Kinematic-based Sedentary and Light-Intensity Activity Detection for Wearable Medical Applications

Kazi I. Zaman, Sami Yli-Piipari, and Timothy W. Hnat
University of Memphis
Memphis, TN, USA
{kizaman, srylppri, twhnat}@memphis.edu

Abstract

A sedentary lifestyle is becoming common for many individuals throughout the United States; however, this comes with a health cost of various preventable diseases such as cardiovascular disease, colon cancer, metabolic syndrome, and diabetes. Many times, individuals are completely unaware of how his or her health has deteriorated because of the slow progression or the demands of a job. We seek to bring attention to these problems by identifying specific sedentary activities and propose that just-in-time interventions could be used to help individuals overcome some of these problems. Our solution involves wearable sensors and utilizes a kinematic-based activity recognition systems to identify sedentary and light-intensity activities. Our system is evaluated with a series of laboratory experiments that include data from 34 individuals and a total of over 1400 minutes of activity. Results indicate that our system has a classification accuracy of up to 95.4 percent across all activities.

Categories and Subject Descriptors

C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embedded Systems; J.3 [**Life and Medical Sciences**]: Health

General Terms

Design, Performance, Experimentation

Keywords

Body Sensor Network, Kinematics

1 Introduction

Sedentary lifestyles, such as those involving sitting, computer work, or otherwise being stationary, can contributed to various preventable diseases such as cardiovascular disease, colon cancer, metabolic syndrome, and diabetes [22, 16, 2]. These diseases contribute to a significant portion of annual medical costs in the United States, and based on some estimations, an additional 77 billion dollars in annual medical costs [17]. The single largest factor contributing to these diseases is the changing lifestyles of modern life resulting in an expected set of future health problems for many individuals.

Many researchers focus on identifying and recording daily activities such as walking, running, jogging, and climbing stairs. A common approach [3] is to attach wearable accelerometers to an individual's wrist, ankle, waist or other locations. Often, these systems are bulky and intrusive to the individual's daily activities and thus interfere with long-term wear. Other research utilizes additional sensors such as a GPS [15] to record location information or a microphone [9] to detect ambient environmental sounds. Another approach is based on camera technology [20] but it is constrained to small indoor environments. Still, most of the research focuses on basic activities that tend toward moderate or vigorous intensities and are weaker at identifying sedentary activities.

In this paper, we utilize our existing K-Sense monitoring system which is based on inertial measurement units (IMUs), consisting of 3-axis accelerometer, gyroscope, and magnetometer which are attached to the waist, wrist, and ankle of a person. Bluetooth radios transmit these data to a remote computer or smart phone. It measures motion and angular position at approximately 50 hertz. This data is utilized to compute kinematic motion features which are used with a standard decision tree classifier. We envision K-Sense as a wearable technology designed for medical practitioners to evaluate a person's behavior and daily activities. Ultimately, our vision of the system involves integrating these techniques into a smart phone, smart watch, and smart shoe.

The main challenge our solution seeks to address is identifying activities that are principally associated with minimal movements such as watching TV or laying on a couch. The hardware is capable of measuring angular changes of more than 0.1 degrees thus enabling the measurement of small changes in body and limb position. In some cases such as sitting or laying, a person's legs typically do not move; however, there angle relative to gravity is a clear distinguishing feature. A different set of activities, such as standing and sitting, result in similar absolute angular positions but the small movements associated with the body's balancing mechanism result in a measurable change. Similarly, every activity has

1st Workshop on Mobile Medical Applications'14, November 6, 2014, Memphis, TN, USA.

http://dx.doi.org/10.1145/2676431.2676433

associated small movements that, if measured, may be able to distinguish it from others. These small motions are the premise of our kinematic based approach to sedentary activity detection.

In this paper, we present K-Senses design, feature generation, and classification system used for activity detection. K-Sense is evaluated with controlled experiments in a laboratory setting across eleven activities. Fifteen subjects followed a twenty minute action sequence consisting of standing, lying down, computer work, walking (3 mph), and running (6 mph) in the first phase. Nineteen subjects performed a thirty minute activity sequence consisting of watching TV, floor cleaning and washing dishes followed by a forty minute activity sequence consisting of computer work, reading a book, put away groceries, and walking (1.5 mph). We collected approximately 1400 minutes of data for analysis and our results indicate that activity detection is 95.4 percent accurate. In comparison, Lin's solution achieved a 83.3 percent accuracy on the same data set [19].

2 Related Work

There are several categories of systems designed to detect and identify human activities: accelerometer-based, multi-sensor solutions, and vision-based. Accelerometer-based techniques are among the most common approaches in use today. In general, accelerometers are placed in various quantities at different locations on a body [4, 11, 12, 8]. One solution provided a 97 percent classification accuracy based on a worn accelerometer; however, it was only tested with four activities [6]. Another study utilized 21 people with five accelerometers and a heart monitor and resulted in 94 percent accurate activity detection [21]. A solution most similar to ours utilized five IMUs and achieved a detection accuracy of 95 percent [1]; however, our solution is based on kinematics and achieves slightly better accuracy with fewer sensors.

Some systems include body-worn sensors that provide both accelerometer and physiological data along with devices in the environment for additional information [18]. Our solution does not rely on any external devices thus is able to operate anywhere a person travels. There are a large variety of methods utilized to detect and classify activities and they utilize a variety of sensors including: altitude, audio, body position, chest acceleration, chest compass, electrocardiogram, humidity, light intensity, heart rate, location, skin temp, and wrist accelerations [14]. We have focused on a simple set of sensors that can easily be worn as part of daily life and do not need addition physiological measurements.

A third category of solutions is based on video cameras, which have become popular in recent years. There is typically a lot of computational overhead associated with vision-based solutions. A common approach utilizes the Microsoft Kinect platform and achieved a classification accuracy of 84 percent [20]. Other solutions utilized a basic camera; however, the accuracy is worse [5, 13]. People tend to view vision-based solutions as intrusive and potential privacy concerns resulting in poor acceptance in private environments such as homes. Since our system is not based on a camera, we believe that a person is more likely to allow it when compared to a camera-based solution.

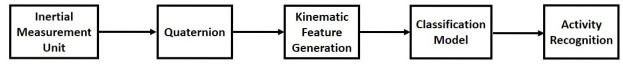

Figure 1. System architecture overview.

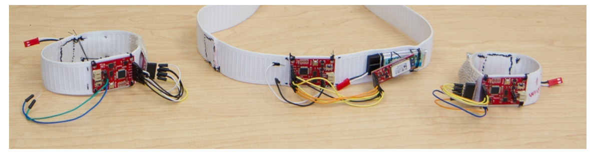

Figure 2. K-Sense's test hardware which includes an inertial measurement unit, Bluetooth radio, and battery. They can be placed on the wrist, ankle and waist.

3 Approach

One of the goals of the K-Sense hardware platform is to detect various classes of activities from sedentary to vigorous. Figure 1 provides an overview of the hardware, signal processing, and classification system. K-Sense utilizes IMUs, consisting of accelerometers, gyroscopes, and magnetometers and produces 27 dimensions of data which is split into windows where features are computed. The windowed features are then utilized to construct a decision tree for classification.

3.1 Hardware

Figure 2 illustrates the hardware used and can be placed at wrist, ankle and waist where a modified version of the Sparkfun Razor 9DoF IMU is used to capture human movement. The system provides three axes of acceleration data, three axes of gyroscopic data, and three axes of magnetic data with three sensors: a freescale ADXL345 triple-axis accelerometer, an IDG3200 3200/s gyroscope and a HMC5883L magnetic sensor. An on-board ATmega328 processes the outputs of all sensors and sends over a serial interface. Custom firmware was used on the controller board to stream sensor data continuously. Data was sampled at 50 Hz per sensor. Bluetooth was used to transmit data to a nearby PC at 115200 bps. Maximum range of the transmitter was found to be 15 m in indoor conditions. The entire system received was powered from a 3.7 V rechargeable lithium-polymer battery power supply. For more details see our previous work [23].

3.2 Signal Processing

Activities can be differentiated according to the movements of various body parts by measuring their kinematic motions, specifically angular position and angular velocity. Because arms and legs are connected to the torso at a shoulder or hip, most of their motion can be modeled as rotations about the joint. Translations can also be modeled; however, one needs to be careful regarding sensor noise and drift. This processing first converts raw data into a quaternion representation then windows the data for feature computation. These windowed features are fed into the classification system to train a decision tree.

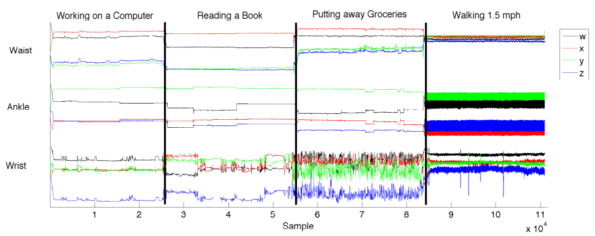

Figure 3. A sample data trace of four activities, working on a computer, reading a book, putting groceries away, and walking, is represented by quaternions (w,x,y,z).

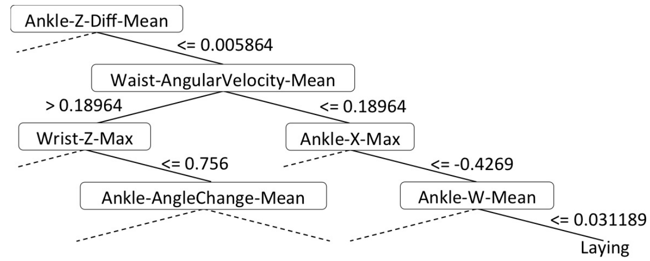

Figure 4. A part of decision tree. Each activity can correspond to more than one leaf.

3.2.1 Quaternion

After getting data from the IMUs, our system transforms the raw data streams into quaternions [10]: a representation for the sum of a scalar and a three dimensional vector. It is a convenient notation to represent orientation in three dimensional space. We do not use Euler angle which suffers gimbal lock, loss of one degree of freedom in three dimensional space. Quaternions provide a fourth axis in an arbitrary orientation to always have a least three axes on which to rotate. Figure 3 illustrates sample data trace of raw quaternion value of three sensors where there are visually distinct attributes for each activity.

3.2.2 Feature Computation

Quaternion data, $Q_n = (w_n, x_n, y_n, z_n)$ where w,x,y,z represent each of the four axes of the quaternion representation, is grouped into non-overlapping five second windows for the purposes of activity recognition. We evaluated several window sizes between 0.5 and 20 seconds and found that accuracy is almost the same in each case. We used a five second window which is sufficiently long enough to capture an activity but not long enough to capture multiple activities. The first class of features consists of basic methods: *mean*, *max*, *min*, *variance*, and *amplitude*. For each set of w,x,y,z the functions are computed over the window $(w_1, w_2, ..., w_n)$ where n is the number of elements. The way this class of features is utilized is based on the difference, $\Delta w = (w_1 - w_2, w_2 - w_3, ...w_{n-1} - w_n)$, of all consecutive values of w,x,y,z in each window. The same features, *mean*, *max*, *min*, *variance*, and *amplitude* are computed for each window.

The second class of features is based on angular change denoted as $\Delta\theta$ and is computed from two consecutive quaternion values

$$\Delta\theta_i = cos^{-1}(2(Q_i \cdot Q_{i+1})^2 - 1)$$

where i varies from 1 to $n-1$ and n is the number of elements in the window. Angular velocity, ω_i, is computed by taking the amount of angular change for each pair of elements and dividing by the time interval for each pair of values.

$$\omega_i = \frac{cos^{-1}(2(Q_i \cdot Q_{i+1})^2 - 1)}{t_{i+1} - t_i}$$

where i varies from 1 to $n-1$ and n is the number of elements in the window. t designates the recorded time stamp on each sample. The same features, *mean*, *max*, *min*, *variance*, and *amplitude* are computed for each of $\Delta\theta$ and ω for all windows.

A third class of features is based on frequency of the measured motions. We calculate frequency of change by computing a fast Fourier transform (fft) of each window of data. We extract the dominate frequency

$$freq_w = max(|fft(w_1...w_n)|)$$

of each window by computing the maximum peak of each window for each of the four axes, w,x,y,z. Additionally, the maximum frequency from all w,x,y,z axes is recorded.

By combining the features for all axes and sensors, we end up computing a total of 165 feature values for each of the five second windows. These kinematic features are passed to the decision tree classifier for activity recognition and can differentiate different activities because angular position and movement are activity and person dependent. Additional features can be added as the types of activities monitored are increased.

3.2.3 Classification

We utilize machine learning to train our system for detecting specific activities. There are several choices for algorithms including: naive Bayes, support vector machines (SVM), C4.5 decision trees, and k-nearest neighbors (KNN). We have chosen to utilize the C4.5 decision tree algorithm as implemented by the Weka machine learning tool as J48 tree [7]. This algorithm takes labeled windows of features as training data and builds a decision tree based on the values where each leaf corresponds to a specific activity. Figure 4 shows a subset of our decision tree. To detect an activity, the algorithm starts at the root of the tree and navigates through the nodes until it reaches a leaf and thus an activity.

4 Experimental Setup

We utilized three K-Sense IMU monitors for two separate trials where each person performed a series of activities. The monitors were attached to the right side of each individual on his/her wrist, ankle, and waist. The right side of the body was chosen because the majority of people are right-handed. In the case of the waist, location is not relevant because the hips can not move independent of each other. Utilizing the right ankle allowed our trials to be consistent and legs either move in a counteracting manner such as walking or a symmetric manner when sitting or laying. Asymmetric movements are rare and do not appear in our experiments. We did not test all permutations of sensor placement due to time and space constraints. Subject demographics were collected; however,

Activities	Intensity
standing	sedentary
reading a book	sedentary
laying	sedentary
watching tv	sedentary
computer work	sedentary
floor cleaning	light
washing dishes	light
put away groceries	light
walking (1.5 mph)	moderate
walking (3 mph)	moderate
running (6 mph)	vigorous

Table 1. Activities can be categorized with different intensities including: sedentary where a person is either sitting or standing, light where a person is standing and moving around, moderate where a person is walking, or vigorous while running.

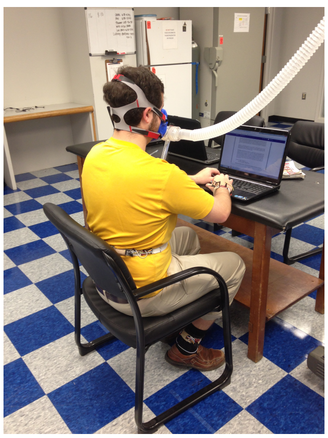

Figure 5. An example testing scenario where an individual is working on a computer while being monitored by several systems.

the results presented here do not depend on this knowledge. The first trial consisted of 15 people did 5 activities, standing, laying, computer work, walking (3 mph) and running (6 mph) over a test duration of 20 minutes and each activity was performed for 4 minutes. The walking and running activities were done on a treadmill. The second trial consisted of two phases where the same 19 people participated in each. The first phase consisted of three 10 minute activities and the second phase consisted of four 10 minute activities for a total of 70 minutes. The first phase included watching tv, sweeping the floor, and washing dishes and the second phase included computer work, reading a book, putting groceries away, and walking (1.5 mph). A summary of test activities is located in Table 1 which also indicates the intensity. All activities were performed in a simulated home environment located in a metabolic laboratory as illustrated in Figure 5.

Ground truth information was determined by a post-test analysis of the data which was aided by the rigid timing structure of the experimental procedure. Starting and ending times of activities were manually determined and recorded by this process. The data set contains over 1,400 minutes of motion data. Our evaluation of the classification system is based on the J48 decision tree which is the implementation of C4.5 algorithm provided by Weka [7] and we utilized a 10-fold cross validation strategy on all the reported results. Additionally, we compare against an accelerometer-based classification system [19] by applying their technique to our data.

5 Evaluation

We evaluate our system in four ways. First, we show how effective our chosen classification system is through a 10-fold cross validation of the classifier. Second, we show the true positive values for each activity of classifying by utilizing each individual sensor, the combination of all three sensor, and finally a comparison with an accelerometer-based solution. An evaluation of the information gain for the decision tree classifier is shown to illustrate how features can be mapped back into real-world semantics. Finally, we show the accuracy of various other machine learning classifiers.

Table 2 shows a comparison of correctly hand-labeled events and the results of the decision tree classifier presented in the form of a confusion matrix. This analysis illustrates that the majority of events are correctly classified as indicated by the high-value main diagonal. Several activities such as floor cleaning or putting away groceries can be incorrectly identified approximately 10 percent of the time. These results indicate that our solution correctly identifies activities and furthermore, when misidentified, the classifications are usually within the same intensity class.

An analysis of the true positive, the number of correctly identified events versus the total number of actual events, rates is shown in Table 3 for each sensor running independently, all sensors combined, and an accelerometer-based comparison from Lin et. al [19]. Precision and recall are not reported due to their nearly identical values as the true positive values. For example, precision (0.954), recall (0.954) and true positives (0.954) for all our sensors are identical. Lin's solution uses one mobile phone sensor which is equivalent to our waist sensor in type and location. In all cases, our solution outperforms Lin's on average over all tested activities. This is because that solution was not designed with light-intensity activities in mind. Instead, it performs well on laying, walking, and running and easily distinguish the various speeds of walking and running we tested. Their solution performs worse in the light-intensity scenarios K-Sense is designed to identify. Our solution provides more than 89 percent true positive value on all activities and the majority of activities are greater than 96 percent, an improvement of 12 percent over our comparison. True positive value of wrist-ankle, wrist-waist and ankle-waist fall in between 93.3 to 94.8 percent which is lower than using all three sensors together. The false positive rate is lower for all sensors, 0.6 percent, than for each pair of sensors which varied between 0.7 and 0.9 percent. Lin's solution shows higher false positive rate at 2.2 percent. These results are promising and indicate that more activities can be added to get a better sense of how people move and behave throughout their day and potentially offer suggestions of exercises while they are doing specific

Activity		a	b	c	d	e	f	g	h	i	j	k
standing	**a**	632	0	0	1	0	2	0	4	0	1	0
laying	**b**	0	625	0	0	0	1	0	0	1	1	0
computer work	**c**	4	0	2467	5	34	11	15	5	0	0	0
watching tv	**d**	0	0	6	1828	2	7	14	15	0	0	0
reading a book	**e**	0	1	31	4	1795	4	10	2	0	0	0
washing dishes	**f**	1	0	13	7	5	1725	39	143	2	0	0
put away groceries	**g**	3	0	21	12	4	48	1878	38	0	0	0
floor cleaning	**h**	6	0	6	6	0	132	45	1822	0	1	1
walking (1.5 mph)	**i**	0	0	0	0	0	0	0	0	1948	12	0
walking (3 mph)	**j**	3	0	0	0	0	0	0	0	12	696	9
running (6 mph)	**k**	0	0	0	0	0	1	0	2	2	10	639

Table 2. Classification results are presented as a confusion matrix where the left column designates the ground truth labeled activity and each row indicates how many times our decision tree labeled the activity as itself or something else. Standing and walking are examples where nearly all events were correctly labeled; however, other activities such as floor cleaning are not as accurate.

Activity	Wr	An	Wa	All	Lin
standing	94.5	97.0	95.3	98.8	67.2
laying	93.5	99.5	99.7	99.5	99.8
computer work	90.5	94.0	92.6	97.1	84.3
watching tv	93.9	94.2	96.8	97.6	86.5
reading a book	81.9	92.4	93.3	97.2	77.7
washing dishes	77.1	83.4	79.8	89.1	73.3
put away groceries	85.2	89.5	82.8	93.7	78.5
floor cleaning	80.3	83.9	81.5	90.2	73.1
walking (1.5 mph)	88.5	99.3	98.8	99.4	99.6
walking (3 mph)	81.4	96.3	96.7	96.7	99.2
running (6 mph)	96.5	97.3	97.1	97.6	96.9
Weighted Avg	**86.4**	**92.0**	**90.6**	**95.4**	**83.4**

Table 3. Activities are individually evaluated in five ways: wrist (Wr) only, ankle (An) only, waist (Wa) only, all three sensors combined, and Lin's method. The best results are obtained when combining all three sensors with an average true positive value of 95.4 percent. Lin's approach is worse at 83.4 percent on average except in moderate or vigorous activities and laying down.

activities such as sitting and watching tv instead of a generic message during any light-intensity activities. This targeted notification is valuable because one does not want to interrupt a person while they are doing chores around the house but only when they engaged in sedentary activities such as watching tv.

Information gain, the expected reduction in entropy caused by the partitioning of the samples according to particular attributes, is a way to quantify the importance of our various features. Table 4 shows the top 5 features for each sensor where the ankle sensor provides the most valuable information. The features that identify the extremes (*max*, *min*) also serve to designate the degree of movement and thus the types of walking and running activity. For the waist sensor, features such as *Angle-Change-Mean* indicate that there is a body rotation occurring and can be useful in detecting activities such as cleaning the floor where a person moves around and rotates his/her body. Finally, the wrist sensor has features that generally indicate extremes of movement; however, this body part has more degrees of rotational freedom and thus these features are not as powerful as the other two. Ultimately, a combination of all the sensors yields the most accurate results.

Classifier	Accuracy
Naive Bayes	73.0%
Support Vector Machine (SVM)	92.8%
C4.5 Decision Tree	95.4%
K-Nearest Neighbor (KNN)	98.5%

Table 5. The accuracy of different classifiers varies between 73 and 99 percent on the same feature set. While k-nearest neighbors yields the highest classification accuracy, we choose to use the C4.5 decision tree because of its intuitive rules based on features.

Table 5 shows a comparison of different machine learning classifiers. The naive Bayes classifier yields the worst accuracy in determining which activity is associated with a given window of data. All other classifiers are better than 90 percent with the KNN algorithm yielding the most accurate results; however, we choose to evaluate with a slightly weaker result, a C4.5 decision tree. This algorithm has a more intuitive mechanism for mapping specific features to outcomes than the KNN algorithm which is a black box method. We will write specific features targeting different light-intensity activities during the next phase of this work and having the ability to identify where and what types of features are useful is advantageous.

6 Conclusions and Future Work

In this paper, we present our K-Sense based activity detection system that is designed to identify various light-intensity activities. Currently, it is based on a set of custom IMU platforms; however, we envision a future where a smart phone carried in a pocket, a smart watch, and a smart shoe can provide the same information. Currently, most modern smart phones contain the necessary sensors to replace our waist

Ankle		Waist		Wrist	
Feature	**Information Gain**	**Feature**	**Information Gain**	**Feature**	**Information Gain**
Y-Mean	1.7024	Y-Diff-Mean	1.4535	Z-Mean	1.3299
Y-Min	1.6369	Z-Max	1.4484	Z-Max	1.3224
X-Min	1.5758	Angle-Change-Mean	1.4388	Z-Min	1.2754
Y-Max	1.5181	Velocity-Mean	1.4386	Y-Diff-Mean	1.2689
Z-Max	1.5134	Z-Mean	1.4217	W-Mean	1.2219

Table 4. The top five features for wrist, ankle and waist sensors and corresponding information gain. We find that the ankle provide the best features but the combination of all the sensors provides the highest activity detection accuracy.

worn device. We have evaluated our system in a laboratory and collected over 1400 minutes of activity data for 34 people. Our results indicate that the system can achieve a 95.4 percent accuracy when using a simple set of features. Our system is tested with controlled environment and subjects are instructed to perform activities in controlled manner. In the future, the system will be tested in free living environments and for concurrent activities. We believe the applications of a low-cost, wearable activity classifier will provide information to enable a variety of mobile health applications such as exercise motivation.

Our future plan is to develop a smart phone activity detection system based on our existing kinematic analysis. We foresee future applications of just-in-time interventions for a variety of diseases and other medical conditions. For example, if someone is motivated to lose weight and change his/her lifestyle, we would anticipate a system to detect when specific sedentary activities are occurring and encourage the user to do something different. Additionally, our ability to accurately monitor small movements of a leg or arm may allow for early detection of Parkinson's or other serious diseases based on muscle control.

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