Manuscript

Ambient and Wearable computing

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Abstract
As computers emerge from the desktop and palm top into everyday life, and on to our bodies there are opportunities to aggregate and present data and to realize and envision applications that have never before been possible. Tracking the physiological state of individuals, at resolutions measured in thousandths of a second instead of in visits per year, now makes it possible to ascertain caloric intake and expenditure, patterns of sleep, contextual activities such as working-out and driving, even parameters of mental state and health. An award wining multi-channel wearable physiological sensor has enabled the collection of data in natural settings from thousands of subjects engaged in diverse activities. The resulting corpus of physiological data from 5 years of aggregation has yielded over 30 million minutes of physiological data. Data modeling efforts are resulting in applications that enable real-time presentation of meaningful and actionable information to users and their designated collaborators (physicians, family members, counselors, coaches, etc.) The SenseWear system, its design and a summary of the experimental results and ongoing research initiatives will be presented. This discussion will show how the design and research efforts of ubiquitous, pervasive, and collaborative computing are converging to manifest the future of computing as: wearable, personal, and sympathetic.

1. Introduction

In retrospect, it seems like few things were more certain in the evolution of computing than that computers would become smaller, cheaper, more sophisticated, and more personal (Weisner, 1993; Weisner and Brown, 1996;Moore, 1965). This has culminated today in the explosion of handhelds (mobile phones, iPods, gameboys, digital cameras, PDAs, etc.) as the new computing platform—cheaper and more sophisticated enabling smaller and more personal interactions. This has been the core of pervasive and ubiquitous computing. But how could computing become smaller *and* more personal? Answer: it is becoming wearable. By making computing intimate to the body these devices can better know our states of mind, our contexts, our states of health, etc. and respond (or have other aspects of the environment respond) in intelligent ways. These responses that know our goals and strive to act, by themselves in concert with other devices, on our behalf are sympathetic products; they can act as symbiotic and persuasive agents (Fogg, 2002; Khaslavsky and Shedroff, 1999). They are driven by computers worn on the body, and are emerging as a new paradigm of wearable physiological computing.

There are already many wearable body monitors today. Watches with ambient temperature sensors and glucose monitors, heart straps for joggers, pedometers for dieters, etc. (e.g. LifeShirt, Wilhelm et al., 2004; Fitsense, 2004; PolarUsa, 2004; Glucon 2005). There are clinical body monitors your doctor can prescribe and your nurse can administer such as holter monitors and ambulatory blood pressure cuffs. These devices are becoming wireless and less dependent on professionals for their application. More and more they are providing the means to transmit information back to caregivers quickly and seamlessly. So is that it? No. The killer applications are just starting to emerge; applications from weight management to fitness to disease management. But the critical element in all of these areas is the interpretation and presentation of the data.

Wearable body monitoring goes from delivering potentially interesting data to delivering life altering information when it does enough of the data analysis to provide consumable, actionable nuggets of body knowledge automatically to wearers and their overseers. This is the difference between the sheet music and the violin concerto, the difference between the haystack and the needle. In that sense the future of wearable body monitoring will be a story about data and data analysis, as much as it will be a story about form factors and size reduction. The physical monitors are conduits to these distilled facts about our bodies, not the value in and of themselves, just as mobile phones are the conduits for wireless spoken communication between people. But even more than portability for mobile phones, wearability is a requirement for physiological sensors. If you can't stand wearing it, you won't wear it. And that means that the constraints of wearability in the most physical and practical sense, the constraints of where sensors can gather useful information on the human body, and the constraints of wearability, sociology and fashion all need be attended to for this vision to be realized. Fundamentally that means that the lines between design (industrial, mechanical, product, communication) and traditional engineering (e.g. electrical engineering, software engineering, biomedical sensors, and data modeling) will continue to blur as the ubiquitous, pervasive, and collaborative computing revolutions manifest a future of computing that is wearable, personal, and sympathetic.

This paper will discuss the design and ongoing research of the SenseWear system and emerging wearable physiological applications. The first sections will describe the sensors, hardware, software and the design parameters and capabilities that enable the tracking of multiple channels of physiology at resolutions up to 32 Hz, in natural settings, for extended time periods, with high degrees of comfort. The sociological challenges of introducing physiological devices and new models of human health metrics to medical research and to consumers will be discussed. This will be followed by an introduction to the data-mining classification efforts and the current limitations. Finally, a promising and diverse array of research findings and ongoing initiatives will be summarized.

2. The system

The SenseWear Armband is a sensor hub worn on the back of the upper right arm (tricep area, Fig. 1) (Teller et al., 2003). It enables continuous collection of low-level physiological vital sign streams and derives from those accurate statements of human body states and behaviors. The device contains five different sensors: 2-axis accelerometer, heat flux, galvanic skin response, skin temperature, and near-body ambient temperature. (Fig. 2) The unit also acts as a receiver for standard heart rate monitors and can communicate wirelessly with scales, blood pressure cuffs, and other medical systems. It can transmit collected sensor data with 916 MHz wireless body-LAN connectivity to a wireless communicator unit with <1 mW power output. The armband is made of flexible ABS, attaches with an elastic Velcro strap (custom designed to have stretch, air/water permeability, and hypoallergenic properties so as to mimic the skin to the greatest extent possible), weighs less than 3 oz., stores 14 days of continuous body data and has enough power for 14 days of continuous wear from a single AAA battery. Using a MSP chip from Texas Instruments it transforms the raw physiological data such as movement, heat flux, skin temperature, near-body ambient temperature, and galvanic skin response into snapshots of the user's lifestyle. The lifestyle data that can be obtained includes energy expenditure, physical activity, step counting, lying down, driving sessions, and sleep/awake state. For example, the monitor infers sleep, primarily from temperature and motion readings, but uses all of the five available sensors at least some of the time to make this determination. Composite data from multiple sensors likewise indicate exercising and even driving. Eventually, it may be possible to capture TV watching, eating, and other behaviors. BodyMedia has

Fig. 1. SenseWear Armband on arm.

active research in new derived body states such as stress, hydration level, and timing of the ovulation cycle. Currently, the manual time-stamp button allows users to mark these and other events that the monitor cannot yet distinguish automatically. This marking also provides annotated data labeling for use in data mining.

2.1. The sensors

Accelerometer. The accelerometer in the Armband is a 2-axis micro-electromechanical sensor (MEMS) device that measures motion. The motion can be mapped to forces exerted on the body and hence energy expenditure. By taking into account gravity, our algorithms can also predict the context in which the Armband is being worn.

Heat flux. The proprietary heat flux sensor in the Armband is a robust and reliable device that measures the amount of heat being dissipated by the body. The sensor uses very low thermally resistant materials and extremely sensitive thermocouple arrays. It is placed in a thermally conductive path between the skin and the side of the armband

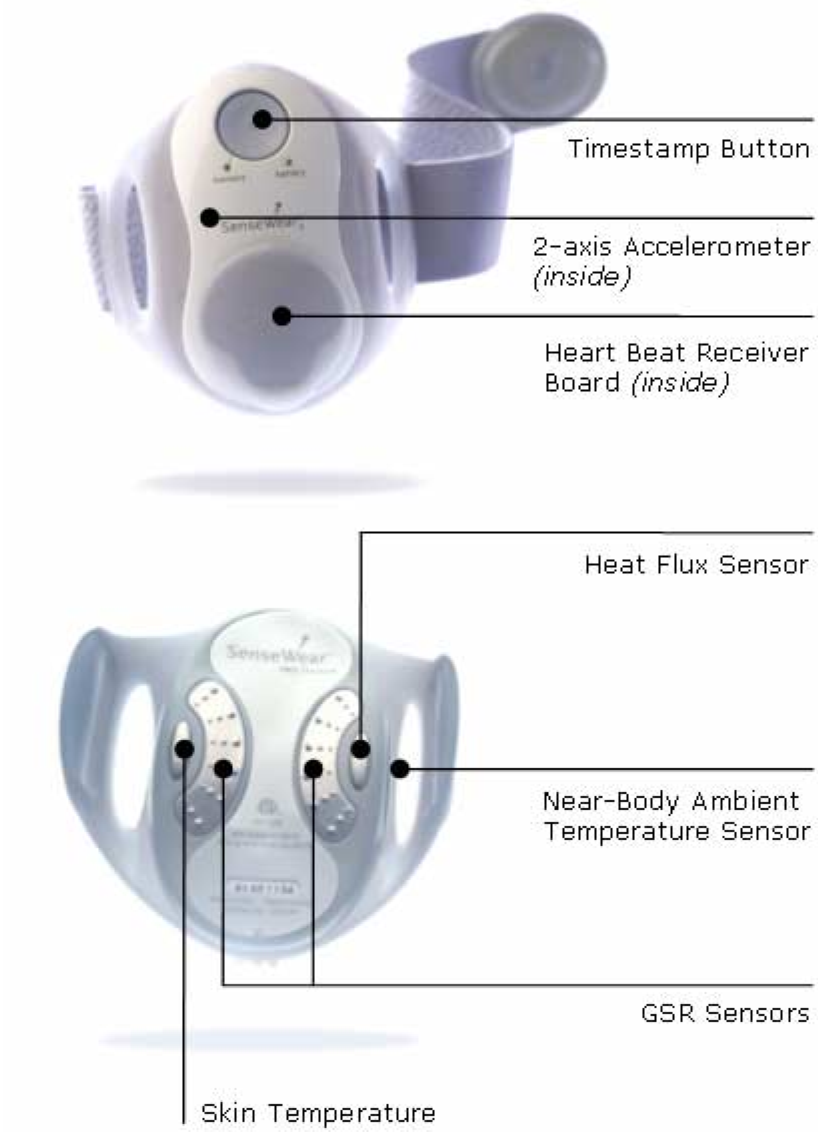


Fig. 2. SenseWear Armband front with time stamp button, and back showing sensor interface.

exposed to the environment. A high gain internal amplifier is used to bring the signal to a level that can be sampled by the microprocessor located in the Armband.

Galvanic skin response. Galvanic Skin Response (GSR) represents electrical conductivity between two points on the wearer's arm. The Armband's GSR sensor includes two hypo-allergenic stainless steel electrodes integrated into the underside of the armband connected to a circuit that measures the skin's conductivity between these two electrodes. Skin conductivity is affected by the sweat from physical activity and by emotional stimuli. GSR can be used as an indicator of evaporative heat loss by identifying the onset, peak, and recovery of maximal sweat rates.

Skin temperature. Skin temperature is measured using a highly accurate thermistorbased sensor located on the backside of the Armband near its edges and in contact with the skin. Continuously measured skin temperature is linearly reflective of the body's core temperature activities.

Near-body temperature. The near-body temperature sensor measures the temperature of the cover on the side of the Armband. The use of these sensors in conjunction with simple body measurements (gender, age, height, weight, handedness, and smoker/non-smoker) allow for accurate calculations of a wide range of higher level body state information.

Each sensor is monitored 32 times per second, and data is tracked over a period of time (typically a minute but this can be adjusted through software). Currently, 41 different features of this multi-dimensional raw data stream are gathered as separate channels. For example, the variance of the heat flux is a channel, as is the average of the heat flux values. Some channels are fairly standard features (e.g. standard deviation) and others are customized. Then typically, these summary features for the epoch are stored and the raw data discarded to save memory. Again, dropping the raw data values can be avoided through a simple software switch.

Enclosed in a shock and splash proof thermoplastic housing, the monitor straps to the user's right upper arm, at 0.8 in. tall by 3.4 in. long and 2.1 in. wide, the housing squeezes under all but the tightest shirtsleeves with barely a bulge. Because it is wearable and unobtrusive, the Armband 'sees' people in the context of their natural daily activities rather than from the constrained viewpoint of the lab.

2.2. Wireless communicator and interface

The SenseWear system includes a wireless communicator as a separate device that can be used in conjunction with the Armband. It uses Radio Frequency (RF) to allow the Armband to wirelessly synch with a computer. The communicator's design allows it to be discretely connected to a computer without adding desktop clutter. BodyMedia's InnerView™ Wearer Software (Fig. 3) is a desktop application that enables users and researchers to retrieve and save lifestyle data from the armband, and then view and annotate it for further analysis. A simple summary page shows high-level information such as total energy expenditure (calories burned), number of steps (step counter), minutes of physical activity, how long the user was lying down, and duration of sleep. BodyMedia's InnerView™ Research Software (Fig. 4) is a similar application with much greater detail for research use. In addition, the software can

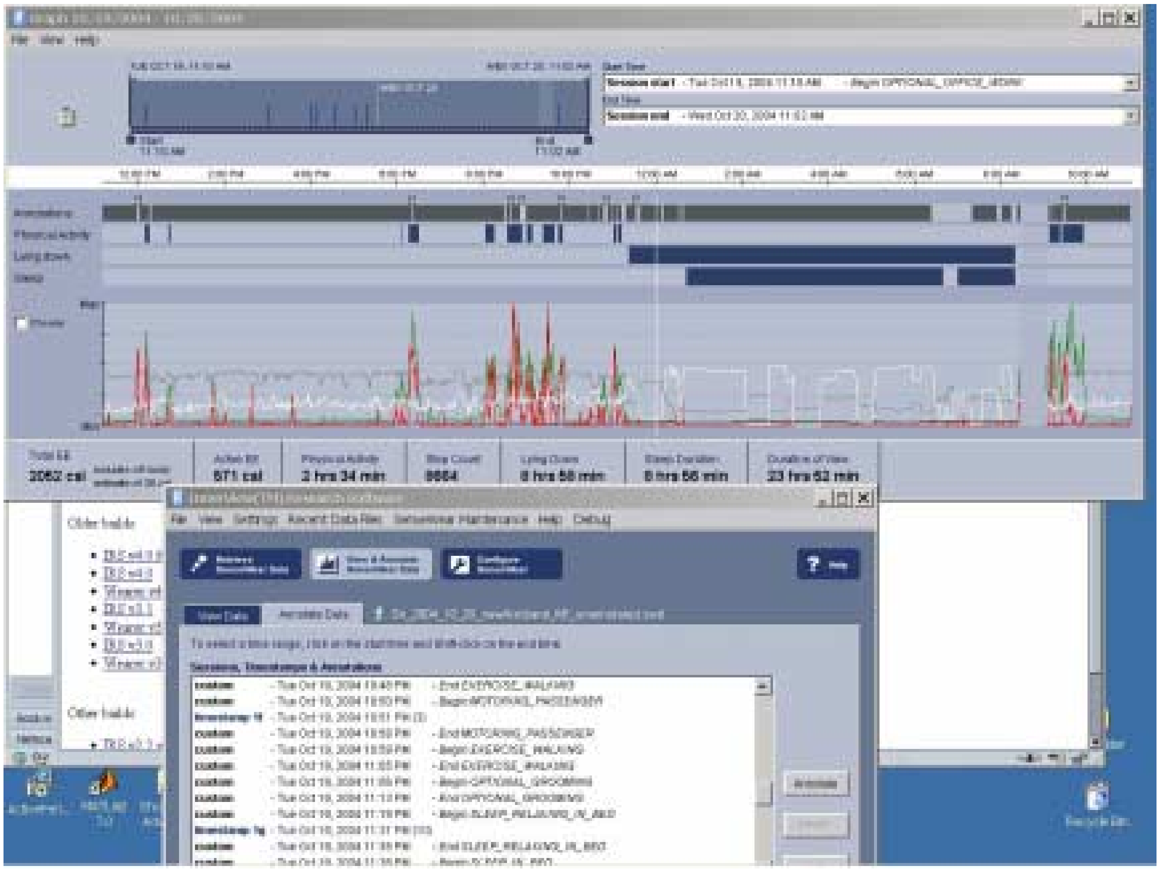


Fig. 3. InnerView™ researcher data visualization (48 h of continuous wear shown here).

Fig. 4. InnerView™ wearer software data visualization.

configure the sampling rates and duration of the 41 data collection channels on the armband. Each armband can be personalized to an individual user according to his needs for more accurate readings or longer recordings. Saved data can be exported for easy data analysis.

3. Designing a physiological computing device for everyday use

The design of a wearable physiological computing device is an effort in finding the synergy among competing criteria ranging from physiological accuracy to comfort, and mechanical engineering to social acceptability. The design of a product that is to be in continuous contact with the human body 24 hours a day is to design for an extreme environment. People carry all sorts of devices around with them every day, PDAs, cell phones, wallets, wrist watches, etc. BodyMedia first had to ask what makes people comfortable and then design all the electronics, sensors, and packaging around those human needs. Through the creation of a multi-channel, ergonomic and durable sensor hub individuals who would otherwise be tethered to machines are being granted greater freedom. For others, they opt to wear the device, though they would never have been suffered the annoyance and cost of a lab device, because the device provides them benefits worth the effort to wear it. In the development of SenseWear, BodyMedia prototyped a number of devices ranging from chest straps to smart rings. These prototypes and the development of the design criteria were informed by studies on wearable computing and medical devices such as those used for sleep apnea research, actigraphy measurements, the accuracy of accelerometers for energy expenditure measurements, and on materials such as elastic straps (Pittman et al., 2002; Surratt et al., 1996; Chun, 1999; Jakicic et al., 1998; Gemperle et al., 1998; Forlizzi and McCormack, 2000). The criteria for the SenseWear Armband included that it had to: accurately work for up to 2 weeks under continuous use (24/7); work during active athletic and work situations as well as during sleep; be manufacturable and robust enough to survive everyday use in low (0 ˚C) and high (45 ˚C) temperature environments; be small enough to keep the overall monitor height and footprint unobtrusive beneath clothing; be non-invasive and non-irritating to the skin and hypoallergenic; have low power consumption; and be cost effective.

To meet these objectives for the device the area of the body that the device would be worn had to be: similar in size and shape on men and women between the 5 and 95% size range; relatively large in surface area (at least 2 in. by 3 in.) to accommodate the required components, including batteries and electronics; low in mobility (non-bending or stretching even during high activity); and have a continuous circumference for easy attachment and detachment. Fig. 5 shows how the upper arm meets many of these criteria. It is unoccupied 'real estate', gender-neutral, least obtrusive and low number of collisions, a relatively soft area where a device can be worn comfortably, device weight in this area does not induce fatigue, it is concealed, and an adjustable strap accommodates a one size fits all design.

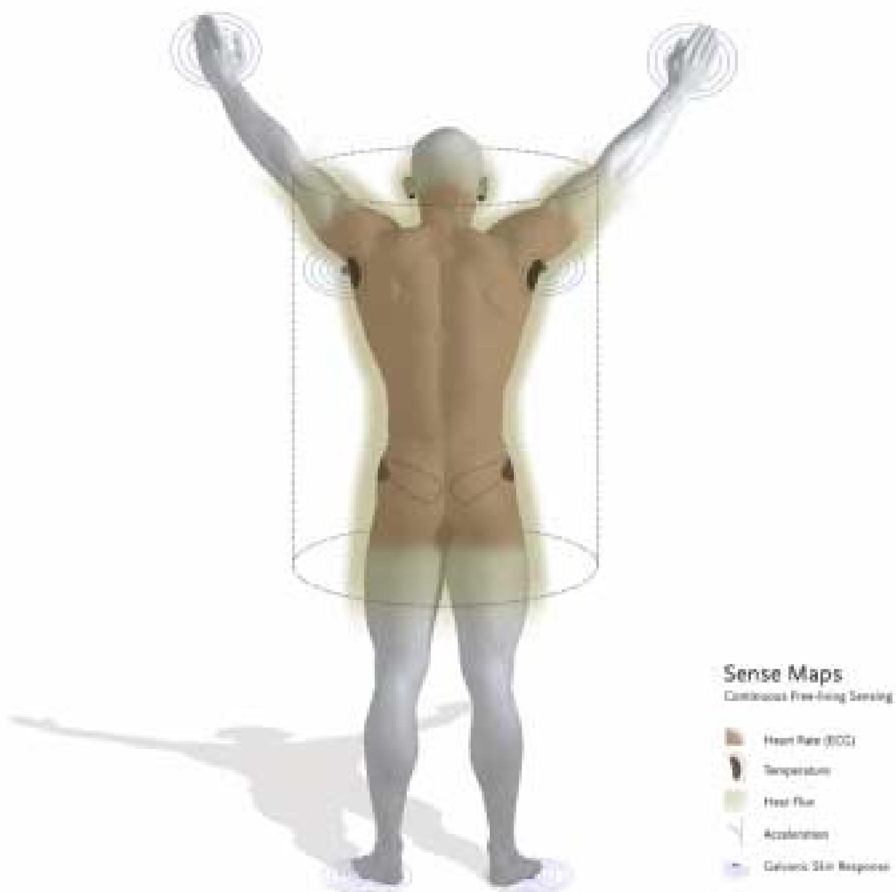
Many of the objectives were met through engineering novel design features. The symmetrical flexible wings stabilize the device, accommodate diverse arm sizes, and create sufficient pressure for the sensors to function. A proprietary hypoallergenic and non-latex elastic strap was developed for appropriate tension and repeatable attachment. Iterative user testing was conducted with hospital patients, football players, factory workers, rescue workers, firefighters, and the general public.

The goal in making this wearable device was actually to make it as invisible to the user as possible. Very comfortable, very easy to use, something that blends into your life so you forget it is there. In a case study, earlier this year, a high school student wearing the monitor for two weeks said, "You kind of get used to it and don't even know you're wearing it." (Spohn, 2004). Fig. 6 illustrates the amount of time users of the device wore it. That 83% of users wear it for more than 7 hours a day is a testament to the wearabilty of the device. To the extent that industry and commercial review is an indicator of reaching the goals for appropriate design, the SenseWear system has won several awards (IDEA, 2002; MEDA, 2004).

4. User interface

The thing that is really going to change society with respect to health care, wellness and fitness is the ability for people to start to learn about themselves. BodyMedia's design mantra is, 'make it fun and meaningful to see how you feel.' The BodyMedia platform creates a feedback loop: people want to manage their own health but until now, trying to do it was like dieting without a scale. The feedback loop is the presentation of actionable information that is otherwise unavailable to them (e.g. sleep/awake states each night down to a per minute basis if desired). This information allows people to assess progress toward their health goals. There are numerous applications that can be supported once data is being tracked. People could track elements of their health as closely as they track their financial portfolios. Having baseline data from an aggregate population and from individuals themselves, it is becoming possible to flag individual anomalies and detect potential health problems.

The armband interface is highly customizable. It can be programmed to beep or vibrate when calorie-burn targets are met or as a reminder to take medicine. It is a communications 'hub' collecting and transmitting data from multiple devices worn on the body, all toward the goal of keeping the wearer alert to danger signals and mindful of health necessities.


Sense Maps
Continuous Free-living Sensing
Heart Rate (ECG)
Temperature
Heat Flux
Acceleration
Galvanic Skin Response

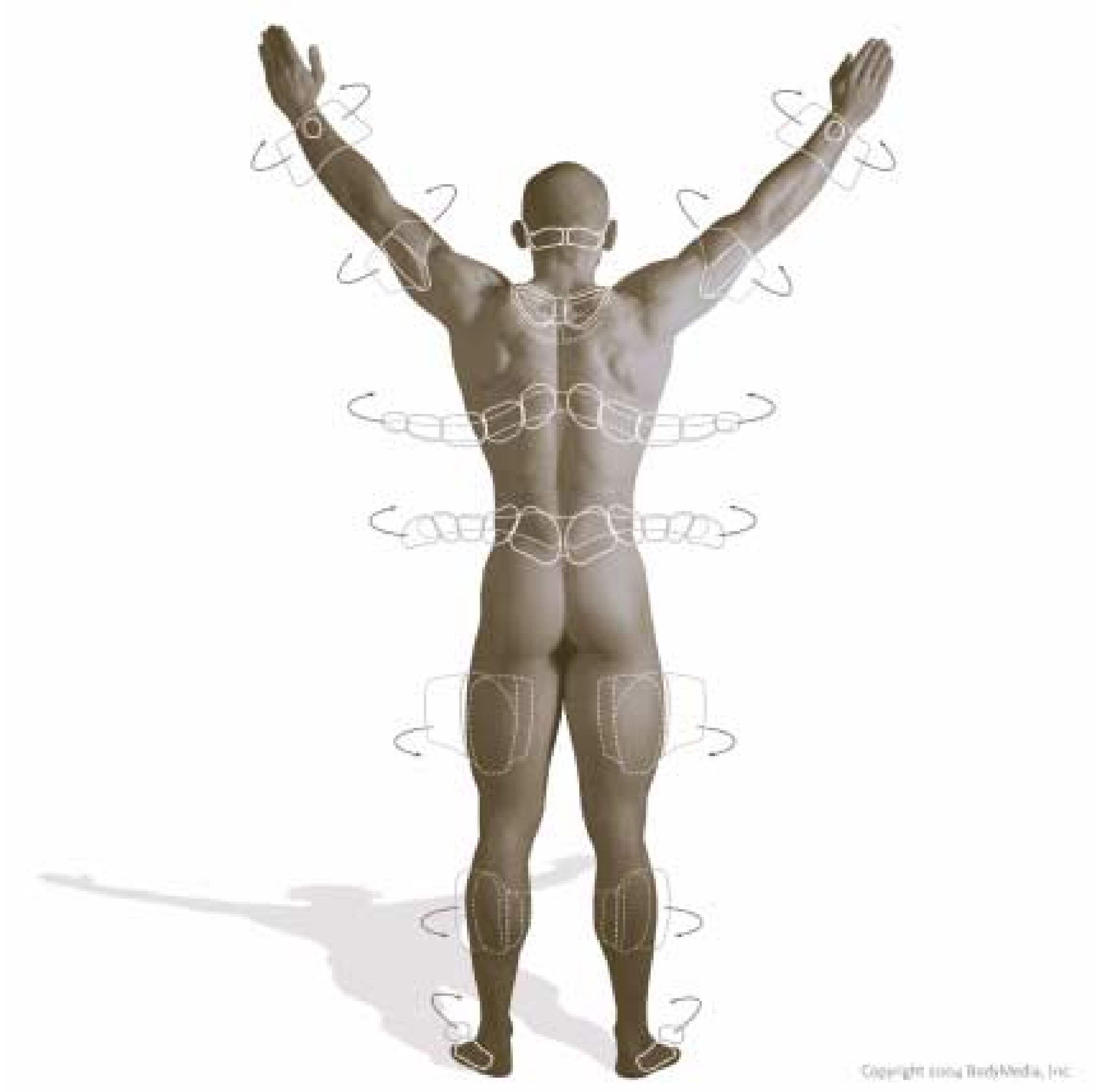


Fig. 5. Wearability maps for comfort, heat flow, GSR, acceleration, and SenseWear.

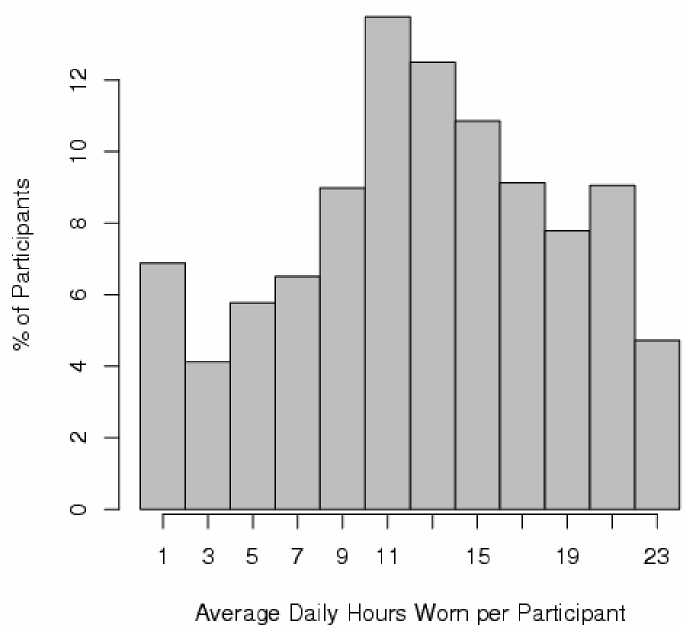


Fig. 6. Daily use patterns from one of Bodymedia's commercial products.

This system provides comprehensive, actionable feedback about a person's body and lifestyle that can be shared with researchers, physicians, dieticians and personal trainers via the Internet (Fig. 7). Internet applications allow consumers to enter additional data such as calories consumed and body fat measurements to add further meaning to the body data gathered from their armbands. BodyMedia's goal is to help people become more aware of themselves in ways they have never done before and have a fun and engaging time doing that. One opportunity that has significant benefits is to employ a relational agent as a physical fitness trainer. Likewise Debra Tate showed that the combination of online information and regular feedback from a coach along with the ability to self-monitor diet and calorie estimates resulted in preliminary successes (Tate et al., 2001). In this same line of exploration, BodyMedia's user interface can enable and enhance personalized body monitoring. In this way, a sympathetic technology has been created. This lets people learn about their bodies and how to modify their behavior for longer, healthier lives. For example, people can discover when they slept well and when they had slept poorly and match that information with how much they had eaten and when, helping them modify their habits for better health.

5. The sociological context of the modeling of human health

Traditionally, models of human health have been models of how the human body works. That the previous sentence sounds like a tautology exposes how deep the bias goes that you cannot model human health without modeling how the human body works. This bias is understandable since until very recently there did not seem to be any alternative.

But the ability to put very small high performance computers on the human body in natural environments over long periods of time has opened a new avenue. That avenue is the modeling of human health through the modeling of the data given-off by the human body, often without any initial deep understanding of why that data is what it is. In Section 6, evidence will be presented that this method is accurate in powerful, valuable, and broad ways. But first, asks the skeptic, "Is this even good science?" "Should this even be allowed to count as a model of human health?"

Science is the making of models of the world and the testing of those models to show their predictive value. A model is nothing other than a simplification of the world, ideally reducing non-essential aspects of the world and retaining just those elements that are 'useful' (that are required for accurate predictions to be made). The 'models' or algorithms that BodyMedia constructs are mathematic simplifications of large amounts of raw data gathered with its devices, gathered in the presence of medical gold-standard lab equipment (such as metabolic carts (Fig. 8) or polysomnography machines) (Timmermans and Berg, 2002; Van Bemmel and Musen, 1997). Ideally, these algorithms have captured the underlying trends in the data so that when worn by a person not in the presence of medical gold-standard equipment, the result a BodyMedia device returns accurately predicts what the medical gold-standard lab equipment would have returned in the same situation. So these are models of human health. They just happen to be models of what the body is doing rather than why it is doing it. These models are tested against the very same yardstick as classic models of human health: their ability to accurately predict what is happening to the body in question.

Fig. 7. Body monitoring system

1. WEIGHT AND WEIGHT TRENDS
2. HEART RATE, ACTIVITY LEVEL, CALORIES BURNED, ALERTS
3. DIASTOLIC/SYSTOLIC PRESSURE
4. GLUCOSE LEVELS, ALERTS
5. I'VE FALLEN DOWN, DISTRESS, INACTIVITY, ALERTS
6. CALORIES BURNED, STEPS, ACTIVITY LEVEL, HEART RATE, SLEEP QUALITY, BLOOD
7. GLUCOSE, BLOOD PRESSURE, WEIGHT
8. CALORIES BURNED, CALORIES CONSUMED, WEIGHT, DURATION OF PHYSICAL ACTIVITY, STEPS, HEART RATE
9. BODY TEMP, ORIENTATION, ALERTS
10. CALORIE BALANCE, CALORIES BURNED, HEART RATE, DURATION OF PHYSICAL ACTIVITY

Cellular Phone Display for: Care Giver, Remote Nursing Center, Loved One/Relative
Web-Based Applications for: Nutritionist, Personal Trainer, Care Provider, Doctor, Nursing/Call Center
Desktop, Web-Based Applications for: Wearer, Clinical Researcher, Academic Researcher
Remote Display Device for: Care Giver, Remote Nursing Center, Loved One/Relative

Fig. 8. Metabolic cart in a lab setting.

The next natural question, once the legitimacy of the method has been satisfied, is the real value of the method. There is a prevalent assumption, in both the medical industry and the general public, that any model built or 'learned' by a machine (as all statistical mathematical models are to some degree) could not possibly be as accurate, or as useful as a model built by a person. More specifically, there is often an unarticulated assumption that when these models are wrong they will be wrong in much larger or much more problematic ways than equivalent models built by a person. The first response to these concerns is that real-time or long-term body monitoring in natural environments involves tens of thousands of times as much data as the current models of human health are built upon (periodic readings of blood pressure, cholesterol, bone density, etc.). Kuhn (1962) describes the institutional adoption of new paradigms as a 25-year process; and it took the medical community the better part of a century to build a set of models of human health around this data. So waiting for a community, even one as smart and as dedicated as today's medical community, to build this next generation of models as we move, metaphorically, from physiologic snap shots to physiologic movies, is not realistic.

The second issue is that statistical mathematical models are built by trying to minimize some error function with respect to the predictions that connect the dependent axes (the inputs, which are in BodyMedia's case the raw data measured many times per second by the SenseWear Armband) to the independent axis (the output, the predicted value, in this case BodyMedia derived values such as sleep state, calories burned in the past day, body position, etc.). Assuming that the data has been properly collected (an assumption that is necessary for verification in all model building exercises) the people and situations on which these mathematical models are built and tested represent the conditions that happen the most often or are the most important to predict correctly. So models such as the ones built by BodyMedia are constructed explicitly to minimize these errors. This cannot honestly be said for more traditional models of human health because they have, as an additional constraint, that the model is understandable to the researcher building the model. The case can be made that special cases not seen during the training and testing phase of a statistical mathematical model may be predicted incorrectly in the real world. But of course, when these same special cases are withheld from human researchers building more classic models of human health, the same risk for a model that miss-predicts in these same situations exists.

6. Data modeling, data mining and sensor fusion from multi-sensor streams

'Bioinformatics,' is the intersection of life science and computer science. The SenseWear system allows for the gathering and interpreting of multiple streams of vital sign data to derive higher level statements about the human body such as calories burned, sleep and body context. The fundamental insight for BodyMedia is this—instead of monitoring individual parameters (symptoms) that healthcare institutions are used to looking at—blood pressure, pulse oximetry, cholesterol level and so on—BodyMedia monitors lower level vital signs many times a second, and then builds mathematical models of the data collected. These models are built in the context of the 'right answers,' medical gold standard equipment such as metabolic carts for energy expenditure or polysomnography for sleep states. This process of building mathematical models goes by several names in different disciplines, but is most commonly called supervised machine learning in the computer science community.

The process of supervised machine learning is the building of a model in some chosen representation (such as an artificial neural network, a decision tree, or a genetic algorithm). Input signals are collected in the presence of the labels to be predicted by the model being learned. This set of input signals and labels is often referred to as the training set. These labels are usually either classifications (e.g. 'Astro was jogging between 2 and 3 pm') or regression values (e.g. 'Astro's level of energy expended in the past minute was 5.65 kcals'). These labels are treated as ground truth though in practice there is almost always some error in them. Statistical machine learning techniques (e.g. back propagation in the case of an artificial neural network) are then used to create, train, or 'learn' a model such that the model accurately relates the inputs to the known outputs (labels). Then further data is collected, both inputs and the outputs (labels), but the labels are withheld and the model is queried on what it believes the right output should be. This second set of inputs and labels is often referred to as the testing set. The model's predictions are then compared to the correct labels and a measure of the model's ability to generalize (make correct predictions on previously unseen data) is associated with that model. In practice, the testing set is then often added to the training set, the model retrained to improve its performance, and another testing set created to test that improved model.

There is considerable science in picking from existing model representations or making a new representation when going through this supervised machine learning process. In addition, it is often the case (as it is with BodyMedia) that the predictions are not made by single classification or regression models, but by hierarchical teams of these models. For example, for a stream of vital sign signals collected by the SenseWear Armband, a first model might attempt to classify the kind of activity represented by these signals (e.g. jogging, biking, resting, sleeping, etc.). Then, for each of these particular activities, a specialized model has been built that is particularly good at rating some regression problem (e.g. energy expended per minute) for that particular kind of activity (e.g. biking). BodyMedia approaches the data modeling process through a variety of statistical methods including symbolic modeling where expert knowledge exists (e.g. Decision Trees, Production Systems,.), numeric modeling to fill in gaps in expert knowledge (e.g. Artificial Neural Networks, Bayesian Networks), state modeling for body states such as sleep states that shift in predictable ways (e.g. Hidden Markov Models, Partially Observable Markov Models), and clustering when all else fails or when labels are not available (e.g. K Nearest Neighbor, Principal Components Analysis).

The bottom line, however, is that for real world problems, what generally makes the most difference is the quantity and quality of the training data available to the models being learned. To date the combined time that users, researchers, subjects, and customers have worn SenseWear Armbands amounts to over 300 million min over the past 4 years. Data from approximately 70 million min, from over 500 individuals, have been collected by BodyMedia to form a corpus of physiological data. And of those 70 million min of physiological data (the inputs in our discussion above), just under 10 million min of that data have been labeled as to their classification (e.g. 'lying in bed') or their level (e.g. stage 2 sleep according to the polysomnography machine). These 10 million min of streaming physiological data have been accrued from over 250 subjects with over 100 different labeled activity types.

The next question is reasonably, 'Are all these different parameters really necessary?' The challenge in real world (i.e. out-of-the-hospital) body monitoring is that there are a lot of states of the human body that are ambiguous when seen from the perspective of a single sensor. By choosing sensors carefully, a higher dimensional space of streaming vital signs can disambiguate these human body states, dramatically increasing what a wearable device, can determine; and increase the accuracy with which those statements can be made.

Fig. 9 shows a simplistic example of how multi-sensors can disambiguate human body states that would appear ambiguous to any single sensor. In this example, the challenge is to identify the type of state the human body is currently in. The use of multiple sensors can also help to more accurately capture the correct level from a particular category. For example in Fig. 10, a model that could see only the motion of a person would credit the person with a higher level of energy expended per minute during the 'walk around the block' activities rather than during the 'climbing stair' activities. This is, it turns out, generally false. And that can be seen by the model built by BodyMedia through the use of multiple sensors. Again in Fig. 10, we see that the rate the person is producing and releasing heat is higher during the stair climbing activities and the models can take advantage of this additional information to more closely approximate what a metabolic cart (one of the medical gold standards on the subject of energy expenditure) would say under these same circumstances.

In practice, these examples do not capture the complexities the models must address. For example, it is possible that if during a period sensor A is increasing and sensor B is decreasing, or vice versa, then the output should be judged to be increasing, but if both or neither of the sensors is increasing, then the output should be judged to be decreasing. This sort of relationship cannot be captured by any first order statistical models as the correlations between A, B, and the output are all zero. This conceptual example highlights the demands on the models being learned to capture arbitrarily complex relationships in the data, not just linear trends. As an example of this, in Fig. 11, examples from four classes of human activity are shown. In all four cases, the two axes represent two orthogonal dimensions of motion and the points represent a trace in that two dimensional space over time (about 2 s, shown at only a few samples per second). What we see here are patterns that might be thought of as 'strange attractors' that help to identify and differentiate these

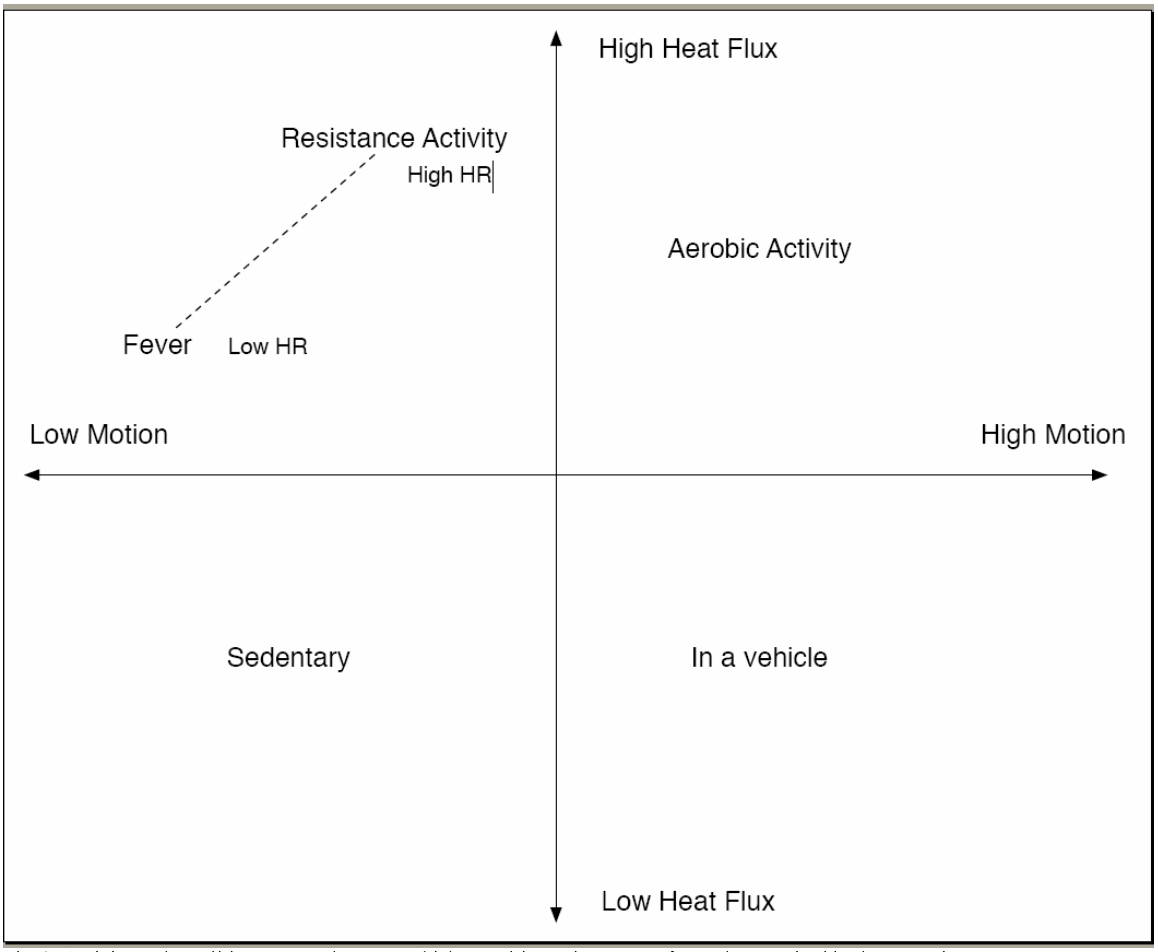


Fig. 9. Activity and condition map: sedentary, vehicle, aerobic, resistance vs. fever characterized by heat, motion and heart rate.

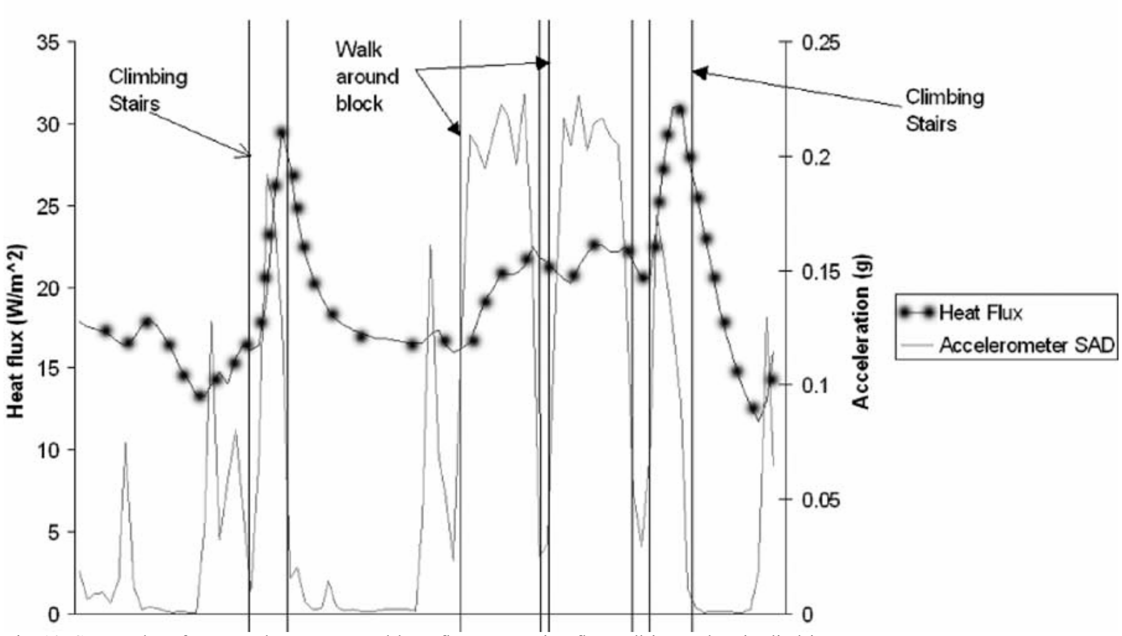


Fig. 10. Sensor data from accelerometery and heat flux comparing flat walking and stair climbing.

different activities. These patterns are not just a matter of the amount of motion per minute, but the kinds or patterns of motion that occur in sequences over short (or even over long) periods of time.

What does all this amount to in the end? These learned models allow BodyMedia, with very high accuracy, to say to a new user who puts on a SenseWear Armband statements such as, “You burned 400 calories over the past hour” or “You were in bed for 8 hours last night, but you only slept for 5 hours and with frequent interruptions.”

Human body data, when aggregated, also has tremendous value beyond the value of the individual statements to individual users. The revolution in the financial services industry over the past 30 years came as a direct result of the access to and real-time analysis of the world’s minute-to-minute financial vital signs. Wearable physiological computing is just at the beginning of a similar revolution as a natural outcome of pulling additional meaning from the long-term, detailed, objective and accurate views of the physical states of large numbers of people and transforming these into meaningful, desirable, and actionable applications. These data mining challenges and opportunities on large collections of group data are in their infancy, but an active area of effort for BodyMedia.

7. Research and development directions

One of the issues in physiological computing is the fusion of sensor data and the calibration of that data to known measurements about those signals. Calibration and accuracy are two issues that anyone who is developing any type of sensor quickly realizes

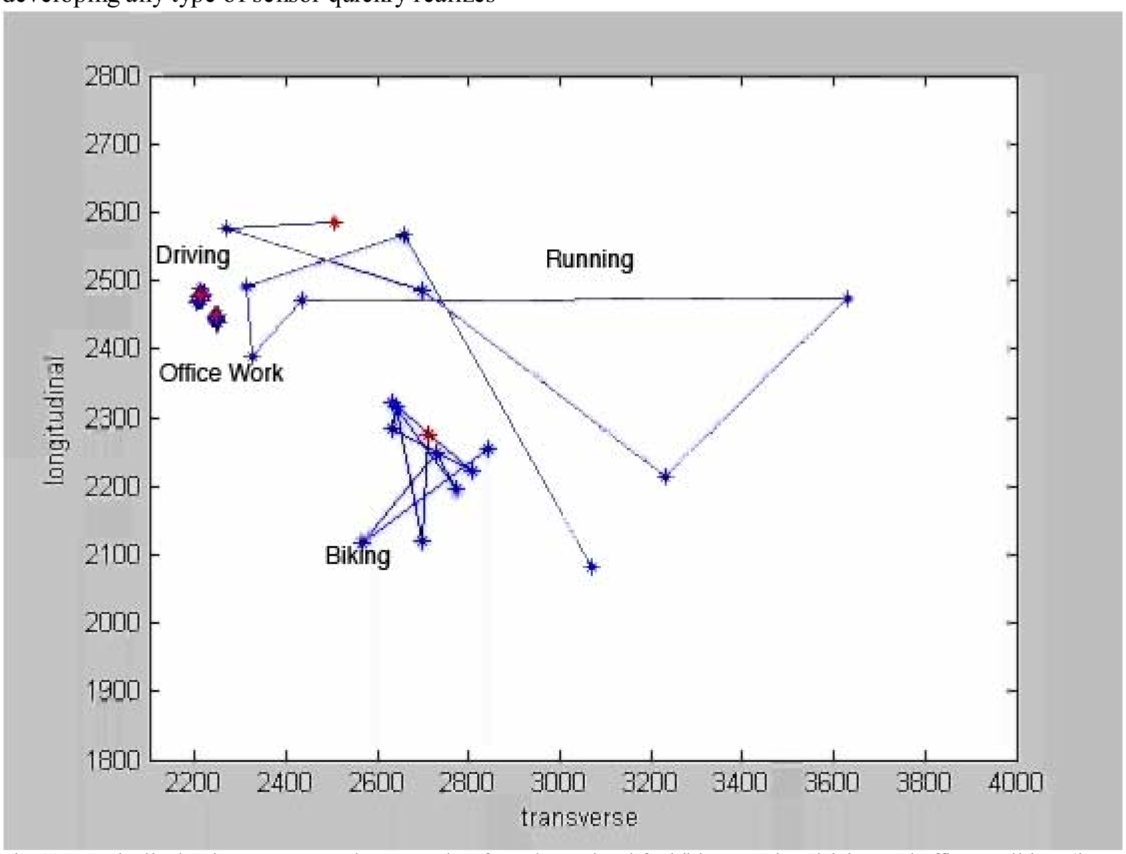


Fig. 11. Longitudinal and transverse accelerometer data from the armband for biking, running, driving, and office conditions (in micrograms per millisecond).

are fundamental. This ‘validation process’ is ongoing, but has already yielded several major achievements. Across broad populations ranging from the very fit to cardiac and pulmonary rehabilitation patients there are high degrees of correlation between the algorithms we have developed and gold standard metabolic measurements under a wide range of activities. Areas that the armband has shown promise in include: total energy expenditure, active energy expenditure, physical activity duration, number of steps, lying down duration, sleep onset, physical interruptions, wake time, sleep duration, and sleep efficiency. Table 1 shows that the accuracy of the SenseWear Armband compares favorably in these categories to Actigraphy, Pedometers, and METS Table (subject's ability to recollect events), normalized for the body mass index (BMI).

Table 1

Accuracy results for the armband vs. other gold-standard sensors

Accuracy results using the SenseWear Armband (inter-person!100%Zfully accurate)		
	SenseWear Armband (%)	Acceler (%)
Total energy expenditure (compared to Vo2 machine)	91.1	
Active energy expenditure (compared to Vo2 machine)	90.3	
Physical activity duration (exercise) (event detection and duration of accuracy)	92.0	
Resting energy expenditure (lying down) (event detection and duration of accuracy)	92.0	Failed
Steps (accuracy in number of steps compared to recall)	97.4	
Lying down duration (event detection and duration of accuracy)	93.8	
Sleep duration (compared to polysomnography machine)	94.5	

All results within 95% confidence interval. All results accomplished without the integration of HR information.

7.1. Current deployment

A number of independent experiments have been conducted to validate the measurements of the SenseWear Armband. For example, the calorimeter measurements have been validated for assessment of energy expenditure during various activities such as treadmill walking, cycle ergometer, stepping, rowing, and arm ergometer protocols (Randall et al., 2004; Cole 2004). It has also been validated as a measure of daily physical activity with findings suggesting that both minute-by-minute, as well as average energy expenditure can be a reliable measurement of physical activity in the laboratory setting and a valid measure of 'free-living' activity (BodyMedia Reliability Reports, 2004).

These findings in the area of energy expenditure while not yet perfect have sufficient repeatability and reliability to have lead to the development of commercial applications and large-scale deployments of the SenseWear Armband. Roche Diagnostics launched HealthWear (a private labeling of the BodyMedia technology) to the general public in the US at the end of 2003. On a daily basis, the HealthWear weight management system monitors and calculates a patient's caloric intake and expenditure and returns to both the patients and their care providers the difference between the two as the patient's day-by-day caloric balance (Roche, 2004). In providing this information, HealthWear is a weight management system that uses the continuous monitoring and collecting of physiological data to show the effect that lifestyle has on weight loss. Depicting calories burned, calories consumed, activity duration, and steps per day, the product strives to increase personal awareness of health and parameters of weight management.

Since July 2004, Apex Fitness has been pilot testing Apex bodybugg™, a SenseWear enabled web-based fitness and weight loss system. In conjunction with the guidance of a Fitness Professional, bodybugg™ users find that the continuous monitoring and interpretation of physiological data allows them to gauge the intensity of their workouts. Fitness Professionals determine users' body-fat percentage and this, along with regular weigh-ins permits the system to accurately predict caloric consumption. Apex bodybugg™ is a fitness system that uses the parameters derived from continuous body-monitoring to empower its users to achieve fit and healthy lifestyles.

The SenseWear Armband and InnerView Research and Wearer Software are also commercially available. Hundreds of systems across four continents over 3 years have enabled researchers to study human physiology in real world situations. Applications have included the study of exercise physiology, sleep behaviors, competition sailing, human computer interactions, physiological response to architecture, and stress response in car and tank drivers. Groups studied range from professional athletes to the elderly to children. The products have survived intact extreme environments such Mt Everest, the South Pole, the highest lake in the world, Steeler training camp, and National Guard live fire fights inside burning planes.

7.2. Future sensors and derived body states

While there are many exciting on-going applications discussed above, BodyMedia is engaging in continued refinements to the platform and the development of new body monitoring capabilities. These including the integration of new sensors and the ongoing development of data models to extract new physiological features and contextual activities. Some of the areas that BodyMedia is focusing on include: fine-grained sleep detail (e.g. Rapid Eye Movement); personal duress; fatigue, alertness, drowsiness; hydration, perfusion, homeostasis; mental stress, anxiety; calories consumed (when, and approximate quantity); surrogates for glucose level; biometric identification ('finger printing' based on personal biometrics); heart information taken on the upper arm; and core body temperature prediction. Efforts to make the device more unobtrusive are also underway. Fig. 12 shows a prototype of a new version of the device.

Fig. 12. A prototype version of a future BodyMedia platform for ambient computing.

To accomplish many of these research goals for additional body state prediction, additional sensors may need to be added to versions of the body monitors made by BodyMedia. BodyMedia is experimenting with micro-needles for the administration of medication and sample collection; ambulatory pulse oximetry; bioimpedance (Grimnes and Martinsen, 2000), acoustic sensors; ambulatory blood pressure; GPS, digital compass, gyroscopic elements; and near-body ambient air and environmental sensors. The potential to increase the understanding of human physiology in natural settings and humans physiological interactions with their environment is substantial. We have already made significant strides in this respect and our continuing developments are generating great interest.

These emerging capabilities and the synergy of the sensor hub, data modeling, and presentation of information draw heavily on the developments of low cost, low power, more efficient computers and sensors. Efforts in the areas of ubiquitous, pervasive, and collaborative computing are now converging to manifest the future of computing as: wearable, personal, and sympathetic.

8. Conclusions

Wearable physiological computing is not only coming into its own, but increasingly looks to be a key technology in the ubiquitous and pervasive computing revolutions now underway. This article has summarized the development of, science behind, and example applications for the SenseWear Armband, a multi-sensor wearable wireless hub for collecting, storing, and interpreting continuous human vital signs. This body monitoring system has been designed, tested, and shown to be robust and comfortable enough to integrate into everyday life and to survive extreme environments. BodyMedia's suite of data models for deriving higher level human body states and levels has been built using millions of minutes of labeled physiological data and validated at several of the top medical research institutions in the US. The representations of these derived body states such as energy expenditure, sleep/wake states, and contextual activities are enabling a wide and dramatic range of new applications, several of which are already on the market. At the same time, an increasingly large and diverse international community of researchers is exploring the future potential of this wearable body monitoring platform. BodyMedia believes that the next wave of computing must necessarily be body worn physiological computing: computers that come with you everywhere, that remain out of sight and out of mind, know your body, learn your behaviors, and share this information with you, with other devices, and with your caregivers; computers that, by watching your body, leave the button pushing paradigm of master–slave behind and become sympathetic and symbiotic. And this vision is real and ready today.

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