A Scalable Wireless Body Area Network for Bio-Telemetry

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Abstract: In this paper, we propose a framework for the real-time monitoring of wireless biosensors. This is a scalable platform that requires minimum human interaction during set-up and monitoring. Its main components include a biosensor, a smart gateway to automatically set up the body area network, a mechanism for delivering data to an Internet monitoring server, and automatic data collection, profiling and feature extraction from bio-potentials. Such a system could increase the quality of life and significantly lower healthcare costs for everyone in general, and for the elderly and those with disabilities in particular.

Keywords: *Body Area Network, Plug-and-Play Biosensors, Telemedicine, Ubiquitous Computing, ECG Monitoring, ECG Feature Extraction*

1. Introduction

According to the Department of Health and Human Services, about one in every seven Americans, or 14.3% of the population, is an elderly person [1]. The elderly segment of the population (65+) will continue to grow significantly in the future. Our work is aimed at developing inexpensive pervasive monitoring of elderly people as they go about their daily routines.

Recent developments in wireless, radio frequency identification (RFID), biosensors and networking have provided incentives for researchers to use them in health care systems. The application of this technology to the care of elderly people has attracted a lot of attention due to its potential to increase the quality of life and reduce the cost of healthcare. While many research works are reported in the literature, and some commercial products and services are available, mature state-of-the-art technology is still far from being realized. Platforms consisting of wearable biosensors with the capability to remotely monitor a large population are in great demand.

The main contribution of this paper consists in offering an inexpensive yet flexible and scalable platform to deliver, train and monitor data provided by biosensors. To prove the concept, we have implemented an ECG monitoring system. A large number of applications, particularly in the health care sector, could benefit from such a platform because it is expected to significantly lower the cost of healthcare. From the perspective of a user, this is a plug-and-play gadget that can be set up quickly by a non-professional, making possible pervasive monitoring of a patient without interrupting that patient's daily routines. We have offered a few technical innovations including miniaturized biosensors, and efficient signal conditioning, ubiquitous connection to the Internet, as well as powerful back-end software that performs data acquisition, profiling, reasoning and decision making.

This paper is organized as follows. In the next section, the related work and the current state of the art are presented. Section 3 describes the system architecture and the functionalities of the different blocks. Sections 4 and 5 discuss the hardware and software modules and the key optimization algorithms that are involved. Finally, the concluding remarks are presented in Section 6.

2. Related Work

It is expected that biosensors and body area networks (BAN) will be used in many applications including healthcare, sport and entertainment. Among those, healthcare applications require a series of miniature biosensors, a data transmission medium (e.g. wired or wireless), and a data collection / processing node. While one can build an experimental platform easily using the current technologies, there are many challenges to making it robust, wearable, secure and scalable. These challenges include the size and power consumption of the biosensor, data rate, scalability in terms of the number of biosensors, and also the number of patients. Today's Bluetooth and Zigbee radios have provided experimental platforms for researchers' investigations. However, they cannot be used in low-power applications in which less than $100\mu W$ power consumption is expected [2].

For the experimentation in this work, we use the heart-monitoring application. Coronary heart disease is the single largest cause of death in the US, with as many as one in every five deaths being attributed to it alone [3]. An estimated 60 billion dollars are spent each year on the treatment and prevention of heart attacks. Due to recent advances in pathological research and the related technologies, the number of deaths attributable to heart disease has decreased in the last decade. Still, the fact remains that it is the world's number one killer. Most of

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these deaths are caused by cardiac arrhythmias resulting in sudden death (deaths occurring within one hour after the first symptoms were felt by the patient). Ventricular Fibrillation, usually caused by Ventricular Tachycardia, is the most severe and life-threatening form of arrhythmia: it stops the heart's pumping action altogether and, if normal rhythm is not restored within three to five minutes, causes irreparable brain and heart damage and, ultimately, death. Implantable Cardioverter-Defibrillator (ICD) devices are put inside the body to constantly monitor the heart's rhythm, and to quickly detect any abnormality and administer the appropriate therapy when needed. Since this is an invasive technique requiring surgery with potential complications and the associated high cost, it is only a recommended solution for high-risk patients. For the majority of potential heart disease patients, abnormal cardiovascular symptoms such as chest pains, fainting, and shortness of breath can be detected before the occurrence of the fatal cardiac arrhythmia. Therefore, it is important to have an effective measurement and reporting system to avoid deaths caused by heart attacks by providing immediate medical help. Several wireless Electrocardiograph (ECG) monitoring systems have been proposed in [4], [5], [6] and [7]. These systems use 802.15.4 (Zigbee) [4], [6], [7] or Bluetooth [5] as the radio interface for the ECG sensors to communicate with a hand-held device. However, neither radio interface was originally designed for real-time, high-speed, low-power continuous data transfer applications. To address some of these limitations, we propose a flexible experimental platform for designing wireless biosensor monitoring.

3. System Architecture

The architectural block diagram of our system is shown in Figure 1. Several non-invasive sensors are worn on the body to collect data and pass it on (via gateway) to the monitoring server where that data is stored, processed, and analyzed, and where action is taken if required. The sensors in our architecture can be classified into two categories: biosensors for the monitoring of vital physiological signs (heart rate, oxygen level in the blood, blood pressure, rate of respiration and body temperature); and motion sensors for the collection of information about the current state of the patient's body (walking, running, standing, sitting, falling, etc.). A brief explanation of each main unit follows.

Biosensors: A wide range of biosensors can be found on the market, including sensors designed to monitor a person's heart rate or temperature, etc. and others that indicate whether a person is falling, bending, and so forth. The hardware of these biosensors usually consists of a microcontroller, a few kilobytes of memory, an ultra-low power RF transceiver, antennae, sensors and actuators, analog signal conditioning circuitry, data converters, and a battery module to power them. These biosensors need to run an operating system which, under the control of application logic, is responsible for (i) moving data between the data converter and the memory, (ii) formatting and encrypting data for transmission, (iii) and reliably transferring data through the RF transceiver. In addition, the OS is also responsible for task switching and managing the system's power.

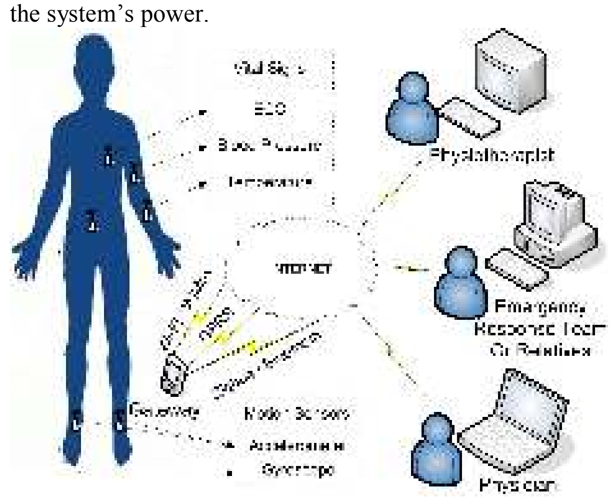

Fig. 1 Example of a Body Area Network

Gateway: Biosensors communicate with the BAN controller, or gateway, which is the main interface between the body area network and the monitoring server. The gateway is responsible for collecting data from sensor nodes; storing data in the local memory in cases where there is no connection with the Internet; and forwarding data on its outgoing port to the Internet for eventual storage in the system's database. Due to the less stringent power requirements of the gateway (they can have large or rechargeable batteries), some of them have the ability to process different data streams and pass only relevant events to the system backend. The gateway is also responsible for the overall management of the BAN network, such as starting up a network with a unique network ID and allowing biosensors on the body to establish a connection with it and transfer data. The gateway can be a Personal Digital Assistant (PDA) with a WiFI or WiMAX interface; a cell phone with a GPRS or UMTS interface; or a low-cost device with Zigbee or Bluetooth interfaces for both collecting data from sensors and forwarding it to the Internet.

Monitoring Server: A monitoring server consists of a database for data storage, and processing and analyzing software for the delivery of the services for which the system is intended. Figure 1 shows a system where, for example, a physician, by examining the ECG signals of a patient, may suggest a further detailed diagnosis in hospital if need be; where a physiotherapist can monitor the rate of recovery of a patient who has fractured a limb in an accident; or where an emergency response team can provide immediate help in the event that an elderly person falls in her/his home. It is well understood that the bio metrics of each individual are very much unique. Thus, for effective processing a personalized profile should be "learned" automatically by the server. This is a crucial step towards minimizing the incidence of (and even achieving zero-level of) *false positives* (i.e. raising the alarm in non-critical situations) and *false negatives* (i.e. missing a critical, perhaps life-threatening situation). To that end, a combination of innovative learning and reasoning algorithms are required to interpret data properly during monitoring.

4. Hardware Units

We have developed three prototype hardware units using off-the-shelf components for our body area network platform. Figure 2 shows the biosensor node base, which consists of an RF transceiver and microcontroller; a Zigbee compliant gateway that connects to the computer using a USB port; and an ECG front-end to capture signals from the body. The three units are explained below.

Biosensor Base Unit: Such factors as wearability, flexibility, power consumption, and cost have influenced the design of the biosensor base unit. Wearability is the most important factor for monitoring different parameters over a long period of time. To the best of our knowledge, none of the commercially available sensors [13, 14] were designed to be worn on the body. Most of the other sensors reported in academic publications [8 - 12] also have large footprints. Table 1 compares our biosensor node with some of the similar platforms mentioned elsewhere in this paper, while Table 2 gives the measured current consumption of the biosensor node and that of the MicaZ mode.

The biosensor node base consists of an 8051 compatible microcontroller running at 32 MHz, 8 KB SRAM and 128 KB flash memory, UART and SPI ports for serial communication, an IRQ controller, reset circuitry, watchdog and general purpose timers, a transceiver (compatible with Zigbee) working in the ISM 2.4 GHz band using the DSSS coding and O-QPSK modulation scheme, a low dropout voltage regulator, an analog to digital converter, a 16-pin IO expansion connector, and a 3V lithium ion coin battery.

Gateway Unit: We have used the same biosensor node base to build a gateway unit that connects to the PC via a standard USB port. The gateway collects the data from the sensor nodes and passes it on to the PC using a USB port to further process and store that data. It consists of an 8051 compatible microcontroller running at 24 MHz, 16 KB of flash memory and 2 KB of SRAM, and a USB transceiver compliant with the Universal Serial Bus Specifications 2.0 that supports Full / Low speed (12 Mbps / 1.5 Mbps) USB peripheral implementation. The microcontroller connects with the biosensor node base via the UART pins on the IO expansion connector.

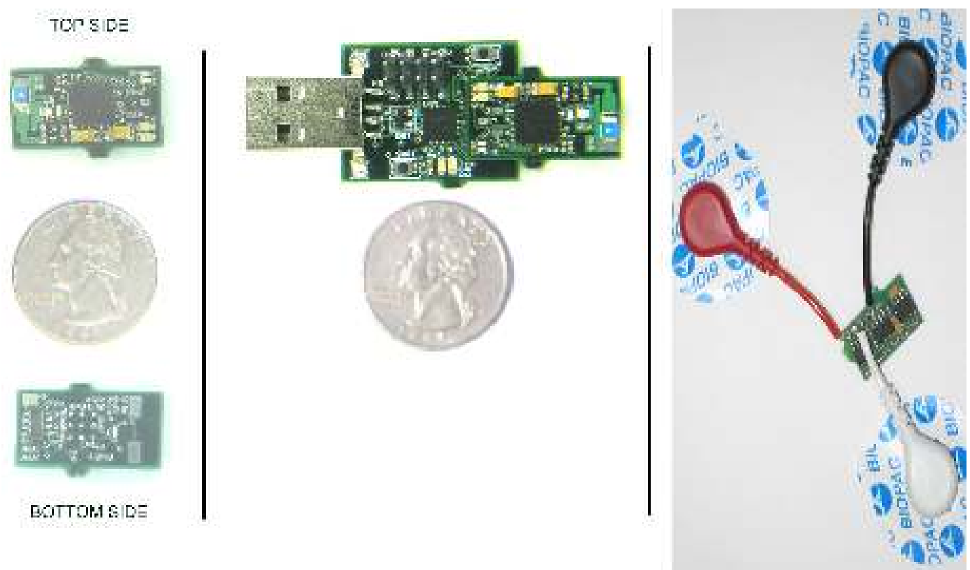

Fig. 2 Hardware Components: [i] Biosensor Base (left); [ii] Gateway (center); [iii] ECG front-end (right)

ECG Front-end Unit: Figure 2 shows a 3-wire ECG sensor. The ECG wires are connected to the instrumentation amplifier, which amplifies the signal from the electrodes (usually a few hundred micro-volts to a few milli-volts). It is conditioned before being passed on to the sensor node base via the IO expansion connector, where the signal is digitized and transmitted wirelessly to the gateway.

Table 1. Comparison of Sensor Nodes

Name	Ref	Controller	Wireless Interface	Size (mm) L x W x H
XYZ	[8]	ARM (32-bit)	Zigbee	35 x 30 x 12
iBadge	[9]	AVR (8-bit)	Bluetooth	70 x 55 x 18
Pluto	[10]	MSP430 (16-bit)	Zigbee	40 x 28 x 6
MITes	[11]	8051 (8-bit)	Custom	30 x 25 x 8

BSN Node	[12]	MSP430 (16-bit)	Zigbee	46 x 31 x 7
MicaZ	[13]	AVR (8-bit)	Zigbee	58 x 32 x 7
iMote2	[14]	PXA271 (32-bit)	Zigbee	48 x 36 x 9
Proposed	--	8051 (8-bit)	Zigbee	25 x 12 x 6

Table 2. Current Consumption Breakdown @ 3.0 V

	MicaZ	Proposed
Voltage	3.0 V	3.0 V
MCU Idle	3.1 mA	1.4 mA
MCU Active	8.4 mA	5.7 mA
Radio Rx	17.3 mA	17.1 mA
Radio Tx	26.4 mA	19.8 mA
Flash Read	8.9 mA	3.0 mA
Flash Write	21.6 mA	8.7 mA
ECG Sensor	--	4.8 mA

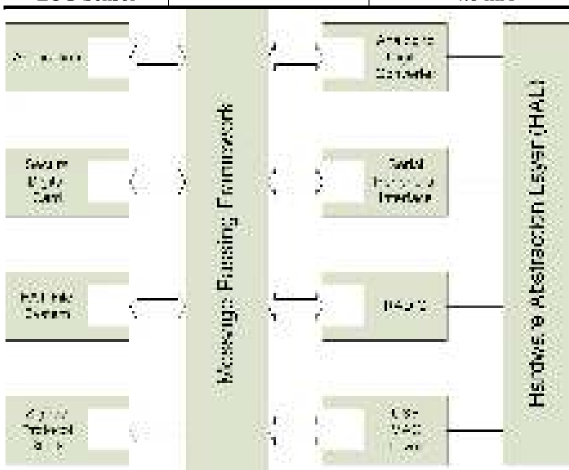

Fig. 3 Event Driven Message Passing Framework

5. Software Modules

There are four important software modules that we have developed for our remote monitoring platform. Details of these are explained below.

Message Passing Framework: The biosensor node base and the gateway need to run a small yet efficient real-time operating system which is responsible for initializing and controlling multiple hardware blocks and moving data among them. The OS also provides synchronization between tasks and runs an MAC protocol stack for communication with the gateway.

Operating systems can be categorized as either multi-threaded or event-driven. In multi-threaded systems, different software tasks are implemented as threads and a *Scheduler* is responsible for multiplexing the execution time between different threads. Software tasks in event-driven architectures are implemented as modules with a single entry point (event handler) called by the *Dispatcher* (the only thread running in the system), based upon the occurrence of particular events of interest.

Figure 3 shows the Event-Driven Message Passing architecture that we implemented as the operating system for our biosensor node base and gateway. Modules implement specific tasks and communicate with each other by sending messages through the Message Passing Framework (MPF). These modules can either abstract a particular hardware (Radio, ADC); or implement a particular software task (protocol stack, application logic). Such factors as low power, concurrency, resource limitation and reusability have influenced the design of the Message Passing Framework. The MPF has a very small footprint (355 bytes of memory) and requires fewer CPU execution cycles (9 + 6 statements in C) to perform the main task of queuing and dispatching messages from and to different modules. No module specific interfaces are exposed by any module, thereby making our framework hardware independent and portable without any change.

Fig. 4 ECG Signal: Before and after digital filtering

ECG Signal Conditioning: The actual bandwidth of the ECG signal is between 0.15 to 40 Hz, but it is digitized at a rate of 250 Hz to improve the Signal-to-Noise Ratio. Since each sample occupies 10 bits, 25 samples are stored in the memory before a packet is formed for transmission. A packet of length 52 is transmitted to the gateway 10 times each second. The last two bytes of the packet represent the battery voltage of the sensor node, which is sent every 5 seconds. The gateway keeps track of the available power left on the sensor node and instructs it to shut down in the event the battery is almost drained.

After the signal has been received on the PC via the gateway, it is passed through a series of digital filters to remove noise and further amplify the signal. First a second order Infinite Impulse Response (IIR) notch filter is used to suppress 60-Hz interference. With the pole zero placement method, the notch frequency is set to 60Hz with a notch width of 10Hz. The transfer function and the pseudo implementation are given below:

$$H(z) = \frac{0.969 - 1.4127z^{-1} + 0.969z^{-2}}{1 - 1.4127z^{-1} + 0.9383z^{-2}} \qquad (1)$$

$$Yn = 0.969.Xn - 1.4127Xn - 1 + 0.969Xn - 2 + 1.4127Yn - 1 - 0.938Yn - 2$$

The second filter is also an IIR Butterworth low-pass filter with a high cutoff frequency of 100Hz. The transfer function and the pseudo implementation are given below as:

$$H(z) = \frac{1 + 2z^{-1} + z^{-2}}{1 - 1.0973z^{-1} + 0.3096z^{-2}} \quad (2)$$

$$Yn = 0.969.Xn - 1.4127Xn - 1 + 0.969Xn - 2 + 1.4172Yn - 1 - 0.938Yn - 2$$

Figure 4 shows the ECG signal before and after digital filtering. The upper waveform shows the signal as acquired by the ADC, while the lower waveform shows the signal after amplification and noise removal. This helps with the beat detection and classification, which is explained below.

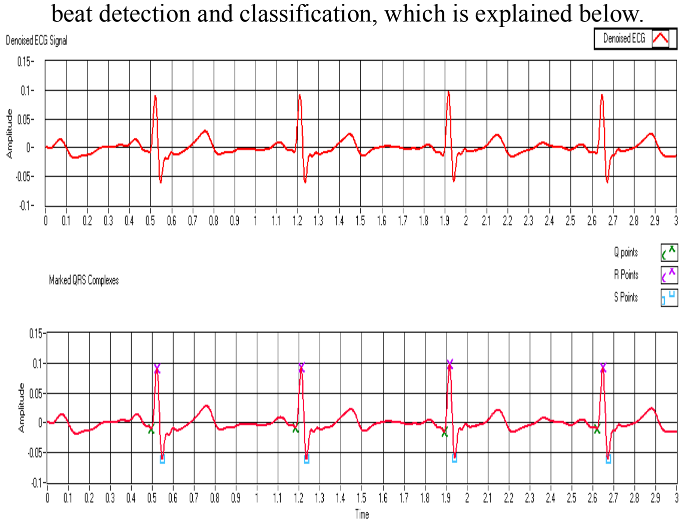

Fig. 5 QRS Complex Detection

ECG Beat Detection: ECG signals from different patients are sent to the monitoring server, where an efficient method of accurately deriving the QRS complexes is employed for analysis. This is a modification of the existing Pan-Tompkins QRS Detection algorithm by using only one threshold derived from the de-noised ECG signal instead of using the moving window integration of the ECG signal. This significantly reduces the number of comparisons that were formerly required to decide whether a fiducial mark would be a QRS complex or not.

The technique employed for ECG feature extraction is a hybrid approach which combines Pan and Tompkin's adaptive thresholding [15] with LabVIEW's wavelet peak and valley detector [16], with which we achieved a significant improvement compared to those two approaches. However, in our design, only one set of thresholds extracted from the De-noised ECG can be applied, because the threshold calculated from the integration waveform was found to be always lower than the other threshold.

ECG preprocessing is performed using LabVIEW's Advanced Signal Processing Toolkit (ASPT), with the help of the Wavelet De-trend and Wavelet De-noise virtual instruments (VI) [16]. The former VI takes care of removing baseline wandering, while the latter suppresses wideband noise. The Wavelet De-noise VI first decomposes the ECG signal into several sub-bands by applying the wavelet transform, then modifies each wavelet coefficient by applying a threshold or shrinkage function, and finally reconstructs the de-noised signal. In the preprocessing phase, we used the *sym5* wavelet as it resembles the QRS wave of the ECG more than other types of wavelets.

After de-trending the signal and applying the wavelet de-noising VI, the resulting signal results in a zero DC offset. We marked the peaks that are above zero and the valleys that are below zero with the help of WA Multiscale Peak/Valley Detection VI in LabVIEW. Let us consider *Peaks* as the array of peaks that the LabVIEW peak detector VI has found. The equations for adaptive thresholding are as follows:

$$\begin{cases} PEAK = Maximum(Peaks) \\ NPK = Minimum(Peaks) \\ SPK = 0.125 \times PEAK + 0.875 \times SPK \\ THR = NPK + 0.25(SPK - NPK) \end{cases} \quad (3)$$

A signal peak that is larger than the threshold *THR* is regarded as a QRS complex, where the R point is detected. Each time a beat (R point) is found, we intentionally move the starting point of the sliding window to a point that is 360*ms* apart from the previous R point detected, as R-R intervals cannot be less than this timeframe physiologically [15].

A search back algorithm is required if a beat is not found within a certain time interval. We maintain only one R-to-R average for the search back algorithm, that being the average of the eight most recent R-R intervals found.

If no beat has been detected within 116% of the current R-to-R average, the search back algorithm is applied. This is a percentage that has been found empirically [15]. In the search back algorithm, we lower the threshold by a certain amount and start looking for a QRS complex from the last *R* point detected. If a signal peak (*SPK*) exceeds the new threshold (THR_{new}=THR_{old}/8), we consider it as a beat (R point). The new signal peak *SPK* and threshold *THR* should then be updated accordingly.

To find the Q and S points of the ECG waveform, we apply this underlying concept by which a Q point is the maximum valley location right before an R point, and an S point is the minimum valley location right after a detected R point. Figure 5 illustrates a de-noised ECG signal and the QRS complexes marked using our approach.

Our algorithm - when evaluated with the MIT-BIH arrhythmia database [17] - achieved an overall performance of 99.51% for a one-minute timeframe of the readings. Table 3 depicts the performance of our algorithm when implemented in LabVIEW. Datasets 207 and 208 have not been included in the evaluation because of the existence of too many ripples and inverted waves.

False positives (FP) and false negatives (FN) have been reflected in the table as erroneously detected beats and missed beats, respectively. The overall error is calculated as follows:

Data #	# of Beat	# of FP	# of FN	Not Detected	Error
100	74	0	0	0	0 %
101	71	0	0	0	0 %
102	73	0	0	0	0 %
103	70	0	0	0	0 %
104	74	0	0	0	0 %
105	83	0	0	0	0 %
106	67	0	0	0	0 %
107	71	0	0	0	0 %
108	58	1	0	1	1.72 %
109	91	0	0	0	0 %
111	69	0	0	0	0 %
112	85	0	0	0	0 %
113	58	0	0	0	0 %
114	54	0	0	0	0 %
115	63	0	0	0	0 %
116	78	0	0	0	0 %
117	50	0	0	0	0 %
118	73	0	0	0	0 %
119	65	0	0	0	0 %
121	60	0	0	0	0 %
122	87	0	0	0	0 %
123	49	0	0	0	0 %
124	49	0	0	0	0 %
200	86	4	3	7	8.14 %
201	90	1	0	1	1.11 %
202	53	0	0	0	0 %
203	102	2	1	3	2.94 %
205	89	0	0	0	0 %
209	93	0	0	0	0 %
210	92	0	0	0	0 %
212	90	0	0	0	0 %
213	110	0	0	0	0 %
214	75	0	0	0	0 %
215	112	0	0	0	0 %
217	72	0	0	0	0 %
219	73	0	0	0	0 %
220	72	0	0	0	0 %
221	78	0	0	0	0 %
222	75	0	0	0	0 %
223	80	0	0	0	0 %
228	70	1	1	2	2.86 %
230	79	0	0	0	0 %
231	63	0	0	0	0 %
232	56	2	0	2	3.57 %
233	104	1	1	2	1.92 %
234	92	0	0	0	0 %
Total Data 46	**Total # (Beats) 3619**	**# of FP (Beats) 12**	**# of FN (Beats) 6**	**Beats Not Detected 18**	**Overall Error 0.49%**

Table 3. Performance Evaluation of our QRS detector on the MIT-BIH Arrhythmia Database

$$Error = \frac{FP + FN}{Total\#ofBeats} \quad (4)$$

To determine the detection rate DER (accuracy), the true positive value TP (the number of correctly identified beats), is used [18]:

$$DER = \frac{TP}{Total\#ofBeats} \quad (5)$$

Sensitivity (*Se*) and Specificity (*Sp*), which are the most important parameters when assessing the efficiency of any beat detection algorithm [18] [19], are specified as follows:

$$Se = \frac{TP}{TP + FN} \quad (6) \qquad , \qquad Sp = \frac{TP}{TP + FP} \quad (7)$$

Our algorithm performed poorly on those readings that had inverted waves and did not look like the sym5 wavelet. Nevertheless, we achieved 99.93% accuracy for the first 23 readings, which resemble normal ECG patterns, while Pan-Tomkins achieved 99.17% accuracy for the same datasets.

The performance of a few QRS detection algorithms that used digital filtering and wavelet analysis are compared in Table 4. Our algorithm performs quite well compared to other approaches.

In general, after de-noising and feature extraction, the ECG features of the patient are fed to another unit for beat classification. Beat classification, however, is beyond the scope of this paper.

Table 4 Comparison of QRS Detector Performances

Algorithm	Ref	Se (%)	Sp (%)	Detection Rate (%)
Pan Tompkins	[15]	99.76	99.56	99.32
Dotsinsky et al	[20]	99.04	99.62	Not specified
Zhang et al	[18]	99.82	99.71	99.53
Zhou et al	[19]	99.43	98.55	Not Specified
Proposed	-	99.83	99.67	99.51

Monitoring Server Software Modules: Figure 6 pictures the main modules running on the monitoring server, which can be classified into five categories as explained below.

- **Set-up:** The initial signal set-up interface checks for the reception of wireless signals, performs network set-up, and resolves the various difficulties that may arise. Additionally, this module makes sure that the BAN and wireless networks are alive and that handshake is performed properly.
- **Registration:** The patient's information is fed into this module and stored in the server. This module includes a graphical user interface (GUI) that simplifies data entry and retrieval. Additionally, the module keeps track of the patient's biosensor data and records all the information required. If any critical situation occurs, the system behaves according to the patient's pre-defined data, requests (e.g. whether to notify the relatives), and the severity of the situation (e.g. whether to notify a hospital).
- **Monitoring & Reasoning:** It keeps track of the patient's health status and, depending on his or her health status, makes a decision regarding the patient's treatment. This is by far the most

important module of the system as making decisions on the basis of logical reasoning using a limited number of biosensors (e.g. ECG, blood pressure/Oxygen/Glucose) is quite challenging. In general, this is done by building a dynamic model (historical profile) for each individual and by using learning/reasoning algorithms to evaluate and grade the severity of each and every significant change. More importantly, this module will be responsible for setting off the alarm while achieving a near-zero incidence of false positives and false negatives.

- **Value Added Service:** This module provides extra information on such factors as the geographical location of the patient, the proximity of hospitals, the availability of doctors in the region, weather conditions, etc. Such services may be desirable for certain categories of patients with special needs or requests.
- **Reports:** It is responsible for communicating (exchange messages) with the outside components, e.g. producing/ sending an alarm or a report to a healthcare provider.

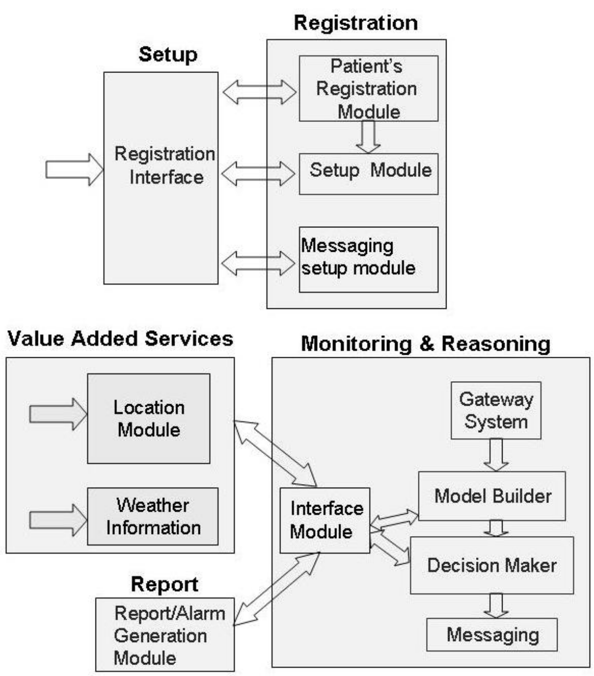

Fig. 6 Flowchart of Modules running on Monitoring Server

6. Conclusion

The non-invasive wireless monitoring of biosensors is in great demand for various applications. In particular, such a system could significantly improve the quality of life and reduce healthcare costs, especially for the elderly and people with various disabilities. In this paper, we have discussed a simple yet flexible and scalable framework for a scalable wireless biosensor system tuned for real-time remote monitoring. The accuracy, power consumption and cost of our platform, built using off-the-shelf components for ECG monitoring, are quite promising. Our future plan is to customize the hardware and software to fit the system within the real-world environment.

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