A Day in the Life in the Universal Village
Applications of a General Platform for Continuous Mobile Monitoring

Rajalakshmi Balakrishnan, Albert Braun, Ajay Chander*, Shreyans Gandhi, Alex Gilman, Jawahar Jain, Yasunori Kimura, Dave Marvit, Daiki Masumoto, Stergios Stergiou
Data Driven Health Care
Fujitsu Labs of America
Sunnyvale, CA, USA
achander@us.fujitsu.com

Abstract—The universal village can be characterized by the ubiquity of sensors and connected infrastructure which enable intelligent services that improve the quality of our lives. In this paper, we describe various novel services built atop a general purpose mobile platform for continuous mobile monitoring. Our platform was developed with next-generation healthcare services in mind, but has applicability more broadly as a platform for deploying real-time services that utilize data coming from arbitrary sensors. We provide an overview of our platform, and highlight a few services that act as new touchpoints between a user and the universal village infrastructure. We thread these services through a prototypical day and describe how they serve to define a new normal for quality of life in the universal village.

Keywords—mobile platform; continuous sensing; services; healthcare; remote monitoring; stress

I. INTRODUCTION

Imagine with us, if you will, a day in the universal village. 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 the size of a bandaid, which 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 your car for the daily commute down to work.

Your smartphone is connected with your chest patch, and receives a continuous ECG (electrocardiogram signal) from it. A real-time application running on your smartphone processes the ECG signal to compute your real-time psychophysiological stress. The same smartphone has also been keeping track of your location, as well as calls, texts, emails, and other communication that you utilize it for. As you place the smartphone in the car mount and start your drive, your smartphone navigator continuously incorporates your real-time stress and driving stress history to route you on a path that it predicts will be the least stressful. 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 to decide to let it go. You have set the car radio 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 allows 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 utilizes your chest patch data to detect anomalies attributable to missed doses and coaches you to keep to your clinical regimen. As you head back home at the end of a productive day, your smartphone and chest strap work in conjunction to guide you back home with as little stress as possible.

At 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 its recommendations based on your expected workload on the following day. You go to bed, giving silent thanks to the continuous guidance you’ve received throughout the day on living another day in the universal village, well.

The scenarios depicted above have been imagined by researchers in the fields of ubiquitous computing for quite some time [2], [3], [4], [5], [6], [7], [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 a manner akin to Moore’s law [9]. Leveraging these cost trends, we are starting to see the introduction of a diverse set of standalone mobile sensors and corresponding vertically built services in a variety of domains [10], [11], [12], [13]. Such services have demonstrated market readiness for sensor-centric services, but suffer from the inability to share data with each other to build richer and more novel services. As an example, a diabetic who is trying to modulate his activity to best maintain his insulin levels and uses a pedometer and glucometer regularly, has to correlate data collected by these sensors manually. A few early platforms are emerging to address the cross-sensor data sharing problem, but typically have no support for real-time data collection and synchronization of continuous data streams, and for real-time

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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], [17], [18], [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 of the universal village 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 the “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 II, we provide detailed specifications about the capabilities of our platform. Sections III through VI each describe a single application built on top of the platform, and the corresponding experiential touchpoints for the user. Section VII discusses the themes and paradigm shifts enabled by our platform, aligned with and contributing to the infrastructure vision for the universal village. In addition, it outlines our ongoing and future work.

II. 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 Fig. 1.

A. Hardware

The current version of the Sprout hardware is based on a 600MHz ARM Cortex A8 CPU with 512MB RAM. The entire software stack is run off an SD card, which also stores all sensor data. The Sprout has support for Bluetooth 2.1, 802.11g WiFi, and Texas Instruments’ low-power SimplexTI RF. The wireless protocol support allows for the integration of compatible wireless sensors. The Sprout also has support for wired sensors, through 3 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]. The current Sprout is 70mm x 55mm and houses a 10Wh cylindrical battery.

Why did we build our own hardware platform? The answer lies in the limitations of past and current mobile platforms. In order 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 several 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 on general purpose mobile devices is a limiting factor, and having specialized hardware allowed us to support a longer battery life when the Sprout is 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 BLE (Bluetooth Low Energy) [21]. Accordingly, in our next iteration of the Sprout hardware, we have chosen to forego the USB ports entirely and provide support for BLE.

B. Software

The Sprout software stack is built on top of Linux; the current version is based on 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, the 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 API to application writers, providing 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 that wish to access and visualize the Sprout data in real-time. The 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 VI.

Last but not the least, the Sprout has support for real-time cloud synchronization, e.g., of bio-data to cloud-based EMRs (electronic medical records).

III. REAL-TIME REMOTE MONITORING

Given the ability of the Sprout to talk to a variety of sensors, and its real-time cloud capabilities, it is quite straightforward to deploy it for remote monitoring applications. We have integrated the Sprout as a data collection, storage, and forwarding device into a cloud-based PHR (personal health record) system. This PHR is developed and maintained by Jardogs Inc., a subsidiary of Springfield Clinic in the state of Illinois in the U.S. The PHR then connects to various EMRs where the patient’s data can be accessed by the hospital’s care teams. This is just one example of a PHR which could be used.
with the Sprout. The flexibility of the Sprout platform allows for the possibility of transmitting data to other cloud based PHRs and EMRs.

We carried out a test deployment of this system with 9 users over a 3 week period. All users had PHR accounts, and were instructed to measure the following on a daily basis: 1) weight, once in the morning and once in the evening, 2) blood pressure, three times a day, and 3) a three minute reading from a pulse oximeter device [22]. All users were given Sprout sets that were pre-paired with their set of sensors (blood pressure cuff, weight scale, and pulse ox).

As depicted in Fig. 2, the simple act of a user getting on a weight scale to take a reading would automatically send the reading to the Sprout, which would then forward it to the cloud-based PHR. The cloud-based PHR could then be accessed through a web-based interface by the user or in general by his care team.

Users were generally positive when they reflected on the new insights into their personal health this technology provided. As expected, no fuss recording of vital signs made users more aware of health conditions. In some cases this prompted changes in behavior; we quote:

- “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 the Sprout I had to conclude without ambiguity that my blood pressure was high and that my health will continue to degrade in the absence of change. 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 from this test deployment provided suggestions for new features and improvements which are being incorporated into the newest generation of Sprout hardware and software [23].

IV. REAL-TIME STRESS ANALYTIC

While the Sprout can be used as a store and forward platform as described in the previous section, it is at its heart a computation platform and has been designed to support real-time analysis of high-frequency time series input. An example of such real-time computation is provided by implementing stress algorithms on the platform, which take as input a high-frequency bio-marker data stream, and output a continuous data stream of instantaneous stress values. In this section, we will describe the use of the platform in implementing a mobile real-time stress analytic.

Stress is a psychophysiological phenomenon. In other words, independent of the cause of stress, 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 effect of these mechanisms can be directly seen in changes to 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 implement various mathematical models of heart rate variability (HRV), and they all typically require as input a continuous interbeat interval stream. We integrated the Zephyr BioHarness chest strap sensor into the Sprout platform, which transmits various bio-variables over Bluetooth in real-time to the Sprout [24]. In particular, the Zephyr sensor computes an electrocardiograph (ECG) sampled at 250Hz, as well as an “R2R” data stream. The R2R data stream is a sequence of time differences between successive R-wave peaks in the ECG [25]. This data stream therefore provides us with the interbeat interval stream that can be used as input to various algorithmic models for stress.

We started by implementing various existing time domain and frequency domain algorithms on the Sprout platform. On the current hardware, these run as C programs that utilize the Sprout backend data access and storage APIs. However, we found that all state of the art methods are susceptible to noise that typically shows up in ambulatory settings, but are relatively robust when interbeat intervals are captured in a static setting. Also, state of the art methods don't work well for people across different disease states, e.g., diabetes, hypertension, cardiovascular disease, etc.

Given these limitations of existing state-of-the-art HRV measures, we designed our own HRV measure. While description of our HRV measure is beyond the scope of this paper, we have found that this measure is robust to noise, and works well uniformly across a whole range of disease states. The measure has been validated quantitatively on a study of 250+ subjects with different disease states, as well as in a qualitative study which 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.

V. 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, blood sugar levels, etc. as well as environmental variables such as location, calendar events, desktop and mobile device activity, etc. Because all 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 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 during his drive to and from work. A Sprout device was present in the car, which computed and stored real-time stress using the Zephyr data as input. In addition, a software sensor running on an iPhone4S in the car sent a continuous GPS data stream collected at about 1Hz to the Sprout during the drives.

After the drives, the stress and GPS data was exported from the Sprout and the GPS Visualizer web service [26] was used to generate interactive maps of the two drives. The data export process quantizes the two data streams such that we end up with one pair of GPS and stress value for each time quantum. For these experiments, the time quantum was set to one second. Each colored dot on the map represents one GPS data point during the drive. The color of the dot corresponds to the user’s stress value for the corresponding time quantum. Cooler colors, like green, represent lower stress, while warmer colors, like yellow and red, represent correspondingly higher levels of stress.

Fig. 3 shows a map of one of these drives. In this case, the user is returning from work in Sunnyvale to his home in San Francisco during the late evening. (San Francisco is on the top left of the figure and Sunnyvale is at the bottom right.) The visualization makes it clear that during the first third of the drive, stress levels are still moderately high but are trending downwards. The second half of the drive is markedly more relaxed.

Fig. 4 shows the same drive in reverse, the next morning, on the way to work. The stress levels here are markedly different, with many red, dark red, and yellow dots spread out all over the map. Both drives were carried out at times when there were no traffic slowdowns during the route.

In both cases, the data reveals very personal patterns of stress which held up during multiple drives carried out for the same user over other days. The user’s subjective interpretation of these patterns was that he was starting to think about work as soon as the drive to work started, which was sometimes also interspersed with work calls. On the way back, there was a mental “cool down” period where the day was being processed and put aside. The user was aware that thinking about potential stressors alone triggers the body’s stress response even in the absence 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 user, who was unaware of it prior to the experiment. The data brought the user 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 may be shared with the car’s navigational and communication and media systems allowing them to incorporate a sensitivity to the user’s bi-state.

VI. CONTINUOUS DAYTIME MONITORING & GUIDANCE

Many of us spend a significant portion of our work days in a sedentary manner, with several attendant health risks. Apart from the longer term risks of being sedentary to cardiovascular health [28], such work patterns are also costly in terms of short to long-term musculoskeletal health. Back and neck pain related costs 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.

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 monitor [30] for the first week that allowed 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 chest strap during their work day. The Zephyr captures other data streams beyond the cardiac ones described in Section IV, including breathing and activity. Each participant was given a tablet with a custom display that reported their heart rate, breathing rate, and activity levels as sensed by the Zephyr, and 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 reporting stress calculated over the last two minutes and over the last hour, respectively. Fig. 5 shows the display as it was rendered for the participants; during the course of the study, the values would update every second. Each participant placed the tablet in a visually accessible area of their work space.

At the end of the 5 day period, each participant underwent a “data counseling” session, where we looked at their bi- variable patterns over the course of the week. Fig. 6 is an example of a visualization used in the course of that session. Like the tablet visualization, it is a web page that is hosted on the Apache web server running on the Sprout. This particular visualization application consists of a series of panels, each of which can be set to any sensor stream. Fig. 6 shows three panels, the first one showing the ECG signal, the second one showing the computed heart rate as it changes with time, and the third one showing the two stress values. Each panel can be customized in various ways, for example in terms of how the data is visualized (line vs. bar, say) or in terms of the time scale shown on the visible part of the panel. All panels are time synchronized on the far right side of the display. So, for example, dragging any of the panels in Fig. 6 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 by itself is not a harmful thing. We all respond to many stimuli during each day, and the body’s stress response mechanisms allow 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 plaguing the world today. An example of a chronic stress pattern can be seen in the bottom panel of Fig. 6; our platform can identify such patterns automatically.

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

**Figure 6: Live Time Series Display**

**VII. CONCLUSIONS AND FUTURE WORK**

The ubiquity of connected sensors and continuous analytics will redefine our everyday interactions with the infrastructure we live within. A platform like the Sprout – which has been designed for the real-time storage and analysis of multiple data streams – allows us to analyze each of those data streams using the context provided by the others. When these streams include bio-marker data, we are left with a richer awareness and understanding of our 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 bio-marker 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 ourselves become increasingly quantified, it becomes possible to quantify the communities that we are part of as well. Our experiences deploying the applications reported on in this paper have consistently confirmed the power of the 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 platform side, we are working on a newer version of the 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 are currently exploring a port of the software system to selected mobile platforms. We look forward to sharing our work in these areas with the community in the near future.
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IX. WORKS CITED


