KNOWME: A Case Study in Wireless Body Area Sensor Network Design

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ABSTRACT

Wireless body area sensing networks have the potential to revolutionize health care in the near term. The coupling of biosensors with a wireless infrastructure enables the real-time monitoring of an individual's health and related behaviors continuously, as well as the provision of real-time feedback with nimble, adaptive, and personalized interventions. The KNOWME platform is reviewed, and lessons learned from system integration, optimization, and in-field deployment are provided. KNOWME is an end-to-end body area sensing system that integrates off-the-shelf sensors with a Nokia N95 mobile phone to continuously monitor and analyze the biometric signals of a subject. KNOWME development by an interdisciplinary team and in-laboratory, as well as in-field deployment studies, employing pediatric obesity as a case study condition to monitor and evaluate physical activity, have revealed four major challenges: (1) achieving robustness to highly varying operating environments due to subject-induced variability such as mobility or sensor placement, (2) balancing the tension between acquiring high fidelity data and minimizing network energy consumption, (3) enabling accurate physical activity detection using a modest number of sensors, and (4) designing WBANs to determine physiological quantities of interest such as energy expenditure. The KNOWME platform described in this article directly addresses these challenges.

INTRODUCTION

Wearable health monitoring systems coupled with wireless communications are the bedrock of an emerging class of sensor networks: wireless body area networks (WBANs) [1–7]. Such networks have myriad applications, including diet monitoring, detection of activity or posture, and health crisis support. This article focuses on the KNOWME network, which targets applications in pediatric obesity, a developing health crisis both within the United States and internationally. To understand, treat, and prevent childhood obesity, it is necessary to develop a multimodal system to track an individual's level of stress, physical activity, as well as other vital signs simultaneously. Such data must also be anchorable to context, such as time of day and geographical location, which provides a greater understanding of how the external environment impacts health. The KNOWME network is a first step in the development of a system that could achieve these targets. In this article, we present the fruits of a multiyear collaboration between communications engineers, computer systems designers, and preventive health researchers toward the development of KNOWME. Specifically, we examined:

- The need for robustness to highly varying operating environments due to subject-induced variability such as mobility or sensor placement
- Balancing the tension between achieving high fidelity data collection and minimizing network energy consumption
- Accurate physical activity detection using a modest number of sensors
- Designing WBANs to determine physiological quantities of interest such as energy expenditure

Obesity, the health risk considered in this article, is a growing health care concern for youth and adults, and outranks both smoking and drinking in its deleterious effects on health and health costs. Understanding how much energy an individual expends in daily life is important in designing interventions to prevent or reduce obesity. The computation of energy expenditure is complex, and intimately tied to age, gender, the amount of body fat vs. lean tissue present, and even emotional state. Energy expenditure is particularly challenging to assess in children and youth due to the biological effects of maturation into adulthood. In this article, we discuss a system design toward the automatic assessment of energy expenditure. A critical component of assessing energy expenditure in daily life is determining the physical state of an individual. Physical activity (PA) has long been studied in preventive health through the use of single accelerometer (ACC) data collection. Unfortunately, this current approach in preventive health has many drawbacks in implementation [8]: participants must wear ACCs for several days and then return them to researchers for data download, processing, and interpretation. Also, most current ACC systems for PA assessment come equipped with proprietary software and only provide processed measurements, not raw ACC data; as a result, data cannot be compared across systems and have limited utility for further signal processing. Thus, the development of WBANs has the potential to revolutionize how preventive health practitioners assess physical activity and energy expenditure. In fact, physical activity detection has been a common application of new WBAN developments [1, 2, 4, 7].

The development of WBANs presents some unique challenges and opportunities due to ongoing design and improvement in sensor technology as well as an evolving set of standards that govern low-power wireless communications. In our efforts, new research problems were revealed during the implementation of a field-deployed system using off-the-shelf components. Additional insights were derived due to our collaboration with preventive health researchers with experience in tracking behavior using sensors such as ACCs.

Several key observations can be underscored. Modern mobile phones are optimized for multimedia and entertainment applications in addition to voice telephony. As such, the systems are good at performing simple operations over large-scale data. In contrast, WBANs require complex operations on relatively small-scale data. While our test subjects were open to wearing sensor systems, only a modest amount of hardware was comfortable. The end goal of this research was to field-deploy the WBAN and collect data in free-living conditions from targeted individuals selected by our preventive health collaborators. Given the requirement for in-field deployment, several key design choices were constrained. First, we employed only a few heterogeneous sensors to maximize compliance. Second, we used off-the-shelf system components to create a functioning WBAN and hence had to make our design work with existing wireless communication protocols, such as Bluetooth. Given the small set of sensors, novel feature design and selection from the biometric signals proved to be a critical research activity. As mobile phones were not designed to be sensor fusion centers, the energy bottleneck turned out to be the phone rather than the sensors — in sharp contrast to the framework for most sensor network research — and innovative mobile operating system design was needed. Finally, the uncertainty induced by human variability and error proved to be larger than expected and also required new design strategies. Perhaps our most radical conclusion is that if new standards were to be written for multiple sensors' access to a mobile platform, they should be substantially different from what is currently in place. We came to this conclusion after observing the significant amount of design effort required to accommodate the existing Bluetooth implementation in the mobile operating system.

This article is organized as follows. We outline four key research efforts toward the realization of the KNOWME system; for each research effort, we summarize our activities and then highlight the important conclusions drawn from this work. We describe our novel system architecture that was adopted for KNOWME. We provide the extraction of new features from our multimodal biometric signals. The design of pattern classifiers employing these novel features is then discussed. As energy can be minimized via the clever sub-selection of sensors, our new sensor selection algorithm is described. Our innovative mapping of motion parameters to energy expenditure is also discussed. The deployment of KNOWME with test subjects is presented, and final conclusions are drawn.

System Architecture

The KNOWME network employs a three-tier architecture [9], depicted in Fig. 1. The first tier is the WBAN layer or sensor layer, which wirelessly provides physiological signals. The second tier is the mobile phone, which acts as a data collection hub for the external sensor data. The mobile phone also processes data locally and provides simple feedback to the user instantly. The last layer is a back-end server that can provide additional processing as well as data storage. The WBAN layer is comprised of the on-body sensors and the mobile device.

As noted earlier, due to the field deployment requirement, we used only off-the-shelf sensors and mobile devices to build KNOWME. KNOWME consists of a Nokia N95, as well as a Bluetooth-enabled oximeter (OXI) and an electrocardiograph (ECG) from Alive Technologies arranged in a star topology with the mobile phone being the hub. While there are newer and more energy-efficient wireless protocols such as Zigbee, we were restricted to using Bluetooth for communication with the sensors since the N95 supports only the Bluetooth wireless protocol for sensor interfacing.[1] Additionally, sensor data are collected from in-built N95 sensors: an ACC and a global positioning system (GPS). The mobile application must gather data from multiple sensors with minimal user intervention and with no interruption to regular mobile device functionality. To achieve continuous long-term data collection (e.g., 12 h/day for multiple weeks), mobile application robustness is necessary. In addition to application robustness, voluntary user participation is essential for data collection. Hence, satisfying the user's primary purpose of using a mobile phone takes priority over KNOWME. KNOWME's execution priority is lower than other higher-priority tasks, such as incoming and outgoing calls. Whenever there is resource contention with higher-priority tasks, the mobile phone will simply terminate the KNOWME application.

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[1] We observe that the 802.15.6 standard for WBAN systems is currently being drafted and will certainly influence WBAN design of the future.

In KNOWME, the most complex data analysis function is user state detection. State detection can take place either on the phone or on the back-end server, which incurs no computation cost to the phone, but does incur a transmission energy cost.

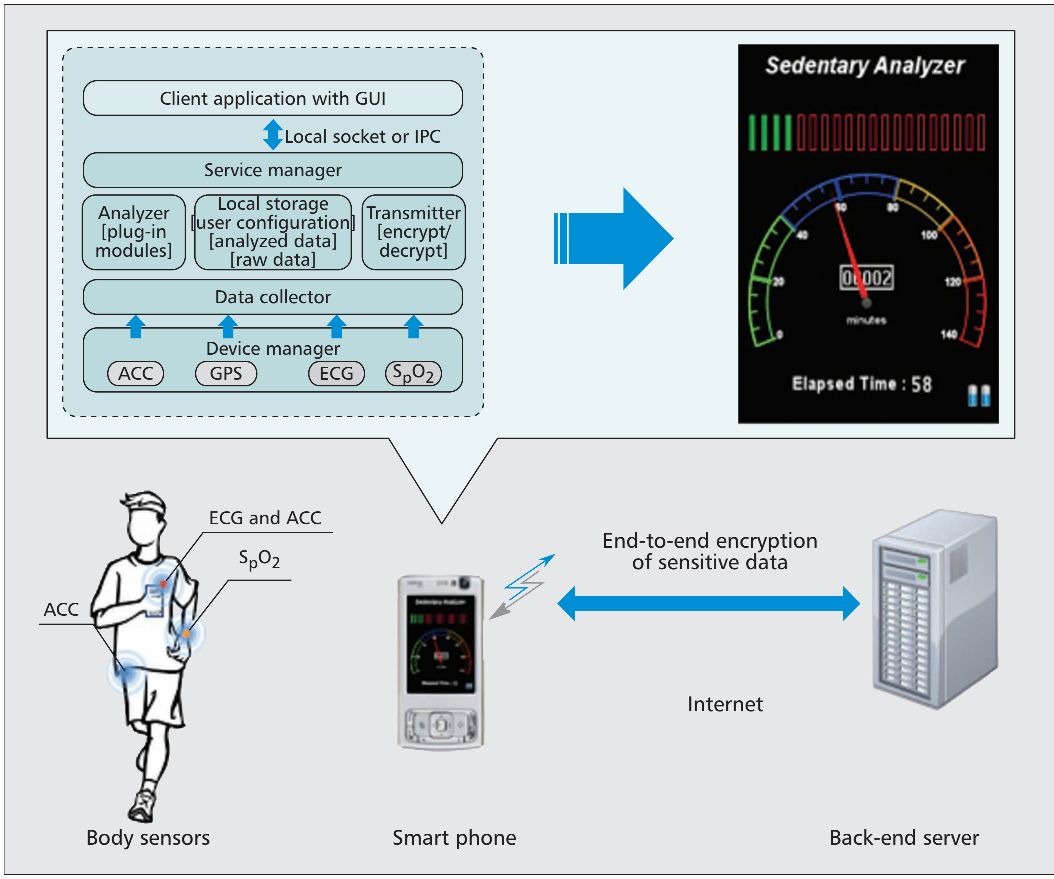

Figure 1. *KNOWME system architecture flow diagram and screen shot from the sedentary behavior analyzer implemented on the mobile platform.*

The mobile application is divided into two components: a background process (KMCore) and a client interface application (KMClient). The KMCore is comprised of seven components arranged in a four-layered hierarchy:
- Device manager (bottom)
- Data collector
- Data analyzer, local storage manager, data transmitter
- Service manager (top)

Figure 1 shows how various components in the KMCore interact with each other. There is one thread per sensor, providing robustness to errors from individual failing sensors as could occur with a single manager for all devices. The data collector thread receives and synchronizes sensor data from each device manager, resulting in a single health record; health records are collected, buffered, and sent to the local storage, the transmitter, and the analyzer. The local storage manager writes the data to flash storage and handles configuration data as well. The transmitter module that transfers data to the back-end handles data compression and encryption for privacy and energy saving. The analyzer modules implement a simplified version of the physical activity detection methods detailed later; while the back-end server currently implements the full-blown classifier. We observe that much effort was employed in designing and operating KMCore key elements that are a direct consequence of the implemented Bluetooth standard and the time-division multiple access (TDMA) strategy. In fact, if a code-division multiple access strategy were employed, most of the functionality of the device manager and data collector could be absorbed into the data analyzer. Non-functioning sensors would be determined during analysis and would not change any of the data collection or formatting. Due to the fact that only a modest number of sensors are being employed, long spreading sequences would be unnecessary. The complexity of multi-user detection is comparable or less than that of the activity detection methods that we have already implemented on the mobile phone and are described in the sequel. Finally, the KMCore service manager communicates with the KMClient graphical user interface (GUI). The GUI framework is fairly complex and resource intensive, but not critical to data collection. If mobile phone resources (memory, computation power) are limited, the KMClient is shut down without affecting the KMCore since the GUI and data collection systems are separate.

Lessons Learned from System Design

Energy Consumption — Energy consumption to support KNOWME operations is significant and motivates the design of a host of schemes to improve battery life. In KNOWME, the sensors simply transmit data to the mobile phone fusion center; the Nokia N95 performs all the coordination, processing, and computation tasks. The energy consumption (in Joules) of the three sensors followed by their sampling rates and their transmission rates (samples/sec) using Bluetooth over a 10 minute interval were: phone ACC (37.8 J, 30, 30); ECG (114.8 J, 300, 4); OXI (1374 J, 100, 10). As the sensors were not programmable, task scheduling and sensor data compression were impossible. However, in KNOWME, the primary energy bottleneck was the mobile phone. Sensors operated comfortably during the course of a day; as such, our energy efficiency research was centered on the mobile phone. If data are collected from all sensors (ECG, OXI, ACC, GPS) and written to a local flash drive on the N95 without buffering, the battery life is 4 h. This is in sharp contrast to the N95's 10 h of rated talk time and 200 standby hours. By using a combination of data buffering, adaptive sensor throttling, and dynamic selection of data transmission methods, battery life can be improved by nearly 200 percent [9].

In KNOWME, the most complex data analysis function is user state detection. State detection can take place either on the phone or on the back-end server, which incurs no computation cost to the phone, but does incur a transmission energy cost. Figure 2 shows the energy cost associated with physical activity detection for local and remote computation based on 10 minutes of ECG and ACC data. We see that the energy consumption of back-end computation is a function of the three transmission options (EDGE, 3G, and WiFi) coupled with compression costs at the mobile phone. When WiFi is available, it is energy efficient to perform remote computation. One anomaly worth noting is that when using compression and WiFi transmission, the energy cost is higher than sending uncompressed data. The reason for this discrepancy is that the energy cost of compressing on the phone far outweighed the reduced communication energy on WiFi radio. When the user is roaming, local computation can be better. Through this experiment, we demonstrate that there is no single, static, best choice when it comes to trading off the energy costs of computation with communication; the choice of remote or local is a complex function of compression, computation and transmission costs.

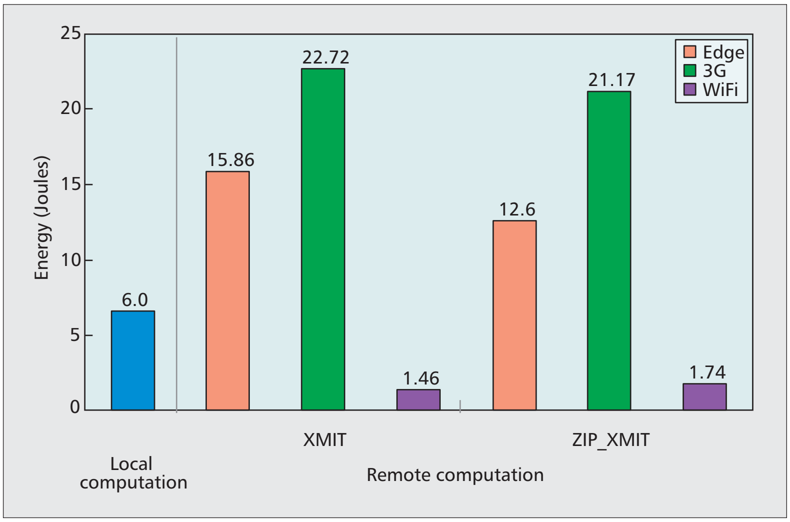

Figure 2. *Local computation costs versus remote computation and energy transmission costs.*

Application Stability — An inherent challenge is developing a mobile application to reside on a mobile device not originally designed for use in a WBAN. Limited memory and computational resources of the mobile phone present major challenges to system stability e.g., an incoming call may receive higher priority, competing for system memory with the KNOWME application, resulting in a non-repeatable memory allocation failure for KNOWME. Debugging crashes during complex system interactions suggested the design approach of separating critical data collection from visualization/data analysis functions.

The choices of available programming paradigms on mobile phones are also limited. For instance, the N95 supports Python, J2ME, or Native Symbian. Each paradigm provides a trade-off between programmer productivity and execution overhead. Due to limited debugging capability, we employed an emulator, which may not faithfully capture mobile phone behavior. Hence, most of the system design effort was focused on the WBAN design with the primary goal of providing robustness under unpredictable operating conditions.

Functional Support — Typical signal processing methods employ complex floating-point computations that are not currently supported by the N95 hardware. Such operations are executed as a software routine, consuming both significant power as well as time. Thus, naive implementation of signal processing algorithms on the mobile phone can cause dramatic application slowdowns. We used either approximations or pre-computed values to reduce this impact.

Multimodal Physical Activity Recognition

As shown in Fig. 3a, the KNOWME Network automatically recognizes physical activities by fusing multimodal sensor signals as well as multidomain subsystems. Machine learning methods are employed in order to perform accurate physical state detection. We have designed and analyzed a significant number of novel features, extracted from the biometric signals. Within these feature sets, we have assessed the most informative features. We have employed personalized models tailored to individuals resulting in further performance enhancement. Finally, we underscore that our approaches account for the inherent variability found within a single individual's behavior due to variations in context.

Feature Extraction and Design

A feature is a characteristic measurement, transform, or structural mapping of the input data that captures important patterns of phenomena of interest. Examples include the standard deviation of an ACC reading or the mean of the instantaneous heart rate via the ECG, which offer cues to distinguish PA types. The classifier attempts to map each realization of the collection of features to a particular activity, or hypothesis. We consider the following nine PA

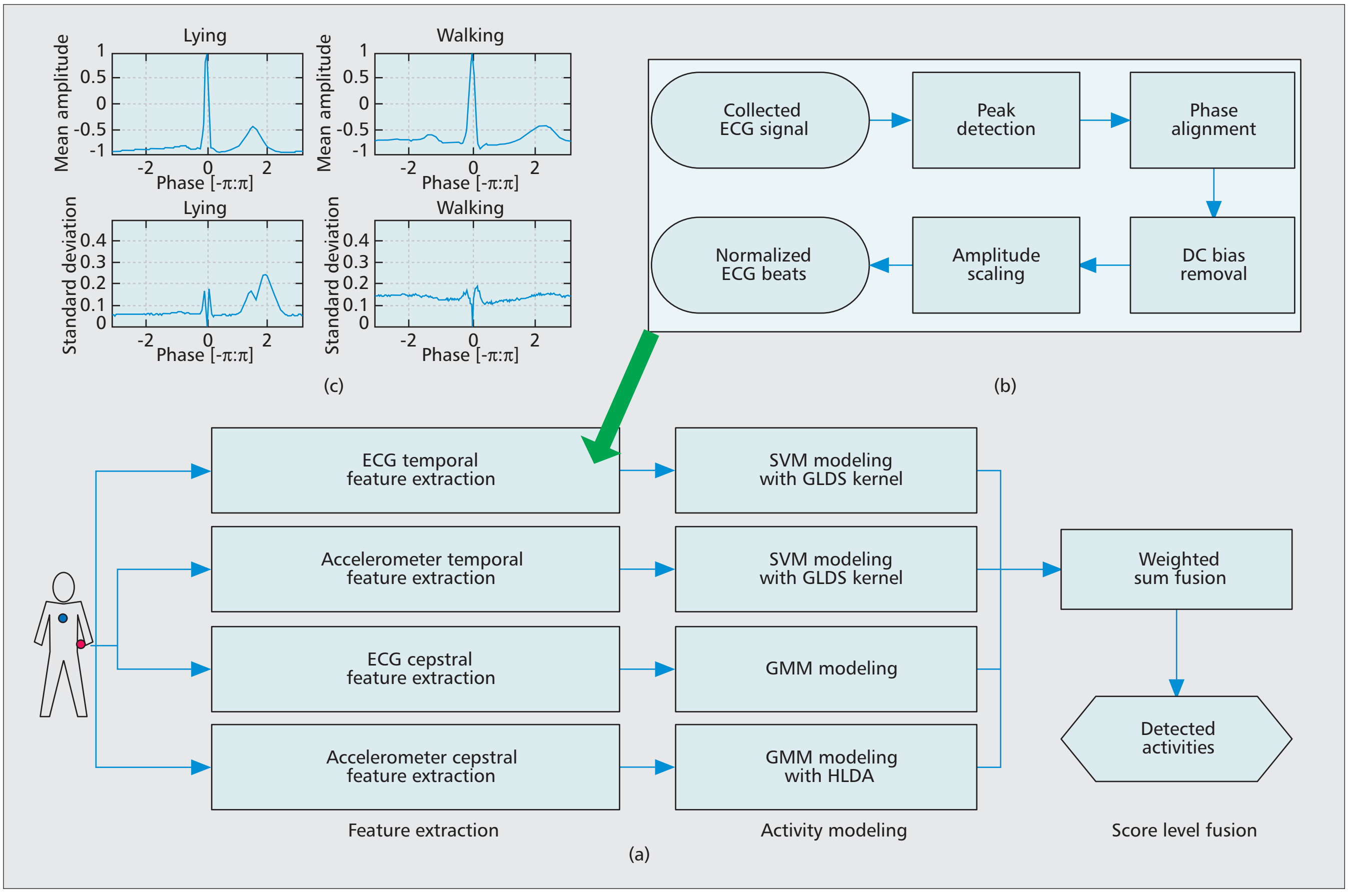

Figure 3. *a) Overview of the proposed system for physical activity recognition; b) ECG pre-processing for the temporal feature extraction; c) mean and standard deviation of normalized ECG signals.*

states: lying down, sitting, sitting and fidgeting, standing, standing and fidgeting, playing Wii tennis, slow walking, brisk walking, and running. Our methods are easily extensible to more states.

ACC signals have long been considered for PA detection [4]; as such, there is a rich feature set considered in the literature. ECG signals are less widely examined. The first set of features, which we denote as conventional, were selected based on the prior state of the art on WBANs. For the ACC, the conventional features are mean absolute deviation, correlations, mean of maxima, mean, median, root mean square, standard deviation, zero crossing rate, mean crossing rate, energy, spectral entropy, kurtosis, and skewness. For the ECG sensor, the mean and variance of the instantaneous heart-rate constitute the conventional features. The other four feature sets comprise the results of our feature design process [10]:

- The Hermite polynomial expansion (HPE) coefficients of the ECG
- The principal component analysis (PCA) error vector for ECG
- The standard deviation of multiple normalized beats from the ECG which is novel to our work, as are
- Cepstrum-based features from both the ECG and the ACC

ECG signal preprocessing (shown in Fig. 3b) is performed at the front-end for extracting the first three feature sets.

Figure 3c shows the mean and standard deviation of the normalized ECG signal for different activities. We can see that both the mean and variance of the normalized waveform carry discriminative information between different PAs. HPEs are polynomial-based orthogonal waveforms employed to reconstruct the ECG signals. The PCA analysis we have used differs from prior efforts as we model both the cardiac activity mean signal as well as the residual artifact noise, the instant heart rate variability, and the heartbeat shape variability. Our final feature set employs cepstral features from ECG and ACC motivated by their potential for separating convolutional noise. The cepstrum is essentially the inverse Fourier transform of the log-magnitude of the Fourier spectrum of a signal. In total, we have examined 56 and 112 distinct temporal features from the ACC and ECG signals, respectively. The additional features have resulted in further improved state detection performance at the cost of complexity, which may challenge the mobile platform. Thus, we have also conducted a feature analysis to determine the most informative features for detection. In contrast to [1, 7], we perform feature selection *a priori* to minimize on-phone computation. Two forms of correlation-based feature selection were compared: a standard correlation and one based on the information theoretic measure of entropy. Our first finding was that both selection methods yielded essentially the same feature sets for our field-collected biometric signals. Another interesting observation was that the key features selected for both the built-in cell phone ACC and the external ACC were typically the same. Our initial analysis did not include the cepstral features.

Classifier Design

A classical machine learning method for classification is used for modeling the temporal features: the support vector machine (SVM). The SVM is trained in a supervised manner to build models for multi-hypothesis testing. In particular, we developed SVMs for the ECG and ACC features separately, using the generalized linear discriminative sequence (GLDS) kernel. The ACC and ECG SVM classifier outputs are fused at the score level. The GLDS kernel, using first-order polynomials, allows computation of the score function via the computationally efficient inner product.

A Gaussian mixture model (GMM) approach is used to model the cepstral features of the ECG and ACC signals. Since the training data for each activity of each subject are too limited to train a good GMM, a universal background model (UBM) in conjunction with a *maximum a posteriori* (MAP) model adaptation approach is used to model different PAs in a supervised manner. The expectation maximization (EM) algorithm is adopted for the UBM training. Under the GMM framework, during testing, each signal segment is scored on all the activities' models from the same subject. The GMM system outputs the recognized activity by maximizing the log likelihood criterion.

By fusing both multimodal (ECG and ACC) and multidomain (time domain SVM and cepstral domain GMM) subsystems at the score level, the overall system performance is shown to improve significantly in both accuracy and robustnesss [10]. Fusion at the score level is particularly useful when the individual subsystems (i.e., the ACC and ECG feature sets or temporal and cepstral domain subsystems) capture complementary information and have different classification performances for different states. This discrepancy in discrimination is leveraged in the development of the optimal sampling protocol to yield an energy-efficient KNOWME health monitoring application. Typical detection accuracies were above 90 percent, sometimes as high as 97 percent [10].

Lessons Learned from Feature Extraction and Classifier Design

The high within-individual variability in biometric signals was unexpected. The observed differences are likely due to sensor placement location, user emotion, fitness, etc.. Even within a single activity, an individual can perform various styles of PA that may not appear in the training set, decreasing system performance. In particular, ECG signals appeared to be more sensitive to intersession variability; robustness was increased through multisession training data. We believe that variability compensation will be an important challenge for future WBAN system design.

Energy-Efficient Sensor Selection

As noted, our selected set of off-the-shelf biometric sensors is Bluetooth enabled. Bluetooth is an access protocol/technology for the exchange of data over short distances between both fixed and mobile platforms. Several modulation formats have been considered since the inception of the standard; currently 8-differential phase shift keying is possible to achieve a 3 Mb/s data rate. To achieve a desired spectral mask, frequency-hopped spread spectrum is employed, although not exploited for multiple access. The Bluetooth protocol is packet-based and enables a master-slave system wherein a single master may have up to seven slaves in a piconet. It is this master-slave piconet that comprises our WBAN. The system works in a time-division multiple access mode wherein slaves communicate with the master in a round-robin fashion; although it is the master (the mobile phone) that determines with which slave it will communicate.

As previously noted, in contrast to the traditional view of a sensor network, it is the cell phone fusion center that is the energy bottleneck of our system. Coordinating and listening to the Bluetooth transmissions from the biometric sensors consumes much more energy for the cell phone than the transmission of those signals from the sensors. As such, to maximize system life, we need to optimally determine which sensors to listen to and for how long — this is the sensor selection problem. In particular, we have considered the problem of allocating a fixed number of transmission samples across the sensors while balancing between classification error and energy consumption. Furthermore, the evolution of physical activity state during the day can be modeled as a dynamic stochastic system. We explicitly considered these properties to determine sequential allocations exploiting stochastic control methods. Finally, a unique feature of WBANs with heterogeneous sensors is that each sensor has different discriminative properties as well as different energy costs.

Ideally, we would derive an optimal sampling protocol based on the SVM classifier. Such an approach faces two important challenges:
- There is no closed form expression for the performance of the SVM to optimize.
- The top performing SVM uses a large feature set and complexity of optimal feature selection would be prohibitive for implementation on a mobile device.

Thus, we considered a single exemplary feature per sensor, exploited Gaussian models for the sensor measurements, and further approximated the probability of classification error in order to convert a combinatorial integer-programming problem into a continuous vector-valued optimization [11]. This approximation effort is largely motivated by the need to implement the sampling strategy on the mobile phone. When the optimal sampling strategy derived in this manner is applied to the SVM classifier, significant energy savings are experienced with no performance loss. We extended our work in [11] by modeling our allocation problem as a partially

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observable Markov decision process (POMDP) [12] to capture the system's sequential nature. POMDPs are well matched to our problem as we can model the dynamics of physical state change via a Markov chain (Fig. 4b). Dynamic programming (DP) and greedy search strategies are employed to optimize the trade-off between classification error and energy cost, and significant energy gains are obtained [13]. We observe that other sensor selection strategies for WBANs often assume correct knowledge of the current PA state [5]. Figure 4a presents a simplified form of our proposed sensor selection scheme. The individual is alternating between a set of physical activities and during this process, a set of measurements is generated and communicated to the fusion center, which then estimates the underlying activity. This estimate is used to update the fusion centers' belief on the underlying true activity (belief state) that in turn determines the subsequent samples' allocation.

Lessons Learned from Energy-Efficient Sensor Selection

The Bluetooth standard mandated the need for sensor selection, revealing how practical implementation can drive research questions. Distinctly novel sensor selection algorithms were necessary due to unique aspects of our problem: heterogeneous discrimination capabilities and energy consumption for each sensor, sensing errors, and imperfect state information. Our proposed methods proved to be quite successful; we can achieve significant energy gains, on the order of 20 percent or more (e.g., Fig. 4c), with a slight degradation in detection accuracy performance. Furthermore, preliminary results show that a greedy search scheme's performance is comparable to that of the full dynamic program; thus, we can achieve near optimal performance with an algorithm implementable on a mobile phone.

Using WBANs to Determine Energy Expenditure

As alluded to in the Introduction, the actual physical state of an individual is typically not the end-goal of health monitoring. In the context of pediatric obesity specifically and obesity in general, one is concerned with how much energy the individual is expending. Energy expenditure is notoriously challenging to assess over the long term due to the expense and bulk

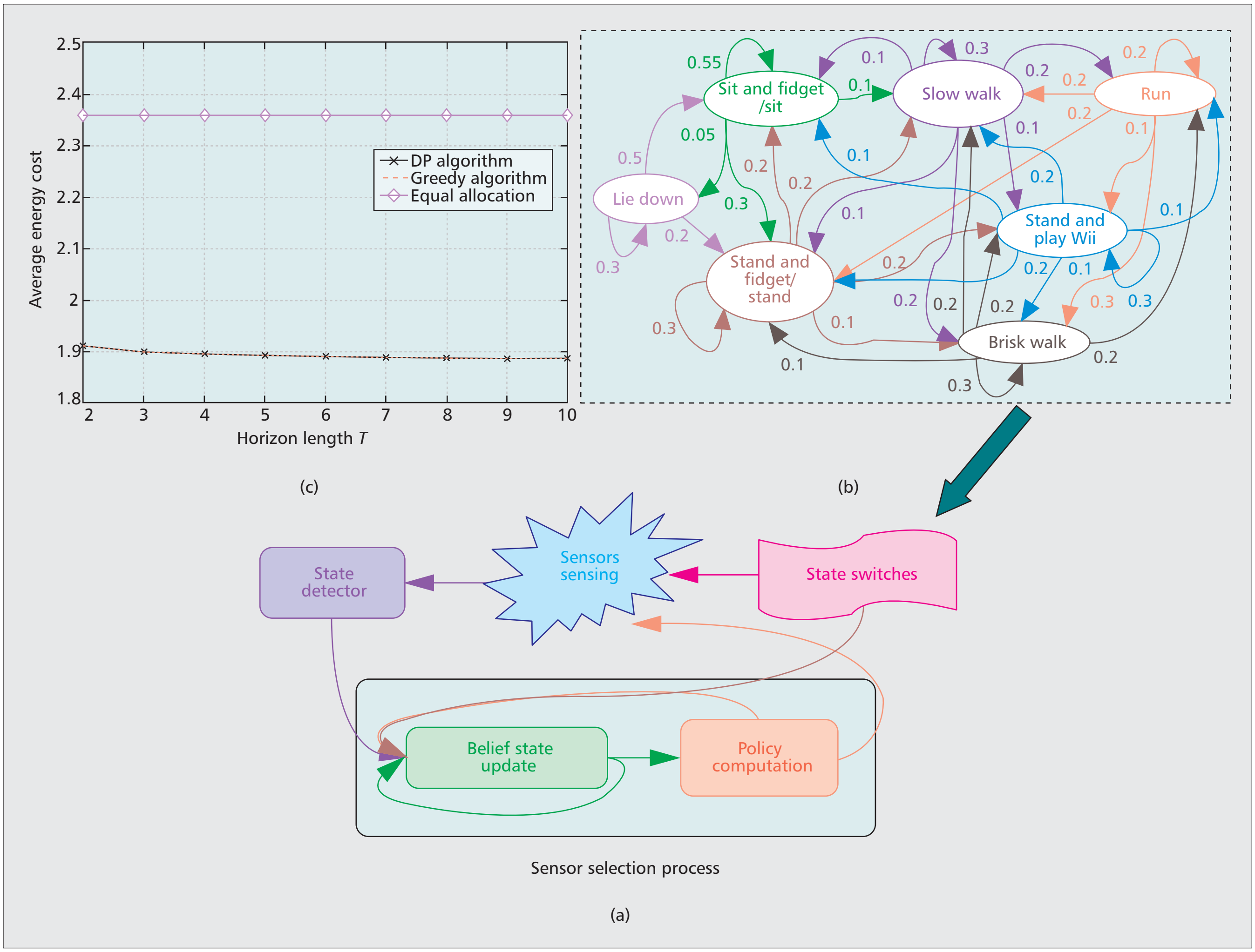

Figure 4. *a) System diagram of sensor selection algorithm; b) Markov chain of seven physical activities; c) improvement in energy consumption via the use of new allocation methods vs. an equal allocation of sensor resources.*

of typical measurement strategies. A common gold standard for energy measurement is the rate of consumption of oxygen (O_2). In our studies [14], calibration of our energy expenditure prediction methods was done against a MedGraphics Cardio II metabolic cart, which measures the rates of O_2 and CO_2 consumption and expiration. Metabolic carts are expensive and bulky. In a typical experiment, the test subject wears a mask that nearly obscures the entire face; a large tube from the mask feeds into the measurement system. Clearly, this technique does not scale well to free-living studies. More portable carts exist; however, they are still cumbersome and prohibitively expensive. On-body sensors, particularly inertial sensors, represent a cost-effective alternative without sacrificing accuracy.

The particular problem we studied was the computation of energy expenditure due to walking using body-worn inertial sensors. An inertial sensor is a device that captures the movement of the object to which it is attached. Our fundamental hypothesis was that the movement descriptors captured using inertial sensors could be used to estimate caloric expenditure. Since no Bluetooth-based inertial sensor was available at the time, we developed our own prototype model to test our algorithms. A single, custom-developed hip-mounted inertial sensor consisting of a triaxial ACC and a triaxial gyroscope was employed (Fig. 5). An important component in our study [14] was to compare the efficacy of gyroscope-based models against ACC-only solutions with respect to predicting energy expenditure. Gyroscopes are much more useful in tracking dynamic activities and do not suffer from the problems of gravitational bias as do accelerometers. Our further innovation was the development of data-driven kinematic motion models mapping movement to energy for walking, which exploited the inherently cyclical nature of walk.

We designed three prediction methods that show significant improvement over simple linear regression fitting: Least Squares Regression (LSR), Bayesian Linear Regression (BLR), and Gaussian Process Regression (GPR). Many accelerometry-based studies on physical activity in the area of health focus on the use of uniaxial ACCs. Not surprisingly, triaxial information is more accurate than uniaxial information. Our data-driven statistical models allowed us to bypass count-based techniques and the use of thresholds yielding improvements over [2]. However, a surprise from our study was the fact that gyroscopic information yielded prediction accuracy equivalant to, if not better, than ACCs. This result was important because it demonstrated the use of a sensor alternative to accelerometers in measuring energy expenditure.

Lessons Learned from Energy Expenditure Estimator Design

Our analysis showed that LSR-based approaches are prone to outlier sensitivity and overfitting. Nonlinear regression methods showed better prediction accuracy, but required an order of magnitude increase in runtime. Our study showed how probabilistic models in conjunction with joint modeling of triaxial accelerations and rotational rates could improve energy expenditure prediction for steady-state treadmill walking, closely matching ground truth.

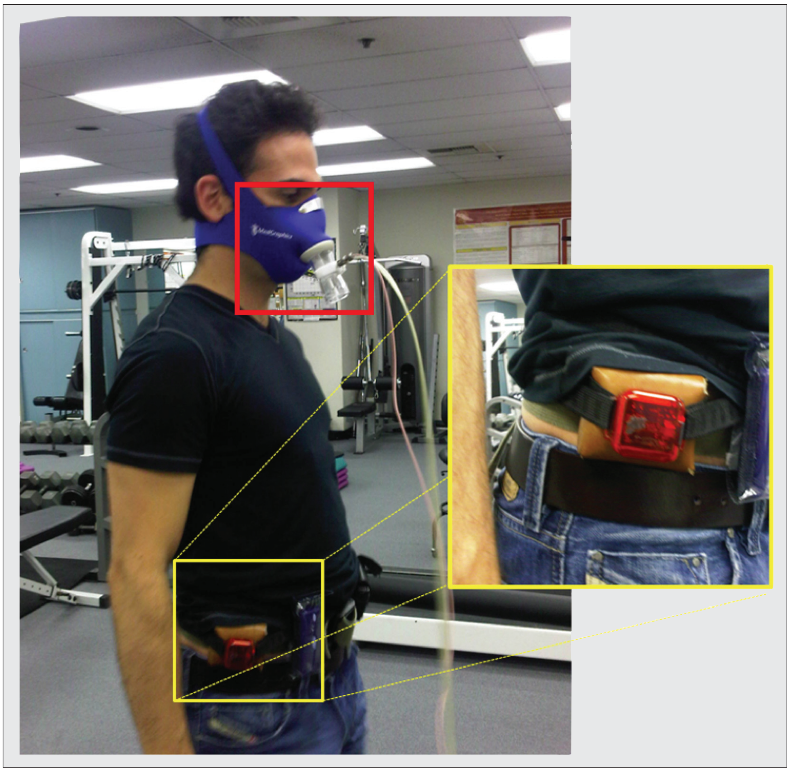

Figure 5. *Illustration of recording procedure. Ground truth collected with a metabolic cart (red box), while being very accurate, is cumbersome. For this purpose, we validate inertial sensors (yellow box) against ground truth using probabilistic techniques.*

Another significant contribution of our work was that our sensors transmitted data via Bluetooth to secondary devices as opposed to local storage. We have successfully connected sensors to both traditional PCs and Android-based smartphones to receive streaming data. Range and the number of simultaneously transmitting Bluetooth devices limited the maximum data transmission rate using Bluetooth. We are currently examining the integration of these inertial sensors into KNOWME.

KNOWME on Real People

The efficacy of KNOWME was evaluated on test subjects recruited from Los Angeles County. The KNOWME version used included one Alive heart-rate monitor and the Nokia N95 mobile device. In-laboratory testing was conducted with 20 overweight Hispanic boys and girls aged 12–17 years [15]. Overweight characterization was assessed via age and gender-specific body mass indices. Our experimental data showed that personal training of the algorithms was essential to good performance. The highest accuracy obtained using this system was 94 percent with seven classes of physical activity using personalized models. For personalized models, the most

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accurately detected activity was running, consistent with prior literature. The least accurately detected activity was sitting. This is most likely due to classification confusion between sitting and sitting fidgeting. When we grouped test subjects by body mass index (BMI) percentile, some trends were observed: there is a noticeable variation in the algorithm parameters between the groups of overweight individuals and heavily overweight individuals. KNOWME has also been used for data collection outside of the laboratory in a so-called free-living setting with 12 overweight Hispanic youth aged 12–18 years with an initialized personalized phase. We achieved 100 percent wear and reporting compliance, validating the feasibility of personalized training in this context. The complete compliance in wearing the system was a surprise, and the test subjects appeared to enjoy wearing the system, seeing their biometric signals, and interacting via texting with the study team. To quote one subject, wearing KNOWME was like "having a doctor in your pocket."

Conclusions

Our experiences with KNOWME have revealed that a high-performance WBAN design is possible employing a modest number of heterogeneous sensors. There are a number of key issues that must be considered with respect to energy efficiency and the inherent variability due to the human element. A full-service obesity mobile health WBAN might include real-time collection, display, and integration of measures of physical activity, diet, stress, mood, physical location and context, and social network activity, combined with modalities to intervene on behaviors in real time, casual and serious games, etc.. KNOWME can enable real-time intervention. Our classification and feature design efforts underscore the need for targeted model development and personalized training.

The system architecture design and optimization focused much effort on sensor device management, thread distinction, and maintaining buffers being fed by signals from different sensors. Biometric sensors are inherently of modest data rate, and the number of different sensor systems is also likely to be small in these mobile health applications. Furthermore, to properly process the signals on the mobile platform will require sophisticated signal processing. *Thus, our major conclusion with respect to wireless communications is that a code-division multiple access system would potentially relieve much of the current burden on the system architecture design for mobile health with limited impact on complexity*. Multi-user detection strategies require a signal processing complexity comparable to our proposed classification designs that we are currently successfully implementing on the mobile platform. Mobile health applications show significant promise and could potentially become a large part of the processing on mobile phones. Thus, given the significant ongoing research in this area with off-the-shelf systems, it could be time to revisit the wireless standards for mobile health.

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