USER ACTIVITY TRACKER USING ANDROID SENSOR

THESIS

Presented in Partial Fulfillment of the Requirements for the Degree Master of Science in the Graduate School of the Ohio State University

By

Chenxi Song

Graduate Program in Electrical and Computer Engineering

The Ohio State University

2015

Master's Examination Committee:

Prof. Xiaorui Wang, Advisor

Prof. Liang Guo

ABSTRACT

Physical activity is a prescription for helping decrease stress; relieve depression, anxiety, heartburn and constipation; increase happiness; and prevent diseases. Everyone knows that exercise is vital to maintaining health, yet many people can't keep regular exercise even they had set targets for themselves. A main reason is that they don't have a convenient method to keep being aware of where they are against their goals at any given point in the process.

In this thesis, we explore methods about using cell phone sensors to detect and track users daily activities and help the user to set personalized exercise goals, which includes: detect different motion pattern, measure amount of exercise of each pattern, calculate total amount of calories consumed and give a daily report of user activities - help user find their fit, stay motivated, and see how small steps make a big impact.

Key Words: Android, Sensor, Pattern Match, Adaptive algorithm, Calorie Count Algorithm

This document is dedicated to my dear families and friends.

ACKNOWLEDGMENTS

Without the help of the following people, I would not have been able to complete my thesis. My heartfelt thanks to:

Dr. Xiaorui Wang, for being my mentor in research. Under his guidance, I learned more professional knowledge and research skills, involved with the exiting research topics, but more importantly, I have got the chance to improved myself with a better understanding of the research methodology, ideas development and research attitude. I feel very grateful for the opportunity to have him as my research advisor.

Li Li, for his valuable suggestions on the algorithm model design and experiment implementation. I do appreciate him for all above helps.

My dear group members: Kuangyu Zheng, Marco Brocanelli, Bruce Beitman, for providing me many valuable comments on my project and and helping to test my android application.

VITA

2009	B.S. Electrical Engineering, Shanghai JiaoTong University Shanghai, China
2009-Present	Graduate Student, The Ohio State University Columbus, Ohio, USA

FIELDS OF STUDY

Major Field: Electrical and Computer Engineering

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

In recent years, there are a lot of applications developed to keep track of user's daily activities such as Fitbit, Jawbones. With price range form $100-200$ dollars, they are too expensive for a lot of people. Moreover, the hardware is fixed and can't be updated once purchased. This paper aims to explore an accurate algorithm in developing cell phone application to realize more accurate and personalized functions by using cell phone sensors. Using the magnitude of the accelerometer data and gyroscope sensor data we found that we could identify general activities preformed by the user, and even have the phone learn new activities. Multiple approaches were implemented to attempt to find the best results. With individual adaption we obtained accuracy of 98%, which could be improved with future work.

In this thesis, we propose user daily activity tracking methods using android sensors, Specifically, this paper has the following contributions:

- Propose advanced algorithm to detect different user activities based on former works done by the others.
- Enable personalized activity detection by providing adaptive algorithm.
- Give algorithm to calculated calorie burned of different exercise and give the user a direct data for their fitness effect.

- Generated report to give user a overall knowledge of the amount of exercise they have done in a certain period of time.

The rest of the thesis is organized as follows. We review the related work in chapter 2, and introduce the background of android development related to motion sensors in chapter 3. Chapter 4 gives the key techniques used in implementation. The result of the experiments are presented in Chapter 5. Finally, Chapter 6 concludes the paper.

CHAPTER 2

RELATED WORK

Activity recognition has recently gained attention as a research topic because of the increasing availability of accelerometers in consumer products, like cell phones, and because of the many potential applications. Some of the earliest work in accelerometer-based activity recognition focused on the use of multiple accelerometers placed on several parts of the users body [1] [2] [3]. In one of the earliest studies of this topic, Bao & Intille [4] used five bi-axial accelerometers worn on the user's right hip, dominant wrist, non dominant upper arm, dominant ankle, and non-dominant thigh in order to collect data from 20 users. Using decision tables, instance-based learning, C4.5 and Nave Bayes classifiers, they created models to recognize twenty daily activities. Their results indicated that the accelerometer placed on the thigh was most powerful for distinguishing between activities. This finding supports our decision to have our test subjects carry the phone in the most convenient location (their pants pocket). Other researchers have, like Bao & Intille, used multiple accelerometers for activity recognition. Krishnan et. al.[5] collected data from three users using two accelerometers to recognize five activities including walking, sitting, standing, running, and lying down. This paper claims that data from a single accelerometer is insufficient for classifying activities such as sitting, lying down, walking, and running. Tapia et. al. [6] collected data from five accelerometers placed on various body locations for twenty-one users and used this data to implement a real-time system to recognize thirty gymnasium activities [7] [8] [9]. A slight increase in performance was made by incorporating data from a heart monitor in addition to the accelerometer data. Mannini and Sabitini [10] used five tri-axial accelerometers attached to the hip, wrist, arm, ankle, and thigh in order to recognize twenty activities from thirteen users. Various learning methods were used to recognize three postures (lying, sitting, and standing) and five movements (walking, stair climbing, running, and cycling).

CHAPTER 3

BACKGROUND

In this section, we introduce the Android platform background knowledge which are related to the application we intend to develop.

3.1 Android Platform

Android is an operating system based on the Linux kernel, and designed primarily for touchscreen mobile devices such as smart phones and tablet computers. Android gives users the opportunity to build and publish their own applications by providing an open development environment. Therefore, Android is popular with technology companies which require a ready-made, low-cost and customizable operating system for high-tech devices.

3.2 Android Motion Sensors

The Android platform provides several sensors that let you monitor the motion of a device. Two of these sensors are always hardware-based (the accelerometer and gyroscope), and three of these sensors can be either hardware-based or software-based (the gravity, linear acceleration, and rotation vector sensors). For example, on some devices the software-based sensors derive their data from the accelerometer and magnetometer, but on other devices they may also use the gyroscope to derive their

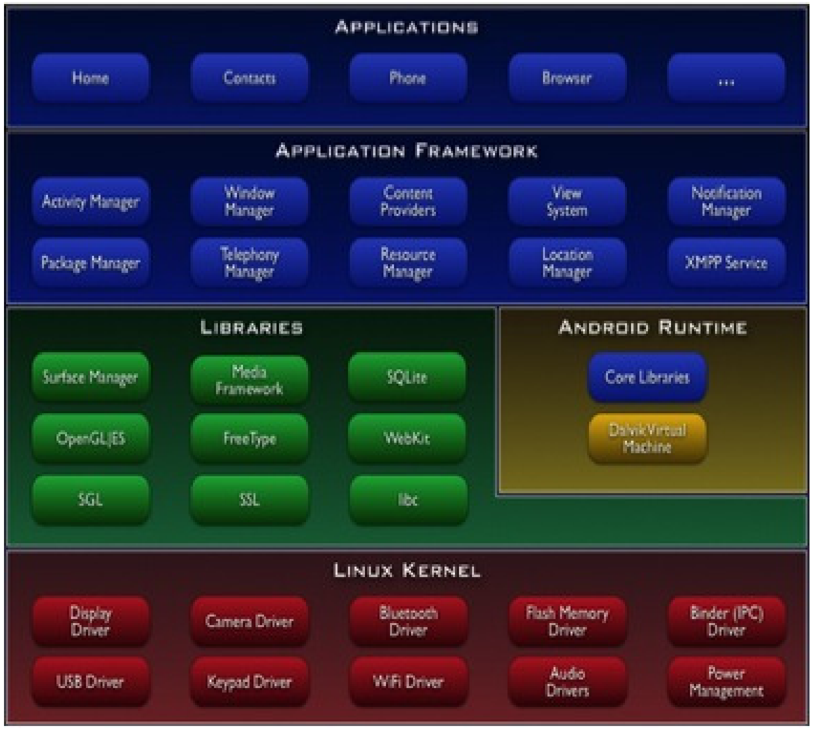

Figure 3.1: Android OS Architecture

data. Most Android-powered devices have an accelerometer, and many now include a gyroscope. The availability of the software-based sensors is more variable because they often rely on one or more hardware sensors to derive their data.

Motion sensors are useful for monitoring device movement, such as tilt, shake, rotation, or swing. The movement is usually a reflection of direct user input (for example, a user steering a car in a game or a user controlling a ball in a game), but it can also be a reflection of the physical environment in which the device is sitting (for example, moving with you while you drive your car). In the first case, you are monitoring motion relative to the device's frame of reference or your application's frame of reference; in the second case you are monitoring motion relative to the world's frame of reference. Motion sensors by themselves are not typically used to monitor device position, but they can be used with other sensors, such as the geomagnetic

Table 3.1: Comparison of three liquid cooling techniques in a data center with 1,280 servers.

Sensor	**Description**	**Units of measure**
ACCELEROMETER	Acceleration force along the axises (including gravity)	m^2/s
GRAVITY	Force of gravity along the axises	m^2/s
GYROSCOPE	Complex implementation	rad/s
GYROSCOPE_UNCALIBRATED	Rate of rotation (without drift compensation) around the axises.	rad/s
LINEAR_ACCELERATION	Rate of rotation around the axises	m^2/s
ROTATION_VECTOR	Rotation vector component along the axises	Unitless
SIGNIFICANT_MOTION	N/A	N/A
STEP_COUNTER	Number of steps taken by the user since the last reboot while the sensor was activated	Steps
STEP_DETECTOR	N/A	N/A

field sensor, to determine a device's position relative to the world's frame of reference (see Position Sensors for more information).

All of the motion sensors return multi-dimensional arrays of sensor values for each SensorEvent. For example, during a single sensor event the accelerometer returns acceleration force data for the three coordinate axes, and the gyroscope returns rate of rotation data for the three coordinate axes. These data values are returned in a float array (values) along with other SensorEvent parameters. Table 3.1 summarizes the motion sensors that are available on the Android platform.

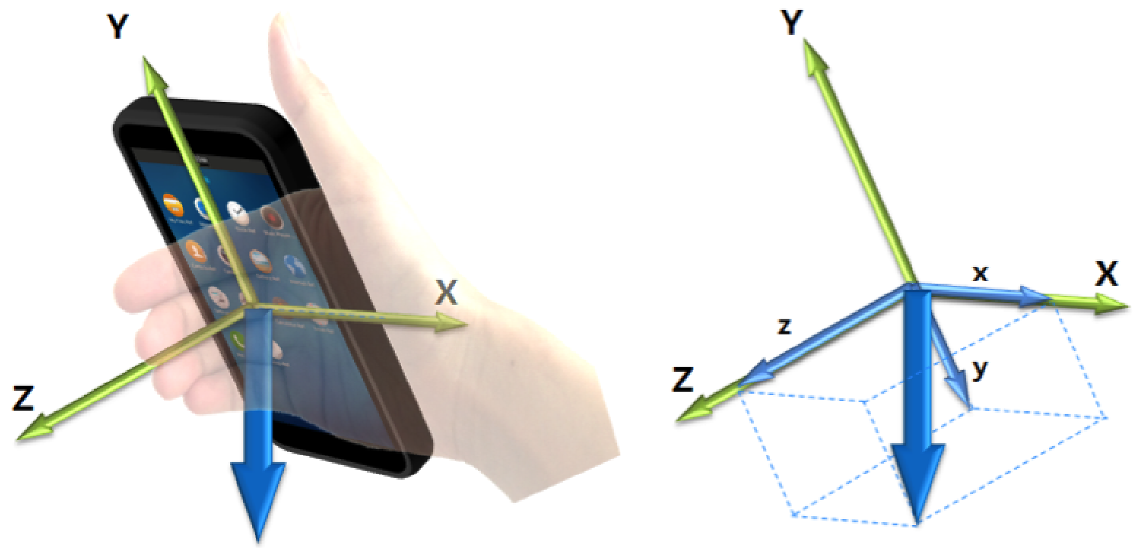

Figure 3.2: Android Accelerometer sensor and Gyroscope sensor coordination

The major sensor we use in this project is the accelerometer, which measures the acceleration applied to the device, including the force of gravity.

The accelerometer is a good sensor for monitoring device motion. Almost every Android-powered handset and tablet has an accelerometer, and it uses about 10 times less power than the other motion sensors. One drawback is that we have to implement low-pass and high-pass filters to eliminate gravitational forces and reduce noise.

Another Sensor we used here is Gyroscope Sensor. Standard gyroscopes provide raw rotational data without any filtering or correction for noise and drift (bias). In practice, gyroscope noise and drift will introduce errors that need to be compensated for. We usually determine the drift (bias) and noise by monitoring other sensors, such as the gravity sensor or accelerometer.

CHAPTER 4

REALIZATION METHODOLOGY

In order to get the total calories consumed by the user, we have to get relevant data and using certain algorithm to process the data. Figure 4.1 is the realization approach of our application.

4.1 Data Collecting

Accelerometers have been used for a variety of uses throughout the world today, from medical to research, from car performance to robotics. However, with the advent of the iPhone and Android, accelerometers are much more commonplace in the world of today. The linear acceleration sensor in Android provides a three-dimensional vector representing acceleration along each device axis, excluding gravity.

Android permits three different modes with different sampling rates that can be used to collect data from accelerometer sensors and Gyroscope sensors. These are called 'Normal'(5Hz), 'UI'(15Hz), 'Game'(50Hz) and 'Fastest'(platform dependent, 'Game'and up to 100Hz). The data collection app uses the 'UI'mode because a Nyquist rate of $15-16$Hz allows a maximum signal frequency of 8Hz which was found to be adequate for human physical activity.

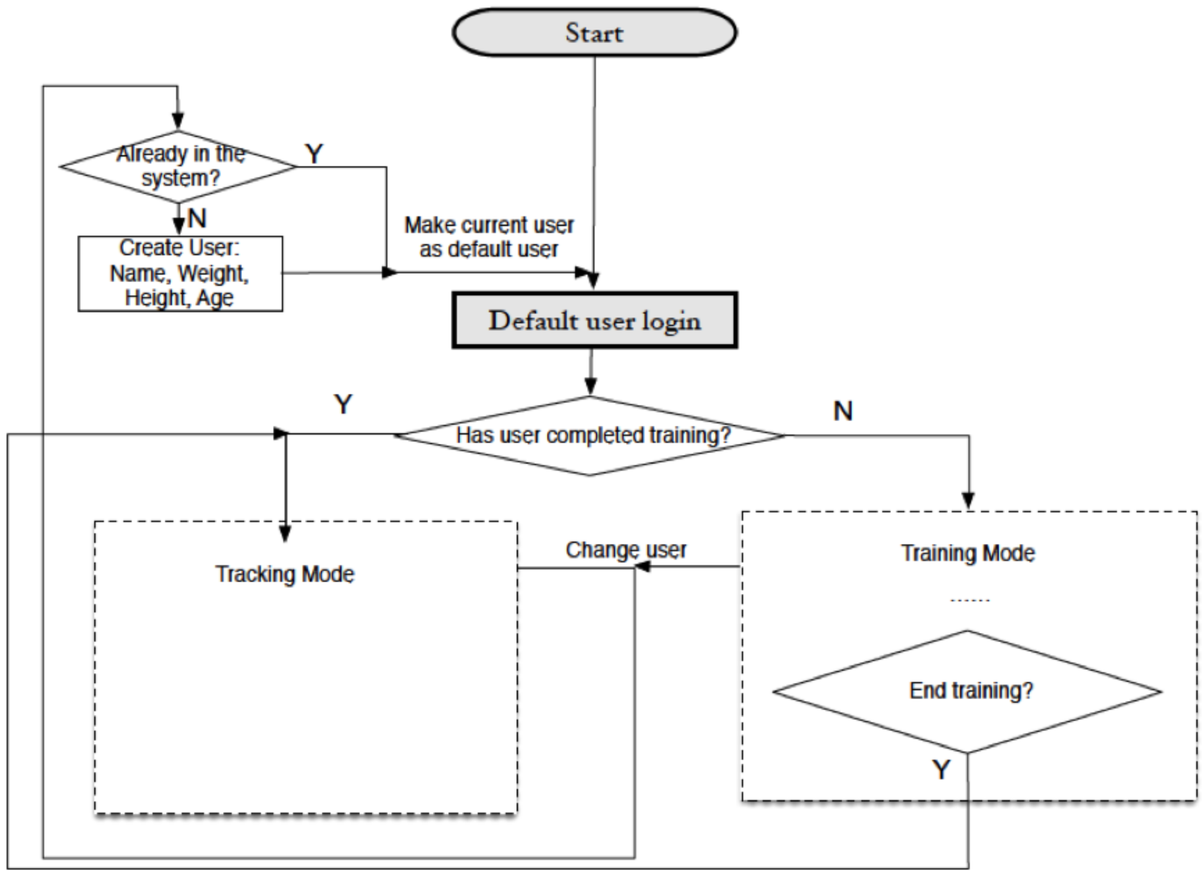

Figure 4.1: Application Workflow

4.2 Activity Recognition

Activity recognition has a number of leading application areas.In this application, 5 different modes of the cell phone are identified.

- Not moving: The user is holding the phone in an idle state
- Walking: The user is walking
- Running: The user is running
- Descending Stairs: The user is descending stairs
- Climbing Stairs: The user is climbing stairs

In order to recognize different activity, we set bounds for those four activity types. The decision flow is shown in figure.

4.3 Speed Recognition

The accelerometer data $a_acc = \sqrt{x^2 + y^2 + z^2}$ collected from both female and male carrying a android device shows a periodic change when they are running, walking, climbing stairs and descending stairs as chart . Here, the accelerometer data: SensorEvent.values[0]=x, SensorEvent.values[1]=y, SensorEvent.values[d]=z. From Figure 4.3 we can find that the a_acc's peak value at speed 5.5mph is slightly larger than the a_acc's peak value at speed 4.5mph. Figure 4.4 verifies out guess. Here, we did a linear regression for the average a_acc data and speed. In statistics, the coefficient of determination, denoted R^2 indicates how well data fit a statistical model. The linear regression shows a very good result since as R^2 getting closer to 1 the better the model are. Polinimial regression of higher order performs even better. In the application, we use polynomial regression of 3 orders.

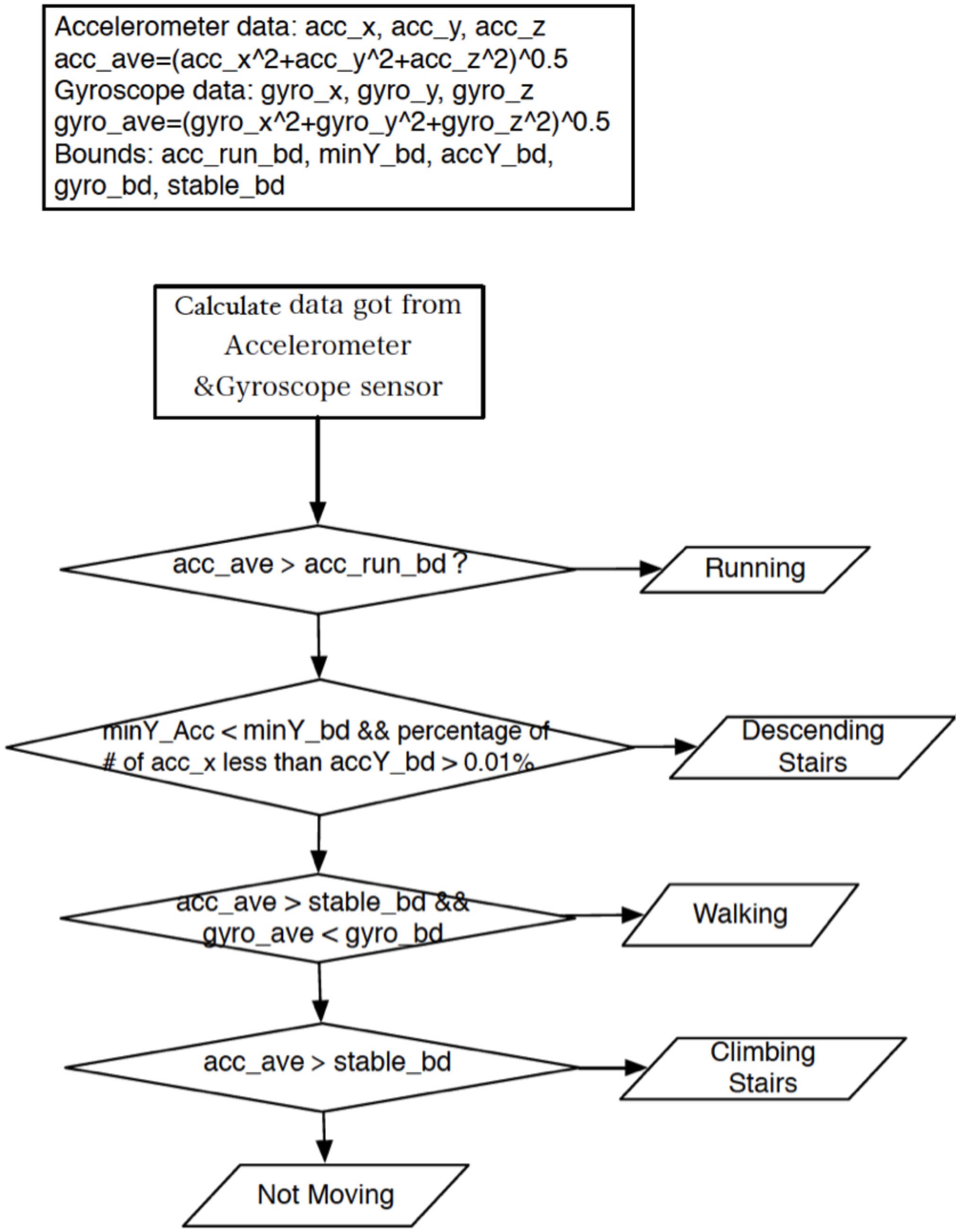

Figure 4.2: Activity Recognition Flow

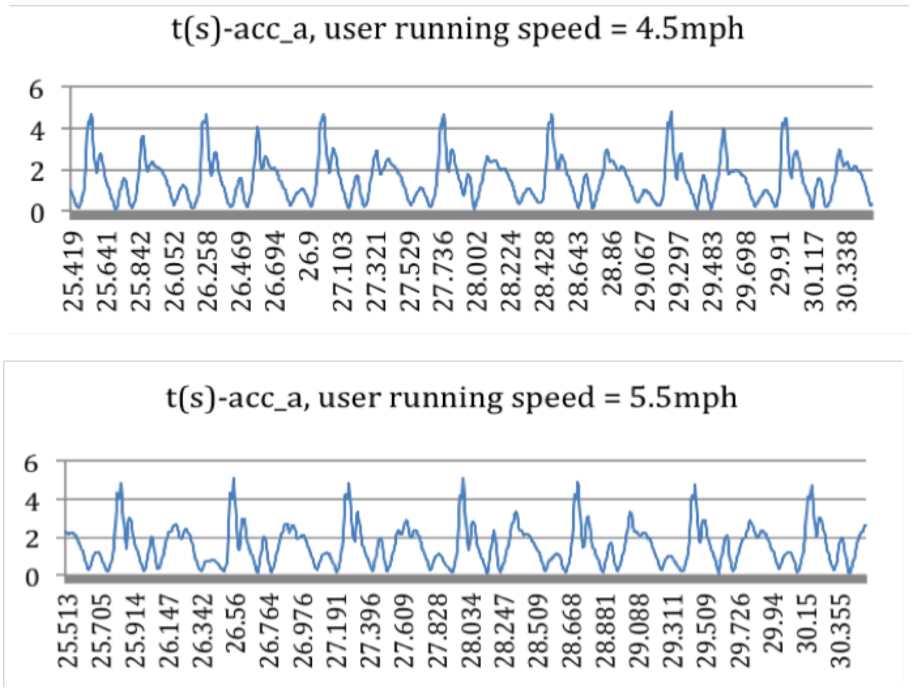

Figure 4.3: Accelerometer data collected when a female user running at speed 4.5mph and 5.5 mph

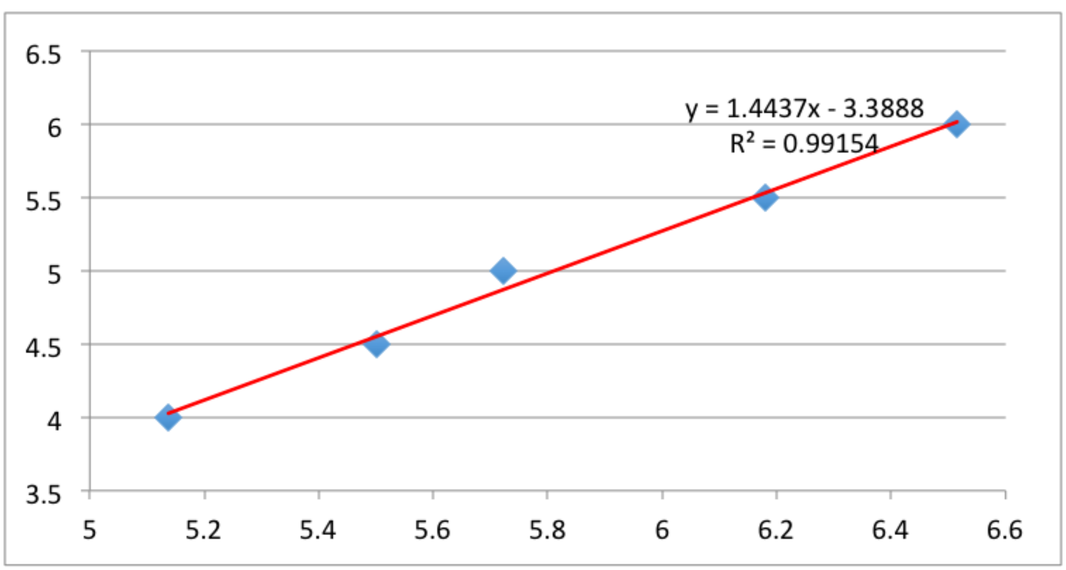

Figure 4.4: Linear regression of average accelerometer data and speed of a running female

However, one formula will not be for everyone. Base on our experiments conducted on several male and female, we found that the accelerometer data is proportionate to user's height. Meanwhile, different cell phones use different sensors. The ranges of data of two sensors made by different factories could vary dramatically.

Therefore, we need a personalized formula to calculate the user's speed. This app has a training mode for every user as they starts their experience with the app. It requires user to input their personal information and it provides a basic set of a_acc's-speed data according to the user's height which could initial a polynomial regression formula at the beginning of the training mode. As the training mode flow chart shows, when the detected speed is different from the user's real speed, the new point: (acc data, user speed) is put into the data pool to adjust the coefficients of the polynomial regression.

4.4 Data Processing

Method of calculating calorie consumed in different activity mode of the user are distinguished from each other.We use a common value MET (Metabolic Equivalent) to measure calorie consumed by the user. MET is the ratio of the work metabolic rate to the resting metabolic rate. One MET is defined as 1 kcal/kg/hour and is roughly equivalent to the energy cost of sitting quietly. A MET also is defined as oxygen uptake in ml/kg/min with one MET equal to the oxygen cost of sitting quietly, equivalent to 3.5 ml/kg/min. MET value according to corresponding activity could be found from the Compendium of Physical Activities site. The values used in this app are shown in Table 4.1.

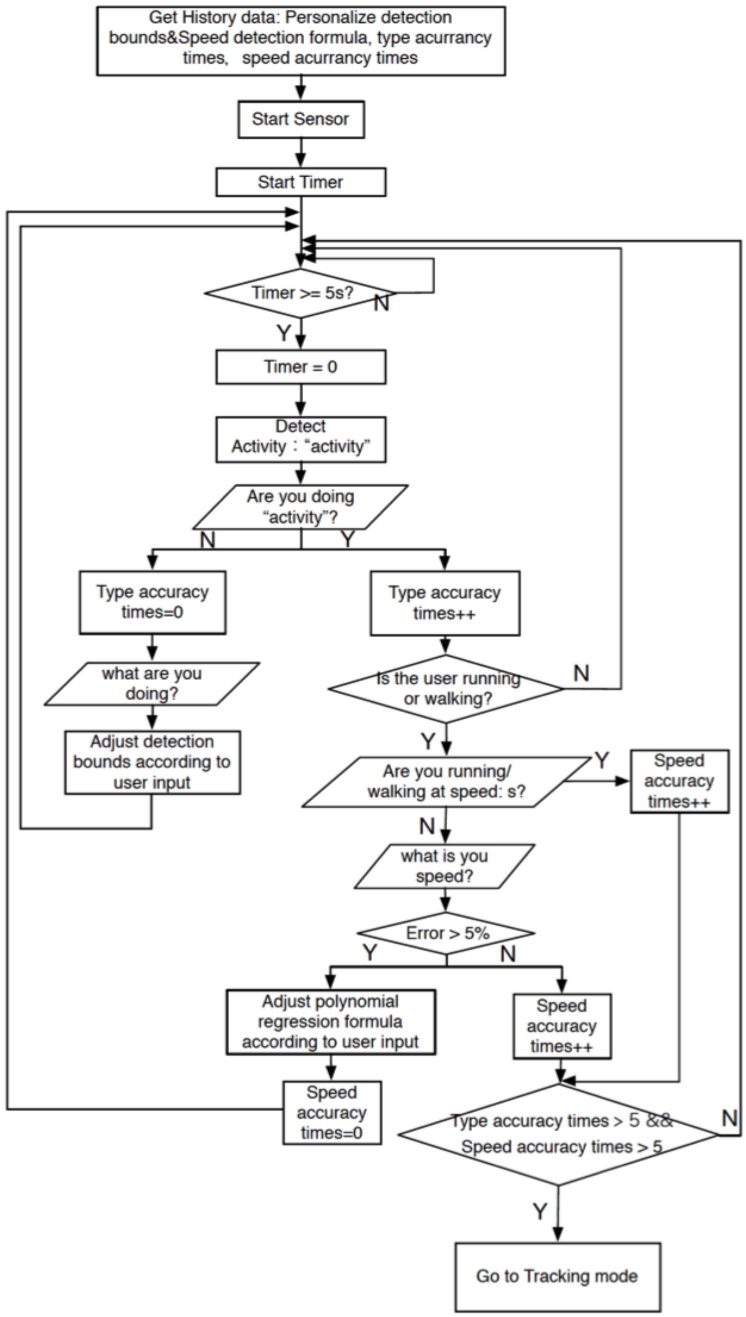

Figure 4.5: Training period flow

Table 4.1: MET Value from Compendium of Physical Activities site

Activity	**MET Value**
walking at 1.5mph	2.0
walking at 2.0mph	2.5
walking at 2.5mph	3.0
walking at 3.0mph	3.5
walking at 3.5mph	4.3
walking at 4.0mph	5.0
walking at 4.5mph	7.3
walking at 5.0mph	8.3
running at 4.0mph	6.0
running at 4.5mph	7.1
running at 5.0mph	8.3
running at 5.5mph	9.1
running at 6.0mph	9.8
running at 6.5mph	10.3
running at 7.0mph	11.0
running at 7.5mph	11.5
running at 8.0mph	11.8
running at 8.5mph	12.3
running at 9.0mph	12.8
running at 9.5mph	13.7
running at 10mph	14.5
running at 10.5mph	15.4
running at 11mph	16.0
descending stairs	3.5
climbing stairs	6.0
Not moving	1.0

4.5 User activity monitoring

After training the user could start using this app to monitor their daily workout amount. The workflow of the tracking mode is shown in Figure 4.6. The app detect user's activity every 5 seconds and calculate calorie resumed by this activity.

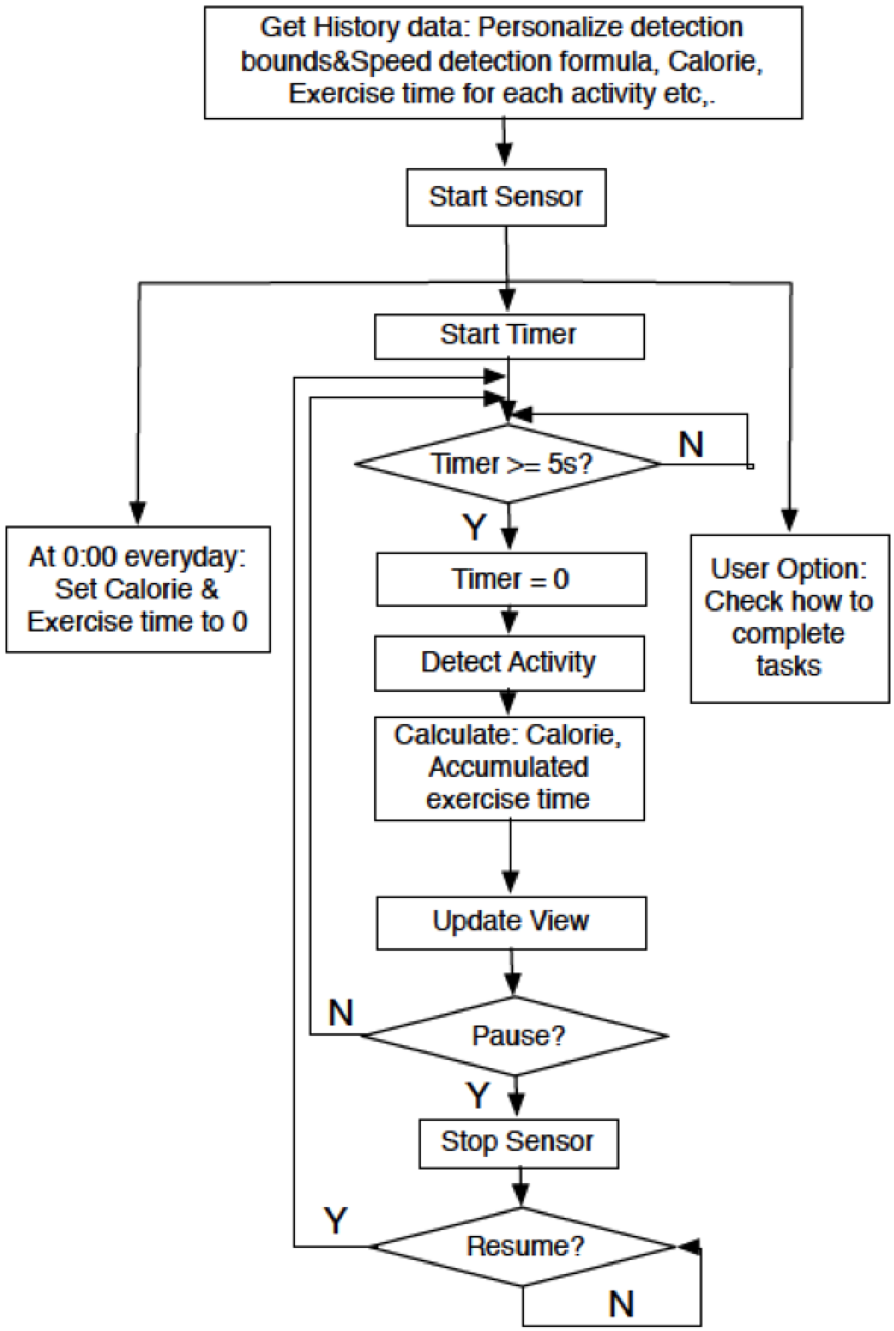

Figure 4.6: Tracking flow

CHAPTER 5

RESULTS

The activity detection test were conducted on 5 persons by carrying the smart phone in their pockets and do different activities at different speeds. The result in Table 5.1 shows that 99% of the activity type detection are accurate and the error occurs when two different states happened in the same detection cycle which is 5 seconds.

The system test were conducted on fifteen persons by carrying the smart phone

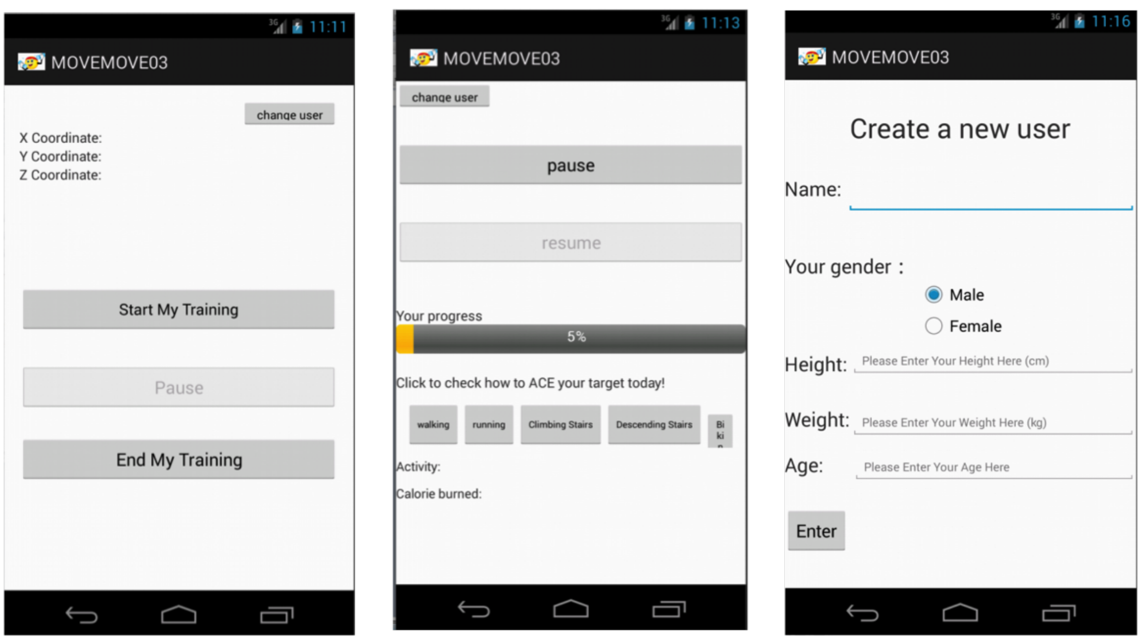

Figure 5.1: Screenshot of the Demo

Table 5.1: Activity Detection Accurancy

Activity	**Accurancy**
Walking	100%
Running	100%
Climbing Stairs	100%
Descending Stairs	99%
Not Moving	98%

Table 5.2: Speed Detection Accurancy

Activity	**Accurancy**
Walking at 1.5mph	19/20
Walking at 2.0mph	20/20
Walking at 2.5mph	18/20
Walking at 3.0mph	18/20
Walking at 3.5mph	19/20
Walking at 4.0mph	20/20
Walking at 4.5mph	19/20
Walking at 5.0mph	19/20
Running at 4.0mph	20/20
Running at 4.5mph	19/20
Running at 5.0mph	18/20
Running at 5.5mph	19/20
Running at 6.0mph	20/20
Running at 6.5mph	18/20
Running at 7.0mph	18/20
Running at 7.5mph	18/20
Running at 8.0mph	19/20
Running at 8.5mph	19/20
Running at 9.0mph	20/20
Running at 9.5mph	18/20
Running at 10mph	19/20
Running at 10.5mph	18/20
Running at 11mph	20/20

in their pants pocket for 5 days, doing training and giving feedback about the calorie calculation accuracy. From these users, most of them completed their training period after 2days and out of which nearly all of them thought the application had given the correct result of their calorie consuming.

CHAPTER 6

CONCLUSION

In this thesis, we reported the design, development and performance evaluation of a smartphone app that performs live detection of user physical activities. This app differentiates itself from previous works on activity recognition in the following: 1) It supports no additional sensing hardware and relies solely on the physical sensors that are standard on even low-end smartphones, 2) It initiates the detection algorithm based on user information, 3) It provides adaptive algorithm which can generate personalized method detection based on user input, 4) It supports the detection of 5 different physical activities, including walking, running, climbing stairs, descending stairs, and remaining inactive, 5)The Decision Tree classifier used by the app is accurate. The average detection accuracy exceeds 97% and 6) The app provide a calorie consuming progress bar to show the percentage of calorie the user has consumed which is base on the amount of calorie sugggested to be consumed. This application lets users monitor their daily physical activity and enables them to make healthier and more informed choices that can lead to healthier habits and lifestyle. Live updates are specifically targeted to encourage decisions based on a healthier lifestyle. In the future, we would like to extend this app further to: 1) Support more physical activities, 2) Conduct experiment to find the optimal degree of the polynomial regression algorithm of the speed detection, and 3) Develop an app function that uses historical information about physical activities and contextual information to gives users pro-active suggestions for lifestyle choices.

BIBLIOGRAPHY

[1] Y. Tao *et al.*, "Integration of vision and inertial sensors for 3d arm motion tracking in home-based rehabilitation," in *Robotics*, 2007.

[2] F. Albinali *et al.*, "Using wearable activity type detection to improve physical activity energy expenditure estimation," in *UbiComp*, 2010.

[3] M. Azizyan *et al.*, "Surroundsense: Mobile phone localization via ambience fingerprinting," in *MobiCom*, 2009.

[4] N. C. Krishnan *et al.*, "Sensors signals and information processing workshop," in *ICCD*, 2008.

[5] S. S. I. Ling Bao, "Activity recognition from user-annotated acceleration data," in , 2004.

[6] E. M. Tapia, S. S. Intille, W. Haskell, K. Larson, J. Wright, A. King, and R. Friedman, "Real-time recognition of physical activities and their intensities using wireless accelerometers and a heart monitor," in *IN: PROC. INT. SYMP. ON WEARABLE COMP*, 2007.

[7] J. Eriksson *et al.*, "The pothole patrol: Using a mobile sensor network for road surface monitoring," in *MobiSys*, 2008.

[8] J. Lester *et al.*, "A hybrid distriminative/generative approach for modeling activities," in *IJCAI*, 2005.

[9] K. Lorincz *et al.*, "A wearable sensor network platform for high-fidelity motion analysis," in *SenSys*, 2009.

[10] A. M. S. A Mannini, "Machine learning methods for classifying human physical activity from on-body accelerometers," in *Sensors 2010*, 2010.