Affordable, quality healthcare is one of the most significant socio-economic challenges worldwide. The aging society, a global trend in almost all developing and developed nations, mandates a drastic reform in the mindset of patients and medical practitioners, and the current medical technologies and practices to make pervasive healthcare truly ubiquitous! Information and Communication Technology (ICT) has become integral to facilitating quality and cost-effective healthcare. Numerous software and hardware solutions have been already developed and are being deployed in several countries, but these are far and few, and are only adopted and afforded by a select population.

The IEEE eHealth Technical Committee (TC) aims to contribute to the advances in this important field by facilitating and stimulating discussions between the researchers from diverse disciplines and medical practitioners. Face-to-face meetings are organized three times a year, in conjunction with GLOBECOM, ICC and Healthcom conferences, and are open to all attendees. Our newsletter, launched in 2012 has evolved into a bimonthly (once every two months) publication that is hosted on our website (http://committees.comsoc.org/ehealth/), and also mailed out to the members. The newsletter covers the wide spectrum of topics related to healthcare technologies and systems; specifically, the open research and design challenges, educational aspects and societal issues, future visions and perspectives, and contributions that are of broad interest to the people connected with the increasingly important field of healthcare. The newsletter is a great medium to “advertise” and create awareness in the research community, industry, and standardization bodies. In this vein, I invite you all to contribute and share your discoveries and thoughts with the e-health community!

Sincerely,

Nazim Agoulmine,
Secretary, e-Health TC of the IEEE ComSoc

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**Human Motion Classification Using Inertial Sensors**
Gregory J. Pottie
UCLA EE Department
UCLA Wireless Health Institute
pottie@ee.ucla.edu

**Abstract**
Many commercial products have appeared that claim to classify human motions using a single inertial sensor. While certain motions can sometimes be accurately classified in this manner, for many medically significant activities, performance is inadequate. In particular, there are challenges in customizing to the activities of interest for particular individuals, dealing with motions of the upper limbs, assessing quality of motions, and coping with members of the general public not following usage instructions precisely. We discuss the design tradeoffs and our progress in building next-generation human motion tracking and classification systems to inspire future efforts in this active field of research and design.

**1. Introduction**
Classification of human motions and the quality with which motions are performed are important in a broad range of applications, including health and wellness promotion, rehabilitative therapy, chronic disease...
management, post-operative recovery, and sports training. Camera-based systems have long been used in the entertainment industry for motion capture, but these are expensive and fixed in location. The Microsoft Kinect system, while inexpensive, suffers from the latter defect and is limited in accuracy to a few cm. Also at the low end of the cost scale, research and commercial systems built around triaxial accelerometers (and sometimes also gyros and magnetometers) have been developed. These typically attach at one location on the body, and then attempt to distinguish among activity classes such as running, walking and inactivity, possibly counting steps and estimating calorie consumption.

A variety of problems arise in attempting to use such systems out of the box. Commercial systems are typically trained to deal with people without significant disabilities, and are easily confused when presented with such impairments. Likewise, misleading results are generated when devices are not attached to the correct limb, and sometimes even when they are. For example, if trained mainly to count steps while walking or running, substantially any periodic activity may be classified as such. Even if successful in classifying gross activity differences, variations in how activities are performed are found both within populations and even for the same individual as she progresses in therapy. Thus models must be tuned to individuals for many applications. A final difficulty lies in the sensors themselves. Using high quality sensors with both accelerometers and gyros enables straightforward integration operations to track sensor position. Unfortunately, with low cost sensors the accelerometer is typically very noisy and double integration for position will lead to unacceptable errors, even with frequent resets. Consequently, typically such systems use features of particular activities to classify them, rather than attempting to reconstruct motion. However, if we are interested in the quality of the motions or to visualize them, we must do better.

The objective of our research is to create an end-to-end low-cost system based on commercially available sensors that can provide reliable inferences when deployed in the general population, while recognizing the expense of ground truth at a large scale and the unreality of strict compliance with operating instructions. Our basic approach is to employ a model that can exploit information at multiple levels: context, sensor pose estimation, activity classification, and motion trajectory, with interaction among these levels. Figure 1 shows the proposed model containing the whole system. While in principle one could train a single classifier to perform the diverse tasks, it would require excessive training data to produce reliable results. A modular approach demands more attention to the physical models underlying the different parts, but yields benefits of reduced computation and training sets. We now describe the practical constraints that lead to such a structure, and briefly describe some of our research progress.

2. Research Challenges and Progress
The main constraints in scaling motion studies to large populations are cost and compliance. Costs include not only sensors and the associated communications system, but also logistical issues such as collection of ground truth for construction and tuning of models, training of personnel to use the system, and manual data processing. Compliance issues include ease of use, including small size, simple procedures, sufficient battery life, and convenient interfaces that deliver messages of readily perceived value. These requirements are somewhat at odds, since smaller low cost sensors demand more sophisticated modeling and signal processing.

Fortunately, the advent of smartphones and low-cost tablets has taken certain challenges off the table and made others much easier. These platforms provide multiple radios that can communicate with sensors placed on the body. They also provide high speed links, possess powerful signal processing and storage ability, provide a variety of user interfaces, and can be used to upload data and download instructions, reminders, and application updates. We envision two modes of operation: sensors store data (no need for a smartphone) or sensors communicate with the smartphone, which acts as the master of the body area network. We now discuss the elements of the system illustrated in Figure 1.

A. Context: One use of a smartphone is to provide context. By refining the definition of context typically used in areas such as pervasive computing (that often entangles physical activities into the definition), we can use context as a high level separator to first determine a set of activities of interest under the user’s current situation before carrying out activity classification. This context-driven approach brings a number of advantages compared to traditional activity monitoring: by pre-selecting the activities of interest (or likely activities), the model complexity of the subsequent activity classification stage is reduced, thus increasing the accuracy, improving classification throughput and enabling sensor operating time and data sample/transmission optimization.

We performed a number of studies where context is defined as a subset of all attributes that characterizes an
environment or situation, external to the user. This clearly distinguishes between attributes of external environment and of the user’s physical motion. For example, a “meeting” environment is a context, and its characteristics may involve certain sound profiles and a set of possible locations. “Sitting in a meeting” in contrast is not a context, as it contains the physical activity “sitting.”

This definition of context can capture a large number of situations, so that users with different objectives can define their own useful sets, identify the required characteristics to distinguish the contexts, and select necessary sensors. The system must however account for a diverse range of data sources such as GPS coordinates, wireless information, audio, and illumination level. In order to detect context based on a variety of data sources, multiple classifiers should be employed for different features and then combined using a committee approach. The individual classifiers are trained separately, and after training they are tested for individual classification accuracy. A voting weight ($\alpha$) is determined for each classifier, proportional to the perceived accuracy. When an unknown class is encountered, the committee performs a linear combination of the individual classifiers, and the context with the highest vote is chosen.

**B. Sensor Misplacement:** One of the main obstacles for motion tracking and classification is sensor misplacement. Even clinicians will place sensors on the wrong limbs, and patients may make any combination of the errors illustrated in Figure 2 in home use. Two typical approaches are:
1. Finding placement invariant features, and
2. Using pre-defined calibration gestures.

Finding invariant features can assist classification but is not directly applicable to motion tracking. Using pre-defined calibration gestures, on the other hand, introduces difficulty in real-life medical applications. Patients can face both physical and cognitive barriers to consistently performing such activities with high quality.

We have explored two variants on these approaches. First, people spend a significant fraction of their time in front of a television. If equipped with a low-cost depth-camera system such as the Kinect, it is possible to map the frames of reference of the patient wearing sensors to the visual frame, and identify the likely misplacement with the aid of a kinematic motion model. Second, for certain activities such as walking we can use an activity classifier that uses placement-invariant features to identify particular segments of the walk. Training data is required for the types of gait that will be used to opportunistically correct for misplacement. The training and testing data are divided into gait cycles. From those gait cycles, the best representatives are chosen based on the dynamic time warping (DTW) distance. They are further passed to an MMSE estimator for the rotation angle. Multiplying the testing data with the rotational matrix, we can obtain the recovered signal data. Results have so far been satisfactory for the misorientation and rotational displacements.

**C. Activity Classification:** Activity classification can encompass a number of levels: static (standing, sitting, lying down) vs. energetic (walking, running, upper body motions) activities, classes within these broad categories, and segments of motions composing the activities. A natural structure to use is a tree classifier. There is no requirement for classifiers used at particular nodes of the tree to be of the same type, and advantages to mixing them. This is because various clusters of activities differ in the types of probability distributions that are produced, and certain classifiers do better with some distributions than others. We have found for example that a Naive Bayes classifier works well with energetic activities while support vector machine is better matched to the static activities. In either case, an advantage of a tree classifier is that the dimensionality of the decision space can be made relatively small at each node (e.g., one to three features) while still preserving classification accuracy if the tree structure and features are carefully chosen. This results in two benefits:

- The size of the training set stays small, even with a large number of activities, and
- The model structure can be built using data from a larger population, and then tuned to individuals with short individual training.

Given the high cost of collecting accurate ground truth and large value of personalizing models in terms of classifier accuracy, this can be a favorable tradeoff in overall human effort compared to fully automated tree construction methods.

Having multiple sensors can significantly improve classifier accuracy, but comes with the cost of requiring periodic synchronization. When the sensors are merely storing data, this can be tricky, as drift can occur even when the sensors are initially synchronized. The basic approach is to either use calibration activities or opportunistically recognize certain strong features. With radios, synchronized time stamps are more easily provided.
D. Trajectory Estimation: The most detailed motion inference is to attempt to reconstruction the trajectory followed by a limb in the desired motion reference frame. Assuming we have learned the sensor pose and the sensors are noiseless, there would still be the problem of estimating initial pose and position of the limb. In principle a 9 degree of freedom (9-DOF) sensor with triaxial accelerometers, gyros and magnetometers could accomplish this. In practice, the accelerometer can reasonably estimate the direction of gravity, but the magnetometer is particularly unreliable in indoor settings. Consequently there is error in estimating orientation in the ground plane. However, for many activities what matters is the relative sets of motions, and thus 6-DOF sensors omitting the magnetometers can be adequate. Here unfortunately there are further problems in the form of noise in the accelerometer measurements and drift in the gyro. Note that use of accelerometer data for double integration is problematic in many respects: small errors in estimating the direction of gravity overwhelm measurements for small accelerations, noise can dominate, and sampling around sharp acceleration events can lead to errors. Thus, it is more plausible to use the accelerometer to identify motion features, and then use gyro data in conjunction with a motion model. So if for example the thigh and calf are modeled as a double pendulum, smooth gyro measurements can be used to reconstruct walking. The drift can be compensated by using heel strikes to reset the orientation. That is, we employ the classifier (using both acceleration and angle features) to segment the activity in order to compensate for drift.

Matters are considerably more challenging when we have only a single sensor on a limb system (e.g., at the ankle or foot). Then the model must do more work to compensate for both sensor errors and missing sensors. We are currently pursuing research into how to approximately reconstruct motion for selected activities in this setting.

E. Data Processing and Storage: A great deal of medical data requires either manual processing or is determined to be unusable well into a study. This is clearly not scalable to large populations. Patients and physicians require feedback in a timely fashion, which is only possible with automation of the classification tasks. This is turn requires careful selection of hardware and experimental procedures so that the processing tasks have reasonable complexity. These must be first class constraints, rather than an afterthought, given the large cost impact. Indeed, the representation of motions via the model suggests means to compress, process and search the data, bringing us in some sense full circle. We have developed a variety of tools to assist in ground truth annotation, synchronization, data formatting, visualization and analysis, but much remains to be done.

3. Concluding Remarks
While considerable progress has been made in low cost human motion classification, many research challenges remain. These include completing other elements of the system in Figure 1, optimizing the interaction between levels of the system, improving the various modules, and developing bounds to characterize the statistical optimality of the individual modules or sets of units. Challenges also exist in the realm of system interactions with both expert users and the general public so that logistical tasks are minimized in large-scale deployments.

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Further Reading

A Quantum Shift from Classical Medicine to e-Medicine
Priya Ganapathy, Tejaswi Tamminedi, Amitabha Ghosh, Chen Liu, and Jacob Yadegar
Utopia Compression Corporation
1150 W. Olympic Blvd., Suite 820, Los Angeles, CA 90064
{Priya, Tejaswi, Amitabh, Chen, Jacob}@utopiacompression.com

The vision of a unified and seamless healthcare system that connects different providers and shares pertinent information about patients and best medical interventions is realizable (shown in Figure 1). We identify ubiquitous sensors, intelligent decision-support and wireless networking as the three main prongs of e-health technology that will bring this vision closer to home (shown in Figure 2). In the following sections, we discuss in detail the current status of each prong of e-health technology and upcoming trends.

A Ubiquitous, Reconfigurable and Studious Sensors: Sensors are becoming cheaper and smarter with non-intrusive comfort befitting true persistent wear. Simultaneously, capabilities are evolving from non-invasive monitoring of primary vitals such as heart rate, respiratory rate, and pulse oximetry to blood pressure, hemoglobin, and blood glucose, hitherto performed invasively. For this capability to translate into utility, the plethora of data must be complemented with actionable items for individuals and caregivers. Consequently, sensors must transcend from their simple measuring functionality, to understanding and interpretation of individual physiology. Inevitably, the requisite software and hardware intelligence must be embedded into sensors for persistent monitoring to be realized. Trust of patients and trained professionals in the competence of described solutions will also be paramount.
In addition to sensor reliability, affordability and comfort will dictate acceptance among patients and care providers alike.

B. Intelligent Decision-Support System: With tremendous improvement in computing capabilities, researchers are now focusing on developing predictive and temporal models that can be trained using large repository of clinical, imaging, and genetic data to generate personalized treatment plans for physicians' use. Integration of advanced decision-support models into physician's workflow will certainly improve patient outcome, reduce medical errors, and associated treatment costs. Once limited to only computed-assisted diagnosis (CAD) on standalone imaging devices, intelligent software is now being ported onto mobile imaging platforms for rapid detection and diagnosis of multiple traumas. Such products are being extensively used by first responders and battlefield medics to minimize mortality and morbidity rates.

After established acceptance of health and wellness tracking apps, vendors are now attempting to build more complex software for screening of disease conditions via sensors attached to smart phones. Consistent efforts by the Food and Drug Administration (FDA) department to streamline the approval process for mobile and persistent remote monitoring technologies will further encourage the development of smart detection and recommendation algorithms for chronic disease mitigation and management. Physicians can also obtain collateral information from family members on the overall well-being of patients. By incorporating physician's knowledge in the reporting app to issue alerts, will result in a timely intervention and well-informed modification of treatment and therapy strategies. If accepted as a norm remote persistent monitoring will result in significant cost savings by reduced patient visits to doctor’s office and hospital stays.

C. Networking Medical Sensors: Recent technological advances in low-power micro-electromechanical (MEMS) systems and wireless communications are making it possible to equip intelligent medical sensors with tiny radios that have medium-to-long range (e.g., 5 feet – 50 meters) wireless communication and interoperable capabilities. With these wireless links, the sensors can be networked with other types of sensors and wireless devices, including smart-phones, tablet computers, PDAs, bedside computers, commercial off-the-shelf wireless sensors, etc. Armed with such communication capabilities, the sensors will be able to perform a variety of tasks that were not possible before in classical medicine, such as (a) reporting medical conditions instantly to a physician without requiring an office visit; (b) raising alarms to caregivers’ mobile devices if a patient’s medical conditions deteriorate; (c) continuous remote patient monitoring, etc.

To this end, the role of ubiquitous sensors, intelligent decision-support software, and versatile information storage and wireless communication infrastructure will have far reaching impacts beginning with empowering physicians to practice case-based medicine to tracking and treatment of victims in emergency disaster scenarios. E-health applications that enable patients to understand their current physiological and mental health status from on-body sensor measurements and also, if necessary, the various parameters listed in their health reports will soon be in demand (the catch-phrase “quantified self”). In addition, these applications may also serve as recommendation systems that can help patients explore customized treatment options and suggest changes for a healthier life. With parallel growth in developing smart human-system interface models for vehicles e-health technology will no longer be limited to home or work place environment, but will be an assiduous companion to individuals and their families.
15th IEEE International Conference on  
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Prospective authors are cordially invited to submit their original contributions covering completed or ongoing work related to the eHealth area. The topics include but are not limited to

- Biomedical and biosensors engineering
- Body sensor networks and wearable sensor systems
- Clinical biofeedback, decision support systems, and tools
- eHealth information and network infrastructure
- eHealth for public health (including disease prevention, emergency preparedness, epidemiologic interventions)
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Important dates

- Paper Submission (extended): May 20, 2013
- Notification of acceptance: July 7, 2013
- Submission of camera-ready papers: August 31, 2013