Physical Activity Monitoring for Assisted Living at Home

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Abstract— **We propose a methodology to determine the occurrence of falls from among other common human movements. The source data is collected by wearable and mobile platforms based on three-axis accelerometers to measure subject kinematics. Our signal processing consists of preprocessing, pattern recognition and classification. One problem with data acquisition is the extensive variation in the morphology of acceleration signals of different patients and under various conditions. We explore several effective key features that can be used for classification of physical movements. Our objective is to enhance the accuracy of movement recognition. We employ classifiers based on neural networks and k-nearest neighbors. Our experimental results exhibit an average of 84% accuracy in movement tracking for four distinct activities over several test subjects.**

Keywords— **Fall detection, movement monitoring, wearable and ubiquitous computing, signal processing.**

I. Introduction

Health care costs in developed countries are rapidly increasing due to a substantial increase the elderly population. Monitoring of daily physical activities 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 (ICT), especially for the homebound [1, 2]. New technology allows the creation of small sensor “Motes” which combine a variety of micro-machined transducers, a micro-controller to reduce data into information, and a wireless link to the outside world. Privacy is greatly increased by a decentralized system, where distributed data cannot be easily corrupted. 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. In this paper we present data and analyses that show differences in movement parameters between young and aged control groups. A new classification scheme is introduced that allows learning the idiosyncrasies of the individual subject (hence group).

In order for ICT-based systems to gain widespread acceptance and use, important social concerns must be addressed and many technical challenges overcome. Some of these concerns involve wearability and ease of use, cost, maintenance and the effectiveness of privacy. One of the technical challenges posed by such systems is the fusion and analysis of the many streams of data provided by numerous sensing elements. In this paper we present a prototype of a Mote-based system that is capable of predicting the need for medical attention, and notifying emergency services of an acute illness or accident. In particular, we want to accurately announce falling of the elderly. This work is a part of the information technology for assisted living at home (ITALH) project at Berkeley.

II. Related work

Various motion sensors can be adapted to monitor daily physical activity, ranging from mechanical pedometers [3], actometers [4] to accelerometers [5].

Accelerometers are the most commonly used motion sensors for physical activity assessments. These sensors respond to both the frequency and intensity of a movement, and are superior to pedometers and actometers, which are attenuated by impact or tilt and can only measure body movement over a certain threshold. Current MEMS technology enables us to build very small and lightweight accelerometer-based Motes that can be worn for days or even weeks.

Anliker et al. proposed a portable telemedical monitor (AMON) [6] for high-risk cardiac/respiratory patients. This system includes continuous collection and assessment of multiple vital signs, intelligent multi-parameter medical emergency detection, and a cellular link to a medical center. By integrating the whole system in a low profile, wrist-worn enclosure, continuous long-term monitoring can be performed without interfering with the patients’ everyday activities and restricting their mobility. Specific movement patterns, however, may not be recognized using AMON.

Najafi et al. suggested a method of physical activity monitoring which is able to detect body postures (sitting, standing, and lying) and periods of walking in elderly persons using only one kinematic sensor attached to the chest [7]. The wavelet transform, in conjunction with a simple kinematics model, was used to detect different postural transitions (PTs) and walking periods during daily physical activity. This approach may not be applicable to light-weight and wearable processing units due to its computational complexity.

The most recent work presents the implementation of a real-time classification system for the types of human movement associated with the data acquired from a single, waist-mounted triaxial accelerometer unit [5]. The decision making algorithm is based on the detection of the angular orientation of the accelerometer. The decision algorithm does not account for individual differences, and signal processing is always performed on a fixed interval of data (one second).

Aminian outlined the advantage of new technologies based on body-fixed sensors and particularly the possibility to perform field measurement [8]. The system integrates outputs from accelerometers and gyroscopes for human movement tracking.

III. System Architecture

We have constructed a prototype of a decentralized sensor Mote that is designed to eventually fit into an integrated communication scheme such as illustrated in Figure 1. The current device uses Bluetooth communication to facilitate connection to mobile phones and laptop computers.

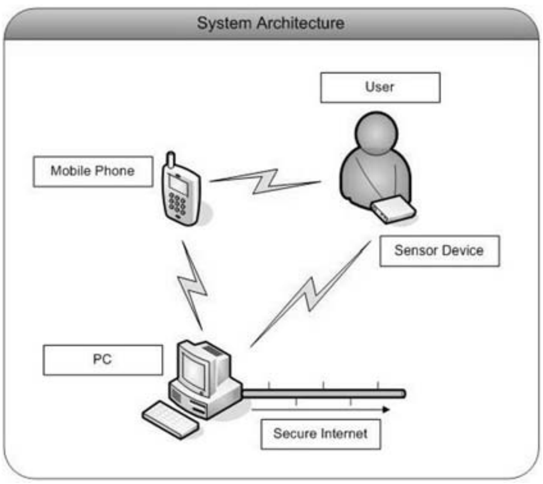

Figure 1. System architecture

The prototype device utilizes three-axis accelerometers for fall detection, and GPS to measure out-of-building mobility, as shown in Figure 2.

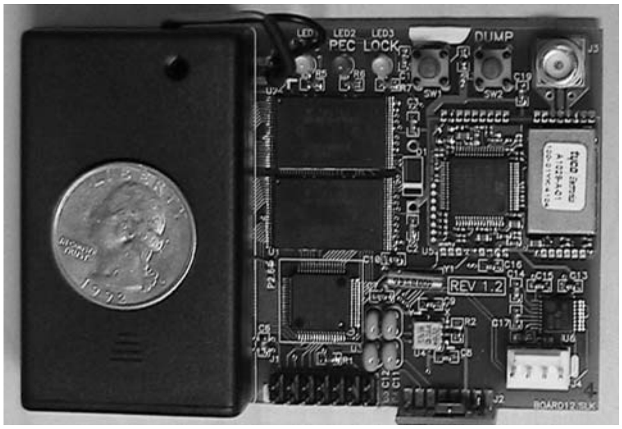

Figure 2. Our Mote device

Laptop PCs were used as the central home server, and Nokia 6680 mobile phones were used as the mobile servers. In addition, the mobile phones are used off the telephone network and communicate with the laptops via Bluetooth, which emulates a remote service, for example, a medical assistance's connection.

IV. Data Acquisition

We propose the following framework for simultaneously detecting falls and classifying physical activities. In particular, we are interested in classifying transition movements including sit-to-stand, stand-to-sit, lie-to-stand and stand-to-lie. These four transition movements all involve rapid changes of acceleration in some or all axes. Rapid falls can be detected by simple thresholding when there is a sharp change of acceleration on the z-axis, but slow falls, such as collapsing after a heart attack, are much harder to discern due to a smaller change in acceleration. In addition normal activates of the subject must be discernible from emergency conditions to prevent false positive alarms. We propose a strategy of detecting falls by integrating three-axis accelerations with a fall-resembling activity classifier. With this approach, we can increase successful fall detection without increasing the rate of false positives. In the future, we can integrate rate gyroscopes and a biological sensor to further differentiate slow falls from a normal stand-to-lie movement (going to bed for example). The following flow chart illustrates our methodology where the board is attached to the body for our experiments.

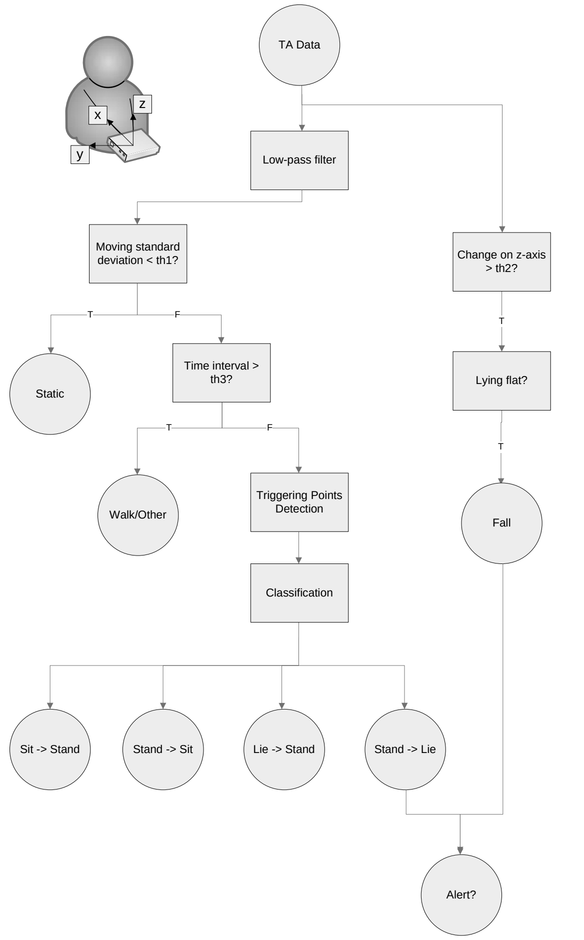

Figure 3. Signal processing flow-chart (*th1*, *th2*, *th3*: thresholds)

Given the goal of classifying movements based on subject motion, the functionality of our automated pattern recognition system is divided into two basic tasks: 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.

A. Preprocessing

The filtering is performed by a sixteen coefficient smoothing filter. The intuition behind using 2^n filter coefficients is that the division can be efficiently performed by the 16-bit MCU with a right-shift register. Unfiltered data is fed into the normal fall detection detector to avoid filtering out potential falls.

For classifying transition movements, hard thresholds (*th1* and *th2*, as shown in Figure 3) are first used to differentiate the activities into static, walk/other and transitions. To distinguish activity vs. rest, a majority vote from all three axes is used to make a decision. A triggering point detection mechanism is then used to further narrow down the regions of interesting activity. We define triggering points as places where the mean of the next *k* samples is greater or less than the mean of the previous *k* samples by a given threshold. This threshold is obtained by multiplying the maximum amplitude change over the transition interval by a given ratio (*r*). The choice of this ratio is only dependent on the window size *k*. We used *r=0.25* in our experiments.

B. Feature extraction

- 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 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 [9, 10]. 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 applied SVD analysis to these local extremums, weighing each extremum by its distance from the preceding extremum.

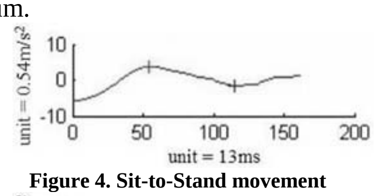

Figure 4. Sit-to-Stand movement

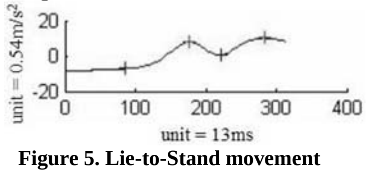

Figure 5. Lie-to-Stand movement

- Skewness: Skewness is computed on a region of interest by treating the signal as a distribution plot rather than a point plot. This is done by generating a sample space in which every acceleration value *v* at sample *t* on the original graph is converted to *v* points with value *t* in the new sample space. Skewness is then calculated based on this sample space. This approach differs from previous approaches because it can estimate the asymmetry of the profile of the signal. This measure is applied to both the x and y axes. The principle drawback of using this feature is that it is computationally expensive.
- Maximum amplitude change: Maximum amplitude change of the signal gives us an idea of how abrupt the transition is. Moreover, there is a direct correlation of this metric with the energy level of an individual. This is one of the causes of classification inaccuracy across different age groups.

C. Classification

We utilize both a neural network [11] and k^{th} nearest neighbor (k-NN) algorithm [12] to classify movements. Neural network classifiers are data-driven, which may better adapt to an idiosyncratic motions over time, whereas k-NN provides scalability for distributed sensing platforms.

V. Experimental results

Two young test subjects aged twenty and twenty-one imitated 68 types of falls. Our fall detection approach (Figure 3), accurately identified 118 out of 132 falls. The subjects also imitated 36 fall-resembling movements. Our normal fall detection approach based on hard thresholds resulted in 23 false-positives out of 168 fall/non-fall movements. The raw data from z-axis of an accelerometer is shown in Figure 6.

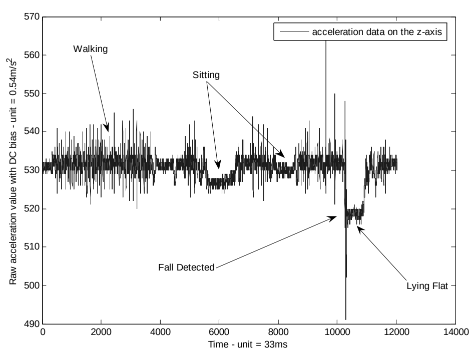

Figure 6. Raw acceleration data from z-axis

Furthermore, we carried out another set of experiments on 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:

- Walking on a straight line over a span of twenty feet and six times (as a control).
- 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.
- Lying down and getting up three times from the same bed.

Corresponding video sequences of the experiments were captured for comparing to and justifying our classification results.

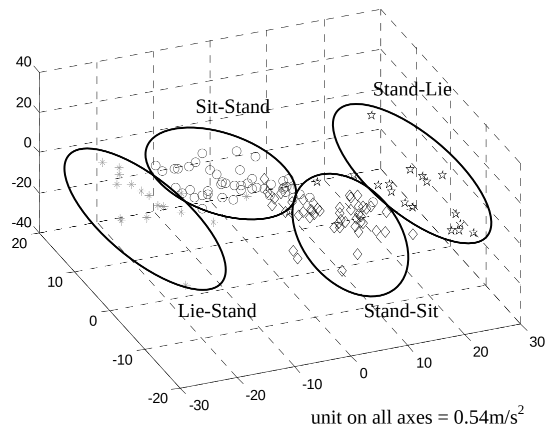

Figure 7. Constant inclination feature

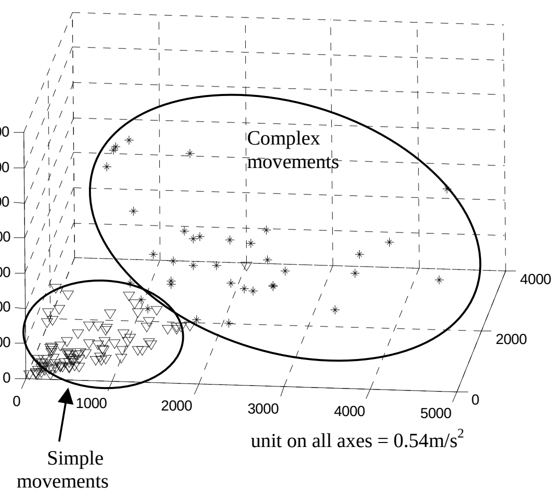

Figure 8. SVD feature

Figure 7 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 8 exhibits the clustering performed with SVD feature. This figure demonstrates SVD can effectively discriminate simple movements from complex movements.

For the neural network classifier, we used a feed-forward design with eight first hidden layer nodes, four second hidden layer nodes and four output nodes for the four activities. The network was trained using back-propagation [13] with 100 epochs and an error margin of 0.01. We also used k-NN with *k* values of 5, 9 and 10.

Tables 1 to 4 illustrate the accuracy of classification using the constant inclination features. In this set of analyses, each classifier is trained and tested on the two age groups separately.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	26	4	4	2	**72.2**
Stand-Sit	0	29	0	8	**78.4**
Lie-Stand	0	0	5	3	**62.5**
Stand-Lie	3	0	0	5	**62.5**

Table 1. Results of using neural network trained with data from elderly subjects and tested on elderly subjects, training set size = 10.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	21	0	3	0	**87.5**
Stand-Sit	0	19	1	2	**86.4**
Lie-Stand	0	0	6	0	**100**
Stand-Lie	0	0	0	6	**100**

Table 2. Results of using neural network trained with data from young subjects and tested on young subjects, training set size = 5.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	31	4	1	0	**86.1**
Stand-Sit	1	35	0	1	**94.6**
Lie-Stand	2	0	5	1	**62.5**
Stand-Lie	0	3	0	5	**62.5**

Table 3. Results of using k-NN trained with the same set of data from elderly subjects and tested on elderly subjects, training set size = 10, k = 10.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	22	0	2	0	**91.7**
Stand-Sit	0	22	0	0	**100**
Lie-Stand	0	0	6	0	**100**
Stand-Lie	0	0	0	6	**100**

Table 4. Results of using k-NN trained with the same set of data from young subjects and tested on young subjects, training set size = 5, k = 5.

Next, we use the same constant inclination feature but train our classifiers with all the data from one age group and test them on the other group, as illustrated in Tables 5 to 8.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	41	5	0	0	**89.1**
Stand-Sit	4	41	0	1	**89.1**
Lie-Stand	8	0	7	3	**38.9**
Stand-Lie	0	7	3	8	**44.4**

Table 5. Trained neural network with constant inclination feature from young subjects and tested on elderly subjects.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	43	3	0	0	**93.5**
Stand-Sit	5	42	0	0	**89.4**
Lie-Stand	2	2	13	1	**72.2**
Stand-Lie	0	2	2	14	**77.7**

Table 6. Trained k-NN classifier with constant inclination feature from young subjects and tested on elderly subjects – k = 9.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	27	0	2	0	**93.1**
Stand-Sit	0	26	0	1	**96.3**
Lie-Stand	4	0	7	0	**63.6**
Stand-Lie	1	2	0	8	**72.7**

Table 7. Trained neural network with constant inclination feature from old subjects and tested on young subjects.

	Sit-Stand	Stand-Sit	Lie-Stand	Stand-Lie	% of success
Sit-Stand	25	0	4	0	**86.2**
Stand-Sit	0	25	0	2	**92.6**
Lie-Stand	1	0	10	0	**90.9**
Stand-Lie	0	1	0	10	**90.9**

Table 8. Trained k-NN classifier with constant inclination feature from old subjects and tested on young subjects, k = 9.

The results indicate that training classifiers with the data from elderly subjects and testing them on the young subjects yields higher accuracies than the reverse. We propose that this discrepancy is due to the fact that movements are more pronounced for the young subjects, thereby resulting in better clustering.

Next, the analysis was performed on classifying simple vs. complex movements. We use the SVD feature and the results are shown in Tables 9 to 12.

	Sit-Stand + Stand-Sit	Lie-Stand + Stand-Lie	% of success
Sit-Stand + Stand-Lie	59	14	**80.8**
Lie-Stand + Stand-Lie	8	8	**50.0**

Table 9. Results of using neural network trained with data from old subjects and tested on old subjects, training set size = 20.

	Sit-Stand + Stand-Sit	Lie-Stand + Stand-Lie	% of success
Sit-Stand + Stand-Lie	43	3	**93.5**
Lie-Stand + Stand-Lie	0	12	**100**

Table 10. Results of using neural network trained data from young subjects and tested on young subjects, training set size = 10.

	Sit-Stand + Stand-Sit	Lie-Stand + Stand-Lie	% of success
Sit-Stand + Stand-Lie	70	3	**95.9**
Lie-Stand + Stand-Lie	2	14	**87.5**

Table 11. Results of using k-NN trained with the same set of data from old subjects and tested on old subjects, training set size = 20, k = 10.

	Sit-Stand + Stand-Sit	Lie-Stand + Stand-Lie	% of success
Sit-Stand + Stand-Lie	40	6	**87.0**
Lie-Stand + Stand-Lie	1	11	**91.7**

Table 12. Results of using k-NN trained with the same set of data from young subjects and tested on young subjects, training set size = 10, k = 5.

For brevity, the classifications results using other features are omitted. On average, the classifications using maximum amplitude change and skewness achieved 76% and 80% success rate respectively.

VI. Conclusion

We have devised four novel features and implemented them through two classification schemes. The features include constant inclination, SVD, skewness and maximum amplitude change. Overall, we can classify four transition movements that include sit-to-stand, stand-to-sit, lie-to-stand and stand-to-lie, with an accuracy of 84%. Both constant inclination and skewness are effective features for classification in the elderly group, while maximum amplitude change is the most effective classification feature for the young group. SVD is useful in distinguishing complex movements from simple movements. The results indicate that training classifiers with the data from elderly subjects and testing them on the young subjects yields higher accuracies than the reverse. We propose that this discrepancy is due to the fact that movements are more pronounced for the young subjects, thereby yielding in better clustering. This is an important issue that needs to be addressed in this domain where the system must be adaptively customized for individuals. This issue was not explored in the previous work.

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