Context Awareness System

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***Abstract*— With the development of mobile devices, cell phones are becoming more sophisticated and indispensable to our daily lives. Whats more, the latest generation of cell phones consist of a great number of powerful sensors including GPS sensors, acceleration sensors (i.e., accelerometers), direction sensors (i.e., magnetic compasses, three-axis gyro), light sensors(i.e., ambient light sensor), environment sensors (i.e., barometer) and even fingerprint sensor (i.e., touch ID). The popularity of cell phones and these build-in sensors provide great opportunities to researchers for detecting different activity modes of mobile phone users without implementing additional sensors rather than the cell phone itself.**

This is worthy researching because with the recognition model of user activity, we can have access to significant knowledge about the habits of billions of people. Additionally, the process of data collection is quite passive. We just need everyone carrying their cell phones during the day which seems to be a trivial task nowadays. This research will have a large scale of potential applications such as modifying cell phone behavior according to the users current activity (e.g., avoiding incoming calls if the user is driving) and providing user feedback of daily life habit.

Although many researches have focused on this questions, but none of them are perfect. For example, [15] points out current algorithm cannot handle well for uncertain result of context awareness; [16] points out some design have low accuracy towards posture recognition, Besides, it only can recognize few activities, so we want to improve the accuracy of recognize user context; [4] says that their design consume a lot of calculation resources and which may not suitable for mobile device.

In our system design, we learn the advantage of using different sensors along with accelerometer, which is the core sensor of our system, to determine users posture and location. Therefore, we try to combine different sensors that integrated in a single phone to track and detect users posture and location to achieve the context awareness goal. Compared with [8], [9], [18], we will use GPS, barometer sensor, and accelerometer that integrated in a single phone to determine the users walking, running, standby, driving and uphill (downhill). Compared with [12], [13], [14], we will using more sensors to detect more personal activity and gestures.

I. RELATED WORK

Theres been an increasing number of paper discussing activity recognition. This topic continues to gain attention because of the easily access of the devices like cellphones which contains of accelerometers. In addition, researchers are looking into various of potential applications of build-in sensors of cellphone.

A lot of previous work in the activity recognition using accelerometers focused on using multiple accelerometers and placing these sensors on different parts of human body which seems to be a direct implementation of using accelerometers. For example, Baos research [1] used five bi-axial accelerometers and placed them on the users dominant wrist, dominant ankle, non-dominant upper arm,non-dominant thigh and right hip. They collected data from 20 users total and are able to recognize twenty activities of users daily life activities. C4.5, decision labels, Naive Bayes classifiers and instance-based learning were used to create models for activity detection. Their experiments results showed that the best results were gained from the sensor that placed on the users thigh. This is a very important support for our research because we are planning using the users cell phone for users activities recognition and almost everyone will carry their own cellphone in their pocket which is very close to the thigh location. Note that Baos paper were using bi-axial accelerometers and the device we are planning to use is iPhone which has accelerometers with three axis. We shall expect more accurate detection results using iPhone.

Bao and Intille tried to recognize different kinds of activities by multiple accelerometers. Krishnan et. al. [2] recognized five different activitieswalking, sitting, standing, running, and lying down though using two accelerometer. Author asserted that it is not enough to recognize differences between such as sitting and lying down, so multi accelerometer is necessary. Whats more, Krishnans et. al. [3] system distinguished seven low body activities by data that are collected from ten people wearing three accelerometers. This paper also set the control group semi-naturalistic to compare with supervised. Tapia et. al. [4] used five accelerometers to collect data from twenty-one users various body locations to implement a real-time system to recognize thirty gymnasium activities. Their system increase accuracy by adding incorporating data from heart monitor. Mannini and Sabitini [5] used five accelerometers attached to five different parts on thirty users to recognize twenty activities. Different methods were used to recognize three pastures lying, sitting and standing and five movements walking, stair climbing, running and cycling. Foerster and Fahrenberg [6] use two of accelerometers that chosen from five accelerometers in one set of experiment. In order to distinguish between postures such as sitting and lying at specific angle and motions such as walking and climb stairs at different speeds, author set classification model.

Besides using single and multi-accelerometers, some researches have focused on using accelerometers along with other sensors. In paper [7], the author Parkka were trying to figure out what kind of sensors can be used to detect users physical activity, these sensors including multi-accelerometers weared in different position and using different sensors such as air pressure, humidity, GPS, etc. The research show some interesting result and give us a hint which sensors may have potential capability to detect users posture in design. However, an important drawback of this paper is that some sensors are weared in optimized position on body such as (chest, arm), and not integrated in the phone. So how to use a single phone with such sensors to achieve the same or better accuracy is a challenge for us. In paper [8], the author proposed a method by using acceleration and angular velocity data to determine a users location, recognize and classify sitting, standing and walking behaviors based on dead reckoning. This paper gives us theoretical support on how to using angular speed. But the drawback of the paper is that using dead reckoning algorithm will generate accumulate error based on the distance that the user travel. For that reason, our design will try to deal with the system error by improve the algorithm. In paper[9], the author proposed how to determine the users location and physical activity by using wearable sensors and GPS, however, the limit of the methods is that when people moving under a roof or with weak GPS, signal, the accuracy will drop off significantly. This is still a problem to us, however, we will try to combine GPS with accelerometers and other sensors together to improve the detection accuracy.

There are other papers considering using a combination of multiple different types of sensors and the accelerometer for activity detection. Cho et. al. [10] proposed to use the combination of a single tri-axial accelerometer and an image sensor. Their approach were able to identify nine different activities. A super sensor which consists of seven different sensors were used in Choudhurys research [6]. The eWatch, proposed by Maurer et al. [11] which can be considered as a device consists of a light sensor and a bi-axial accelerometer were used for activity detection. As lots of types of sensors are being built-into our mobile devices, we can see clearly all the multi-sensor implementation mentioned above are pointing to the great potential of cell phone sensor approach.

Papers mentioned above were using either a combination of accelerometers and other other sensors or multiple accelerometers. It is true that these sensors are capable of detecting a great number of user activities but they are limited in research and experiments because their implementation all involve attaching multiple sensors to different parts of users body. However, nowadays a personal cell phone like iPhone is not a nice-to-have but rather a must-be device of everyones daily life. Therefore, we are focusing on a larger perspective of activity recognition and great potential of applications.

The above discussion focused on using integrated sensors to detect users posture and location, but they all need extra devices and we notice that user may show reluctantly to wear extra device. Fortunately, with the incredible developing speed of mobile phone, we now can integrate many sensors into a single smart phone. And how to use a single phone to detect users posture and location worth our further discuss. In paper[100], the author gives us an overall description on a single sensor based approach which is suitable for mobile environments, the author use a tri-axis acceleration sensor to detect the sensor position on the users body. However, the purpose of this paper is to discuss the possibility of using mobile phone as a context awareness device and didnt give too much explanation, besides, using just one acceleration is not enough to give accuracy classification of personal activity and postures.

In paper[12], the author developed a software called move your story, in this paper, the author try to detect users activity by using accelerometer data and GPS speed together.This paper is a further improvement by combining GPS together with accelerometer compared with [13], but the author limits their focus on walking and bicycling detection. Therefore, we try to develop a system that can be used in more scenario such as adding more gestures support. Apiwat Henpraserttaes [14] paper provide us a guideline of issues when using cell phone embedded with tri-axial accelerometer for activity detection. They looked into the difference in orientations and locations of the device and the experimental results show that there is a need for different models when placing the sensor on different parts of users body for detecting certain activities.

In paper [21], the author come up with a method to detect which floor is user in. By using air pressure sensor, they can compare air pressure with every floor's pressure data, then they can get which floor are user in. [22] talked the method to analyze the pressure change in same location at different days, by using their approach to help blind find the floor of destination. [23] introduce the filter to smooth the data of barometer. [24] using barometer to estimate the elevation of destination. [25] using barometer to help user located themselves in subway station.

II. System Design

A. Approach

To detect users activities, our new approach is to integrate multiple context awareness method into one system. With the lated the iPhone, we now have access to GPS, accelerometer and barometer data with high accuracy. The Core Location Framework in iOS provided easy to use API for us to access not only the latitude and longitude data of the iPhone, but also allow developers to acquire the speed of the device. Even though the sampling rate of the speed is limited to one data per second, our system is able to use the speed of the device to detect whether the user is driving or not. After categorized the user into driving and not driving. The accelerometer and barometer data are used to detect the user activities for more specific scenarios. The accelerometer can be used to recognize user activities such as walking, standing still and running. These different activities will have different regularity over the accelerometer data. To detect the user driving situations such as regular driving, uphill and downhill, our system monitor the changing of barometer data. A decrease of the barometer data indicating the increase of the altitude of the device. On the other hand, the increase of barometer reading indicating the decrease of altitude. Our program will continually monitoring and analyzing the speed, accelerometer and the barometer data, providing the detection of users activities. Specifically, the detection of user driving situation can be used to improve the navigation rerouting speed.

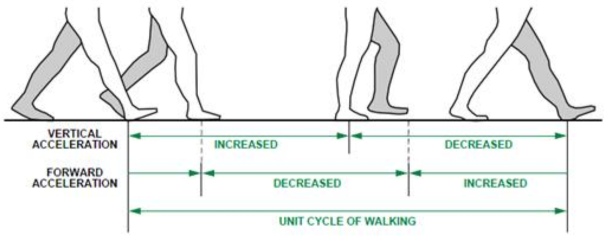

Fig. 1. Human walking acceleration

B. Design

We provide the general idea of system design in this section. Since the system need amount of continuos data to process the detection, the system have a detection cycle. For every detection cycle, the system first collects data from GPS, accelerometer and the barometer. Then at the end of the detection cycle, out system analyzes the data collected through the cycle and provide a detection conclusion. The system have two level of detection process. At the first level, the system use the speed of the device to detect driving situations. We compare the speed of the device with a threshold. If the speed of the device is larger than the threshold, the system categorizes the activity as driving. If the speed of the device is smaller than the threshold, the system categorizes the activity as not driving, that is, either walking, running or standby. At the second detection level, the system detect more specific situations. Under the not driving condition, the system analyzed the accelerometer data and making decisions upon the different patterns of the accelerometer reading. If the user is categorized as driving, the system will analyze the changing of barometer reading to provide detection of driving uphill and downhill situations. Different configurations of threshold in the detection algorithms will have significant impact on detection accuracy. For example, if the speed threshold is too small, the system may detect the user as driving when the user may actually running very fast. Details will be discussed in the algorithms section and experiment section.

C. Algorithms

In this section, we will discuss the detection algorithms for classifying different situations under driving condition and non-driving condition. To distinguish the walking from running, we need a algorithm to detect the different pattern in accelerometer reading. To do so, we need to conduct a reference value from the accelerometer data. As illustrated in Figure 1, the average of human walking frequency is about 1.5 Hz per step.

Therefore, the average of walking frequency of one unit cycle is 3 Hz. As the user carrying the iPhone, the vertical acceleration of motion will be detected by the 3-axis accelerometer of the iPhone. Since there is no guarantee of how the iPhone is positioned near the user. All 3 axis of the accelerometer have the potential to detect the most intense fluctuation on its direction. Obviously, the most intense data will be shown on the axis which is nearest to the vertical direction. In addition, the gravity is an acceleration. The accelerometer of the iPhone will no doubt receive the acceleration created by the gravity regardless of the motion of the device. Therefore we could use the gravity as a reference value to recognize different pattern of acceleration data. To reveal the gravity value hidden inside the vibration caused by the motion. We apply a low pass IIR filter to filter out the signal having frequency higher than 1 Hz. The IIR filter is specified as below:

$$value[i] = value[i-1] + \alpha * (input[i] - value[i-1]) \quad (1)$$

The parameter Alpha is set as 0.314 in our implementation. Ideally, the acceleration data after the low pass IIR filter will show a clear straight line indicating the gravity acceleration value on the direction of each axis. Figure 2 is the example acceleration data of user carrying the iPhone in motion and Figure 3 shows the filtered data. We chose the axis closest to vertical to conduct the analysis of data since the data on that axis will have the biggest value and therefore smallest error compared to other two axis. We set the acceleration threshold as two times as the relative gravity value. Then we calculate how many data points exceeded the threshold over a whole detection cycle. If 10% of all data points exceeded the threshold, the system classifies the user as running. To detect the walking and standby situations, we introduce a new walking threshold, simply as the 60% of the running threshold value. The program counts the number of intersects between acceleration data and this walking threshold over one detection cycle. If the number of intersects is equal or larger than 2, the system classify the activity as walking. Otherwise, the system will yield a conclusion as standby. This configuration is proved to be highly accurate by the experiments we conducted. The experiments and results will be discussed in later sections.

To detect different situations while driving, we design and implement an simple algorithm to analyze the barometer data. The sampling rate of the barometer in iPhone is theoretically one data per second as same as the speed sampling rate. However, the barometer API provided by the apple is not always available in practice. Therefore the barometer data our program can obtain over one detection cycle varies. In practical, the number of data points we obtain over one detection cycle ranges from 2 to 4. The detection algorithm will calculate the relative value of every two adjacent data points. Then it compare all relative values to a barometer threshold. Larger than the positive threshold indicates a downhill situation and smaller than the negative threshold indicates the uphill situation. If all the relative value points to the same direction, either uphill or downhill, the system will classify the activity as uphill or downhill. Otherwise, if the indicators do not agree with each other, the detection results remains as driving. To determine the proper value of barometer threshold, we conducted several experiments. Details will be discussed in the experiments section.

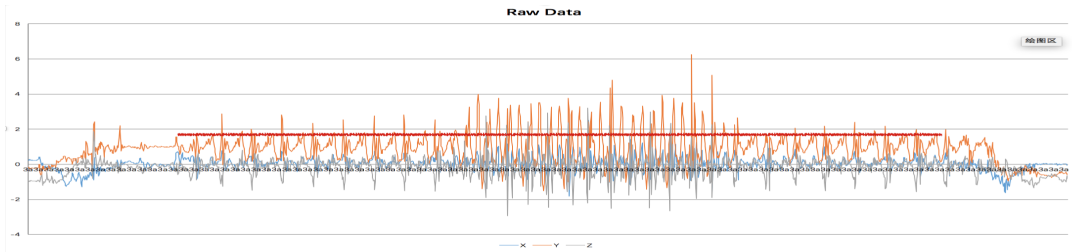

Fig. 2. Raw data of walking and running

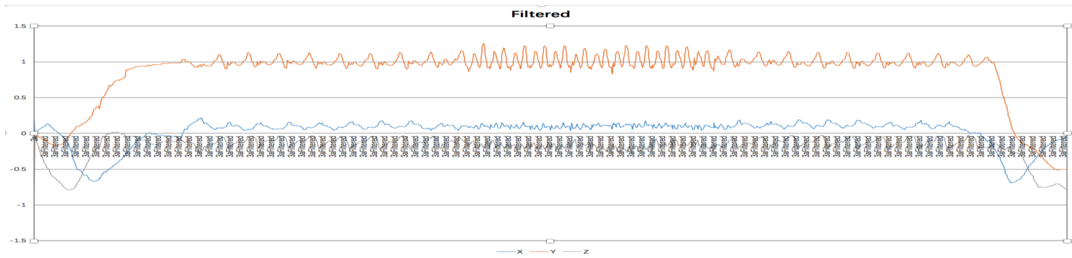

Fig. 3. Filtered data of walking and running

III. Experimental Design

It is important to test the practical value of our app, therefore we design and conduct a series experiments to test our app. In the experiment we try to answer the following questions: Can our app separate walking, running, stand by and driving behavior with high accuracy? If the app can distinguish above behaviors, what is the time cost need to do it? When a driving behavior is detected, can our system further distinguish uphill, down hill and flat road with high accuracy? To answer the above questions, we first test the walking, running and stand by behaviors, then we test the driving behavior. The detail of experiment design is explained below.

A. Human Motion Detection Experiment

In the human motion detection experiment, we notice that the phone can be placed in a random position and place, for example, when you are running, the phone may probably put in your pocket with a random laid position, and when you are walking while playing music, you may hold the phone in your hand. Therefore, the detection accuracy should consider all the situations.

We test our app in the parking lot in front of Library of Science Medicine, the reason why we choose here because the parking lot area has a small hill that we need to climbing and go done, therefore it can mimic the mountain area. If the motion detection accuracy is good here it can expand the using place of our app. Below figure shows the test route that include a small uphill, down hill and flat road.

We start in the front of LSM with a few second stand, then we take a walk uphill to the parking lot and began to run for a few seconds, next we take a few second stand again and began to walking back, at last we run down the small hill to the start place of LSM. We repeated the test for 50 times during two days and try to get the accuracy result.

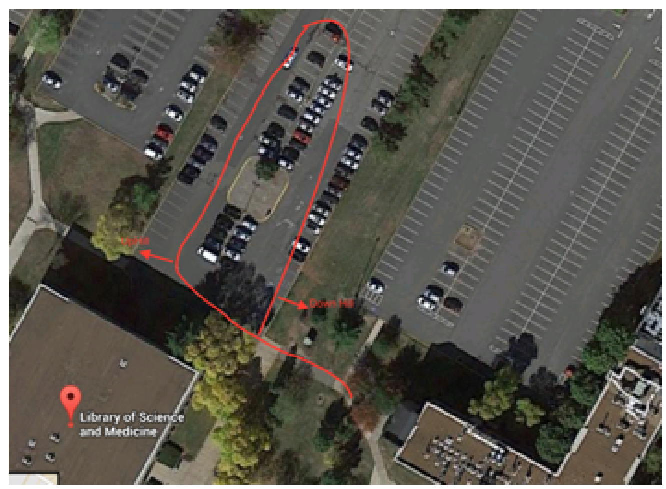

Fig. 4. The route used for motion detection

Meanwhile, we set the detecting frequency to 2 seconds so every 2 seconds the app will return user current motion state. Since people may not change their current motion too frequently within a two second period, we think two second is a short enough time for our app to detect the motion behavior.

We considered the phone position and place may have a major impact to our experiment result, therefore, we try to put the phone in different place near the experimenter. We put the phone in the front jack pocket, back jeans pocket, hand and a pack bag carried by the experimenter. For each case, we test them 50 times and get the result.

We also considered some other factors that may effect our experiment, such as different people, age, gender, and body form, but since we dont have enough resource to test all the case, and those factors are not the major course to effect the result, we ignore them.

Fig. 5. The route used for motion detection

Fig. 6. Test for downhill exit detection

Fig. 7. Test for uphill exit detection

B. Driving behavior detection

The most important feature of our app is to quickly detect whether a driver is going out the wrong exit on highway. So the first thing we should do is to detect the driving behavior. As we mentioned in the algorithm part, we only use velocity to detect driving and none driving behavior. One problem we must face is that when we set the velocity too slow, we may not able to distinguish driving and running behavior, but if we set the velocity threshold too high, we may not able to detect driving behavior. Therefore, to find a proper velocity that can maximum distinguish driving and non-driving behavior is the priority task.

Since running in the non-driving part is the most possible behavior that can misclassified to driving behavior, so we concentrate on deal with running. Because average human running speed may fall into 5m/s, and 10m/s can be considered as a world record breaker, so we thought the velocity threshold should not be more than 10m/s. Therefore, we choose 5m/s, 10m/s and 20m/s to test the best velocity threshold. The driving route we use is shown in the below figure. This route starts from RU stadium, contains an uphill, downhill, highway driving and traffic light, which is perfect to mimic the real driving situation. We test each velocity five times and found 10m/s is the best we can get to separate driving and running while still able to detect most driving situation.

C. Uphill and Downhill detection

The uphill and downhill driving detection experiment is much like the human motion detection experiment. We need to know the accuracy and respond time. One different is that the position and place of the phone will not effect the uphill and downhill detection because we dont need accelerometer, so the experiment is much simplified. We use the Ford fusion 2014 as the experiment car, and pick two roads near College Avenue Campus as the downhill and uphill test road.

Since our main goal is to compare the wrong road detection time with Google Map, we also open the Google Map and set to the navigation mode. The experiment procedures describe below: For both uphill and down hill, we first set the Google Map navigation to the main road, but we drive to the wrong exit road on purpose, then we use a stopwatch to record when will the Google map detect we are going on the wrong road and make rerouting, compared with the downhill and uphill detection time by using our app. Second, we set the Google Map also navigation to the main road and we drive to the same main road to detect whether our app will misdetect uphill and downhill behavior. For the two step, we repeated them both five times to get the average accuracy and response time.

Because the algorithm we use for uphill and downhill detection can not guarantee fixed respond time, and related to the threshold, so we also do the experiment with different threshold to find the best result that balance the accuracy and response time.

IV. Results

A. Result of human motion detection

As we can see in table 1, the human motion detection approach get really good result in two positions (front jacket pocket and back jean pocket). Because smart phone shark alone with the human body, when user put smart phone in bag or hold it in hands, it's motion is so close to body motion.

Phone Position	Walking	Running	Stand By
Front Jacket Pocket	100%	100%	100%
Back Jean Pocket	100%	100%	100%
Pack Bag	84%	96%	100%
Hands	100%	96%	100%

TABLE I

HUMAN MOTION ROUTE

Velocity	Can Detect Driving?
5 m/s	always
10 m/s	always
15 m/s	some times

TABLE II

DRIVING BEHAVIOR DETECTION

B. Result of driving behavior detection

As table 2, we know 5 m/s is too low to running speed, human can easily reach this speed. Because we test our system in campus, we find some times it's too long for car to reach this speed in low speed area. And the reason we choose 10 m/s as threshold for driving is running speed can touch 5 m/s and sometimes 15 m/s is too fast for driving speed in campus.

C. Result of uphill and downhill detection

Threshold	Uphill(s)	Accuracy	Downhill(s)	Accuracy
0.5	6.5/18.3	80%	8.5/20.5	90%
0.7	7.2/17.9	100%	9.4/19.6	100%
1.0	7.8/18.7	90%	10.7/19.8	90%

TABLE III

UPHILL AND DOWNHILL DETECTION

The results of uphill and down hill latency is shown in table 3. We tested five in the main road and five in the export road. The lowest threshold has lowest response time, but it also cannot make right decision because it's too sensitive. The highest threshold has highest latency and it also can not make right decision because it can not detect the uphill and downhill. So for our test road, we chose 0.7 as threshold because we balance the accuracy and latency, this is the best choice.

V. CONCLUSION AND DISCUSSION

This paper presents a system that integrated several motions' awareness in to one system. This integrated system can provide many support to other application that need context awareness. So other application developers do not need to implement context awareness function by themselves

What's more, context awareness system using novel, easy to implement approach to do off route detection. Compare to traditional off route detection using GPS, the approach in paper using barometer to detect off route. This method can save about half time than approach that using GPS.

For our future work, we want to increase the number of motion for context awareness system. We also want to decrease the time of off route detection.

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