A Low-Power Multi-Modal Body Sensor Network with application to Epileptic Seizure Monitoring

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Abstract—Monitoring patients' physiological signals during their daily activities in the home environment is one of the challenge of the health care. New ultra-low-power wireless technologies could help to achieve this goal. In this paper we present a low-power, multi-modal, wearable sensor platform for the simultaneous recording of activity and physiological data. First we provide a description of the wearable sensor platform, and its characteristics with respect to power consumption. Second we present the preliminary results of the comparison between our sensors and a reference system, on healthy subjects, to test the reliability of the detected physiological (electrocardiogram and respiration) and electromyography signals.

I. INTRODUCTION

RECENT advances in ultra-low-power wireless and microelectronic technologies are revolutionizing healthcare. Miniaturized and low-power wearable sensors allow monitoring of vital signs, activity and physiological signals in daily life environments, providing an unprecedented opportunity to delocalize healthcare from hospital to home. Multiple body sensor network platforms have been introduced for the monitoring of various biological and physiological signals. A majority of them aim at monitoring and tracking activity, mainly using accelerometers and gyroscopes. On the other hand, several cardiac activity monitors have been reported, which consist of a single sensor node logging the data, or interfacing to a receiving unit. These have been shown to be extremely valuable for ambulatory detection of cardiac arrhythmia. Other pathologies, such neuro-degenerative diseases for instance,

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P. Bonato is with the Department of Physical Medicine and Rehabilitation, Harvard Medical School, Spaulding Rehabilitation Hospital, Boston MA 02114, USA (corresponding author, phone: 617-573-2770; fax: 617-573-2769; e-mail: pbonato@partners.org). require a multi-parameter monitoring approach, in which activity and physiological signals are combined. Multiparameter recording is also expected to improve the specificity of detection devices.

Epilepsy is a chronic neurological disorder that affects more than 50 million people worldwide. Approximately 25% of epileptic seizures cannot be treated using available therapies [1]. Refractory patients are treated with Anti-Epileptic Drugs (AED). The strong side effects associated to AED motivates a careful drug selection and titration. Today this is done through long-term electroencephalogram (EEG) and video monitoring. This very invasive technique cannot be used to quantify seizures over long time period, and in natural environments. Wearable sensors offer a very attractive alternative for seizure monitoring in daily life situations. They exploit the fact that seizures induce movement of certain parts of the body, and are reflected in various physiological changes.

The benefits of wearable sensors for epileptic seizure detection have been demonstrated in several studies [2][3]. Wearable 3D-accelerometers have been used successfully to detect seizures [4][5]. And it has been shown that seizures could be differentiated from activities of daily life [6]. The possibility to detect seizures from specific patterns in the heart rate has also been reported [7][8]. Most of the work reported to date on wearable technology for seizure detection has however been limited to the use of single modality sensors. Going multi-modal is expected to improve specificity by reducing the number of false detections. In this paper, we present a low-power, multi-modal, wearable sensor platform for the simultaneous recording of activity and physiological data from different body limbs. We describe the wearable sensor platform and present results from its evaluation on healthy subjects.

II. LOW-POWER MULTI-MODAL BODY SENSOR NETWORK

A. System overview

The system developed for this study is composed of a set of wireless sensors attached to the body. The sensors are able to measure both inertial and physiological data. More specifically, the Human++ sensor nodes are based on a generic sensor node platform, allowing sensors to be interchanged easily based on the demands of the target application. Sensor nodes measuring surface electromyography (EMG), electrocardiogram (ECG), respiration and acceleration can be easily added to the network, depending on the use case. Once a network has been established data can be streamed to a PC or mobile phone [9], stored on a micro-SD card, or processed on the node.

B. Low-power multi-modal sensor node

The sensor node hardware architecture includes a wireless sensor board which provides processing and external communication features (MSP430F1611 and nRF24L01+), an ultra-lower power ExG sensor readout [10], the ADXL330 accelerometer from Analog Devices, and a microSD-card offering a compact and low-power storage capability (Fig. 1).

The ExG sensor front-end readout circuit relies on a proprietary single channel ASIC for biopotential read-out. The ASIC is an ultra low power and high performance front end for bio-potential applications. It consists of AC coupled chopped instrumentation amplifier, a spike filter, and amplification stage with constant gain, and a variable gain amplifier stage. The variable gain amplifier can be used to electronically adjust the gain of the readout for varying needs of EMG and ECG applications.



Fig. 1. Hardware architecture of the sensor nodes.

Similarly, high cut-off frequency of the readout channel can be electronically adjusted via bandwidth select switches (see Table 1). Furthermore, its low-power consumption $(21\mu A \text{ at } 3V)$ allows to dramatically reduce the size of the battery, hence of the entire monitoring system

TABLE I SENSOR NODE CONFIGURATION FOR DIFFERENT SIGNALS			
Signal	Gain	Bandwidth	Sampling frequency
ECG	Low - 390	Low cut-off – 0.25 Hz	256 Hz
EMG	high - 1450	High cut-off – 25 Hz	512 Hz

The low-level firmware structure is shown in Fig 2. The system is able to sample data up to 1KHz per ADC channel, while handling data storage and radio communication. The ECG and EMG signals are sampled, respectively at 256Hz and 512Hz, while acceleration is sampled at 64 Hz. Data is then forwarded to the embedded algorithms, and buffered for

on-request data visualization or SD-card writing. A limited File Allocated Table (FAT16)-compliant file system has also been implemented to allow for multi-session recordings.



Fig. 2. Firmware architecture of the sensor nodes.

C. Embedded processing and real-time HR

Firmware has been optimized for low power and low memory usage. The microcontroller on the generic hardware platform is the MSP430F1611 by Texas Instruments. It is equipped with 10KB of RAM, 4 of which are used by data storage (filesystem and SD card driver), TDMA MAC protocol and radio driver. The ECG node requires 2 additional KB of memory to allow for an optimization of a wavelet based beat detection algorithm. A robust and accurate beat-detection algorithm is indeed crucial for HR based algorithms. The implemented real-time beat detector is based on a state-of-the-art algorithm optimized for ambulatory monitoring [10]. The embedded version reports similar state of the art performances (sensitivity (Se) of 99.8% and positive predictive value (PPV) of 99.77%) on the MIT/BIH database, a reference database in the field of beat detection.

The EMG sensor nodes are kept in low power mode, sampling and data transmission are interrupt driven to limit MCU usage (see section II.E for an accurate breakdown of power consumption). On the other hand, the ECG node is active 20% of the time while computing the beat detection. This implementation leaves enough room for additional processing, e.g. ECG derived respiration, or feature extraction from EMG data such as envelope, dominant frequency, root mean square value and mean absolute value. This will however reduce the lifetime of the system.

D. Communication protocol

Low-power Time Division Multiple Access (TDMA) Medium Access Control (MAC) and communication protocol have been implemented to enable several sensor nodes to work within a star-topology network efficiently.

Each sensor samples and stores the data, before sending it during the pre-allocated time window. Every 200 ms the sensor nodes receive a beacon from the base-station, and enabling time synchronization bidirectional communication. Fig.3 illustrates this protocol implementation. This method has the advantage of providing guaranteed latency per cycle. For most of the applications static TDMA is a good trade-off between efficiency and complexity, as depicted in Fig. 4, where the use of the radio, one of the most power hungry component of the system, is shown to be very limited due to the TDMA MAC protocol.



Fig. 3. TDMA-MAC, example with three nodes sending ECG, respiration, EMG and acceleration.

E. Power consumption

Customized power management circuitry was developed to optimize power consumption of the sensor node. Power consumption of the ExG sensor board is 25μ A at 3V. The average power consumption of the generic wireless node ranges from 2.5 mA (max current consumption for high data rate nodes, such as EMG 512 Hz and acceleration 64 Hz, or nodes that require embedded beat detection and SD card storage) to about 700uA for low data rate applications (ECG and acceleration only, with no embedded algorithms or data storage). This results in 2 to 7 days of autonomy on a small Li-Poly battery (110 mA/h battery). See Fig. 5 for a detailed power consumption breakdown.



Fig. 4. Power consumption of the sensor nodes during execution (sampling, synchronization with the network and data transmission).



Fig. 5. Power consumption breakdown for the worst case scenario, in which the sensor node is sending data through the radio, storing it on the microSD card, and computing real-time beat detection (9mW consumption @ 3.7 V).

III. RELIABILITY TESTS ON HEALTHY POPULATION

In order to improve the reliability of the system in real life conditions a multi-stage low-complexity QoS layer was implemented [11]. The QoS layer defined a re-transmission protocol which consists of a set of linked-lists interconnected in such a way that different types of defined services could be guaranteed. To accurately assess the performances of the proposed QoS layer, data was collected on four healthy volunteers. Each of them was asked to follow a defined evaluation protocol, simulating ambulatory conditions, while wearing a sensor network. The QoS layer allows to significantly reduce the Packet Error Rate (PER), from 2.5% without retransmission to almost 0% for the experimental conditions considered in the study. The cost of this PER reduction in terms of energy and latency is quantified. In average, a 90% reduction in PER is associated to an increase of 7% in energy consumption, and to a latency of 350ms.

IV. PRELIMINARY RESULTS ON HEALTHY SUBJECTS

We collected data from 5 healthy subjects for a preliminary analysis to compare the Human++ sensor nodes with a reference system, the Vitaport 3 ambulatory recorder (Temec BV, The Netherlands). Data were synchronized between the two systems with the help of a digital marker. We collected the ECG, the respiration and the EMG signal from the gastrocnemius medialis muscle during four different conditions: lying, sitting down, standing and walking, in order to replicate the typical simple living activities of a patient. Data analysis was performed by extracting features for each task. These features were 1) the mean heart rate, 2) the respiration rate and 3) the root mean square value (RMSV) of the EMG. Overall, data from the two systems showed good correlation. Figure 6 and Figure 7 show the mean value of heart rate and of the respiration rate derived from both systems. An example of the RMSV for a subject during the test is shown in figure 8.

Average correlation between the measured parameters from the Human++ and the Vitaport system showed a high level of correlation for ECG (0.94 < r < 0.99) and EMG (0.98 < r < 0.98). Respiration rate for the static conditions (lying, sitting and standing) showed a high level of correlation (r > 0.95) for two subjects but the correlation for walking was poor (r < 0.4).



Fig. 6. Mean value of the heart rate [beats per minute (bpm)] evaluated for the four different tasks.



Fig. 7. Mean value of the respiration rate [Hz] evaluated for the four different tasks.



Fig. 8. Example of RMSV of the EMG signal $[\mu V]$ for a subject, during the four different tasks.

V. CONCLUSION AND FUTURE WORK

The Human++ has been designed to provide a low-power, wearable and multi-modal BSN platform for a variety of health monitoring applications which require simultaneous recording of activity and physiological signals. Preliminary comparison with a benchmark system showed that our BSN can provide good quality data. We are currently deploying it to gather data from patients with epilepsy.

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