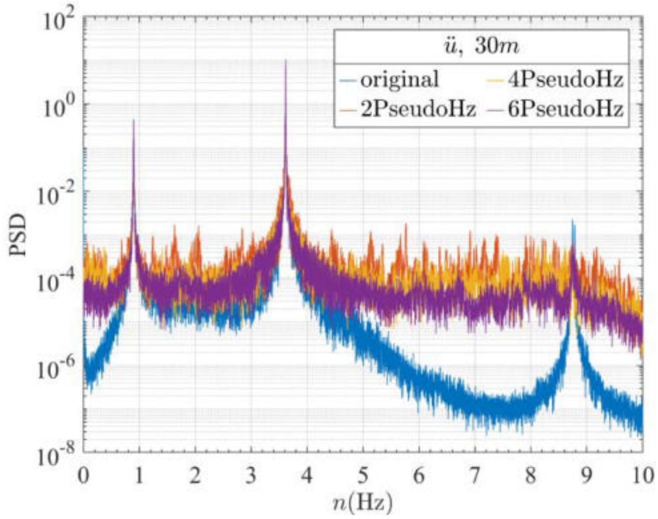

Figure 1. PSD of original and compressed accelerations of the lightning rod

These results are particularly relevant for IoT-based SHM systems, where constraints on energy consumption, bandwidth, and data transmission are critical. However, the effectiveness of CS depends on the level of sparsity of the response signals; structures exhibiting less sparse dynamic behaviour may require further investigation. Future research should focus on extending the proposed approach to more complex structural systems and on the development of real-time CS-based monitoring frameworks.

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