BEAT: Bio-Environmental Android Tracking

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***Abstract*—The popularity of wireless devices has been pushing the envelope for medical applications. These devices, paired with a personal health monitoring framework can enable early detection and increased quality of life of citizen of developed nations. These devices are helping supplement the available disease detection and treatment techniques, as well as increasing the quality of life of the users of the system. BEAT (*B*io-*E*nvironmental *A*ndroid *T*racking) provides methods for collecting, processing, and archiving ones' daily vital and spatiotemporal statistics using commercially available biologic and environmental sensors. The device analyzes the data and attempts to classify the behavior by using context information from accelerometers, GPS, previous behavior, and user feedback. Algorithms are executed to calculate statistics (e.g. heartbeat variance, time above/below certain thresholds, and flag abnormal readings). Options are available for adjusting thresholds used to issue user and third party alerts automatically. In addition, statistics, previous records, and real-time data, can be displayed to the user or transmitted to a medical professional for analysis. Integration of additional bio-sensors including blood pressure, glucose, and weight will enable the BEAT framework to be a complete personal health monitoring system.**

I. Motivation

A. Heart Disease

Heart disease is among the leading causes of death in most developed nations today. In the United States, cardiac related fatalities rank first on the list, responsible for 26% of all deaths. The most common sub-group of which is coronary heart disease, attributable to 17.5% of all fatalities [1]. Coronary heart disease is the decreased or diminished ability to provide circulation to the cardiac muscle, which can lead to cardiac attack and arrest. According to statistics from the National Heart, Lung, and Blood Institute there are 1,255,000 new and recurrent coronary attacks per year; approximately 34% are fatal. However, 20% of mortality can be prevented with home monitoring systems [2]- [3].

B. Personal Health Monitoring

Individuals are beginning to take on a more active role in management of their personal health care. Emphasis has been placed on moving away from centralization of medical care and into the age of telemedicine.

Following suit have been products incorporating various methods to collect and analyze vital stats. A typical example incorporates peripheral bio-sensor(s) and a computing device. Historically, these devices have been laptop computers, or external storage media later connected to a desktop computer for analysis. However, with the continual increase of the computational capabilities and storage capacities of the typical smartphone, detailed collection and analysis can be performed locally, eliminating the need for laptop or desktop component.

II. Current Systems

Several systems have been developed to bring medical grade data gathering and analysis out of the hospital and into the home. The system presented in [4] incorporates mobile devices and uses threshold based algorithms to detect life threatening arrhythmias (Ventricular Fibrillation and Ventricular Tachycardia). Others have used sensors to monitor medical conditions such as obstructive sleep apnea [5] Even detection of stress levels [6] has been proposed using threshold based home monitoring systems.

A. Wireless Body Area Networks

Mobile devices have also become the center of Wireless Body Area Networks (WBAN) WBANs are intended to be composed of passive sensor nodes, active actuator nodes, and a wireless personal device [7]. The passive nodes collect data (accelerometer, GPS, temperature, pressure, heart rate, etc..) and the active nodes perform operations (dispense medicine, release insulin, etc..), Both communicate with a personal device for more complex operations. However, the main focus has been on system architecture and service platforms for extra-body communication [8]. Bigger challenges are how to engage patients in a dialog about their health, and how to make it easy for patients to manage their chronic care [9].

B. m-Health

The MobiHealth system developed a way to transmit highly customizable vital signals over public wireless networks to health-care providers. It predominately relies on an m-health platform that connects medical professionals with end users [10]. The use of third party monitoring services may be problematic due to lack bandwidth and coverage in the current network.

MIT's Mobile Care project is an m-health system for patient diagnosis in developing countries. It utilizes a technique called *Chunking* to avoid resending data in the event of network failure [11]. However, wireless carriers may not support chunking. This constraint, along with the high power demands for wireless transmission, highlights the need for extracting and processing on the device whenever possible.

C. Fitness

The fitness industry has also adopted home systems that monitor weight [12]- [13] and physical activity levels [14]. Numerous devices have been created that use accelerometers as pedometers or use wrist watch type devices to display heart rate. Several of these systems operate with an external personal device for storage, additional processing, user inputs, and other communication.

III. BEAT Design

Given the lack of an open and self contained framework that incorporates real time health monitoring, long term storage, localized pattern analysis, and emergency response, we introduce BEAT: (*B*io-*E*nvironmental *A*ndroid *T*racking). BEAT provides methods for collecting, processing, and archiving ones' daily vital and spatiotemporal statistics by integrating an Android device with commercially available biologic and environmental sensors.

With all the capabilities of modern smartphones, data can be processed and analyzed locally, helping to limit required network bandwidth overhead [15]. This approach not only saves power, but provides immediate feedback to the user and can include their input into decision making processes. Additionally, by performing more computation on the mobile device itself, the dependency for third party services is reduced.

A. Context Computing

In the BEAT system, applications attempt to categorize events by processing the collected data. Based on the current state and patterns of the biologic and environmental sensors, logical information can be gathered [16]. For example if the heart rate monitor detects an increase in pulse rate, the accelerometer detects movement, and the GPS detects a frequent change in location, it can be inferred that the user is exercising. Threshold parameters are then adjusted automatically to minimize interaction with the user.

In cases where only heart rate may spike and no accelerometer and GPS activity is detected the user is quickly prompted to provide simple feedback. This feedback is stored to be used in machine learning algorithms for future decisions. This is comparable to similar emerging systems such as automated wandering detection for dementia patients [17]. Based on such results, the data set can be flagged for further analysis by medical professionals as a supplement to a more complex analysis of the patient.

By incorporating user feedback into the system, users are engaged in a dialog about their activities. This approach makes it easier for them to better manage their health. It also gives the user the opportunity to help reduce the number of false positives [18].

B. Mobile Operating System Landscape

Selection of an appropriate operating system (OS) is critical when designing an open framework that will be deployed on multiple device types. Common mobile platforms include Symbian, Research in Motion (RIM), Windows Mobile, iPhone OS, or Google Android as the embedded operating system. Accordingly to the latest Gartner research, Symbian and RIM devices continue to dominate the global smartphone market. However, their market shares, along with Windows Mobile, have experienced declines, while Android and iPhone are gaining rapidly [19]. Android and iPhone OS both have highly sophisticated application marketplaces, which provides easy access to both software distribution and maintenance channels. In terms of application development, the iPhone platform is the more mature, boasting a more extensive collection of programs available for download. However, Android has been gaining considerable momentum, with 70,000 applications and over 1 billion downloads in July of 2010 [20].

C. "Open" Android

There is a major distinction between the two promising operating system options. In contrast to Apple's proprietary source code, Google's Android is open-source, which provides developers access to operating system code.

This paradigm enables rapid development of prototypes that can utilize system resources. Programming the device at both application and OS levels provide superior customization and functionality over the iPhone OS. Android also utilizes s the Java programming language at the application layer which enables apps to be run in a Java Virtual Machine, Android also utilizes Java and runs applications in a virtualized execution environment. This allows an application to behave consistently on every device using the platform. This environment helps reduce the problems of platform dependencies and backwards compatibility [21]

D. Power Management

A major design requirement of the BEAT system is low power consumption. This relates to both the collection of external sensor data as well as in the transmission of this data to third parties. External storage buffers such as those found on the BEAT transceiver allow the sensors to collect data independent of the Android device. Periodically, the device will poll the external sensor and transfer the contents of the buffer into long term storage. The device is able to enter decreased power states during periods when not actively polling sensors. User-tunable parameters can also help reduce the polling frequency if verbose data is not required.

Offloading of sensor data to medical care providers also influences the power overhead of the system. Data compression algorithms can help limit the size of the required transmission; smaller data sets require less power to transmit. Unfortunately, the compression process itself requires power to perform. To sidestep this constraint, compression, analysis, and transmission can be deferred until the device is connected to a external power supply.

IV. IMPLEMENTATION

A. Hardware

Polar brand monitors are used predominantly by the fitness industry to provide accurate monitoring of the heart during exercise. It is a small, lightweight sensor that is worn across the chest. The embedded electronics uses an integrated internal power supply to listen for cardiac rhythm. When a heat beat is sensed by the device, it utilizes the on-board transmitter to send a 5 kHz electromagnetic pulse (EMP) for 5 ms. The EMP amplitudes produced by the Polar transmitter operate in the 5 uT range for close proximities, to around 1 nT at about 1 meter distance [22]. Continual sensing of the electromagnetic field surrounding the device in the 5 kHz range allows reliable monitoring of each heart beat event.

EMPs from the chest strap are detected wirelessly via a Polar RMCM-01 receiver. When the RMCM-01 senses a heartbeat, it forwards a digital pulse to an integrated circuit which measures the time between successive heart beat events. This temporal data is used to calculate the beats per minute and the latest 30 calculations are stored in a local buffer.

An embedded ATmega 328 I/O micro-controller handles communication between the RMCM-01 and the Android device via Bluetooth serial as shown in Fig 1. The time duration between buffer polling is controlled by an internal algorithm that adjusts the polling period based on recently received BPM data. This threshold can be adjusted by the user to permit trade-offs between power consumption and granularity of the data [23].

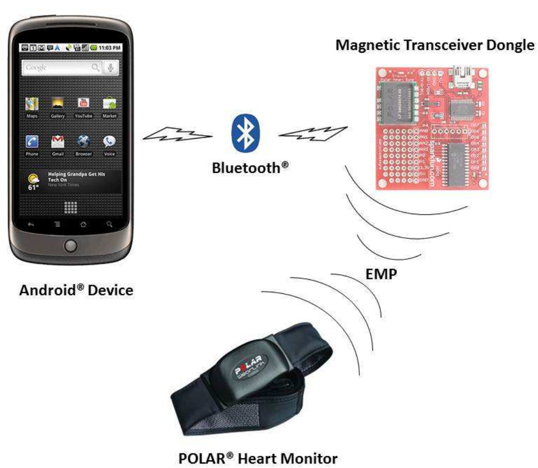

Fig. 1. Experimental system monitoring heart rate

B. Real-time Monitoring

BEAT performs analyses of both short term and long term patterns and provide notifications to the user. Threshold based algorithms are used for real-time monitoring. If the beats per minute detected fall below or exceed user defined thresholds for alarm, the unit invokes a pre-defined handler function. For example, if the user is exercising and their heart rate is no longer within the desired range a notification is sent informing the user to pick up the pace or slow down. The data is also stored at user specified granularities for inspection and trend analysis. Optionally, the data can be remotely uploaded to health professionals.

C. Emergency Response

In the event of an emergency, notifications are first issued to the user. If there is no response within a defined time, communication to the user's pre-specified social contacts is attempted. If contact is made, social contacts can evaluate the situation further and automatically alert emergency personal. By using this multilevel flow emergency alerts can be canceled by the user All thresholds values can be customized based on individual needs [24].

D. Long-term Analysis

Long-term patterns are analyzed by creating base-line check points of various readings. As check points are accumulated daily they are averaged into wider granularity. Even gradual changes can be tracked thus enabling the earliest possible detection of an emerging condition. With the users permission, health history and analysis can be periodically (or on demand) uploaded from the device to health professionals.

E. Storage

The storage requirement for saving data from multiple sensors must be taken into account. While short term monitoring and archival of data may require a trivial amount of storage space, long term storage necessitates additional design considerations. Fig 2. displays an example of the sampling rates required by various sensors.

Sensor Polling Frequency (# polls/period)

Reads per	Heart Rate	GPS	Accelerometer
min	3	2	180
hour	180	120	10800
day	4320	2880	259200
week	30240	20160	1814400
month	907200	604800	54432000
year	10886400	7257600	653184000

Fig. 2. High-end example of the sampling rates for various sensors

Fig 3. displays an estimate of the storage requirements of this raw data as generated by each sensor. This is well within the range of today's devices, even without employing filtering techniques or data compression that can be used to further reduce the storage requirements.

F. Compression

The compression algorithm used for sensor data storage depends upon the mode of operation and the nature of the sensor data collected. For data that will be exported to a medical care provider, all data points are retained via a lossless

Raw Storage Requirements (KB)			
Data size per	Heart Rate	GPS	Accelerometer
day	22	6	310
week	154	42	2170
month	4620	1260	65100
year	55440	15120	781200

Fig. 3. Size estimation for data generated by various sensors

compression algorithm. The selected option uses a hybrid of differential encoding and LempelZivWelch (LZW) compression. To exploit the uniform structure of the collected data, heart rates are periodically stored using differential encoding. The initial beat within a period in the series is fully stored, with the remainder beats stored as the difference from the previous rate. Thus, rather than storing: (60, 60, 60, 61, 61, 60, 59, 58 ...) heart rates are stored as (60, 0, 0, +1, 0, -1, -1 ...). In the second stage of compression, LZW reduces the storage overhead by using back-references to shrink recurring series of byte strings.

Compressed Storage Requirements (KB)			
Data size per	Heart Rate	GPS	Accelerometer
day	6	3	150
week	42	21	1050
month	1260	630	31500
year	15120	7560	378000

For locally stored, long-term sensor data, patterns and trends have more utility than raw data. This allows the use of lossy compression algorithms for even greater levels of storage efficiency. Sensor data stored locally utilizes an algorithm variant of the Discrete Cosine Transform (DCT). A DCT is similar to the discrete Fourier Transform. Primarily used in compression of lossy media files, JPEG and MPEG, DCT allows storage of the monitored sensor data as the sum of cosine coefficients rather than a sequence of data points. The cyclical nature of daily heart rates periods, such as exercise and sleep can be efficiently modeled in this way. A history of every single heart beat, location, movement, and other vital readings in a person's lifetime only requires a few gigabytes.

G. Future Hardware Improvements

Current Android devices are manufactured with a sensor to detect magnetic orientation relative to the Earth's magnetic field, but are not able to detect the signal output by the Polar monitor [21]. If future Android device designs integrate a local magnetic field sensor the need for the external transceiver will be eliminated. Additional sensors can be incorporated to gather other vital readings. A recent study has shown that the majority of doctors would also like to monitor blood pressure, glucose, and weight [25]. Bio-sensors capable of monitoring these variables can be paired via Bluetooth radio and integrated into the BEAT monitoring framework.

V. Beyond the Individual

The large volume of uniform data collected by the BEAT system from multiple individuals can also be of importance to medical professionals. This enables the use of correlation studies on observed variables. New early warning signs for life threatening conditions may be identified based on these studies. In addition, there is the potential for more timely and detailed feedback for large scale medical studies of new treatments or medications.

VI. Conclusion

By leveraging the power of Android, the BEAT system provides the short term information needed for users and caregivers to react quickly, or even prevent, life-threatening events. It also provides the long term information needed for health care providers to make lifestyle and medication recommendations. In combination, these will afford the user a more independent and higher quality of life. Through the use of apps, the system can be tailored to the individual, and with the ability to integrate additional sensors, the system has the potential to do even more.

References

[1] Jiaquan Xu, Kenneth D. Kochanek, Sherry L. Murphy, and Betzaida Tejada-Vera. Deaths: Final data for 2007. *National Vital Statistics Report*, 58(19), May 2010.

[2] Nihir B. Shah, Elaine Der, Chris Ruggerio, Paul A. Heidenreich, and Barry M. Massie. Prevention of hospitalizations for heart failure with an interactive home monitoring program. *69th Scientific Sessions of the American Heart Association*, November 1997.

[3] Robyn A. Clark, Cally C. Inglis, Finlay A. McAlister, John F. Cleland, and Simon Sweet. Telemonitoring or structured telephone support programmes for patients with chronic heart failure: Systematic review and meta-analysis. April 2007.

[4] Peter Ledijdekkers and Valerie Gay. Personal heart monitoring system using smart phones to detect life threatening arrhythmias.

[5] Nuria Oliver and Fernando Flores-Mangas. Healthgear: A real-time wearable system for monitoring and analyzing physiological signals.

[6] Rosalind W. Picard and Charles Q. Du. Monitoring stress and heart health with a phone and wearable computer. *Offspring*, 1(1), 2002.

[7] K. Van Dam, S. Pitchers, and M. Barnard. Body area networks: Towards a wearable future. *Proceedings of WWRF kick off meeting*, March 2001.

[8] Benoit Latre, Bart Braem, Ingrid Moerman, Chris Blondia, and Piet Demesster. A survey on wireless body area networks.

[9] Phd. Peter Boland. The emerging role of cell phone technology in ambulatory care. *J Ambulatory Care Manager*, 30(2):126–133, 2007.

[10] Aart Van Halteren, Richard Bults, Katarzyna Wac, Dimitri Konstantas, Ing Widya, Nicolay Dokovsky, George Koprinkov, Val Jones, and Rainer Herzog. Mobile patient monitoring: The mobihealth system. *The Journal on Information Technology in Healthcare*, 2(5):365–373, 2004.

[11] L.A. Celi, L. Sarmenta, J. Rotberg, A. Marcelo, and G. Clifford. Mobile care (moca) for remote diagnosis and screening. *Journal of Health Informatics in Developing Countries*, 3(1):17–21. from http://www.jhidc.org/index.php/jhidc/issue/view/6.

[12] Juha Parkka, Mark van Gils, Timo Tuomisto, Raimo Lappalainen, and Ilkka Korhonen. A wireless wellness monitor for personal weight management. 2000.

[13] Thomas G. Zinnerman and Keng hao Chang. Simplifying home health monitoring by incorporating a cell phone in a weight scale.

[14] Jonathan Lester, Tanzeem Choudhury, Gaetano Borriello, Sunny Consolvo, James Landay, Kate Everitt, and Ian Smith. Sensing and modeling activities to support physical fitness. September 2005.

[15] Val Jones, Valerie Gay, and Peter Leijdekkers. Body sensor networks for mobile health monitoring: Experience in europe and australia. *The Fourth International Conference on Digital Society*, February 2010.

[16] Stuntebeck, Davis, Abowd, and Blunt. Healthsense: Classification of health-related sensor data through user- assisted machine learning. *HotMobile*, February 2008.

[17] Frank Sposaro, Justin Danielson, and Gary Tyson. iwander: An android application for dementia patients. *Conf Proc IEEE Eng Med Biol Soc*, September 2010.

[18] Sposaro F. and Tyson G. ifall: An android application for fall monitoring and response. *Conf Proc IEEE Eng Med Biol Soc.*, 1, 2009.

[19] Mathew Miller. Google android smacks down windows mobile in latest gartner data. May 2010.

[20] Eric Zeman. Android market: 70,000 apps, 1 billion downloads. *InformationWeek*, July 2010.

[21] Google. Android developer's site. July 2010. developer.android.com.

[22] Polar. Rmcm-01 heart rate receiver. *Adding Heart to Your Technology*.

[23] Atmel. 8-bit microcontroller with 8k bytes in-system programmable flash. *ATmega48/V, ATmega88/V, ATmega168/V*. Rev. 2545RAVR07/09.

[24] Frank Sposaro and Gary Tyson. Geriatric medical application suite on a sweet phone. First AMA IEEE Medical Technology Conference on Individualized Healthcare, March 2010.

[25] Sparsh Agarwal and Chiew Tong Lau. Remote health monitoring using mobile phones and web services. *Telemedicine and e-Health*, 16(5), June 2010. DOI: 10.1089/tmj.2009.0165.