Elderly Safety: A Smartphone Based Real Time Approach

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Abstract. As the number of elderly people living worldwide and average life expectancy increases, older adults' safety assurance has become increasingly important. There are many works on safety issues of the elderly focusing on human activity classification. Most of them use external sensor devices and/or completely or partially user input based classification and prediction systems. In this paper, we have developed an algorithmic model, monitored and documented elderly people`s daily activities by using the gyroscope and accelerometer of a smartphone and with the use of those data and model, we calculated how much activity is required or overdone for a subject in order to maintain a healthy lifestyle. More importantly, we built a real time system that could not only judge what basic activity the subject is currently doing, but also protect the subject from possible injury that might happen to the subject if abnormal data is received.

Keywords: Pervasive Systems, elder-care, physical and health safety, smart space.

1 Introduction

According to statistics, in 2012 there were approximately 6.2 billion mobile subscribers in the world, which is roughly 87 percent of the Earth's population [1]. Since the technology for smart phone sensors is growing rapidly, most smartphones now have internal sensors such as light, sound, gyroscope, proximity, accelerometer, orientation and GPS (Global Positioning System).

In recent years, the spending on healthcare in the United States has almost exceeded 2 trillion dollars [2]. People have a variety of health issues, such as a sedentary life style, heart disease, high cholesterol, diabetes and so on. Also people have automobile accidents every day that are caused by negligence. This is very common for older people. About 39,000 adults aged 65 and older die each year in the United States from injuries; worldwide this annual toll is about 946,000 persons. The top three causes of injury related death in this age group in the United State are falls, injuries related to motor vehicle crashes, and suicide [3].

Based on these issues, this paper is aimed at improving the health and safety of the elderly in daily activities. We separate safety issue into two parts; the first is health safety which could be harmed by unhealthy habits and longtime improper activity. Another is physical safety that could quickly be compromised when critical behaviors occur. Therefore, we first built a framework that could be used to easily monitor, get and record sensor data from smartphones. Both accelerometer and gyroscope data are recorded in the SD card. We used a list to keep real time data for both the gyroscope and accelerometer for a short period time. Then we built an algorithmic model to differentiate basic activities such as walking, resting, running, and driving using the sensor data. Based on the collected sensor data and the algorithmic model, we can differentiate basic activities, record the time of each activity for health calculation purposes and conclude how much exercise is needed for the subject to at least maintain current their health status. Also, it reminds the subject what problems might arise if the situation is not changed. Furthermore, our algorithm can also estimate sudden fluctuations in sensor data which might indicate a sudden change of activity. We detect running, turning sharply, moving backwards, and sudden changes in activities. Once one of these is detected, the application warns the subject that there might be potential danger. The goal is to prevent dangerous behavior and anticipate it before it happens. We get weather data and combine that data with our algorithm to make a more accurate judgment on the danger estimation.

2 Related Works

There are many research papers focusing on human activity classification. Most of them use external sensor devices like external tri-axial accelerometer [4] or any other external sensor devices worn by the subject [13]. Some of them use smart phones to collect activity data [5]. One of them [14] use database to store data collected from a MEMS based monitoring system. And then use a fuzzy rule based approach to define each activity. The activity monitoring system is also based on an external device. Although, most of research studies on human activity classification who use smart phones in any phase of their research [8], [9], [10], [11], [12] are good at classification on the algorithmic level, it is difficult to implement on a cell phone as a real time monitoring system because their algorithm requires a large amount of activity data. There is no current work that directly relates real time elderly safety with various human activities, particularly physical safety completely based handheld device.

3 Our Approach

3.1 Framework

In order to efficiently retrieve data from sensors, we created a library that could provide basic sensor operation on Android. In this library, it could list detailed information about the sensor, such as power, frequency, manufacture, and so on. It can also show all this sensor information and real time data on the UI.

It can record sensor data and write it onto the phone's SD card. Each recorded file is named by the current system time. The format of the data file is set as 'time X value Y value Z value', While the format of the filename is set as 'month-date, year hour-minutes-seconds'.

All data stored in the file will be recorded with an indicator of the current system time plus the X, Y, Z value of the sensors. Each time the application starts up or restart there will be a new file created in case of filename duplicate or data overwriting. If the application is running all the time without stopping or closing, the data would still be record to one file until any output interruption occurred.

There are four methods in this library each responsible for listing sensors, showing sensor information, showing sensor values and recording sensor data. Any other classes in other projects could easily do these four operations by simply importing the library and call methods.

3.2 Data Recording

After we created the framework that allowed us to easily retrieve data from sensors and record data on the SD card, we added the library to our project. Then we call methods from the library in order to collect sensor data from the accelerometer and gyroscope. We set the delay frequency as normal, which means the time interval between two recordings is 200 milliseconds. Then we keep a record of the system current time that corresponds to each recording. Finally, we write all this information – system time, and value of X, Y, Z of gyroscope and accelerometer on the SD card. The files stored on the SD card are primarily used for static analysis, which requires a relatively large amount of recording.

On the other hand, in order to keep track of short time changes for dynamical analysis, we make several array lists to store information as system time, gyroscope data and accelerometer data. The length of these lists is set to 25 because within that each list would record 5 seconds of continuous data, and we assume the subject could complete at least one cycle of activity. For example, no matter whether the subject is walking or running, we assume that in 5 seconds he or she already finish a set of actions (step left foot – step right foot – step left foot).

3.3 Algorithmic Model

In activity classification, our system has five categories: resting; walking; fast walking; running; and fast running, fast driving. In order to build the algorithm, we used a smartphone (HTC g11) to record both accelerometer data and gyroscope data as training data. In our system, we set the delay frequency of the sensor listener as normal, which means that the sensor takes a recording approximately every 0.2 second (based on testing results of our model phone). Then we take 25 data as a cycle to perform feature extraction, which means only the average value from every 5 seconds will be used to calculated activity classification. In order to eliminate negative number influence, we integrate the sum of the three axis' absolutely value. Here are the steps of algorithm:

- Step1. Create five lists e, t with length of 25;
- Step2. Add the system's current time into list t; add the sum of absolute X, Y, and Z value to list e; t1 XYZ t0(we call the result of this integration energy to describe how much activity the subject has done in a period of time), t1 stands for current recording time

- Step3. Calculate energy with the formula: energy=e(i)*(t(i+1)-t(i));

With the help of the sensor energy, we can calculate how violent of an activity the subject is performing irregardless of direction and orientation. Also, we can judge whether the change from one activity to another is smooth enough to ensure potential safety by comparing the average energy in a short time segment with the real time energy.

In order to do feature extraction, we calculate the average value of sensor data fluctuations of the time segment chosen before. Within this time segment, there are maximal and minimal values for each activity cycle. We try to find the limits of the highest maximal value and the lowest minimal value as a range for activity fluctuation. We define any data beyond those limits to indicate either an activity change or abnormal fluctuation which would refer to a potential danger.

With the help of data mining software tool (WEKA [6]), we build the algorithm that classify human activities into five steps:

- Step 1. Calculate energy (the algorithm we mentioned before);
- Step 2. Calculate the average energy value in order to compare with limits.
- Step 3. Check if GPS is available. If not, skip driving classification. If yes, retrieve speed data.
- Step 4. If the speed data is close to zero, then classify that activity to rest. If not, classify it as driving.
- Step 5. Compare the average energy with multiple limits. Judge which limits the average value is within. And then classify activity to corresponding category.

4 Danger Estimation

4.1 Physical Danger Estimation

Physical safety is different from mental issues and health problems, it is a special kind danger that could happen very quickly and cause physical damage to the subject. For example, running fast on a rainy day may cause slipping. Slipping can happen at any time if subject keeps running and may cause physical injury when he or she falls down. In our system, we defined five types of 'physical danger: suddenly speeding up, turning too fast, losing balance, driving too quickly and moving backwards.

Suddenly speeding up. This is determined when there is a surge of accelerometer energy during walking or resting. We assume that there should be a warm-up process for whatever activities the subject is performing. For example, when a subject wants to run, he or she should go from resting to walking, then to jogging, and finally to running. A sudden change from a low speed activity to a high speed activity is not allowed in our system, such as from resting or walking to fast running. This is also true for changing from a high speed activity to a low speed activity. Although the surge in the data might happen due to other intensive activity, we include them all in this type. Therefore, sudden activity changes, such as violent movement when in a low energy activity are taken as this particular danger type. The safe limits are first determined at the same time as activity classification and then calculated real time.

Turning too fast. This is similar to speeding up fast. The difference is that for this physical danger type we use the gyroscope to identify sharp increases in energy. Because we assume that no matter how the subject puts his or her phone into his or her pants pockets, the Z axis is always vertical. And when he or she is turning, the X value of gyroscope would change tremendously. For example, if a subject is turning in a circle then the accelerometer energy would show very little difference between that activity and rest. But the gyroscope could better identify that activity. So we use the gyroscope to determine if a subject is turning violently, which we assume would detrimental to elderly people`s muscle and tissue health. The algorithm is similar to speeding up quickly; the difference is that we use gyroscope data instead of accelerometer data.

Losing balance. This type of threat might be caused by falling or jumping down. Even when a subject is static, the sensors still have data that indicates balance. Once the energy is far less than the gravity value or getting close to zero, it indicates that the subject is falling. In our system, we use this threat type to estimate falling down and to warn elderly people

Driving too quickly. Driving is similar to the rest of the categories as it uses data from both the gyroscope and the accelerometer. When the subject is driving the data from the gyroscope and accelerometer look similar to the rest except with a little fluctuation when speeding up and speeding down. Therefore, we use GPS or a network as an additional quantifier to determine the subject's speed. If these additional quantifiers are present then the activity is in driving type. If not, we classify it as rest. Then we monitor the speed and record the time, as either driving for too long or driving too fast can be dangerous. We also calculate safe limits for driving activity. These limits would be narrower and more restrictive since any little sensor data change indicates a much more violent change.

Moving backwards. This is the most difficult type among these five. Because smartphones may be kept in different orientations, and the integration of absolute accelerometer data or gyroscope data is done it can be very hard to tell whether the subject is moving forwards or backwards. We used feature extraction within a time segment, and this time kept the sign in front of sensor data. If there is a number of opposite sign to the average value (calculated during the time segment), and if the absolute value of that number is larger than the absolute value of any number of the same sign, we conclude that there is backwards movement or at least there is a trend of backwards movement. Here is the algorithm we used to estimate backwards movement:

- Step 1. Use lists x, y, z to store accelerometer data X, Y, Z;
- Step 2. Use lists maxx, maxy, maxz, minx, miny, minz to store the maximal and minimal value of x, y, z;
- Step 3. By comparing (maxx-minx), (maxy-miny), (maxz-minz), identify along which axis the activity has highest fluctuation;
- Step 4. After finding the highest fluctuation axis, calculate the sum value and the absolute sum value;
- Step 5. Compare the last value of the highest fluctuation list with the calculation result. If the absolute value of the last value is larger than the average of the absolute sum and the sign of it is opposite to the sign of sum, the moving backwards condition is satisfied.

Integration. After we use activity classification to classify each type of threat to elderly safety, we call those algorithms of different threat types to judge whether the threat condition is satisfied and which threat condition is satisfied. If the threat condition is satisfied, the phone will warn the subject with sound and vibration as a reminder that he or she should watch what is going on.
Additional Features. We added the weather condition to our physical safety condition to ensure more accuracy with it. The thought is that most activities take place outdoors, which would be influenced a lot by weather condition. Our system first find the longitude and latitude of the phone at its current location, and then retrieve weather data from Google weather report. Based on temperature, wind speed, and weather condition, we can add the weather factors into threat factors.

4.2 Health Danger Estimation

For health safety, we are aiming at evaluating the subject's health condition from daily activities and forward approximations that determine whether the subject is or is not within a safe activity range to maintain health. In order to reach this goal, we use the MET value as a numerical way to measure activity[7].

Every time we collect activity data from the smartphone, we first classify activities. Then we transfer those classified activities into a MET value by a specific MET-Relation table (from health science research). The table shows 600 kinds of activities and their related MET values. For our system, we only choose running, waking and resting. We record daily running and walking activities and transfer them into MET values, then we calculate how many MET values the subject has acquired for one week. After that, we compare the MET value with a MET-Disease table to draw conclusions about whether the subject participated in enough activity or not.

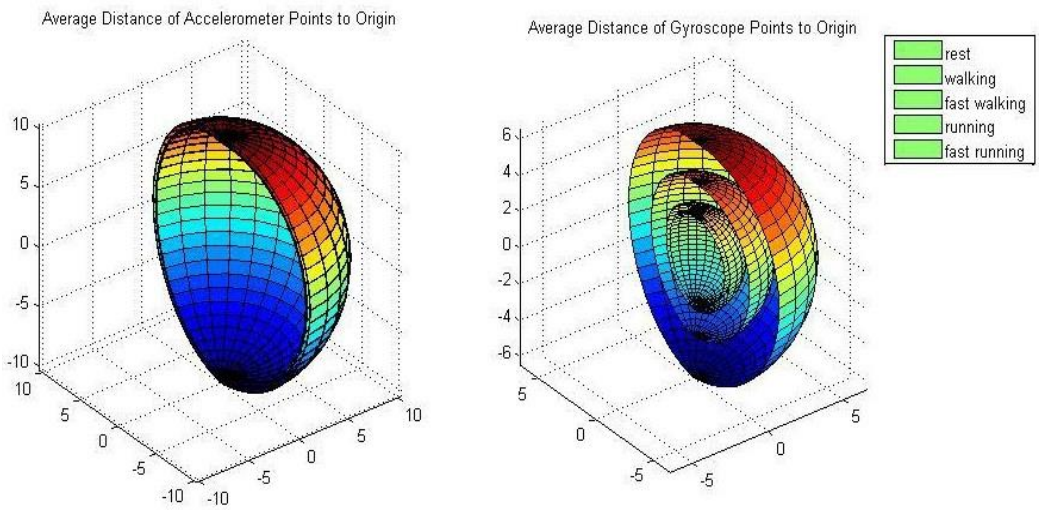
Furthermore, we keep a record of how long a subject is at rest. We take the rest time as sedentary time. By counting the sedentary time, our system will draw a simple graph that indicates the danger ratio of a subject based on his or her sedentary time. In our system, the automatic health threat estimation can only analyze basic activities such as resting, walking, running and driving. It is limited by the algorithm that we used to classify activities. In our system, we integrate the definition of other complex activities into those classified basic activities instead of building more categories. In order to make the analysis results more precise and in case the subject does not carry a phone, we added the manual input as another way to help adjust auto estimation error. We built a manual input UI to allow the subject to choose what activities he or she did (from the 600 activities table) and input how long he or she did each activity. Then we calculate that data, transfer it into MET values and use them as additional help to our automatic threat estimation. A subject can either choose to input his or her activities manually or let the application record or classify the basic activities automatically.

5 Evaluation

We collected training data of five activities for one subject; resting, walking, fast walking, running, fast running. We can see that maximal values are different for each activity; the ranges of fluctuation are different – the more violent the activity is the bigger the range of fluctuation it has. Yet, when we compare walking with fast walking, we find that they are very similar. The only difference is on the limit of positive and negative values.

Then we collected gyroscope data of these five activities in order to make a comparison with the accelerometer. Before the comparison, we calculated sum of the absolute value on X, Y, and Z axis'. Then we calculated the integral of the real time sensor value. Finally, we calculated minimal and maximal values of both the sum and the integration results. We could see that there was overlap between a previous activity's maximal value and the next minimal value in the accelerometer. But for the gyroscope it seemed that there was a better classification with the integration value. Because data in the accelerometer and the gyroscope both have X, Y, Z three values, we drew a three-dimensional graph to compare the difference among different activities. It is obviously from this data we collected from our model phone for one subject, that the gyroscope is better to identify different activities than the accelerometer. Therefore we choose the gyroscope as the primary sensor used to identify and classify activities. Yet, since gyroscope data and accelerometer data are both types of acceleration values, they could both be converted to each other by multiplying or dividing the angle between movement direction and axis of the sensor.

Before calculating average energy, there are some crosses and overlapping between the activities of walking and fast walking. After calculating average energy, the activity line becomes straighter without any cross or overlapping. The difference between walking and fast walking is intuitive and obvious.



(a) (b)

Fig. 1. Gyroscope data and Accelerometer data on three-dimensional space of different activities (a) Accelerometer data (b) Gyroscope data

6 Conclusion

We built a threat monitor system for application on smartphones in order to improve older people`s health and minimize the potential dangers that could happen in future.

To reach this goal, we classify basic human activities with the help of the accelerometer and the gyroscope inside of a smartphone. Once activity classification is done, we set up an algorithm to calculate several types of threat for each activity category. When the threat condition is found, our system would alarm phone users of the potential future danger. Since our system is the first step on ensuring the safety of elderly people, especially since it precisely anticipates potential danger by classified activity, we need large amounts of testing data and feedback from the real time users.

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