Platform Design for Health-care Monitoring Applications

Roozbeh Jafari[1], Ruzena Bajcsy[2], Steven Glaser[3], Bruce Gnade[1], Marco Sgroi[4], Shankar Sastry[2]

[1]Electrical Engineering Department, University of Texas at Dallas
[2]Electrical Engineering and Computer Science Department, University of California, Berkeley
[3]Center for Information Technology Research in the Interest of Society, UC Berkeley
[4]WSN Lab sponsored by Pirelli and Telecom Italia, Berkeley, CA
rjafari@utdallas.edu, bajcsy@eecs.berkeley.edu, glaser@ce.berkeley.edu, gnade@utdallas.edu, marco.sgroi@wsnlabberkeley.com, sastry@eecs.berkeley.edu

***Abstract*— Advances in technology have led to development of various sensing, computing and communication devices that can be woven into the physical environment of our daily lives. Such systems enable on-body and mobile health-care monitoring, can integrate information from different sources, and can initiate actions or trigger alarms when needed. In this paper, we describe the general characteristics of medical monitoring applications and use physical movement monitoring as the pilot application. Furthermore, we elaborate several important design techniques that can be tightly coupled with real-time signal processing, and may enhance the system performance. Finally, we present our preliminary results on the movement monitoring application and demonstrate the feasibility of our proposed design techniques.**

I. Introduction

HEALTH care costs in developed countries are rapidly increasing due to a substantial increase of the elderly population. Medical monitoring can be a key to evaluating the actual quality of life among the elderly. We believe that the overall health and wellness of elderly sectors of the population can greatly benefit from the use of information and communication technology, especially for the homebound. On the other hand, continuation of Moore's law along with development of novel sensing devices have led to the introduction of a variety of COTS wireless sensor platforms. These platforms can measure physical attributes such as temperature and acceleration, perform limited local computation and storage, and communicate within a short range. Wireless sensor platforms enable ubiquitous presence of sensing, computing and communication capabilities and hence, enable a large number of application domains. In particular, they can be mounted on human body or clothing, or even be woven into the very fabric that we wear to realize various health monitoring applications. We take special interest in such systems, generally referred to as Body Sensor Networks (BSN), due to the unparalleled significance of their application domain and their very specific requirements and implications. Sensor platforms integrated into clothing provide the possibility of enhanced reliability of accident reporting and health monitoring. Such devices improve the independence of people needing living assistance.

Despite their immense potentials to impact both quality of life and economy for members of society, such health monitoring applications and their host BSNs are still developed in a very inefficient manner today. There is not enough known on generic methodologies to efficiently compose, setup and configure a BSN out of COTS products, and to efficiently develop and adaptively execute multiple applications on a particular BSN.

II. Health Monitoring Systems

Health monitoring systems based on BSN usually rely on pattern recognition techniques to extract from the raw sensor data relevant medical information.

Given the goal of classifying objects based on their attributes, the functionality of an automated pattern recognition system usually consists of the following basic tasks:

- a description task that generates attributes of an object using feature extraction techniques,
- a classification task that assigns a group label to the object based on the attributes with a classifier.

There are two different approaches for implementing a pattern recognition system: statistical and structural. Each approach utilizes different schemes within the description and classification tasks which incorporates a pattern recognition system. Statistical pattern recognition [1, 2] concludes from statistical decision theory to discriminate among data from different groups based upon quantitative features of the data. The quantitative nature of statistical pattern recognition, however, makes it difficult to discriminate among groups based on the morphological (i.e., shape-based or structural) sub-patterns and their interrelationships embedded within the data. This limitation provided the impetus for development of structural approaches to pattern recognition.

Structural pattern recognition [3, 4] relies on syntactic grammars to discriminate among data from different groups

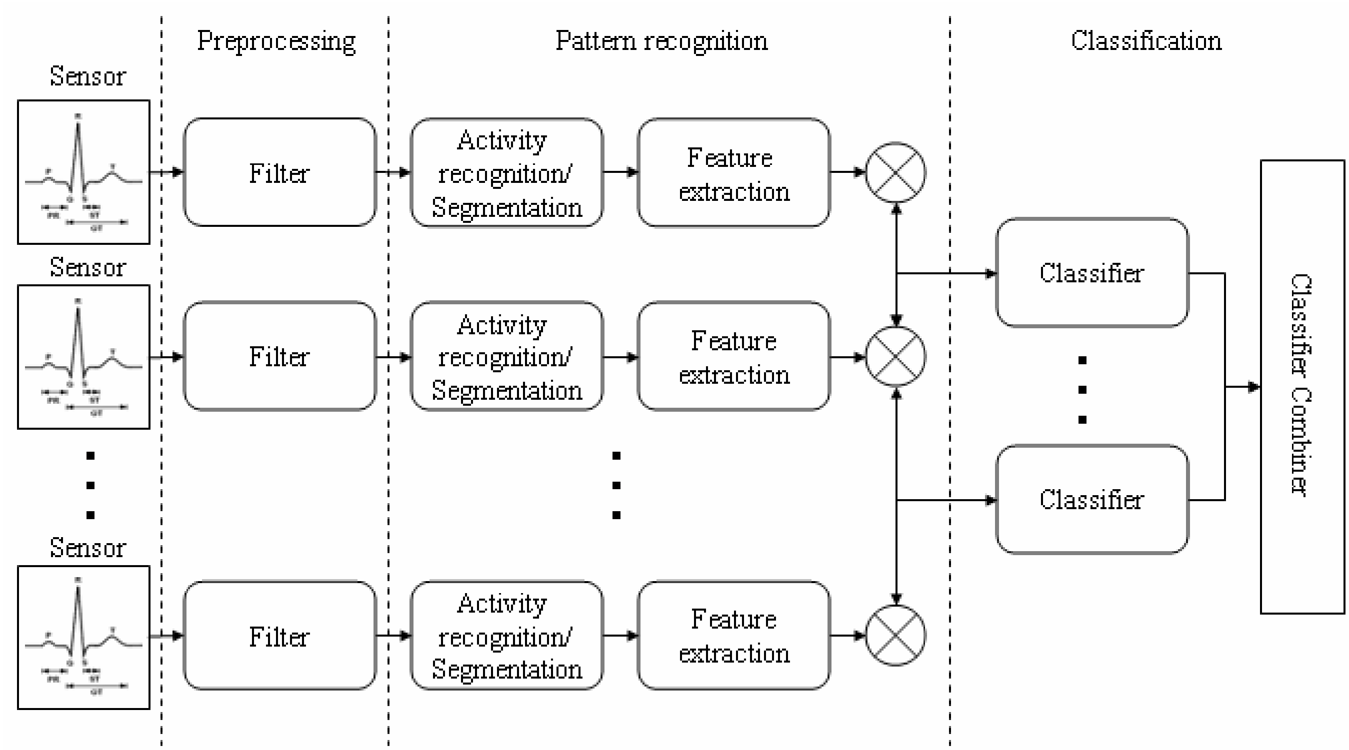

Figure 1. System architecture of distributed sensing platform for health-care monitoring

based upon the morphological interrelationships (or interconnections) present within the data. Structural pattern recognition systems are effective for image data as well as time-series data.

For our target platform, we consider medical monitoring applications with distributed sensors based on structural pattern recognition (as depicted in Figure 1). The signal processing consists of three stages: preprocessing, pattern recognition, and classification. We perform preprocessing and pattern recognition locally, i.e., within close proximity to sensors. The preprocessing includes filtering, while the pattern recognition includes segmentation, as well as feature extraction. Once the features are extracted, they are processed for classification.

As to our network models, we envision single hop topologies where sensor nodes communicate directly with a central gateway. A common implementation performs the preprocessing and pattern recognition tasks locally, while classification is executed on a centralized node. However, what is the optimal implementation architecture largely depends on the application requirements. Hence, it is critical to adopt methodologies that allow to evaluate tradeoffs and select case by case the implementation that allows meeting the application requirements and at the same time optimizes the resource usage.

III. APPLICATION SCENARIO

A. Physical Movement Monitoring

We use physical monitoring as the pilot application for our study. While health-care monitoring systems using body sensor networks encompass many applications, they mostly share the general characteristics of distributed sensing and pattern recognition (feature extraction and classification) on biomedical signal with extensive variations.

We propose the following framework for movement assessment and classification of physical activities. In particular, we are interested in classifying transition movements such as sit-to-stand, stand-to-sit, lie-to-stand and stand-to-lie etc.

Given the goal of classifying movements based on subject motion, the functionality of our automated pattern recognition system is divided into three basic tasks: the preprocessing and filtering, the description task which generates attributes of a movement using feature extraction techniques, and the classification task which classify this movement based on its attributes. For this particular application, the features that we present in this paper include:

- Postural orientation: We employ the concept of postural orientation as indicated in [5]. We do this by tracking the angle between all sensors and the gravity (Constant inclination feature) from the beginning to the end of a movement. In fact, the absolute value of the z-axis accelerometer itself is a fairly reliable indicator of the lying posture, since the axis would be usually pointing in a direction parallel to the floor, and does not change much even the person rolls from side to side.
- Singular value decomposition (SVD): One of the challenges of bio-signal analysis is to develop efficient methods to perform structural pattern recognition. SVD

can be a valuable measure in obtaining such a characterization. SVD is a common technique for analysis of multivariate data, and therefore, data with unknown morphology might be well suited for analysis using this metric [6, 7]. Daily physical activities are composed of basic individual movements. For example, lying down can be composed of first sitting down and then lowering the upper part of body. Moreover, sitting and lying movements themselves may be decomposed into more fundamental motions. Such compositions are typically seen as several data segments with local maximums and minimums, as shown in Figures 4 and 5. We devise to apply SVD analysis to these local extremums, weighing each extremum by its distance from the preceding extremum.

IV. System Architecture

The system architecture includes the following components:

1. Sensors. Most biomedical applications, including the physical activity monitoring and ECG analysis, require a set of sensors and processing units that are spatially distributed because of (a) diversity for sensitivity, performance, accuracy, and robustness, and (b) constraints posed by the location of the desirable sensing points on the surface of the human body. The sensors are responsible for collecting data.

2. Data processing and communication nodes. Processing power is needed to perform data filtering and noise reduction on the data readings. Due to the nature and usage of our devices and their wearability concerns, the processing units must be fairly simple. These local circuits will not be capable of handling complex computations. Furthermore, the amount of energy available to the system (i.e. batteries) is very constrained which prevents us from using high performance processing units with high power consumption. Therefore, collaborative task execution may seem to be a more natural approach. A typical architecture usually includes several types of nodes with different processing and communication capabilities. Some nodes must be very tiny and low power to be placed close to the human body. Other nodes, usually called hubs or gateways, collect data from the sensor nodes, perform more intense data processing and transmit the data remotely. For example, data from the sensors can be collected, displayed, and transferred using lightweight Pocket PCs or mobile phones.

A. Traditional wearable sensors

Target applications may call for many types of continual physiological measurements, as well as environmental measurements, Sensors required for these measurements that include motion sensors, pressure sensors, galvanic skin response sensors, flex sensors, and piezoelectric film sensors:

Accelerometers: We have been using MEMS type 3-axis accelerometers to measure the motion. They can also be used to measure the vibration, as well as acceleration due to the gravity.

Gyroscopes: Gyroscope is a device for measuring or maintaining orientation, based on the principle of conservation of angular momentum. In addition to accelerometers, gyroscopes can be used for physical movement monitoring.

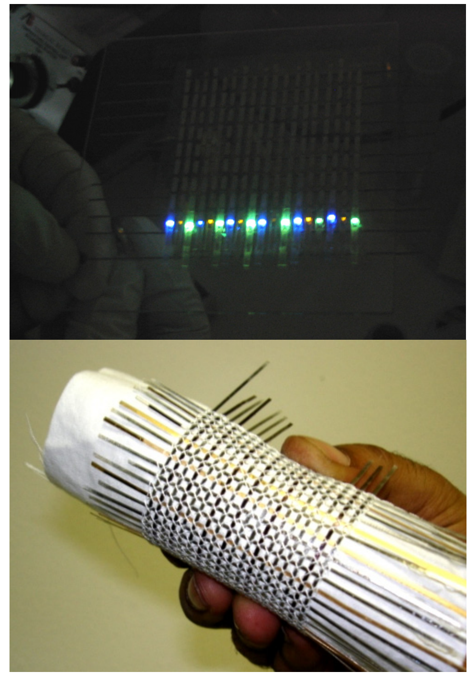

Figure 2. Electronic textile architecture example showing integrated OLEDs on the left, and flexibility of textiles on the right.

Electrocardiogram sensors: ECG sensors provide a record of variation of bio-electric potential with respect to time as the human heart beats. These sensors can play an important role in physiological monitoring in many applications.

Flex sensors: Flex sensors change resistance when bent. They are uni-directional.

Pressure sensors: These sensors are ideal for measuring forces without disturbing the dynamics of a test. They can be used to measure both static and dynamic forces. They are thin enough to enable non-intrusive measurement. The resistance of the sensor decreases as force is applied.

Piezoelectric film sensors: Piezoelectric thin film sensors generate analog voltage signals in response to applied dynamic forces. They have a variety of applications from monitoring physical abuse in Alzheimer patients to detecting heartbeat rate.

Galvanic Skin Response (GSR) sensors: The galvanic skin response (GSR) also referred to as the electro-dermal response (EDR), measures electrical skin conductance from the fingers or palms that is associated with sweat gland activity. It is commonly used in psychophysiology experiments to infer emotional state and cortical arousal. The GSR is commonly used in biofeedback experiments as well as stress evaluation.

B. Sensors on threads

We have developed sensor elements that can be integrated on ribbons. Our current electronic textile capabilities focus on ribbons that include organic light emitting diodes. An example is shown in Figure 2.

The three sensors that have been developing are a pressure sensor, a temperature sensor, and a skin level conductance sensor. We will evaluate two pressure sensor concepts; 1) the first based on a capacitive sensor where we measure the change in capacitance caused by a change in gap between two electrodes, and 2) the second based on the piezoelectric materials PVDF (polyvinylidene difluoride) where a voltage is generated by applying pressure to the material. The temperature sensor will be based on a band-gap reference circuit, which we will fabricate utilizing our current organic TFT (OTFT) and organic diode process flow. While OTFTs may have relatively low drive current and moderate switching speeds, they do have a linear regime which should allow us to design and fabricate low power, linear amplifier for local processing.

C. *Computational units*

The most important component of our system is the distributed processing units along with batteries which can support various types of sensors for physiological reading from human body. These blocks are responsible for reading from the sensors, executing preprocessing (filtering, segmentation,…etc), feature extraction and local classification. Furthermore, they enable communications that will lead to global classification on a centralized node.

D. *Gateways*

A pocket PC/mobile phone is responsible for collecting data from processing units and classifying them. It dispatches the critical events detected by processing units or the gateway to the Internet or the hospital. Moreover, it coordinates and controls the overall functionality of the system and performs resource management.

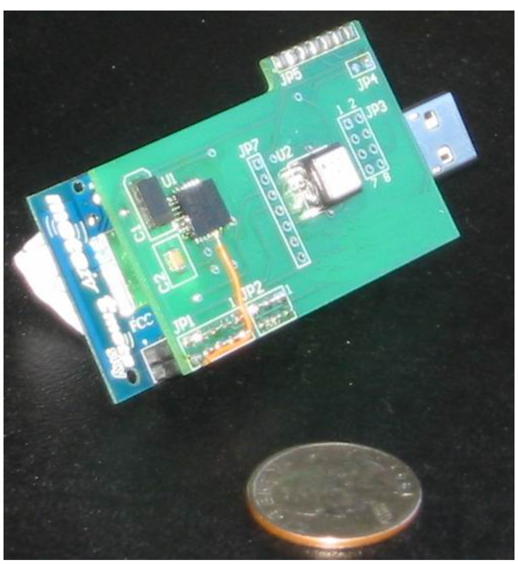

Figure 3. A picture our processing unit (Telos motes) and our custom-design motion sensor board

V. Design Challenges

The following design challenges are present at various stages of system design:

A. *Size and Wearability*

The wearability factor is perhaps the most important concern in these systems. In most cases, the system is being carried by individuals with less than average physical ability. In addition, the nodes and processing units should not interfere with the patient's daily activities. Therefore, we take this into account in choosing the COTS nodes, as well as placing them on the human body.

B. *Low-Power*

Minimizing the energy consumption of our platform is an essential hurdle to overcome. Since the device will be so close to human body, the production of heat must be severely limited to eliminate adverse effects and to prevent any possible discomfort. The size of batteries must also remain highly compact due to the wearability concerns. Therefore, the power consumption due to computation and communication must be highly optimized. The nodes must remain off when they are not needed. In distributed sensing, specifically from human body, at times the sensor readings may be highly correlated. In such scenarios, the nodes which are providing redundant information must be turned off. This problem can be reduced to a distributed set-cover problem where the nodes with redundant information form sets.

Dynamic power management technique is another feature of the run-time environment of our system. This technique dynamically reconfigures the system to provide the requested services and performance levels with a minimum number of active components or a minimum activity level on such components. Utilizing distributed processing units not only enables us to perform more complex tasks, but also brings a great level of robustness to a system exposed to various physical failures.

C. *Limited communication bandwidth*

The communication and more specifically wireless communication exhaust a large portion of the battery resources. In addition, the available wireless bandwidth is highly constrained. Meanwhile, in many medical monitoring applications, due to the distributed nature of sensing, and the existence of collaborative algorithms, the wireless communication becomes inevitable. Therefore, it is imperative to perform the wireless communication in highly efficient manner and the nature of the applications imply that the communication be highly predictable (latency) and reliable. To utilize the bandwidth efficiently, application-aware date compression techniques may be used.

D. *Calibration and validation*

One main question that must be addressed is if the system provides meaningful and accurate observation of certain medical patterns. Therefore, the system validation becomes an important concern. For the movement monitoring, we intend to use vision data that provides multi-modality and will enable the designer to verify the functionality of the system.

We have built such virtual reality environment (at UIUC and UCB) by deploying a large camera networks which enable to capture/digitize and reconstruct three dimensional images and sound of moving people and integrate this multimedia data from geographically distributed sites [8]. We further, developed a tool that extracts the skeleton of the subjects. The skeleton provides information on displacement of every joint as shown in Figure 4.. We compare this data with the data reading from motion sensors to confirm if the sensor readings from the motion sensors are accurate. Our system consists of 48 cameras in 12 stereo clusters.

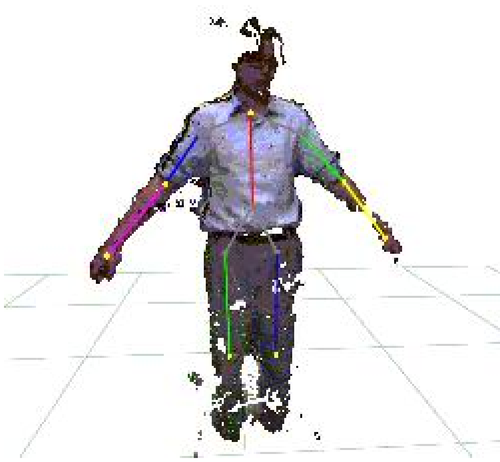

Figure 4. Skeleton construction from 3D vision and using our virtual reality environment

The calibration of sensors has been always a complicated task. This is in particular more complex due to the fact that the initial orientation of the motion sensor device may not be known.

E. Node Coordination

Due to the extensive variation of morphologies from medical/biological sensors, potentially many features can be considered on data readings. A selected set of features must be communicated for a centralized classification. The features detected and communicated simultaneously, may introduce wireless collusion, and may affect system performance adversely. To avoid this, and to coordinate the communication, we suggest utilizing congestion graphs. In congestion graphs, the nodes represent the features and the links correspond to the simultaneous communication of the features. In this context, to coordinate the communication, we seek to obtain the maximal cliques. We also suggest taking into account a "significance" measure on the features. The significance can be defined as how well each feature can contribute to an accurate classification. Therefore, in the case where there exists several features to be communicated with a central node, the system may choose the most significant set in case they all cannot be communicated. This may occur due to the resource constraints or the time sensitivity in communications (i.e. the communication must be completed by a deadline). In addition, we would like to take into account the correlation between features. When the features provide highly correlated information, communication of redundant features may be eliminated.

F. Application-aware software reconfiguration

We propose to utilize component-based feature extraction. As the requirements of the system alter, or new environments create the need for new observations, new feature extraction modules may be employed. This can be facilitated by the means of dynamic software migration. The software migration, in general, can effectively handle transient and permanent faults by means of reconfiguration and iterative resource allocation.

G. Fast prototyping/ user-centric design

The rapid prototyping and fast customization capabilities enable the user to easily evaluate and validate inter-application behavior and test its performance on various subjects, instead of spending time on the system design issues. A modular design similar to what we proposed with component-based feature extraction can speed up the design process.

VI. Preliminary Results

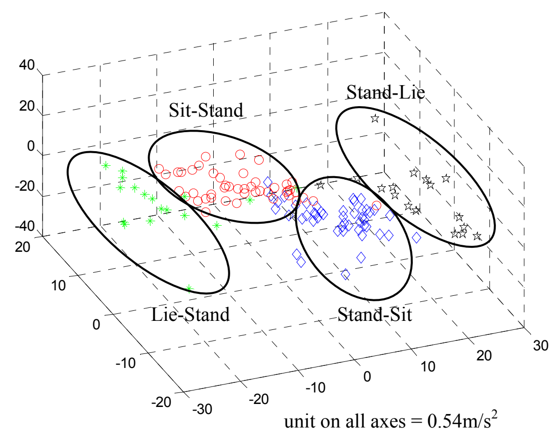

Figure 5. Movement classification with constant inclination feature

We have carried out several experiments for posture recognition. Our preliminary test case includes four young subjects with an average age of twenty and seven elderly subjects with an averaged age of sixty four. They were asked to perform the following tasks:

1. Walking on a straight line over a span of twenty feet and six times (as a control).

2. Sit down and stand up three times each, from three different seats. The seats were a hardtop and a cushioned chair, as well as a couch. The test subjects were allowed to pause or walk around in between these actions.

3. Lying down and getting up three times from the same

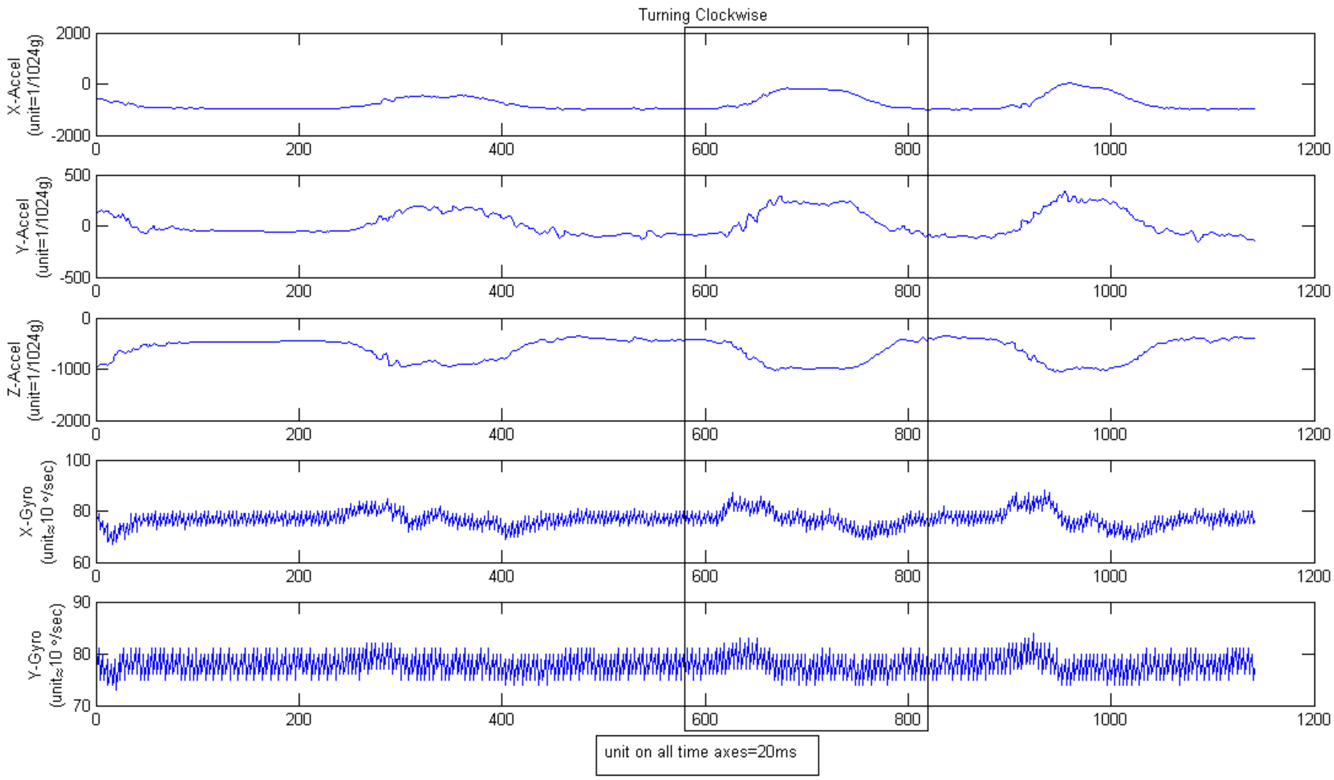

Figure 7. Raw data readings from motion sensors (accelerometers and gyroscopes) placed on the waist – 'turning clockwise' movement

bed.

Corresponding video sequences of the experiments were captured for comparison and justification of our classification results. Throughout these experiments, we used a single waist-mounted motion sensor.

Figure 5 illustrates the clustering performed using the constant inclination features. The four movements, that include sit-to-stand, stand-to-sit, lie-to-stand and stand-to-lie, have been presented with several legends. Figure 6 exhibits the clustering performed with SVD feature. This figure demonstrates SVD can effectively discriminate simple movements from complex movements.

Finally, Figure 7 exhibits the raw sensor reading from motion sensors (accelerometers and gyroscopes) placed on the waist. As outlined with a black box, the sensor readings are highly correlated. Yet, some are more pronounced than the rest. By this observation, we may derive that some features may be more effective and significant.

VII. RELATED WORK

From system integration prospective, numerous research institutions have been active in this area. The Smart Shirt from Sensatex [9] is a wearable health monitoring device that integrates a number of sensory devices onto the Wearable Motherboard from Georgia Tech [10]. The Wearable Motherboard is woven into an undershirt in the Smart Shirt design. Their interconnect is a flexible data bus that can support a wide array of sensory devices. These sensors can communicate via the data bus to a monitoring device located at the base of the shirt. The monitoring device is integrated into a single processing unit that also contains a transceiver. Several other technologies have been introduced by MIT called MIThril [11], e-Textile from Carnegie Mellon University [12], Wearable e-Textile from Virginia Tech [13], CustoMed and RFab-Vest from UCLA[14][15].

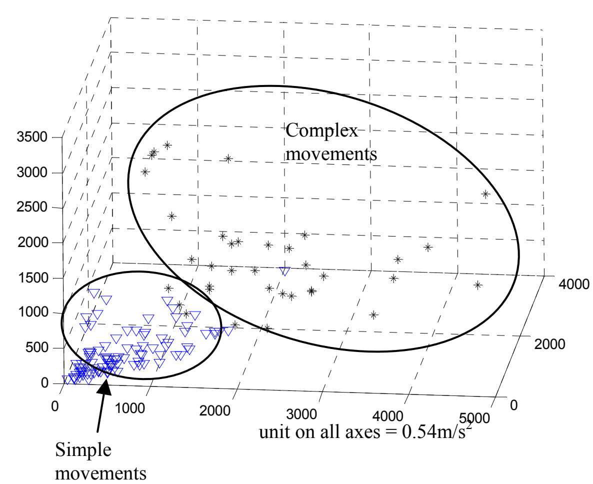

Figure 6. Movement classification with SVD feature

Furthermore, the Lifeguard project being conducted at Stanford University is a physiological monitoring system comprised of physiological sensors (ECG/Respiration electrodes, Pulse Oximeter, Blood Pressure Monitor, Temperature probe), a wearable device with built-in accelerometers (CPOD), and a base station (Pocket PC). The

CPOD acquires and logs the physiological parameters measured by the sensors [16].

The Assisted Cognition Project conducted at the University of Washington's Department of Computer Science explored the use of AI systems to support and enhance the independence and quality of life of Alzheimer's patients. Assisted Cognition systems use ubiquitous computing and artificial intelligence technology to replace some of the memory and problem-solving abilities that have been lost by an Alzheimer's patient [17]. Nevertheless, none of the above projects or systems supports the concepts of scalability and systematic design techniques that are tightly coupled with signal processing.

VIII. CONCLUSION

This paper has given an overview of the main characteristics of medical monitoring applications where distributed sensing is required. We presented a set of sensors that we have been using, and portrayed a number of design techniques that can be combined with signal processing. We used movement monitoring as the pilot application, and presented our preliminary results.

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