# Quantifying the Benefits of Compressed Sensing on a WBSN-based Real-Time Biosignal Monitor

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***Abstract*—Technology scaling enables today the design of ultra-low power wearable biosensors for continuous vital signal monitoring or wellness applications. Wireless Body Sensor Networks (WBSN) integrate wearable sensing nodes for an accurate measurement of the desired physiological parameter, e.g. Electrocardiogram (ECG), and a personal gateway for the collection and processing of the data. The diffusion of smartphones enables their use as advanced personal gateways, with the ability to provide user interaction features, connectivity and real-time feedback to the user. Both the sensing node(s) and the smartphone are battery powered and resource-constrained devices, hence energy efficiency is one of the key design goals. In this work, we explore the use of compression techniques to improve the efficiency of a wireless ECG wearable monitor. In the presented system, the wearable node is used for bio-signal acquisition, pre-processing and compression, while a smartphone is used for real-time signal reconstruction. The system aims at medical-grade signal quality and the impact of lossy compression is tested on real signals acquired by the node and its effects are evaluated on system-level energy consumption. We analyze performance/energy trade-offs considering online data compression on the wearable device and real-time reconstruction on the smartphone. Our results show that Compressed Sensing pays off only when the SNR requirement is below 20 dB due to the non-ideal sparsity of ECG signal. We propose a hybrid compression scheme based on CS and under-quantization to address these limitations.**

## I. Introduction

Heart activity monitoring is of primary interest in a large variety of human activities, since cardiovascular lifestyle-induced diseases affect a growing portion of the world population. In general, human behavior-related illnesses require accurate and long-term medical supervision, which is unsustainable for the traditional healthcare system due to the increasing costs and medical management resources needed [1]. To tackle this problem, personal vital signs monitoring systems are able to offer a cost-effective solution on a large scale. Wearable miniaturized biosensing nodes, integrated in a Wireless Body Sensors Network (WBSN) to continuously measure and remotely report biomedical signals, can provide the ubiquitous, long-term and real-time monitoring required by the patients. Beside medical grade monitors, such as Holter monitors and Electrocardiogram (ECG) loop recorder devices, a growing market segment is represented by reduced-leads ECG monitors used for lifestyle heart activity monitoring. Typical commercial applications include wellness and sport activity trackers as well as obesity and stress detectors [2]. In the WBSN context, such utilizations imply that the sensed information is displayed in real-time on the personal gateway to offer live information to the user. In general, these applications differ from the classical doctor-patient monitoring as the monitored ECG is streamed to the personal gateway (e.g. smartphone) of the patient to be eventually aggregated with other biosignals and visualized or streamed over the Internet for further analysis [3], [4].

In this scenario, designing a system for biosignals monitoring with energy efficiency in mind is of great importance, both for the WBSN node and the gateway lifetimes. In particular, wireless data transmission represent the most energy demanding task for the WBSN nodes and the choice of the communication protocol greatly impacts the data exchange capabilities of the system as well as its hardware requirements. Bluetooth (BT) is the de-facto communication standard for interfacing a smarthphone to remote sensors and actuators. Unfortunately, BT has been designed to support large data streaming and it is not optimized for low power transmission with limited data rates. The Bluetooth Low Energy (BLE) specification has been developed to overcome these limitations and to increase the efficiency of the radio communications [5]. Even when using dedicated hardware and optimized communication protocols, the power consumption and the battery lifetime of the sensing node is dominated by the data transmission cost [6], [7], [8].

Data compression can be adopted to reduce the energy consumption for data transmission on the WBSN node. Approaches suitable for resource-constrained nodes include integrated analog [9] and digital [10] solutions. Lately, Compressed Sensing (CS) [11] has shown to be capable to achieve high compression ratios with low computational and memory requirements, therefore making it suitable for use in embedded bio-sensing nodes [6], [12], [13]. Unfortunately, it is associated with complex reconstruction algorithms with a high computational load, thus it is not clear how it matches the constraints of a battery powered gateway with real-time constraints. Moreover, most of the literature works exploring data compression use database signals recorded with high-end bench-top instruments, which exhibit very different characteristics when compared to signals acquired by a miniaturized wearable device. This is of primary importance for CS as the effectiveness of this compression scheme depends on the sparsity of the signal. To the best of our knowledge, there are no studies on the impact of ECG data reconstruction on a mobile, battery-powered device and, even if several wireless ECG monitors are present in the market, none of them takes advantage of the better performance promised by the CS approach.

In this work, we investigate the adoption of different compression techniques applied to ECG signals collected from a wearable device. We employ a custom wearable platform

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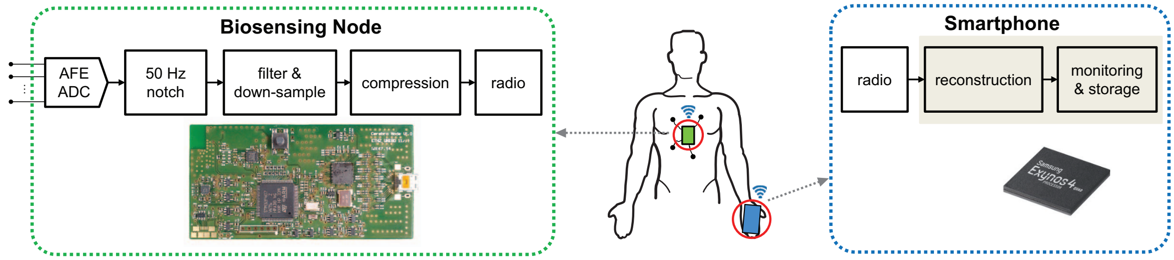


Fig. 1. Wearable WBSN-based ECG Monitoring System: block scheme of the biosensing node and of the personal gateway (smartphone).

[14] to acquire and compress the signal and we evaluate the real benefits of CS in reducing the energy consumption of the entire ECG monitoring chain. To prove its benefit, we compared CS against a naif lossy compression, i.e. discarding of the least significant bits.

The main contributions of this work are the following:

- We demonstrate the complete chain of a real HW system for wearable ECG monitoring, composed by state-of-the-art sensing, encoding, transmission and decoding, based on cutting edge technologies;
- We evaluate the trade-offs between Quality of Service (QoS) and energy consumption of different compression schemes considering real ECG traces and signal reconstruction on a mobile platform, with accurate power measurements;
- We show that CS for ECG signals is beneficial w.r.t the naif lossy compression when low QoS is required by the ECG monitor or the energy efficiency of the biosensing node is more critical than the personal gateway. This is primarily due to the ECG signal itself which is not perfectly sparse.

The rest of the paper is organized as follows. In Section II the ECG monitoring hardware is presented as well as the considered compression schemes. Next, in Section III we describe the experimental setup and the results of the evaluation in terms of reconstruction quality and energy efficiency for both compression and reconstruction. Finally, the conclusions are presented in Section IV.

## II. Materials and Methods

In this section, we first present a description of the hardware that builds up the system, then we describe the theoretical background on compression schemes and reconstruction algorithms considered in our analysis.

### A. System Description

A graphical representation of the WBSN architecture considered for ECG monitoring is presented in Fig.1, which shows the wearable monitor, worn by the patient, and the gateway, depicted as a smartphone. The proposed wearable device is a bio-potential acquisition and processing system, composed by a dedicated multi-channel Analog Front End (AFE), an ARM Cortex M4 microcontroller (MCU) and a Bluetooth transceiver for wireless communication, allowing the system to be effectively employed for various biomedical applications [15]. The Cerebro AFE [16] has $8$ differential channels, each consisting of a variable-gain instrumentation amplifier followed by a first order active RC low-pass filter. The channels are multiplexed in a single 16-bit sigma-delta ADC with an acquisition frequency of $1$ KHz per channel. The AFE shows $0.82\,\mu V_{rms}$ of noise in a $100$ Hz bandwidth, it was used with a gain of $8$ and it consumes $\approx 15$ mW.

The acquired signals are digitally pre-processed by the MCU, applying a notch filter and a low-pass filter to respectively eliminate the $50$ Hz power line interference and to reduce the high-frequency noise. The pre-processing step is executed at the original sampling frequency and is followed by a sample decimator, which allows to reduce the data rate according to the application. Given the spectral characteristics of the ECG signal, the pre-processed data is down-sampled to $500$ Hz and then data compression techniques are applied to further reduce the amount of data to be transmitted and therefore improve the energy efficiency of the system.

High data transmission rates are guaranteed by the use of a standard BT transceiver (Bluegiga WT12), which allows to stream reliably in real-time the data acquired from $8$ channels at $1$ KHz. The standard BT protocol is employed for its wide usage and its compatibility with the majority of the mobile computing devices available today (such as tablets, smartphones, etc.), thus eliminating the need for additional hardware. The downside of this choice is its high impact on the overall power consumption. The introduction of BLE (Bluetooth 4.0) added an interesting alternative, which is now well supported and adopted, hence we also connected our board to an external BLE transceiver to evaluate its benefits for ECG monitoring applications.

In the proposed architecture, a smartphone acts as a personal gateway and receives the data from the WBSN node. The high computational performance of recent smartphones allows the creation of advanced applications for real-time analysis of the sensed data, beside basic gateway or storage functionalities. However, if compression is used to reduce the transmitted data, the smartphone needs also to cope with the data reconstruction step. To analyze the energy consumption and the quality of service on the personal gateway, we considered the Hardkernel Odroid-XU3 board [17], which is based on the Samsung Exynos 5422, the same CPU found in many modern high-end smartphones. It implements the ARM big.LITTLE heterogeneous multi-processing solution with a cluster of four Cortex-A15 “big” out-of-order processors, and a cluster of four Cortex-A7 “LITTLE” in-order processors. Since both cluster cores are architecturally compatible (ARMv7-A architecture), workloads can be allocated on demand on each one, to suit performance needs. However, the two clusters have very different floating point performance.

In this scenario, both the compression and the reconstruction is performed on battery-powered devices, introducing the need for a system level evaluation of the impact of data compression on the final data quality, considering the constraints on real-time reconstruction and power consumption.

### B. Compression Schemes

CS is an emerging tool and it has been investigated in many applications such as low-power sensing and compression, radar and communication signal processing and high dimensional data analysis. The main idea behind CS is fairly simple and it assumes that the given data has a sparse representation, which can be exploited to highly reduce the dimensionality of data. Let $\mathbf{x}$ be the real-valued $N$-dimensional biosignal vector ($\mathbf{x} \in \mathbb{R}^N$) that is sparse or has a sparse representation in some known dictionary $\mathbf{x} = \mathbf{\Psi}\boldsymbol{\alpha}$. By sparse we mean that $\boldsymbol{\alpha}$ has only few non-zero elements. If we collect a vector of linear measurement $\mathbf{y} \in \mathbb{R}^M$ by $\mathbf{y} = \mathbf{\Phi}\mathbf{x}$, it is possible to recover the original signal $\mathbf{x}$ form the measurements vector by solving a convex optimization problem. In the CS context, $\mathbf{\Phi} \in \mathbb{R}^{M \times N}$ is the sensing matrix and preferably $M \ll N$, so that the size of the measurement vector $\mathbf{y}$, i.e. the data to transmit, is much smaller than the original vector $\mathbf{x}$. To guarantee the recovery, the sensing matrix $\mathbf{\Phi}$ must obey the key restricted isometry property (RIP) [18]. Verifying the RIP condition in practice is a NP-hard problem, however it is proven that random matrices with independent identically distributed (i.i.d.) entries formed by sampling a symmetric Bernoulli distribution $(P(\mathbf{\Phi}_{i,j} = \pm 1/\sqrt{N}) = 1/2)$ will satisfy the RIP [19]. On top of i.i.d. matrices also random partial Fourier matrices satisfy a near-optimal RIP with high probability [19]. If RIP holds, then an approximate sparse signal reconstruction can be accomplished by solving the following convex optimization problem:

$$\begin{aligned} \tilde{\boldsymbol{\alpha}} &= \min \|\boldsymbol{\alpha}\|_1 \\ \text{s.t.} \quad & \|\mathbf{\Phi\Psi}\tilde{\boldsymbol{\alpha}} - \mathbf{y}\|_2 \leq \sigma \end{aligned} \tag{1}$$

where $\|\cdot\|_1$ and $\|\cdot\|_2$ are respectively the standard $l_1$ and $l_2$ norms, while $\sigma$ bounds the amount of noise corrupting the data. It must be noted that the reconstruction noise $\sigma$ depends on the sparsity of the signal, thus non-sparse signals are affected by an intrinsic reconstruction noise which is independent on the measurements accuracy.

Beside CS, we consider the simplest lossy compression scheme: discarding of the least significant bits of the ECG samples acquired by the Cerebro AFE. This compression, denoted as *LSB-discarding* or BD, is trivial and was chosen as a baseline for comparative analysis. It consists of a logical shift of the last $k$ bits of the acquired sample while, in the decoding stage, the reconstruction of the signal is achieved by the opposite logical shift. Therefore, BD has a minimum impact on the usage of the MCU in the wearable node and it is the least computationally demanding decoding scheme.

Finally, to investigate the possibility of a hybrid technique combining the two approaches previously described, we considered a compression scheme that applies BD to the compressed CS measurement vector $\mathbf{y}$ to further reduce the amount of data to transmit. With this approach, we aim at balancing the effects of reconstruction and quantization noise in the reconstructed signal.

### C. Reconstruction

In the last two decades a large amount of contributions was presented to solve the optimization problem (1), with applications in different areas such as spectral estimation, image restoration and denoising. In this work we consider one of the most stable and studied approaches named FOCal Underdetermined System Solver (FOCUSS) [20], [21]. It is composed of a low-resolution initial estimation of $\boldsymbol{\alpha}$, followed by an iterative process that refines the solution to the final sparse vector $\tilde{\boldsymbol{\alpha}}$. Each FOCUSS iteration comprises a weighted $l_2$-norm minimization based on the Singular Value Decomposition (SVD) of the operator $\mathbf{\Phi\Psi}$, which is updated at each iteration by a proper set of sparsity promoting weights [20], [21]. There are two very interesting characteristics of the FOCUSS algorithm: (*i*) from a computational point of view the complexity is mainly represented by the SVD, which has potential for acceleration and (*ii*) the work in [21] presents a multi-lead implementation of FOCUSS to reconstruct multi-lead signals by a unique decoding algorithm. More details of the reconstruction algorithm running on our WBSN-gateway mobile platform will be provided in Section III.C.

## III. Experimental Results

The focus of this work is to evaluate the effectiveness of CS in increasing the energy efficiency of a real ECG monitoring chain. In particular, we evaluate the trade-off between QoS and energy consumption for the different compression schemes under real-time reconstruction constraints. The wearable device described in Section II was used to collect raw ECG signals. We collected about 5 minutes of recording from $4$ users and these signals were used to test the pre-processing and compression techniques. To quantify the compression performance while assessing the diagnostic quality of the compressed records, we consider as QoS metric the Signal to Noise Ratio (SNR), defined as

$$SNR = 20 \log_{10} \frac{\|\mathbf{x}\|_2}{\|\mathbf{x} - \tilde{\mathbf{x}}\|_2}$$

where $\tilde{\mathbf{x}}$ represents the reconstructed signal. The SNR[1] is reported in relation to the Compression Ratio (CR), defined as $N/M$ for the CS and as the ratio of transmitted bits with respect to the original signal for BD.

### A. Preliminary Analysis

To separate the contribution to the SNR related to the characteristics of the ECG signal from the one related to the architecture and algorithm chosen, we compared the two compression schemes on a reference sinusoidal signal, which has a perfectly sparse representation. According to signal processing theory, by choosing a signal which has an extremely sparse representation in a given basis, the CS is capable to exploit this sparseness and exhibit a higher reconstruction SNR compared to a simple bit discarding. To evaluate our acquisition setup

[1]The SNR values reported in the following analyses are based on the Basis Pursuit Denoise reconstruction algorithm, implemented in the SPGL1 Matlab toolbox [22], while for the embedded implementation on the WBSN-gateway we used the FOCUSS algorithm as described in the following.

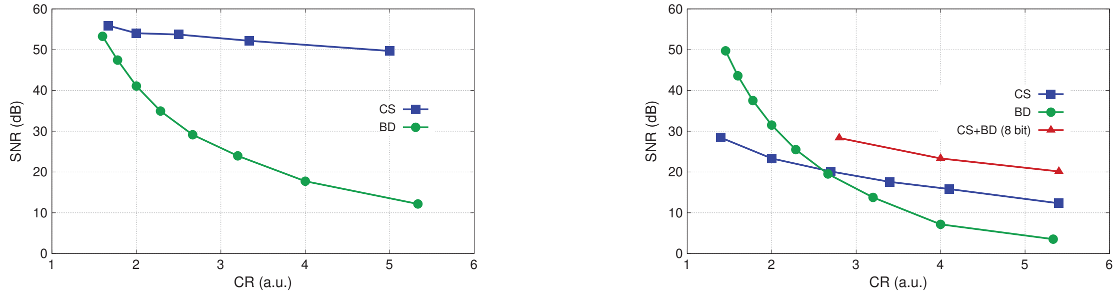


Fig. 2. Average SNR vs. CR for a sinusoidal waveform (left) and ECG signals (right) acquired by the wearable node.

and to verify that the acquired signal is not over-quantized, we acquired a sinusoid with the Cerebro board, with amplitude and frequency in the range of ECG signals. We used an analog signal generator to create a sinusoidal wave with an amplitude of $20\,mVpp$ and a frequency $f_w = 20$ Hz, sampled and preprocessed as described in the previous section. For the CS compression, we expressed the signal in the frequency domain, where it is extremely sparse, and applied random sampling. Hence, we considered an FFT sampling matrix and we varied the compression ratio by choosing a different random subset of its rows. In the BD case the compression is straightforward (logical shift) as described above.

The result of this analysis is reported in Fig.2 (left), showing the reconstruction SNRs achieved at different CRs. The sharp reduction observed in the BD trend shows how the information content of the sinusoid is not preserved and leads to a SNR reduction as the CR increases. On the other hand, the CS technique shows a significantly lower SNR degradation with the increase in CR and dominates BD for all CRs.

### B. *Compression (Biosensing node)*

Following the preliminary analysis, we evaluate the two compression techniques on real ECG data acquired by the wearable platform and we explore a hybrid solution combining the two techniques. The performance was analyzed considering the effects on reconstruction quality and energy efficiency, here evaluated from the perspective of the biosensing node. The reconstruction quality in terms of average SNR for the two compression techniques for different compression ratios is shown in Fig. 2 (right). Differently from the previous results, we can observe that the BD approach now has a better reconstruction quality for CR $< 2.7$, while for higher CRs the CS shows a better performance. This is due to the not ideal sparsity of the ECG signal. If we now consider the hybrid approach, which applies 8 bit BD after CS, we can notice that it combines the benefits of the two schemes and dominates over both. Indeed, the hybrid approach achieves the same QoS level of pure CS but at higher CRs, which translates into a reduction of the energy spent in data transmission. In Fig. 6 we can see how such SNR values translate visually in signal reconstruction quality.

To evaluate the energy costs in the different cases, the power consumption of the wearable biosensing node was measured connecting a shunt resistor of $10\,\Omega$ in series to the board power supply. The board is designed to allow the selective power gating of its components, hence we were able to measure the contribution of the different parts to the total power consumption. For the measurement of the BLE transmission costs, we used a TI CC2541 chip[2] on a breakout board, which was connected to the serial interface of the microcontroller, while the on-board BT was disabled.

The breakdown for the energy consumption of the different node components is shown in Fig. 3 for the CS case when using BT and BLE. In these experiments we measured the power consumed to compress and transmit one window of $500$ samples corresponding to 1s of acquired signal. The stacked bars report the individual consumption for the radio, both connection (Radio conn.) and transmission (Radio TX) costs, and for the digital part (MCU) responsible of the preprocessing and of the compression algorithm on the biosensing node. The case of CR = 1, i.e. no compression, is included as a baseline. We can see how the BT (Fig. 3, left) has a constant consumption of 10 mJ to maintain the connection, while BLE (Fig. 3, center) has been optimized to eliminate this consumption, which is not used for actual data transmission. This result highlights the benefits of BLE, which allows to

[2]Texas Instruments [ONLINE] http://www.ti.com/product/cc2541

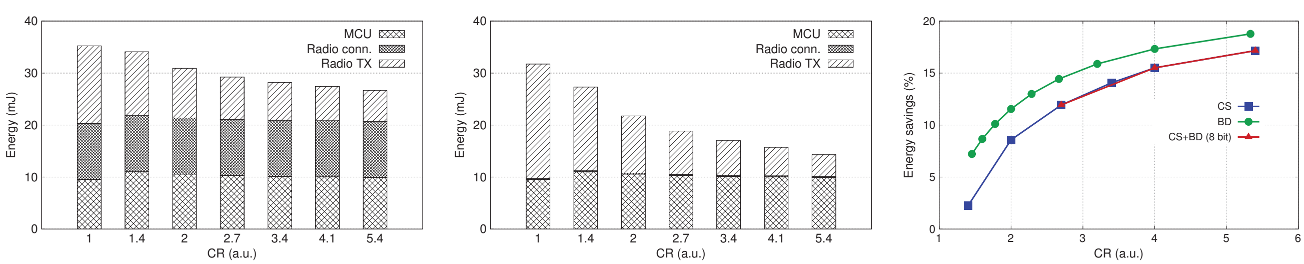


Fig. 3. Energy consumption of the wearable node: power breakdown for CS using Bluetooth (left) and BLE (center) data transmission. Energy savings for the entire biosensing node considering the no compression case as baseline (right).

further improve energy reduction when using data compression. When compared to the no compression case, the energy saving of the node introduced by the two techniques increases with the increase of the CR, with the CS constantly lower due to its higher computational demand. It must be noted that these figures do not include the BD breakdown, which shows a constant MCU component always equal to the case of no compression and exactly the same power figures for what concerns the radio.

A comparative analysis of the energy efficiency of the compression techniques is presented in Fig. 3. The plot shows the energy savings for the biosensing node over the CR range. This results highlight the implicit benefits of the BD algorithm, i.e. no MCU consumption for the biosensing node beside the cost of pre-processing the ECG samples. Table I shows the energy saving on the biosensing node with respect to the no compression case for the three techniques considering a target SNR of 25dB. We can notice that the hybrid approach achieves the best energy efficiency on the biosensing node.

TABLE I. ENERGY SAVINGS FOR 25 DB OF TARGET SNR.

| SNR | CS | BD | CS+BD (8-bit) |
|---|---|---|---|
| 25 dB | 8.4% | 13.1% | 15.7% |

### C. Reconstruction (Smartphone)

To analyze the energy consumption and the quality of service on the WBSN-gateway, we implemented the reconstruction algorithm and profiled its power consumption. On top of the Odroid-XU3 runs Ubuntu 14.04.1 LTS (GNU/Linux 3.10.51+ armv7l) and the toolchain used is gcc 4.8.2. The FOCUSS algorithm was implemented in C++ to run on the ARM cores. To ease and optimize the algorithm implementation, the C++ Armadillo library (v. 4.2) was used for linear algebra operations [23]. To measure the power consumption of the system, we deploy the on-board voltage/current sensors and split power rails, which allow to measure separately the power consumption of A15 cores, A7 cores, GPU and DRAM. To not affect power measurements, the readout of the sensors was implemented in a low-priority thread, with a sampling interval of 25ms and an average CPU consumption below 3%.

To test the system, we evaluate the effects of real-time and battery powered constraints in the CS reconstruction task in the gateway. For this purpose, we mapped the FOCUSS solver on both the A7 and A15 cores at the respective minimum and maximum frequency. We measured the maximum SNR

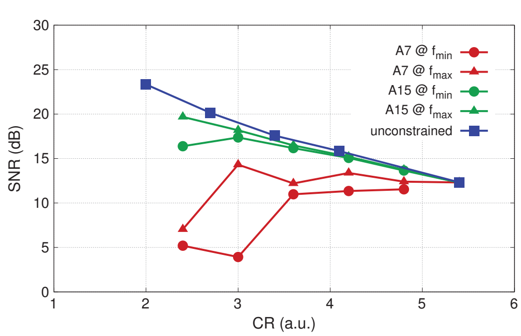


Fig. 4. Real-time SNR in reconstruction considering different operating points on WBSN-gateway (CPU, frequency) varying the CR.

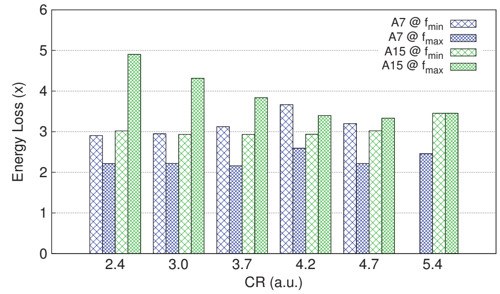


Fig. 5. Energy loss in the WBSN-gateway due to the CS reconstruction for different operating points (CPU, frequency) varying the CR.

achieved within the real-time constraint (1s time windows with 500 samples each), while executing the algorithm on a single core. The results are reported in Fig. 4 for the different cores at their respective minimum (0.8 GHz) and maximum frequencies (1.3 GHz for A7 and 1.9 GHz for A15). This analysis shows that the theoretical SNR, in principle set by a given CR, can only be achieved in some configurations due to the real-time constraint and the computational capability of the underlying HW. Indeed, by reducing the frequency of the core the achievable SNR is reduced.

For the same configurations, in Fig. 5 we show the energy loss due to the execution of the reconstruction algorithm when compared to the no compression case, which has the system in idle in the same operating point (CPU and frequency). The BD case is assumed to be equivalent to the no compression case, since it involves only a logical shift per sample. From the plot we can notice that when the system has enough computational capabilities (A15 @ $f_{max}$) the energy efficiency of the CS reconstruction increases with the CR, as for the biosensing node. This is due to the internal steps required by the FOCUSS algorithm, which computes the singular vector decomposition for the $\mathbf{\Phi\Psi}$ matrix, whose complexity is inversely proportional to the CR. On the other hand, when the computational capabilities of the personal gateway are limited by frequency scaling strategies, the achievable SNR decreases and the maximum efficiency is achieved with a lower CR. This translates in a lower efficiency on the biosensing node. Finally, adopting CS with real-time constraints leads to a significant energy loss in the gateway with respect to the BD strategy.

It must be noted that in this analysis we are considering only the smartphone CPU power consumption, thus this represents a worst case scenario. As a matter of fact, when compared with other simpler compression techniques, the CS shows its better QoS vs. energy trade-off when working with high compression ratios. For CRs below 2.4, the reconstruction leads to a 7x energy overhead on the smartphone, which reduces below 2.5x for CRs larger than 4. In this operating point its usage significantly saves energy in the biosensing node and has a reduced impact on the smarthphone. Where signal degradation is not tolerated or where the power budget of the personal gateway is critical, simpler compression schemes such as BD must be preferred.

### D. Visual Quality

To conclude the analysis, we present in Fig. 6 the plots of the original and pre-processed signals (left) and the reconstructed ones with CR = 2 (center) and CR = 4 (right). From

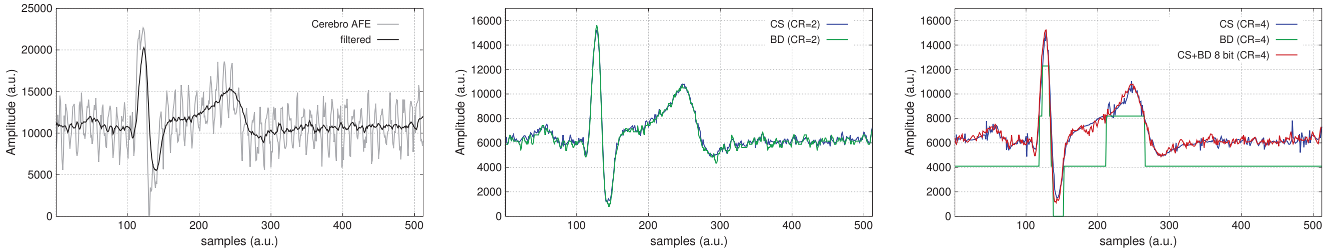


Fig. 6. Raw ECG signal segment acquired from Cerebro AFE and its filtered version (left). Visual quality at CR=2 (center) and CR=4 (right).

the data plots, we observe that for CR $< 2$ the two techniques have comparable reconstruction visual quality, hence the BD is the preferred one for its higher efficiency. For higher CRs, only CS and the hybrid approach are still capable to reconstruct the data thanks to the more sophisticated compression and reconstruction algorithms.

## IV. Conclusions and Future Works

In this paper we show a real implementation, with cutting-edge technologies, of an entire system for wearable ECG monitoring composed by a biosignal sensing node and a smartphone acting as personal gateway. In this test-bed, we evaluated the QoS vs. energy tradeoffs of CS compared to Nyquist sampling and to the simplest lossy compression scheme, i.e. LSB discarding. We used this simple comparison to define the perimeter in which CS is beneficial. Differently from state-of-the-art works, we used real ECG signals acquired with the proposed system to compute the final reconstructed signal.

Our experimental results show that CS always increases the energy efficiency of the biosensing node compared to Nyquist sampling. For compression ratios lower than $2.5$ the BD approach outperforms the CS in both energy savings and final reconstructed signal quality. Moreover, this compression scheme has zero overhead in reconstruction on the smartphone. This result is directly linked to the performance of our HW chain and we will investigate it in future works. As opposite, for CRs larger than $2.5$ the CS approach leads to better final signal-quality and energy-savings than BD. The energy-saving w.r.t. Nyquist sampling for the biosensing node increases by increasing the compression ratio and also the overhead and energy-efficiency loss introduced by the CS on the reconstruction side reduces with higher CRs. For this reason, CS shows its better advantages at the higher compression ratios where it leads to almost the $40\%$ of energy-saving in the biosensing node with the smallest energy-cost in the personalized gateway. In future works we will extend the present study to include optimized versions of the CS algorithm, which shows better QoS in ECG signals for a given compression ratio and can increase the application domain in which CS is beneficial. For what concerns the HW components, we will extend the current study with an application specific ultra-low power processor and we expect it will preserve the validity of the current results while further extending the battery life.

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