A Mobile Platform for Real-time Continuous Monitoring

● Ajay Chander ● Albert Braun ● Rajalakshmi Balakrishnan ● Alex Gilman
● Stergios Stergiou ● Dave Marvit

Advances in information and communications technology (ICT) are expected to help people lead healthier lives amidst the many stressors in today's fast-paced society. While smartphones and tablets continue to overtake desktops and laptops, the next computing revolution—Human-Centric Computing—is taking root. This shift in computing is enabled by the increasing ubiquity of sensors that are around us, on us, and even in us. Deploying intelligent, human-centric services using these connected sensors requires advancements in the underlying IT infrastructure itself. In this paper, we describe various novel services built atop a general-purpose mobile platform developed by Fujitsu Laboratories of America, Inc. for continuous mobile monitoring. Our platform was developed with next-generation healthcare services in mind but has broad applicability as an extensible platform for deploying real-time services that incorporate data from arbitrary sensors. We provide an overview of our platform, and highlight several services that act as new points of contact between a user and the IT infrastructure. In the domain of health and wellness, we show how continuous bio-monitoring enables us to measure stress and to provide stress management services. We describe how such services may be used in a typical day, contributing to a new and improved quality of life.

1. Introduction

Imagine with us, if you will, a day in the future. After a refreshing shower, by habit, you step on a connected body composition scale, which automatically records various body indices and sends them immediately to your cloud-based electronic medical record. As you get dressed for the day, you put a small patch on your chest that will continuously record your cardiac activity and other biomarkers during the day.[1] Putting on such sensors is second nature for you by now, akin to putting on socks. You grab your smartphone and head to the train station for your daily commute to work.[note]

Your smartphone is connected with your chest patch and receives a continuous electrocardiogram (ECG) signal from it. A real-time application running on your smartphone processes the ECG signal to compute your real-time psychophysiological stress level. The same smartphone has also been keeping track of your location, as well as usage of calls, texts, e-mails, and other applications. As a phone call comes in, the call application makes you aware of your current stress in a helpful manner so that you are better prepared to take the call or possibly ignore it. You have also set your smartphone radio app to dynamically select content that is most appropriate given your current bio-state. You arrive at work refreshed and ready for the day.

During the day, an application running on your desktop provides a continuous customizable visualization of biomarkers of interest to you. It tracks your posture, as computed by your chest patch, and suggests personalized interventions. Being connected to your electronic activity enables it to suggest matches between your bio-state and your task list as you schedule and carry out your day. A medication adherence application running on your smartphone uses your chest patch data to detect anomalies attributable to missed doses and reminds you to take your medication. As you head back home at the end of a productive day, your smartphone and chest patch sensor work in

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conjunction to guide you so that you feel as little stress as possible.

That night, a sleep manager application encourages you to get the right amount of sleep; it has been tracking how sleep affects your stress the next day, and it makes recommendations on the basis of your expected workload the following day. As you go to bed, you give silent thanks to the continuous guidance on living well you've received throughout the day.

The scenarios depicted above have been imagined by researchers in the fields of ubiquitous computing for quite some time.[2)–8)] One may argue that wearable ubiquitous sensing was first made mass-affordable through on-smartphone sensors, and the trend continues through standalone sensors that keep getting cheaper and smaller in accordance with Moore's law.[9)] Given these cost trends, we are starting to see the introduction of a diverse set of standalone mobile sensors with vertically integrated services in a variety of domains.[10)–13)] Such services have demonstrated the readiness of the market for sensor-centric services but suffer from the inability to share data with each other, which makes it difficult to build richer and novel services. As an example, a diabetic who is trying to modulate his activity to best maintain his insulin levels and who uses a pedometer and glucometer regularly has to correlate data collected by these sensors manually. Emerging platforms being developed to address this problem typically do not support real-time data collection and synchronization of continuous data streams or real-time access to multi-sensor data for third-party applications.[14),15)]

As sensors get smaller and cheaper, personal quantification will become easier and widespread. It will be common to have sensors on us, around us, and even in us.[16)–19)] In this paper, we give an overview of a platform that supports easy collection and coordination of heterogeneous streams of sensor data. We describe how several of the applications described in the "day in the life" narrative have been built on top of it. Our platform supports continuous real-time storage, analysis, and visualization of arbitrary sensor streams. It supports the general abstraction of a sensor stream, can be integrated with arbitrary sensors that communicate over compatible wireless protocols, and time synchronizes data coming off of all the integrated sensors. We designed our platform to be mobile and pocketable; we call it "Sprout" in deference to the adage that from good small things, good things will grow.

The rest of this paper is organized as follows. In Section 2, we provide detailed specifications of the capabilities of our platform. Sections 3 through 6 each describe a single application built on top of the platform and the corresponding experiential touchpoints for the user. Section 7 discusses the themes and paradigm shifts enabled by our platform and outlines our ongoing and future work.

2. The "Sprout" platform

The Sprout platform is a combination of hardware and software designed to support mobile, real-time collection, analysis, and storage of heterogeneous data streams. The current version of the hardware prototype is depicted in **Figure 1**.

2.1 Hardware

The current version of the Sprout hardware is based on a 600-MHz ARM Cortex A8 CPU with 512-MB RAM. The entire software stack is run off a Secure Digital (SD) card, which also stores all sensor data. Sprout supports Bluetooth 2.1, 802.11g WiFi, and Texas Instruments' low-power SimpliciTI RF. The wireless protocol support enables integration of compatible wireless sensors. Sprout also supports wired sensors through three USB 2.0 ports and an analog port. The analog port was designed to integrate a respiration sensor, which, in combination with other wearable sensors, permits the remote diagnosis of medical conditions like sleep apnea.[20)] This version of the Sprout is 70 × 55 mm and houses a 10-Wh cylindrical battery.

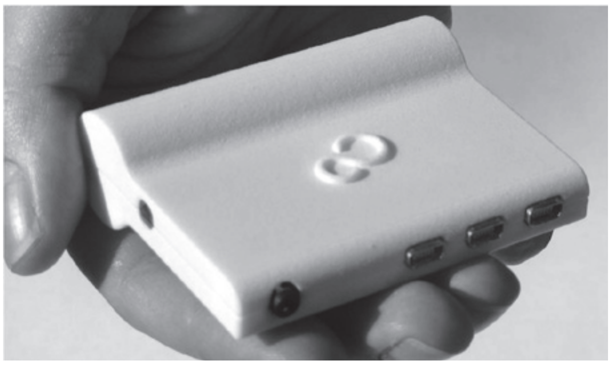

Figure 1
The Sprout device.

Why did we build our own hardware platform? The answer lies in the limitations of past and current mobile platforms. To support real-time storage of multiple sensor data streams, we needed to build a native custom backend, and the application platforms available on mobile devices at the time limited our ability to do so. That limitation still exists on some current mobile platforms. Next, no support was available for certain networking modes that we needed to support for serving data from the platform to off-Sprout data visualization clients, which continues to be the case. Finally, the battery life of general purpose mobile devices is a limiting factor, and having specialized hardware enabled us to support a longer battery life when collecting data from sensors or serving data to clients.

Sensor evolution has brought with it broader support for wireless transmission of collected data through protocols such as Bluetooth Low Energy (BLE).[21] Accordingly, in our next iteration of the Sprout hardware, we have chosen to forego the USB ports entirely and provide support for BLE.

2.2 Software

The Sprout software stack is built on top of Linux (currently Linux 3.0). A custom backend provides support for continuous sensor data stream storage and inter-sensor synchronization using the Sprout clock. As an application platform, Sprout supports a general abstraction of a sensor stream, enabling easy integration of sensor data from new hardware or software sensors. In addition, it provides an application programming interface (API) that enables access to the stored multi-sensor data streams in real time. An application that uses stored data streams as input and creates its own data stream as output is considered a "meta-sensor" by the system. That is, the application's output data stream is viewed as yet another sensor stream by other applications. This modular architecture supports the easy creation and composition of multi-sensor data-based services.

Beyond the general API, we provide particular support for Web-based applications wanting to access and visualize multi-sensor data in real time. Sprout runs an Apache Web server, which responds to such requests in real time. We have built various Web-based customized visualizations using the Web interface to Sprout data; one of those is described in Section 6.

Last but not least, Sprout supports real-time cloud synchronization, e.g., synchronization of bio-data with cloud-based electronic medical records (EMRs).

3. Real-time remote monitoring

Given Sprout's ability to "talk" to a variety of sensors and its real-time cloud capabilities, it is quite straightforward to use it for remote monitoring applications. We have integrated Sprout into a cloud-based personal health record (PHR) system as a data collection, storage, and forwarding device. This PHR system was developed and is maintained by Jardogs Inc., a subsidiary of Springfield Clinic in Illinois in the U.S. This system connects to the various EMRs where a patient's data can be accessed by the patient's care team. This is only one example of a PHR system that could be used with Sprout. The flexibility of the Sprout platform enables the transmission of data to other cloud-based PHR systems and EMRs.

We carried out a test deployment of this system with nine users over a three-week period. The users were given PHR accounts and instructed to measure three biomarkers on a daily basis: 1) weight, once in the morning and once in the evening, 2) blood pressure, three times a day, and 3) pulse-ox level, once a day (three-minute reading).[22] They were given Sprout sets that were pre-paired with their set of sensors (weight scale, blood pressure cuff, and pulse oximeter).

As depicted in **Figure 2**, the simple act of a user getting on a weight scale to take a reading would automatically send the reading to his or her Sprout, which would then forward the data to the cloud-based PHR system. This system could then be accessed through a Web-based interface by the user and by members of his or her care team.

Users were generally positive when they reflected on the new insights into their personal health this system provided. As expected, the easy recording of their biomarkers made them more aware of their health conditions. In some cases, this prompted changes in behavior, as exemplified by some of their comments:

- "I would definitely use Sprout to self-report my health to my physician."
- "...the data gathered helped me to understand the effect of caffeine on my heart rate."
- "Through daily measurement via Sprout, I came to realize that my blood pressure was high and that

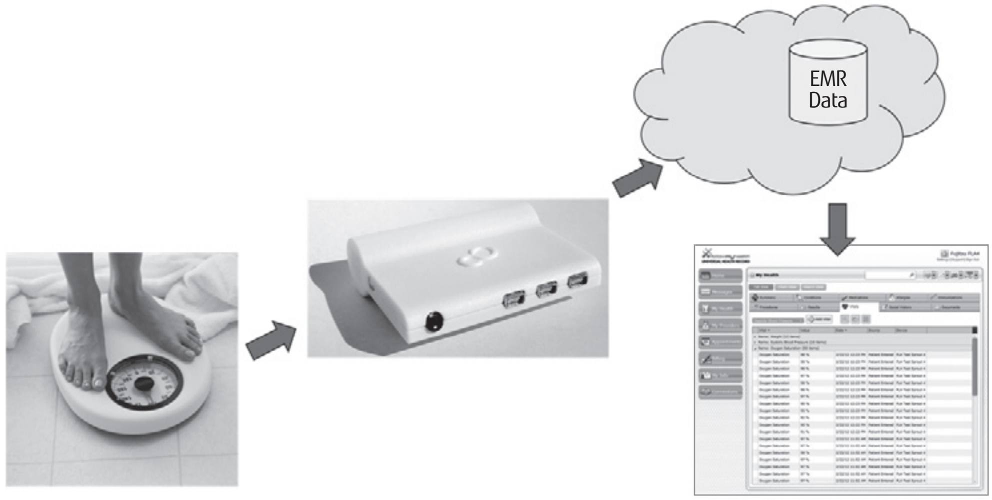

Figure 2
Real-time cloud synchronization.

my health would continue to degrade unless I changed my behaviors. Since my Sprout monitoring, began I have started making healthier food choices and begun a daily exercise routine in an effort to curb my high blood pressure."

In addition, user feedback provided suggestions for new features and improvements that have been incorporated into the newest generation of Sprout hardware and software.[23]

4. Real-time stress assessment

While Sprout can be used as a store-and-forward platform, as described in the previous section, it is at heart a computational platform as it was designed to support real-time analysis of high-frequency time series input. It is thus able, for example, to host stress algorithms that take as input a high-frequency biomarker data stream and output a continuous data stream of instantaneous stress values. Here we describe the implementation of such algorithms for mobile real-time stress assessment.

Stress is a psychophysiological phenomenon. That is, regardless of the cause, the body's response to stress consists of a set of physiological mechanisms that are regulated primarily by the central nervous system and the endocrine system. The effects of these mechanisms are directly evident in changes in heart activity. In particular, heart rate variability—which measures how much the instantaneous heart rate varies from heartbeat to heartbeat—is directly affected by stress.

State-of-the-art measures of stress use various mathematical models of heart rate variability (HRV), and they typically require as input a continuous interbeat interval stream. We integrated the Zephyr BioHarness chest strap sensor, which transmits various bio-variables over Bluetooth in real time, into the Sprout platform.[24] In particular, the Zephyr sensor records an ECG signal sampled at 250 Hz as well as an "R2R" data stream. The R2R data stream is the sequence of time differences between successive R-wave peaks in the ECG signal.[25] This data stream therefore provides the interbeat interval stream needed as input by various algorithmic models of stress.

We started by implementing various existing time domain and frequency domain algorithms on the Sprout platform. These currently run as C++ programs that utilize the Sprout backend data access and storage APIs. We found that the state-of-the-art HRV measures are susceptible to noise, which typically appears in ambulatory settings; however, they are relatively robust when interbeat intervals are captured in a static setting. Moreover, they do not work well for people across different disease states, e.g., diabetes, hypertension, and cardiovascular disease.

Given these limitations of existing state-of-the-art HRV measures, we designed our own HRV measure. While the description of our HRV measure is beyond the scope of this paper, we found that it is robust to noise and works uniformly well across a wide range of disease states. The measure was validated quantitatively in a study of 250+ subjects with different disease states as well as in a qualitative study that used advanced medical imaging equipment to measure the direct effect of stress on the body. We will be reporting on the underlying details in upcoming biomedical and bioengineering venues.

5. During the commute: Stress maps

With a robust, real-time ambulatory stress metric implemented on the Sprout platform, we can measure and visualize stress in the context of other variables that are also captured on the platform. In general, these variables can include the entire spectrum of bio-variables such as weight, activity, and blood sugar level as well as environmental variables such as location, calendar event, and desktop and mobile device activity. Because such data streams are time synchronized when stored on the Sprout platform, we can compute accurate correlations between real-time ambulatory stress and other variables. These correlations can then be mined further to contextualize stress patterns, to anticipate stress occurrences, and to generate personalized plans for stress management.

In this section, we look at one example of such correlations—that between stress and location. In our experiment, one of the authors—who lives in San Francisco and works in Sunnyvale in Silicon Valley—wore a Zephyr chest strap sensor during his drive to and from work. A Sprout in the vehicle used the sensor data to compute real-time stress values and then stored them on the device. A software sensor running on an iPhone 4S sent a continuous GPS data stream collected at about 1 Hz to the Sprout.

After each drive, the stress and GPS data were extracted from Sprout, and the GPS Visualizer Web service[26] was used to generate an interactive map of the drive. The two extracted data streams were quantized such that we had a GPS and stress value pair for each time quantum, which was set to one second. Each dot on the map represented one GPS data point during the drive. The size of the dot was varied in accordance with the corresponding stress value; the higher the stress, the smaller the dot.

Figure 3 shows a map of one of these drives. The narrower portions of the plotted route were the more stressful portions while the wider portions were the less stressful portions. In this case, the driver was returning from work in Sunnyvale to his home in San Francisco during the late evening. (San Francisco is at the top left of the figure, and Sunnyvale is at the bottom right.) The visualization makes it clear that, during the first half of the drive, the stress levels were moderately high but trending downwards. The second half of the drive was markedly more relaxed.

Figure 4 shows the same drive in reverse, the next morning, on the way to work. The stress levels were markedly different, with many segments of high stress distributed throughout the drive. Both drives were not affected by heavy traffic and slowdowns.

In both cases, the data revealed personal patterns of stress that were also evident in other drives by the same driver on other days. The driver's subjective interpretation of these patterns was that he was starting to think about work as soon as the drive to work started and that the occasional work calls made during the drive also had an effect. On the way home, there was a mental "cool down" period during which the events of the day were being processed and put aside. The driver was aware that thinking about potential stressors alone triggers the body's stress response even in the absence

Figure 3
Stress map–Sunnyvale to San Francisco.
Wider areas depict lower stress.

Figure 4
Stress map–San Francisco to Sunnyvale.
Wider areas depict lower stress.

of those stressors and perceived this as a significant contributor to the driving stress patterns.[27] The drive-to-work pattern stood out primarily for the driver, who was unaware of it prior to the experiment. The data brought the driver the insight that experimenting with stress management measures at the beginning of the day could provide significant benefit throughout the day.

One can also imagine that such real-time psychophysiological data streams could be shared with the car's navigational, communication, and media systems, enabling them to adjust to the driver's bio-state.

6. Continuous daytime monitoring and guidance

Many of us spend a significant portion of our work day in a sedentary manner, with several attendant health risks. Apart from the longer term risks to cardiovascular health,[28] such work patterns are also costly in terms of short- to long-term musculoskeletal health. Costs related to back and neck pain are among the biggest contributors to corporate health costs in the U.S.[29]

Continuous personal monitoring has the potential to make us more aware of ourselves during the work day. With a platform like ours, mobile health and wellness applications can be deployed that motivate us to engage in beneficial changes.

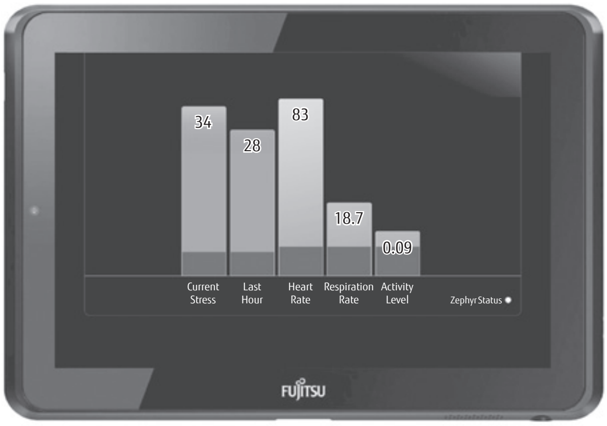

Figure 5
Stress and physiology data display.

To gather some experience with the daytime setting, we carried out a pilot experiment with five office workers over a couple of weeks. Each participant was given a Zeo sleep sensor[30] for the first week to enable them to get comfortable within the paradigm of continuous sensing and wearable sensors. For the second week, each of our volunteer participants additionally wore a Zephyr BioHarness chest strap sensor during the work day. This sensor captures other data streams beyond the cardiac ones described in Section 4, including breathing and activity. Each participant was given a tablet to be placed in a visually accessible area of their work space. It displayed their sensed heart rate, breathing rate, and activity level as well as their stress levels as computed in real time on the Sprout platform. Two stress levels were computed and reported—one computed using inter-beat differences over the last 120 beats and one over the last 3600 beats. These correspond roughly to the stress levels calculated over the last two minutes and over the last hour, respectively. The values were updated every second. **Figure 5** shows an example display.

At the end of the five day period, each participant underwent a "data counseling" session during which we looked at their bio-variable patterns over the course of the week. **Figure 6** shows an example visualization used during these sessions. Like the tablet visualization, it is a Web page that is hosted on the Apache Web server running on Sprout. This visualization consists of a series of panels, each of which can be set to any

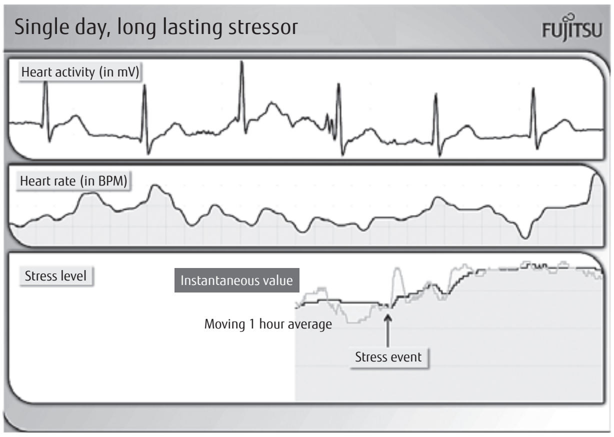

Figure 6
Visualization of bio-variable patterns display.

sensor stream. Three panels are included in the example shown: the ECG signal, the computed heart rate, and the two stress values. Each panel can be customized in various ways, for example, in terms of how the data is visualized (e.g., line vs. bar) and in terms of the time scale. All panels are time synchronized on the far right side of the display. Therefore, dragging any of the panels will shift all three panels in unison.

The data counseling sessions were very revealing, both of the participants and to the participants. Stress events—which we visually identified as occasions where short-term stress markedly increased or decreased over the long-term stress—were invariably correlated with meaningful events in the person's day. We should note that stress itself is not a harmful thing. We all respond to many stimuli during each day, and the body's stress response mechanisms enable us to deal with those stimuli effectively. Chronic stress—where our stress response mechanisms continue to fire even when an external stressor is not present and is only imagined—is well recognized as a major contributor to the majority of chronic diseases. An example of a chronic stress pattern can be seen in the bottom panel of Figure 6; our platform can identify such patterns automatically.

The participants were uniformly fascinated by being able to look within themselves in this way. Everyone reported higher degrees of awareness about their biomarkers, a curiosity about how these biomarkers were affected by non-work situations such as socializing, parenting, and exercising, and the desire to experiment with apps and other tools for stress management.

7. Conclusion

The ubiquity of connected sensors and continuous analytics will redefine our everyday interactions with the ICT infrastructure supporting our lives. A platform like Sprout—which supports real-time storage and analysis of multiple data streams—enables each of those data streams to be analyzed using the context provided by the others. When these streams include biomarker data, users can obtain a richer awareness and understanding of their own health and the factors that affect it. Applications built on top of the Sprout platform with continuous access to such real-time data streams enable a variety of novel experiences, some of which we described in this paper. With access to our biomarker streams, applications can now modulate our interactions with our infrastructure, as well as provide real-time awareness and personalized interventions to motivate self-action. As we become increasingly quantified, it will become possible to quantify the communities in which we live as well. Our experiences deploying the applications reported on in this paper have consistently demonstrated the power of the Sprout data-driven platform to guide us towards a higher quality of life.

We are actively addressing research and development problems related to the platform and applications outlined in this paper in various ways. On the hardware side, we have developed a newer version of Sprout that is cheaper, supports energy-efficient wireless protocols, and is more wearable on the go. On the analytics side, we continue to develop and refine our stress metrics. On the software platform side, we have recently ported the software system to Android. We plan to provide an API for the 'open Sprout' for internal use in the near future.

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References

1) D. He et al.: A wearable vital signs monitor. MTL Annual Research Report, 2010. *https://www-mtl.mit.edu/wpmu/annualreport/?p=1399*
2) H. MacInnis: The clinical application of radioelectrocardiography. *Canadian Medical Association Journal*, Vol. 70,

No. 5, pp. 574–576 (1954).
3) T. Togawa: Home health monitoring. *J Med Dent Sci*., Vol. 45, No. 3, pp. 151–160 (1998).
4) I. Korhonen et al.: Health Monitoring in the Home of the Future. *IEEE Engineering in Medicine and Biology Magazine*, Vol. 22, No. 3, pp. 66–73 (2003).
5) K. Montgomery et al.: Lifeguard—A Personal Physiological Monitor For Extreme Environments. Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 3, 2004, pp. 2192–2195.
6) M. Alwan et al.: Passive in-home health and wellness monitoring: overview, value and examples. Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Vol. 1, 2009, pp. 4307–4310.
7) D. Roggen et al.: Life Style Management using Wearable Computer. 4th International Workshop on Ubiquitous Computing for Pervasive Healthcare Applications, 2006.
8) E. Jovanov et al.: Prolonged Telemetric Monitoring of Heart Rate Variability Using Wireless Intelligent Sensors and a Mobile Gateway. 24th Annual Conference and the Annual Fall Meeting of the Biomedical Engineering Society EMBS/BMES Conference, Vol. 3, 2002, pp. 1875–1876.
9) D. Kwong: Bringing the Benefits of Moore's Law to Medicine. Institute of Microelectronics, Agency for Science, Technology, and Research, Singapore, 2011.
http://www.ieee-jp.org/japancouncil/chapter/ED-15/2011/MQ2011Oct_presentation/Presen2-1.%20D.%20Kwong.pdf
10) FitBit, Inc.: Fitbit Dashboard.
http://www.fitbit.com/home
11) Zeo, Inc.: Welcome to Zeo Sleep Manager | Zeo Sleep Manager.
http://www.synthenet.com/pages/320_myzeo.cfm
12) Nike, Inc.: Nike+.
http://nikeplus.nike.com/plus/
13) Progressive Auto Insurance, Inc.: Snapshot, Snapshot Discount: Pay As You Drive (PAYD) – Progressive.
http://www.progressive.com/auto/snapshot.aspx
14) Shimmer Research: Shimmer - Wireless Sensor Platform for Wearable Applications.
http://www.shimmer-research.com/
15) Qualcomm, Inc.: Medical Technology | Health Information Technology | Qualcomm Life.
http://www.qualcommlife.com/
16) D. H. Kim et al.: Epidermal Electronics. *Science*, Vol. 333, No. 6044, pp. 838–843 (2011).
17) K. Motoi et al.: A fully automated health-care monitoring at home without attachment of any biological sensors and its clinical evaluation. Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2009, pp. 4323–4326.
18) 'Smart' Clothing Responds to Wearer's Emotions. *Tech News Daily*, June 8, 2010.
http://www.technewsdaily.com/577-smart-clothing-responds-to-wearers-emotions.html
19) Proteus Digital Health: Digital Health Feedback System.
http://proteusdigitalhealth.com/technology/
20) D. Sommermeyer et al.: Detection of sleep disordered breathing and its central/obstructive character using nasal cannula and finger pulse oximeter. *J Clin Sleep Med*., Vol. 8, No. 5, pp. 527–533 (2012).
21) B. Horowitz: New Bluetooth 4.0 Medical Devices to Hit the Shelves by December 2011. *eWeek*, June 9, 2011.
http://www.eweek.com/c/a/Health-Care-IT/New-Bluetooth-40-Medical-Devices-to-Hit-the-Shelves-by-December-2011-563465/
22) Jardogs, Inc.: Test Regimen. Jardogs, Inc., Springfield, Illinois, USA, 2012.
23) Jardogs, Inc.: Sprout Feedback. Jardogs, Inc., Springfield, Illinois, USA, 2012.
24) Zephyr, Inc.: Zephyr BioHarness 3.
http://www.zephyranywhere.com/products/bioharness-3/
25) R. Kleiger et al.: Time domain measurements of heart rate variability. *Cardiology Clinics*, Vol. 10, No. 3, pp. 487–498 (1992).
26) A. Schneider: GPS Visualizer.
http://www.gpsvisualizer.com/
27) O. Kelly et al.: Psychosocial stress evoked by a virtual audience: relation to neuroendocrine activity. *Cyberpsychology and Behavior*, Vol. 10, No. 5, pp. 655–662 (2007).
28) T. Warren, et al.: Sedentary behaviors increase risk of cardiovascular disease mortality in men. *Medicine and Science in Sports and Exercise*, Vol. 42, No. 5, pp. 879–885 (2010).
29) R. Loeppke et al.: Health and productivity as a business strategy. *Journal of Occupational & Environmental Medicine*, Vol. 49, No. 7, pp. 712–721 (2007).
30) V. Potter: Better sleeping through technology: Zeo Sleep Manager - Mobile. Computerworld, December 16, 2011.
http://www.computerworld.com/s/article/9222713/Better_sleeping_through_technology_Zeo_Sleep_Manager_Mobile

Ajay Chander
Fujitsu Laboratories of America, Inc.
Dr. Chander leads R&D in data-driven life innovations at FLA. He joined FLA in 2011 and has been developing techniques for transforming healthcare through data, platform, and service-oriented technologies.

Alex Gilman
Fujitsu Laboratories of America, Inc.
Dr. Gilman joined FLA in 2007 and is investigating computational approaches to cross-disciplinary innovation.

Albert Braun
Fujitsu Laboratories of America, Inc.
Mr. Braun is a software developer and data scientist and has been working with FLA since 2006 on a variety of projects.

Stergios Stergiou
Fujitsu Laboratories of America, Inc.
Dr. Stergiou is a senior member of the research staff at FLA. He joined FLA in 2006 and has since been engaged in R&D of formal verification and logic synthesis algorithms, as well as Web-related and health care information processing technologies.

Rajalakshmi Balakrishnan
Fujitsu Laboratories of America, Inc.
Ms. Balakrishnan is currently developing embedded and mobile applications and researching the use of statistical analysis and data mining techniques on large biomedical datasets.

Dave Marvit
Fujitsu Laboratories of America, Inc.
Mr. Marvit is Vice President of Strategy at FLA. He has led projects ranging from automated negotiation systems to sensor-based healthcare, from automated ontology generation to novel interface methodologies.