Ultra-Low Power Design of Wearable Cardiac Monitoring Systems

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***Abstract*—This paper presents the system-level architecture of novel ultra-low power wireless body sensor nodes (WBSNs) for real-time cardiac monitoring and analysis, and discusses the main design challenges of this new generation of medical devices. In particular, it highlights first the unsustainable energy cost incurred by the straightforward wireless streaming of raw data to external analysis servers. Then, it introduces the need for new cross-layered design methods (beyond hardware and software boundaries) to enhance the autonomy of WBSNs for ambulatory monitoring. In fact, by embedding more onboard intelligence and exploiting electrocardiogram (ECG) specific knowledge, it is possible to perform real-time compressive sensing, filtering, delineation and classification of heartbeats, while dramatically extending the battery lifetime of cardiac monitoring systems. The paper concludes by showing the results of this new approach to design ultra-low power wearable WBSNs in a real-life platform commercialized by SmartCardia. This wearable system allows a wide range of applications, including multi-lead ECG arrhythmia detection and autonomous sleep monitoring for critical scenarios, such as monitoring of the sleep state of airline pilots.**

***Index Terms*—Wearable Embedded Systems, Bio-Medical Signal Processing, Wireless Body Sensor Nodes.**

I. Introduction and Motivation

Embedded cardiac monitors are wearable and miniaturized devices, providing the acquisition, on-board processing and wireless transmission of cardiac bio-signals for prolonged periods of time. These wireless body sensor nodes (WBSNs) allow non-intrusive and long-term monitoring of cardiac parameters of patients, such as electrocardiogram (ECG) and pulse oximetry (SpO2). They represent novel solutions in the healthcare domain [1], both for the prevention of acute episodes (e.g., strokes) and for the assessment of chronic conditions (e.g., sleep disorders, stress-related pathologies).

The design of cardiac monitoring platforms is application-driven, because relevant data for medical examination strongly depends on the considered scenario. As an example, sleep monitoring applications involve the analysis of heart rate variability over a time window of the acquired bio-signal while the assessment of the recovery after a stroke instead requires the detailed analysis of the morphology of heartbeats. Minimizing the bandwidth on the energy-hungry wireless link [2] according to the application requirements is therefore an effective strategy for the design of ultra-low power cardiac monitors. To this end, on-node signal processing can be employed to derive the data of interest at different levels of abstraction *before transmission*, as illustrated in Figure 1.

This paper investigates how the energy efficiency of cardiac monitors can be enhanced by leveraging embedded processing and hardware-software optimization methodologies. We address its design space in a top-down fashion. First, cardiac applications and their requirements are introduced in Section II. Then, in Section III we detail how signal processing algorithms can support such applications and, in Section IV the challenges

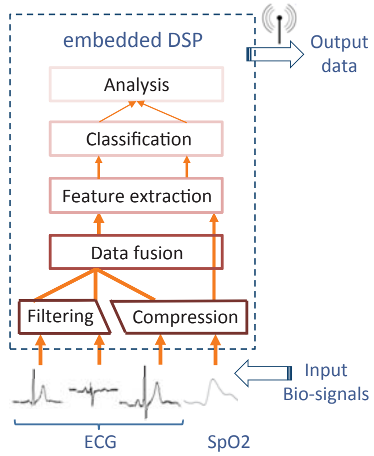

Fig. 1. On-node digital signal processing increases the energy efficiency of cardiac monitoring by rising the abstraction level and decreasing the bandwidth of transmitted data.

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involved in embedding them in resource-constrained cardiac monitors. Section V reports the performance of embedded cardiac monitors in real-world scenarios and finally section VI outlines promising future directions in this field and concludes the paper.

II. Wireless Body Sensor Nodes Applications

While traditional cardiac monitoring equipment are bulky and target patient monitoring for short periods of time, recent advances in technology have enabled the development of ultra-small and wearable monitoring devices. With the development of embedded cardiac monitors, we can envision a new generation of wearable systems where different sensors are integrated directly in the user's dress, processing and streaming the vital signs information to a mobile phone or a cloud server.

This opens up new application domains for cardiac monitoring, ranging from extracting behavioral information of the user (mental and emotional state), sleep/fatigue information and early detection and prevention of diseases.

The digital signal processing required for such different application scenarios varies widely. Applications that extract behavioural information typically only require processing of beat-to-beat intervals, while the diagnosis of heart problems requires the processing of more detailed morphological information of each heartbeat. Applications such as driver sleep monitoring require classifiers that are trained over different population sets and driving scenarios, and ported onto embedded micro controllers. The noise level of the signal and the required filtering algorithms also vary based on the application. For a cardiac system embedded in vehicles that use non-contact sensors, a major challenge is to remove the common mode electrical noise and obtain a clean signal, while for ambulatory monitoring of stroke patients, the challenge is to remove muscular and motion artifacts. Towards this end, in this paper, we present an application driven methodology for cardiac and bio-signal processing.

III. Cardiac signal processing methods

As illustrated in Figure 1, digital signal processing on embedded cardiac monitors typically follows a number of phases. A filtering stage is mandatory before performing further processing steps. To further counteract noise, different signals with the same modality (e.g.: multi-lead ECGs) can be combined after filtering. Afterwards, characteristic features are derived from the the cardiac signals with processes such as ECG delineation, and classification is performed to detect abnormalities in each heart-beat. Information at each level is instrumental to perform automated diagnosis for different cardiac-related pathologies.

An alternative solution, also effective in minimizing transmission bandwidth, is to compress the signal on the cardiac monitor, and reconstruct it for further analysis on the receiver side. The two approaches are not mutually exclusive. In [3], in fact, a classification methodology on compressed ECG signals has been proposed.

This section illustrates promising solutions for the automation of the different phases.

A. ECG compression

Today's state-of-the-art WBSN-enabled ambulatory ECG monitors still fall short of the required energy efficiency and longevity. This is mainly because of the raw data transfer over energy-hungry wireless links. It is today acknowledged that the achievement of truly WBSN-enabled ambulatory monitoring systems requires more breakthroughs not only in terms of ultra-low-power read-out electronics and radios, but also in terms of dedicated digital processors, which execute the associated embedded feature extraction and data compression algorithms in order to reduce airtime over wireless links.

In [4], the potential of the compressed sensing (CS) signal acquisition/compression paradigm for low-complexity energy-efficient ECG compression has been investigated. It is shown that CS could outperform its state-of-the-art counterpart compression algorithms, thanks to its low complexity and CPU execution time in terms of overall energy efficiency. With more advances on the reconstruction algorithm, in [5], the possibility of a real-time CS decoder running on an iPhone (acting as a WBSN coordinator) has been demonstrated.

Building on these initial works which proves the suitability of using CS for ECG compression on the resource- and energy-aware WBSN, the technique has been extended to fully leverage and exploit underlying structural information, like any state-of-the-art compression technique. More specific recovery algorithms for single lead and multi-lead ECG has been presented in [6].

Beyond all these works, CS is usually used as a very low cost and easy to implement compression technique. Signals should be acquired with the traditional limitations on the bandwidth (BW) and after the major portion of redundant data should be discarded. The main challenges are then taking the whole design of the front-end and read-out devices to the next level based on the promises of the CS and merging the sampling and compression steps. This removes a large part of the digital architecture and considerably simplifies analog-to-information (A2I) conversion devices.

This so-called "analog CS", where compression occurs directly in the analog sensor readout electronics prior to analog-to-digital conversion, could thus be of great importance for applications where bandwidth is moderate, but computationally complex, and power resources are severely constrained. Different realization of the CS-based "analog-to-information" readout devices has been introduced in the literature [7], [8], although designing a truly CS-based A2I still remains as a challenge.

B. Noise filtering and source combination

Cardiac bio-signals are usually affected by noise, which must be filtered before relevant features can be retrieved from the acquisitions. Different sources of noise range from those coming from environmental factors (e.g. electromagnetic interference) to others of biological nature (e.g. muscular activity). The authors of [9] propose a filtering technique based on the application of two morphological operators (*erosion* and *dilation*), which removes unwanted components from

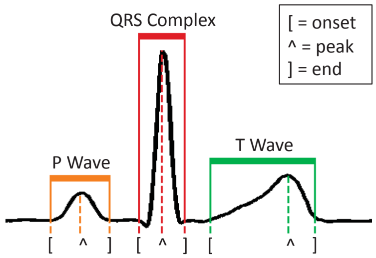

Fig. 2. Delineated normal sinus beat.

the input signal. Alternatively, [10] proposes a technique for removing low-frequency components causing the so called baseline wandering. This method, based on cubic splines, searches for "knots" in a characteristic *silent* region of the acquired signal (before each QRS complex), and interpolates three consecutive knots to estimate the baseline.

In [11], it is shown that the effect of noise can be also reduced by combining different ECG leads before the analysis and/or delineation phase. Simple root mean square (RMS) aggregation of inputs, is presented as a light-weight, yet effective, implementation strategy.

C. ECG Delineation

ECG delineation is the process of identifying the fiducial points (start, peak and end) of the characteristic waves composing each heart-beat (Figure 2). The information enables the diagnosis of a large set of cardiac conditions, such as arrhythmias. For this purpose, [12] propose a method based on wavelet decomposition, relying on the fact that different waves present distinct frequency components.

An alternative strategy, presented in [13], proposes to use a morphological transform of the ECG to automate the delineation of fiducial points. The method gives an effective solution to the problem of delineation, as minima in the transformed signal indicates the presence of peaks in the original wave, while maxima (or sudden changes in slope) delimit the start and end point of each wave.

D. Embedded classification

Higher-level ECG processing, after the delineation phase, can further reduce the amount of data to be transmitted, while also adding further information about the processed signal. The work presented in [14] proposes the utilization of a classifier to identify abnormal heartbeats and trigger delineation only in those cases. The authors describe a methodology to implement a fuzzy network into a state-of-the-art WBSN meeting real-time and sensitivity constraints.

An important problem in classification is to identify a set of representative features for each heartbeat. The random projection approach introduced in [15] is particularly promising in this context. It allows the minimization of the number of features (and therefore a simplified classification process) as well as the efficient computation of the feature set.

IV. Embedded cardiac monitoring platforms

The design of a truly effective embedded cardiac monitor has to overcome diverse challenges. The most important design goals are to require low maintenance and allow long-term execution, at the same time causing as little discomfort as possible to subjects. Moreover, accurate diagnostic data should be retrieved for medical evaluation.

These conflicting goals require a careful system-wide evaluations in the platform design. Energy efficiency is a key objective, as it allows to minimize the battery size and weight while retaining continuous operations for extended periods of time. This section describe several effective strategies (both at the hardware and software levels) allowing ultra-low power regimes while performing embedded processing.

Moreover, physical constrains impede the continuos acquisition of important cardiac parameters. We show how parameters such as Blood Pressure (BP) can instead be estimated from other ready-obtainable quantities.

A. Software optimizations

The filtering, delineation and classification algorithms proposed in Section III must be carefully tailored to be executed on resource-constrained embedded cardiac monitors. Typically, these platforms (like the SmartCardia device presented in Figure 4) operate at a clock frequency of few MHz and only support integer arithmetic operations.

Computationally-intensive parts of applications must therefore be analyzed to derive light-weight implementations. This approach is exemplified in [12], where a proper choice of the filter bank coefficients leads to an efficient execution of the wavelet-based delineation on a state-of-the-art embedded device. In the cases of morphological filtering and delineation, if a flat structuring element is employed, the computational demands of the morphological operations can be drastically reduced by keeping track of only the center value, maximum and minimum in a sliding window of the input signal.

The approximation of complex functions is also as an effective strategy to reduce algorithmic complexity. For instance, in the scenario of heartbeat classification, which usually involves the evaluation of many gaussian functions, a four-segments linearization is shown to achieve close-to-optimal results [14], while vastly simplifying the computational requirements. Moreover, by using random projections (described in Section III-D) memory usage can be minimized considering a projection matrix only composed by elements of value 0, 1 and -1, which can be represented using only two bits per component.

Sparsity considerations are important to minimize computation and memory usage. In [16], it is shown how few non-zero elements in the sensing matrix suffice to achieve close-to-optimal results when performing compressive sensing, while minimizing the run-time workload.

Along the same lines, the knowledge of the structure of coefficient vectors can be exploited to increase the quality of compressed sensing by differentiating signal information from recovery artifacts. A first approach stems from the observation that wavelet coefficients are naturally organized into a tree structure, and the largest coefficients cluster along the branches of this tree. A CS reconstruction algorithm based on the

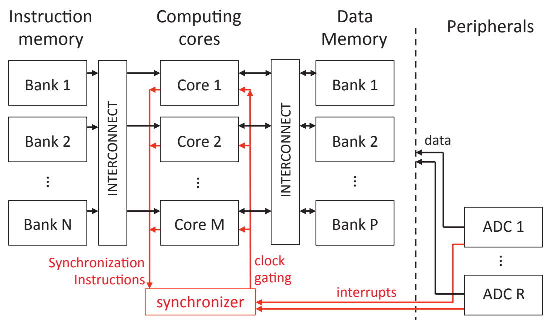

Fig. 3. Hardware architecture of a typical multi-core WBSN. In red, hardware support for synchronization.

connected tree model has been proposed in [17]. Second, in case of the multi-lead ECG compression, there is a strong correlation between the sparsity structure among the leads, each lead therefore conveying useful information about other leads. In particular, non-zero coefficients are partitioned in subsets or groups, and this information can be employed to enhance the compression performance across all leads [6].

B. Ultra-low-power architectures for cardiac monitoring

Cardiac monitoring applications present a high degree of parallelism, either because multiple sources are processed by the same algorithms (e.g., filtering of multiple ECG inputs) or because processing is divided into consecutive different phases of computation (as introduced in Figure 1). These characteristics allow the parallelization of the workload on a multi-core core architecture by exploiting voltage scaling to achieve substantial energy savings.

In [18] we propose a platform interfacing multiple processors to independent multi-bank program and data memories (cf. Figure 3). Low-overhead mechanisms are introduced to synchronize code execution and enable single-instruction multiple-data (SIMD) operations, resulting in a decrease of the energy consumption of the instruction memory subsystem. To this end, the employed *broadcasting* mechanism, which is implemented by the interconnect networks, merges multiple identical read requests from different cores into a single memory access. Moreover, this architecture includes a software technique based in barrier insertion to maintain cores in lock-step and recover from de-synchronization after data dependent branches. This technique requires a reduced instruction set extension that annotates the synchronization status on dedicated data words stored in the shared memory to allow the synchronization hardware to properly orchestrate the execution flow. This architecture enables the use of producer-consumer relationships among computational stages and the application of the proposed methodology allows to correctly map bio-medical applications onto the multi-core platform in order to avoid program memory conflicts, and therefore unnecessary stalls and performance degradation. Interestingly, fine-tuned load balancing is not a necessary precondition for energy efficiency in cardiac monitoring systems.

A complementary approach for minimizing power consumption in this kind of devices is to include application-specific accelerators. In the case of compressed sensing, the authors of [19] highlight that a minimal hardware support accompanied by a specific instruction set extension of a RISC core can achieve more than ten-fold power saving with respect to a baseline implementation while performing compressed sensing over an ECG signal.

C. Real-time estimation of multiple cardiac parameters

In clinical scenarios, information extracted from the ECG is analyzed along with other cardiac bio-signals, such as blood pressure (BP) and pulse oximetry, to assess the global health status of the cardiovascular system. The realization of multi-modal cardiac monitors integrating diverse sensors in a wearable device is, therefore, desirable but not straightforward. As an example, sensors capable of directly measuring blood pressure are either cumbersome (e.g., inflating cuffs) or extremely complex (e.g., arterial tonometry).

An interesting approach for multi-modal analysis is to combine available information to estimate parameters which cannot be easily measured. For instance, the pulse arrival time (PAT), calculated using ECG and a simple and inexpensive photoplethysmograph (PPG) finger probe, can be used to estimate the pulse wave velocity (PWV), which is a surrogate marker for arterial stiffness and BP [20].

In addition, when signals of multiple modalities are considered, the correlation between the different inputs can be used to facilitate signal processing. Most cardiac bio-signals originate from the response to the bioelectric stimuli reflected in the ECG. The signals are, therefore, time-locked to these stimuli. This information can be used to remove noise (which is instead uncorrelated to the stimuli) with different techniques such as ensemble averaging (EA) and adaptive impulse correlated filtering (AICF). In [21] it is shown that ECG information can be employed to calculate, among other parameters, the EA of the pulse oximetry. Also, AICF can be used to filter the ECG signal [22] and to de-noise PPG signals [23]. The disadvantage of using EA is that the beat-to-beat variation of the signals is lost after the processing. AICF, on the other hand, is also capable of tracking dynamic changes in the signal.

V. Experimental Results

Embedded cardiac monitors enable a new family of application scenarios in the healthcare domain. Although they are computationally- and energy- constrained, these devices are able to perform the advanced signal processing algorithms described in Sections III and IV, allowing novel breakthroughs in the healthcare monitoring field. As an example, the SmartCardia device [24] depicted in Figure 4 is able to perform 3-lead ECG monitoring and execute a set of algorithms for real-time ECG filtering and arrhythmia detection. In particular, it allows the automatic detection of abnormal cardiac events and the remote notification of such phenomena to a centralized server infrastructure, thanks to an on-board radio transceiver. Compressed Sensing is employed to efficiently transmit excerpts of the acquired signals, periodically or when an abnormality is detected. This SmartCardia device embeds

Fig. 4. SmartCardia 3-lead ECG monitoring device.

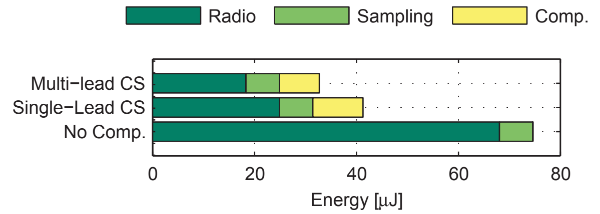

Fig. 6. Breakdown of energy consumption for our target platform.

an ultra-low-power micro-controller for digital processing, an acquisition front-end and a wireless transmission stage, all in a compact form factor. The mean time between charges is typically one week.

This level of functionality is achieved by an optimized implementation of hardware and software components, such as the ones described in this paper. Moreover, these optimizations do not have major impact on the obtained quality of the retrieved data. As an example, the performance of the illustrated ECG delineation algorithms are in line with the results reported by computing-demanding off-line variants, while requiring only a fraction of the resources (7% of the duty cycle and 7.2kB of memory [12]). For this application, the measured sensitivity and specificity of retrieved fiducial points are above 90% in all cases, which is at the target level for medical use in this field.

Figure 5 compares the averaged signal-to-noise ratio (SNR) results over different compression ratios (CR) for single-lead and multi-lead CS compression [6]. These results show that an averaged SNR over $20\ dB$ (corresponding to good reconstruction quality [16]) is reached for $CR = 65.9\%$ and $CR = 72.7\%$ for single and multi-lead CS, respectively. To characterize the power figure, the compression algorithms are implemented on our target WBSN running FreeRTOS on a 16-bit processor and simple medium access control (MAC) scheme for wireless communication (IEEE 802.15.4) between the node and the base station. Figure 6 depicts the share of radio, OS and compression in the total node power consumption for raw data streaming and two CS-based compression for good quality of reconstruction. The average power reduction estimates are 44.7% and 56.1% compared to raw-data streaming for single-lead and multi-lead CS compression. This proves the suitability of CS as a promising low-power compression technique for wearable cardiac monitoring systems.

In addition, similar results have been obtained for applications performing a diagnosis at a higher level of abstraction, such as Atrial Fibrillation (AF) detection [25]. This cardiac monitoring application uses the results of the ECG delineation to analyze the regularity of the heart beat rate as well as the shape of the P wave, which constitute two characteristic irregularities of AF episodes. The results generated after the observation of these irregularities can be subsequently analyzed in real-time using a fuzzy classifier. This low-complexity approach achieves 96% sensitivity and 93% specificity, which are comparable figures to state-of-the-art off-line AF detection algorithms while operating in real-time on an embedded device.

Finally, the use of multi-core computing architectures in cardiac monitoring systems (cf. Section IV-B) increases further the energy efficiency of the processing stage. In particular, Figure 7 shows how the filtering (3L-MF), delineation (3L-MMD) and classification (RP-CLASS) applications described in Section III can be efficiently executed on the presented multi-core platform of Figure 3 (MC), reducing up to 40% the global power consumption with respect to a single-core variant (SC).

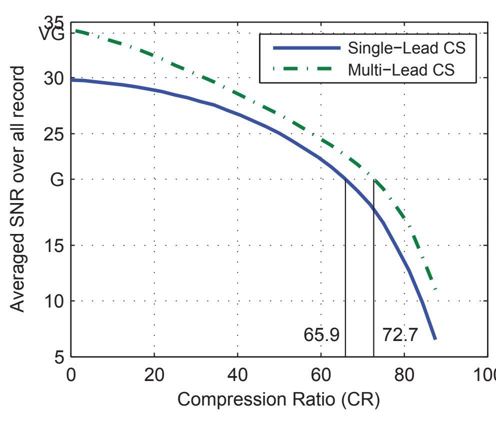

Fig. 5. Output averaged SNR over all records over different compression ratios for single-lead and multi-lead compression.

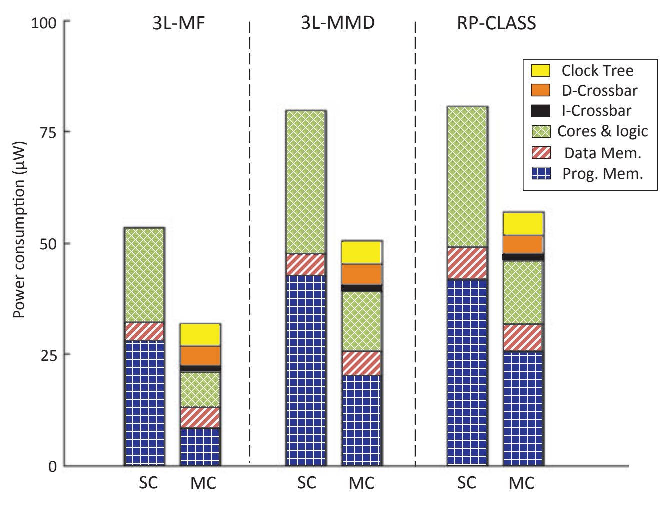

Fig. 7. Average power consumption decomposition of a synchronized multicore (MC) system and an equivalent single-core (SC) architecture.

VI. Conclusions and Future Applications

In this paper we have presented the main design challenges and latest approaches targetting next-generation ultra-low power wearable cardiac monitors, which need to perform an energy-efficient real-time acquisition and processing of ECG, thus providing the possibility of performing on-line diagnosis and analysis of the cardivascular state of a person. In order to develop this new cardiac monitoring systems, we have shown that multiple optimizations exploiting the target bio-signal features need to be performed at both hardware and software levels in order to achieve the target ultra-low power figures needed to extend autonomy of the systems for long-term bio-signals monitoring.

As a result, these new ultra-low power cardiac monitoring WBSNs will be able to enable novel medical approaches for the diagnosis of diverse ailments. In particular, a promising direction to be investigated in the near future is related to neurodegenerative disorders, such as, Alzheimer Desase (AD). Even though the mechanisms linking the autonomic regulation of the heart activity to AD are not fully understood, recent studies have demonstrated a correlation between neurological degeneration and aberrant ECG signals, indicating the latter as a potentially useful bio-marker of AD progression [26].

Moreover, researchers have explored the neural basis of bodily self-consciousness and have showni in very recent studies that a tight relationship exists between the brain processes and the body states, such as, the heartbeat [27]. Therefore, expected development of wearable cardiac monitors has the potential to open up several new applications in neuro-rehabilitation by exploiting the relationship between the brain processes and cardiac factors, as well as enabling effective mind training and improvement of children with learning disabilities.

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