Design and Implementation of a sustainable Wireless BAN Platform for Remote Monitoring of Workers Health Care in Harsh Environments

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Abstract—**This paper presents experimental results on a body area network platform that accurately and precisely captures, processes, and wirelessly transmits six-degrees-of-freedom inertial and electrocardiogram data in a wearable, non-invasive form factor. The platform is designed to be low-energy enabling health care applications and remote monitoring of workers in harsh environments. The challenges tackled in this article include the following: (1) reducing the radio channel contention, (2) reducing the energy consumption, and (3) managing diverse Quality of Service (QoS). The system is evaluated regarding to the accuracy and the energy consumption efficiency.**

I. INTRODUCTION

Wireless Body Area Networks (BAN) are formed by several low-energy wirelessly interconnected biomedical or inertial sensor devices. The sensors may capture various physiological parameters of the human body (*e.g.* temperature, heart rate, Electroencephalography (EEG), Electrocardiography (ECG), blood pressure, blood oxygen saturation levels, etc.) as well as parameters of the physical environment, such as the amount of sunlight exposure or ambient air quality. In a typical BAN architecture, sensor data are transmitted wirelessly to a gateway where the data are forwarded over Internet to a remote medical server for storage and analysis. Due to constraints such as energy and computation capability, nondeterministic sensor failures, radio links instability, and distrusted environments, designing and deploying a robust BAN platform is still challenging.

Motivation. The BANs have become a leading approach for several promising applications in the medical and healthcare field. But despite the rich availability of works, there are not many fully functional applications that can be actually employed in real cases. In particular, limited resources in energy and in radio communications make difficult real-world deployment. As a result, there is a need for low-energy communication protocols reducing both traffic contention and energy consumption. In this paper, we present a BAN platform monitoring workers who are subjected to hard environmental conditions during their work. The platform implements similarity filtering and polynomial interpolation techniques. These lightweight mechanisms are suitable for low-power microcontroller and allow to efficiently reduce the amount of data that must be transmitted. In addition, we show that, even with an important compression with loss, they still allow to detect fall or anomaly in heart beat.

Contributions. In this article, we address these challenges and make the following contributions:

- Firstly, the architecture of the BAN platform is presented and application scenarios are described. Three types of signals are considered: electrical activity of the heart or electrocardiography (ECG), orientation measurement via a tri-axial gyroscope, and linear acceleration measurement via a tri-axial accelerometer.
- Secondly, similarity filtering and polynomial regression are proposed to provide large compression while maintaining high accuracy.
- Finally, the paper presents a scenario allowing to evaluate the performances of the proposed architecture in terms of accuracy, efficiency and energy saving.

Novelty. WBANs area has been recently the subject of intense research by many researchers worldwide and there are available many good results in all such topics in particular in efficient physical layer and networking protocols. However, only a few studies related to the development of practical, efficient and low-energy WBANs system have been proposed. In this paper, we experimentally evaluate the accuracy and efficiency of two mechanisms allowing energy saving while staying accurate according to the state of the monitored subject.

The rest of this paper is organized as follows. Section II provides an overview of previous work insisting on information which is relevant to the context of this paper: previous experimental BAN architectures and existing standards are presented. In Section III, an overview of the proposed BAN architecture is proposed: application scenarios and communication architecture are detailed. In Section IV, the experimental results on the platform and performance are presented. Finally, Section V concludes the contributions of this paper and discusses potential further work directions.

II. RELATED WORK AND SCOPE

Recent developments in electronics and ultra low power radio communications have enabled the design of tiny and smart wearable sensors which can be worn on, or implanted into, the human body. The resulting Wireless Body Area Network (WBAN) is currently considered as one of the key technologies of the future that will enable the emergence of a wide range of applications, such as Indoor Localization [1], patient's insomnia monitoring [2], soldier's activity monitoring [3], emotion detection [3], assets protection [4], worker's safety monitoring [5], etc.

In order to address the specific requirements and challenges of WBANs, the IEEE 802.15.6 standard [6] has been recently released. In this context, three main physical have been proposed (i.e. narrowband, ultra wideband and human body communications), and both contention-based (e.g. CSMA/CA, Slotted-Aloha) and time division-based (e.g. TDMA) Medium Access Control (MAC) protocols have been designed. However, to the best of our knowledge there are still no commercial or publicly available IEEE 802.15.6 standard compliant radio transceivers. So, Internet of Things related standards [7] remain the preferred solution to build short-term and ready-to-use WBAN solutions [8]. In this context, several WBANs monitoring platforms [9] have been designed and evaluated, especially in the context of patient's health monitoring, using a combination of existing communication technologies, such as Bluetooth Low Energy, IEEE 802.15.4 (Zigbee), IEEE 802.11 a/b/g/n (WiFi), and 3G/LTE (cellular).

Despite the increased interest in the WBANs areas, there have been only a few studies related to the development of practical, efficient and low-energy WBANs system enabling the real-time and remote monitoring of physiological parameters. Moreover, to the best of our knowledge, the WBANs network lifetime, energy consumption and quality of service have not been evaluated in a comprehensive manner.

III. Overview of the Proposed BAN Platform

This section describes the wearable BAN platform which was designed, implemented and evaluated to enable to remote monitoring of workers in harsh environments. The target application scenario is firstly described in what follows, followed by an overview of the hardware, software and communication components.

A. Application scenario

In this study, we focus on the remote monitoring of workers in harsh environment. With 5 fatal injuries per 100.000 workers and despite its high-income economy, Qatar still exhibits relative shortcomings in safety performance (this rate is double that of the European Union) [10]. A part of the injuries is due to harsh environment, in particular high temperature. As a result, there is a need to monitor physiological signs (*e.g.* body temperature, pulse rate, respiration rate, blood pressure, etc.). With wearable sensors and BANs, workers can be monitored remotely and quick assistance can be given if anomalies on the vital signs are detected. To be practical in such context, a BAN should be able to send data continuously to a remote server for storage and analysis, while being energy efficient and accurate. In that purpose, low-power technologies, compression techniques and filtering are targeted. Moreover, the monitoring of the body movements (e.g. acceleration, orientation, etc.) can be useful to implement safety related algorithms, such as fall detection or activity recognition, and thus to ensure the safety of the workers.

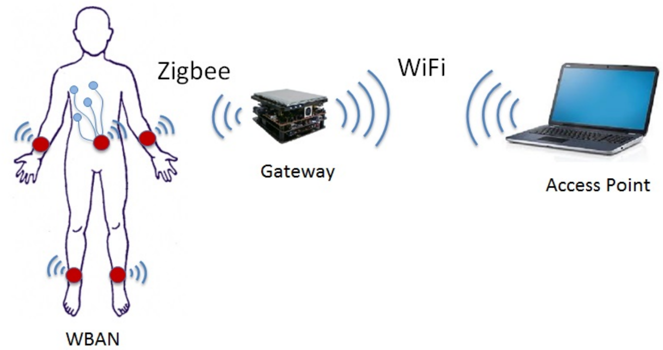

Fig. 1: Overview of the Ban Architecture

B. Communication Architecture

In this paper, wearable sensors use the IEEE 802.15.4 / Zigbee standard [11]. Zigbee is a standard defining the PHY and the MAC layer. Due to its good performance in terms of energy consumption, Zigbee makes a good candidate constrained devices such as battery-powered wearable sensors. CSMA/CA MAC protocol is used by sensors to transmit data to the gateway node. Zigbee devices can theoretically transmit up to 250 kbs at 2.4 GHz which is sufficient data rate for typical WBAN applications. Each node will encapsulate its sensor data into an 802.1.5.4 MAC frame and transmit it to the gateway node.

The gateway node aggregates the traffic from the sensor nodes and forwards it to an access point. Zigbee is used for the communication with the sensors and IEEE 802.11 / WiFi for the communication with the access point. CSMA/CA MAC protocol is used by the gateway to transmit data to the access point, as shown in Figure 1

C. Algorithms and Applications Layers

In order to enable efficient on-body communications in terms of latency, delivery ratio and energy consumption, we designed and implemented two specific algorithms: one filtering algorithm at the WBAN sensor device level, and one data compression algorithm at the gateway level.

1) Filtering algorithm: As illustrated in Figure 1, sensor nodes gather sensory information and communicate with the gateway. With respect to their constraints in computational power, a lightweight filtering algorithm is implemented. It is defined to limit the amount of data sent by the sensor nodes. To form a packet, each sensor aggregates 7 values of each signal (e.g. acceleration and angular velocity for 6-axis sensors, lead I and lead II for the ECG sensor). Then, it sends the packet to the gateway. The filtering algorithm compares the previously sent packet and the current packet to defines their similarity by comparing the mean of each signal and by computing the quadratic distance between them. Let two vectors v and w in R^n be as follow: $v = (v_1, v_2, ..., v_n)$, $w = (w_1, w_2, ..., w_n)$. The quadratic distance dq is: $dq = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(v_i - w_i)^2}$. If the difference of mean or the quadratic distance between the two packets is higher than a given threshold (*i.e.* defined accordingly to the state of the patient *e.g.* Table I), the current packet is sent. Otherwise, a tiny 4-octet packets is sent instead

		P1	P2	P3
	State of the worker	Critical	Worrying	Normal
Filtering Algorithm	Mean threshold	5%	10%	20%
	Quadratic distance threshold	2%	5%	10%
Compression Algorithm	RMSE Threshold	1%	5%	20%
	Maximum polynom order	10	10	10

TABLE I: Thresholds of the filtering and LSPF Data Compression algorithms.

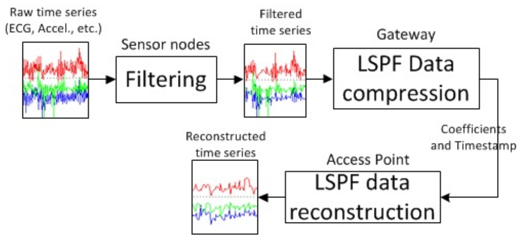

Fig. 2: Flowchart of the BAN architecture

to inform the gateway of the similarity of the packet with the previously transmitted packet.

2) Data Compression Algorithm using Least-Squares Polynomial Fitting: As shown in Figure 1, the gateway is responsible for the real-time collection of data from the different wearable sensor devices. Each sensor is responsible for the monitoring of specific physiological parameters (e.g. ECG, EEG, etc.), at a predefined sampling rate, and to send the corresponding time series to the gateway. This later aggregates all the received data and transmit them via Internet to a remote back-end server for further data processing and to enable timely decision making.

In order to enable efficient and low energy communications between the deployed gateway and remote back-end server, we designed and developed a data compression algorithm using *Least-Squares Polynomial Fitting* (LSPF). The proposed algorithm works as follows. For each received time series, $Y^i = \{Y_t; t \in T\}$ from a wearable sensor, i, the WBAN coordinator computes the coefficients of a polynomial $P_t^i(x) = a_n x^n + a_{n-1}x^{n-1} + ... + a_0$ of degree $n \leq N$ which better fits Y^i such that the corresponding *Root Mean Squared Error* (RMSE) is lower than a given threshold E_{max}.

This process is done recursively where the algorithm starts with a polynomial order $n = 1$, and keeps increasing it until the obtained RMSE is lower than the defined error threshold, E_{max}. In case, the algorithm is not able to find a good polynomial fit for the received time series, it divides it into two sub time series and apply the same logic on each part of the time series. Finally, once the polynomial coefficients,$\{a_n, a_{n-1}, ..., a_0; n \leq N\}$, are properly identified, the gateway transmit them to the remote back-end server, along with the sampling rate, initial and last timestamps of Y^i, instead of the original time series. Based on the received information, the remote server is thus able to reconstruct the original time series with an error lower than E_{max}. The flowchart of the 2 processes is illustrated by Figure 2.

IV. EXPERIMENTAL EVALUATION

A. Methodology and materials

The system used for experimentation consists of three main devices:

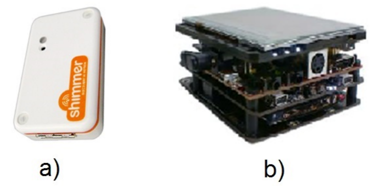

Fig. 3: a) Shimmer node, b) gateway

Device Manufactor	Shimmer Node	Gateway
Microcontroller	MSP430	AM37x 1GHz ARM Cortex-A8
Radio	TI CC2420 (802.15.4) [15] and RN Bluetooth module	TI CC2420 (802.15.4) and Ralink RT2571WT (802.11.b/g)
TX Power	0 dBm	Zigbee: 0 dBm, Wifi: 13 dBm
Radio sensitivity	-95 dBm	Zigbee: -95 dBm, Wifi: -70 dBm
TX/RX consumption	17.4 mA/18.8 mA	Zigbee: 17.4 mA/18.8 mA, Wifi: 390 mA/270 mA
Battery	280 mAh, 3.7v	8400 mAh, 5V
Sensing capabilities	3-axis Accelerometer, 3-axis Gyroscope, ECG	None
OS	TinyOS	Ubuntu 11.10
MAC protocol	CSMA/CA	CSMA/CA (WiFi and Zigbee)

TABLE II: Summary of the platform characteristics.

Sensor Nodes which (Fig. 3.a) consist in five Shimmer Nodes [12]. The Shimmer node is a small sensor platform well suited for wearable applications. It low-power communication capabilities enable long-term data acquisition and real-time monitoring. In this work, four nodes integrate 3-axis accelerometer and 3-axis gyroscope and one node is dedicated to heart monitoring and integrate a 3-lead ECG. Each node is running with TinyOS [13]. The Shimmer nodes characteristics are summarized in Table II.

Gateway Node as shown in Figure 3.b, consists of: (i) a Beagleboard XM [14], (ii) a BeagleTouch Screen (iii) an 802.11 module for Wi-Fi connection and (iv) an 802.15.4 module for Zigbee connection. The Ubuntu 11.10 OS is used to run the gateway. A lightweight server is implemented on the platform to perform the forwarding and the polynomial data compression (LSPF). The gateway characteristics are summarized in Table II.

Access Point which carries the proper storage, database and application softwares. It is intended to be highly available (*i.e.* 24/7) and be scalable to enable the monitoring of a large number of patients. The server runs real-time analysis of sensors data, provides user access to the database at various levels (e.g. patients, relatives, physicians, etc.) and generates alarm in case of emergencies.

The signal is amplified, converted to digital on the Shimmer Node and quantized at a chosen sampling frequency from $1Hz$ to $1kHz$. The shimmer node then transmits the data (i.e. 7 samples per packet) to the gateway.

B. Experiment parameters and scenarios

Scenario. Three phases of 10 minutes have been defined. In phase 1, the monitored subject is standing or is sitting at a workstation. Generally, his movements and his heartbeat are slow. In phase 2, the subject is walking in a treadmill at 4 km per second. His legs and arms move faster and his

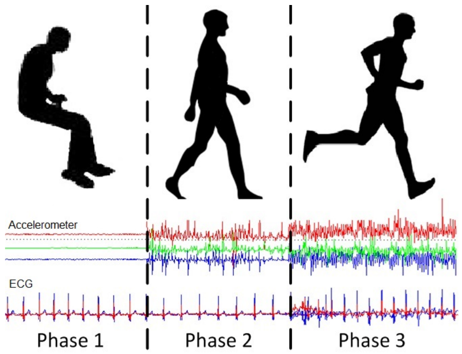

Fig. 4: Overview of the 3 phases (P1: standing, P2: walking at 4 km per hour, and P3: running at 10 km per hour)

heartbeat is moderate. In this phase, periodicity in acceleration and orientation measurements can be noticed. During phase 3, the subject is running in a treadmill at 10 km per second. His legs and arms move faster and his heartbeat is high. Again, we can notice a periodicity in acceleration and orientation measurements.

C. Performance Metrics

To gain insight concerning the BAM platform performances, the following metrics are measured:

Filtering rate is defined as the ratio between the size of the data received at the gateway after filtering and the size of the data generated by the biomedical sensors. This metric measures the efficiency of the similarity filtering.

Data compression ratio of the polynomial approximation is defined as the ratio between the size of the data received at the access point and the size of the data received at the gateway. This metric measures the efficiency of the polynomial approximation.

Total data compression ratio is defined as the ratio between the size of the data received at the access point and the size of the data generated by the biomedical sensors. This metric measures the efficiency of the entire platform.

Root Mean Square Error (RMSE) represents the sample standard deviation of the differences between raw signal generated by the biomedical sensors and the signal received at the access point after filtering and polynomial approximation. This metric measures the accuracy of the platform.

D. Results

To quantify the potential of energy saving, the filtering and LSPF rates have been computed and illustrated on Figures 5 and 6. The efficiency is measured by the gain in size and the accuracy by the RMSE for both filtering (Fig. 5) and compression (Fig. 6) processes according to the three states (P1, P2 and P3) of the subject as described in Table 1. It represents the average values from the 4 movement sensor nodes (accelerometer and gyroscope). As expected, with low filtering thresholds (P1, Table I), the filtering gain does not exceed 15 %, but also RMSE remains low and does not exceed 0.002 (Fig. 5). Note that 95% of the gain during the filtering process is obtained during the phase 1, when the subject is standing. Indeed, during this phase, several successive packets could be very similar.

With increasing filtering thresholds (P2 and P3, Table 1), the filtering gain is increased; however, RMSE increased significantly, in particular for P3 (0.011). This increase is mainly due to the relaxation of the threshold on the quadratic distance between two successive packets. As a result, for P3, the filtering is more coarse and the error increases. The filtering gain for P2 and P3 is also obtained mainly on the phase 1: 93% and 78% respectively.

The compression gain obtained by Least-Squares Polynomial approximation is significant for the three states P1, P2 and P3 (Fig. 6). For instance, the gain is up to 60% for P1 with a very low RMSE; it does not exceed 0.003. However, the relaxation of the threshold for P2 and P3, does not result in a large increasing in terms of compression rate (72% and 74%), despite a significant increase in terms of RMSE (0.023 and 0.032). Note that the approximation gain is obtained during the three phases in a balanced way, by contrast with the filtering gain which was mostly obtained during the first phase.

For the ECG signals, the LSPF provides good results, whereas the filtering is inoperative. The raw ECG signals have been compared to the compressed signals during the three phases (Fig.9). Given the periodicity of the ECG signal, the LSPF provides a low RMSE and a good compression rate (from 72% to 75%). The graphical representation allows to visualize the signal difference between the raw and compressed signals according to RMSE thresholds (0.01 (P1), 0.05 (P2) and 0.20 (P3)) for the three phases (standing, walking and running). The signal difference is particularly visible when the RMSE threshold is the higher (P3). In that level of compression, the signal is clipped, but the heart beat rate is still clearly visible.

In Figure 8, raw acceleration signals are compared to the compressed signals during phases 1, 2 and 3. The differences are clearly visible for P2 and P3 (see threshold in Table I). This is particularly significant during the phase 2 and 3, when the movement is more important.

V. Conclusion and Future Work

In this paper, we conducted a study on a BAN platforms with 5 sensor nodes, a gateway and an access point. By implementing lightweight but powerful filtering and LSPF data compression, it allows to reduce both the radio channel contention and the energy consumption, while staying accurate (*e.g.* with a low RMSE).

Future works. To be more efficient, the similarity filtering should be adapted to the signal and a better calibration of the thresholds could also be a great improvement. Currently, the levels P1, P2 and P3 are chosen statically. Adapting the level of compression accordingly to the signal observed is a direction of our future work. In addition, it seems to us that, the flow of the data and its periodicity make more suitable slotted MAC layers that CSMA. As a result, we also plan to investigate the impact of the MAC layer on the energy saving and performance.

VI. Acknowledgments

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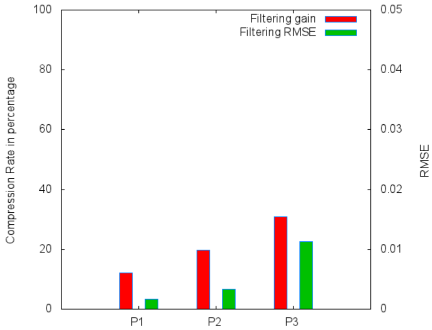

Fig. 5: Accuracy and efficiency of the filtering algorithm according to the state of the subject

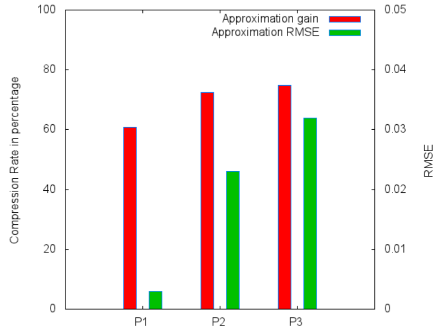

Fig. 6: Accuracy and efficiency of the compression algorithm according to the state of the subject

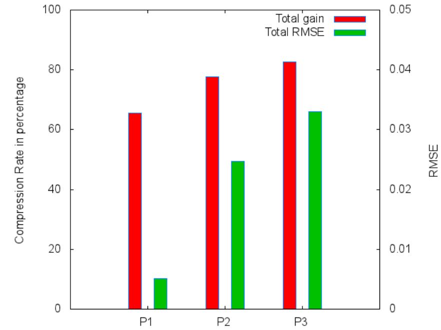

Fig. 7: Accuracy and efficiency of the platform according to the state of the subject

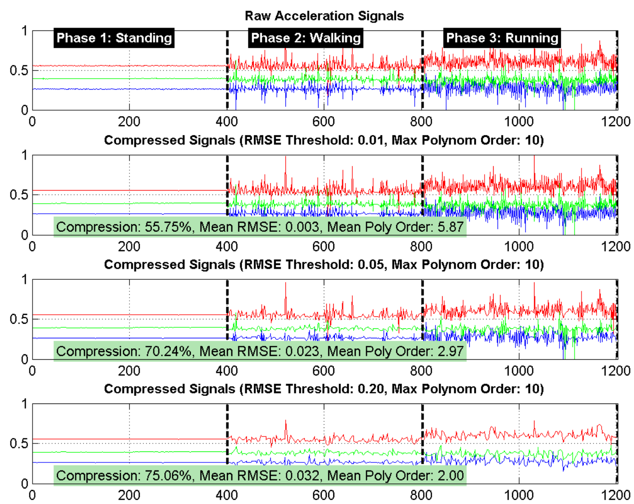

Fig. 8: Acceleration measures during the 3 phases according to P1, P2 and P3 thresholds.

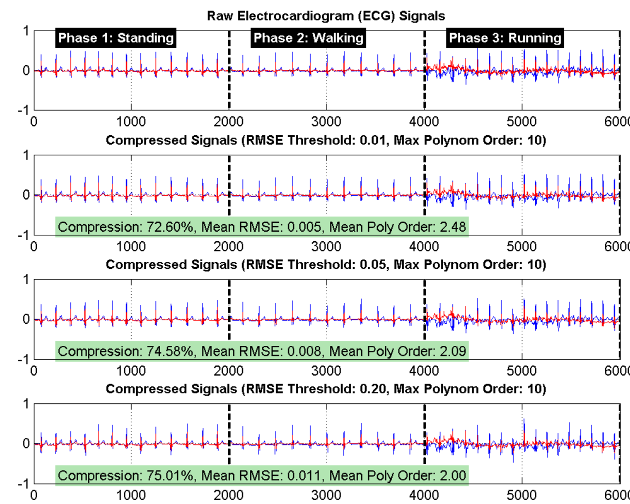

Fig. 9: ECG measures during the 3 phases according to P1, P2 and P3 thresholds.

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