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eSysId: Embedded System Identification for Vibration Monitoring at the Extreme Edge

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Abstract. Enabling extreme edge processing functionalities will lead a breakthrough in the development of the next generation of Structural Health Monitoring (SHM) systems, thanks to the adoption of sensor–near data analtycs which will make the structural inference process faster and more advantageous in terms of power consumption and data volume. In this work, we specifically endorse this paradigm in the context of vibration–based diagnostics by proposing a novel, intelligent accelerometer sensor combining, in an embedded device, advanced edge data analytics implementing System Identification algorithms, and energy–aware custom hardware supporting it. The effect of the bit–depth quantization of the collected signal on the quality of the retrieved structural parameters is assessed; moreover, a cost–benefit analysis is also encompassed, showing how the developed solution might be globally more advantageous from an energy point of view, reaching up to 10x power saving if compared with standard alternatives.

Keywords: Energy saving, Embedded System Identification, Extreme Edge Processing, Smart Accelerometer Sensor, Vibration Monitoring

1 Introduction

Structural Health Monitoring (SHM) aims at assessing the integrity condition of structures throughout their life cycle and in their normal operative conditions [1]. Conventionally, SHM is implemented with sensor networks transmitting raw data to central aggregators for information processing. Scaling up this approach for structures with very large and dense networks is one of the major technical challenges currently under investigation [2, 1]. To overcome this issue, recent advancements in the field of micro–system design promoted the investigation of new solutions built on the extreme edge computing paradigm: i.e., information processing in strict proximity where it is sensed [3].

Such an edge–enabled approach presents three main benefits: i) it compresses all the meaningful structural parameters in a batch of damage-sensitive features (scalars), thus offering a very powerful means for data compression and network

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load reduction, ii) it reduces the data–to–user transfer time, hence supporting real–time diagnostics, and iii) it ensures long–term functionalities by extending sensor battery life–cycle, which is one of the most crucial challenges in autonomous systems. In this scenario, the contribution of this work is to present the HW/SW co–design of a novel monitoring architecture featuring the three above–mentioned characteristics. In particular, the proposed solution consists in the extreme edge embodiment of System Identification (henceforth referred to as eSysId) algorithms on a purposely developed *intelligent*, wireless accelerometer sensor. The device is designed to make eSysId feasible, notwithstanding the complexity of the entailed algorithmic routines. The main reason for preferring eSysId among the list of available estimators is that it presents a twofold advantage: firstly, it offers an indirect means for network load reduction, which is a very desirable functionality in large–scale applications; secondly, it presents a very potent tool for dynamics analysis and, by extension, for vibration–based structural assessment, which is the prospective application scenario considered in this work.

The final objective is to extend the preliminary studies discussed in [5] and [6] by:

(i) considering the effect of the bit–depth quantization on the quality of the computed eSysId parameters and, in turn, of the computed structural parameters
(ii) quantitatively estimating the saving on the power budget while running eSysId on the developed prototype board. To this end, a comparison with alternative data compression strategies classically adopted in the context of vibration–based inspection is also encompassed

The content of the manuscript is organized as follows. In Section 2, the principles behind eSysId and the embedded programming strategies are explained, then introducing, in Section 3, the novel wireless acceleration board and its constitutive elements. The effect of the bit-width of the input data on the quality of the retrieved eSysId parameters is assessed in Section 4.1, while the power savings in comparison with alternative compression strategies are discussed in Section 4.2. Conclusions are drawn at the end.

2 The Software: eSysId implementing ARMA models

System identification refers to an ensemble of signal processing techniques applied in a broad range of application domains, including vibration–based structural characterization. In particular, its realization via output–only autoregressive models is compatible with extreme edge implementations, for two main reasons: 1) it is built on a filter representation which can be readily implemented via simple multiply–and–accumulate operations and 2) it does not require the measurement of the input exciting force, which is, instead, assumed equal to a zero–mean white noise Gaussian term $e(t) \sim \mathcal{N}(0, \sigma_e^2)$ with variance σ_e^2. SysId belongs to the class of *parametric* spectral analyzers, meaning that time series can be modeled via stationary processes whose spectral density function $S(f)$ is uniquely determined by a set of N_p *model parameters*, the latter corresponding to the filter taps used to model the system transfer function. By knowing $S(f)$, the identification of frequency–dependent structural features, also referred to as modal parameters (e.g., the natural frequencies of vibration) can be performed by looking at peak–related quantities in the power spectrum.

Autoregressive with Moving Average (ARMA) models are particularly effective in modeling the structural dynamics, proving better performances with respect to pure Autoregressive ones. Its mathematical representation at a generic instant $k \in \{0, \ldots, K-1\}$ for a K–long discrete–time signal $s[k]$ sampled with periodicity T_s is given by:

$$s[k] + \sum_{i=1}^{q} \theta_i s[k - iT_s] = e[k] + \sum_{s=0}^{p} \gamma_s e[k - sT_s] \tag{1}$$

in which q and p indicate the number of parameters preserving memory of the past p input and q output instances, while θ_i and γ_s are the feedback and feed–forward taps of the corresponding filter. p and q are also known as the orders of the filter numerator and denominator polynomials, while their summation $N_p = p + q + 1$ equals the total amount of model coefficients to be determined. Therefore, the SysId problem turns into the estimation of the N_p parameters, a goal which can be efficiently fulfilled via ordinary least–squares algorithms. Finally, the system power spectrum can easily be estimated as the square power of the associated filter transfer function:

$$S(f) = \left| \frac{1 + \sum_{s=0}^{p} \gamma_s e^{-j2\pi f s T_s}}{1 - \sum_{i=0}^{q} \theta_i e^{-j2\pi f i T_s}} \right|^2 \tag{2}$$

Noteworthy, despite its simple algebraic formulation, porting the entire SysId workflow on resource–constrained processors as the ones typically equipped on low–cost and low–power computing architectures is a challenging task. To this end, an embedded system–oriented version, the eSysId procedure, has been presented by the authors in [5]: it leverages strategies from the dense linear algebra processing field to shrink both the algorithmic and memory complexity, proving to be portable on microcontrollers.

3 The Hardware: an intelligent accelerometer sensor

A novel smart accelerometer node has been designed to support the eSysId processing. The device consists of four main components (see the prototype in Figure 1):

1. the Digi XBee 3 wireless communication module based on the 802.15.4 protocol [7], ensuring two-way data transfer between the sensor node and a central network gateway. Among the main features of this component, the

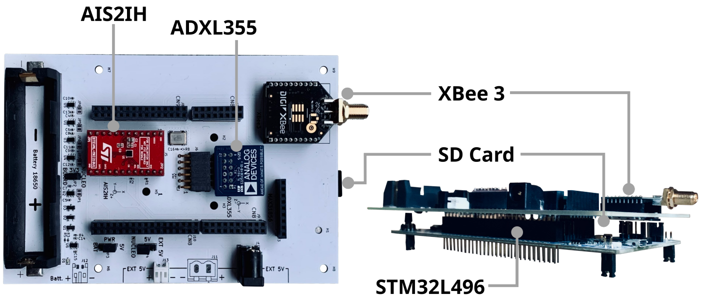

Fig. 1. Top and lateral view of the developed accelerometer sensor node.

following can be listed: a consumption of 17 mA and 135 mA in reception and transmission mode, respectively, while only 50 µA are drained in sleep mode;

2. a high–performance STM32l496 microcontroller unit (MCU), which integrates an ARM Cortex–M4 core operating at a frequency up to 80 MHz, with a Floating Point Unit, a Digital Signal Processing instruction set, 320 KiB of SRAM and 1 MB of Flash memory. It also provides a consistent variety of power–saving modes, which make it appealing for ultra–low–power applications: e.g., 15 nA in shutdown mode, 115 nA in standby mode and 1.1 µA in stop mode;
3. a combination of two tri–axial MEMS accelerometers, necessary to efficiently trigger the acquisition of vibration signals based on energy thresholds while maximizing the power saving. One is the ADXL355 digital accelerometer, that is characterized by an ultra–low noise density of $22.5\,\mu g/\sqrt{\mathrm{Hz}}$, 20–bit Analog–to–Digital Conversion (ADC) resolution and a maximum sampling rate of 4000 Hz. The second one is the AIS2IH device, featuring a sub-1 µA current consumption, 12–bit resolution in low–power mode and an output data rate from 1.6 Hz to 1600 Hz;
4. an SD card necessary to expand to storage capability.

4 Experimental validation

4.1 Effect of bit–depth quantization

Defining the format and the depth of the data resolution might have a huge impact on the required memory space necessary for temporary data storage, while also determining the dimension of the payload to be delivered over the sensor network, i.e., the lower the number of bits used to represent a single piece of information, the higher the gain in the sensor performances. On the other hand, an excessively coarse quantization might hamper the possibility to achieve an accurate structural characterization. As such, an experimental campaign has been executed in which three different types of data resolutions

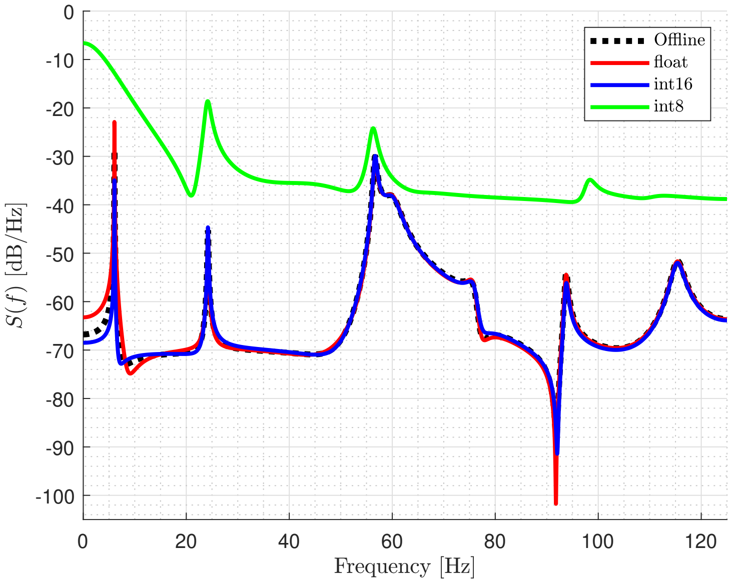

Fig. 2. Spectral estimation results for different quantization strategies.

have been considered, namely `int8`, `int16` and `float`, whose power spectra (computed according with Eq. (2)) have been compared with the ones obtained via offline data processing performed in the MATLAB environment working with full–precision `double`.

To this end, the sensor node was installed on a laboratory steel beam under ground motion excitation to mimic real field scenarios [6]. After sampling, data were processed directly aboard via an ARMA model requiring $N_p = 17$[1] parameters; then, these parameters were transmitted to a remote PC serving as a central gateway, where the spectral profile was reconstructed and the structural parameters were finally retrieved. Results are depicted in Figure 2, from which it is immediate to observe that both `float` (red curve) and `int16` (green curve) quantization strategies are really effective in preserving the meaningful structural information, the latter being even more precise with respect to the target (black dotted curve) offline computation. This outcome might be due to the fact that, when reducing the bit depth, minor details, which might be associated with high frequency noise, are implicitly filtered out by the quantization process, thus yielding to a smoother spectral profile. Conversely, despite showing a good alignment in correspondence of the second and third peak, 8 bit precision is not sufficient in pursuing the same task.

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[1] This quantity has been estimated in a preliminary phase via the Bayesian Information Criterion, as presented in [5].

4.2 Cost–benefit analysis

Finally, the actual gain in running eSysId on the edge accelerometer board was numerically quantified by computing the energy expenditure assuming a duty–cycle of one hour. The latter value has been chosen since it is commonly adopted in large–scale real–field scenario considering the long inertia of structural changes on the dynamic response of the monitored asset [5]. In order to make the analysis as much accurate as possible, the overall power consumption due to data sampling, processing and transmission are thoroughly estimated by taking into consideration the power requirements in Section 3 for increasing payload sizes. Beside eSysId, two additional processing frameworks are considered: compressed sensing techniques (label 'CS'), which is a well–known solution in the field [8], and the absence of any edge processing (label 'No DSP'). Concerning CS, an MCU implementation has been pursued as well assuming a static compression matrix statically load in the device memory at the network start up phase and consisting of random entries. The compression factor for eSysId has been fixed to 45, which corresponds to the ratio between the total number of collected samples and the number of model parameters, while a compression factor equal to 5 has been imposed for CS since higher rates are barely exceed in CS–based applications [5].

In Figure 3, the energy curves are depicted, proving how the combination of the eSysId software and the hardware characteristics of the designed sensor node make the extreme edge implementation of eSysId energetically more efficient than CS and up to 10 times more efficient than centralized processing solutions. More specifically, even in the worst configuration, eSysId is at least 1.37x and 3.03x times more convenient with respect to its competitors, reaching a gain up to 2.70x and 10.61x for very long data payloads.

5 Conclusions

In this work, the edge implementation of system identification (eSysId) algorithms for vibration–based structural inspection is presented and validated on a novel wireless accelerometer sensor. The proposed architecture was shown to be more efficient in terms of energy consumption with respect to state–of–the–art alternatives available in the field. Furthermore, an analysis has been conducted, in which the impact of the bit–depth precision has been specifically evaluated with respect to the consistency of the spectral estimation.

References

1. Alokita, S., Rahul, V., Jayakrishna, K., Kar, V. R., Rajesh, M., Thirumalini, S., Manikandan, M.: Recent advances and trends in structural health monitoring. Structural health monitoring of biocomposites, fibre-reinforced composites and hybrid composites, 53-73 (2019)

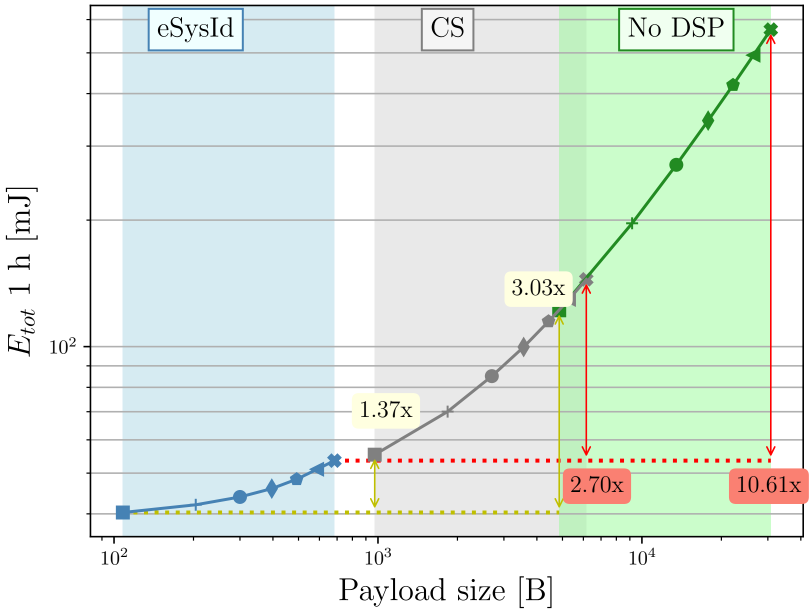

Fig. 3. Energy expenditure over one hour for different sensor node configurations: eSysId running on the MCU (blue curve), CS running aboard (grey curve) and no DSP enabled (greeen curve).

2. Abdulkarem, M., Samsudin, K., Rokhani, F. Z., A Rasid, M. F.: Wireless sensor network for structural health monitoring: a contemporary review of technologies, challenges, and future direction. Structural Health Monitoring, 19(3), 693-735 (2020)
3. Abner, M., Wong, P. K. Y., Cheng, J. C.: Battery lifespan enhancement strategies for edge computing-enabled wireless Bluetooth mesh sensor network for structural health monitoring. Automation in Construction, 140, 10435 (2022)
4. Reynders, E.: System identification methods for (operational) modal analysis: review and comparison. Archives of Computational Methods in Engineering, 19(1), 51-124 (2012)
5. Zonzini, F., Dertimanis, V., Chatzi, E.,De Marchi, L.: System Identification at the Extreme Edge for Network Load Reduction in Vibration–based Monitoring. IEEE Internet of Things Journal (2022)
6. Zauli, M., Zonzini, F., Coppola, V., N., Dertimanis, V., Chatzi, E., Testoni, De Marchi, L. A Novel Smart Sensor Node with Embedded Signal Processing Functionalities Addressing Vibration–Based Monitoring. In European Workshop on Structural Health Monitoring (pp. 1000-1008). Springer, Cham (2023)
7. Digi: XBee 3 Zigbee 3 RF Module `https://www.digi.com/resources/library/data-sheets/ds_xbee-3-zigbee-3`
8. Zonzini, F., Carbone, A., Romano, F., Zauli, M., De Marchi, L.: Machine Learning Meets Compressed Sensing in Vibration-Based Monitoring. Sensors, 22(6), 2229 (2022)