The Fifth International Conference on Railway Technology
RAILWAYS 2022
22–25 August 2022
Montpellier, France

Proceedings of the Fifth International Conference on
Railway Technology:
Research, Development and Maintenance
Edited by J. Pombo
Civil-Comp Conferences, Volume 1, Paper 27.17
Civil-Comp Press, Edinburgh, United Kingdom, 2022, doi: 10.4203/ccc.1.27.17

A Self-Consistent Artificial Intelligence-Based Strategy for Structural Health Monitoring

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Abstract

The scope of this work is to present a novel and comprehensive strategy for structural health monitoring (SHM), the focal aspect of which is the technological innovation made in the design and performance of the MonStr data acquisition sensors. The SHM method we propose benefits from the use of a variety of products designed by ASDEA Hardware and ASDEA Software for each specific task in the complex chain of operations needed to obtain near-real-time, reliable outputs for the assessment of structural health conditions. This paper illustrates the main advantages derived from the installation of a MonStr sensor network in terms of signal sampling, noise reduction, and synchronization management. Emphasis is also placed on how the proposed system extracts information from the tremendous amount of data collected by these high-performing devices, as this requires carefully configured algorithms and fast units for computing. The strategy used for the algorithms is briefly presented, and it combines all the usually occurring passages necessary for SHM with deep learning tools provided by Python for parallel GPU computing for the purposes of feature classification and anomaly detection. Global performance of the system is rendered even more efficient through the adoption of a common data format and shared environment provided by the STKO software. Finally, the OpenSees FEM solvers and the STKO pre and postprocessors allow for the construction of a digital twin of the structure under examination, which can then be exposed to what-if analyses and used to gauge the reliability of system alerts.

Keywords: structural health monitoring, artificial intelligence, sensors, digital twin.

1 Introduction

Artificial Intelligence (AI) has become a standard tool for data analysis and prediction making for problems arising in all scientific applications. This is mainly due to the adaptability of AI-inspired algorithms to diverse areas and the capability modern computers have for managing the vast amounts of data such algorithms require to produce reliable results in a suitable timeframe. Specifically, the AI-based approach has demonstrated its validity in the field of structural health monitoring (SHM), as early anomaly detection may prevent damage by providing a near-real-time overview of structural conditions [1], [2]. This is usually achieved using a well-defined data-driven paradigm within a machine learning (ML) framework [3]: in the preliminary stage, a series of data is recorded from the structure, assumed to be in a healthy state, using a network of sensors. In this training phase, the algorithm constructs a reference pattern characterizing the system under various external conditions and dynamic perturbations in order to cover the widest range of possibilities. During the actual monitoring phase, the algorithm's core classifies the incoming signals according to the existing framework: if the output turns out to be statistically far from the healthy reference pattern, an alarm is emitted. Otherwise, the same data can be used to refine the healthy pattern itself. This way, the ML model is constantly adjusted, thus keeping track of any long-term changes affecting the structure under assessment (such changes typically result from degradation or low-impact events). Thus, the ML purpose of learning through experience is met.

Although various options for constructing a data-driven approach for SHM are currently available, their limitation resides in the data acquisition strategy, influencing the quality of data and, consequently, the prediction performance. To overcome this limitation, we introduce a robust method that spans the whole process from data acquisition to damage detection, although herein, we mainly focus on the acquisition part. What makes our strategy extremely reliable is its self-consistency. All necessary steps are performed using suitable hardware and software products realized by ASDEA [4] itself, including the MonStr sensor, novel high-performing devices for signal acquisition. Moreover, all data analysis APIs are managed in the same virtual environment provided by the STKO software [5], which was initially designed for finite-element method analysis (FEM) and is, therefore, suitable for constructing a digital twin of the structure. Our proposed solution is also based on GPU parallel programming to speed up the analysis.

2 Methods

The starting point for proper analysis in the context of SHM is the availability of a robust sensor network. Quality hardware components and a suitable network distribution are required for maximizing the amount of salient information recorded when using a limited number of sensors. The quality of the data input into the AI-based classifier greatly affects the algorithm's performance and the reliability of the outputs obtained.

In this context, ASDEA's MonStr devices represent a major innovation in the field of data acquisition (Figure 1). Each unit is a MEMS-technology-based sensor equipped with a triaxial accelerometer, a gyroscope, an inclinometer, a magnetometer, and a thermometer. The latter instruments are essential for calibration, although temperature is also a crucial input feature for ML, as possible temperature-induced stiffness variations of the structure may lead to false alarms if not taken into account [6]. The precision of these instruments is reported at https://asdeahw.net/MonStr_O.pdf.

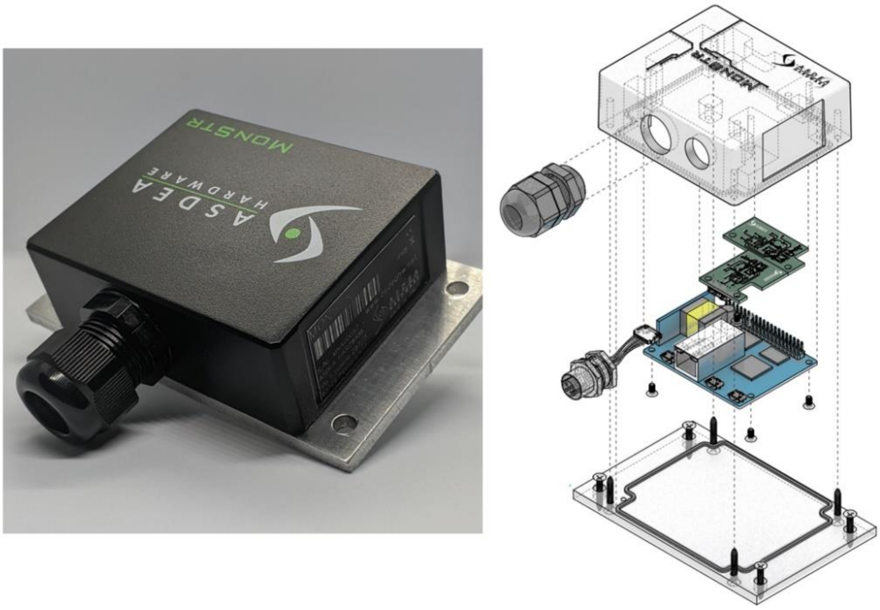

Figure 1 – The MonStr device and a sketch of its components.

A MonStr-based network (Figure 2) is able to support up to a thousand or more channels (considering that a single unit hosts nine channels) synchronized to under 1 ms. This feature should be compared with the standard network capability, which can manage around 50 channels simultaneously. MonStr devices linked in a network operate at a 1 kHz sampling rate; however, if used individually, this rate can be increased up to 4 kHz on a single unit, although such performances are out of reach for a complete network due to synchronization issues. It is also worth mentioning that the whole network never stops recording, unlike most currently available devices that remain in a quiescent state until activated randomly or when a certain threshold is exceeded. The inclinometers and accelerometers also contain precomputing tools that support AI. Finally, it should be stressed that all the acquired signals are managed through the opensource HDF5 format for databases, which is completely portable, has no limits on the number or size of data sets, and is supported by many different programming languages.

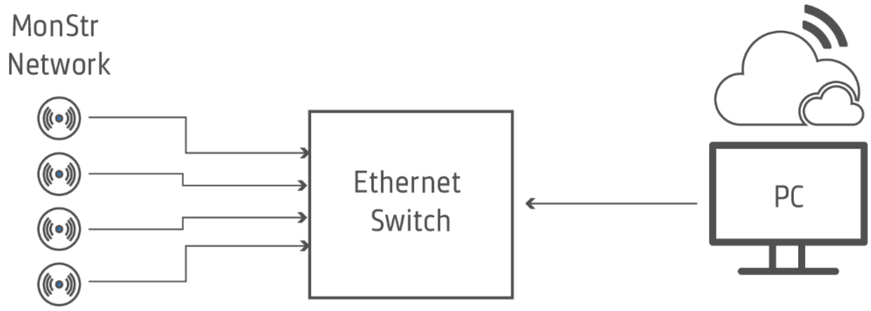

Figure 2 - Schematic representation of the acquisition process.

Given the high-sampling potential of the network, the software counterpart needs to be capable of processing all the non-redundant data in a reasonable time and producing reliable results. For this task, we developed a deep learning algorithm for classification, exploiting the Python tools by means of dedicated libraries for parallel computing.

3 Results

This section presents the performance tests involving preliminary versions of the MonStr sensors, mainly regarding software synchronization issues and noise level detection. Each device measures its inner time through an underlying oscillator with its own vibrational frequency, which may differ from one device to another. A suitable protocol was then carefully chosen and implemented to continuously update each inner clock with an observed discrepancy of less than 1 ms. Figure 3 shows accelerometric data obtained from a test where an infinitely rigid plate was subject to a single activating impulse. A network of 76 devices was set up for recording, although, for the sake of clarity, signals from only 20 devices were plotted. It is evident that all the devices began recording at approximately the same moment.

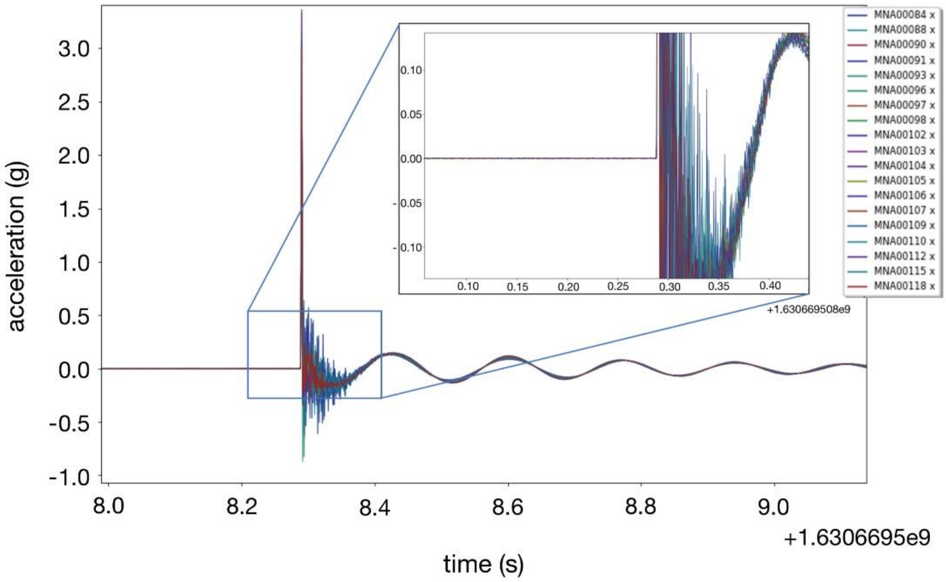

Figure 3- Accelerometric data obtained from an infinite rigid plate equipped with MonStr sensors.

Concerning noise density detection, we obtained a value of ~ 25 μg/√Hz performing Bartlett's analysis for a signal of known spectral components, then cutting such frequencies in the time domain. This is the actual value that should be accounted for in further analysis, since no other sources of noise exist.

Further testing was carried out at the EUCENTRE laboratory located in Pavia (Italy) in order to compare the performance of MonStr devices with analogous sensors furnished by the EUCENTRE itself. Both sensors types were installed on two types of server racks mounted on a shake table, which was then excited using several series of loads to simulate earthquakes and high impact events. Figure 4 shows how MonStr's sampling rate is significantly higher with respect to that of analogous sensors, although the signals are actually overlapping.

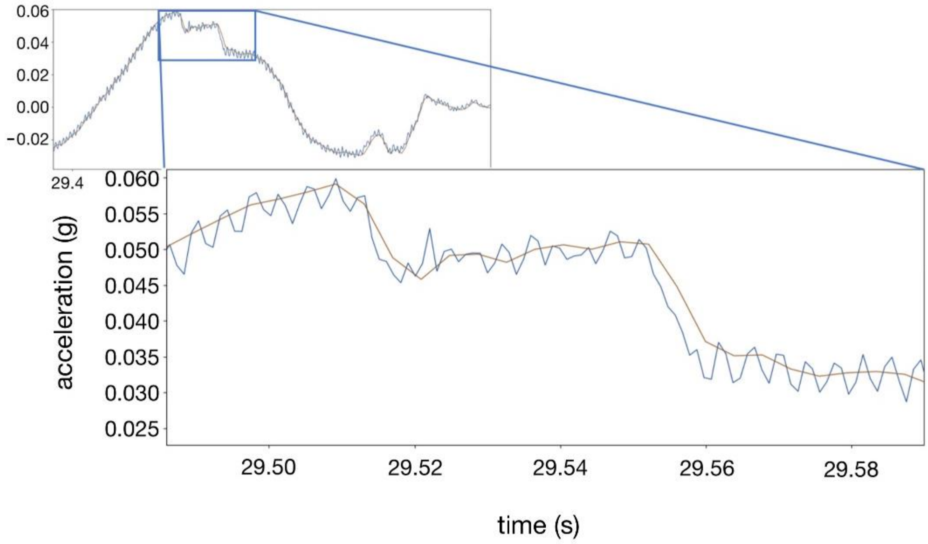

Figure 4 - The same signal recorded through the two available sensors.

Accelerometric data acquired by MonStr sensors with a reduced sampling rate of 256 Hz were used to infer modal parameters of the structure [7]. For this purpose, an output-only algorithm for modal identification was fed with several series of data coming from sensors placed at three different heights excited with random input in the three main directions. Experimental results obtained for the three first vibrational modes are in good agreement with the expected values available in the relevant literature [7], [8] (Figure 5).

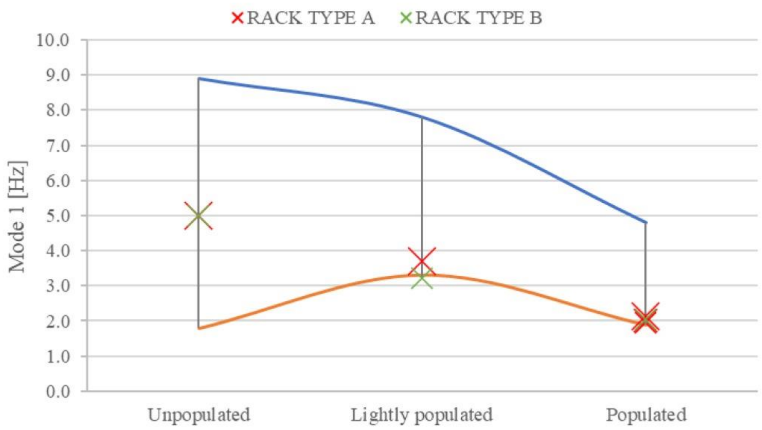

Figure 5 – The first three vibrational modes extrapolated from data for two types of racks. The two curves delimitate the confidence region for these modes [7].

4 Conclusions and Contributions

The first unavoidable step for a consistent SHM apparatus is the use of high-performance devices for data acquisition. Beyond the enormous strides made in lowering noise levels and inner synchronization times by our system, one of the most remarkable features consists of the network being wholly embedded within STKO's virtual environment. The beauty of the approach is in its simplicity and regularity, as the recorded and preprocessed data are stored in the HDF5 database format used as the base of each step, meaning the data is always ready for the next phase. Before classification, the data go through mandatory preliminary passages to reduce computational costs and classification, employing time-frequency transforms like continuous and discrete wavelet transforms for noise filtering and principal component analysis for database reduction. Relevant features are then extracted from the cleaned data and moved to the classifier. Meanwhile, these properly processed data are used to update the numerical twin of the structure constructed previously in STKO. This double-pronged approach guarantees complete monitoring of the structure since each alert can be double-checked against the twin by running a numerical simulation. The improvements to the technology introduced by our strategy lead us to believe that it will come to be used as the standard for structural health monitoring in the future.

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