HealthGear: A Real-time Wearable System for Monitoring and Analyzing Physiological Signals

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Abstract

We present HealthGear, a real-time wearable system for monitoring, visualizing and analyzing physiological signals. HealthGear consists of a set of non-invasive physiological sensors wirelessly connected via Bluetooth to a cell phone which stores, transmits and analyzes the physiological data, and presents it to the user in an intelligible way. In this paper, we focus on an implementation of HealthGear using a blood oximeter to monitor the user's blood oxygen level and pulse while sleeping. We also describe two different algorithms for automatically detecting sleep apnea events, and illustrate the performance of the overall system in a sleep study with 20 *volunteers.*

1 Introduction and Previous Work

In recent years there has been increasing interest in wearable health monitoring devices, both in research and industry. These devices are particularly important to the world's increasingly aging population, whose health has to be assessed regularly or monitored continuously. The implications and potential of these wearable health monitoring technologies are paramount.

A good portion of these devices have been developed for the sports conditioning and weight management areas. There are sophisticated watches available today [12] that provide real-time heart rate information and let users store and analyze their data on their home PCs. Bodymedia [2] has developed an armband that has multiple sensors to continuously collect physiological data for a few days at a time.

The areas of wearable health monitoring devices [13, 3, 11, 10, 5, 4, 1] and wireless sensor networks for physiological monitoring [9, 6] have also experienced very active research recently. However, most systems to date do not perform real-time analysis of the physiological signals in the wearable devices. The physiological data is typically analyzed on a home PC at a later time. Moreover, proprietary data formats prevent users from consolidating and correlating health monitoring data from different devices.

In this paper we describe HealthGear, a wearable real-time health monitoring system. HealthGear consists of a set of physiological sensors[1] wirelessly connected via Bluetooth[2] to a Bluetooth-enabled cell phone. We describe our experience using HealthGear with an oximeter to constantly monitor and analyze the user's blood oxygen level (SpO_2), heart rate and plethysmographic signal[3] in a light-weight fashion.

Given all previous work, the main contributions of this paper are: (1) The implementation of a real-time, light-weight wearable health monitoring architecture, to wirelessly send physiological data to a cell phone; (2) The real-time storage, visualization and analysis of the physiological data on a cell phone; (3) The implementation of two algorithms for automatically detecting sleep apnea events from blood oximetry; (4) The validation of the complete system (hardware and software) in a study with 20 participants.

With HealthGear we also address some of the limitations of previous systems, by allowing real-time physiological data collection, analysis and visualization, and by developing an architecture that is agnostic to the type and nature of the sensors.

2 System Overview

We shall describe in this Section the three main hardware components of HealthGear's current implementation.

2.1 Oximetry Sensor

Pulse oximetry is a state-of-the-art noninvasive method for determining the percentage of hemoglobin (Hb) satu-

[1] The current implementation of HealthGear includes an oximeter, but the system architecture allows for any number of sensors of heterogeneous nature.

[2] We chose Bluetooth because of its pervasiveness in the market today. Any other short-range wireless communication protocol could be used instead.

[3] Plethysmography is a term for a set of noninvasive techniques for measuring volume changes in parts of the body, such as those caused by blood being forced into vessels.

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rated with oxygen. Our choice for HealthGear was Nonin's Flex Oximeter, an off-the-shelf constant monitoring oximetry sensor – depicted in Figure 1 (top-center). This sensor is small, light-weight, flexible and capable of long-term monitoring, all of which make it particularly suitable for wearable applications. The sensor is connected to Nonin's XPod board, a processing unit that captures and processes the raw analog sensor data and outputs a digital serial stream containing SpO_2 and heart rate at 3 Hz. The XPod also provides a plethysmographic signal sampled at 75 Hz. The XPod board is beneath the batteries on the left of Figure 1 (top). Operating ranges for the heart rate are $18 - 300$ bpm and $70 - 100\%$ for the oxygen saturation. The sensor's LEDs drain 3 mW each, while the total power consumption, including the XPod module, is 60 mW at 3 V.

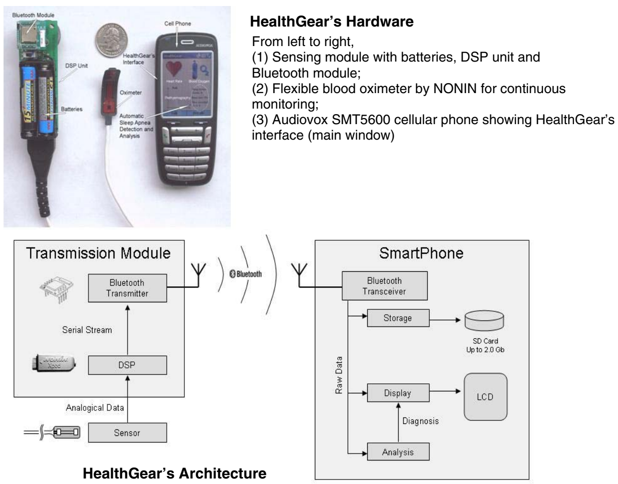

Figure 1. Top: HealthGear's hardware, from left to right: Sensing module (with BT module, XPod board and batteries), sensor (oximeter) and cell phone, showing HealthGear's interface. Bottom: HealthGear's client-server architecture.

2.2 Wireless Data Transmission

Once a serial data stream is produced by the sensor, a wireless transmitter is required to send the data to the cell phone. We chose Bluetooth (BT) because of its pervasiveness, availability on today's cell phones and other mobile devices, and relatively low power consumption. After evaluating several BT transmission modules, we chose the Promi-ESD-2 module by Lemos International (see Figure 1, top-left). This is a class 2 transmitter with a built-in antenna, 30 m range, current consumption of 28 mA at 9600 bps (HealthGear's current data transmission speed) and 3 V operating voltage. The module can be configured by means of AT commands.

HealthGear can run continuously for about 12 hours with two AAA rechargable batteries (see Figure 1, top-left) which provide power to the sensor, the XPod and the BT transmitter.

2.3 Cell Phone

The central processing unit in HealthGear is an Audiovox SMT5600 GSM cell phone, running the Microsoft Windows Mobile 2003 operating system. It has built-in support for Bluetooth, 32 MB of RAM, 64 MB of ROM, a 200 MHz ARM processor and about 5 days of stand-by battery life.

HealthGear is implemented as a Windows Mobile application, with all its modules (sensor data reception, analysis, display and storage) running simultaneously in real-time on the cell phone. Figure 1 (top-right) illustrates the cell phone with the main window of HealthGear's interface.

2.4 Architecture

Figure 1 (bottom) depicts a block diagram of HealthGear's client-server architecture. HealthGear's service is registered in the Service Discovery Protocol (SDP) record of the cell phone, using the Serial Port Profile (SPP) standard through a socket interface. Once the service is up and running, the physiological sensing modules connect as clients to the cell phone's physical address. The cell phone can accept an arbitrary number of client connections from different sensing modules.

3 Automatic Detection of Sleep Apnea

Sleep apnea is an under-diagnosed, but common sleep condition that affects both children and adults. It is characterized by periods of interrupted breathing (apnea) and periods of reduced breathing (hypoapnea). The most common form of sleep apnea, called *obstructive sleep apnea* (OSA), is caused by the partial or complete constriction of the patient's upper airway. Regular sleep apnea leads to repeated hypoxemia[4], asphyxia[5] and awakenings, and produces immediate symptoms such as increased heart rate and high blood pressure and long term symptoms such as extreme fatigue, poor concentration, a compromised immune system, slower reaction times and cardio/cerebrovascular problems.

In HealthGear we have implemented two methods for the automatic detection of sleep apnea events. The first method operates in the time domain, while the second operates in the frequency domain.

3.1 Multithreshold Time Analysis

The first algorithm is inspired by the description of sleep apnea appearing in [7], where "there is no minimum dura-

[4]Deficient oxygenation in the blood.
[5]Inability to breathe and suffocation.

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tion for an apnea event. Desaturation starts as soon as the oxygen level falls below a baseline by a specified amount, and continues until the signal recovers to a level, which is lower than the baseline by 25% of the specified amount".

This definition establishes different levels of drop for desaturation (drop gap) and resaturation (return gap), and requires the computation of a baseline.

In HealthGear, we compute the baseline as the moving average over a window of 5 minutes of data, but using only the top 5% of the samples. We futher extend the definition above to enable handling an arbitrary number of thresholds (typically from 5% to 15% below the baseline) instead of just one threshold.

We measure the severity in % of desaturation below the baseline and in total duration of the event in minutes. The lower the oxygen saturation level and the longer the duration, the more severe the event.

3.2 Spectral Analysis

Our second method is inspired by the work of Zamarron *et al* [14], who evaluate the spectral characteristics of nocturnal oximetry and heart rate variability obtained from an oximeter as a diagnostic test for obstructive sleep apnea. They report that the spectral analysis of those signals could be useful as a diagnostic technique for patients with OSA.

In our analysis, we compute the periodogram of the mean-subtracted oximetry signal, which provides an approximation to the power spectral density (PSD) estimate of a sequence of data [8].

The periodograms for subjects with nonexistent, mild and severe apnea are depicted in the bottom row of Figure 2. Note that in the case of sleep apnea, there is a significant peak in the frequency range of $0.015 - 0.04$Hz. This makes it possible to automatically detect that there were sleep apnea events. Moreover, the larger the amplitude of the peak, the more severe the sleep apnea during that time window.

This frequency range has a physiological explanation, due to periodicities in ventilation both in subjects with and without sleep apnea.

4 Experiments

4.1 Subjects

For our experimental study we recruited 20 volunteers, mostly male (80%) between 25 and 65 years of age. All participants signed an informed consent form prior to the study. We had two different sets of subjects: healthy individuals (30%) and individuals who either knew or suspected they had sleep apnea (70%).

Before the experiment, all subjects filled out a sleep questionnaire where they provided some demographic, sleep quality and health information. From the subjects that either knew or suspected they had sleep apnea, 79% reported snoring, 75% reported feeling tired after their sleep at least 3-4 times per week and 50% reported being overweight.

4.2 Sleep Recording

The experiment consisted of using HealthGear for one full night in their own homes. The day of the experiment, we met with each participant for about 15 minutes to explain them how to use the system. After the meeting, they took the hardware with them and wore it during that night in their homes. They returned the system to us the next morning. After the experiment, they were asked to fill out a second questionnaire which focused on rating the experience and the usability of HealthGear.

4.3 Analysis and Discussion

Our sleep study was a success on multiple fronts: (1) None of our volunteers experienced any technical problem and they all collected data successfully, which we find remarkable given that participants took the system to their own homes and had no supervision or guidance once at home; (2) Our automatic OSA detection algorithms identified with 100% accuracy all 3 cases of known OSA and clearly identified 1 case of severe and 2 cases of mild OSA, among the pool of participants who suspected they might be suffering from the condition, but had not undergone any medical diagnosis; (3) 100% of participants were willing to wear HealthGear to monitor their sleep on a regular basis and would recommend the system to friends and family.

Figure 2 depicts typical analysis graphs for healthy subjects and those with mild and severe OSA. The top row contains about 30 minutes of raw oximetry data in % of blood oxygen (blue line), and the output of the multithreshold detection algorithm (green line), where the higher the value of the green plot, the more severe the OSA event is.

The middle row depicts the histograms of time spent (y-axis, in minutes) in desaturations from 5 to 15% below the baseline (x-axis). Note how healthy individuals had no desaturations at all, while subjects with OSA had various degrees of desaturation. The worse the condition, the wider the spread of the histogram, meaning that the events were more severe.

The bottom row shows the periodograms of the oximetry signal, processed in 834 sample windows. As the severity of the OSA condition increases, so do the peaks in the $0.015 - 0.04$ frequency range. We can therefore automatically detect OSA events and their severity from the periodogram signal.

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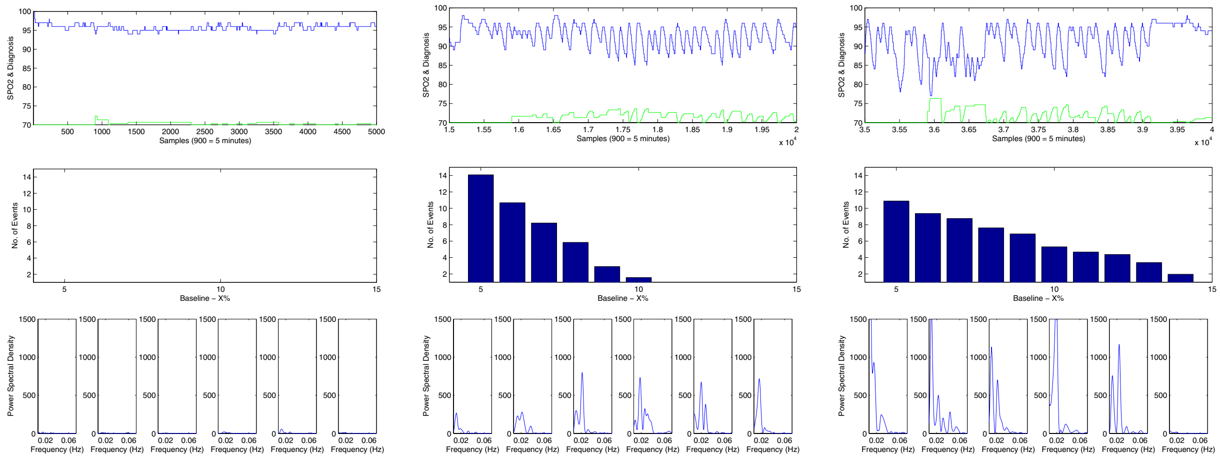

(a) No apnea (b) Mild apnea (c) Severe apnea

Figure 2. Typical oxygen saturation graphs (top), histograms (middle) and periodograms (bottom) of users (a) without sleep apnea and (b) with mild apnea. The graphs depict approximately 30 minutes of night data.

The average number of hypoxemia events per hour for subjects with non-existent, mild and severe OSA in our user study was: 0, 5.7 and 17.7 for 5% below the baseline, and 0, 1.4 and 3.9 for 10% below the baseline.

Finally, the results of the usability questionnaire were very positive: (1) 100% of our participants answered that they would be interested in using HealthGear again and that they would recommend it to friends and family. (2) In terms of comfort, the average comfort rating was 4.2, on a 1 to 5 Likert scale, with 1 being "very bad" and 5 being "very good". (3) The average rating of the experience as pleasurable was 3.8, on the same scale.

5 Future Work

Some areas that we would like to explore in future research include: (1) incorporating other sensors in HealthGear, such as galvanic skin response (GSR), ECG, skin temperature, etc; (2) finding correlations between lifestyle variables such as current activity, diet, exercise, stress levels, etc. and changes in physiological signals; (3) developing algorithms for extracting respiration rate and blood pressure from the plethysmographic signal; (4) carrying out a study on blood oximetry at high altitudes (pilots); (5) comparing HealthGear's performance with polysomnography in a sleep clinic; (6) collaborating with medical doctors in further user studies; (7) addressing the so important issues of privacy, liability and security.

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