On The Problem of Energy Efficient Mechanisms Based on Data Reduction in Wireless Body Sensor Networks

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***Abstract*—Wireless Body Sensor Networks have emerged as a low-cost solution for healthcare applications and telemedicine solutions replacing unnecessary hospitalization and ensuring continous health monitoring. Many challenges exist in such a network, especially because the sensor nodes have limited resources. In this paper, the energy consumption problem due to periodic transmission is targeted. We present a work in progress on energy-efficient mechanisms based on data reduction for body sensor networks. Many approaches have been proposed in the literature that aim to reduce the size and the amount of data collected and sent via the network. Our main idea in this paper is to confront Compressive Sensing (CS) and adaptive sampling techniques in order to come out with a problem formulation and a comprehensive comparison. The objective is to show if the adaptive sampling approach which is based on on-node processing ensure a better Performance/Energy trade-off than CS theory applied on biosignals.**

***Keywords*-Wireless Body Sensor Networks, Energy Consumption, Compressive Sensing, Adaptive Sampling**

I. INTRODUCTION

Wireless Body Sensor Networks (WBSNs), a subset of Wireless Sensor Networks (WSNs), have been gaining popularity in the last decade due to the potential they bring out in telemedicine solutions. They are mainly composed of sensor nodes deployed on the patient's body as wearables and a coordinator. The former sense and collect physiological measurements such as the heart rate, the blood pressure and the ECG etc. The latter receives the collected measurements and signals from the sensor nodes for fusion and manages the whole network.

The fusion process, depending on the monitoring scenario and application needs, includes: the detection of emergencies, the identification/detection of the patient's medical and/or physical status, the making of a diagnosis, the making of health decisions, the aggregation of the collected data before transmission to a higher level such as a sink or a server for storage and further processing.

Many challenges exist in such a network, especially because the sensor nodes have limited power, storage and processing resources. Energy consumption is one of the main issues given that WBSNs are characterized by periodic power consuming transmission of huge amounts of collected data namely signals and measurements. Many approaches concerning energy-efficient models and mechanisms have been proposed in the literature [1] [2] [3] [4] [5]. Data reduction is one of the means ensuring an efficient usage of the transmission unit of the sensor nodes and energy savings in the whole network. On the one hand, we have proposed in previous works [6] [7] an adaptive sampling rate model at the sensor node level. The approach aims at periodically specifying the amount of measurements to be collected by each sensor node depending on the variations presented by each vital sign in the last two periods. Furthermore, the amount of transmitted measurements is reduced by employing an early warning score system. Thus, only measurements indicating a change in the status of the vital sign are sent to the coordinator. On the other hand, many approaches [3] [4] [8] [5] [9] based on Compressive Sensing (CS) have been proposed in the literature due to its potential. CS guarantees the reconstruction of sparse signals such as the ECG while largely reducing the amount of sampled data. Thus, it reduces the amount of wirelessly transmitted data and consequently the energy consumption on the sensor node level.

In this paper, we present a work in progress on energy-efficient mechanisms based on data reduction for body sensor networks. Our objective is to confront adaptive sampling and CS as two different approaches ensuring energy-efficiency in WBSNs and come out with a problem formulation. Several CS approaches and data samling methods are compared in order to give open research issues in this domain.

The remainder of the paper is oragnized as follows. In Section II, the components of the sensor nodes are presented and their energy characteristic is dicussed. In Section III, a classification of the energy-efficient mechanisms from the literature is given. In Section IV, a previsouly proposed method which is based on adaptive sampling is briefly

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discussed. In Section V, compressive sensing is defined and different approaches from the literature are exlpained and compared. In SectionVI, further discussions are presented and the problem is formulated. Finally, Section VII concludes the paper.

II. Wireless Sensor Nodes: Components and Energy Characteristic

A wireless sensor node is constituted of three components: the sensing unit, the processing unit and the transmission unit. All three units need power to perform their tasks (see Figure 1) [10]. Yet, transmission is considered to be the most power-hungry task. The sensing unit is composed of the sensor and the ADC (Analogic-Digital Convertor) which converts the analog signal sensed with a given frequency (Nyquist-Shannon)[11] into a digital signal. The latter is fed to the processing unit, including a processor and a memory, where the digital signal processing algorithms are run. These include: compressive sensing, traditional compression techniques, feature extraction in the temporal and frequential domains, vital signs extraction (calculation) such as heart rate, classification, and other on-node processing algorithms. Furthermore, the processor controls the sensing and the transmission units and it activates and/or changes their status according to the application and the used protocol. Many energy-efficient mechanisms have been proposed in the literature, namely for WBSNs.

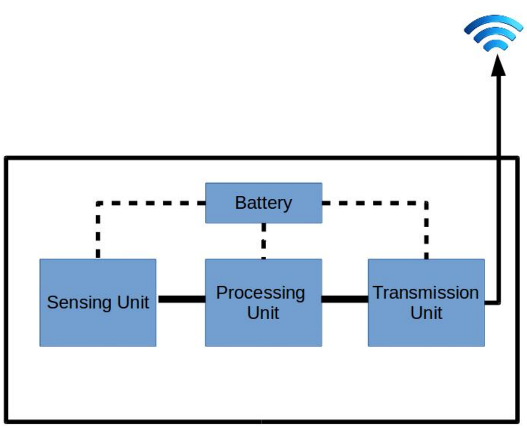

Figure 1. A wireless sensor node

III. Classification of Energy-Efficient mechanisms in WSNs

Energy-efficient mechanisms dedicated to wireless sensor networks are classified into five categories as follows [12]:

- Data reduction approaches: Aggregation, adaptive sampling, compression and network coding.
- Sleep/Wakeup schemes: Duty-cycling, passive wake-up radio, scheduled based MAC protocols and topology control.
- Radio optimization techniques:transmission power control, modulation optimization, cooperative communication, directional antennas and energy efficient cognitive radio.
- Energy-efficient routing methods: cluster architectures, energy as a routing metric, multipath routing, relay node placement and sink mobility.
- Battery repletion: energy harvesting and wireless charging.

These approaches can be split up into software and hardware strategies [1]. In addition, some of these mechanisms are suitable for large scale networks such as environmental monitoring, industry, public safety of military systems etc. applications. Thus, they cannot be applied in WBSNs where the network characteristics are different. For example, energy-efficient routing methods as well as transmission power control and topology control approaches cannot be directly used in WBSNs [2]. Many existing approaches have used context-awareness based on activity recognition to perform adaptive sampling or adaptive sensing. Some of them applied these approaches only on WBSNs composed of inertial detection sensor nodes such as accelerometers and gyroscopes [2]. Others used activity recognition to adapt the sensing rate of a vita sign of interest in the context of a give disease [13].

IV. Adaptive Sampling as an Energy-Efficient Mechanism

In order to increase the network lifetime and to reduce the huge amount of the collected data adaptive data collection models have been proposed in the litterature [14] [15] [6]. The main idea behind these models is to allow each sensor node to adapt its sampling rate to the physical changing dynamics of the monitored phenomenon. In this way, the oversampling can be minimized and the power efficiency of the overall network system can be further improved.

In [6], we proposed a distributed self-adaptive data collection approach in the context of WBSNs. Two contributions have been highlighted. First, a local detection system based on an early warning score system is proposed to be used on the biosensor node. The latter reduces the amount of transmitted data by only sending detected changes in the monitored vital sign measurements. Thus, reducing the amount of redundant information as well as the overall amount of transmitted measurements. Changes in vital signs are identified when the local detection system detects a change in the score of the measurement indicating a deterioration or improvement of the status of the vital sign. Second, an adaptive sampling rate schema, having a direct impact on the sensing task of the biosensor node, has been proposed. Using a Quadratic Bezier Curve as a BehaVior (BV) Function [14] [15], it takes into account two parameters: the evolution of the monitored vital sign over time and its monitoring importance, based on a medical judgment, regarding the patient's health condition. These parameters are, respectively, determined by the Fisher Test and One-way ANOVA model[15] which study the variances of the sensed measurements over time and by a risk level variable r^0 whose values range between 0 and 1. We have defined two risk levels, pointing out the importance of a given vital sign to be monitored knowing the patient's health condition:

- Low Risk: $0 \leq r^0 < 0.5$
- High Risk: $0.5 \leq r^0 \leq 1$

However, the overall health condition of a patient, being continuously and remotely monitored on a long-term basis, changes over time. It is subject to many health events which can be acute or even chronic. Thus, it can vary from day to day as well as from an improvement state into a deterioration state and vice versa. As a consequence, the monitoring importance given to each vital sign should be adapted with these changing conditions. This matter, has a direct influence on the sensing and processing tasks; therefore on the energy consumption of the WBSN and the early detection of critical events. In another work [7], we have proposed to dynamically adapt the risk level r^0 of a vital sign according to the health condition of the patient. Thus, the corresponding biosensor node will be given a higher risk level r^0 when the health condition of the patient is at a higher risk and it will be given a lower risk level r^0 when the health condition of the patient is at a lower risk. The proposed distributed and on-node approach is a software-based strategy and it belongs to the data reduction category.

V. Compressive Sensing

In the recent years, Compressive Sensing (CS) theory emerged as an energy-efficient approach for wireless communication. Capitalizing on signal sparsity, CS guarantees an accurate signal reconstruction by sampling signals at a much lower rate than the traditional Shannon-Nyquist theorem. Thus, it has the potential to dramatically reduce the power consumption since the amount of wirelessly transmitted data is considerably reduced. Furthermore, it reduces the amount of resources required for processing and storage and it promises significant compression rates while using computationally light linear encoders compared to traditional compression methods. CS theory has been applied in diverse domains including WSNs. Particularly, many contributions based on CS theory have been proposed in the literature so far for WBSNs due to the fact that biosignals such as the ECG are sparse [9], [5], [8], [4], [3].

Mamaghanian et al. [9] have proposed compressed sensing for real-time and energy-efficient ECG compression. They have demonstrated that CS extends the node's lifetime of about 37.1 % compared to the traditional compression method by DWT (Discrete Wavelet Transform). This is mainly due to the fact that the former requires less computation for the code execution than the latter. The have used Shimmer motes for the validation of their proposal. However, they have clearly stated that they have proposed ”digital CS” which takes place after the ADC, thus raw samples are sensed at a Nyquist rate and only digital samples are sampled using CS theory. In accordance, the results showed that the node's lifetime extension is only 6 % compared to no compression at all. This is due to the amount of energy consumed to execute the code. Therefore, ”analog CS” remains the ultimate goal, where the compression occurs in the analog sensor read-out prior to ADC. It would then reduce the energy consumption due to sampling and running the OS. Unfortunately, it still requires extensive work.

Faust et al. [5] have proposed to apply CS for heart rate(HR) monitoring. They have demonstrated that the ECG signal after the R-wave form extraction is a sparse signal in the time domain, thus the CS theory is applicable. The latter shows the spikes in the ECG signal which indicate a heart beat, thus the HR can be calculated from this signal. However, the density of the ECG signal changes from a disease to another thus, CS does not provide a good signal reconstruction for all types of ECG. They have concluded by proposing an implementation of their system on sensor nodes at the analog level.

Wang et al. [3] have proposed a configurable energy-efficient compressed sensing architecture for wireless body sensor networks. They have focused on the effect of the quantization in CS and studied the impact of the sampling rate M as well as the number of quantization bits b on the energy consumption. They have proposed an algorithm which finds the best configuration pair (M,b) meeting the performance-energy trade-off requirement. However, the authors only studied the energy consumption due to transmission and did not mention the power resources required for sensing and processing the data. The results showed very close energy consumption when comparing traditional CS and configurable CS, however, the latter showed much better reconstruction error rates. Figure 2 summarizes the three works chosen from the literature.

VI. Further Discussion and problem formulation

All the CS approaches that have been previously discussed as well as the proposed approach contribute on the digital signal processing level. All of them focus on reducing the energy consumption due to transmission by reducing the amount of wirelessly transmitted data. The CS approaches reduce the sampling rate used to sample the digital signal, thus reducing the amount of samples to be transmitted. The proposed adaptive sampling approach, as described in section IV, is twofold:

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Approach	Objective	Contributions	Assumptions	Inputs	Outputs	Constraints	Context	Validation	Results	Drawbacks
Mamaghanian et al. (2011)	Comparison between CS theory and DWT	Several compression algorithms implementations and optimizations	ECG sparsity	Digital ECG samples	Compressed low-dimensional vector	Limited energy and resources	Real-time ECG monitoring using WBSNs	Real implementation on Shimmer motes, ECG data from the MIT-BIH Arrhythmia Database	MSP430 is not suited for digital signal processing operations Digital compression does not extend the lifetime of the node up to considerable amounts CS theory has a better trade-off between energy consumption and compression ratios than DWT	Default reconstruction algorithm with high computation resources
Faust et al. (2012)	Apply CS theory for heart rate monitoring	Apply CS theory on time domain sparse signal	Sparsity of R-wave form extraction of ECG	Digital R-wave extraction of ECG samples	Compressed low-dimensional vector	----------------	Heart rate monitoring	ECG data from the MIT-BIH Arrhythmia Database	HR signals are sparse in time domain thus CS can be used, CS reduces the data rate compared to standard sampling method, Practical realization of the proposed system is a must to validate it	No contribution at the compression and reconstruction algorithms, Limitations of resources are not taken into consideration, No solution is given in case of different ECG patterns corresponding to different diseases
Wang et al. (2016)	Configurable CS Architecture : Sampling rate and quantization	Impact of quantization and sampling rate on signal reconstruction and energy consumption, Proposal of an optimization algorithm RapQCS	Sparsity of biosignals	High-dimensional raw analog signal	Quantized random measurements	Limited energy and resources	Biosignals monitoring using WBSNs	ECG data from the MIT-BIH Arrhythmia Database	Energy consumption in traditional CS and configurable CS are close but there is a remarkable difference in the reconstruction error rate, RAPQCS has good results in terms of speed and performance	The energy required for sensing and processing the data is not taken into consideration (the sampling rate is much greater in configurable CS than in traditional CS), The energy setup is not clear

Figure 2. Compressive Sensing approaches in the context of wireless body sensor networks taken from the literature.

- Adaptation of the sampling rate: It adapts the sampling rate at which a vital sign is extracted(calculated measurement) from the digital signal.
- Local Detection: It transmits the calculated measurement of a vital sign only if its score indicates a change in the status of the vital sign.

The adaptation of the sampling rate is done based on vital signs, which are in most of the cases calculated based on raw sensed signals. For example the HR (bmp) is calculated from the R-wave extraction of the ECG signal. Thus, the adaptation of sampling rate indicates at what rate (time interval) the processor should process a new vital sign measurement, regardless the sensing frequency of the sensor node which is usually fixed by the type of the raw biosignal. However, the adaptation of the sampling rate can be extended to not only impact the processing of a new measurement but also to manage the sensing task of the sensing unit. In other words, it could allow the sensor node to control the sensing unit by activating/desactivating the sensor each time interval δ_t based on the adaptation of the sampling rate. However, this still needs extensive work in terms of delay and power consumption especially if it needs to be implemented on a real architecture where some hardware limitations might exist. Finally, none of the approaches contribute directly on the analog raw signal aquired by the sensor nor on the sensing frequency, thus none reduces the energy consumption due to sensing. Nevertheless, all of the approaches can be adapted in order to do so. However, the CS approaches face hardware limitations as for the proposed approach it can be extended to control the sensing tasks by activiting/desactivating the sensor.

Since, the chosen approaches from the literature and the proposed approach have one common goal: reduce the energy consumption due to transmission. Furthermore, for the following reasons:

- All of the techniques are software-based.
- All of them rely on data reduction mechanisms.
- All of them contribute on the same level: digital signal processing.

Then, the adaptive sampling approach is comparable to the chosen approaches from the literature. The only difference remains in that the CS theory is complemented by a reconstructionn algorithm at the base station in order to reconstruct the sensed biosignal for further processing.

The open question can be formalized as follows: *Does the adaptive sampling approach which is based on on-node processing (extraction of vital signs from biosignals and local detection) ensure a better Performance/Energy trade-off than CS theory applied on biosignals ?*

The performance metric englobes: the detection of critical events, the detection of improving/worsening conditions, the reduction of redundant data, execution time of the code, complexity. The energy metric includes: the energy consumption due to sensing (if our approach is extended), and especially the energy consumption due to processing (executing the code) and transmitting.

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VII. Conclusion and Future Work

In this paper, we presented a work in progress on energy-efficient mechanisms based on data reduction for body sensor networks. We reviewed compressive sensing and adaptive sampling approaches that have been proposed in order to reduce the amount of data collected and transmitted over the network. We provided a discussion about the differences and the advantages of the different techniques and we formalized an open question concerning tha data compression in body sensor networks.

Our main objective for future work is to reduce the number of bits needed to represent the sensed data prior to transmission, while taking into consideration the trade-off between the computational cost and the compression ratio. Then, we intend to combine the compressive data model with an adaptive sampling technique to further reduce the collected data prior to transmission.

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