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Evaluating the effect of intrinsic sensor noise for vibration diagnostic in the compressed domain using Convolutional Neural Networks

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Abstract. Machine learning allows designing intelligent sensing networks capable to perform automatic inferences about the integrity of technical facilities. Compression techniques decrease significantly energy requirements of the sensing networks proving essential when sensing nodes are not supported by constant power sources. Existing schemes pass through the reconstruction of the original time series data before moving to the diagnosis phase. However, this passage can be avoided, i.e., inference can be performed directly in the compressed domain, by exploiting the specific information retained in the compressed patterns. This paper fulfills the goal above in the context of vibration-based structural health monitoring by proving, from an empirical perspective, that Convolutional Neural Networks (CNNs) can be used to predict the structural health status directly in the compressed domain when properly combined with adapted Compressed Sensing mechanisms. Importantly, the study analyses the effect of the intrinsic noise that affects digital accelerometer sensors. Results confirm that CNNs can mine information in the compressed domain even in presence of strong noise components, i.e., accuracy remains above 94% even for ultra-low-cost solutions featuring a signal-to-noise-ratio below 20 dB.

Keywords: CNNs, Compressed Sensing, Intrinsic Accelerometer Noise, Structural Health Monitoring, Vibration Analysis

1 Introduction

Structural Health Monitoring (SHM) implemented via dense and distributed sensor networks has become a dominant paradigm in modern inspection systems aimed at ensuring the serviceability of civil and industrial appliances. SHM has largely benefited from the progress achieved by the Information and Embedded system community, paving the way to the permanent inspection of large facilities via low-cost and low-power electronics offering sensor-near processing functionalities [1]. Indeed, implementing algorithms at a sensor level has significant advantages, such as the possibility to extract damage-sensitive features at the sensing stage, opening new scenarios for the compression of long time series into a reduced vector of meaningful parameters which could be passed directly to the diagnostic unit for the retrieval of the health status. In such framework, data reduction techniques, such as those based on the Compressed Sensing (CS) theory, are among the most effective for vibration-based SHM [2]. The latter is a non-destructive testing technique which can be used to inspect structures dominated by an oscillatory behaviour: accordingly, the analysis is usually performed by observing the evolution over time of spectral features [3].

The existing approaches for damage detection with CS must face a burdensome decoding procedure: after compression at the sensor level, data transmitted to the aggregation unit are reconstructed in the time domain with onerous iterative procedures before the meaningful information is extracted, and then passed to the diagnostic process [4]. However, since the reconstruction stage works by applying some optimization metrics to the residual data [5], this means that, in principle, the residual information itself could suffice to discriminate healthy from damaged patterns without the need to reconstruct the global properties of the structure. In this work, we explore the feasibility of this decompression-free approach from a Machine Learning (ML) perspective, also encompassing the effect of intrinsic sensor noise typical of digital low-cost accelerometers. The motivation is that this unavoidable source of noise can easily contaminate the quality of vibration data under noise ambient excitation, i.e., scenarios in which the vibration response is induced by very faint forces (e.g., environmental agents or vehicles) and, hence, it can significantly compromise the discrimination capabilities of ML models.

2 Processing framework

The monitoring network consists of a distributed set of extreme edge vibration nodes (i.e., sensing units), each of them equipped with a Microelectro-Mechanical System (MEMS) accelerometer mastered by a microprocessor with enabled digital signal processing functionalities. Accordingly, individual nodes acquire and compress onboard vibration signals, thus outsourcing the compressed information to a central aggregator where the inference phase is performed in a supervised manner by means of a tiny Convolutional Neural Network (CNN). It is worth noting that the merging step is mandatory to provide a global and robust judgment of the health status, hence preventing the relative position of single devices to bias the results [3].

2.1 Extreme edge level: CS-based compression

CS works by compressing data via a matrix-vector multiplication: in case an N-long time series x_i is collected by a sensor S_i, the reduced version $\hat{x}_i = \Theta x_i$ is computed by exploiting the so-called *compression matrix* $\Theta \in \mathbb{R}^{M \times N}$ having $M << N$. A proper design of Θ is crucial to boost the compression performance and maximize the content retained at the reduction stage. To this end, adaptive methods have demonstrated superior capabilities thanks to their physics-informed nature, i.e., they can allow deriving the compression matrix as a function of the *a priori* known spectral properties of the structure under analysis. Adapted approaches show two additional advantages: i) they can provide conservative solutions, namely, the resulting sensing scheme does not over adapt to the statistics used during the design process, therefore, ii) they accurately capture variations even in the presence of damages, without needing Θ to be updated over time. This is a desirable feature in sensor-near computing frameworks, in which the limited storage and processing capabilities of the microprocessor hamper a streaming estimation of the compression matrix.

2.2 Aggregation level: CNN-based inference

In the proposed sensing scheme, a sensing node sends a set of compressed measures $\hat{X} = [\hat{x}_1, \ldots, \hat{x}_R] \in \mathbb{R}^{M \times R}$ collected over R successive intervals. The aggregating unit then receives N_s matrices, one for each sensor, that are further aggregated into a tensor $\mathcal{X} \in R^{M \times R \times N_s}$ such that it can be fed as input of a ML detector for structural diagnostics. Hence, classification can take place in the compressed domain: the key idea investigated in this work is to seek changes in the configuration and magnitude of the compressed coefficients, that are likely to be caused by changes in the vibration pattern due to potential defects. The literature presented many approaches to mining and classifying information based on the resources available on the sensing nodes [6, 7]. Among the possible options, CNN based on 1D filters through time can represent an appealing solution to detect such abnormalities because these models prove effective in retrieving defective recurrent patterns or changes in the overall behavior while maintaining limited computing requirements [7]. The same approach can easily be extended to multi-class classification problems by properly defining the output layer of the convolutional architecture with minimal increment in the overall computational burden [8].

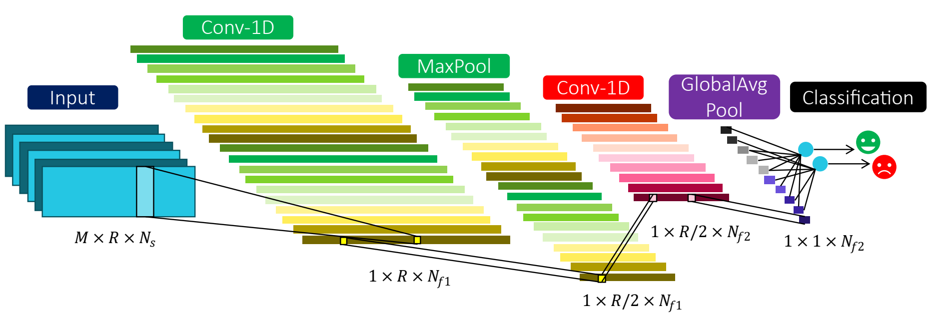

Fig. 1. Summary of the proposed architectures

Accordingly, the devised approach consists of training CNNs with a filter of size $M \times K_s \times N_s$, where K_s is the kernel size, that are convoluted with the original input. The overall structure of the proposed architecture is schematized in Figure 1. Since the information is embedded in the specific configuration of the coefficients, multiple levels of stratification are not involved and a relatively shallow, single-branch architecture can instead be adopted: a 1D convolutional block (Conv-1D) with N_{f1} filters processes the input followed by a max pooling layer. A second Conv-1D layer with N_{f2} filters is stacked, followed by a Global Average Pooling for the extraction of a second set of features; a fully connected layer predicting the (binary) class of the input datum completes the model.

3 Experimental validation

Dataset: The benchmark use case of the Z24 bridge has been exploited to showcase the performance of the proposed monitoring approach. The dataset consists of 5651 labelled time series collected over one year of monitoring of a highway viaduct between Bern and Zürich, which was then interrupted in 1999 for modernization. The infrastructure has been artificially damaged via a rigorous experimental protocol, introducing slight to very severe flaws [9]. The first 4922 coincide with healthy conditions, while the remaining ones pertain to the structure under progressive damage tests.

Noise injection: High-sensitivity piezolectric accelerometers were used in the original sensor installation. However, their cost, size and electrical features are far from the modern low-cost and low-power MEMS counterparts integrated in embedded devices, as those dominating in state-of-the-art SHM architectures. To assess the robustness of the devised strategy against these additional sources of noise, data were perturbed by adding the intrinsic noise characterizing two cut-of-the-shelf MEMS accelerometers widely applied for vibration-related applications: the LSM6DSL from STMicroelectronics [10] (noise density $80\,\mu g/\sqrt{\mathrm{Hz}}$) belonging to the class of ultra-low-cost sensors, and the ADXL355 accelerometer fabricated by Analog Devices [11] and characterized by better noise properties (noise density $24.5\,\mu g/\sqrt{\mathrm{Hz}}$). By simulating the characteristics of the former accelerometer, a Signal-to-Noise Ratio (SNR) equal to 20 dB was measured, while the same quantities increases to 30 dB for the second and more performative sensor.

CS setting and CNN architectures: Data were compressed using the Model-assisted Rakeness-based (MRak-CS) strategy in [12] because i) it demonstrated better robustness against the perturbations induced by environmental and operational parameters and ii) it allows to attain high compression level with negligible loss in the accuracy of the reconstructed damage-sensitive features. A constant compression ratio $CR = 8$ has been imposed, a quantity which is comparatively higher with respect to conventional solutions found in the literature, where the compression depth hardly exceeds 4 to 5 [13]. From a ML viewpoint, two CNNs architectures were designed: the first one, termed as *small CNN*, used 5 and 3 filters for the first and second layer, respectively. The second architecture, called *large CNN*, disposed of 30 and 10 filters in the convolutional layers. For both configurations, $K_s = 3$ was set. Models were validated using a standard 5-fold cross-validation procedure. A validation set was extracted from the training set selecting a random subset of 20% of the training data. Then, the testing fold was not involved in any parameter tuning. Keras and Tensorflow supported the implementation of the ML models.

Results: Table 1 summarizes the results in terms of standard classification metrics (accuracy, precision, recall, F1) including the model type, the CR, the MEMS-related corrupting noise. Moreover, scores obtained by the baseline one-class classifier neural network (OCCNN) model in [14] are reported to corroborate the quality of the attained performances in comparison with state-of-the-art supervised alternatives dealing with the same noise settings, but with lower $CR = 6$. Best scores for each setting have been magnified in bold font.

Table 1. Classification results of the proposed workflow by considering various MEMS-related noise levels. Better values for each noise case are highlighted in bold.

Model	CR	Sensor Type	Accuracy	Precision	Recall	F1
small CNN	8	LSM6DSL	0.933	0.952	0.972	0.962
large CNN	8	LSM6DSL	**0.945**	**0.961**	0.976	**0.969**
OCCNN [14]	6	LSM6DSL	0.901	0.893	**1.000**	0.940
small CNN	8	ADXL355	0.949	0.966	0.976	0.971
large CNN	8	ADXL355	**0.956**	**0.973**	**0.977**	**0.975**
OCCNN [14]	6	ADXL355	0.935	0.927	0.994	0.962
small CNN	8	N/A	0.957	0.974	0.977	0.975
large CNN	8	N/A	**0.967**	**0.983**	**0.979**	**0.981**
OCCNN [14]	6	N/A	0.930	0.940	0.950	0.910

As can be observed, CNNs can extract valuable information in the compressed domain as proved by classification scores always above 94%, even when a very low-cost and high noise density (i.e., LSM6DSL) sensor is considered. Among the two ML implementations, the largest CNN model attained the best performances, with an average increment of 1% in comparison to the tinier version. This outcome is reasonably due to the increased number of filters which allow a better understanding of the damage pattern contained within compressed data. Beside, it is paramount to emphasize that the proposed workflow always outperforms, apart from one isolated case, the prediction capabilities characterizing the previous OCCNN implementation: proof is the fact that the metrics increase from a minimum of 2% to a maximum of 7%, additionally working with a compression level which is 1.33x higher than the one tested in the previous configuration. Finally, compared with compression-free scenarios (N/A label), a negligible decrement in all the scores has been reported, with a worst case reduction of 2.5% for the LSM6DSL sensor.

4 Conclusion

This paper presented an analysis of the interaction between intrinsic sensor noise typical of MEMS accelerometers, compressed sensing and structural classification implemented via CNNs in the compressed domain. The empirical results confirm that CNNs can master noisy data yielding high-quality prediction even when noise signal ratio deteriorates significantly, improving up to 7% the inference metrics of state-of-the-art alternatives in the field.

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