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Development of SmartStep: an insole-based physical activity monitor

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Abstract— **In our previous research we developed a SmartShoe – a shoe based physical activity monitor that can reliably differentiate between major postures and activities, accurately estimate energy expenditure of individuals, measure temporal gait parameters, and estimate body weights. In this paper we present the development of the next stage of the SmartShoe evolution – SmartStep, a physical activity monitor that is fully integrated into an insole, maximizing convenience and social acceptance of the monitor. Encapsulating the sensors, Bluetooth Low Energy wireless interface and the energy source within an assembly repeatedly loaded with high forces created during ambulation presented new design challenges. In this preliminary study we tested the ability of the SmartStep to measure the pressure differences between static weight-bearing and non-weight-bearing activities (such as no load vs. sitting vs. standing) as well as capture pressure variations during walking. We also measured long-term stability of the sensors and insole assembly under cyclic loading in a mechanical testing system.**

I. Introduction

Physical Activity (PA) and Energy Expenditure (EE) monitoring is used in many research and clinical applications.

One application that heavily relies on monitoring of PA and EE of individuals in their community (free-living) environment is the study of obesity. Obesity, or excessive body fat, have been linked with low levels of physical activity and sedentary lifestyles [1]. Study of sedentary behavior and physiology of inactivity [2] demands physical activity monitors that not only are capable of quantifying the gross amount of PA and EE, but also accurately differentiate and quantify sedentary behaviors, that remains a challenge for many common types of PA monitors.

Monitoring of PA also has extensive applications in post-stroke rehabilitation. Individuals after a stroke are typically much less active than healthy individuals [3]. One of the significant challenges for many stroke survivors is regaining ability to walk and increasing the levels of physical activity and community participation. Failure to improve PA levels leads to further deconditioning, which in turn plays a role in the development of secondary complications and an increased dependence in activities of daily living [4]. Thus, the effectiveness of the post-stroke rehabilitation may be gauged by continuous monitoring of PA.

Historically, single accelerometer based PA and EE monitors have been popularly used as monitoring tools [5], [6]. Since the accelerometry is fundamentally based on measurement of motion, it is not very accurate in recognition of sedentary postures (e.g. sitting) or differentiation of weight-bearing and non-weight bearing activities (e.g. cycling vs. walking). Such monitors typically are not very accurate in estimation of EE and fail to explain a considerable portion of energy expenditure variability in daily living tasks.

A commonly utilized approach to improve accuracy of PA and EE measurement is to use multiple sensors, typically distributed on the body of the user. As an example, 6 body locations (ankle, hip, thigh, upper arm and wrist) were used in [7], while [8] utilized 9 sensor locations. While the accuracy of PA recognition is improved by such multi-sensor systems, they present a high burden to users and have limited practical applicability restricted to research studies.

The wear burden is reduced in PA monitors that combine sensors in a single location. For example, the PA monitor described in [9] included 8 different sensors: accelerometer, audio, light, high-frequency light, barometric pressure, humidity, temperature, and compass. However, most multi-sensor, single location monitors experience challenges in recognizing and quantifying sedentary behaviors and differentiation of weight-bearing and non-weight-bearing activities.

Our proposed solution to the challenge of accurate PA monitoring from a single, unobtrusive location on the body has been a development of a shoe-based physical activity monitor (SmartShoe) that combines pressure transducers and an accelerometer for reliable recognition of postures and activities. Shoe sensors have been previously used to characterize gait of individuals [10], [11] but with a few exceptions [12]-[13] have not been extensively used in PA and EE monitoring. The past studies conducted on SmartShoe platform demonstrated accurate (98%) classification of the six major postures and activities [14], including reliable recognition of sedentary postures and differentiation between weight-bearing and non-weight-bearing activities. SmartShoe monitor was equally effective in monitoring of PA in individuals recovering after a stroke [15], [16] achieving 95% accuracy in classifying sitting, standing, and walking activities. Use of activity-branched prediction models in EE estimation by SmartShoe allowed to achieve high accuracy of measuring energy expenditure [17]. SmartShoe has also been used to accurately capture temporal gait parameters of healthy and post-stroke individuals [18] and estimate the body weights of SmartShoe

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users [19].

These results demonstrated feasibility, reproducibility, and validity of PA and EE monitoring with the SmartShoe. However, a typical limitation of the various generations of the SmartShoe monitors was the need to either modify the shoe or attach a small clip-on to the shoe to accommodate the sensors and wireless electronics. In this paper we present a development of the next stage of the SmartShoe evolution – SmartStep, a physical activity monitor that is fully integrated into an insole, maximizing convenience, applicability, and social acceptance of the monitor.

II. Sensor System

A. Wearable sensor system

The SmartShoe [20] utilizes a flexible insole inserted with pressure sensors and a small enclosure with an accelerometer, a processor and a Bluetooth link to a smart phone. Transitioning from original SmartShoe to an insole-based monitor presents several challenges. First, the size of the electronics needs to be dramatically decreased, so that the electronic board can be integrated into the space available under the arch of the foot. Second, the power consumption of the electronics has to be significantly reduced to decrease the capacity and size of the battery needed to power the electronics. Third, the sensors, electronics and the battery need to be integrated into an assembly that is repeatedly loaded with high forces during ambulation.

A prototype of the SmartStep monitor attempting to address these challenges is shown in Figure 1. The whole assembly is based on flexible FR4 printed circuit board. Three pressure sensors (12.5mm FSR402, Interlink Electronics) are located under biomechanically important support points: the heel, the 1st metatarsal head, and the big toe. The electronic assembly integrating a 3D accelerometer, flash memory and a Bluetooth Low Energy micro assembly is encapsulated in epoxy resin under the arch of the foot, where forces developed during ambulation are minimal. The whole assembly is encapsulated in urethane rubber for cushioning and protection. The insole weighs 71 g in total.

The block-diagram of the SmartStep monitor is shown in Figure 2. There are three major components in the system: the insole hardware, the insole software containing a custom profile of Bluetooth Low Energy, and the phone software permitting data collection from the SmartStep. The following is a detailed description of each component.

B. Electronic Hardware

The 0.8 mm thick, 4 layer PCB is 24 mm x 19 mm in size. The fully assembled board together with the battery weighs 4g. The embedded system hardware is comprised of BR-LE4.0-S2A Bluetooth Low Energy (BTLE) module, a three-dimensional accelerometer (ADXL 346), power management circuitry, pressure sensor interface, AT25DF641 flash and ML2020 45 mAh rechargeable Lithium battery.

BTLE is used for transferring small, infrequent packets of data and achieving the lowest possible power

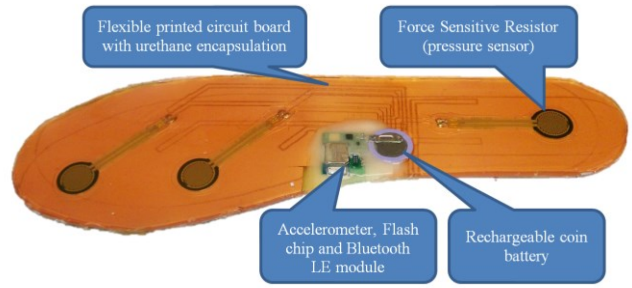

Figure 1. SmartStep insole monitor (men's size US 9). For illustration purposes the monitor is shown without the foam padding on top.

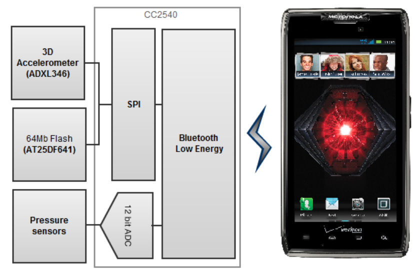

Figure 2. The block-diagram of the SmartStep.

consumption. Smart step is based on Blueradios BR-LE4.0-S2A BTLE module, which utilizes Texas Instrument's CC2540 System-On-Chip, and has a foot print of 11.8 mm x 17.6 mm. In BTLE, the data transmission happens in 'connection events' lasting for ~2.8 ms or longer with the peak current consumption on the order of 30mA.The processor remains in the sleep mode a majority of the time, other than during sensor read events. The SmartStep insole monitor communicates with Motorola Razr smart phone (running Android 2.3.4) over BTLE and the smart phone logs the data.

C. Firmware

All the wireless communication is handled by the BTLE stack from Texas Instruments. The stack makes sure that the processing core enters appropriate sleep modes when the processor is not reading sensors or not transmitting data during connection events. Generic Attribute Profile (GATT) is used and extended to suit our needs. In GATT, the server (SmartStep) has defined services with 16 bit Universally Unique Identifiers (UUIDs). These services can contain multiple characteristics which can expose their attributes as readable/writable/notifiable to the client (phone or computer). Enabling notification on a characteristic is a way to get periodic data over BTLE which is essential for SmartStep to communicate with the client. The SmartStep notifies the client of a characteristic value. The client does not need to prompt the SmartStep for the data, nor need to send any response when a notification is received, but it must first configure the characteristic to enable notifications. The profile used defines when the SmartStep is supposed to send the data. The SmartStep has a 'send data' characteristic which is exposed as notifiable to the client.

The firmware is also responsible for reading signals of the accelerometer and pressure sensors. The periodic event timer provided by TI BTLE stack is used to generate 'sensor read' events every 40 ms and 'set notification' event every 120 ms. Upon each sensor read event, three axes of accelerometer are read with 8 bit resolution through the SPI interface. Next, the pressure sensors are supplied with power and ADC measurements are taken with 8-bit resolution. Three consecutive measurements of accelerometer and pressure sensors were buffered in an 18 byte array. Connection interval of 250ms is used, so that 2 sets of notifications are sent together to save energy on establishing a wireless connection.

D. Phone software

An Android application for the Motorola RAZR is developed to log data transmitted by the SmartStep. At the time of the development of this work, BTLE is still not standardized by Android Community. We used the Motorola BTLE API's to develop our Android application [22]. The phone application can connect to a BTLE server (SmartStep), determine the characteristics available from the server and read/write data to them, enable notification, collect periodic data, save them to a file in CSV format, and disconnect from the server.

III. Methods

Three tests were performed on the SmartStep monitor:

A. Power consumption test

To measure real-life energy consumption of the SmartStep monitor and to estimate expected battery life of the wearable insole, a power consumption test was conducted. The power consumption by the SmartStep depends on the number of sensors being read at the same time and state of the BTLE stack. Average current consumption for the connection events and during sensor read events were calculated from the oscilloscope trace, which had the voltage waveforms across a 10 Ω resistor in series with the battery.

B. Static and dynamic human subject tests

To demonstrate ability of the pressure sensors in the SmarStep register variations in pressure levels during static (not wearing the shoes, sitting, standing) and dynamic (walking) activities, a single healthy individual with the shoe size equal to the size of the manufactured SmartStep insole (US M9) wore the monitor while performing transitions from no load, to sitting, to standing, to walking and in the reverse sequence back to no loading. The sensor signals were wirelessly captured and analyzed for relative changes in comparison to no load condition.

C. Cyclic loading test

The cyclic loading test assessed durability of the SmartStep assembly under cyclic loading conditions typical of normal gait. MTS 810 uniaxial servo hydraulic test frame with Flextest SE controller was used to perform the cyclic loading test over the full area of the insole monitor (Figure 3). The insole was tested with a 2 Hz sine wave loading profile. The amplitude was 350 N and a mean load –325 N, which results in a R-ratio (Pmin/Pmax) of 0.3, while Pmax = -500 N and Pmin = -150 N. The test ran for 36 hours with a total of 262,900 cycles. The sensor readings were captured over BTLE and the percentage changes in readings over time were calculated to understand the drift in sensor readings.

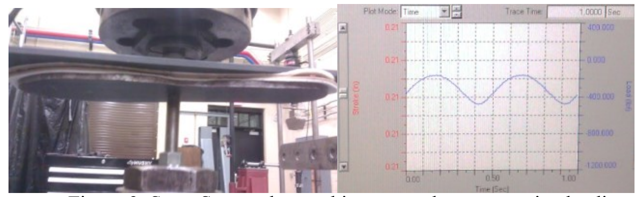

Figure 3. SmartStep under machine test and representative loading profile for cyclic loading test with 2Hz sine wave profile

IV. Results

A. Power consumption test

Figure 4 shows the scope trace during the wireless connection events (occurring at 4 Hz rate) and during sensor reads (25 Hz). The average current consumed during 4.2ms long connection events is calculated to be 12.71 mA and for 1.6ms long pressure sensor read events it is 10 mA. The average current consumption during the device is in connected state (for 1 s) is 0.61 mA (CC2540 sleep current is 1 uA) translating into the expected battery life of 73.3 Hrs.

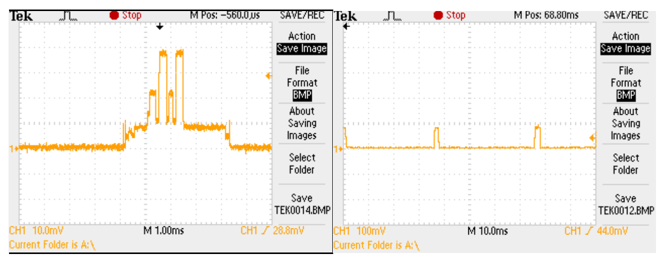

Figure 4. Oscilloscope traces of connection events (left) and sensor reads (right).

B. Static and dynamic human subject tests

Figure 5 shows sensor signal traces for the activity transitions captured by the heel sensor, demonstrating observable response to each posture and activity. Table I shows the relative percentage change in sensor reading for the different loading conditions.

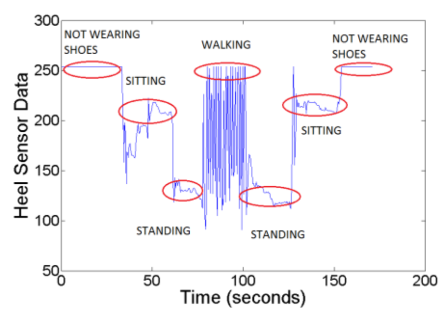

Figure 5. Activities of not wearing the shoes, sitting, standing, walking monitored with heel sensor (top graph).

TABLE I. RELATIVE CHANGE IN SENSOR READING

	Sitting to No Load, %	Standing to No Load, %	Walking to No Load, %
Heel Sensor	17	48	56
Toe Sensor	8	40	60

C. Cyclic loading test

Figure 6 demonstrates the signal waveforms obtained from the pressure sensor in the metatarsal head position.

After 5 hours of the test there was a 6% drift and after 36 hours there was 13% drift in sensor readings to that of initial test respectively.

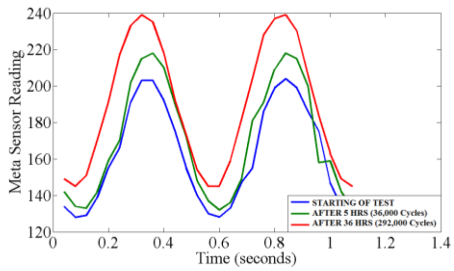

Figure 6. FSR signal after 0, 5 and 36 hours of loading.

V. DISCUSSIONS

This paper described the development and initial tests of the SmartStep – an insole based physical activity monitor with Bluetooth Low Energy. The power tests demonstrate power consumption two orders of magnitude lower than that of regular Bluetooth (0.61 mA vs. 40 mA @2.5 V) in the original SmartShoe monitor. Such low power consumption enables miniaturization of the electronics within the insole, while enabling continuous operation for multiple days on a single charge. With expected wear of approximately 12hrs per day, the expected battery life is more than 6 days of continuous wearing between recharges.

Static and dynamic tests on a human subject, demonstrated the abilities of the monitor to differentiate between no load, sitting, standing, and walking conditions. The observed difference in pressure levels is not only sufficient for the computer recognition of physical activity and the classification of weight-bearing and non-weight-bearing activities but could also be used for the compliance checking (to determine whether the person is wearing the monitor) and automatic powering on/off of the device.

Cyclic loading test on MTS demonstrate acceptable (13%) levels of pressure sensor drift over the time period equivalent to 23-46 days of continuous wearing (based on estimates of 5,000-10,000 steps per day). Finally, a practical data collection system has been created by logging the sensor data acquired by the SmartStep on an Android smart phone. Future tests of SmartStep will focus on durability of the sensor assembly under realistic loads of everyday wear.

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