User Mobility Detection using Foot Force Sensors and Mobile Phone GPS

Zelun Zhang

Submitted for the degree of Doctor of Philosophy

School of Electronic Engineering and Computer Science

Queen Mary, University of London

2014

Declaration

The work presented in the thesis is the author's own.

DATE: 02-June-2014

SIGNATURE: Zelun Zhang

To my beloved family and friends

Abstract

A user (or human) mobility context is defined as a type of user context that describes a type of whole body posture (e.g., standing versus sitting) and/or a type of travel or transportation mode (e.g., walking, cycling, travel by bus, etc). Such a context can be derived from low-level sensor data and spatial contexts, including location coordinates, 3D-orientation, direction (with respect to magnetic north), velocity and acceleration. Different value-added services can be adapted to users' mobility contexts such as assessing how eco-friendly our travel is, and adapting travel information services such as maps to different transportation modes. Current sensor-based methods for user mobility detection have several key limitations: narrow range of recognition, coarse user mobility recognition capability, and low recognition accuracy. In this thesis, a new Foot-Force and GPS (FF+GPS) sensor method is proposed to overcome these challenges that leverages a set of wearable FF sensors in combination with mobile phone GPS. The novelty of this approach is that it provides a more comprehensive recognition capability in terms of reliably recognising various fine-grained human postures and transportation modes. In addition, by comparing the new FF+GPS method with both an accelerometer (ACC) method (62% accuracy) and an ACC+GPS based method (70% accuracy) as baseline methods, it obtains a higher accuracy (90%) with less computational complexity, when tested on a dataset obtained from ten individuals.

In addition, the new FF+GPS method has been further extended and evaluated. More specifically, the trade-off between the computation and resources needed to support lower versus higher number of features and sensors has been investigated. The improved FF+GPS method reduced the number of classification features from 31 to 12, reduced the number of FF sensors from 8 to 4, and reduced the use of GPS in mobility activity recognition.

Acknowledgements

I would like to take this opportunity to thank my supervisor, Dr. Stefan Poslad, for his helpful advice and direction throughout the entire work. His wide knowledge and logical way of thinking have been of great value for me. His understanding, encouraging and personal guidance have provided a good basis for the present thesis.

I would like to thank Dr. John Schormans, Dr. Gareth Tyson and Dr. Bo Zhong, who provided valuable ideas and helpful advices.

I would also like to thank all my friends at QMUL, with whom I spent four pleasurable years, especially, Bo Zhong and Ran Tao.

Finally, my love and gratitude go to my beloved family. For my parents who raised me and love me. I am extremely grateful to my wife, who sacrificed her career in China and supports me for years.

Table of Content

Table of Figures

Table of Tables

List of Abbreviations

ACC	Accelerometer
ADC	Analogue to Digital Conversion
ANN	Artificial Neural Network
AGPS	Assisted Global Positioning System
BAN	Body Area Network
CoP	Centres of Pressure
CSV	Comma Separated Values
DTa	Decision Table
DTr	Decision Tree
DC	Direct Current
DFT	Discrete Fourier Transform
DHMM	Discrete Hidden Markov Model
FFT	Fast Fourier Transform
FF	Foot Force
GIS	Geographical Information System
GPS	Global Positioning System
GSM	Global System for Mobile Communications
HMM	Hidden Markov Model
iHCI	implicit Human Computer Interaction
IoT	Internet of Things

kNN	k Nearest Neighbour
MEMS	Micro Electro-Mechanical System
NB	Naïve Bayes
NFC	Near Field Communication
PAN	Personal Area Network
POI	Points Of Interest
PoCoA	Post Correction Algorithm
RF	Radio Frequency
Std. Dev.	Standard Deviation
SVM	Support Vector Machine
TM	Transportation Mode
UP	User Posture
Ubicomp	Ubiquitous Computing
WEKA	Waikato Environment for Knowledge Analysis
WIFS	Wireless In-shoe Force System

1 Introduction

1.1 Motivation

The Internet of Things (IoT) is a vision for the Internet where more diverse smart devices can operate and interact with more of the physical environment, and interact with each other both locally, and with remote services. Here, the concept smart means that the entity is active, digital, networked, can operate to some extent autonomously, is reconfigurable and has local control of the resources it needs such as energy and data storage [1]. The early IoT application focus was on tracking and sensing more things in the physical world to ascertain if things would arrive at the planned time [2]. There are two different designs for smart devices to track moving things: smart (mobile) device versus smart environment (devices) [1, 3]. Smart (mobile) devices can be embedded or accompany a mobile host such as a person or vehicle and sense its changing mobile context such as location or velocity. Here, the mobile context data can be acquired in a mobile device and uploaded in offline mode or in real-time for use in remote services. The set of mobile context form a mobility profile. A smart environment is one in which smart devices are embedded in it, e.g., embedded readers can detect the proximity of Near Field Communication (NFC) electronic tags embedded in other devices, or fixed position video cameras can monitor a physical space. Here the mobile context is acquired by the smart environment device and is again uploaded at some time.

The focus in this research is on the use of smart mobile devices that accompany humans (such as smart phones and wearable devices) that can be used to create mobility profiles of human (mobility) rather than on the use of smart environments. One can distinguish a low-level mobility context profile versus a high-level one. A low-level context represents the raw unclassified sensor data, such as a location or velocity. A high-level context is the processed, classified, mobility context, e.g., this movement represents somebody walking or cycling. The focus here is on the use, classification, of high-level mobility contexts rather on low-level ones.

High-level user mobility contexts can enable a whole raft of services: Physical activity monitoring, e.g., mobile phone sensors may detect how many hours a person walks every day and provide personalised healthy travel advice [4, 5]; Environmental impact monitoring, e.g., Personal Environment Impact Report (PEIR) and UbiGreen [6, 7] along with commercial offerings such as Carbon Diem and Ecorio [8, 9]; Crowd mobility awareness where mobility context based profiles (time, location, transportation mode traces) of multiple users can be fused to determine spatial-temporal (distributed) mobility contexts and patterns [10-12]; Mobility-aware service adaptation: Mobility profiling systems can enable specific services to better adapt to the type of mobility [13, 14]. Although, mobility profiling can enable a range of applications that can adapt to the profile, the focus of this research is on achieving better profiles rather on the adaptation. Better mobility profiles entail a more accurate and fine-grained classification of types of user mobility because without this, the adaptation will be faulty [15].

1.2 Challenges in Profiling Fine-Grained User Mobility

It is useful to classify user mobility, also referred to as user mobility activity, across a broad range of activities and to be able to differentiate certain types (and sub-types) of activity, to enable the above applications that can adapt to changes in mobility. Different types of mobility contexts can be defined. The location of key way-points, such as start, end and on-route points may vary with respect to the mobility activity, e.g., taxi versus bus. Hence, the location could be used to differentiate the mobility activity. But note in some cases, taxis may travel on bus routes because they are less congested, hence the use of simple fixed locations to classify mobility activity may be error-prone. The rate of change of location with time and direction, hence velocity or acceleration could also be used to differentiate different types of mobility. The average movement velocity for free-flowing people and vehicles varies, e.g. increases from walking, cycling to taking a vehicle. However, for a bus that is stuck in congestion, cycling or even walking may be quicker. The speed of movement between motorised and non-motorised individuals may vary based upon ability, propensity for speed and due to environmental conditions. For example, road vehicle speed has specific limits by law but these specific limits vary along different routes. Hence, use of a simple threshold for speed, to differentiate between motorised and non-motorised mobility, or differentiate different sub-types of motorised modes (use of a car or taxi, bus, or differentiate sub-types of non-motorised modes such as standing, walking, or cycling), is quite complex. Whole body posture, i.e., standing versus sitting, varies between different transportation modes, e.g., people sit on a bike, car or taxi but stand while walking but people may remain standing, or walk to get to seat, on a bus but not in a car, taxi or bike. Thus, a simple classification of whole body posture alone cannot consistently differentiate the use of different sub-classes of motorised transport. In addition, it may be useful to differentiate both posture and transportation mode to provide adapted services. For example, when detecting the user is standing (rather than sitting) on a moving bus, the menu icon of the smarting phone might automatically grow bigger to facilitate tapping on them.

For some types of on-route transport information service, it may be useful to differentiate the driver versus passenger. For example, bus drivers may require route navigation information but bus passengers are more concerned with knowing which stop is the closest stop to a destination and where to get off the bus, rather than seeing the whole bus route. It may also be less safe to distract a road vehicle driver with an incoming or outgoing phone call than a passenger. Hence, it may be useful to divert an incoming call automatically by a mobile phone when detecting the user is driving a road vehicle.

People use a mixed sequence of different types of mobility and posture during different journeys. People tend to walk to the nearest public transport stop to take public transport, walk during interchanges if changing between public transport vehicles on-route, and walk from the end stop to a destination. However, people may also cycle to a tube[1] station and fold up their bike whilst continuing part of their journey by tube and cycle from the destination tube stop to the end destination. They may instead cycle to their nearest bus or tube stop from where they live, leave their bike and not take it on the public transport and walk from the destination tube stop to the end destination. People who travel by taxi, private car or bike may tend to walk only at the start and end of the journey without interchanges. There are different

[1] The tube is the local name given to the London urban underground metro train

patterns with different journeys or trips in terms of a mixed sequence of each mobility type, e.g., walk to nearest public transport stop, travel on public transport instance A, walk at interchange, travel on public transport instance B, walk from final public transport stop to a destination. A multi-transport mode journey can be characterised in terms of a sequence of the transport modes used or summarised as the longest distance travelled by the main type of public transport or non-motorised journey used, e.g., someone travelled by bus or train even although a longer time may be spent walking to and from the departure or destination stop.

1.3 Existing Ways of Sensing User Mobility

The user (or human) mobility context can be determined using either on-body sensors, or fixed environment sensors. On-body sensors may be wearable, so that their position is often fixed, and accompanied, i.e., a motion-band device with integrated sensors is normally attached to a user's wrist or ankle [16]. The earliest human mobility monitoring systems used sensors fixed into the environment, such as foot-force plates [17, 18], and video cameras that were often combined with on-body tags rather than sensors, whose movement could then be analysed to detect the corresponding activities [19, 20]. Fixed environment tags or sensors can provide accurate measurements of human motion, however their chief disadvantage is that these cannot be used for pervasive monitoring of people during daily life, as it is not scalable to instrument the whole daily physical environment in this way.

Key technology enablers for pervasive user mobility context awareness are firstly, inertial sensors, such as accelerometer, gyroscope and compass, manufactured as a Micro Electro-Mechanical System (MEMS). These can also be embedded in more complex computation and communication devices such as mobile phones. Research has shown that there is a good agreement between on-body motion sensor measurements and body motion movements [13, 21]. The deployment of these on-body motion sensors varies in terms of the different types of sensors used and different (sensor) configurations. Based on the survey (Chapter 3), the majority of work uses accelerometer (ACC) or GPS type of sensor for user mobility analysis. Whereas, one main focus of this thesis is to investigate the pros and cons of using a FF type sensor (instead of an ACC sensor). Other types of sensors (e.g., gyroscope) can be used for mobility classification but they tend to be less accurate, cannot be used in a pervasive setting or are usually only combined with GPS or ACC sensors for assistive purposes (Chapter 3).

An additional challenge with using mobile phones as sensors is that these tend to accompany the body rather than be worn on the body. The position of accompanied mobile phone sensors, unlike wearable sensors, is not fixed. The position can vary, e.g., can be handheld, carried in a front top or bottom back or hip pocket, or carried in different types of bags (rather than being worn in a fixed position), or even decoupled from the human body and left on another stationary or moving object. When a phone temporarily does not accompany the mobile human host but is left on another stationary or moving object, the movement with the phone gives us no information about the movement of the (accompanying) phone's owner.

The different positions for accompanied, i.e., mobile phone, sensors can produce different sensor measurements. Hence one needs to be able to differentiate different sensor measurement values due to different positions or configurations and those due to different movements. The accelerometer is the most popular inertial sensor used for activity detection, while other inertial sensors, such as gyroscope and compass, are mainly used as assistive sensors due to their limitations in detecting user activities alone [13]. However, accelerometer-based methods are not capable of providing fine-grained mobility detection, e.g. there is no single accelerometer-based method that can sub-differentiate stationary posture into standing and sitting (see the survey in Chapter 3). In addition, the accuracy of the accelerometer-based method in mobility detection sometimes is also affected by other different habitual body motions such as bending, swaying and twitching [15]. The accelerometer may not sometimes recognise user posture during travel as the acceleration patterns from a user's motion and a vehicle's vibration as these can overlap [15].

Second, wearable sensors that for example measure a (body's) force can also be utilised in activity monitoring [22, 23]. There are well-defined foot movements and foot force (FF) patterns generated when walking or pedalling a cycle that can make these types of motion relatively easy to sense [24]. More recently, commercial wearable sensors have become available to profile user activities by analysing data from wearable sensors, at fixed body positions, on mobile devices. An example commercially available wearable sensor system is the Nike+iPod system [25]. This mounts a single sensor that can be used as a pedometer inside one shoe in a pair of Nike running shoes connected to an iPod device that acts as a data hub. This can be used to profile one specific type of user mobility, i.e., walking, jogging or running, via the foot pressure surges, as someone repeatedly steps on the ground. As only one sensor is used for the whole of one foot, the system does not monitor the overall ground reaction force generated from one foot. This limits the system from detecting fine-grained user postures e.g. differentiating between standing and sitting. In addition, by only sensing the movement in one foot rather than in both feet, it cannot differentiate other mobility activities that involve both feet, e.g. cycling and driving a car. These limitations may also introduce more errors in differentiating between a body rocking and swaying versus stepping.

Single sensor, multi homogeneous sensor and heterogeneous/hybrid sensor based configurations are the main types of sensor configurations. Single sensor based methods (whilst to some extent achieving some useful mobility recognition results) tend to suffer some common limitations such as low accuracy, narrow range and a coarse mobility recognition capability [26-28]. In contrast, multi-sensor based methods that combine two or more sensors normally outperform the single-sensor based methods in terms of higher accuracy but they also require more resources, e.g., higher computation, higher cost, and can be harder to maintain [21, 29]. Despite the added deployment challenges, multi-sensor based methods and hybrid sensor methods that combine wearable sensors and mobile or accompanied device sensors, have increasingly received attention [25, 30, 31].

In contrast to a single wearable sensor used as a pedometer to classify user mobility, multi-homogeneous sensors , e.g., a multiple wearable foot force sensor system can be used to capture richer and more fine-grained user foot force variations caused by different user postures, e.g. standing and sitting and activities, e.g., cycling and driving in real time [22]. However, use of foot force sensors to support richer mobility activities recognition also faces significant challenges. Different mobility activities may exhibit similar foot force patterns, which can be hard to differentiate, e.g., car passengers and seated bus passengers sometimes generate quite similar foot force patterns. This can be addressed through using a hybrid multi-sensor approach e.g. combining FF sensors with GPS to provide additional distinct patterns. The variability in where sensors are placed can produce different sensor measurements. This can be addressed, when feasible, by fixing the sensor position, e.g., using a standard shoe inset. For the same type of user activity, user movement may vary. This makes it more difficult to compare sensor readings across different subjects, e.g., foot force signal noises from small body movements such as swaying may influence the classification results. However, many mobility activities involve a regular shift of pressure between the left and right foot such as walking and cycling; the accuracy of detecting and classifying these activities can be improved if a method can monitor this pressure shift and use this to classify these activities.

In addition to sensing, a portable data storing and computing capability is also required to support pervasive mobility detection. The rising memory and processing power of the smart phone enables it to act as a local data processing and information storage hub or as a relay for data from body area networks of wearable sensors [30, 31]. In addition, smart phones also have integrated transceiver type positions sensors such as GPS, WiFi and GSM that use in-network measurements of signal time arrival and signal strength to determine user spatial contexts such as location and speed [32-34]. These are able to support a range of user context aware services during everyday activities [35-37]. These spatial contexts are also potentially useful to enable other wearable sensors for better mobility detection [38].

1.4 Research Objectives and Contributions

This thesis concerns the problem of improving the classification of types of user mobility using body area network (BAN) sensors (as opposed to fixed environment sensors such as video cameras). Currently, the main BAN methods use either an accelerometer sensor or GPS, or a combination of the two, but these have limitations in terms of low accuracy and a coarse-grained classification capability (see Chapter 3). The primary research objective is thus, to investigate whether or not an alternative, FF sensor based, method can improve user mobility classification compared to state-of-the-art (mobile phone based) accelerometer sensor and GPS based methods. A sub-objective of this is to investigate the effect of different FF sensor configurations and derived feature sets that affect the system computation load, cost and maintenance versus the accuracy trade-off, when used for user mobility detection.

The main, novel, contributions of this thesis are summarised as follows:

1. A sensor based method that leverages a set of FF sensors, assisted by mobile phone GPS (FF+GPS), has been proposed, designed, implemented, tested, and evaluated. To the best of my knowledge, the FF+GPS method for mobility detection has never been examined before. The FF+GPS method is evaluated by comparing it with state of art inertial sensor use, e.g., accelerometer (ACC) [27], and a ACC+GPS combination, which are used as baseline methods. The FF+GPS sensor method provides a more fine-grained user mobility detection capability in terms of both reliably sub-differentiating stationary postures into standing and sitting, and reliably sub-differentiating motorised transportation mode into bus passenger, car passenger, and car driver. The experimental results show that by comparing this with the ACC-based baseline method, the FF+GPS method achieves a substantial improvement in accuracy (increased from a level of 70% to a level of 90%) when tested on a dataset obtained from ten individuals (see Chapter 4).

2. An additional contribution was to investigate how the accuracy of the FF+GPS method at detecting user mobility is affected by different FF sensor configurations. The minimal most effective insole positions (two per foot) for sensing. 12 (out of 31) maximally informative features were derived and identified. A new hybrid GPS use-plan was identified to improve the energy efficiency of the FF+GPS method, when used for mobility detection. The improved FF+GPS method was tested and the results showed that the improved FF+GPS method, even although it reduced the number of FF sensors, the number of features, and the use of GPS, this hardly reduced the overall user mobility detection accuracy (only a 2% accuracy loss is identified) (see Chapter 5).

Other contributions of the work in this thesis are as follows.

1. A thorough survey of methods in mobility activity recognition has been conducted (see Chapter 3).

2. A novel user mobility detection system (see Section 4.1.3) has been proposed. With this system, users only need to perform required activities once to collect data for three different methods (the core FF+GPS, ACC, and ACC+GPS). This eliminates the variability caused from different instances during data collection, which may affect the comparison results.

3. Two hardware prototypes of the experimental equipment for user mobility activity sensing using external foot force sensors, accelerometer, and mobile phone GPS have been designed and implemented (see Sections 4.2.2 and 5.2.2).

4. An accelerometer-based method (identified as the best practice method in the survey) has been reproduced and an ACC+GPS based method has been produced to provide baseline methods for the evaluation of the new FF+GPS method (see Section 4.1.4).

1.5 Author’s Publications

The R&D contributions in this thesis have resulted in the following publications.

Journal Papers

1. Z. Zhang, and S. Poslad., “Design and Test of a Hybrid Foot Force Sensing and GPS System for Richer User Mobility Activity Recognition,” Sensors 2013, vol. 13, no. 11, pp. 14918-14953, November 2013.
2. Z. Zhang, and S. Poslad., “Improved Use of Foot Force Sensors and Mobile Phone GPS for Mobility Activity Recognition,” IEEE Sensors Journal, Accepted.
3. T. O. Oshin, S. Poslad, Z. Zhang., “Energy-Efficient Real-Time Human Mobility State Classification Using Smartphones,” IEEE Transactions on Computers, Accepted.

Conference Papers

4. Z. Zhang, and S. Poslad., “Fine-Grained Transportation Mode Recognition Using Mobile Phones and Foot Force Sensors,” *9th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (Mobiquitous 2012)*, Beijing, People's Republic of China, Dec. 2012.
5. Z. Zhang, and S. Poslad., “A New Post Correction Algorithm (PoCoA) for Improved Transportation Mode Recognition,” *IEEE International Conference on Systems, Man, and Cybernetics (SMC 2013)*, Manchester, United Kingdom, Oct. 2013.

1.6 Thesis Outline

The remainder of this thesis is organised as follows:

The key user mobility context awareness background concepts of the thesis are presented (Chapter 2). Related work on sensor-based user mobility detection is surveyed (Chapter 3). The common limitations in the existing system are analysed and discussed. In addition, a common accelerometer-based method is identified and is selected as a baseline to validate the new proposed method. In order to resolve the identified limitations in user mobility detection, a new FF+GPS based method is proposed, designed, implemented, and evaluated (Chapter 4). The FF+GPS method is evaluated by comparing it with a baseline accelerometer based method (identified from Chapter 3). A further improvement of the FF+GPS based method for mobility activity detection is proffered in terms of reducing the number of features, the number of sensors, and the use of GPS (Chapter 5). Finally, the overall conclusions are presented (Chapter 6), and the thesis closes with some suggestions about how the work could be extended.

2 Background

The user mobility context can be seen as one sub-type of user context. This thesis concerns the recognition of the mobility context for individual, adult, users focusing on daily urban travel.

2.1 User Mobility Context

A user's mobility context is defined as a type of user context that describes the type of whole body posture, e.g., standing versus, sitting, and/or the type of transportation (or travel) mode, e.g., walking, cycling, travel by bus, etc. These are normally derived from the raw sensor data and spatial contexts, such as location coordinates, 3D-orientation, direction (with respect to magnetic north), velocity and acceleration. The (high-level) user mobility context is derived from (low-level) user spatial contexts [39].

Currently, although there is much research and development focusing on user mobility context awareness, little of this is capable of capturing the (high level) user mobility activities in the daily living environment. Most of them focus on (low level) user spatial contexts, such as using a positioning system to capture users' locations [40]. Spatial contexts have played a significant role in ubiquitous computing research [39, 41]. However, only the spatial context itself is not enough, since the system requires (high level) user mobility context to support advanced mobility context adaptation services [42, 43].

2.2 User Mobility Context Awareness

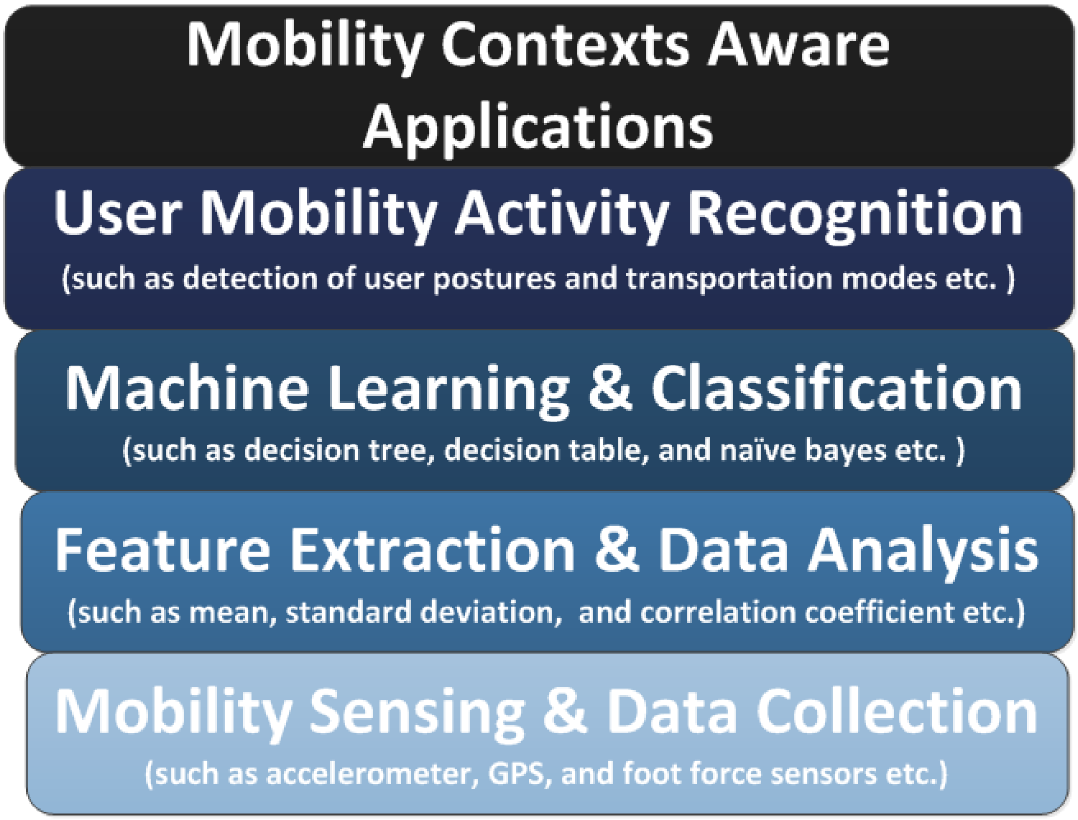


Figure 2.1 A General Framework for Analysing Sensor Based User Mobility Awareness

This thesis focuses on high-level user mobility activity recognition using BAN sensors. Figure 2.1 shows the general framework for BAN sensor based user mobility context awareness. As the focus is on the "User Mobility Activity Recognition" phase, all layers, except for mobility context-aware applications are described in the following sections.

2.2.1 Mobility Sensing and Data Collection

User mobility contexts are derived from lower level mobility contexts determined by various motion sensors such as accelerometer, GPS etc. [1, 39]. The raw sensor data collection phase is the first phase for user mobility context awareness (Figure 2.1). Hence, the sensor technology that focuses on capturing the user motion characteristics is the focus in this thesis.

A sensor can be defined as a device that detects (senses) changes in the ambient conditions of its environment and converts these changes into an analogue or digital signal whose changing values indicates changes in the state of the environment [44]. Various sensors such as GPS, accelerometer, ultrasonic sensor, orientation sensor, compass, and gyroscope etc., can be used to capture a user's moving velocity, moving acceleration, and moving orientation, as they move. A mobile phone has three benefits for use as a user mobility sensing platform: it is in common use and accompanies users during daily life [37], it has many sensors embedded in it, it offers a significant data storage and computing capability [45]. Hence, this thesis focuses on using specific sensing modalities that are available or viable to be used in smart phones to detect a user's mobility activities.

2.2.1.1 Inertial Sensors

Inertial sensors, notably accelerometers, gyroscopes, and compasses, have been widely used in activity detection systems [46]. The accelerometer is the most popular inertial sensor used for activity detection, while other inertial sensors, such as gyroscope and compass, are mainly used as assistive sensors due to their limitations in detecting user activities alone [13, 47].

An accelerometer is a device that measures magnitude and direction of proper acceleration. The proper acceleration measured by an accelerometer is not necessarily just the coordinate acceleration (rate of change of velocity) as the acceleration is also associated with the weight experienced by any test mass at rest in a frame of reference of the accelerometer device, e.g., an accelerometer at rest on the surface of the earth will measure an acceleration g= 9.81 m/s^2 straight upwards, due to its weight. There are single-axis and multi-axis models of accelerometers. The 3D-accelerometer can also be used to sense and determine the orientation, magnitude of acceleration, vibration, and falling of a bonding object [48]. In addition, 3-D accelerometers are now widely integrated into most smart phones such as Apple's iPhone and Goolge's Android.

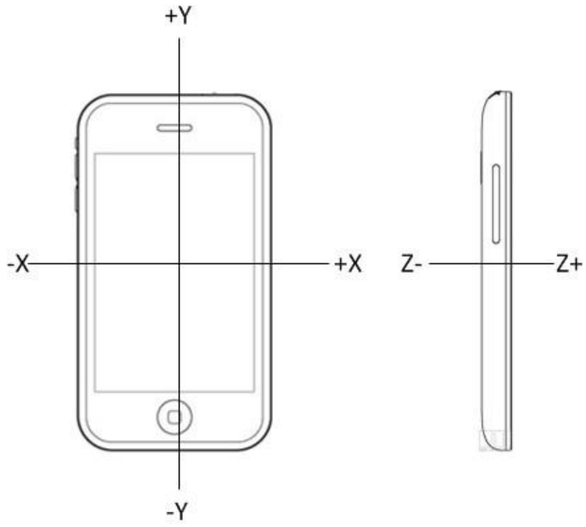


Figure 2.2 Smart Phone Built-in 3D Accelerometer

As the Figure 2.2 shows, X, Y and Z are three axes that a typical built-in 3D-accelerometer supports to sense. The value of each axis corresponds to the acceleration sensed in each vector direction. This smart phone built-in accelerometer is very useful in detecting the acceleration variations generated in different user activities i.e., differences between stationary postures and dynamic postures [49].

2.2.1.2 Physical Sensor

Physical environment sensor is one sub-type of generalised sensor that detects and senses the changes of the physical aspects of the external environment such as sound, pressure/force, magnetic field and so on. In the field of activity recognition, foot force sensors are of particular interest because when a user performs different mobility activities, foot force sensors can be used to capture the variations of ground reaction force. Other physical sensors, such as Microphone, magnetic sensor, although have been used for activity detection but they are mainly used as assistive sensors and their accuracy is relative and varies [21, 50]. Hence, they are not considered further in this thesis

A force sensor is a device that can detect and sense the force or pressure applied on its sensing area. It is normally composed something such as a ‘force-sensing resistor’ whose resistance changes when force or pressure applied. As the advancement of the manufacturing technology, the size of some current force sensor is small enough to for embedded usage. Research has shown that there is a good agreement between wearable foot force sensors and fixed environment force sensor measurements [51] [22]. Hence, the wearable foot force sensor is of particular interest of this thesis, because in different mobility activities i.e., walking and cycling, the ground reaction force patterns are different, which can be further analysed and utilised to detect different user postures and transportation modes.

2.2.1.3 Location Sensing System

The location sensing system can be defined as a system that continuously and in real-time can determine its position in space [40].

The location sensing system is used to detect user spatial context, and the spatial context is an important low-level mobility context to infer high-level user mobility activity [52]. Several systems can be used for location-sensing: Global Positioning Systems, Radio Frequency (RF)-based Systems, and Cell-Identification Systems.

RF-based system mainly uses inexpensive wireless local area networks (WLAN, also referred to as WiFi) as the fundamental infrastructure. Its coverage is limited typically to indoor environments as its transmitters are situated indoors but this depends on the transmission power [53]. As this thesis focuses on the mobility activities that are mainly performed in the outdoor environment, such RF-based systems are not considered in this thesis.

Two types of widely adopted outdoor positioning systems are GPS and Cell-based system. Cell-based system relies on the fact that mobile networks can identify the approximate position of a mobile handset by knowing which cell site the device is using at a given time. However, the accuracy of the method is generally low, normally in the range of 200 meters, depending on the GSM cell size [54].

The GPS is the most well-known global location sensing system today [55]. In this system the satellites transmits navigation messages, GPS receivers process the signals to compute position in 3D – latitude, longitude, and altitude with an accuracy of 5 meters or less [56]. Some mobile phone GPS systems use Assisted-GPS (A-GPS) technology. This utilises other types of network, e.g., WiFi, or a third party service provider, to assist the handset to improve the accuracy of location identification calculations [56].

Hence, comparing to Cell-based systems, GPS is still preferred in this thesis for its better accuracy and ubiquitous availability in the outdoor environment.

2.2.2 Feature Extraction and Data Analysis

2.2.2.1 Windowing Techniques

Windowing techniques are required in activity detection to divide raw sensor signal in to smaller segments. Activity classification algorithms are then applied to each segment. There are mainly two different windowing techniques have been used in activity detection: sliding windows and event-defined windows.

For sliding windowing methods, the sensor signal is divided into segments of fixed length with no inter-window gaps. Some studies included a degree of overlap between adjacent windows [57, 58]. The window size ranges from 0.25 s in [59] to 8 seconds in [27].

For event-defined windowing methods, predefined events are required to segment successive windows. A number of different approaches have been proposed for identifying events, such as sitting down, starting to walk, prior to explicitly identifying the specific activities. Given that such events may not be uniformly spaced in time, the size of these windows is not fixed [60].

As pre-processing is required by the event-defined windows to locate a specific event, the sliding window approach, which does not require pre-processing, is preferred as it is better suited for real-time applications on mobile devices. The sliding windowing method also has the advantage of implementation simplicity. Hence, the majority of activity detection studies (including those in this thesis) have employed this approach.

2.2.2.2 Feature Generation

Features are needed to characterise windows of the raw sensor data. These features are then used as inputs to classification schemes to discriminate different activities. Two types of feature are mainly used in existing activity detection studies: time-domain features and frequency-domain features.

Time-domain features are normally derived directly from a window of sensor signals. These features are typically statistical measures (such as mean, median, max, standard deviation, and so on) of the sensor readings e.g., acceleration values from accelerometer, or the ground reaction force values from the foot force sensors.

In the frequency-domain, the features are normally derived from the output of a Fast Fourier Transform (FFT) with a time domain signal as an input [58]. FFT gives a set of basis coefficients which represent the amplitudes of the frequency components of the signal. The features include amplitudes of the frequency components of the signal, the distribution of the signal energy, and so on.

Time domain features are preferred for its simplicity and ideally for mobile devices to keep the computational costs low [13, 45].

2.2.3 Machine Learning and Classification

Once features have been derived to characterise a window of sensor data, they are used as input to a classification algorithm. There are many different machine learning schemes. These vary from simple threshold-based schemes (e.g., decision tree, decision table) to more advanced models, such as artificial neural networks or hidden Markov models [61, 62]. These machine learning algorithms, once appropriately implemented, can learn to recognize and associate patterns in the input features with each activity. Machine learning techniques are generally considered to fall within one of the three main categories, supervised, unsupervised, or semi-supervised [63, 64]. With supervised learning, all activity data is required to be fully labelled in the training phase. Once the training phase is complete (which means the machine learning model is trained), in the next testing phase, the classifier is able to classify an unknown sample (window of sensor data) with respect to an activity type. With unsupervised/semi-supervised approaches, a significant amount of activity data is required to be unlabelled during the training dataset. Instead, all the sensor data are passed to the algorithm, which automatically identifies a number of states or clusters, each of which may correspond to a particular activity. However, unsupervised/semi-supervised approaches are not normally applied to differentiate activities with similar feature characteristics, e.g., sub-classifying motorised mobility into bus-passenger and car-passenger. Hence, there has only been a very small amount of work applying unsupervised techniques to activity detection. Based on this, the supervised machine learning scheme is mainly considered in this thesis for its simplicity and non-ambiguity in defining (from labelling) the fine-grained mobility activities.

The classification algorithms used in this thesis are Decision Tree, Naive Bayes, and Decision Table, which have been chosen due to their simplicity and good performance in terms of computational delay and weight [45].

2.2.3.1 Decision Tree

The decision tree approach is similar to a hierarchical scheme in terms of the derived data patterns that go through a tree-like set of nodes. In each node, a condition related to the value of an attribute is checked. In this way, depending on whether the condition is fulfilled, the condition of the following node is checked until a leaf that contains the classification result is found. However, the decision tree is different with the hierarchical scheme in terms of automation of the decision-structure construction process. In the decision tree classification, rather than constructing the decision structure manually, it is generated automatically. These algorithms examine the discriminatory ability of features or parameters one at a time. By iterating this process, a set of rules will be set up which ultimately leads to a complete classification system [65].

2.2.3.2 Naive Bayes

A Naive Bayes classifier is a probabilistic classifier based on an independence assumption. In the Naive Bayesian model (also known as independent feature model), the input contexts (or features) are assumed to be independent of each other. Under this assumption, the likelihood function for each destination (which is one of the mobility activity types) can be expressed as the product of N simple probability density functions, where N is the number of contexts. In the case of classification, given an unclassified sample, the destination, whose likelihood function achieves the maximum value of probability (among all other destinations), will be classified as the type of the current sample. The Naive Bayes approach is of particular interest due to its simplicity and the ease of implementation [66].

2.2.3.3 Decision Table

Decision tables, similar to decision trees, are models used for prediction or classification. A decision table is a tabular representation used to describe and analyse decision-making situations, where the state of a number of conditions of an entry (which is a mobility sample) determines the execution of an action (which is one of the mobility activity types) [67]. Decision tables associate conditions of an entry (which contains values or attributes) with an action (which is the classification result in this case) [68].

Decision tables vary widely in the way the condition alternatives and action (classification) entries are represented [69]. Some decision tables use simple true/false values to represent the alternatives to a condition (like if-then-else), other tables may use numbered alternatives (like switch-case) [70]. Action entries normally represent as an action is to be performed.

2.2.4 Cross Validation Scheme

Cross-validation schemes are techniques for assessing how the results of a statistical analysis can be generalised as an independent data set or a new data set. It is also used to estimate how accurately a classifier performs in practice. For instance, one round of cross-validation involves partitioning a sample of data into complementary subsets, performing the analysis on one subset (called the training set), and validating the analysis on the other subset (called the testing set) [71].

In practice, in order to reduce the variability caused by different samples, multiple rounds of cross-validation are performed using different partitioning schemes. The validation results are averaged over different rounds. In this thesis, two types of cross validation that are commonly used for user activities recognition are employed: 10-fold cross validation and leave-one-user-out cross validation.

2.2.4.1 10-fold cross validation

In a 10-fold cross validation, the original sample set is randomly partitioned into 10 subsample sets. Of the 10 subsample sets, a single subsample set is retained as the testing data for validating the model, and the remaining 9 subsample sets are used as training data. The cross-validation process is then repeated 10 times, with each of the 10 subsamples used exactly once as the testing data. The 10 times results from the folds then are averaged to produce a single validated result. The advantage of this method over repeated random sub-sampling is that all observations are used for both training and validation, and each observation is used for validation exactly once.

2.2.4.2 Leave-one-user-out cross validation

The leave one user out cross validation involves using data set from a single user as the testing data, and the dataset from the remaining users as the training data. This is process repeated so that each user in the samples is used once as the testing data set. This is similar to the 10-fold cross validation with number of folds being equal to the number of individuals in the original sample. Normally speaking, leave-one-user-out cross validation is more time-consuming and computational expensive because it requires many repetitions of training data from different individuals of the experiments.

2.3 Summary

In this chapter, the definition and classification of user mobility contexts have been described. An overview of a general framework for sensor-based user mobility context awareness is presented. In order to contribute to the mobility detection, the limitations of the current state-of-the-art methods in this field need to be identified.

Hence, various existing work and systems for mobility detection are reviewed, discussed, and analysed in the following chapter (Chapter 3).

3 Literature Survey

3.1 Scope of the Survey

Currently, the most popular types of sensors used for user mobility detection are inertial sensors (mainly accelerometer) and GPS. Typically, these sensors are embedded into widely used smart phones. Hence, smart phones are also commonly used by researchers as user mobility sensing devices. Hence, the use of accelerometer and GPS is a focus in this survey. The second main focus in this survey is on the use of FF sensors, including hybrid FF sensor techniques. The critical analysis of related work is partitioned according to different sensor configurations – homogeneous sensor configuration and hybrid sensor configuration.

3.2 Homogeneous Sensor Configuration

3.2.1 Accelerometer

Accelerometer measurements are a typical way to recognise types of user activity. Mizzel et al. [72] showed that the accelerometer signal can produce a good estimate of the vertical and horizontal acceleration components. The vector holds an estimation of the magnitude of the dynamic acceleration of the human host that carries the sensor device. Different mobility activities, such as walking and cycling, may generate different acceleration patterns that can be differentiated. Ravi et al. [26] have found that several user activities can be recognised with a reasonable accuracy by wearing a single tri-axial accelerometer near the pelvic region. Bao et al. [73] used five biaxial accelerometers worn around different parts of the body to recognise different user activities. Their results show that the thigh and wrist sensor placements can recognise everyday activities with an overall accuracy rate of 84%.

In [74], Parkka et al. utilised a wireless motion band attached to a user's ankle to sense the acceleration generated by the ankle during different activities. This work has successfully differentiated different user mobility activities such as walking, running and cycling through using a binary decision tree classification method. A personalised classification method also increases the accuracy of detection. Similar work has also been done by Myong-Woo in [75] and by Brezmes in [76].

Accelerometer-based methods can achieve an increased accuracy when people carry their smart phones in a fixed place. However, people normally tend to carry their mobile phones more freely, such as near the waist, in a front pocket, in a knee-high pocket, by hand and so on. The use of the accelerometer for classification is limited because different on-body placements of the device will greatly change the nature of the motion signal and cause noises, which finally leads to a low accuracy of specific placement trained classifiers for free use. Wang et al. [27] have also considered this issue and attempted to differentiate user mobility activities without any placement restrictions for the accompanying mobile device. They used a smart phone embedded accelerometer to recognise six kinds of mobility activities, but the accuracy is relatively low at 62% on average.

3.2.2 GPS

GPS, as a global-wide positioning system, has already been integrated into mobile phones. The potential usability of GPS in profiling (outdoor) user mobility activities has been widely presented, such as in [28] and [77]. Lin Liao et al. in [28] have developed a probabilistic temporal model that can extract high-level mobility activities from a sequence of GPS readings. Two main types of mobility activity (human powered and motorised) are inferred based on the conditional-random-fields model. Though they achieved over 80% percentage in accuracy, the range of the user mobility recognised is coarse - it can only detect two main types of mobility activity, human powered and motorised. In addition, this method cannot differentiate between different mobility activities with similar speed characteristics, e.g. a slow travelling bus during traffic congestion can be miss-classified as cycling.

In contrast to [28], Zheng et al. used a supervised learning based approach to infer more kinds of mobility activity from the raw GPS data in [77]. They proposed a change-point (between different transportation modes) based upon a segmentation method. The results show that a change point based segmentation method achieved a better accuracy compared with uniform-duration based segmentation and uniformlength based segmentation. However, GPS information alone cannot detect the change point precisely, since on many occasions, a person could take a taxi immediately after he or she gets off a bus and this very short changing segment between these two transportation modes can be hard to detect using GPS alone. This issue jeopardised the usability of this change point based segmentation method.

This existing single GPS-based method exposes its inherent limitation. GPS information alone is too coarse to enable fine-grained mobility activity recognition with a good accuracy. For example, GPS performs poorly for the recognition of different transportation modes with similar speeds such as with fast walking, cycling, and slow motorized travelling. GPS based methods can only be used to recognise different mobility activities with marked speed differences and cannot detect user postures, e.g., standing, sitting, which are not speed-related.

3.2.3 Foot Force Sensors

It is well known that different user activities may generate different ground reaction forces [22]. This FF characteristic makes the FF sensing approach potentially useful in differentiating different foot-related activities and in providing a fine-grained user mobility recognition capability. For example, gait analysis, based upon FF sensing, has had a long history in computer science terms, the origin of it dates back about 30 years ago, when Dion and his colleagues first made use of a thin force transducer to monitor walking [17]. Similar foot plate based gait analysis was also performed later by Hoyt and his colleagues in 1994 [18] and by Zijlstra in 2010 [78].

Though these early laboratory-based gait approaches were accurate, they are not so applicable for the use in daily life. These techniques are based upon the use of fixed environment sensors, the cost of which is too high for ubiquitous use as it is unrealistic to deploy such force transducers throughout outdoor environments. In addition, another key limitation of a gait laboratory approach is that people’s behaviour during a lab experiment does not necessarily mirror that in their daily activities.

Hence, suitable lightweight sensors are needed to instrument the body to provide user data pertaining to user activities in daily life environments. Nowadays, there is a range of research, such as [21, 22, 43, 51, 74, 79-81] that used more lightweight foot force sensor method for human posture and mobility activity detection. However, most of the work focuses on indoor usage of foot force sensing with a limited range of activities and does not examine its extended use to recognise a wider range of mobility activities in daily environment. The awareness of a wider range of mobility contexts is considered to be an important part of the vision of ubiquitous computing [82]. Hence, this thesis focuses on using suitable lightweight foot force sensor methods to provide user data pertaining to user mobility activities during daily life.

Veltink et al. [83] measure the ground reaction forces and centres of pressure (CoP) using two six-degrees-of-freedom movement sensors under each shoe. By comparing their measurements with the ground reaction force measured by a fixed environment foot force plate, this work illustrates the potential usefulness and feasibility of using portable foot force sensors to measure foot force during daily activities. This work also shows that mobility activity detection is feasible through ambulatory measurement of the force generated from both the heel and forefoot under each foot. However, this work only measured the foot ground reaction force during walking. Other mobility activities were excluded from this research. There are also other limitations of this work. The pair of experimental shoes was instrumented with four (15.7 mm in thickness) 6-axis force and moment sensors, which are too cumbersome to be worn in daily life. Another limitation of this work is that only one test subject has been included. Similar work has also been done by Tao [84] and by Zhang [85].

Zhang et al. [22] assessed more mobility activities such as walking, jogging and running by using a small, portable insole pressure measurement device. This device can be used to estimate the speed of walking and can be used in daily environment. This work studied 40 subjects and achieved a fairly high accuracy of walking activity recognition (95%). One obvious drawback of this work is that only user activities involving walking and running are considered. Fine-grained user postures during travelling such as standing, sitting, and use of other common daily transportation modes such as cycling and taking a bus have not been studied. Another limitation of this work is that a total of 32 foot force sensors are used. A further examination regarding a more efficient configuration of foot force sensors is desired in order to decrease the system complexity and system costs for ubiquitous use. Although there are obvious limitations of this work, nevertheless, the potential for using foot force sensors to recognise daily user mobility activities has been illustrated.

The foot force sensing systems mentioned thus far have been wire-based. This means the foot force sensors are connected for power and the monitoring data are transmitted via wires to a receiver. In order to extend the foot force sensors based methods to a more ubiquitous use, a more non-intrusive wireless way is required. Tracie et al. [51] designed and implemented a Wireless In-shoe Force System (WIFS) to acquire, process and transmit foot force sensor information. This pilot study shows the feasibility of using a wireless foot force monitoring system in a variety of locations rather than just in a laboratory setting. In addition, this work also proved that when using a limited number of foot force sensors, 4 on each foot, as long as they are properly arranged under the supporting bones of each foot, this enables accurate foot force monitoring information to be obtained, when compared with using force plate monitoring as the ground truth. However, the key limitation of this work is that only mobility activities such as walking and standing are considered. An extension of using wireless foot force sensing system to detect other mobility activities is of particular interest. Similar wireless pressure-sensitive foot insoles have also been done by Macro in [86].

In summary, foot force sensors can be used to recognise foot related activities e.g., walking and running, at a fairly high accuracy using a limited number of sensors. Existing foot force sensor based methods' usefulness in recognising a wide-range of mobility activities is limited. Many mobility activities cannot be recognised by using foot force sensors alone, e.g., driving a car, because different mobility activities may exhibit similar foot force patterns. Based upon this, a hybrid based method is desirable to combine foot force sensors with extra mobility context information from other types of sensors to improve user mobility detection.

3.3 Hybrid Sensor Configuration

Yang et al. in [80] make use of three body-worn sensor boards to detect abnormal human activities. Abnormal activities such as slipping on the ground, falling down forward and falling down backward can be detected with an accuracy of over 90%. Some mobility activities such as walking and running are also included. The limitations of this work are as follows. First, for each sensor board, there are five different types of sensors included such as light, temperature, microphone, 2D-accelerometer, and two-axis magnetometer. This means a user carries an intrusive system that may affect and restrict the behaviour of a user in different mobility activities. Second, no stationary posture, such as sitting and standing or outdoor transportation modes were studied. Thirdly, the system uses a total number of 15 (3 × 5) different sensors, which is not energy and cost efficient for ubiquitous use.

In [87], Chon and his colleagues presented a smart phone-based context location aware system that fuses accelerometer, WiFi and GPS, to track and to automatically identify Points Of Interest (POI) with room-level accuracy. The smart phone built-in accelerometer is used to capture and represent user activities. The combination of these sensors can detect some mobility activities and track this at different locations. The benefit of this system is that it does not require any specialised instrumented environment and require extra sensors to be worn on the human body. However, there are also limitations with this system. The use of GPS combined with accelerometer for mobility activity recognition is not capable of recognising more fine-grained mobility activities such as differentiating between being a car-passenger versus being a car-driver. In addition, this system is also not capable of recognising both user posture and transportation mode simultaneously, e.g., when a user is standing on a moving bus.

Varkey et al. in [88] utilised a set of support vector machines (SVM) to recognise user activities in real time using a wearable wireless sensor-based system that contains an accelerometer and gyroscope. This can recognise six different activities-walking, standing, writing, smoking, jacks and jogging. When tested on three different subjects, the accuracy of the proposed system in detecting the required activities is around 84%. A key limitation of this work is that two devices are required to be placed on two fixed positions, on the right arm wrist and on the right foot, in order to acquire the linear acceleration and angular rate. In daily living, people tend to carry their mobile devices more freely. A more flexible method with no placement restrictions of the mobile phone is required. Another limitation is that although several daily activities are detected, other useful mobility activities, such as the use of different transportation modes, is not considered.

Reddy et al. in [32] proposed the use of both accelerometer and GPS to recognise different mobility activities. Features are extracted from a series of acceleration magnitude readings, which represent the magnitude of a three axis acceleration vector. This work can effectively discriminate human powered mobility activities such as walking and cycling. However, it is unable to provide a more fine-grained recognition capability such as sub-differentiating motorised travel into taking a bus, taking a car or driving. And this method cannot detect both human posture and transportation mode simultaneously. Moreover, in order to guarantee the high accuracy, this work utilised a complex two stage classifier (Decision Tree + Discrete Hidden Markov Model), which is relative expensive computationally to be applied on mobile devices.

Minnen et al. in [21] utilise three microphones, two accelerometers and a wearable computer to recognize different user activities. By mounting microphones on the chest, elbow and right hand respectively, and by comparing the sound intensity of these three microphones, this method can be used to automatically profile the captured journals of a person's life. Further, by attaching two 3D accelerometers on each wrist, the motion pattern of both hands can be captured. A comparison of the acceleration generated between the left hand and right hand is used to infer daily activities such as hammering and sawing. There are many limitations of this work. First, the activities that can be recognised by this system have to be sonant otherwise the use of the microphone is useless. Second, mobility activities related to the motion of legs and foot, such as walking, standing and cycling, are not considered. Similar work has also been done by Takuya in [50].

Weijun et al. in [23] used three accelerometers, three gyroscopes and five tri-axial force sensors to recognise user mobility activities. By mounting three pairs of accelerometers and gyroscopes on three fixed positions (foot, calf and thigh) in combination with a set of foot force sensors, the system achieved a very detailed ambulatory gait analysis capability. By dividing a normal gait cycle into four gait phases and four swing periods, it can provide useful information for multiple health-related applications. This work shows that by combining FF sensors with other types of sensor, they are extensible and can provide a more fine-grained mobility activity recognition capability. However, the scope of this work is narrow, i.e., only walking is considered. It excludes a wide range of mobility activity recognition such as transportation mode recognition.

To summarise, current hybrid-sensor-based methods achieve a higher accuracy, compared with homogenous sensor based methods. However, they still tend to lack support for a wide range and for more fine-grained mobility recognition capability.

3.4 Discussion

Table 3.1 classifies mobility detection methods with respect to multiple dimensions: the number and types of sensors, sensor position, the types of mobility, the types of features extracted, the classifiers used, and the classification accuracy. The 6th dimension, the classification accuracy, is affected by the first five dimensions and these all vary across the related work.

It is noted from Table 3.1 that the average accuracy for current user mobility recognition is comparatively low, at about 75%, i.e., only a little over two thirds of trips are recognised correctly. Moreover, this error maybe amplified for daily mobility profiling, i.e., with an overall accuracy of 75%, around 3 hours of data may be misclassified given that 10 hours of activities are logged typically per day. This offers a good opportunity to increase its accuracy.

Table 3.1: Classification of Related Work Concerning User Mobility Recognition

Ref.	**Sensor No. & Type**	**Sensor Placement**	**Mobility Activity**	**Features Extracted**	**Classifiers**	**Acc-uracy**
[73]	5, (2-axis) ACC	Ankle, wrist, waist	Still, walk, Cycle, Run	Mean, energy, freq. domain entropy, correlation features, sum of the squared discrete FFT component, FFT DC component	NB, Decision Table (DTa), Decision Tree (DTr), Instance-based Learning	84%
[76]	ACC	Chest, trousers, jacket	Still, Walk, Run	Raw 3-axis vector readings from the Accelerometer	K-Nearest Neighbours (k-NN)	60%
[26]	ACC	Hip	Still, Walk, Run, Stairs	Mean, std. dev., Energy, Correlation	DTa; DTr (C4.5), k-NN, Support Vector Machines (SVM), naïve Bayes	84%
[89]	ACC, GPS, Audio	Trousers, hip, chest	Still, Walk, Run	Mean, std. dev., No. of accelerometer reading peaks; mean and std. dev. of DFT power of audio sensor readings	DTr (J48)	78%
[22]	32, FF	Under foot	Walk, Run, Stairs	6 force parameters, chronological incidence of occurrence, heel & toe vertical ground reaction. Sum of vertical ground reaction forces.	Artificial Neural Network (ANN), Hidden Markov Model (HMM)	93%
[21]	3, micro-phones 2, ACC	Wrist, Waist, shoulder, chest	Still, hammering, sanding	No. of peaks, mean amplitude of 2 ACCs, FFT coefficients	HMM	67%
[32]	ACC & GPS	Waist, chest, hand, In-bag	Still, Walk, Bike, Motorised	filters, sum of FFT coefficients from magnitude of the accelerometer; average GPS speed	Bayes Net, DTr (J48), SVM and HMM	89%
[29]	ACC & GPS	Right hip	Walk, run, bike, skate, Motorised	Mean, median & interquartile range for accelerometer, counts & steps and GPS mean speed	Discriminant function analysis (SAS PROC DISCRIM)	86%
[27]	ACC	Free	Still, Walk, Bike, Bus, Car	Mean, std. dev., mean-crossing rate, third-quartile, sum & std. dev. of frequencies 0~4 HZ, ratio of frequency components (0~4 Hz) to all components, spectrum peak position.	DTr (J48), k-NN, SVM	62%
[77]	GPS	Hand	Still, walk, bike, car, bus	Mean, Max., std. dev. of velocity, Length	Bayes Net, DTr, Conditional Random Field, SVM	76%
[28]	GPS	Hand	Still, Walk, Motorised	Mean GPS speed, Temporal information (time of the day),	Hierarchical Conditional Random Fields	83%
[90]	GSM, Pedometer	Waist	Still, Walk, Motorised	Mean, Max, Variance of Euclidean Distance; correlation coefficient, No. of cell towers between 2 measurements	NB, SVM, AdaBoost and MultiBoost	85%

From Table 3.1, it is discovered that there is no single method that can sub-classify stationary postures into sitting and standing. Although, the related work seems to perform well in differentiating between stationary and dynamic postures, the recognition of more fine-grained transportation modes, i.e., walking and cycling and fine-grained stationary postures, i.e., standing and sitting, still needs to be improved. The majority of the related work does not support sub-differentiating motorised transportation modes. However, for potential applications such as fine-grained user mobility profiling and individual environmental impact monitoring, the motorised transportation mode needs to be sub-classified into more specific types, i.e., car-passenger, bus-passenger and car-driver. This is because these different sub types of motorised mode may have quite different characteristics in terms of user needs and hazard exposure level. i.e., generally speaking, travelling by bus is more eco-friendly than travelling by private car (assuming the car is not carrying more passengers than the bus and is not using a more eco-friendly type of fuel).

Most of the surveyed systems have restrictions depending on how users should carry their (accompanied) mobile devices except [27]. [27] also recognises more activities and has more sub-classes of motorised transportation mode (bus passenger, car passenger) compared to other work, which better fits one of the aims in this thesis – a wider range of mobility activity recognition. In addition, [27] only used a single stage classifier which fits one of the aims in this thesis, a Lightweight Mobility Data Computation (see Section 4.1.1). Though [32] which uses both GPS and accelerometer achieved the best accuracy, it utilised a two stage classification method, i.e., DTr + DHMM. Clearly, the accuracy of mobility activity recognition maybe higher if one utilises multistage classifications or more complex classification models. However, for the purpose of assessing the value add of the new sensor combination of FF+GPS compared with the use of accelerometer-based methods for daily mobility activity recognition, the accelerometer-based, single-stage classifier, method used in [27] is chosen as a baseline to evaluate the method in terms of recognising user mobility activities. For the reason that the new proposed method (see Chapter 4) also uses GPS as a assistive sensor to measure speed, [27] is also extended to form a ACC+GPS based method by adding the GPS as a assistive sensor. The recognition results from this reproduced ACC+GPS method will also be used to validate the FF+GPS method. The other existing ACC+GPS based methods, such as [29, 32], are not considered because they all employed advanced classification models, e.g., two stage classification model (DTr + DHMM) were used in [32]. In addition, in using the same GPS speed related features in both the ACC+GPS method and the FF+GPS method, a fairer comparison between using FF and ACC for mobility activity recognition, can be achieved.

3.5 Summary

Related work, which uses different sensor types and configurations, has been reviewed, analysed, and discussed in this chapter. Three main limitations of the current methods for user mobility detection have been identified: a narrow range of recognition, coarse user mobility recognition capability, and a low recognition accuracy. A typical ACC-based method has been selected as the baseline method for evaluation.

The next chapter will focus on designing and implementing a new sensor-based method to address the above limitations in order to provide improved user mobility detection.

4 Core FF+GPS based Method for Mobility Activity Recognition

The purpose of this chapter is to assess the value-add of the FF + GPS method for mobility activity recognition compared with the use of both ACC and ACC+GPS based methods. In this chapter, the range of the user mobility concerns both human postures and transportation modes, which includes standing, sitting, walking, cycling, bus-passenger, car-passenger, and car-driver.

4.1 Method Design

4.1.1 Design Considerations

Before describing the design of the new mobility activity recognition method, the design requirements in order to develop a (smart phone enabled) daily activity recognition system are discussed. Based on the analysis of the surveyed work, the following requirements are proposed for the daily mobility activity recognition system.

- *Wider Range and Fine-Grained Mobility Detection Capability:* In order to better understand user contexts for interacting with services in daily life, richer mobility activity recognition is needed in terms of both a fine-grained recognition capability and the ability to recognise both human postures and transportation modes, possibly simultaneously. A fine-grained recognition capability is required, because people in different mobility contexts may have different requirements. Consider the following scenario: when detecting that a user is driving a car, a mobile phone may automatically divert a call in order to ensure the user's safety on the road, while this is not necessary if the user is a passenger in a car. Hence, the traditional "travel-by-car" mode needs to be sub-differentiated into driver or passenger. It is also found that given the same transportation mode, different human postures may lead to different user requirements for service adaptation. For example, when detecting that a user is standing, or walking to a seat, rather than sitting in a fast moving bus, map views and controls may be adjusted to highlight travel information more than normal, e.g., to display larger labels and controls. In order to better serve this purpose, the system should be able to recognise both human posture and transportation mode simultaneously and also be able to sub-classify motorised transportation mode into bus-passenger, car-passenger and car-driver.

- *Local Sensor Data Analysis:* Sensor data analysis can be performed either remotely or locally. The mode of local sensor data analysis is preferred for the following reasons: First, the data is not shared with remote services and can be kept private. Second, it does not require an on demand data connection to a remote server that can be subject to intermittent interference and a subsequent lack of service access. Third, local data analysis can also lead to better near real-time data classification and mobility service adaptation (providing the computation is light enough to be performed on mobile devices). Finally, it also avoids the need for an on-demand data connection that tends to drain the battery that may not be rechargeable when moving.

- *Lightweight Mobility Data Computation*: Current mobile devices, whilst increasing in computing power and functionality, still have a limited processing capability compared to laptops, servers and embedded systems (with specialised hardware such as digital signal processors). In addition, mobile devices cannot dedicate the majority of their computing resources to auxiliary applications given its primary roles are for interaction and communication. Based upon opportunistic, changing, local mobility activities, continuous computation is needed, without exceeding the local computational resources [81]. Hence, lightweight mobility data computation is highly desirable.

- *Sensor Error Tolerance:* A system should be able to tolerate sensor errors arising in a typical daily living environment, e.g., occasional GPS data inaccuracy and interruption. Moreover, it will be more computationally efficient if a system can tolerate these occasional sensor errors, rather than continuously requiring additional data pre-prossessing for sensor error filtering.

- *High Mobility Classification Accuracy:* According to the survey (summarised in Table 3.1), the average accuracy of current mobility activity recognition methods is approximately 75%. This accuracy statistically means one in every four samples will be misclassified on average. This offers a good opportunity to increase its accuracy. In order to satisfy the potential applications (mentioned in the introduction), the accuracy of the mobility activity recognition method needs to be improved at a higher level [91].

- *No On-Body Placement Restrictions for Accompanied Mobile Devices:* People tend to carry their mobile phone in variable places and orientations. For some sensor signals, e.g., from accelerometers, the signal depends heavily on the sensor body position and orientation, whereas other (accompanied) sensor signals, e.g., mobile phone GPS, are not dependent on sensor body position. A pervasive system should support such flexibility in terms of the position and orientation of the mobile phone [91].

- *Reduced Training to Classify Individuals:* a generalized method can be used with new users without requiring much individual user training [92]. Most existing systems for mobility activity recognition did not employ a generalised method. In these cases, they require a training phase for new users in order to conduct individual-specific training to personalise the system so as to use it with a high degree of accuracy [93]. A mobility activity recognition system should require minimal individual-specific training.

4.1.2 Rationale for Choosing FF+GPS

Table 4.1 summarises the different properties of the different main stream sensors and different sensor combinations in user mobility detection.

Table 4.1 The Sensing Modalities Used and Properties in Supporting Mobility Activity Recognition

Sensors Type	**Recognisable User Postures (UP)**	**Recognisable Transportation Modes (TM)**	**Recognise both UP and TM Simultaneously?**	**Existing Work**
GPS	N/A	Human-Powered TM, Motorised TM	No	[28, 94, 95]
Accelerometer (ACC)	Stationary, Dynamic	Walking, Cycling, Motorised TM	No	[26, 27, 76]
Foot-force (FF) Sensors	Stationary, Walking, Climbing stairs	Walking, Cycling	No	[22, 83]
ACC+GPS	Stationary, Walking, Running	Walking, Cycling, Motorised TM	No	[29, 92]
FF+GPS	Standing, Sitting, Walking, Running, Cycling.	Walking, Cycling, Bus-Passenger, Car-Passenger, Car-Driver.	Yes	None

From Table 4.1, it is discovered that accelerometers can accurately recognise different mobility activities with obvious acceleration variations, such as between walking and stationary, but are less accurately in sub-differentiating motorised transportation modes. GPS can perform well in detecting different activities with different speed characteristics, such as between human powered and motorised transportation modes, but GPS is also too coarse to recognize user postures such as standing and sitting. With respect to transportation mode, the GPS speed alone is not capable of sub-differentiating motorised transportation mode, since in many cases, such as between car-passenger and car-driver, the speed contexts are quite similar. Based on these reasons, both accelerometers and GPS cannot provide fine-grained mobility activity recognition. It is also noted both accelerometers and GPS cannot recognise both human posture and transportation mode simultaneously. Using a scenario when a user is standing on a moving bus as an example, current GPS methods appear too coarse-grained to recognise this. The acceleration signal from both user motion and vehicle vibration may overlap and confuse the system [15]. This limits the recognition of both human posture and transportation mode simultaneously using accelerometers and/or GPS.

In summary, typical sensor based methods using accelerometers or/and GPS face some key limitations in recognising mobility activities. For accelerometer-based methods, the key limitations are:

- *Varying on-body placements:* People normally tend to carry smart phones more freely (waist, front pocket, knee-high pocket, hand and so on) in their daily living environment, which greatly changes the nature of the motion signal [15]. For instance, different mobility activities may exhibit similar acceleration characteristics in certain areas of the body.

- *User variability:* As the accelerometer-based method requires the sensor to be carried along with users, the sensed acceleration signal changes according to the natural body motion, which may vary from user to user. For example, typical nature body motions (such as bending, swaying and twitching) sometimes may exhibit dominant acceleration patterns and affect the recognition accuracy of the accelerometer-based method.

- *Overlapping sensor signal*: Typical accelerometer-based methods can recognise human posture or transportation mode. However, accelerometer-based methods may not be able to recognise both human posture and transportation mode at the same time. This is because the acceleration signals from both user motion and vehicle vibration (during travelling) may overlap with each other [15]. This overlap affects the recognition accuracy for both human posture and transportation mode.

For the single GPS-based method, the common limitations are:

- *Loss of signal:* there is no GPS signal indoors, underground, under bridges or tunnels, between narrow buildings, or sometimes inside some moving vehicles when seated as a passenger. These signal-loss scenarios may affect the reliability of single GPS-based methods.

- *Coarse grained recognition*: A single GPS-based method is not capable of providing fine-grained human posture recognition, i.e., GPS-based methods cannot sub-differentiate stationary posture into standing and sitting. Moreover, GPS is also too coarse grained to differentiate user mobility activities with similar speeds, such as walking quickly, cycling or slow motorised travel [28].

As a FF sensor measures the ground reaction force patterns during different activities, they can be used to detect both stationary postures (such as standing and sitting) and other foot-related mobility activities (such as walking and cycling).

The foot force patterns with different human postures are showed below.

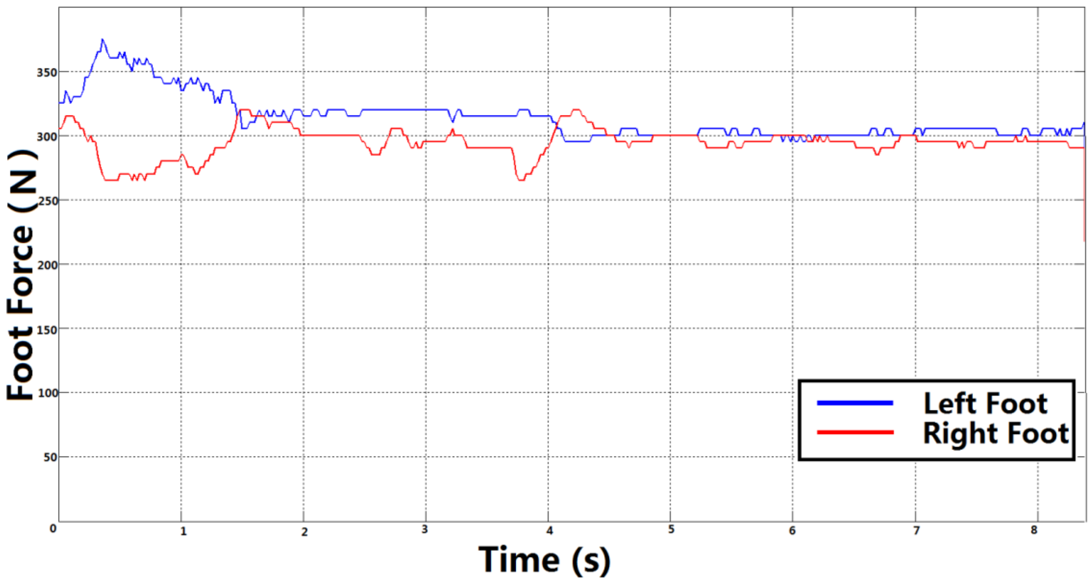


Figure 4.1 Experimental Ground Reaction Force Patterns for the Standing Posture

When a user is standing, the sum of the ground reaction force from a user's both feet is directly related to the user's weight. The user may sometimes lean either on his left foot or on his right foot. This generates different force patterns between each foot, i.e., sometimes the left foot force is higher than right foot force, and vice versa. Another feature that can be observed from Figure 4.1 is that as one foot force increases the other foot force decreases, this is because (when standing) the sum of ground reaction force from both feet should remain the same.

Figure 4.2 shows an example of foot force patterns during a sitting posture.

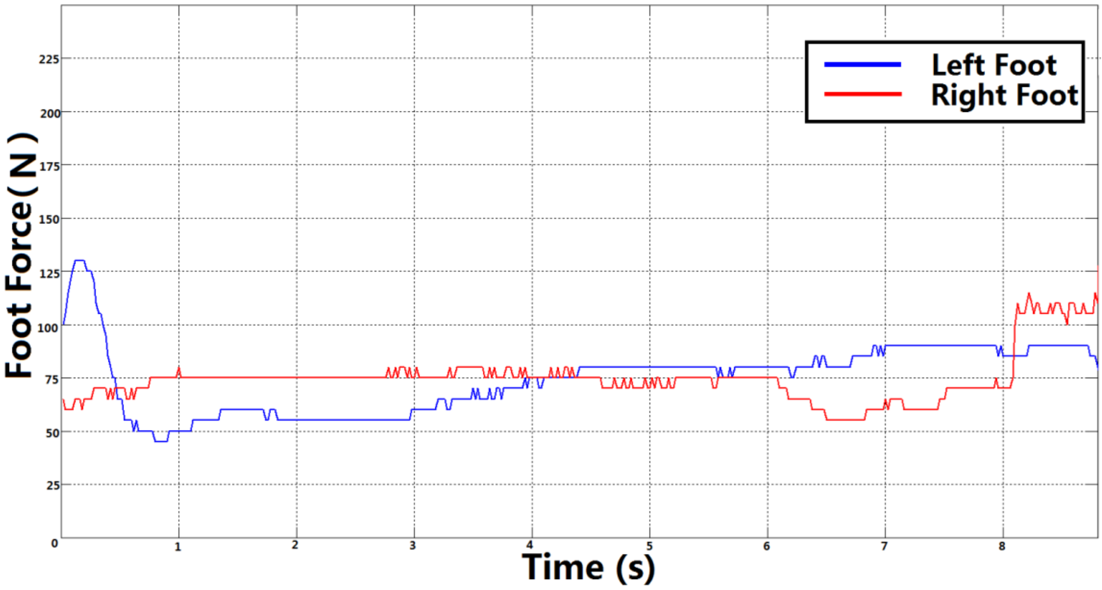


Figure 4.2 Experimental Ground Reaction Force Patterns for the Sitting Posture

In the sitting posture, the majority of a user's weight is supported by the chair, so both feet will generate less ground reaction force compared with it from the standing posture e.g. the sum of ground reaction force from both feet is about 600 N in Figure 4.1, while it is about 140 N in Figure 4.2. Besides, in the sitting posture, one foot force may increase but this does not necessarily lead to the other foot force decreasing. This is another difference between a standing and sitting posture.

Both the standing posture and the sitting posture are types of stationary postures, which have no obvious period waveforms in the ground reaction force patterns. Figure 4.3 shows an example of foot force patterns during walking.

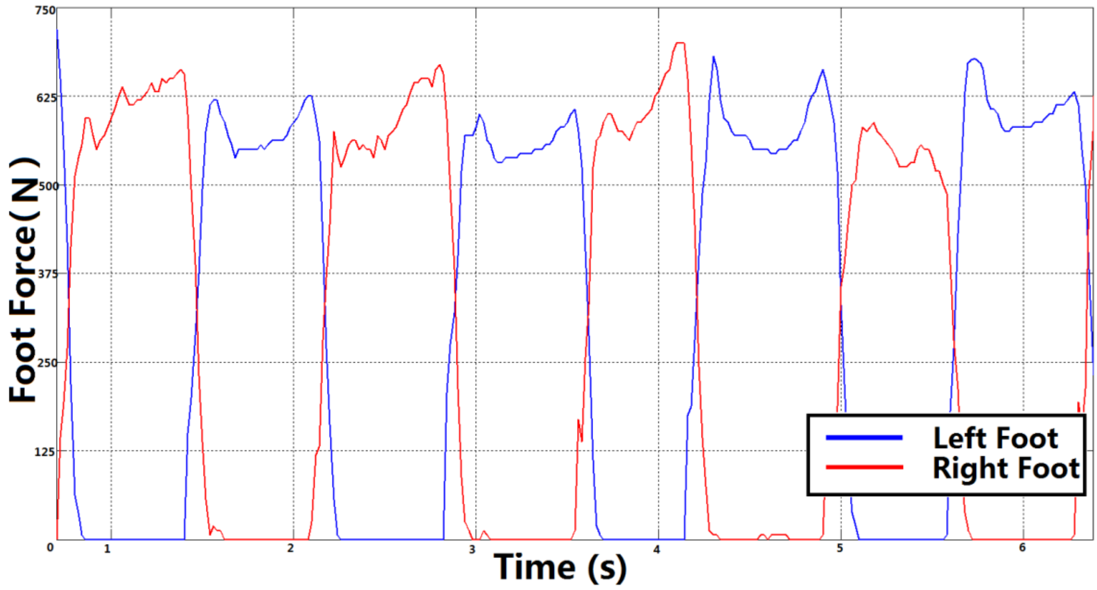


Figure 4.3 Experimental Ground Reaction Force Patterns for Walking

Compared to the standing posture, each user foot will support the whole user weight in turn when walking. The walking posture generates period waveforms with the peak values close to the user weight, and trough values close to zero. Compared with the standing posture, the walking posture generates waveforms with a higher standard deviation value. This is because though both standing and walking postures have a similar mean force value, the walking posture has far greater peaks and troughs.

For the cycling posture, Figure 4.4 shows an example of foot force patterns during cycling.

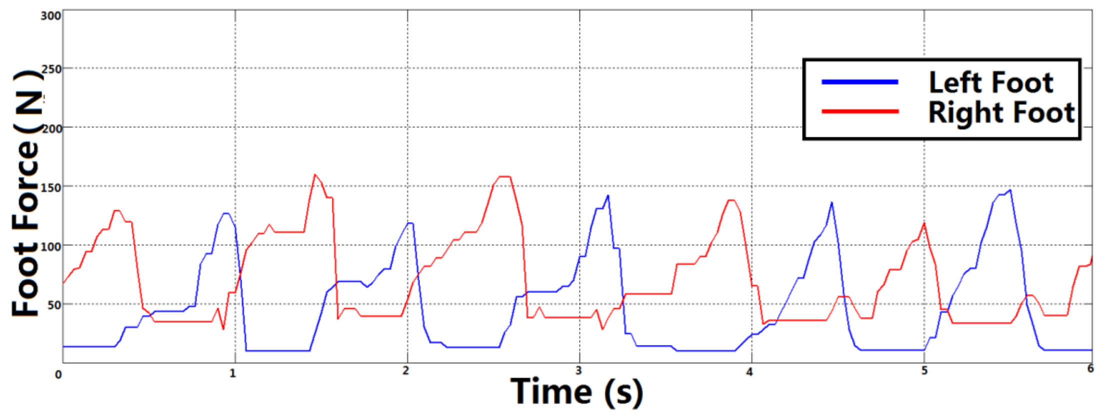
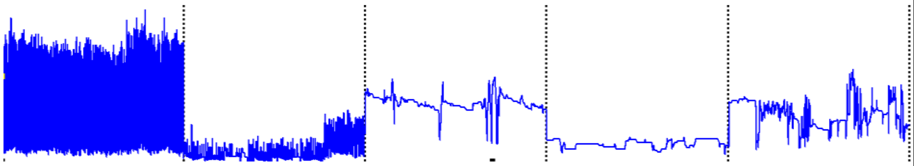


Figure 4.4 Experimental Ground Reaction Force Patterns for Cycling

To some extent, cycling is similar to the walking, e.g. each foot generates a similar force in turn. But there are clear differences between walking and cycling. First, cycling generates a smoother waveform compared with walking. Secondly, the amplitude force from both feet is much less than that from the walking. This is because the majority of the user weight is supported by the bike's seat, only the foot force generated from pedalling is sensed.

With regards of different transportation modes, the use of foot force sensors alone is not capable of sub-differentiating motorised modes into more fine-grained types (i.e., into car-passenger, car-driver, and bus-passenger). Hence, a hybrid method is proposed that combines a set of foot force sensors with mobile phone GPS. The rationale for combining these two types of sensors is because of the different (and in some cases complementary) variations in sensor data with different mobility activities. Different transportation modes with a similar GPS speed pattern tend to have different foot force patterns and vice versa (see Table 4.2).

Table 4.2: Variations in Average Speed and Foot Force Patterns in Different Transportation Modes.

	Walking	**Cycling**	**Bus-Passenger**	**Car-Passenger**	**Driving**
GPS Speed (m/s)	1.3±0.2	2.5±1.2	7.2±3.9	11.3±5.3	10.8±4.8
Left Foot Force (Percentage of one unit user weight)	67%±51%	18%±11%	53%±5%	21%±3%	35%±12%
Correlation Coefficient between left & right foot force	-0.47±0.06	-0.33±0.2	0.34±0.42	0.01±0.31	0.15±0.27
Left Foot Force Pattern (5 min duration)					

In summary, the combination of FF and GPS has shown a great potential of providing more fine-grained mobility activity recognition. For example, FF can be extended to sub-differentiate stationary postures into standing and sitting, which have many applications for health monitoring. Foot force patterns are also different for different human powered mobility activities such as between cycling and walking. The FF+GPS combination can also be extended to differentiate different fine-grained motorised transportation modes.

One of the novelties of the FF+GPS method is that it can also be extended to support the recognition of both human posture and transportation mode. For example, the aim is not only to recognise whether a person is taking a bus, but also to provide more information about whether that person is standing or sitting on a moving bus. This is because for the same kind of transportation mode, different human postures (during travelling) may require different kinds of service/information adaptation. Hence, the main aim of this chapter is to assess how well a combination of wearable foot force (FF) sensors and mobile phone GPS (FF+GPS) recognises different user daily mobility activities.

4.1.3 System Overview

To the best of my knowledge, the use of (mobile phone) GPS in combination with foot force sensors to improve mobility activity recognition in a pervasive setting has not been proposed or examined in detail to date. In order to provide richer mobility contexts in terms of recognising both user postures (during travelling) and transportation mode, in the FF+GPS method, the user posture will be inferred from the foot force sensor data, while the transportation mode will be inferred from data of both foot force sensors and GPS. This is because based on the analysis in section 4.1.2, foot force sensors alone are hypothesised to be capable of recognising various human postures and human-powered activities at a fairly high accuracy, while the additional spatial context of GPS speed changes is only required for recognising fine-grained transportation modes with similar foot force patterns. The scope includes two different human postures (sitting, standing) that are normally performed during daily travel and other daily transportation modes (walking, cycling, bus-passenger, car-passenger and car-driver) that are most often used for commuting. Standing and sitting postures include both the scenario of standing or sitting stationary and the scenario of standing or sitting in a moving vehicle, e.g. in a bus. The walking posture also includes both fast walking and jogging in some travelling scenarios, e.g., people may run to a bus-stop to catch a leaving bus.

Therefore, the following system architecture is proposed to examine how well foot force sensors in combination with mobile phone GPS can recognise both user postures (including during travelling) and transportation modes compared with the baseline, ACC-based and ACC+GPS methods.

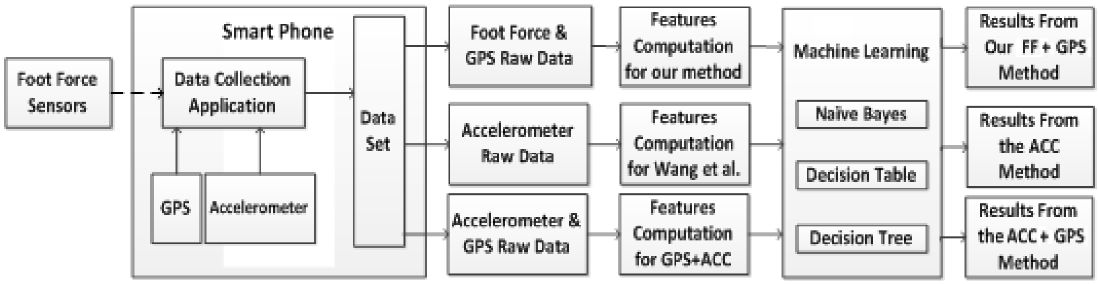


Figure 4.5: Architecture of the Mobility Activity Recognition System

In order to examine the usefulness of the FF+GPS sensor-based method, the mobility activity recognition system shown in Figure 4.5 is proposed. The FF+GPS mobility activity recognition system also collects the data from different sensors simultaneously. Sensors include FF sensors, mobile phone GPS and mobile phone accelerometer. For comparison purpose, in addition to the mobility activity recognition results from FF+GPS, the mobility activity recognition results from both an accelerometer-based method [27] and an ACC+GPS based method are also generated. With this system, a user only needs to perform any activities once to collect the data for three different methods. This eliminates the variability caused by different data samples, which may affect the comparison results. Hence the evaluation results are better able to evaluate the FF+GPS method through comparing it with both an accelerometer-based method, e.g., [27], and a ACC+GPS based method as baselines.

There are three main data processing phases in the system: Raw Data Collection, Feature Extraction, and Machine Learning & Mobility Classification. In the raw data collection phase: The data from foot force sensors, GPS and accelerometer are collected simultaneously during different performed activities by the smart phone.

The data is saved in CSV (Comma Separated Value) format. A Google Android application has been designed and implemented to enable volunteers to acquire and clearly label the data for the performed mobility activity; the latter values are used as the ground truth.

In the feature extraction phase, the raw data collected from the previous phase is extracted without any prepossessing. This means that all the sensor errors arising via daily living environment are presented to the feature extraction phase, which meets the “Sensor Error Tolerance” requirement defined in section 4.1.1. Three sets of sensor data features are computed: ACC, ACC+GPS and FF+GPS. The former two methods are used as a baseline for comparison.

In the machine learning and mobility classification phase: the output from the feature extraction phase is converted as the input for the machine learning tool. The outputs from this phase form the results for both user posture recognition (Section 4.2.4.1) and transportation mode recognition (Section 4.2.4.2).

4.1.4 Feature Extraction

A uniform-duration (8 seconds window) sample (without overlap) as used in [27] is used by all three methods. For the collected sensor data, no noise filtering is carried out.

For the ACC method, the following 11 features (as described in [27]) are extracted from magnitude series (acceleration magnitude of three axes) of the accelerometer data: mean, standard deviation, mean crossing rate, third quartile, sum and standard deviation of frequency components between 0~2 HZ, ratio of frequency components between 0~2 HZ to all frequency components, sum and standard deviation of frequency components between 2~4 HZ, ratio of frequency components between 2~4 HZ for all frequency components and spectrum peak position.

For the comparison with the use of the ACC+GPS method, the following 14 features are extracted from each window segmentation of data collected from both GPS speed and magnitude series of the accelerometer data: the mean, maximum and standard deviation of the GPS speed; mean, standard deviation, mean crossing rate, third quartile, sum and standard deviation of frequency components between 0~2 HZ, ratio of frequency components between 0~2 HZ to all frequency components, sum and standard deviation of frequency components between 2~4 HZ, ratio of frequency components between 2~4 HZ to all frequency components and spectrum peak position.

Then for the FF+GPS method, the following time-domain features are extracted from each window segmentation of data collected from both GPS and FF sensors: the mean value, max value and standard deviation of the GPS speed; overall mean value (equation 1), overall averaged standard deviation (equation 2) and max value of foot force readings from both the left insole and the right insole; cross-correlation coefficient between the left foot force and the right foot force (equation 3).

For each window for the foot force data, "L_x" is used to denote the force values from the left foot and "Rx" to denote the force values from the right foot. The mark "X" represents the number of the sampled sensor value. For a data window with N samples (N is the window size), the following set of value pairs is generated (L_1, R_1), (L_2, R_2), … , (L_N, R_N).

The overall mean value of force readings from both feet can determine whether or not the whole body weight is supported by the user (e.g., when sitting, a part of the user's weight is supported by a chair or seat). The overall mean value "M_A" of the ground reaction force from both insoles is generated is as follows:

$$M_A = \bar{L} + \bar{R} = \frac{\sum_{i=1}^{N} L_i}{N} + \frac{\sum_{i=1}^{N} R_i}{N} \qquad (1)$$

In the equation above, $\bar{L}$ and $\bar{R}$ are the mean force values from both the left foot and right foot.

The overall averaged standard deviation "S_A" of the foot force (generated from both feet) is calculated using the following equation:

$$S_A = \frac{S_L + S_R}{2} = \frac{\sqrt{\sum_{i=1}^{N}(L_i - \bar{L})^2} + \sqrt{\sum_{i=1}^{N}(R_i - \bar{R})^2}}{2} \qquad (2)$$

In this equation, S_L and S_R are the standard deviations of the force readings from both left foot and right foot.

Besides the two features mentioned above, another key feature is the cross-correlation coefficient between left foot force and right foot force. This is used to monitor the regular pressure shift between both feet. The cross-correlation coefficient between the left foot force and the right foot force is useful in detecting periodical foot related activities that need both feet to generate a force in turn, such as cycling and walking. The cross-correlation coefficient between the left foot force and the right foot force is computed from the following equation:

$$\gamma_{LR} = \frac{\sum_{i=1}^{N}(L_i - \bar{L})(R_i - \bar{R})}{S_L S_R} = \frac{\sum_{i=1}^{N}(L_i - \bar{L})(R_i - \bar{R})}{\sqrt{\sum_{i=1}^{N}(L_i - \bar{L})^2 \sum_{i=1}^{N}(R_i - \bar{R})^2}} \qquad (3)$$

In the equation above, γ_{LR} is the correlation coefficient between the left foot and the right foot force patterns. The range of γ_{LR} is between -1 and 1. In a positive relationship as the left foot force increases, the right foot force tends to increase too. In this case, the value tends to be 1. In a negative relationship as the left foot force increases, the right foot force tends to decrease. In this case, the value tends to be -1. If the left foot force and right foot force are independent, then the coefficient will tend to be zero, e.g., this value tends to be zero, when a user is sitting.

4.1.5 Machine Learning and Mobility Classification

Three light-weight classifiers, Naive Bayes (NB), Decision Tree (DTr) J48 and Decision Table (DTa) as provided by the WEKA[2] (Waikato Environment for Knowledge Analysis) toolkit are used to compare the performance of these three different (ACC, ACC+GPS, FF+GPS) methods (see Figure 4.5) [45].

[2] See http://www.cs.waikato.ac.nz/ml/weka/.

For the ACC method, all features computed from accelerometer readings (see Section 4.1.4) are fed into the above three classifiers to generate the results for both human posture and transportation mode recognition.

For the ACC+GPS method, all features computed from both accelerometer and GPS readings (see Section 4.1.4) are fed into the above three classifiers to generate the results for transportation mode recognition.

For the FF+GPS method, all features computed from foot force sensors readings (see Section 4.1.4) are fed into the above three classifiers to generate the results for human posture recognition, while all features computed from both foot force sensors and GPS readings (see Section 4.1.4) are fed into the above three classifiers to generate the results for transportation mode recognition.

All experiment data collected from 10 volunteers are equally divided into 10 folds (see Section 2.2.4.1). A 10-fold cross validation mechanism is used for evaluation, which includes data from each subject in both the training and testing sets [71].

4.2 Experiments and Results

4.2.1 Experiment Objectives

The following experimental hypotheses are introduced in order to illustrate the benefits of the use of FF+GPS sensors to profile user mobility activities, versus typical methods based upon either ACC only or on an ACC+GPS combination,

1. FF sensor data clusters differently with respect to different human postures and human-powered mobility (standing, sitting, walking and cycling) compared to typical accelerometer sensor data (see Section 4.2.3).

2. FF and GPS sensor data clusters differently with respect to different (human-powered and motorised, e.g., walking, cycling, bus passenger, car passenger and car driver) transportation or mobility modes compared to typical accelerometer data (see Section 4.2.3).

3. The FF method for human posture and human-powered mobility recognition can outperform a typical ACC-based (ACC only) method for detecting these (see Section 4.2.4.1).

4. The FF+GPS method for transportation mode recognition can outperform both an ACC-based method and an ACC+GPS based method for detecting these (see Section 4.2.4.2).

5. The FF+GPS method requires less computational resources than the ACC-based and ACC+GPS based methods, in both the feature extraction and activity recognition phases (see Section 4.2.5).

4.2.2 Raw Data Collection

All study procedures were approved by the Research Ethics Committee at Queen Mary University of London (see Appendix A. QMUL Ethical Approval) and participants signed a written informed consent form (see Appendix B. Privacy Policy Agreement for Mobility Data Collection). Data collection took place over a 12-months period from December 2011 to December 2012. Each of the human postures and transportation modes (sitting, standing, walking, cycling, bus passenger, car passenger and car driver) were performed by 10 volunteers (six male; four female) with an age range from 24 to 56.

During the experiments there are two main phases: calibration phase, and operational phase. In the calibration phase, testers who wear the foot force sensing system need to adjust the sensor positions to be under the weight-bearing points of the foot. This is calibrated by ensuring that the combined sensors readings are around 75% of the a priori known user weight. If the combined sensor readings are below 75% and the sensors are still intact, one of more of them are repositioned based upon experience until the 75% threshold is exceeded. In the operational phase, a specialised android application has been developed to enable the testers to clearly label the data with the performing mobility activity. There are 3 sub-phases to the operational phase. First, the tester or the accompanied researcher enters the current time (from the phone clock) and the type of the mobility activity (that is about to be performed), e.g., 2012-06-12 14:15 Walk. Second, testers start collecting the data using an associated Mobile Phone app by clicking on the start button. Third, when the current activity ends, testers stop collecting the data by click on the stop button. Fourth, in the operational phase, sub-phases one to three can be repeated as often as required to form a more complete sequence of transport mode and posture shifts.

All the mobility data collected from different participants are clearly labelled in this manner, which forms our raw datasets for further analysis and evaluation. All the mobility data collected from different participants are clearly labelled in this manner, which forms the raw sensor datasets for further analysis and evaluation.

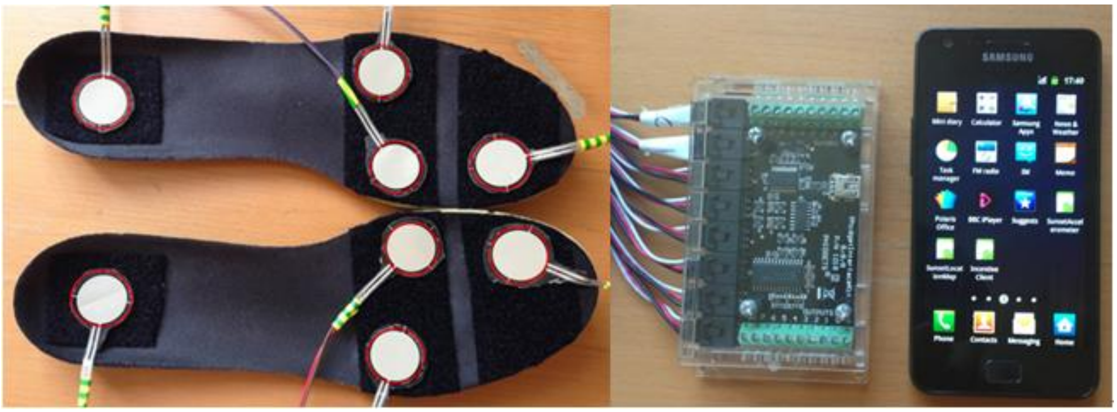


Figure 4.6: Experimental Equipment (1st Prototype): insoles with 8 Flexiforce sensors instrumented (left), a Flexiforce hub and a Samsung galaxy II smart phone (right)

During data collection, volunteers had the liberty of carrying the mobile phone device in any orientation and position that they desired, such as near the waist, in a knee-high pocket, in a back-pack, in the top jacket and by hand. The data collected totalled 12,104 samples, of which 2,198 samples are from standing, 2,032 samples are from sitting, 1,584 samples are from walking, 1,603 samples are from cycling, 1,892 samples are from riding buses, 1,437 samples are from taking car/taxi and 1,358 samples are from driving.

During the data collection procedures, each participant carried a Samsung Galaxy II smart phone and wore a pair of special insoles. Each of the special insoles was instrumented with four Flexiforce sensors (eight sensors in total) as shown in Figure

4.6. Both insoles are instrumented with force sensors in order to monitor the ground reaction force shifting between left foot and right foot. The sum values of the four sensors readings form the force readings of one foot. It has been shown that four force sensors arranged under the supporting bones of the foot and mounted inside the shoe can obtain an accurate ground reaction force value [51]. Hence, four Flexiforce sensors have been mounted directly under the major weight-bearing points of each foot in order to cover the force reaction area of heel, forefoot, and toe for both feet as shown in Figure 4.6. The reason for choosing both heel and forefoot as the focused area is based on a previous work, which has proved the usefulness of measuring force reaction in these (two) underfoot placements [23, 51, 83]. The distribution of sensors is based on the distribution of ground reaction force of each foot during walking. The distribution of ground reaction force on in-shoe plantar pressure during walking is illustrated in Figure 4.7. For each foot, the force peaks are mainly generated from one point at the heel and three points at the forefoot.

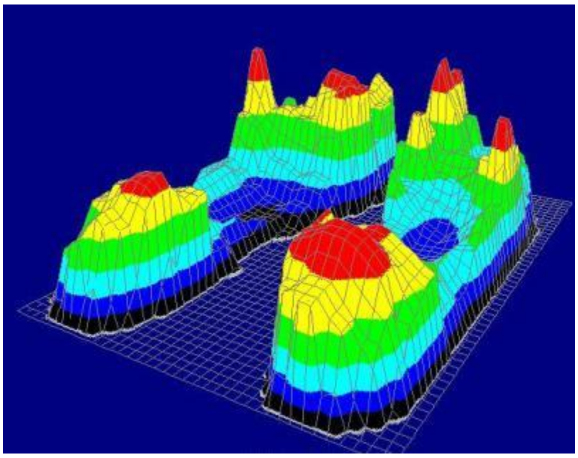


Figure 4.7: Distribution of Ground Reaction Force on In-shoe Plantar Pressure During Walking [96]

Figure 4.8: Participants with the First Prototype (that used a Phidget device, laptop and Smart Phone) During Mobility Data Collection

In version 1 of the FF data acquisition system, all Flexiforce FF sensors are interfaced to a Phidget[3] sensor hub which performs three functions Analogue to Digital Conversion of the FF sensor data, powering the FF sensors and interfacing to a data collection device (Figure 4.6). As the Phidget had only a USB interface and can't connect directly to a mobile phone, it is connected to a laptop via long cables to a backpack containing the Phidget and laptop (Figure 4.8). The laptop uses WiFi to connect to a smart phone which collects the FF data. The FF data is collected on the smart phone because this also collects the data from the inbuilt GPS and ACC sensors for the baseline method comparison. Flexiforce sensor readings are set to 35 Hz, and mobile phone embedded GPS is set to 1 Hz over the Android 2.3.3 OS platform. The smart phone embedded accelerometer (for comparison purpose) is set to 35 Hz according to the settings used in [27]. All raw sensor data from Flexiforce force sensors, mobile phone embedded accelerometer and mobile phone GPS were collected simultaneously during each experiment.

[3] Phidget Website, http://www.phidgets.com/products.php?product_id=1018,

4.2.3 GPS, FF and ACC Sensor Data Clustering for Different Mobility Activities

One of the main design considerations (see Sections 4.1.1) is to minimise the computational load used for mobility activity classification. Hence, time-domain features, which require less computational resources than frequency-domain features [45], are selected. Figure 4.9 to Figure 4.12 show the clusters of FF-based method and ACC-based method using only two basic time-domain features. Each different user mobility activity contains 30 different samples that were collected from 10 different subjects in daily living environment. Figure 4.9 to Figure 4.12 illustrate that if time-domain features are chosen the FF+GPS method achieves better clustering than the typical ACC, and ACC+GPS methods. Figure 4.9 to Figure 4.12 are actually the preliminary results that lead to the main experiment results (see section 4.2.4).

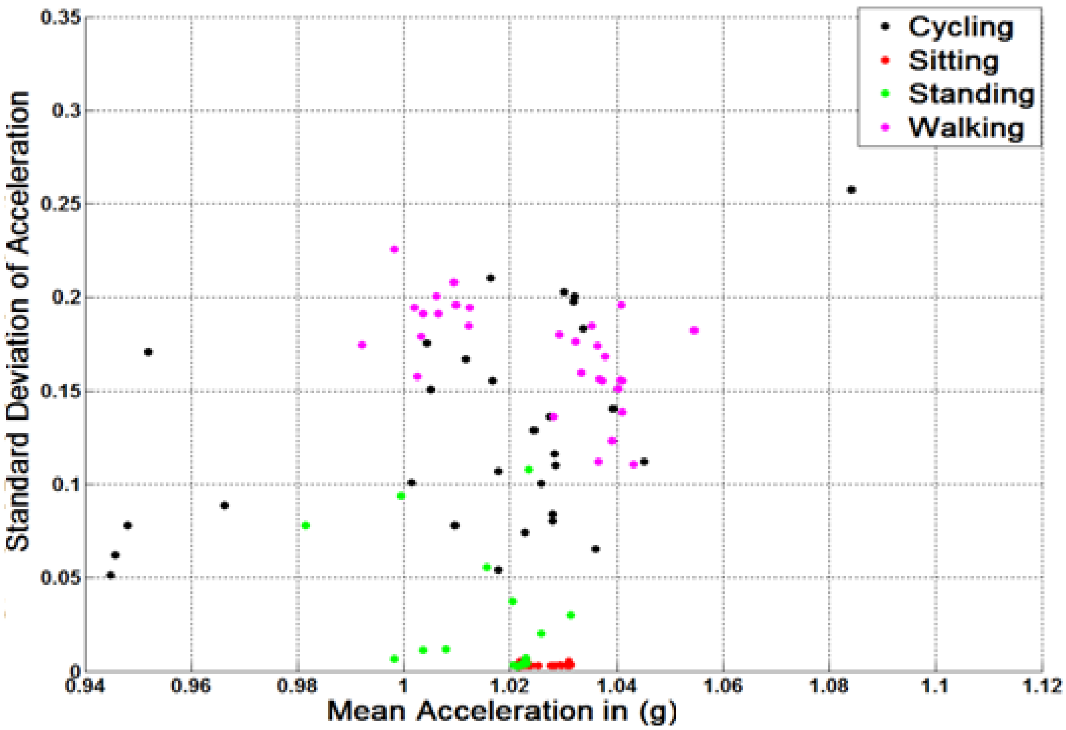


Figure 4.9: Clustering Results of 120 Samples from Four Human Postures using Accelerometer

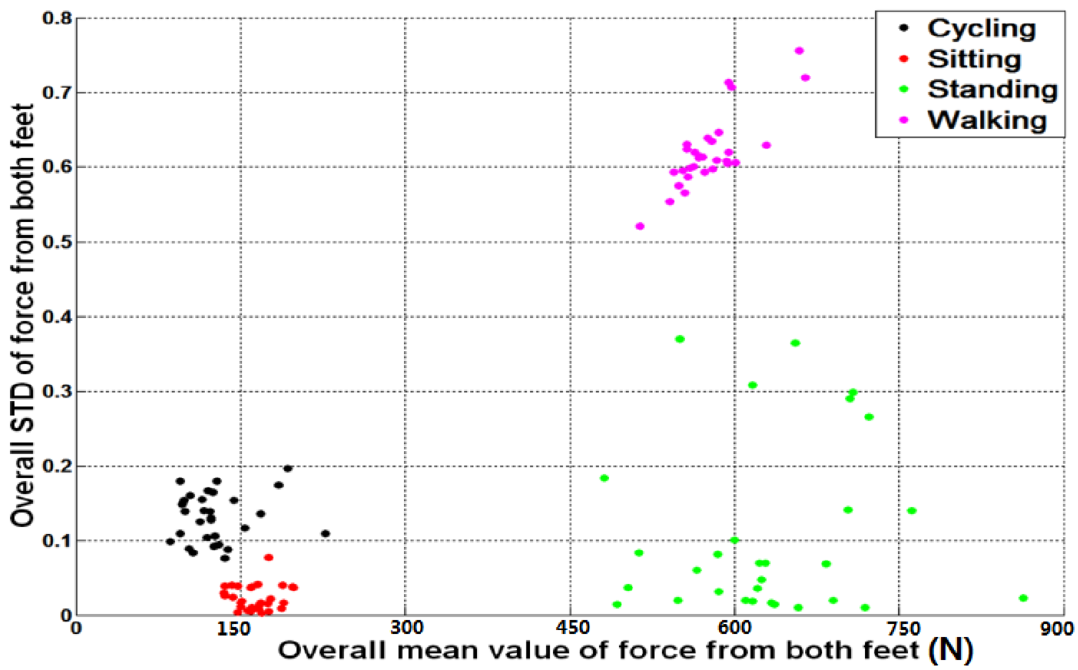


Figure 4.10: Clustering Results of 120 Samples from four Human Postures using Foot Force Sensors

Figure 4.9 and Figure 4.10 illustrate the clustering results of different human postures using different methods. Samples from different postures are marked in different colours. Samples from cycling are in black, sitting are in red, standing are in green and walking are in pink. Figure 4.9 shows the clustering result of using an accelerometer. For each sample, the mean (X-axis) and the standard deviation (Y-axis) of the accelerometer readings are calculated according to 4.1.4. Figure 4.10 shows the clustering of measurements of different human postures in a similar manner to Figure 4.9, but using foot force sensors instead of accelerometer measurements.

In Figure 4.9, it is noted that samples corresponding to sitting and standing are quite close to each other, with the lowest standard deviation values. This is because both postures exhibit quite similar acceleration patterns, which makes them hard to be differentiated using an accelerometer. Samples from both cycling and walking have a larger standard deviation compared to stationary postures. Figure 4.9 also shows a large overlap between walking samples and cycling samples. This is because the mean and standard deviation values of the acceleration patterns from both walking and cycling activities sometimes are quite similar.

In contrast to accelerometer results, it is noted that mean values of FF measurements for sitting and standing are quite distinct (Figure 4.10). This is because the full user weight is sensed when standing, while only part of user weight is sensed when a user is sitting. Samples from both cycling and walking also differ. This is because both standard deviation and mean values of foot force readings from the walking samples are higher than those from the cycling samples (see section 4.1.2).

Figure 4.11 and Figure 4.12 show the clustering results of different transportation modes using different methods. Samples from cycling are in black, bus-passengers are in red, car-passengers are in blue, car-drivers are in green and walking are in pink. Figure 4.11 shows the clustering results using accelerometer in terms of the mean value (X-axis) and standard deviation (Y-axis). It is noted that except for walking, the measurement of the other transportation modes are similar. The reasons for this similarity are as follows. First, for some transportation modes such as car-passenger and car-driver, the human movements, in some cases, are quite similar. Second, in many cases, the standard deviation values of acceleration from different transportation modes are dependent on multiple variables e.g., vehicle types, how the phone is being carried, and the road conditions.

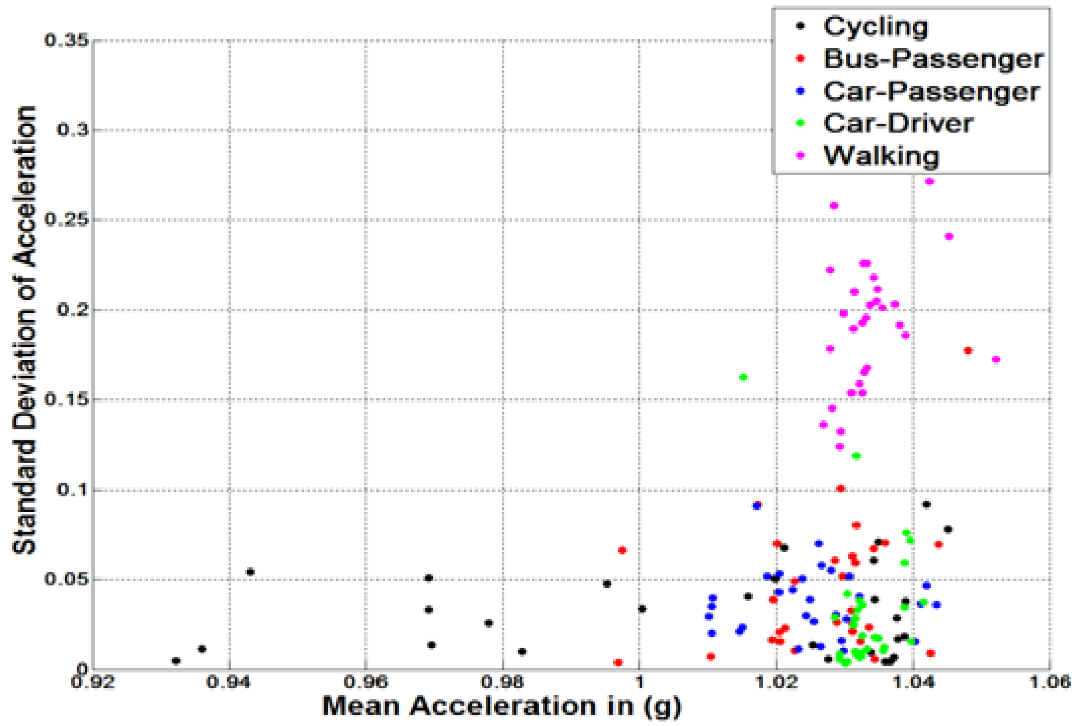


Figure 4.11: Clustering Results of 120 Samples from Five Transportation Modes using Accelerometer

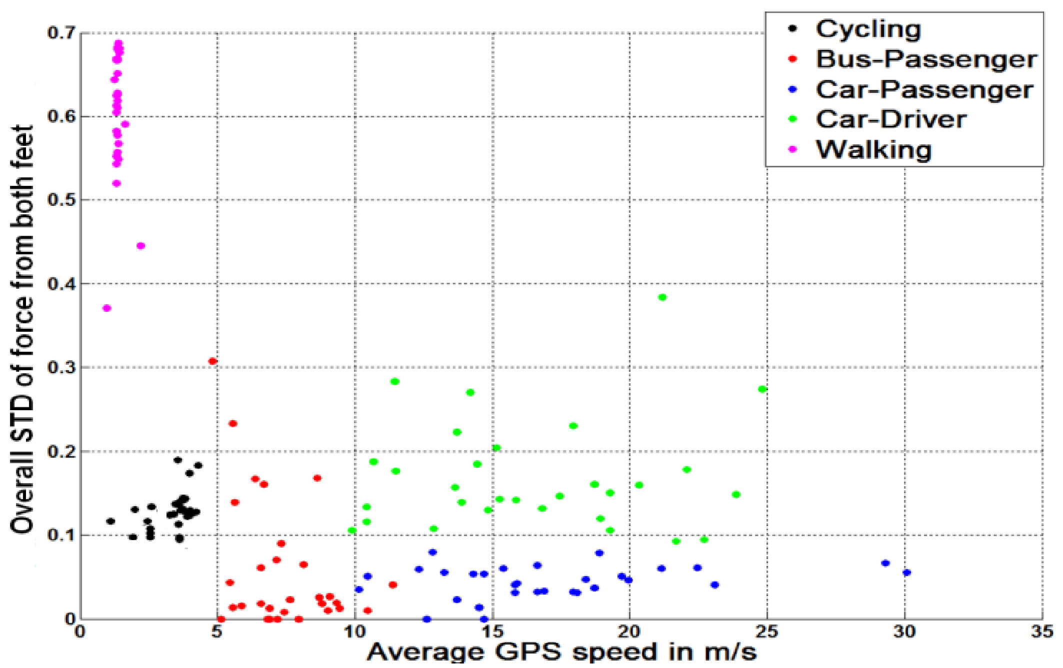


Figure 4.12: Clustering results of 120 Samples from Five Transportation Modes using the Combination of Foot Force Sensors and GPS

Figure 4.12 illustrates the clustering results of different transportation modes using foot force sensors and mobile phone GPS. For each sample, the average GPS speed (X-axis) and overall standard deviation of ground reaction force (Y-axis) of both feet (sensed during performing different transportation modes) have been calculated. This means for each sample corresponds to one point in the two dimensional diagrams as presented in Figure 4.11 and Figure 4.12. From the Figure 4.12, samples from walking, exhibit the highest foot force variance and the lowest average GPS speed, which are distinct from samples from other transportation modes. This is because walking generates the most vigorous ground reaction force compared with other transportation modes. It is also found that samples from cycling, another human powered transportation mode, have the second lowest average speed. With regard to different motorised transportation modes, bus-passengers have the lowest average GPS speed. This is because buses need to travel slower for safety consideration and stop regularly at bus stops. Although, samples from car-passengers and car-drivers have a very similar GPS speed, they are distinct in terms of variance of ground reaction force. This is because drivers need to step on both brake pedal and acceleration pedal frequently to control the car.

4.2.4 User Mobility Activity Recognition

For each kind of mobility activity, the true positive, true negative, false positive, and false negative are defined as follows (The walking activity is selected as an example to illustrate the point): A true positive occurs when a sample from a particular kind of mobility activity is classified as the same kind of mobility activity. For example, a sample from walking is classified as walking. This is a true positive for the walking activity. A true negative occurs when a sample from one other kind of mobility activity is classified as of not of this particular kind of mobility activity. For example, a sample from cycling is classified as not walking and is a true negative for the walking activity. A false positive occurs when a sample from other kinds of mobility activity is classified as this particular kind of mobility activity. For example, a sample from cycling is classified as walking is a false positive for the walking activity. A false negative occurs when a sample from a particular kind of mobility activity is classified as other kinds of mobility activity. For example, a sample from walking is classified as cycling and is a false negative for the walking activity.

Hence, the overall accuracy from three selected classifiers is presented. The detailed precision and recall results of each classifier are also given. Accuracy tells us how well a method is able to identify positives and negatives correctly. Accuracy is defined as the sum of true positives and true negatives over the total number of classifications. Precision tells us how well a method is able to discriminate between true and false positives. Precision is calculated as the number of true positives over the total number of true positives and false positives. Recall tells us how well a method is able to recognize one particular mobility activity given all samples from this kind of mobility activity. Recall is calculated as the number of true positives over the sum of true positives and false negatives.

4.2.4.1 User Posture and Human Powered Mobility Recognition using FF Sensors

The experimental results for user posture recognition using accelerometer versus using foot force sensors (only) are presented in Figure 4.13. From Figure 4.13, it is noted that the proposed FF method obtains a higher recognition accuracy than the ACC-based method, which was reproduced according to [27]. Among all three selected classifiers, the FF method achieves an accuracy of around 95% on average, which is 28% higher than the accelerometer method (around 67% on average). In addition, the use of a decision tree (J48) classifier obtains the highest recognition accuracy for all three methods. The precision and recall for each human posture of each classifier are presented from Figure 4.14 to Figure 4.16.

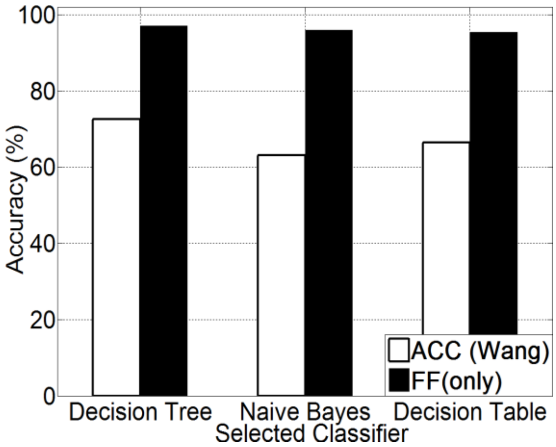


Figure 4.13: Human Posture and Mobility Recognition Results using Different Classifiers

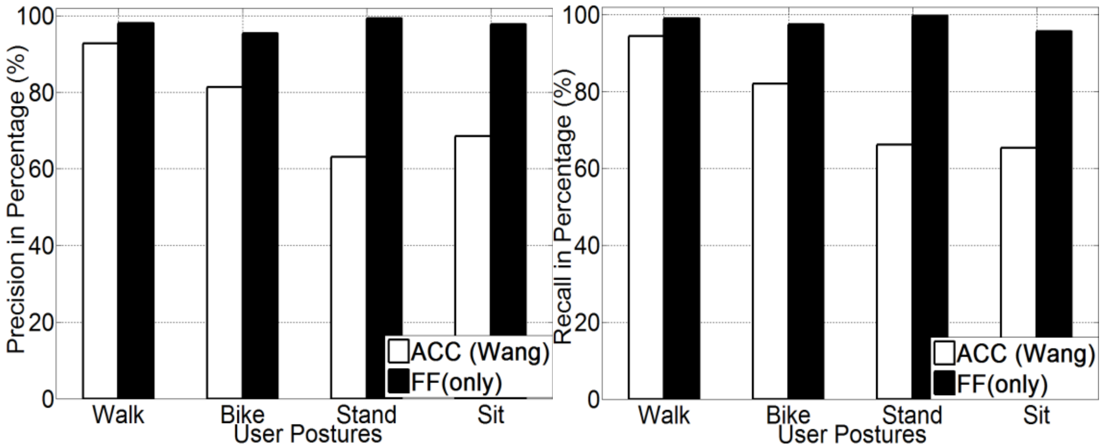


Figure 4.14: Human Posture and Mobility Recognition Results using Decision Tree: (a) precision; (b) recall

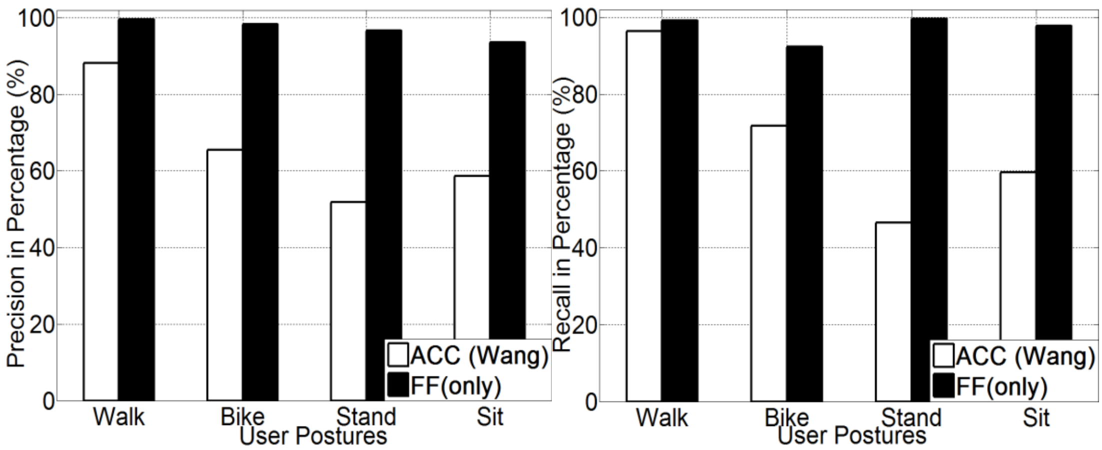


Figure 4.15: Human Posture and Mobility Recognition Results using Naive Bayes: (a) precision; (b) recall.

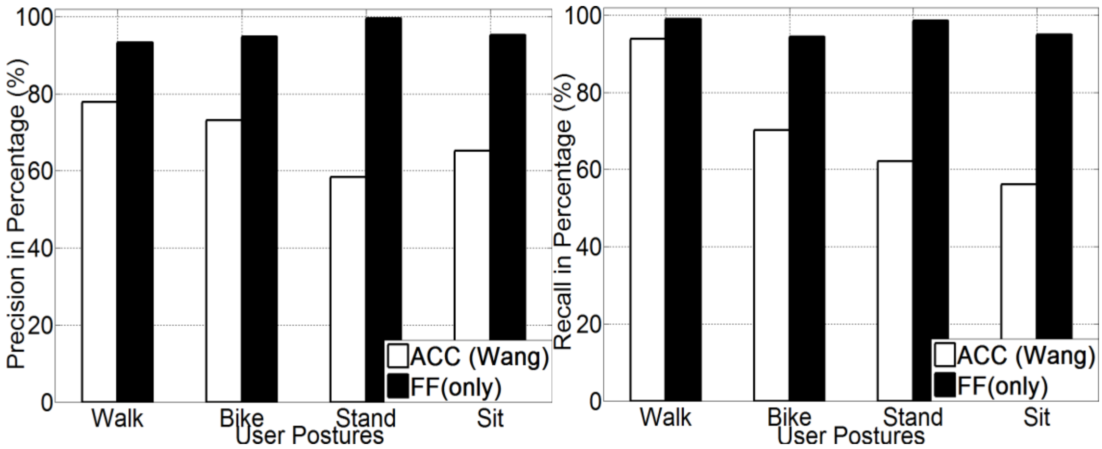


Figure 4.16: Human Posture and Mobility Recognition Results using Decision Table: (a) precision; (b) recall

Regarding the precision and recall results, it is noted that the FF method outperforms the accelerometer based method in all aspects, especially in recognising cycling and in sub-differentiating the stationary postures into standing and sitting.

It is also noted that both methods perform equally well in detecting walking. This is a reasonable result, since there are three obvious stances in a normal human walking motion: heel strike, mid-stance and toe-off [20, 97]. The accelerometer can detect the quite different acceleration patterns generated from these three stances, which are quite different compared with other human postures. Hence, the accelerometer-based method can detect walking posture at a high accuracy. The FF method can also detect foot force pattern variations generated from normal walking motion, the patterns of which are also unique in terms of both mean and variance.

From Figure 4.14 to Figure 4.16, it is discovered that the FF method can detect cycling at a higher accuracy (around 95%) compared with the accelerometer-based method (around 67%). This is because cycling also apparently differs from other types of human-powered mobility in terms of its foot force pattern. As people tend to power a bike by pedalling regularly when cycling, the foot force patterns generated are also distinct from other human postures (as shown in Figure 4.4). While the accelerometer-based method, in some cases the acceleration patterns are mainly affected by the road conditions, rather than the posture itself. Based on this reason, in case of cycling over smooth roads, samples are quite similar with those from the stationary postures. On the other hand, for the case of cycling over rough roads, some samples are even similar to those from the walking posture. This variability introduces more false negatives.

For the case of recognising fine-grained human postures, it is remarked that the accelerometer-based method is unable to sub-differentiate stationary postures into sitting and standing. Both precision and recall for both sitting and standing postures are quite low, at a level of 55% (Figure 4.15). This is because the acceleration patterns from both postures are quite similar, even visually identical. Though the accelerometer-based method can differentiate between stationary and dynamic human postures, it is not capable of sub-differentiating stationary posture (into standing and sitting) at a high accuracy.

However, the FF method in this case achieved an overall 95% accuracy on average in differentiating between sitting and standing postures. This is mainly because the amplitude of foot force patterns from both sitting and standing tend to be very different. In a standing posture, the whole user weight is fully supported by both feet, thus is sensed by the foot force sensors; while in a sitting postures, only part of user weight is supported by both feet. So for the case of standing, the amplitude of force sensed by the sensors from both feet is obviously higher than that of the sitting posture and unlike the accelerometer, FF sensors can be used to recognise them.

4.2.4.2 (Human-powered and Motorised) Transportation Mode Recognition using FF+GPS

The experimental results for transportation mode recognition using different methods (ACC, ACC+GPS and FF+GPS) are presented in Figure 4.17. From Figure 4.17, it is noted that the FF+GPS method obtains the highest recognition accuracy (95% on average). The second highest accuracy (68% on average) is achieved by the ACC+GPS method, which is higher than the accelerometer-based method [27] (61%

on average). In addition, the use of a decision tree (J48) classifier obtains the highest recognition accuracy for all three methods.

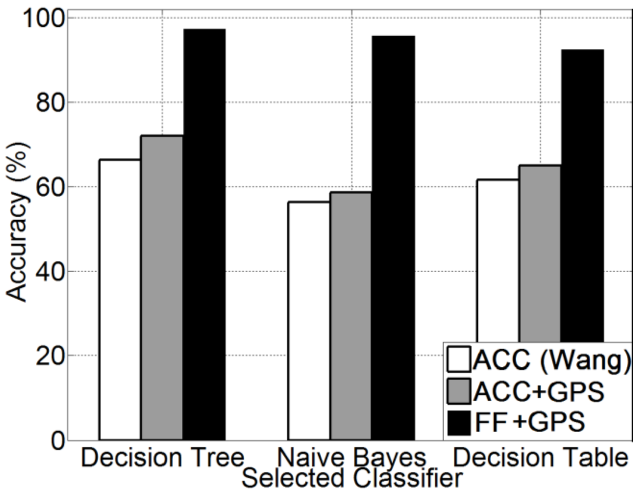


Figure 4.17: (Human-Powered and Motorised) Transportation Mode Recognition using Different Classifiers

The precision and recall for each transportation mode of each classifier is presented from Figure 4.18 to Figure 4.20. With respects to the precision and recall results, it must be remarked that the FF+GPS method outperforms the other two typical methods (accelerometer-based method and ACC+GPS based method) in all aspects, especially in recognising cycling and in sub-differentiating the motorised transportation mode into car-passenger, bus-passenger and car-driver.

It is also noticed that all three methods perform equally well in detecting walking. There are three stances in a normal human walking motion: heel strike, mid-stance and toe-off [97]. The accelerometer can detect the acceleration generated from these three stances, which are quite different compared with other transportation modes in terms of variance. GPS can detect the travel speed in real time (as shown in Table 4.2). The FF+GPS method can also detect foot force patterns generated from normal walking motion, the variations of which are quite unique in terms of mean and variance.

From Figure 4.18 to Figure 4.20, it is discovered that the accelerometer based method achieved the lowest accuracy in detecting cycling. This is because in some cases, the acceleration patterns that are mainly affected by the road conditions are similar with those instances from motorised transportation mode. This introduces a lot of errors from false negatives. With respect to the ACC+GPS based method, it is noticed that the accuracy for detecting cycling, increased but the improvement is little compared with the FF+GPS method. This is because there are still many motorised samples that exhibit similar characteristics in both acceleration and GPS speed with cycling. These are unable to be differentiated using the ACC+GPS method. It is also noted that the FF method can detect cycling at a very high accuracy (around 95%) compared with the two other methods (around 65%). This is because cycling differs from other transportation modes in terms of both foot force patterns and mean GPS speed. As shown in Figure 4.4, as people need to power the bike by pedalling regularly when cycling, the foot force patterns generated are also distinct from other transportation modes. As Table 4.2 shows, the average speed from cycling samples is also different with other motorised modes.

For the case of sub-classification of motorised transportation mode, it is noted that the instances from one motorised mode are easily misclassified as those of another motorised mode (or even cycling) using either a typical accelerometer-based method or a ACC+GPS based method. Motorised modes were sometimes mistaken as cycling since sometimes a bike exhibits a similar speed and acceleration to a slower moving vehicle. Moreover, samples from car-driver and car-passenger are identical in terms of the GPS speed patterns. In addition, the acceleration patterns from these samples are also not distinct enough to be differentiated at a high accuracy. In some cases, the acceleration is also affected by the vibration of the vehicle propulsion and that caused by road conditions. This makes motorised modes sensed by accelerometers hard to be differentiated using the typical classifiers.

The FF+GPS method in this case achieved a higher accuracy on average. This is mainly because foot force patterns in different sub-motorised modes tend to be different. As in the driving cases, people need to step on both the acceleration and breaking pedal regularly in order to control the car. In the bus cases, people may stand and walk around inside the bus, which would almost never happen for a car passenger. Moreover, sometimes the GPS speed patterns from bus is also different with GPS speed patterns from private-car. For example, in some cases buses tend to stop more regularly at bus stops and to move slower than private cars, including taxis, for safety consideration.

With respect to results obtained from the FF+GPS method, it is noted that some instances of driving have been mistaken as being a bus-passenger. This is because in some cases, users have spontaneous foot movements when seated in a bus. The foot force patterns generated from these spontaneous foot movement sometimes are similar to the foot force patterns from when drivers step on pedals to control vehicles. Some instances of driving have also been mistaken as being a car-passenger. These errors normally occur during slow speeds or after stopping for a period of time. In these cases, foot force patterns tend to be similar, since drivers tend to be stationary and were not operating the pedals.

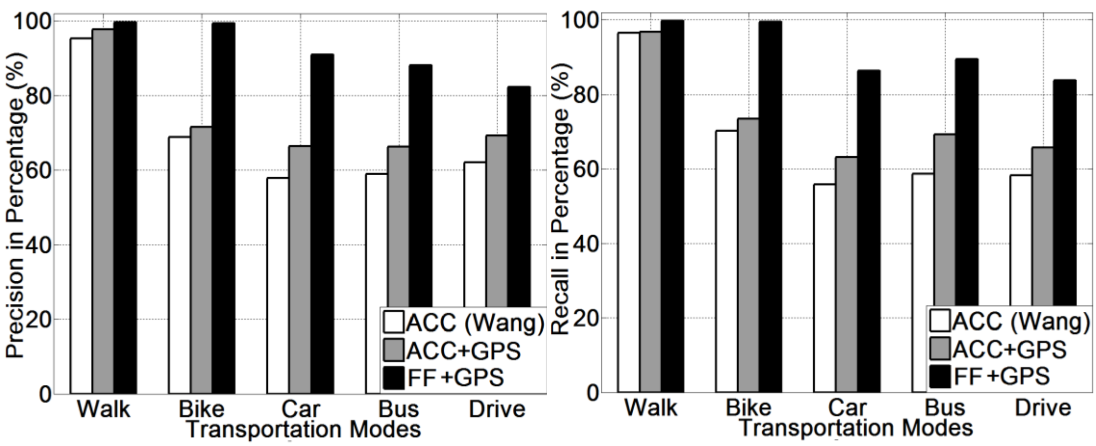


Figure 4.18: (Human-Powered and Motorised) Transportation Mode Recognition Results using Decision Tree: (a) precision; (b) recall

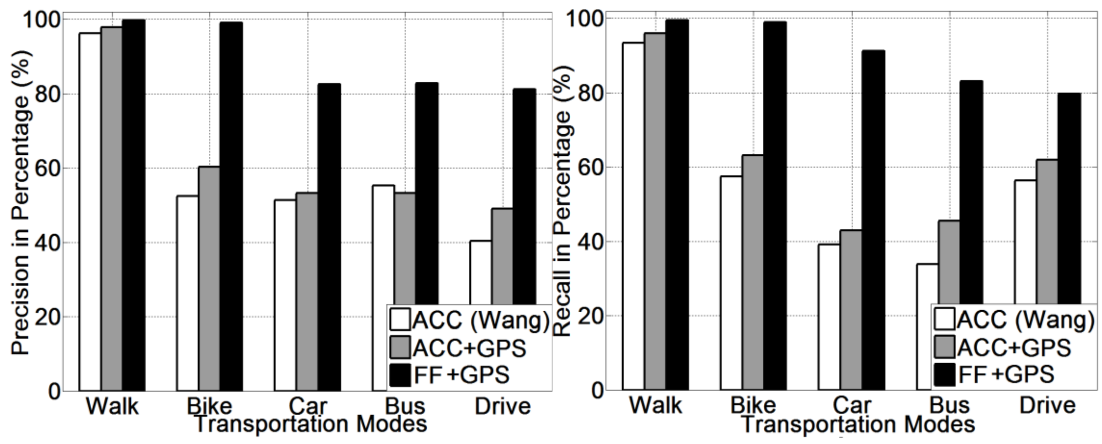


Figure 4.19: (Human-Powered and Motorised) Transportation Mode Recognition Results using Naive Bayes: (a) precision; (b) recall

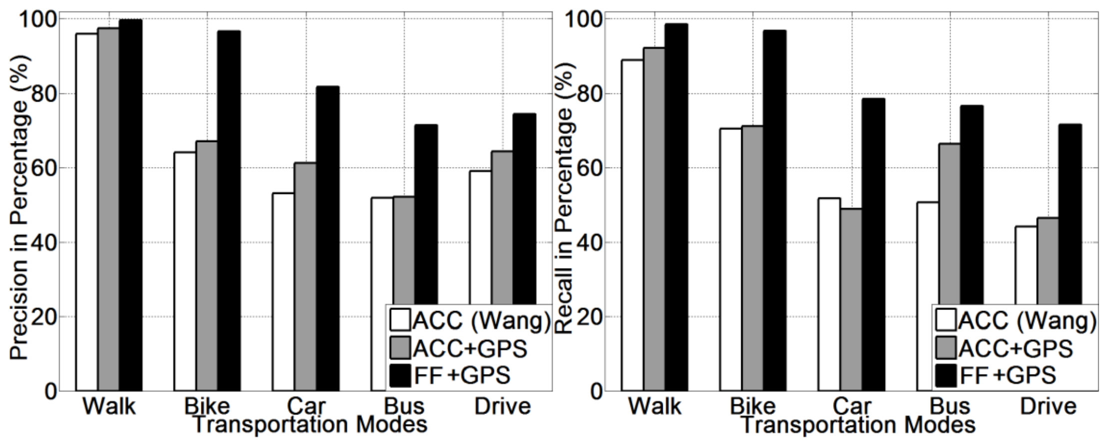


Figure 4.20: (Human-Powered and Motorised) Transportation Mode Recognition Results using Decision Table: (a) precision; (b) recall

To conclude, the results above show that the FF+GPS method is capable of recognising both human posture and transportation mode at the same time. The FF+GPS method achieved the overall recognition accuracy at a level of 90%, and is able to detect cycling and sub-classify motorised transportation mode at a fairly high accuracy. The FF+GPS method also achieved a more fine-grained mobility activity recognition capability, in terms of sub-differentiating stationary postures into standing and sitting and sub-differentiating motorised transportation mode into bus-passenger, car-passenger and car-driver. Hence, these results also show that the FF+GPS system meet both "Wider and Fine-Grained Range Mobility Recognition

Capability” and “High Mobility Classification Accuracy” requirements as depicted in Section 4.1.1.

Moreover, during the data collection, as all participants had the liberty of carrying the mobile phone device in any orientation and position desired, hence the “No On-Body Placement Restrictions for Accompanied Mobile Devices” requirement (as depicted in Section 4.1.1) has been met. Besides, as there is no data prepossessing, which means all sensor data errors were present in the training data for the chosen classifiers, the “Sensor Error Tolerance” requirement (as depicted in Section 4.1.1) has been met.

4.2.5 Computational Complexity

As depicted in Section 4.1.1, the computational-load is an important concern for mobile phone sensing applications, because the smart phone has limited resources and supports a range of tasks including higher priority communication. Most of the surveyed work is based upon an analysis of frequency domain features, which are more computationally expensive to perform on the mobile device, compared with time-domain features [81].

The computational complexity of mobility activity recognition systems mainly resides in two main aspects: feature computation phase and mobility activity classification phase. In the feature computation aspects, the FF+GPS method tends to consume less computational resources as only several basic time-domain features (included mean, standard deviation and max) are required. In contrast, the typical accelerometer-based methods normally derive many frequency-domain features (frequency components between 0~2 HZ, spectrum peak position, etc.). Since all raw data collection is in the time-domain and because the frequency domain features require Fourier Transforms, these impose higher computational loads on mobile devices (than basic time-domain features) [45].

Table 4.3: Number of Tree Leaves, Tree Size (number of nodes) and Number of Rules for Classifiers.

Sensors	**Decision Table No. of Rules**	**Decision Tree**	
		Size	**No. of Leaves**
ACC	774	1,377	689
ACC+GPS	1,669	1,901	951
FF+GPS	123	47	24

With respect to the mobility activity classification, the computational load for a classifier depends on the complexity of the trained model [45]. As Table 4.3 shows, given the same set of training samples, the classifiers trained by FF+GPS method have a reduced complexity compared with the same classifiers trained by both the accelerometer-based method and the ACC+GPS based method. With regard to the decision table classifier, The FF+GPS method requires fewer rules than those required by the ACC and ACC+GPS methods (see Table 4.3).

In addition to the fewer number of (decision table) rules, the size of decision tree classifier trained by the FF+GPS method is also much smaller than that trained by the other two methods. For example, the size and No. of leaves trained by the FF+GPS method are 47 and 24, while size of No. of leaves trained by the accelerometer are 1,377 and 689, by ACC+GPS are 1,901 and 951. To conclude, compared with both an ACC only method and an ACC+GPS based method, the FF+GPS method saves computation in both feature computation phase and the mobility activity classification phase. Hence, the “Lightweight Mobility Data Computation” requirement as depicted in section 4.1.1 have also been met.

4.2.6 Use of Normalisation to Compensate for Mobility Variations between Users

4.2.6.1 User Mobility Variability Analysis

Variability is an important issue in user activity recognition, since different people tend to have different personal profiles i.e., different user weight. These differences between people make foot force patterns different even when performing the same kind of activity.

Accelerometer methods can depend on personal training. For example people tend to have different habits of how to carry a mobile phone. Moreover, the acceleration signal is easily affected by the normal body motions, which varies differently from person to person.

The proposed method which uses a set of FF sensors and mobile phone GPS has the same problem of variability, especially for human posture recognition. This is because the value of foot force sensed during different activities highly depends on the user weight. For example: men normally generate higher ground reaction force than women when standing because on average. This is because, within the dataset used in this thesis, men normally are heavier than women.

4.2.6.2 Normalisation

In this thesis, foot force normalisation is used to eliminate the discrepancy in terms of user weight. All user foot force values are normalised by taking the overall user weight sensed when standing as one unit (e.g., a 250N foot force reading is normalised as value of 0.5 given the overall user weight sensed when standing is 500 N). After normalisation, it is also found that users with different weights tend to have similar foot force patterns for the same type of activity.

With respect to the "Reduced Training to Classify Individuals" requirement (Section 4.1.1) another factor that affects the usability and feasibility of the mobility activity recognition system is whether or not the system would work for new users without much individual user-specific training. To assess this, two distinct experiments are performed: firstly, a 10-fold cross validation, where the classifier is trained with all users; secondly, a leave-one-user-out validation (see Section 2.2.4.2), where classifiers are trained with all but one user (nine out of ten) and tested with the one not in the training set. The results for the 10-fold cross validation have already been presented and analysed in Section 4.2.4.

Table 4.4: Decision Tree leave-one-user-out overall accuracy results

User 1	94.6%	User 6	94.1%
User 2	87.9%	User 7	98.4%
User 3	93.1%	User 8	93.7%
User 4	96.1%	User 9	90.3%
User 5	95.3%	User 10	94.5%
		Average	93.8%

Table 4.4 shows the results from the leave-one-user-out validation test on the FF+GPS method. When training and testing are done on an individual user basis, the overall accuracy decreases by 1.4% compared to a generalised classifier that is trained and tested on all users. Thus, creating user specific classifiers decreases the accuracy, although the loss in accuracy is minimal when compared with generalised classifiers.

With the leave-one-user-out validation, the FF+GPS method achieved an average accuracy of 93.8% and a minimum accuracy of 87.9% is obtained as Table 4.4 shows. Based on the results, one can conclude that certain users might be unique and hence a training set is necessary that has a broad range of how activities could be performed. Different users may perform mobility activities differently, i.e., different people have different walking, cycling, and driving styles. Some people may tend to use the forefoot more compared with others who use their heal more. This does not affect the user mobility accuracy because the overall ground reaction force from each foot is sensed, i.e., the user variation differences are marginal compared with the difference in features used for detecting walking. However, some differences from other (non-walking) activities may affect a specific user. For the users that had the worst performance in terms of accuracy (user 2 and user 9), the decrease in performance mainly came in the cycling, bus-passenger and car-driver for which individuals often have different styles both in terms of foot force patterns and GPS speed variations. For example, a user may cycle intensively, which generates quite different patterns (for both GPS speed and FF) compared with others who cycle more moderately. People also have different habits when taking a bus, e.g., some people like to be seated, some people prefer standing, or leaning against inside a bus. These differences mean FF patterns may vary when detecting the bus-passenger mode. Driving styles also differ from user to user, e.g., some users tend to use the pedals more intensively to drive than other users. Although, different driving styles do affect the accuracy in detecting a specific user, the accuracy is still relatively high, at a level of 85%. It is also observed that the accuracy for a new user can be increased with a broader range of training data that includes samples of these variations.

The results from both experiments indicate that it is possible to achieve good performance without requiring users to provide specific training data as long as the training set contains enough variation in terms of different mobility activities. As Table 4.4 shows, even with 10 individuals, the minimum accuracy level was still above 85%.

4.3 Discussion

In this new FF+GPS method for mobility activity recognition, the GPS sensor is only used to measure the velocity. It can be replaced or combined with other transceiver type position determination sensors, e.g., GSM, WiFi, for speed detection. The reasons why transceiver type positions sensors are chosen for speed detection rather than inertial sensors, e.g. tri-axial accelerometer, are as follows. First, speed detection involves temporal aggregation of acceleration readings in a mobile phone and this is not accurate, especially under daily use circumstances. This is mainly because there is no fixed placement of how users carry their mobile phones. These frequent changes of the phone’s position and orientation may introduce large errors. In addition, the error in using temporal acceleration aggregation for speed detection propagates dramatically as the distance increases. Secondly, tri-axial accelerometer based speed detection is not able to provide other valuable information, e.g., user spatial contexts, during daily activities. Some combination of the user spatial contexts and other GIS information can be used to further improve the mobility detection in future work. For example, through knowing that a user is travelling by bus, and by matching user location sequences with a specific bus routes, one can infer that a user is travelling on a specific bus.

In order to be used in potential applications (Chapter 1) in daily life, in practice, the FF+GPS method has to be built as a commercial product. Here are some initial thoughts. Existing single shoe pedometer type footwear designs, e.g., Nike+iPod, could be advanced or modified to use FF sensors on both feet. Existing research prototypes have already used multiple FF sensors integrated into an insole, e.g., 16 sensors have been integrated in an insole [22]. In contrast, the proposed FF+GPS method, which uses only four sensors per insole, is much cheaper in order to be commercialised. The source of power for the integrated FF sensors is a major issue. However, new material technologies, piezoelectric material may be used as a power generator to generate electricity during foot movement, such that in the near future, FF sensors can be powered by the insole during the impact of the foot while walking.

4.4 Summary

In this chapter, the potential benefits of using a set of foot force sensors in combination with mobile phone GPS to improve mobility activity recognition have been examined here. Two normal stationary human postures (sitting and standing) and the use of five daily transportation modes, including walking, cycling, bus passenger, car passenger and car driver, have been performed by ten different users. Postures and transportation modes have been profiled and evaluated, by comparing the FF+GPS method with both an ACC method [27] and an extended ACC+GPS method of this.

Given the sample size of this pilot and based on the classification algorithms employed, the new FF+GPS method has improved the user mobility activity recognition accuracy from 65% to 90%, on average. The FF+GPS method achieves a wider range recognition capability which is capable of recognising both human posture and transportation mode simultaneously. This can contribute towards better mobility context profiling for smarter adapted services, e.g., to highlight information more for a decreased locus of focus when users are not seated in a moving bus.

Another key contribution of this work is to provide more fine-grained mobility activity recognition capability in terms of both sub-differentiating stationary postures (into sitting and standing) and sub-differentiating motorised modes, i.e., into bus passenger, car passenger and car driver with an accuracy of 92.8% on average. In addition, the FF+GPS method also has other advantages in terms of requiring less computational resources and requiring less individual training.

However, in a practical system, one must consider the efficiency of the system e.g., energy efficiency and production cost. GPS could be switched from active mode to inactive mode depending on the values of the FF sensors. It is discovered that all human-powered activities can be determined by using FF (only) with a relatively high accuracy (98% for walking and 95% for cycling, see Section 4.2.4.1). It is hypothesised that, when detecting these human powered activities, the GPS could be switched off to save energy, without significantly affecting the accuracy and then be switched on again when activity transitions are detected. In addition, a total number of 8 foot force sensors are used in the current FF+GPS method. However, the effectiveness of different FF sensor configurations (e.g., different number of sensors, different sensor positions) is not yet evaluated. Hence, it is also desirable to further examine and optimise different FF sensors configurations in user mobility detection. At last, the foot force sensors are powered by portable notebooks in the current FF+GPS prototype equipment. Foot force sensors can be powered by a portable battery (e.g., portable battery box). In which case, the sensor data will be transmitted to, and be stored at, the smart phone via a BAN (e.g., Bluetooth). Improved prototype equipment for the FF+GPS method is also desirable to make it more usable.

These issues are addressed in the next chapter.

5 An Improved FF+GPS-based Method for User Mobility Recognition

The purpose of this chapter is to consider the energy, computation, and cost efficiency of the proposed FF+GPS method. The efficiency of the system is improved by reducing the number of features (used for classification), the number of foot force sensors, and the use of GPS. The motivation for the reduced sensor, energy and computation cost is in the future to perform the data analysis on the mobile phone data hub device rather than remotely via exchanging the sensor over a WAN link to remote data analysis services. The main benefit of the local device processing it is avoids the time delay (and energy cost) required for the remote data exchange and processing, enabling more near real-time service adaptation to occur, e.g., to notify a user that his or her target for walking or cycling for that journey has been reached.

5.1 Method Design

The FF+GPS method introduced in Chapter 4 uses four foot force sensors per foot (8 sensors in total). However, even within the same sensor type, there are different detailed sensor configurations in how to use foot force sensors, e.g. different foot force monitoring plan (both-feet-monitoring [51, 83] or single-foot-monitoring [22, 23]), different numbers of sensors for each foot (ranging from one [25] to sixteen [22]), and different sensor placements on the foot (heel, middle, forefoot, or toe). Methods that use fewer sensors have potential benefits, such as system simplicity and a lower capital cost. However, methods that use more sensors are expected to be superior in terms of a better accuracy. How to find the trade-off between the numbers of FF sensors used in the FF+GPS method and its performance, and how to balance between the complexity and the accuracy of this FF+GPS method are the main research challenges investigated in this chapter.

To the best of my knowledge, no other work has examined the above research challenges for FF sensors. Thus, this chapter aims to solve these research challenges and to find an improved way of using FF sensors and mobile phone GPS for mobility activity recognition. The experiment is that by identifying the maximally informative features, the use of FF sensors and GPS can be optimised which can still produce the same level of recognition effectiveness, hence optimising the deployment of FF sensors with respect to simplicity of sensor configuration and with respect to computational and energy efficiency is desirable.

5.1.1 System Overview

In order to examine the above hypothesis, the following system is proposed to answer the following research questions: Is monitoring both feet better than monitoring just one? Where are the most effective insole positions to monitor foot force patterns? Which features are the maximal informative ones in differentiating mobility activities? How can one reduce the use of GPS to improve the energy-efficiency of the whole system?

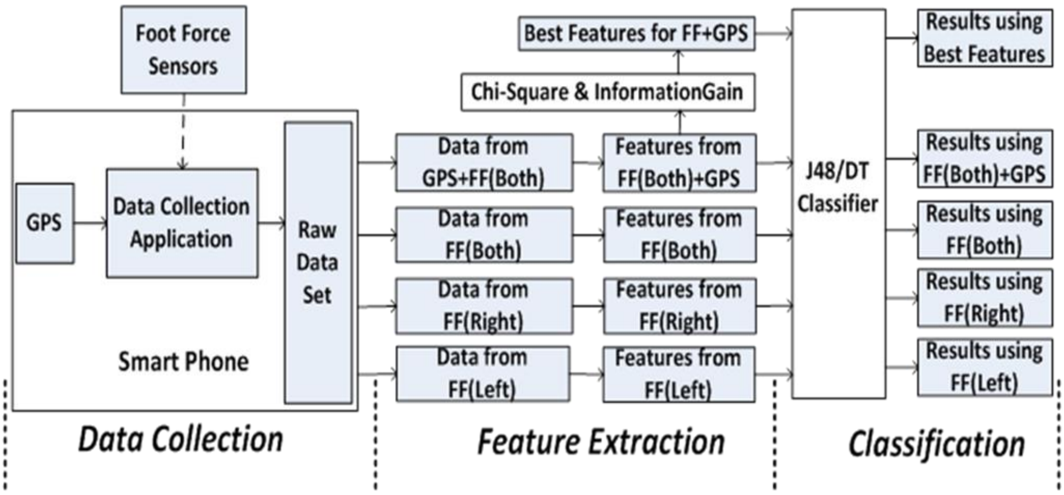


Figure 5.1: Architecture of the FF+GPS System with Different Sensor Configurations for Mobility Activity Recognition

In the data collection phase of Figure 5.1, data is acquired from both a set of foot force sensors and mobile phone GPS. In total, 8 foot force sensors from both feet are used (as the sensor pool) for foot force monitoring, and the corresponding insole positions of these sensors are clearly labelled as Figure 5.2 shows. The data from foot force sensors and mobile phone GPS are collected simultaneously to form the raw data set, which means all the results generated at the classification phase all originate from the same raw data set. This scheme can minimize the effect of variability from different instances of samples during data collection.

5.1.2 Feature Extraction

Table 5.1: Feature Numbers and Corresponding Features

Number	Feature	Number	Feature
1	GPS Mean Speed	17	P4 Max Force
2	GPS Max Speed	18	P4 STD Force
3	GPS STD Speed	19	P5 Mean Force
4	P0 Mean Force	20	P5 Max Force
5	P0 Max Force	21	P5 STD Force
6	P0 STD Force	22	P6 Mean Force
7	P1 Mean Force	23	P6 Max Force
8	P1 Max Force	24	P6 STD Force
9	P1 STD Force	25	P7 Mean Force
10	P2 Mean Force	26	P7 Max Force
11	P2 Max Force	27	P7 STD Force
12	P2 STD Force	28	Cor-Coe of P0 & P4
13	P3 Mean Force	29	Cor-Coe of P1 & P5
14	P3 Max Force	30	Cor-Coe of P2 & P6
15	P3 STD Force	31	Cor-Coe of P3 & P7
16	P4 Mean Force		

In the feature extraction phase of Figure 5.1, a uniform-duration (8 seconds window) segmentation (without overlap) as used in Chapter 4 is applied to all methods. It has been shown that the time domain features are more computational light than frequency domain features [38, 45]. This chapter still focuses on using the following time domain features: mean, max, and standard deviation. Hence, the following 31 features (as shown in Table 5.1) form the features pool of this chapter: mean, max, and standard deviation of GPS speed, mean, max, and standard deviation of force readings from positions P0, P1, P2, P3, P4, P5, P6, P7 (see Figure 5.2). The correlation coefficient between counterpart sensors from both feet are represented as: $\gamma(P0, P4)$; $\gamma(P1, P5)$; $\gamma(P2, P6)$; $\gamma(P3, P7)$ (see equation 3 in section 4.1.4). In the same order, numbers from 1 to 31 are used in the following paragraph to denote these features as shown in Table 5.1.

The usefulness of these features for mobility activity recognition has been proven in Chapter 4. The mean and max value of foot force readings can be used to determine whether whole body weight is supported by the feet during different activities, e.g., between walking and car-passenger. The standard deviation value of foot force readings can be used to specify whether or not an activity involved dynamic foot force variations e.g. cycling. The mean and max value of GPS speed can be used to differentiate between human powered activities and motorised activities. The standard deviation of GPS speed can be used to determine whether the motorized activity involved frequent speed variations e.g., to differentiate between car and bus. The correlation coefficient between left foot force and right foot force can be used to determine whether or not the activity involved regular force shifting between left foot and right foot e.g., to differentiate between cycle-pedalling and motorised vehicle drive-pedalling.

As Figure 5.1 shows, different sensor configurations have been employed which included FF (left), FF (right), FF (both), and FF (both) +GPS.

The comparisons between FF(left), FF(right), and FF(both) configurations are used to prove the usefulness of the correlation coefficient between left foot and right foot force in detecting human powered activities (more details in section 5.2.3).

The combined FF (from both feet) sensors plus GPS configuration is used to identify the maximally informative features and the corresponding best insole positions in detecting the required mobility activities (more details in section 5.2.4 and 5.2.5).

Table 5.2: Different Sensor Configurations and Corresponding Feature Set

Sensor Configurations	Features used (in number according to Table 5.1)
FF(both) + GPS	1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31
FF(both)	4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29,30,31
FF(Right)	16,17,18,19,20,21,22,23,24,25,26,27
FF(Left)	4,5,6,7,8,9,10,11,12,13,14,15

Table 5.2 shows the different features extracted for different sensor configurations, which generate the corresponding classification results that are used for the following comparison and evaluation purpose.

5.1.3 Machine Learning and Mobility Classification

In the classification phase of Figure 5.1, the decision tree classifier which proved to be an effective classifier in mobility activity recognition (in Chapter 4) was used to generate the final classification results. All experiments data collected (from 10 volunteers) were equally divided into 10 folds so that a 10-fold cross validation mechanism is used for validation [71].

5.2 Experiments and Results

5.2.1 Experiment Objectives

The following experiment hypotheses are proposed in order to examine the feasibility of improving the efficiency of the proposed FF+GPS method:

1. Without using GPS, the FF (both feet) configuration will be able to detect human powered mobility activities (e.g., walking, cycling) at a relative good accuracy.

2. The GPS speed context is still required to detect motorised mobility e.g., bus-passenger, car-passenger, and car-driver.

3. The less-informative features of foot force patterns can be pruned without much significant reduction in accuracy.

4. The less-effective insole positions can be pruned without much significant reduction in accuracy.

5.2.2 Raw Data Collection

This is the same as described in section 4.2.2 including how the raw data was manually labelled with the transport mode or posture. All study procedures were approved by the Research Ethics Committee at Queen Mary, University of London (see Appendix A. QMUL Ethical Approval), and all participants signed a written informed consent form (see Appendix B. Privacy Policy Agreement for Mobility Data Collection). Data collection took place over an 8-month period from Oct, 2012 to June, 2013. Five transportation modes (walking, cycling, bus passenger, car passenger, and car driver) were performed by 10 volunteers (6 male; 4 female) with ages ranging from 24 to 56.

During data collection, volunteers had the liberty of carrying the mobile phone device in any orientation and position that was desired. The data collected totalled 7536 samples in total, of which 1643 samples are from walking, 1521 samples are from cycling, 1597 samples are from riding buses, 1403 samples are from taking car/taxi, 1372 samples are from driving.

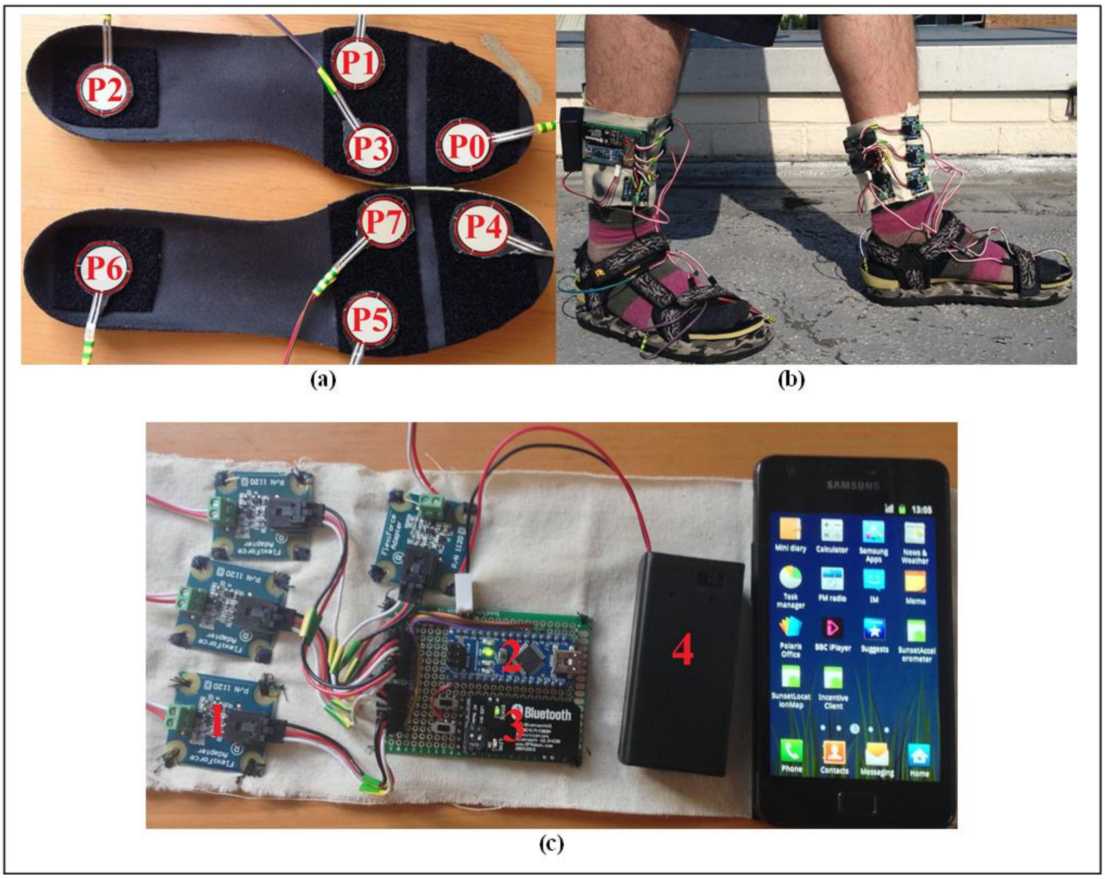


Figure 5.2: Experiment Equipment (2nd Prototype): (a) Two insoles with 8 Flexiforce sensors instrumented; (b) the 2nd version wearable FF+GPS prototype; (c) The foot force sensing system and a Samsung galaxy II smart phone.

During the data collection procedures, each participant carried a Samsung Galaxy II smart phone, and wore a pair of special insoles. The special insoles were instrumented by eight Flexiforce sensors. It is proved that four force sensors arranged under the supporting bones of the foot and mounted inside the shoe can obtain accurate ground reaction force value [51]. Hence, four Flexiforce sensors have been mounted directly under the major weight-bearing points of each foot in order to cover the force reaction area of heel, forefoot, and toe for both feet as shown in (Figure 5.2a). All Flexiforce sensors are interfaced to the smart phone via Bluetooth connection from two designed foot force sensing systems (as shown in Figure 5.2 b).

The foot force sensing system (Figure 5.2c) is implemented with four adaptors (as marked in 1), one Arduino Nano Board (as marked in 2), one Bluetooth module (as marked in 3), and one 9v battery box (as marked in 4). The sensor data hub in version 2 is improved over that of version 1 (Section 4.2.2). Rather than use the Phidget device interface via USB to a laptop to interface to the FF sensors, an Arduino Nano Board performs the ADC for the FF sensors, powers them and uses a Bluetooth module rather than USB to upload the data to the mobile phone. Instead of participants having to wear a backpack, participants wear instead a far lighter band of electronics around the lower leg. The sensor data is sampled in the same way as in Chapter 4. Flexiforce sensor readings are set to 35 Hz, and mobile phone embedded GPS is set to 1 Hz over the Android 2.3.3 OS platform according to settings used in Chapter 4.

5.2.3 Mobility Activity Recognition Using Different FF Sensors Configurations (without GPS)

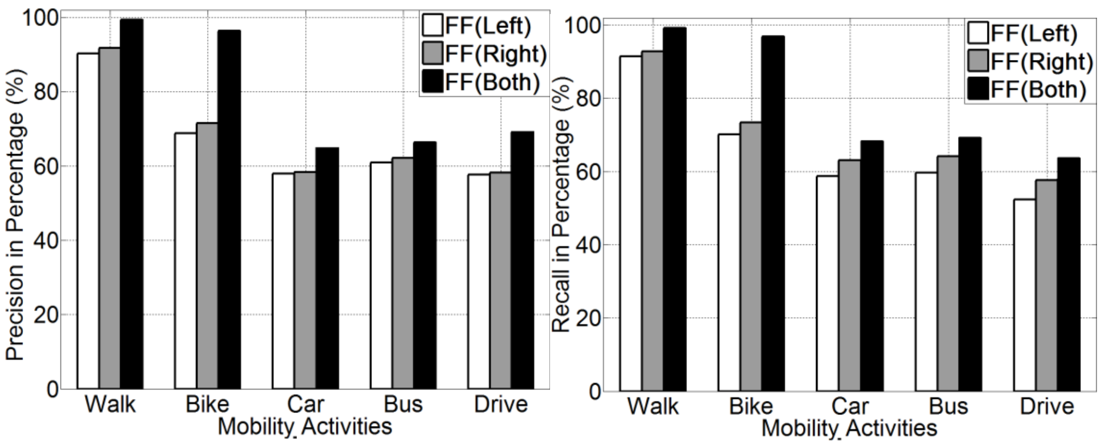


Figure 5.3: Precision and Recall Results from using Foot Force Sensors Alone

From Figure 5.3, it is noticed that all three settings (FF-Left, FF-Right, and FF-Both) perform equally well in detecting walking. This is because there are three stances in a normal human walking motion: which are heel strike, mid-stance, and toe-off [97]. The foot force patterns from either left or right are quite unique in terms of both mean and standard deviation [24]. It is also illustrated in Figure 5.3 that sensing both feet can achieve a better accuracy in detecting cycling rather than sensing either one of them. This is because by knowing the correlation coefficient between left and right feet, noise arising from body motion, e.g., leg rocking, can be ruled out. It is also found that by using the correlation coefficient between left foot and right foot, cycle-pedalling can be differentiated from other foot movement e.g., motorised vehicle drive-stepping.

However, the use of FF sensors alone cannot detect fine-grained motorised mobility activities at a high accuracy. This is because on many occasions, the foot force patterns from motorised modes are quite similar, e.g., seated bus passengers have quite similar foot force patterns with car passengers. It is also noticed that sensing the FF in only one foot may mislead the system into inferring false user postures during travel, which in turn affect the accuracy in differentiating mobility activities. For example, a standing bus passenger may lean the majority of weight on his (or her) left leg, which makes his right FF patterns similar to that of a car passenger. Also a car passenger sitting with one leg over another leg may also be misclassified as a standing bus passenger or even a car driver if only the weight-bearing foot force is sensed. The majority of these misclassifications can be resolved by sensing both feet plus the GPS-speed-sensing. Hence, it is proposed that the following hybrid GPS use-plan, presented in Figure 5.4, is used to improve the use of GPS for the FF+GPS method.

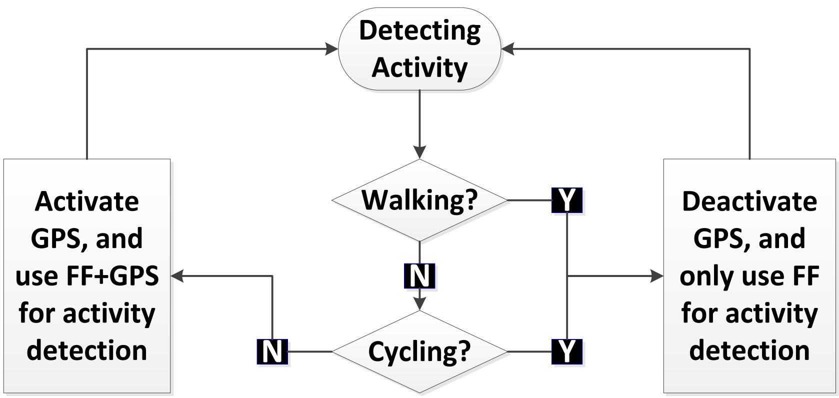


Figure 5.4: Hybrid Use-plan of GPS for the FF+GPS Mobility Activity Recognition Method

As Figure 5.4 shows, the GPS is only activated when detecting motorised mobility activities. For the majority foot related activities such as walking and cycling, only

FF sensors are used. The merit of using this hybrid GPS use-plan is to reduce the use of GPS, but without affecting the overall accuracy much. The final results of employing this new GPS use-plan are presented in section 5.2.6.

5.2.4 Best Feature Selection

Table 5.3: Classification Feature Ranking and Selection

Selection Algorithms	Features Rank in Number (from left to right is the order from 1^{st} to 31^{st})
InfoGain	**02,12,10,24,21,30,20,01,03,09,22,29,31,11,23,08,05,15,18,19,17,06,04,28,16,26,25,27,14,13,07**
ChiSquare	**12,02,30,21,10,24,22,03,01,29,20,31,09,16,06,19,17,26,13,27,14,18,25,11,23,08,04,05,15,07,28**

It has been shown that sensing both-feet is better than single-foot sensing for detecting walking and cycling (Section 5.2.3). GPS speed is also needed to help better differentiate different motorised mobility activities. However, it is hypothesised that, given the range of the feature set and insole positions, maybe there are less informative features and less useful insole positions when detecting mobility activities, which can then be pruned to improve (simplify) the FF+GPS method. Hence, the following two commonly used feature selection algorithms: ChiSquare [98] and information gain [98], have been employed to identify the best feature set.

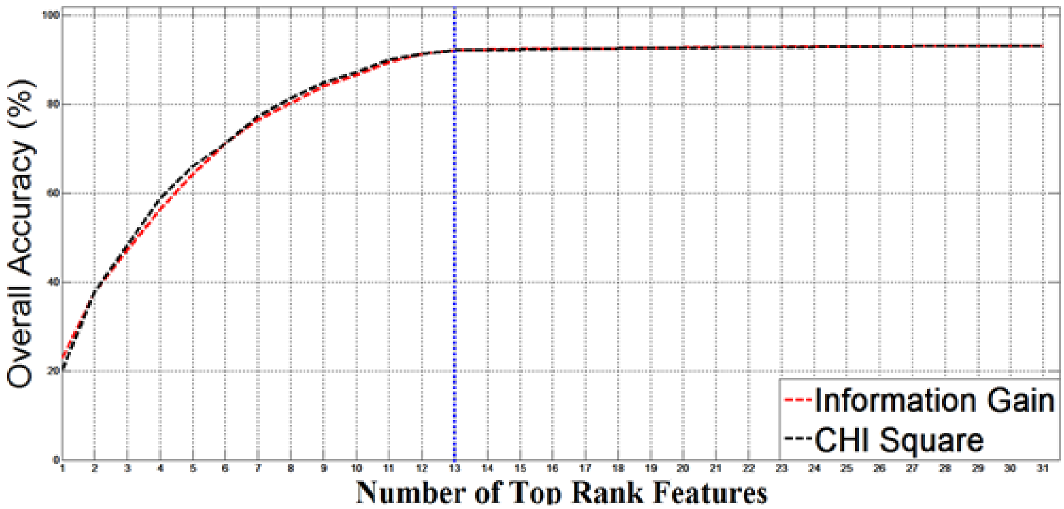


Figure 5.5: Overall Mobility Activity Recognition Accuracy as a Function of the Number of Top Rank Features

From the results as shown in Figure 5.5, it can be seen that the increment of accuracy tapers off at around top 13 features (in Figure 5.5) for both feature selection algorithms. If more features beyond the top 13 are picked, the performance only improves slightly with the accuracy only improving, less than1% for all 31 features. From

Table 5.3, It is also noticed that though the order of 13 top rank features is not the same, the set of 13 top rank features (as marked in grey) is the same for both Chi Square [98] and Information Gain [98]. This gives an indication that the pool of these 13 top rank features contains the maximally informative features.

5.2.5 Best insole positions selection

Table 5.4: The Percentage of Features from the Top 13 that Originated from the Different Sensors

Sensor	Related Top 13 Features	No. of Features
GPS	1, 2, 3	3
FF Sensor P0	None	0
FF Sensor P1	9,29	2
FF Sensor P2	10, 12, 30	3
FF Sensor P3	31	1
FF Sensor P4	None	0
FF Sensor P5	20, 21, 29	3
FF Sensor P6	22, 24, 30	3
FF Sensor P7	31	1

The practical advantage of best insole positions selection is that the equipment cost can be reduced significantly, without drastically affecting the performance. The best insole positions selection is based upon the best features selection, as the insole positions that provide the maximally informative features need to be retained.

Table 5.4 shows that within the range of 13 top rank features identified in section 5.2.4, no feature is selected from insole positions P0 and P4. This is because little force is generated on both toes during the required mobility activities, so P0 and P4 are pruned. In addition, the insole positions P3 and P7 only contribute to one feature (No. 31), which is the correlation coefficient between P3 and P7. Moreover, it is also discovered that the overall accuracy only decreased 1% by removing this feature

(31). This is because the information provided by this feature is also covered by other similar features such as feature 30, which is the correlation coefficient between P2 and P6. Hence, feature 31 is also removed from the selective feature set. The corresponding insole positions (P3 and P7) are also pruned.

Finally, the following 12 top ranking features are selected as the optimum feature set: 1 (GPS mean speed), 2 (GPS max speed), 3 (std. dev. of GPS speed), 9 (std. dev. of P1 force), 10 (P2 mean force), 12 (std. dev. of P2 force), 20 (P5 max force), 21 (std. dev. of P5 force), 22 (P6 mean force), 24 (std. dev. of P6 force), 29 (correlation coefficient between P1 and P5), and 30 (correlation coefficient between P2 and P6). Correspondingly, the following insole positions are selected as the optimum insole positions: P1, P2, P5, and P6

5.2.6 The improved FF+GPS method

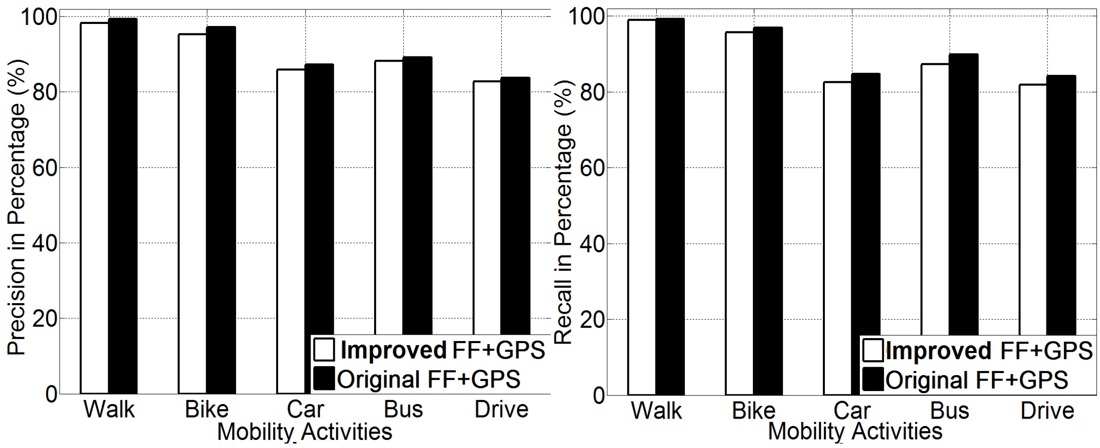


Figure 5.6: Precision (left) and Recall (right) Accuracy of using the Improved FF+GPS Method

According to the results from sections 5.2.3, 5.2.4, and 5.2.5, the following improved FF+GPS method is proposed that only employed the 12 best features (out of 31), 4 best insole positions (out of 8), and the new hybrid GPS use-plan. Figure 5.6 shows the results of using the improved FF+GPS method (white bars) for detecting the 5 predefined mobility activities. Compared with the original FF+GPS method (black bars), the precision and recall accuracy of using the new improved FF+GPS method dropped slightly. For the decision tree classifier, only a 2% reduction in overall accuracy is noticed when using the improved FF+GPS method. This indicates that the improved FF+GPS method, although has slight lower accuracy, can still detect the required mobility activities at a decent level of accuracy.

5.3 Discussion

It is shown that the number of features used in the FF+GPS method can be reduced to 12 to still achieve a decent level of accuracy. Following this, the best insole positions with respect to the selected features are also identified. In addition, the total number of foot force sensors used in the FF+GPS method is also reduced from 8 to 4.

Table 5.5: Best Insole Positions and Overall Accuracy for Different Number of FF Sensors Used

Number of FF Sensors per foot	**Best insole Positions**	**Overall Accuracy**
1 (2 in total)	P2 and P6	75%
2 (4 in total)	P1, P2, P5, and P6	91%
3 (6 in total)	P1, P2,P3, P5, P6, and P7	93%

As Table 5.5 shows, given the configuration of using only one sensor per foot, the overall accuracy of FF+GPS method is relatively low at level of 75%. This is mainly because of the lack of sensing in the fore part of the foot. Though the best positions (in this particular configuration), P2 and P6 in heal can detect walking at a high accuracy and can give a hint of whether a user is sitting in a car or standing on a bus, heal sensing still cannot sense the force variations of pedalling e.g., during cycling or driving. Given the configuration of using only two sensors per foot, the overall accuracy has been increased to 91%. This is because by adding two forefoot sensors P1 and P5, most of the foot force variations during different mobility activities can be sensed and contribute to classification. However, the configuration of using three sensors per foot only leads to a 2% gain in accuracy. This is because the information gained by adding the insole sensor positions P3 and P7 do not appear to contribute much in differentiating various mobility activities.

It is also discovered that the correlation coefficient (between the left foot and right foot) feature and the both-feet-sensing shown to be effective in detecting walking and cycling. The potential correlation between other features is also of interest. The foot force variation of the driver relates to speed variations when driving the car, e.g., step on the accelerate pedal to speed up, while step on the brake pedal to slow down. It is hypothesised that by finding a proper correlation function between foot force and car speed, the accuracy of detecting the most challenging mobility activity – car driver can be highly improved. However, there are many challenges from different circumstances that need to be considered and resolved. More specific experiments and data analysis of car-driving will be included in a future study.

With regard to energy efficiency, the improved FF+GPS method reduces the use of GPS and reduces the number of required foot force sensors to 4 - 50% more efficient than the original FF+GPS method (which uses 8 foot force sensors). However, a detailed energy consumption analysis of the current hybrid GPS use-plan and 4 sensors based foot force monitoring sensors is not included in this work. Exploring the energy efficiency of the improved FF+GPS method is left for future work.

5.4 Summary

An improved (more energy-efficient and computation-cost efficient) FF+GPS method for mobility detection has been designed and evaluated. This improved FF+GPS method reduced the number of sensors, the number of features extracted from the sensor data and classified and reduced the use of GPS. A 2% accuracy loss has been identified as the impact of these energy and cost reduction, compared to the original FF+GPS.

6 Conclusion and Further Work

6.1 Conclusion and Contribution

This thesis investigated user mobility activity recognition, which is an important research topic in ubiquitous computing, iHCI, and artificial intelligence. In this thesis, the following problems are studied: how to support a more comprehensive mobility detection range, how to support a more fine-grained mobility activity recognition capability, and how to improve the efficiency of the proposed FF+GPS method. For each problem, related work was investigated, challenges were discussed and solutions to solve these specific problems were also given and evaluated.

First, after the investigation of various existing sensor-based mobility activity recognition methods, a new FF+GPS based method has been proposed, and implemented. The potential benefits of using a set foot force sensors in combination with mobile phone GPS to improve mobility activity recognition have been examined for the first time. Two normal stationary human postures (sitting and standing) and five daily transportation modes, including walking, cycling, bus passenger, car passenger and car driver, have been included. The FF+GPS method is evaluated by comparing this with both an accelerometer-based method as in [27] and a ACC+GPS based method as an extension of this. Given the sample size of this pilot and based on the classification algorithms employed, the new FF+GPS method has improved the user mobility activity recognition accuracy from a level of 70% to a level of 90%, on average. The FF+GPS method achieves a wider range recognition capability, which is capable of recognising both human posture and transportation mode. Another key contribution of this work is to provide a more fine-grained mobility activity recognition capability in terms of both sub-differentiating stationary postures (into sitting and standing) and sub-differentiating motorised modes, i.e., into bus passenger, car passenger and car driver with an accuracy of 92.8% on average. In addition, the FF+GPS method also has other advantages in terms of requiring less computational resources and requiring less individual training.

Following this, an improved FF+GPS method to detect mobility activities was further researched and developed. The coefficient correlation between the left foot force and right foot force has been shown to be able to detect walking and cycling reliably using only FF sensors. Hence, a new hybrid GPS use-plan has been proposed to improve the FF+GPS method, which can reduce the use of GPS for mobility activity detection. In addition, 12 (out of 31) max informative features and corresponding to the 4 (out of 8) most effective insole positions (two per foot), have also been identified. When a decision tree classifier employed, only a 2% reduction in overall accuracy is noticed when using the improved FF+GPS method, compared with the original FF+GPS method. The improved FF+GPS method that uses the 12 best features, 4 best insole positions, and the new energy-efficient GPS use-plan, can still achieve a fairly high accuracy in detecting the following mobility activities: walking, cycling, bus-passenger, car-passenger, and car driver.

6.2 Further Work

The future work directions are outlined as follows.

1. *More participants for experiments*: According to the survey, the average number of participants for experiments in other mobility detection work is around 10. Although a total number of 20 participants have been included in the data set of this thesis, more people from various background are still desirable in the experiments to form a more representative sample of a more general population.

2. *Optimum sampling frequency and window segmentation*: It is shown in this work that different user mobility activities, such as between walking and driving, normally produce different low level mobility characteristics, such as speed, acceleration, ground reaction force. These low level mobility characteristics can be captured from different sensors using specified sampling and windowing schemes. However, such sampling and windowing schemes are hard to be configured in practice. The sampling frequency and window segmentation determine how granular the raw sensor data is captured. A higher frequency and larger window size can lead to better detection accuracy, but this may also consume more energy and more computational resources. Hence, a trade-off needs to be considered. The optimum sampling frequency and window

segmentation for mobility activity detection are of particular interest for further work.

3. *Additional feature characteristics*: Both time-domain and frequency-domain features are considered in this work. However, other feature analysis techniques e.g., Wavelet analysis, could also be potential useful in detecting more fine-grained mobility activities. Further research regarding additional feature analysis schemes and other types of features could be of interest.

4. *Integrated use of a GIS*: The recognition accuracy for car-passenger, bus-passenger, and tube-passenger can be further improved by combining the use of FF+GPS sensors with the use of a local GIS e.g., the TFL (Transport for London) GIS in London. As the FF+GPS method can determine the transition points during daily travelling, the accuracy for mobility activity recognition could be further improved in combination with publicly available transportation information such as bus or tube stops coordinates. For example, the transition point between walking and taking a bus should be near a bus stop, so the distance between this transition point and the nearest bus stop could be very useful in differentiating bus-passenger and (private) car-passenger. Further research considering the local GIS information may improve the accuracy in classifying user mobility.

5. *Combining FF+GPS with ACC*: It is noted that FF+GPS is not capable of detecting the mobility activity of being a passenger in an underground train journey, where the GPS signal is not available. However, this limitation could be resolved by combining the FF+GPS with ACC-based method. The accelerometer could be used to detect the type of tube-passenger by sensing the vibration of the moving tube. The implementation and evaluation of a combined FF+GPS with ACC method is further work.

6. *Combining FF+GPS with a 2nd stage classification scheme*: It is shown that by applying a 2nd stage classification algorithm after the typical classifier (e.g., Decision Tree), the mobility detection accuracy could be further improved [99]. This is achieved by smoothing out the random miss-classified samples by

applying an additional post-processing scheme (which is known as a 2nd stage classification). A further examination and evaluation of the improvements after applying different 2nd stage classifications schemes (e.g., DTr + PoCoA in [99], DTr + DHMM in [32]) are also of particular interest in future work.

7. *Walking rehabilitation usage*: One important application of the FF+GPS mobility activity detection method proposed in this work is for health-related applications. By using additional, situated, foot force sensors, this work can be extended to enable more fine-grained gait analysis research for use in the field of rehabilitation e.g., to help a patient's rehab when recovering from foot or leg injuries.

References

[1] S. Poslad, *Ubiquitous computing: smart devices, environments and interactions*: Wiley, 2011.

[2] G. Broll, E. Rukzio, M. Paolucci, M. Wagner, A. Schmidt, and H. Hussmann, "Perci: Pervasive service interaction with the internet of things," *Internet Computing, IEEE*, vol. 13, pp. 74-81, 2009.

[3] N. Streitz and P. Nixon, "Special issue: The disappearing computer," in *Communications of the ACM*, 2005, pp. 32-35.

[4] S. Consolvo, P. Klasnja, D. W. McDonald, D. Avrahami, J. Froehlich, L. LeGrand, *et al.*, "Flowers or a robot army?: encouraging awareness & activity with personal, mobile displays," in *10th international conference on Ubiquitous computing*, 2008, pp. 54-63.

[5] Moves. (2013). *Moves - Activity Diary of Your Life*. Available: http://www.moves-app.com/

[6] M. Mun, S. Reddy, K. Shilton, N. Yau, J. Burke, D. Estrin, *et al.*, "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research," in *7th international conference on Mobile systems, applications, and services*, 2009, pp. 55-68.

[7] J. Froehlich, T. Dillahunt, P. Klasnja, J. Mankoff, S. Consolvo, B. Harrison, *et al.*, "UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits," in *27th international conference on Human factors in computing systems*, 2009, pp. 1043-1052.

[8] CarbonHero. (2008). *Carbon diem - Is that knowledge now.* Available: http://carbondiem.com.

[9] J. Kao, Lam, R., Pong, G., Talukdar, T., AND Wong, J. (2008). *Ecorio - Track Your Mobile Carbon Footprint*. Available: http://ecorio.org

[10] E. Agapie, G. Chen, D. Houston, E. Howard, J. Kim, M. Mun, *et al.*, "Seeing Our Signals: Combining location traces and web-based models for personal discovery," in *9th workshop on Mobile computing systems and applications*, 2008, pp. 6-10.

[11] S. Reddy, K. Shilton, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using context annotated mobility profiles to recruit data collectors in participatory sensing," *Location and Context Awareness*, pp. 52-69, 2009.

[12] M. J. Chorley, G. B. Colombo, S. M. Allen, and R. M. Whitaker, "Visiting Patterns and Personality of Foursquare Users," in *Cloud and Green Computing (CGC), 2013 Third International Conference on*, 2013, pp. 271-276.

[13] S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, D. Howard, K. Meijer, and R. Crompton, "Activity identification using body-mounted sensors—a review of classification techniques," *Physiological measurement*, vol. 30, pp. R1-R33, 2009.

[14] M. J. Williams, R. M. Whitaker, and S. M. Allen, "Measuring individual regularity in human visiting patterns," in *Privacy, Security, Risk and Trust (PASSAT), 2012 International Conference on and 2012 International Confernece on Social Computing (SocialCom)*, 2012, pp. 117-122.

[15] J. Liu, M. Goraczko, A. Kansal, D. Lymberopoulos, S. Nath, and B. Priyantha, "Subjective Sensing: International Awareness for Personalized Services," *NSF Workshop on Future Directions in Networked Sensing Systems: Fundamentals and Applications*, 2009.

[16] N. FUELBAND. (2013). *NIKE+ FUELBAND - THE SMART, SIMPLE, AND FUN WAY TO GET MORE ACTIVE.* Available: http://www.nike.com/us/en_us/c/nikeplus-fuelband

[17] J. Dion, J. Fouillot, and A. Leblanc, "Ambulatory monitoring of walking using a thin capacitive force transducer," in *Proceedings of the fourth International Symposium on Ambulatory Monitoring and the Second Gent Workshop on Blood Pressure Variability*, 1981, pp. 420-424.

[18] R. W. Hoyt, J. J. Knapik, J. F. Lanza, B. H. Jones, and J. S. Staab, "Ambulatory foot contact monitor to estimate metabolic cost of human locomotion," *Journal of Applied Physiology*, vol. 76, pp. 1818-1822, 1994.

[19] O. Brdiczka, M. Langet, J. Maisonnasse, and J. L. Crowley, "Detecting human behavior models from multimodal observation in a smart home," *IEEE Transactions on Automation Science and Engineering*, vol. 6, pp. 588-597, 2009.

[20] Y. Makihara, B. S. Rossa, and Y. Yagi, "Gait recognition using images of oriented smooth pseudo motion," in *Systems, Man, and Cybernetics (SMC), 2012 IEEE International Conference on*, 2012, pp. 1309-1314.

[21] D. Minnen, T. Starner, J. Ward, P. Lukowicz, and G. Troster, "Recognizing and discovering human actions from on-body sensor data," in *IEEE International Conference on Multimedia and Expo,ICME*, 2005, pp. 1545-1548.

[22] K. Zhang, M. Sun, D. Kevin Lester, F. Xavier Pi-Sunyer, C. N. Boozer, and R. W. Longman, "Assessment of human locomotion by using an insole measurement system and artificial neural networks," *Journal of biomechanics, ACM*, vol. 38, pp. 2276-2287, 2005.

[23] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait analysis using wearable sensors," *Sensors*, vol. 12, pp. 2255-2283, Feb 2012.

[24] Z. Zhang and S. Poslad, "Fine-Grained Transportation Mode Recognition Using Mobile Phones and Foot Force Sensors," in *Proceedings of the Mobiquitous -- 9th*

International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (Mobiquitous 2012), 2012.

[25] T. S. Saponas, J. Lester, C. Hartung, and T. Kohno, "Devices that tell on you: The nike+ ipod sport kit," *Dept. of Computer Science and Engineering, University of Washington, Tech. Rep,* 2006.

[26] N. Ravi, N. Dandekar, P. Mysore, and M. L. Littman, "Activity recognition from accelerometer data," in *American Association for Artificial Intelligence*, 2005, pp. 1541-1546.

[27] S. Wang, C. Chen, and J. Ma, "Accelerometer based transportation mode recognition on mobile phones," in *2010 Asia-Pacific Conference on Wearable Computing Systems (APWCS)*, 2010, pp. 44-46.

[28] L. Liao, D. Fox, and H. Kautz, "Extracting places and activities from gps traces using hierarchical conditional random fields," *The International Journal of Robotics Research,* vol. 26, pp. 119-134, 2007.

[29] T. Philip, M. Oliveria, C. Matthews, E. Cromley, S. Melly, and B. Craig, "Prediction of Activity Mode with Global Positioning System and Accelerometer Data," *Medicine and science in sports and exercise*, vol. 40, pp. 972-978, 2008.

[30] A. Subramanya, A. Raj, J. Bilmes, and D. Fox, "Recognizing activities and spatial context using wearable sensors," in *Proceedings of the Twenty-Second Conference on Uncertainty in Artificial Intelligence*, 2006.

[31] D. Gordon, J. H. Hanne, M. Berchtold, T. Miyaki, and M. Beigl, "Recognizing Group Activities using Wearable Sensors," 2011.

[32] S. Reddy, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Determining transportation mode on mobile phones," in *12th IEEE International Symposium on Wearable Computers. ISWC*, 2008, pp. 25-28.

[33] Y. SCHUTZ and R. HERREN, "Assessment of speed of human locomotion using a differential satellite global positioning system," *Medicine & Science in Sports & Exercise,* vol. 32, pp. 2276-2287, 2000.

[34] T. Witte and A. Wilson, "Accuracy of non-differential GPS for the determination of speed over ground," *Journal of biomechanics,* vol. 37, pp. 1891-1898, 2004.

[35] C. L. Accupedo. (2011). *Accupedo - Pedometer Widget*. Available: http://www.accupedo.com/

[36] Apple. (2012). *Nike + iPod Sensor*. Available: http://www.apple.com/ipod/nike/

[37] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell, "A survey of mobile phone sensing," *Communications Magazine, IEEE,* vol. 48, pp. 140-150, 2010.

[38] Z. Zhang and S. Poslad, "Design and Test of a Hybrid Foot Force Sensing and GPS System for Richer User Mobility Activity Recognition," *Sensors*, vol. 13, pp. 14918-14953, 2013.

[39] J. Yin, *Probabilistic activity recognition from low-level sensors*: Hong Kong University of Science and Technology (People's Republic of China), 2006.

[40] C. di Flora, M. Ficco, S. Russo, and V. Vecchio, "Indoor and outdoor location based services for portable wireless devices," in *25th IEEE International Conference on Distributed Computing Systems Workshops,*, 2005, pp. 244-250.

[41] J. Krumm and E. Horvitz, "Predestination: Inferring destinations from partial trajectories," *UbiComp 2006: Ubiquitous Computing*, pp. 243-260, 2006.

[42] Z. Liang, "Spatial-Aware Personalised Maps for Mobile User," Thesis, School of Electronic Engineering and Computer Science, Queen Mary University of London, London, UK, 2011.

[43] C. Zhu and W. Sheng, "Wearable sensor-based hand gesture and daily activity recognition for robot-assisted living," *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans*, vol. 41, pp. 569-573, 2011.

[44] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer networks*, vol. 38, pp. 393-422, 2002.

[45] H. Martín, A. M. Bernardos, J. Iglesias, and J. R. Casar, "Activity logging using lightweight classification techniques in mobile devices," *Personal and Ubiquitous Computing*, pp. 1-21, 2012.

[46] A. Avci, S. Bosch, M. Marin-Perianu, R. Marin-Perianu, and P. Havinga, "Activity recognition using inertial sensing for healthcare, wellbeing and sports applications: A survey," in *Architecture of computing systems (ARCS), 2010 23rd international conference on*, 2010, pp. 1-10.

[47] M. J. Mathie, A. C. F. Coster, N. H. Lovell, and B. G. Celler, "Accelerometry: providing an integrated, practical method for long-term, ambulatory monitoring of human movement," *Physiological measurement*, vol. 25, p. R1, 2004.

[48] O. I. Series. *Accelerometer support*. Available: http://docs.garagegames.com/it2d/official/content/documentation/Tutorials/iOS Series/Input.html - Accelerometer_Support

[49] J. Liu, R. Chen, L. Pei, W. Chen, T. Tenhunen, H. Kuusniemi, *et al.*, "Accelerometer assisted robust wireless signal positioning based on a hidden Markov model," in *Position Location and Navigation Symposium (PLANS), 2010 IEEE/ION*, 2010, pp. 488-497.

[50] T. Maekawa, Y. Kishino, Y. Sakurai, and T. Suyama, "Activity recognition with hand-worn magnetic sensors," *Personal and Ubiquitous Computing*, pp. 1-10, 2012.

[51] T. L. Lawrence and R. N. Schmidt, "Wireless in-shoe force system [for motor prosthesis]," in *Engineering in Medicine and Biology Society, 1997. Proceedings of the 19th Annual International Conference of the IEEE,* 1997, pp. 2238-2241.

[52] G. Gartner, H. Huang, and M. Schmidt, "Smart Environment for Ubiquitous Indoor Navigation," *NISS '09. International Conference on New Trends in Information and Service Science,*, 2009.

[53] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *Communications Surveys & Tutorials, IEEE,* vol. 11, pp. 13-32, 2009.

[54] G. M. Giaglis, P. Kourouthanassis, and A. Tsamakos, "Towards a classification framework for mobile location services," *Mobile commerce: technology, theory, and applications,* pp. 67-85, 2003.

[55] J. G. McNeff, "The global positioning system," *IEEE Transactions on Microwave Theory and Techniques,* vol. 50, pp. 645-652, 2002.

[56] G. M. Djuknic and R. E. Richton, "Geolocation and assisted GPS," *Computer,* vol. 34, pp. 123-125, 2001.

[57] L. Bao and S. S. Intille, "Activity recognition from user-annotated acceleration data," in *Pervasive Computing*, ed: Springer, 2004, pp. 1-17.

[58] S. J. Preece, J. Y. Goulermas, L. P. J. Kenney, and D. Howard, "A comparison of feature extraction methods for the classification of dynamic activities from accelerometer data," *IEEE Transactions on Biomedical Engineering,* vol. 56, pp. 871-879, 2009.

[59] T. Huynh and B. Schiele, "Analyzing features for activity recognition," in *Proceedings of the 2005 joint conference on Smart objects and ambient intelligence: innovative context-aware services: usages and technologies*, 2005, pp. 159-163.

[60] A. Mansfield and G. M. Lyons, "The use of accelerometry to detect heel contact events for use as a sensor in FES assisted walking," *Medical engineering & physics,* vol. 25, pp. 879-885, 2003.

[61] S. Dreiseitl and L. Ohno-Machado, "Logistic regression and artificial neural network classification models: a methodology review," *Journal of biomedical informatics,* vol. 35, pp. 352-359, 2002.

[62] M. Brand, N. Oliver, and A. Pentland, "Coupled hidden Markov models for complex action recognition," in *Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on*, 1997, pp. 994-999.

[63] R. O. Duda, P. E. Hart, and D. G. Stork, *Pattern classification*: John Wiley & Sons, 2012.

[64] A. R. Webb, *Statistical pattern recognition*: Wiley. com, 2003.

[65] J. R. Quinlan, *C4. 5: programs for machine learning* vol. 1: Morgan kaufmann, 1993.

[66] G. H. John and P. Langley, "Estimating continuous distributions in Bayesian classifiers," in *Proceedings of the Eleventh conference on Uncertainty in artificial intelligence*, 1995, pp. 338-345.

[67] R. Kohavi, "The power of decision tables," in *Machine Learning: ECML-95*, ed: Springer, 1995, pp. 174-189.

[68] C. Development. (2012). *A History of Decision Tables*. Available: http://www.catalyst.com/products/logicgem/overview.html

[69] J. Harey. (1998). *Decision Tables*. Available: http://www.cems.uwe.ac.uk/jharney/table.html

[70] G. Wets, F. Witlox, H. Timmermans, and J. Vanthienen, "Locational choice modelling using fuzzy decision tables," in *Fuzzy Information Processing Society NAFIPS. Biennial Conference of the North American*, 1996, pp. 80-84.

[71] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," 1995, pp. 1137-1145.

[72] D. Mizell, "Using gravity to estimate accelerometer orientation," in *7th IEEE International Symposium on Wearable Computers*, 2003, pp. 252-253.

[73] L. Bao and S. Intille, "Activity recognition from user-annotated acceleration data," *Pervasive Computing*, pp. 1-17, 2004.

[74] J. Pärkkä, L. Cluitmans, and M. Ermes, "Personalization algorithm for real-time activity recognition using PDA, wireless motion bands, and binary decision tree," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, pp. 1211-1215, 2010.

[75] M.-W. Lee, A. M. Khan, and T.-S. Kim, "A single tri-axial accelerometer-based real-time personal life log system capable of human activity recognition and exercise information generation," *Personal and Ubiquitous Computing*, vol. 15, pp. 887-898, 2011.

[76] T. Brezmes, J. L. Gorricho, and J. Cotrina, "Activity recognition from accelerometer data on a mobile phone," *Distributed Computing, Artificial Intelligence, Bioinformatics, Soft Computing, and Ambient Assisted Living*, pp. 796-799, 2009.

[77] Y. Zheng, L. Liu, L. Wang, and X. Xie, "Learning transportation mode from raw gps data for geographic applications on the web," in *Proceedings of the 17th international conference on World Wide Web*, 2008, pp. 247-256.

[78] W. Zijlstra, R. W. Bisseling, S. Schlumbohm, and H. Baldus, "A body-fixed-sensor-based analysis of power during sit-to-stand movements," *Gait & posture,* vol. 31, pp. 272-278, 2010.

[79] B. Lee, B. Won-Chul, J. D. K. Kim, and K. Chang Yeong, "Orientation estimation in mobile virtual environments with inertial sensors," *IEEE Transactions on Consumer Electronics,* vol. 57, pp. 802-810, 2011.

[80] J. Yin, Q. Yang, and J. J. Pan, "Sensor-based abnormal human-activity detection," *IEEE Transactions on Knowledge and Data Engineering,* vol. 20, pp. 1082-1090, 2008.

[81] J. Baek and B. J. Yun, "Posture monitoring system for context awareness in mobile computing," *IEEE Transactions on Instrumentation and Measurement,* vol. 59, pp. 1589-1599, 2010.

[82] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer Networks,* vol. 54, pp. 2787-2805, 2010.

[83] P. H. Veltink, C. Liedtke, E. Droog, and H. van der Kooij, "Ambulatory measurement of ground reaction forces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering* vol. 13, pp. 423-427, 2005.

[84] T. Liu, Y. Inoue, and K. Shibata, "A wearable ground reaction force sensor system and its application to the measurement of extrinsic gait variability," *Sensors,* vol. 10, pp. 10240-10255, 2010.

[85] X. Zhang, Y. Zhao, Z. Duan, and Y. Liu, "Design and Test of a Soft Plantar Force Measurement System for Gait Detection," *Sensors,* vol. 12, pp. 16628-16640, 2012.

[86] M. Donati, N. Vitiello, S. M. M. De Rossi, T. Lenzi, S. Crea, A. Persichetti*, et al.*, "A Flexible Sensor Technology for the Distributed Measurement of Interaction Pressure," *Sensors,* vol. 13, pp. 1021-1045, 2013.

[87] J. Chon and H. Cha, "Lifemap: A smartphone-based context provider for location-based services," *Pervasive Computing, IEEE,* vol. 10, pp. 58-67, 2011.

[88] J. P. Varkey, D. Pompili, and T. A. Walls, "Human motion recognition using a wireless sensor-based wearable system," *Personal and Ubiquitous Computing,* vol. 16, pp. 897-910, 2012.

[89] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi*, et al.*, "Sensing meets mobile social networks: the design, implementation and evaluation of the cenceme application," in *Proceedings of the 6th international conference on Embedded network sensor systems*, 2008, pp. 337-350.

[90] T. Sohn, A. Varshavsky, A. LaMarca, M. Chen, T. Choudhury, I. Smith*, et al.*, "Mobility detection using everyday GSM traces," *UbiComp 2006: Ubiquitous Computing,* pp. 212-224, 2006.

[91] M. Keally, G. Zhou, G. Xing, J. Wu, and A. Pyles, "PBN: towards practical activity recognition using smartphone-based body sensor networks," in *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*, 2011, pp. 246-259.

[92] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using mobile phones to determine transportation modes," *ACM Transactions on Sensor Networks (TOSN),* vol. 6, pp. 13:01-13:27, 2010.

[93] M. Berchtold, M. Budde, D. Gordon, H. R. Schmidtke, and M. Beigl, "Actiserv: Activity recognition service for mobile phones," in *Wearable Computers (ISWC), 2010 International Symposium on*, 2010, pp. 1-8.

[94] Y. Zheng, L. Wang, L. LIU, and X. Xie, "Learning transportation modes from raw gps data," *Proceedings of the 17th international conference on World Wide Web Pages,* 2009.

[95] Y. Zheng, L. Zhang, X. Xie, and W. Y. Ma, "Mining interesting locations and travel sequences from GPS trajectories," in *Proceedings of the 18th international conference on World wide web*, 2009, pp. 791-800.

[96] B. Chuckpaiwong, J. A. Nunley, N. A. Mall, and R. M. Queen, "The effect of foot type on in-shoe plantar pressure during walking and running," *Gait & posture,* vol. 28, pp. 405-411, 2008.

[97] S. Yeh, K. H. Chang, C. I. Wu, H. Chu, and J. Y. Hsu, "GETA sandals: a footstep location tracking system," *Personal and Ubiquitous Computing,* vol. 11, pp. 451-463, 2007.

[98] I. Guyon and A. Elisseeff, "An introduction to variable and feature selection," *The Journal of Machine Learning Research,* vol. 3, pp. 1157-1182, 2003.

[99] Z. Zhang and S. Poslad, "A New Post Correction Algorithm (PoCoA) for Improved Transportation Mode Recognition," in *Proceedings of the IEEE International Conference on Systems, Man, and Cybernetics (SMC 2013),* 2013.

Appendix A. QMUL Ethical Approval

Queen Mary, University of London
Room E16
Queen's Building
Mile End Road
London
E1 4NS
Queen Mary Research Ethics Committee
Hazel Covill
Research Ethics Committee Administrator
Tel: +44 (0) 20 7882 2207
Email: h.covill@qmul.ac.uk

c/o Dr Stefan Poslad
Eng 306
Department of Electronic Engineering
Queen Mary University of London
Mile End Road
London E1 4NS

7th February 2012

To Whom It May Concern:

Re: QMREC 0706 – Mobility Profiling

I can confirm that Mr Zelun Zhang has completed a Research Ethics Questionnaire with regard to the above research.

The result of which was the conclusion that his proposed work does not present any ethical concerns; is extremely low risk; and thus does not require the scrutiny of the full Research Ethics Committee.

Yours faithfully

Ms Hazel Covill
Research Ethics Committee Administrator

Appendix B. Privacy Policy Agreement for Mobility Data Collection

1. Information Collection

Collection of this mobility data will include the following data:

1.1 Unidentifiable information (such as gender, age range, etc.) of testing individuals.
1.2 Foot force data during user mobility activities (standing, sitting, walking, cycling, etc.).
1.3 Phone built-in sensors (accelerometer, GPS, etc.) data during user normal activities.
1.4 Positioning data (include coordinates and speed) during user daily travel.

2. Your Data and how it is used

Primarily, we collect and store data about you to research into how machines can learn to recognize different user postures and travel modes automatically. The following are how we may use your data:

2.1 Data patterns (in the time or frequency domain) will be plotted for analysis.
2.2 Basic signal processing techniques will be applied to find the useful signal indices for recognition.
2.3 Some pattern recognition algorithms will be applied to evaluate the accuracy.
2.4 The anonymized data (e.g. statistical of all testing subjects) will be presented in research documents for comparison and illustration usage.

3. Storage of Your Data

Data collected from you will be stored on secure devices of the School of Electronic Engineering and Computer Science, which is located inside the Queen Mary College University of London.

4. Information Sharing

4.1 Your data will only be shared among our research group members, who will be only granted the right to access the anonymized database once they agreed to abide to protect the anonymity and privacy of the participants under all conditions. (Note: Information is shared only when applicable)
4.2 No compromises will be made in terms of risking the data flowing to the hands of non-authorized instances, e.g. Non-QMUL researchers

5. Accessing Information

We provide you with the right to access the information that we collect about you. Please note any demand for access may be subject to take 2 days, which covers our time in providing you with the data requested. The contact information below needs to be used to request access the data we collect and store on you.

6. Opt-Out Right

We also provide you with the right to withdraw the data we collect about you. Please note any demand for withdraw data will be conducted under your supervision. The contact information below needs to be used to request withdraw the data we collect and store on you.

7. Contacting Us

We welcome any queries, requests, or comments you may have regarding this Privacy Policy for Mobility Data Collection. Please do not hesitate and feel free to contact us at:
stefan@eecs.qmul.ac.uk; zelun.zhang@eecs.qmul.ac.uk; thomas.oshin@eecs.qmul.ac.uk; zhenchen.wang@eecs.qmul.ac.uk; siamakt@eecs.qmul.ac.uk; ran.tao@eecs.qmul.ac.uk

(**Note:** All the policies stated above are made pursuant to the 'Regulation Concerning Information Technology' from Queen Mary College, University of London)

Volunteer Information:

Gender: Male ☐; Female☐;
Age Range: 16 – 25 ☐; 26 – 35 ☐; 36 – 45 ☐; 46 – 55 ☐;
Occupation: Students☐; Employee☐; Others☐;

Please sign your name below to indicate your agreement of the policy stated above.

Signature: **Date:**