Sensing Gait on Smartphones to Support Mobile Exercise Applications and Games

by

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Abstract

To encourage and support physical activity in increasingly sedentary lifestyles, many are turning to mobile technology. Modern smartphones are equipped with a wealth of sensors, including Global Positioning Systems (GPS) and accelerometers, suggesting great potential to be integrated with fitness and exercise applications. So far, GPS-enabled devices have been used to support running, cycling, or even exercise games that encourage people to be physically active, but GPS-enabled devices lack fine-grained information about the user's activity. Accelerometers have been used to some effect to detect step count and walking cadence (step rate), and even to classify activity (distinguishing walking from cycling, for example), but require a known carrying location and orientation. In this work, we examine the role of location in two application areas - real-time cadence estimation and gait classification - and develop algorithms to accommodate diverse carrying locations.

In the first application area, real-time cadence estimation, our algorithm (Robust Real-time Algorithm for Cadence Estimation, or RRACE) uses a frequency-domain analysis to perform well without training or tuning, and is robust to changes in carrying locations. We demonstrate RRACE's performance and robustness to be an improvement over existing algorithms with data collected from a user study. In the second application area, gait classification, we present a novel set of 15 gaits suitable for exercise games and other fitness applications. Using a minimal amount of training for participants, we can achieve a mean of 78.1% classification for all 15 gaits and all locations, an accuracy which may be usable now in some applications and warrants further investigation of this approach. We present findings of how our classification scheme confuses these gaits, and encapsulate

insights in guidelines for designers. We also demonstrate that our classification performance varies dramatically for each individual *even when trained and tested on that individual*, suggesting strong individual differences in performing gaits. Our innovative methodology for simple and quick collection of accelerometer data is also described in detail. Future work includes planned improvements to both algorithms, further investigation of individual differences, and extension of this work to other application areas.

Preface

There are several collaborators without whom this work could not have happened as it did. In this preface, I describe the relative contributions of all people involved in the research presented in this thesis, all resulting publications, and ethics approval.

At the moment of writing, there are three publications planned that are associated with this thesis. The first planned publication reflects the cadence estimation work, primarily described in Chapter 3. The second planned publication describes the gait classification work, described primarily in Chapter 4, Chapter 5, and Chapter 6. The third planned publication describes a software package, *GaitLib*, developed as a result of software development conducted during this research. The details of these collaborations are described below.

The cadence estimation work was conducted with the following people: PhD student Idin Karuei, undergraduate research assistant Bryan Stern, undergraduate research assistant Michelle Chuang, and supervisor and principal investigator Karon MacLean. Idin was the primary researcher for this work. Oliver's contribution to this work included planning and helping to conduct the main study; implementing, testing, and training the time-domain algorithm; reimplementing the cadence algorithm for further testing; consultation when analyzing the results; and contributing major sections to the journal manuscript, which the group has prepared as a result of this work. Chapter 3 has been written to include the entire work for framing and readability, with Oliver's contributions elaborated upon and his non-contributions minimized. Essentially, the chapter is a "fish-eye" view of the manuscript, highlighting Oliver's contributions.

The gait classification work includes the following collaborators: Idin Karuei,

post-doctoral researcher Kerem Altun, undergraduate research assistant Michael Ming-An Wu, and Karon MacLean. This work was primarily done by Oliver. Dr. Maclean provided a great deal of mentorship, guidance, and feedback. Idin was available for consultation, given his experience with the cadence detection. Dr. Altun provided valuable information regarding machine learning and sensor (accelerometer and gyroscope) use. Michael provided advice with insights drawn from his development of the GaitLib software system.

Finally, the GaitLib software system involved the following contributors: Idin Karuei, Bryan Stern, Michelle Chuang, Michael Ming-An Wu, and Karon MacLean. Michael was the primary developer for this system and writer of the planned publication. Oliver was a major contributor and principal architect for the software package, and provided mentorship and advice to Michael's development. Idin, Bryan, and Michelle provided the original software development with the cadence detection software package. Michael took the software developed for both of these studies and, with help from Oliver, Idin, and Dr. MacLean, developed it to incorporate gait classification.

At the time of this writing, all three publications are at different stages. The cadence estimation manuscript is titled "RRACE: Robust Real-time Algorithm for Cadence Estimation" by Idin Karuei, Oliver Schneider, Bryan Stern, Michelle Chuang, and Karon MacLean; this paper is about to be submitted for review to a top-tier journal. The gait classification manuscript, based on Chapter 4, Chapter 5, and Chapter 6 of this thesis, is in preparation for submission to a journal or conference with Oliver as the primary author. The GaitLib software publication, tentatively titled "Coding Gait: A Library for Gait Recognition in Mobile Phones" by Michael Ming-An Wu, Oliver Schneider, Idin Karuei, and Karon MacLean, is in preparation for submission to a conference.

Finally, this work was approved by the University of British Columbia (UBC) Behavioural Research Ethics Board (BREB), with ethics number #H01-80470. All study forms can be found in Appendix A.

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Acknowledgments

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I owe a big thank you to my family. Kevin Schneider, Karen Wood, Samuel Schneider, and Anna Schneider gave me much-appreciated advice, and were always around when I needed to take a break.

Finally, I could not have done this without Elyse Clancy's love, support, and constant encouragement. She kept me on track when needed, and answered my worries with her sense of humour. The steady supply of coffee on late nights did not hurt either.

Dedication

Mom, Dad, Sam, Anna, Elyse - this is for you.

Chapter 1

Introduction

If I could not walk far and fast, I think I should just explode and perish.
— Charles Dickens

We are in a health crisis. Over 38% of Canadians, and 10% adults worldwide, are classified as overweight or obese [58, 63]. Obesity is a risk factor for many diseases, including heart disease and stroke, diabetes, and some cancers [63]. Though a result of both genetic and environmental factors [42], successful prevention of obesity can be achieved by reducing sedentary behaviours and increasing active behaviours. Sedentary behaviours, often including activities such as watching television or playing video games, can increase the likelihood of being overweight [62]. However, turning sedentary activities into active ones can more than double energy expenditure [37]. Exercise, more than diet, has been shown to be effective for achieving healthy weight loss [50]. Indeed, simply increasing step count can provide overall health benefits [7]. All of this points towards a need for people to to be active; unfortunately, 31% of adults worldwide aged 15 and over were insufficiently active in 2008 [64]. There exists a need to better support and encourage physical activity.

Recently, many technological solutions have arisen to promote or facilitate physical activity. Modern smartphones[1] have a wealth of sensing techniques, such as accelerometers, gyroscopes, and Global Positioning System (GPS) units. These

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[1]"A cell phone that includes additional software functions (as e-mail or an Internet browser) on their person." [44]

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sensors allow for novel mobile applications to support physical activity in a natural way, such as matching a song's beat to a users' running cadence (*i.e.*, step rate) [47]. This support for physical activity can help people maintain their exercise or weight goals [9]. Knowledge of this physical activity can also be provided to context-aware applications, such as a mobile song recommendation system, that take into account both physical walking information as well as time and location [15]. Others have shown that automatically sensing higher-level activities, such as cycling or climbing, is important for supporting persuasive fitness applications [9].

In particular, automatically sensing different gaits[2] as higher-level activities lends itself well to applications involving physical activity. Walking and running are common exercise activities; even everyday choices, such as taking the stairs to the office rather than the elevator, are closely coupled to physical activity. Mobile exergames[3] can also benefit from sensing novel gaits as an input modality, as many only use location-based sensing or approximations of overall physical activity. Movement on foot is often a context in which users carry smartphones, allowing applications and games to naturally use smartphones' sensing capabilities. All of this points towards the ability to sense gait on smartphones as a promising potential means of supporting physical activity.

However, techniques for sensing a user's gait are not yet robust enough to be widely adopted on commodity smartphones. Although GPS has been widely used for fitness and exercise applications, accelerometers (which sense more fine-grained information) often require major constraints, such as carrying external sensors or placing the smartphone in a known location and orientation [45, 47]. Wearing external sensors is intrusive and social inhibitive [9, 21], costs additional money, and ties the application to a hardware platform that could become obsolete. Using the smartphone's internal sensors solves these problems and leverages the pervasiveness of smartphones, but limiting them to a known location and orientation ignores the diverse ways that people carry their mobile devices [12]. To truly support physical activity and exercise in a mobile context, modern sensing

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[2]"A manner of walking or moving on foot." [44]. In this work, we use it to refer to diverse movements, but all are bipedal, directional movements on land, or analogous movements with land vehicles (such as cycling, skateboarding, and driving a car).

[3]Exercise games; see Section 2.1.2 for a definition.

techniques must be able to handle diverse carrying locations on the mobile devices themselves.

1.1 Contributions

In this work, we strive to develop better techniques for accelerometer sensing that can handle different carrying locations robustly. We do this for two types of sensed entities: cadence estimation and the classification of the user's gait. Both of these are suitable for mobile exercise applications, the burgeoning area of exergames, and mobile context-aware applications. We make the following contributions to modern science:

- A demonstration that carrying location has a major effect on mobile device's accelerometer signals. Carrying location must be considered in future work involving smartphones.

- A robust cadence estimation algorithm, Robust Real-time Algorithm for Cadence Estimation (RRACE), that is robust to carrying location. We include:

  - A thorough validation study of the RRACE algorithm on mobile smartphones.
  - A thorough comparison of RRACE with the (previously) best-performing published cadence estimation algorithm.

- A gait classification algorithm developed to recognize a wide variety of gaits with a variety of carrying locations. Though not robust to individual differences, this algorithm can be rapidly trained or personalized by collecting only 30 seconds of each gait. We include:

  - A selection of gaits suitable for exercise applications and games, as well as a set of criteria used to determine these gaits.
  - A demonstration that we can use accelerometer data to infer the users' gait in real-time (with lag time of only a 2 seconds).
  - Characterization of influence that carrying location, individual differences, and types of gait have on classification, and evidence that gait analyses must consider individual differences.

- A methodology for rapid gathering and experimentation of gait analysis data and techniques.

- Plans for future work: how we can use gait detection and feedback to help combat obesity and physical inactivity.

1.2 Thesis Outline

We begin by reviewing the relevant literature in Chapter 2. Next, we cover our work in cadence estimation, including descriptions of the RRACE algorithm, our methodology, a validation study of RRACE, and an analysis of a status quo algorithm Chapter 3. The next 3 chapters focus on the problem of gait classification, starting with a description of our gait selection process and gait classification data collection methodology in full in Chapter 4. After, we detail our gait classification algorithm, including design decisions and performance results in Chapter 5. We then discuss our analysis of the gait classification algorithm in Chapter 6. We conclude with a summary of our findings and plans for future work in Chapter 7.

Chapter 2

Related Work

Only thoughts reached by walking have value.
— Friedrich Nietzsche

This work is related to many different application areas and draws upon a diverse area of previous work. In this chapter, we will review the related work. First, in Section 2.1, we discuss application areas related to robust gait analysis and how this work is positioned in consideration of these works. After, in Section 2.2, we review previous work in robust mobile gait analysis.

2.1   Application Space

Gait analysis has a wide variety of applications. In this section, we review the space of major application areas for this work. Though not exhaustive, this review will give a thorough introduction to the prominent motivating application areas and the body of research contained there-within.

First, in Section 2.1.1, we explore mobile exercise applications not implemented as games. Second, in Section 2.1.2, we present an overview of the burgeoning area of exercise games, focusing on mobile exercise games and their input modalities. Next, in Section 2.1.3, we examine work on context-aware applications on a mobile platform. Finally, in Section 2.1.4, we explain how our methodology is designed to support these varied application areas simultaneously.

2.1.1 Exercise Applications

Using on-person sensors to support exercise is not a novel concept. Pedometers have long been a fitness tool for dedicated walkers and runners, both for meeting fitness goals (such as a target daily step count) and for general awareness of activity. As mobile devices become more prevalent, many mobile applications have been developed to encourage or support physical fitness and exercise. Examples of these range from self-reported logging of exercise and nutrition to smartphone-based pedometers and GPS-based location sensing for running or cycling [19, 41, 47, 60]. More elaborate sensing solutions have also been developed, such as the Nike+ project [45]. Nike+ is a suite of solutions for exercise monitoring and sensing. It includes a mobile application that uses GPS to record runs, and specialized equipment to provide additional sensing if the user chooses: the Nike+ FuelBand, a wrist-based sensor and display that tracks step count and overall movement; a heart rate monitor, connected via Bluetooth; Nike shoes, orchestrated with additional sensors; or even several brands of exercise machines. Previously, Nike also included the Nike+ Sensor, which was placed in the user's shoe.

Step detection techniques are often used to estimate walking cadence (*i.e.*, step rate). This can be used as part of an exercise logging application, or to motivate users by matching music tempo to the users' current or desired walking or running cadence. Oliver's & Flores-Mengasand's MPTrain system uses song tempo to help the user achieve a desired heart rate using a chest-mounted accelerometer and heart-rate sensor [47]. MPTrain's interface was later extended to include a glanceable display and competitive running support as the TripleBeat system [14]; these changes made TripleBeat more effective than MPTrain at encouraging users to maintain their training heart rate, although only half their participants enjoyed the competitive aspect. Elliott & Tomlinson provide a prototype "PersonalSoundtrack" that matches music to the users' current walking pace (detected with a hip-mounted accelerometer that detects user steps) [16]. All of these works sought to encourage users to maintain or reach a certain cadence.

Recent studies have shown that pedometers can influence physical activity levels. Lin et al. use Prochaska's Transtheoretical Model of Behaviour Change to encourage participants to increase their daily step count [39]. Their results sug-

gest that tying step count to an ambient display (in this case, with fish avatars) may encourage people to walk more. Consolvo et al. show that more than simple step count is needed [9]. They developed a mobile fitness journal connected to a pedometer, and found that though pedometers were motivating, there was a need to support other activity beyond walking via cumulative step count. Because pedometers did not register other activities, such as cycling or climbing, participants were frustrated when the system failed to report their full set of activities (both to themselves and to groups when a social network sharing was used). As well, external pedometers were large and unsightly - unsuitable for a pervasive application used in day-to-day life.

Consolvo et al.'s follow-up work, the UbiFit system, improved matters by using a multimodal external sensor, the Mobile Sensing Platform (MSP), to detect varied activities [10]. UbiFit provides an ambient visual metaphor of a user's exercise activity with a garden that grows with your activity. Each flower's type is determined by the type of exercise (such as a walk, etc.), and butterflies appear as weekly goals are met. Drawing from [39], positive enforcement was used exclusively: there were no wilting flowers. The MSP inferred walking, running, cycling, using an elliptical trainer, and using a stair machine, but also allowed users to manually log activities. The MSP was relatively accurate: 77% of inferred activities were unmodified in the UbiFit log [8], but only 39% of recorded activities were inferred (the rest were manually entered into the system) [11]. A twelve week study reinforces that having ambient (in this case, *glanceable*) display of the garden improved the maintenance of a regular exercise schedule.

Motivation to exercise is especially desirable in today's youth. Poole et al. investigated the role of ubiquitous computing in schools as an interventionist method for youth physical activity [48]. Physical activity levels encounter an "adolescent slump", where physical activity levels drop dramatically around age 12. They instigated the "American Horsepower Challenge", a pedometer based pervasive health game for middle school students aged 9-13, and found that rituals and structured time are important for such an intervention. They used a virtual race accessible on a website to encourage students to compete to collect a greater number of steps. The desire to bring exercise to youth has been one of the primary motivators for recent work into exergames.

2.1.2 Exergames

Since the release of Dance Dance Revolution in 1988 [53], many exergames have been developed, and an increasingly large body of research was been created. Recent work tends to focus on the use of exercise games as persuasive applications to promote physical activity in a variety of ways, from using stationary bicycles [56, 61] to the dynamic construction of virtual worlds based on your activity level and location in the physical world [13].

There is unfortunately a great discrepancy in terminology between authors, including "active game", "exercise game", and "exergame." In this work, we will use Oh and Yang's definition of exergame, which is based upon a recent survey of exergame literature: "An exergame is a video game that promotes (either via using or requiring) players' physical movements (exertion) that is generally more than sedentary and includes strength, balance, and flexibility activities" [69]. Please note that this definition includes location-based games that do not explicitly require strength, balance, or flexibility. A subset of these games, mobile exergames, are defined in this thesis as exergames that are not tied to a traditional desktop computer or stationary device. In this section, we will discuss exergames, focusing on a mobile context.

Sinclair, Hingston, & Masek provide a thorough motivation for exercise games [53]. There is a rising epidemic of obesity, often caused by poor eating habits and lack of exercise. Their review of the literature suggests that exercise is the "best, safest, and most effect way to prevent obesity" [53]. As well, electronic sources of entertainment, such as TV, Internet, and videogames, consume a large amount of children's time. Encouraging children to make healthy lifestyle choices is important for combatting obesity, as it can establish early lifestyle habits.

Mobile devices have many unique advantages for exercise games. By not being constrained to a single location, experiences can vary to help keep user interest. As well, the sensing options in modern smart phones are very powerful (as we will describe in Section 2.2), and lend themselves well to pervasive games played in day-to-day life. Finally, mobile exergames provides an exciting opportunity to add interactivity to outdoor activities.

Location is often used in mobile exercise games, with sensing typically done by

GPS. Jensen et al. developed a location-based game called PH.A.N.T.O.M., which uses GPS to identify a users' location; the user then interacts with the game to complete a military-themed mission [28]. This is similar to Geocaching, a popular activity of hiding items in locations around the globe, and having other people use a shared service to find items or hide their own [23]. Another location-based game is Stanley et al.'s PiNiZoRo, a GPS-based game designed for families that allows non-programmers to provide their own scenarios, or "quests", to the game [57]. Sensing can also be done by wifi access points, as in Bell et al.'s "Feeding Yoshi" game [3]. By using location to provide input to games, users can be encouraged to walk (or even jog or run) more; simply increasing step count can provide overall health benefits [7].

Heart rate is another common input modality to exercise games. Wylie and Coulton implemented the classic game Space Invaders on a mobile phone, modified to include random bonus stages that required a certain heart-rate to pass [66]. These stages would provide a bonus to the player, such as a shield or bomb powerup in the game. The authors recommended a direct link between the level of exertion and the bonus received for this style of exercise game. Sinclair et al. second this notion of intensity with the concept of game flow: by balancing the intensity of the workout with the user's level of fitness and including proper warm ups and cool downs, they suggest that games can be more engaging to the user [53]. Stach et al. also looked at using heart rate as input, but scaled it to balance games for players of different fitness levels [56].

Davis et al. combined both heart rate and location as input in *'Ere Be Dragons* [13]. *'Ere Be Dragons* constructs a digital world based on the user's real-world location (detected by GPS). In this world, the landscape flourishes when the user's heart rate is elevated, and is impoverished otherwise (similar to UbiFit's garden representation [10]).

Accelerometers are also a powerful method of input for exercise games via gestures, overall activity level, or (less commonly) gait analysis. Fujiki, Kazakos, Pavlidis, Levine, and others developed NEAT-O-Games (NEAT meaning Non-Exercise Activity Thermogenesis) [20, 21, 32]. Their goal was to increase "energy expenditure of all physical activities other than volitional sporting-like exercise," such as moving around to do chores [20, 32]. They created simple games that used

hip-mounted external accelerometers to infer an overall physical activity level. They developed two main games: NEAT-o-Race and NEAT-o-Sudoku [20, 21]. Two studies suggest that people might adopt these games and exercise more with them, but further study is needed [32].

However, at the time of this writing there are no exercise games that use gait as an input modality; that is, no exercise games directly take into account *how* the user is moving. Previous work has focused on non-mobile (*i.e.*, situated) contexts. Stach et al. classified existing exergames (or "active games") into a set of *abstract inputs*: gesture, stance, point, power, continuous control, and tap [55]. Brehmer et al. then developed a toolkit to handle all these types of inputs [4]. Their General Active Input Model (or GAIM) toolkit allows programmers to specify interactions with these abstract inputs rather than deal with individual hardware. Although some aspects of gait can be fit into these abstract specifications, emphasis was on non-mobile input techniques. Hardware types include accelerometers (mostly for gestures), cameras, ergometers (*e.g.*, stationary bicycles and other resistance devices), pressure sensors, and touch sensors. We believe that gait analysis techniques provide a unique means of input for future exercise games.

2.1.3   Mobile Context-Aware Applications

Accelerometers have been used for sensing context other than gait, such as the wearer's manner of transportation, the device's carrying location, or remote health monitoring.

Froelich et al. developed a similar application to UbiFit, designed to keep users aware of their traveling habits and aid those who want to environmentally-friendly modes of transport [18]. An ambient display showed either a tree or a family of polar bears, and as more green options were chosen the displays become more lush and environmental. Vehicle transportation was detected by location change via GSM cell towers, but the type of vehicle could not be inferred: participants self-reported their methods of transportations after transportation was completed. Automatic sensing of the means of transportation could be valuable for this. They also used the MSP (mobile sensing platform) to distinguish sitting, standing, walking, running and cycling activities, but participants did not like wearing an additional

sensor. This suggests that using an everyday mobile device for sensing might be more accessible for end users.

Biometric data, including gait information, can also be used as a security measure for mobile devices. Briggs and Olivier suggest a "Biometric Daemon", a robot pet or partner that has a one-to-one relationship to a user, which can be used for authentication or mediation in work or personal matters [6]. Tamviruzzaman et al. propose a method to use location and gait features to infer the current user of a mobile phone [59].

Remote health monitoring, sometimes subsumed under the term "eHealth", provides a means to help risk detection or aid rehabilitation. Zheng et al. used accelerometers as part of a comprehensive remote health monitoring environment [71]. Their present prototype uses accelerometers to measure gross levels of activity, such as walking around the house, standing, sitting, and lying. Worringham, Rojek, and Stewart used GPS-based speed, GPS-based location, single lead electrocardiograph (ECG), and heart rate monitor for recovering cardiac patients [65]. Remote monitoring is an increasingly important application area, and gait sensing can be a part of that.

Komninos, Wallace, and Barrie detected step count to help infer user affect (*e.g.*, an agitated user might walk more quickly) [35]. They endeavored to make this more robust by detecting a mobile device's location-on-person, but were only able to distinguish between a trouser pocket and one of 4 jacket pockets. However, they showed that if this knowledge was gained, step detection could be improved dramatically. Dornbush et al. use a number of mobile sensors, including accelerometers, to classify songs for users based on their context [15].

2.1.4 Positioning this work in the application space

Mobile sensing techniques are a strong method for providing novel interactions for exercise applications, exergames, and context-aware applications. We propose to extend this work in two fundamental ways. First, we plan to investigate a number of gaits suitable for these varied application areas. As a compelling domain, we will focus on exercise applications and games. However, by looking at a variety of gaits previously uninvestigated, we will gain valuable insight into the general

capabilities of mobile sensing platforms for mobile context-aware applications.

Second, mobile devices are able to provide compelling pervasive applications. They can be used in the background of everyday life, making them more accessible than non-mobile exercise equipment or computers. However, mobile devices can be carried in many different ways. Previous sensing approaches, discussed in Section 2.2, often require knowledge of the mobile device's carrying location and orientation. We aim to study gait analysis in a way that makes it robust to carrying location and orientation, and thus able to operate in the background without requiring a particular carrying location. As well, given our primary domain of exercise applications and games, and to allow for interactive context-aware applications, we are focusing on real-time sensing[1]. We should note that we are focusing on cyclic motions, not ephemeral movements (such as the foot gestures in [52]).

2.2 Real-Time Mobile Gait Analysis

Because of the wide variety of application areas for mobile gait analysis (described in Section 2.1), there is a large body of work conducted on gait analysis using accelerometers. In this section, we describe the related body of work used to analyze gait using methods that can work in real-time or robustly in the wild. In Section 2.2.1, we describe previous work related to detected footsteps and cadence estimation in real-time. In Section 2.2.2, we describe previous work related to classifying gait or physical activity in real-time. In Section 2.2.3, we describe related work on other application areas, including individual identification of users through gait. Finally, in Section 2.2.4, we discuss the role that carrying location plays in these algorithms.

2.2.1 Step detection and Cadence Estimation

Step detection and cadence estimation are powerful tools. However, it can be difficult to develop a robust method: pedometer accuracy can vary by age, weight, BMI, and (most powerfully) walking speed [43], and by carrying location (as we

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[1]With the problem of gait detection, real-time sensing is defined as follows: given a sensing task for a time t, we have only knowledge of the past and present (data for $t' \leq t$), and a desire to calculate with a delay on the order of seconds. Exact acceptable delay time depends on application.

show in Chapter 3). Though robustness remains a challenge, Melanson et al. found that pedometers in a fixed location can be quite accurate [43]. In particular, piezo-electric pedometers perform better than spring-loaded pedometers, achieving 97% accuracy with walking speeds of 1.8-2.0 miles per hour (MPH). The most accurate published cadence estimation method on a mobile device uses a step-detection method with chest-mounted accelerometer in a known orientation [47]. Elliott & Tomlinson provide a prototype "PersonalSoundtrack" that matches music to the users' current walking pace [16]. As well, Nishiguchi et al. showed that smartphone accelerometers can produce gait parameters similar to external accelerometers [46]. They attached an external accelerometer to a smartphone, and compared the results of gait parameters calculated from the two signals. Gait parameters were found to be consistent between the two devices, lending credibility to smartphone accelerometers as sensors. It is worth mentioning that one of the gait characteristics, peak frequency, was found using a frequency-based approach. We also use a frequency-based approach in our cadence estimation algorithm, RRACE (see Section 3.1), although we use different filtering and numerical procedures to accomplish this.

Though smartphone accelerometers were found to be valid sensors, we encountered major barriers in *accessing* them through the smartphone operating system; see Section 4.4.2 for a discussion. The main consequence of these barriers is a variable sampling rate, which we accommodate in our algorithms. To our knowledge, this has not been discussed in any detail in the literature (though Nishiguchi et al. briefly mention the use of interpolation to handle this in [46]).

2.2.2 Activity Detection and Gait Classification

Gait analysis is a complex field, bridging kinesiology, engineering, artificial intelligence, and human-computer interaction. Here, we limit our discussion to works relevant to robust or pervasive activity detection and gait classification via accelerometer signals, with a focus on real-time analysis for an interactive system.

Statistical features are often used for activity detection. Figo et al. discuss preprocessing techniques for using mobile sensors for context-aware applications [17]. They classify preprocessing techniques into three domains for work: the time

domain, the frequency domain, and discrete representation domains. In both the time and frequency domains, algorithms can use basic descriptive statistics, such as mean, median, variance, standard deviation, minimum, maximum, correlation, and cross-correlation, or other mathematical functions, such as the signal-magnitude area (SMA) or the DC component of frequency. Discrete representation domain analysis involves symbolic string based algorithms such as the Levenshtein distance and Dynamic Time Warping (DTW).

Most analyses with a smartphone or single inertial mass-unit (IMU) have a known location or orientation. Huynh and Schiele looked at the best features and window size[2] needed for activity detection of 6 activities: standing, walking, jogging, skipping, hopping, and riding a bus [25]. They gathered 200 minutes of data from two participants with a multisensor on a backpack strap, and determined the best feature and window size for each activity. Features were always a frequency spectrum band. Best window sizes by activity were: hopping 4s, skipping 2s, jogging 1s, riding bus 1s, walking 1s, standing 0.5s. Classification results varied depending on activity; hopping and walking performed the best (F-scores not reported, but graphically look like they resemble 90%), while the other activities performed more poorly. They suggest that unequal sample sizes for activities might influence the results.

When contextual information about the phone (such as the phone's orientation) is not known, it can sometimes be inferred. Kawahara, Kurasawa, and Morikawa (2007) used a manually created rule-based system to infer phone location and orientation, and then used this information to classify activity for a exercise coaching system [31]. Training on three subjects and testing on a fourth, they achieved between 96.7% to 100% accuracy of four activities (sitting, standing, walking, and running), and 97.4% to 98.7% accuracy for three locations: pants, chest pocket, and bag (trained on a variety of bags brought by subjects). One notable technique in their approach is the use of events to help select locations - for example, if someone leaned forward in a chair, it would help infer the chest pocket location. Their accelerometer sensor, attached to a mobile phone, read samples at 20 Hz. Window sizes varied depending on features. 10 minutes of data was collected from each

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[2]A *window* is a subsection of a signal, which is used for calculating features. The window size is the length of such a subsection.

subject.

A hierarchical classification considering carrying location improved classification [33]. Khan et al. found that, by dividing their classifier into recognizing resting activities at all locations, dynamic activities at upper body locations (breast pocket, inner jacket pocket), and dynamic activities at lower body locations (left front trouser pocket, right front trouser pocket, and rear trouser pocket) improved classification from 58.7% to 94.4%. The activities detected were resting (sitting/standing/lying down), walking upstairs, walking downstairs, walking, running, cycling, and vacuuming. They used 8 subjects with a minimum of 2 minutes per location/gait/subject combination, extracting features from 1 second windows.

Zhang et al. also used a hierarchical classification based on motion [70]. Their algorithm uses manually tuned thresholds of acceleration change to detect whether the subject is moving or not, then uses an support vector machine (SVM) classifier to classify the activity into one of three non-moving activities (sitting, standing, lying down) or one of three moving activities (walking, posture transition, and gentle motion). This improved performance from a naïve SVM classifier on all 6 activities from a mean of 63.8% to a mean of 82.8%. The algorithm was trained on one subject, then tested on 10 subjects (including the training subject). Though they also assumed perfect detection of motion vs. no motion, this suggests that hierarchical algorithms based on gait sets can improve performance. Their algorithm ran on a single mobile phone attached to the belt in a horizontal orientation.

Iso & Yamazaki used the Kohonen self-organizing map (KSOM) on features extracted with wavelet packet decomposition, resulting in 80% accuracy for gait classification [27]. Robustness was achieved by generating pseudodata through rotational transformation of their original data. Evaluation was with only two subjects but with phones located in the breast pocket and the hip pocket.

So far, the most robust system has been presented by Yang [68]. By estimating the gravity vector, Yang was able to separate motion into vertical and horizontal components of the gravity plane. Analysis achieved 88-90% accuracy on sitting/cycling/driving/running/walking/standing with a 10s window. The system was trained on three subjects and tested on a fourth; there were approximately 10-30 minutes per activity of data, with no knowledge about orientation or carrying location.

In summary, gait classification approaches on cell phones have achieved high accuracy (90%), which is suitable for our application areas. We must note that methodologies vary considerably between studies, with different data windows (often longer than ours), a large amount of training data (a larger amount than we collect, as we aim for rapid collection of data to facilitate experimentation with the analysis of novel gaits), whether or not classification is done in real-time (our work strives for real-time classification), and the number of subjects involved in a study (often very small numbers; we collect data from 12). See Chapter 4 for more information on our methodology, and Table 2.1 for a summary table of the work in this section.

Table 2.1: Overview of related work for real-time activity detection and gait classification with data from smartphones or loosely-carried accelerometers. Please note that this table is intended to highlight the most prominent features of these works, but there are additional differences in classification strategy, extracted features, signal processing, and methods for calculating accuracy. Please see the text for these details.

Publication	Collected Data	Locations Considered	Activities/Gaits	Accuracy
Khan et al. 2010 [33]	2+ minutes per data cell for each of 8 subjects	5: breast pocket, inner jacket pocket, and left, right, and rear trouser pockets	7: resting, walking upstairs/downstairs, walking, running, cycling, and vacuuming	94.4%
Zhang et al. 2010 [70]	2 hours overall for 10 subjects	1: belt (horizontal orientation)	6: sitting, standing, lying down, walking, posture transition, and gentle motion	82.8% (trained on 1 subject, tested on all 10)
Yang 2009 [68]	10-30 minutes per gait for each of 4 participants	N/A: freely carried	6: sitting, cycling, driving, running, walking, standing	88-90% (trained on 3, tested on 4th)
Kawahara, Kurasawa, & Morikawa 2007 [31]	10 minutes from each of 4 subjects	3: pants, chest pocket, and bag	4: sitting, standing, walking, and running	96.7% to 100% (trained on 3, tested on 4th)
Iso & Yamazaki 2006 [27]	15 minutes per gait for each of 2 subjects	2: breast pocket and hip pocket	5: walking, going up-/down stairs, walking rapidly, and running	80%
Huynh & Schiele 2005 [25]	200 minutes overall for 2 subjects	1: backpack strap	6: standing, walking, jogging, skipping, hopping, and riding a bus	90%

2.2.3 Gait-Based Individual Identification

A highly related area to gait classification is gait-based individual identification. As mentioned in Section 2.1.3, discerning a device's user by gait has been proposed as a means for security or personalization [6, 59]. We review robust methods for this style of sensing here. Although a different problem from cadence estimation or activity detection, we can draw from their efforts to be robust to different gaits, carrying locations, and orientations.

Previous efforts have been quite successful at identifying a user based on the output of smartphone sensors. Sprager and Zazula used principal components analysis (PCA) with a support vector machine (SVM) with cumulants (higher order statistics similar to moments) as features to achieve an average of 90.8% accuracy when identifying 6 individuals walking at 3 walking speeds: slow, normal, and fast [54]. However, the phone was in a known orientation and location for all participants: the cell phone was affixed at the hip in a landscape orientation. Gafurov and Bours recently examined 100 subjects using a "natural walking style" with a template matching system, and achieved an identification rate of 81.4% [22]. Again, location and orientation of the accelerometer was known. Although many locations, such as shoe, pocket, wrist, waist, and hip, have been examined by themselves previous work, we are unaware of any who has investigated location [22].

Kobayashi, Hasidi, and Nobuyuki Otsu worked on developing a rotation-invariant feature set by using an autocorrelation matrix of the frequency spectrum [34]. This was used for individual gait identification with 58 subjects as they walked freely in daily life, and was able to work with approximately 49% mean accuracy. However, the phone was held in a single location - the hand. This again suggests that robust sensing given different orientations and carrying locations is a challenging problem.

2.2.4 The Role of Location

A major shortcoming of most gait analysis approaches is that they are rarely robust to carrying location. In 2007, Cui, Chipchase, and Ichikawa conducted a cross-cultural study on mobile phone carrying locations and personalization [12]. Through a series of street interviews in 11 cities on 4 continents, they discovered

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that people carried phones using a variety of methods. These were coded into the following categories: bags, trousers/skirts, belt case/clip, upper body, hands, neck, "not with me", and for 1.97% of men and 6.11% of women, "other". The researchers tabulated reasons for the various carrying locations; the majority of users (67.34%) chose their carrying location based on "instrumental" reasons, such as: ease of carrying or fetching their phone, detecting notifications, or security of the phone. Cui et al. also found that the detection rate of phone notifications varied by position, and catalogued reasons for personalization of phones, such as through custom cases, straps, or stickers.

Some researchers have considered carrying location in their analysis of IMU sensors. Kunze et al. used the magnitude (Euclidean norm) of accelerometer sensors to detect different locations on the person [36]. Accelerometers were affixed to four locations (head, breast, trousers, and wrist) using a strap. Classification was conducted using a one second sliding window to detect whether the subject was walking, and if so, to detect location. Using non-real-time analysis, they were able to accomplish a precision of 100% for the detection of walking segments, however, no recall was reported. For real-time performance, they achieved their best performance by a C4.5 decision tree achieved accuracy of 69% - 95% (mean 82%). This was for a single gait (walking vs. not walking). Given that the user was walking, location detection was a mean of 89.81% accurate for 4 locations: wrist, head, left trouser pocket, and left breast pocket. Using non-real-time analysis and event recognition, they were able to achieve a precision (not accuracy) of 100%. Basically, they were reducing false positives as much as possible.

As mentioned in Section 2.2.2, hierarchical classification considering carrying location improved classification [33]. Khan et al. found that, by dividing their classifier into recognizing resting activities at all locations, dynamic acitivities at upper body locations (breast pocket, inner jacket pocket) and dynamic activities at lower body locations (left front trouser pocket, right front trouser pocket, and rear trouser pocket) improved classification from 58.7% to 94.4%. The activities detected were resting (sitting/standing/lying down), walking upstairs, walking downstairs, walking, running, running, cycling, and vacuuming. They used 8 subjects with a minimum of 2 minutes per location/gait/subject combination. 1 second windows with no overlap were used.

Komninos, Wallace, and Barrie looked detecting a mobile device's carrying location, using it to improve an algorithm for step detection [35]. Unfortunately, they were only successful in differentiating between two sets of locations: trouser pocket, and jacket pockets. They did show that, if phone location was known, then step detection could be improved dramatically. However, they only used 3 basic features: mean, standard deviation, and the ratio between the two (as "intensity"). Thus, robust treatment of carrying location remains an open problem in gait analysis.

Chapter 3

Cadence Detection

> *My grandmother started walking five miles a day when she was sixty.*
> *She's ninety-seven now, and we don't know where the hell she is.*
> — Ellen DeGeneres

In this chapter we describe the development and validation of a novel real-time frequency-based cadence detection algorithm, RRACE, that is robust to carrying location and orientation. First, in Section 3.1, we describe this algorithm. Second, in Section 3.2, we describe the main data collection procedures as well as participant demographics. Third, we describe the implementation and tuning of a gold-standard time-based cadence detection algorithm in Section 3.3. We demonstrate that this time-based reference algorithm is sensitive to location-on-person and individual differences. We then show that the frequency-based algorithm is more accurate and robust to carrying location and individual differences by comparing it with best-case scenario tunings of the time-based cadence detection algorithm in 3.3.2. Finally, we discuss major results about RRACE's performance in Section 3.4, and then conclude with the summary of our findings and future work in Section 3.5.

As described in the Preface, this work is the result of a collaboration. As such, portions of the work are written to demonstrate the relative contributions of the author. Parts primarily done by other contributors (Section 3.1, Section 3.2.1, 3.3.2, Section 3.4) have been reduced but included for framing, while the author's main contributions are described in full. The full manuscript is currently being prepared

for submission to a peer-reviewed journal [30].

3.1 The RRACE Algorithm

Our cadence-detection algorithm, Robust Real-time Algorithm for Cadence Estimation (RRACE), performs a spectral analysis on a four-second window of sampled 3-axis accelerometer data. Our approach ensures that the algorithm is robust to orientation, and accommodates non-uniform sampling rate present to smartphones. RRACE accomplishes this with the following implementation details.

Supporting orientation-invariant information: To estimate overall movement from a triaxial accelerometer signal and to make it independent of orientation, we use the magnitude (Euclidean or ℓ-2 norm) of the three accelerometer axes, x, y, and z, as our signal, as in [38]. This is a simple solution for creating robustness to orientation, which we later show to be effective.

Accommodating Non-uniform Sampling (FASPER): Most smartphones supply accelerometer data that is not sampled at a constant rate, making the most common spectral analysis methods (such as the Fast Fourier Transform (FFT)) inappropriate. The Lomb-Scargle periodogram approach (also known as Least-squares spectral analysis) is appropriate for nonuniformly sampled data [40, 51].

In particular, the FASPER algorithm ("Fast Calculation of the Lomb Periodogram") [49] employs four parameters: the vector time series along, the time coordinate of each sample, an output gain (we used 0.25), and an oversampling parameter (controls resolution of the computed spectrum; we used 4.0). It computes the relative power for each of a discrete set of frequencies. The maximum frequency computed is the average Nyquist frequency scaled by the supplied gain [49].

RRACE uses FASPER to find the spectrum of the overall movement of the device. We report window cadence as the most powerful frequency in the spectrum. We define our algorithm's latency as half the window length (*e.g.,* a 4 second window has a latency of 2 seconds).

Android-Based Validation Platform: For our validation study, we used six Google Nexus One smartphones running Android OS version 2.3.4 (Gingerbread). Our

main application was implemented in Java, the most commonly used programming language for Android development. Numerical programming algorithms (including FASPER) were implemented in C for speed benefits and because of readily-available C implementations [49]. We used the Java Native Interface (JNI) to connect the two languages.

3.2 Cadence Study Data Collection

In this section, we describe the data collection for the Cadence study.

Apparatus: The experimental apparatus consisted of six Google Nexus One smartphones, an external GPS receiver connected to one of the phones via Bluetooth, our *reference* cadence measurement consisting of two FSR (force sensing resistor) sensors [26] connected to a Bluetooth-enabled Arduino board [2] to detect footfalls, two laptops (one main computer (a laptop) for logging trials and a second (a small netbook) to log footfalls sent from the Arduino board via Bluetooth), a stop watch, and two flags for experimenters to send timing signals to each other. The study required three experimenters to run.

Prior to the experiment, subjects were asked to wear pants with front and back pockets, but exact pocket locations were not controlled. The Arduino board and six phones were synchronized with the main computer at the start of the experiment. The GPS receiver, netbook and Arduino were put in the *bag*. The bag had a filled weight of approximately 2 kg. See Table 3.1 for general phone locations, which were chosen as the places people used most frequently for their mobile phones while commuting [12].

Trial Length and Speed Measurement: Our goal was to collect 20 seconds of walking data for each trial and compute average step frequency. We asked subjects to walk a known distance, either 30m or 60m (marked by small flags along the walkway), depending on whether 20 seconds had elapsed by the time the 30m point (first end time) had been reached (Figure 3.1). Timespan was manually recorded via stopwatch.
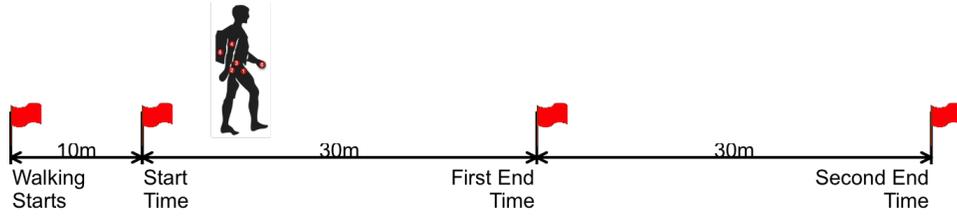
Figure 3.1: Experiment walkway, start and end points.

Table 3.1: Experiment design

Factor	Number of Levels	Factor Levels
Window Size	4	1, 2, 4, or 8 seconds
Body Location	6	*back pocket*, *bag (backpack)*, *dominant hand (held)*, *front pocket*, *hip (mounted on belt)*, *upper arm (mounted)*
Condition	5	*typical (0)*, *fastest (2)*, *leisurely (-2)*, *faster than typical (1)*, *slower than typical (-1)*
Repetition	2	first time, second time

3.2.1 Experiment Design, Metrics and Subjects

The design was within-subjects repeated-measures, with independent variables of *window size*, *body location*, and *speed condition* (Table 3.1). The five speed conditions and their repetitions (10 trials) were randomized. An indoor pilot study conducted on a treadmill indicated good performance for both 4- and 8-second windows; we added 1- and 2-second windows, to capture any possible advantage of lower latency and computational load.

Metrics and Analysis: In this first study, we assessed RRACE's accuracy by comparing it to our FSR-based reference (Section 3.2). Our primary metric was the "Error Ratio" or *ER*, defined as the ratio of RRACE's measurement "error" (the difference between the frequency measurement produced by RRACE, F_a, and the reference frequency, F_r) to the reference frequency F_r:

$$ER = \frac{|F_a - F_r|}{F_r} \tag{3.1}$$

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where

$$F_r = \frac{1}{T_{FSR}}$$

T_{FSR} =The median of the last three intervals of each of the two feet to filter errors caused by false positives (extra footfall detected) or false negatives (footfall missed).

We conducted analysis with Linear Mixed-Effects Models, using unpaired Z-test[1] comparisons for post-hoc analysis. We used a level of significance of $p = 0.05$, applying a Bonferroni correction to counteract the multiple comparisons problem. Note that we report differences between effect levels as z-scores, and because z-scores are normalized by standard deviation, differences between means in our analysis are analogous to Cohen's d statistics of effect size.

Subjects: Eleven individuals (6 female and 5 male), aged 21-30 years (mean=25.2, SD=3.3), 155-179cm tall (mean=165.9, SD=7.0), and weighing 46-80kg (mean=59.1, SD=10.0) volunteered. No subjects had physical impairments.

3.2.2 Results for Outdoor Validation of 4 Second Window RRACE

We chose the 4 second window RRACE as the baseline for our algorithm. Theoretically, 4 seconds is enough to detect a wide range of walking cadences; this was verified by our pilot study. To improve clarity of the results we divide the analysis into two parts: (a) first, we analyze the four second window RRACE and (b) then, we analyze the use of alternative window sizes.
Because the phones blacked out a few times during the study and we had missing data, for the analysis, we used Linear Mixed Effect Models which is robust to missing data.

Main Effects: Body location has a significant effect on *ER*. *Front pocket*, *belt*, *arm*, and *bag* (light-green box plots of Figure 3.2) are significantly more reliable than *back pocket* and *hand* (dark-red box plots of Figure 3.2). Walking speed also has a significant effect on *ER*; the slowest speed performs more poorly.

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[1]The Z-test is appropriate because of our large sample sizes; we calculate cadence every 200ms.

Interaction Effects: Interaction effects of both location / condition and of location / window size on *ER* are significant. *Arm*, *bag*, and *front pocket* are more consistent and remain below 5% under all speed conditions, with their minimum at the middle (typical speed). *Belt* produces the lowest Error Ratio at faster than typical speed, *back pocket* produces lower error ratios at higher speeds and *hand* produces lower error ratios at lower speeds (Figure 3.2).
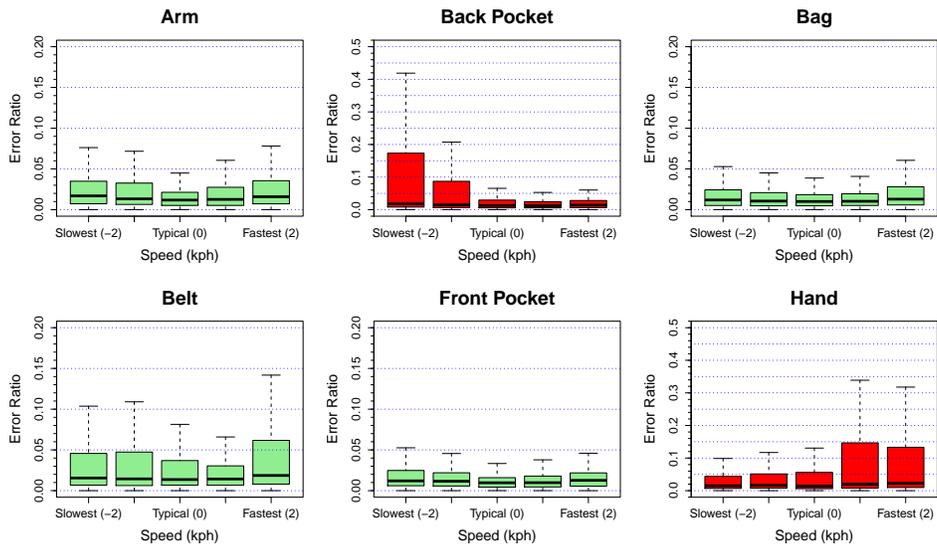
Figure 3.2: Error Ratio as a function of speed condition for 4-second window RRACE. Please note that dark-red boxplots have a larger range for Error Ratio and light-green boxplots have a smaller one.

Table 3.2: Error Ratio differences by body location for *four-second window* RRACE through an unpaired Z-test. The second column contains the mean Error Ratio of each body location.

Body Location	ER	Difference from				
		Front Pocket	Bag	Arm	Belt	Back Pocket
Front Pocket	0.028	-	-	-	-	-
Bag	0.031	not sig	-	-	-	-
Arm	0.036	0.003	0.001	-	-	-
Belt	0.055	0.022	0.020	0.014	-	-
Back Pocket	0.079	0.045	0.043	0.037	0.030	-
Hand	0.114	0.078	0.076	0.071	0.052	0.026

Table 3.3: Error Ratio differences by window sizes of RRACE , with walking speed and body location lumped. Window sizes are ordered by increasing *ER* mean.

Window Size	ER	Difference from		
		8 Seconds	4 Seconds	2 Seconds
8 Seconds	0.058	-	-	-
4 Seconds	0.058	not sig	-	-
2 Seconds	0.071	0.011	0.011	-
1 Second	0.115	0.054	0.054	0.041

Table 3.4: RRACE Error Ratio differences by body location for all window sizes and walking speeds (unpaired Z-test). Locations are ordered by increasing *ER* mean.

Body Location	ER	Difference from				
		Bag	Arm	Front Pocket	Belt	Back Pocket
Bag	0.041	-	-	-	-	-
Arm	0.048	0.005	-	-	-	-
Front Pocket	0.055	0.012	0.004	-	-	-
Belt	0.071	0.028	0.020	0.013	-	-
Back Pocket	0.105	0.061	0.053	0.046	0.030	-
Hand	0.128	0.083	0.076	0.069	0.053	0.019

3.3 Comparing RRACE with a Threshold-based Time-domain Algorithm

As described in Section 2.2.1, there are many commercial pedometers on the market, but most use proprietary algorithms that have not been released to the public.

We compared our frequency-based algorithm to MPTrain's algorithm [47]. MPTrain uses two low-pass filters. One removes noise in the original accelerometer signal, producing a smoothed signal; the second has a lower cutoff frequency, and its output is used as a dynamic threshold. Footsteps are detected when the smoothed signal crosses the dynamic threshold from above to below (Figure 3.3). Because the MPTrain accelerometer is required to be situated on the user's torso and oriented to detect accelerations in the superior-inferior axis (*e.g.*, *y*-axis), it detects footsteps on both feet. Foot falls are translated to instantaneous steps-per-minute (SPM) using the following formula:

$$SPM_i = (int)\frac{60.0 * SamplingRate}{\#SamplesSinceLastStep} \tag{3.2}$$

Finally, the MPTrain algorithm applies a median filter to the instantaneous SPM to calculate estimated SPM. The MPTrain study reported a constant sampling rate of 75Hz for accelerometer data, achieved by using an external chest-mounted device to capture the accelerometer signal. The authors report that the MPTrain algorithm is comparable to those found in commercial pedometers by [43], but provide no details on cadence accuracy.

3.3.1 Implementation of Time-based Algorithm for Comparison

We implemented a modified MPTrain algorithm. Since no implementation details were reported for either low-pass filter, and no window was given for the median filter, these elements had to be reconstructed. As well, we made other modifications to accommodate the variable sampling rate found in smartphones, and measured cadence in steps-per-second instead of steps-per-minute to compare it with RRACE. Because we measured steps-per-second, and to avoid rounding error, our value is a real number, and is not converted to an integer as in MPTrain's algorithm.

Time-Based Algorithm for Subject 10 - Arm
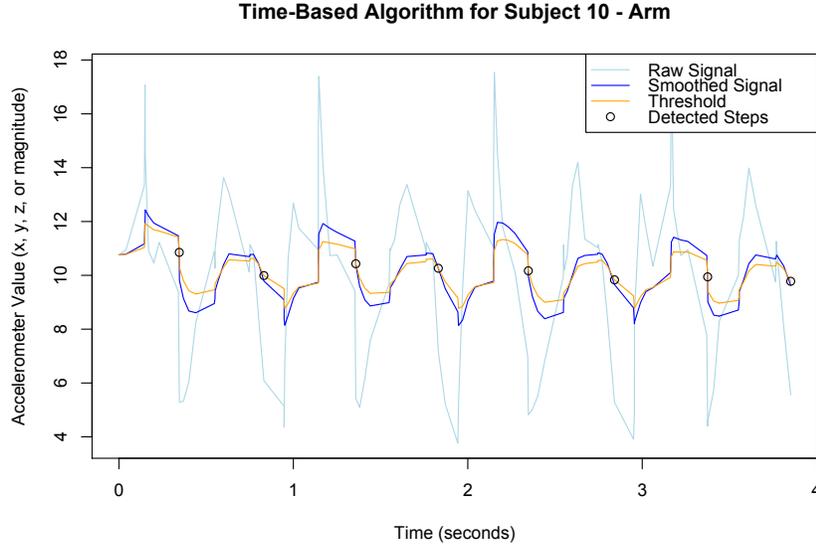
Figure 3.3: Example of the MPTrain time-based step detection algorithm

Finally, given that we do not have a sensor in a known orientation, we also consider each of four different axes in our analysis: *x*, *y*, *z*, and *mag* (the magnitude of the vector). Our implementation follows.

For efficiency and simplicity, we implemented low-pass filters as an exponentially-weighted moving average (EWMA). An EWMA is defined as follows:

$$S_i = \alpha x_i + (1 - \alpha)S_{i-1} \tag{3.3}$$

where S_i is the i-th smoothed (low-passed) value, x_i is the i-th raw accelerometer value, and α is the smoothing parameter (with $0 \leq \alpha < 1$). The two low-pass filters (for accelerometer data smoothing and dynamic threshold) employ two parameters, α and β (with $\alpha < \beta$). These parameters were tuned on our data, as described in Section 3.3.2.

As in the MPTrain algorithm, steps are detected when the smoothed signal crosses the dynamic threshold from above to below. The difference between step

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times is used to calculate instantaneous cadence by the formula:

$$1/CurrentDifferenceBetweenSteps$$

For example, if the two previous footsteps were detected at $StepTime_i = 100ms$ and $StepTime_{i+1} = 600ms$ and we wanted the instantaneous cadence at any time $t \geq 600ms$, the instantaneous cadence would be $1/(600 - 100) = 0.002$ steps per millisecond, or 2.0 SPS. Final cadence estimates were calculated by averaging each instantaneous cadence estimate with one previous estimate (*i.e.*, a 2-sample smoothing filter).

3.3.2 Training of the Time-based Algorithm

To compare the MPTrain time-based algorithm as favourably as possible to RRACE, we optimized the low-pass filter smoothing parameters α and β (Section 3.3.1) for several datasets involving different combinations of subjects and locations-on-person (LOP):

- All data (all subjects and LOPs): 1 set

- Each subject (over all LOPs): 11 sets

- Each LOP (over all subjects): 6 sets

- Each subject-LOP combination (e.g. Subject 1, Arm) minus 9 (missing data): $11 \times 6 - 9 = 57$ sets

We thus considered 75 parameterizations of the time-based algorithm in a thorough search to compare the time-based algorithm as favourably as possible to RRACE. During analysis, data was only scored on the dataset on which it was tuned. This was done to give a best-case scenario of tuning the algorithm for a certain individual and/or LOP, which could be the situation in real-world use cases with one individual using a personal device in a consistent way.

Within a dataset, we used a uniform search for the best combination of smoothing parameters (α and β) with a granularity of 0.05 (*i.e.*, $\alpha \in \{0.05, 0.1, ..., 1.0\}$ and $\beta \in \{0, 0.05, ..., 1.0\}$), one of the three axes or magnitude ($\gamma \in \{x, y, z, m\}$ where

$m = \sqrt{x^2 + y^2 + z^2}$), as well as four scaling factors ($\delta_{x,y,z} \in \{\frac{1}{2}, 1, 2, 4\}$ for individual axes and $\delta_m \in \{\frac{1}{4}, \frac{1}{2}, 1, 2\}$ for magnitude, which scaled the cadence estimated values to compensate for possible harmonics). The best of all these 20 αs $\times$ 20 βs $\times$ 4 axes $\times$ 4 δs $= 6400$ combinations for each dataset was determined by having the lowest mean squared *ER* by comparing to the FSR golden standard.

Analysis of Time-based Algorithm

We found it was not possible to train the time-based algorithm to work on all body locations and for all subjects with an Error Ratio below 5%; the best we could reach was $ER = 74\%$. The best time-based algorithm for all LOP on one subject achieved $ER = 18\%$, but this was a best case scenario and may not be achievable for all users.

We found that tuning the time-based algorithm for one best-case body location on all subjects was more feasible: it achieved $ER = 12\%$ for *bag*. If we tune the algorithm for one body location of each subject we may even get a lower error ratio; when tuned for Subject10's *arm* , the algorithm reached $ER = 7.8\%$ (Figure 3.4).

Comparisons with Frequency-based Algorithm

Figure 3.4 shows boxplots of Error Ratio of all the RRACE and time-based algorithm variants ordered by the median of Error Ratio (ER). We divided them into five categories: (a: green) 4 window sizes of RRACE and time-based algorithm trained on: (b: cyan) all subjects' body locations, (c: pink) all body locations of each single subject, (d: yellow) one body location of all subjects, and (e: grey) single body location of one subject.

Because it is unproductive to compare each of these algorithms with the rest, we have chosen the best of each category in addition to the worst-case RRACE variant (one-second window) which are marked red on Figure 3.4. This is a highly conservative comparison which tends to favor the time-based algorithm. We used the same data for verification of each time-based algorithm that was used for their training and secondly, the Error Ratio of all versions of the frequency-based algorithm is measured across all body locations of all subjects. RRACE was not trained or tuned in this comparison.

All Algorithms
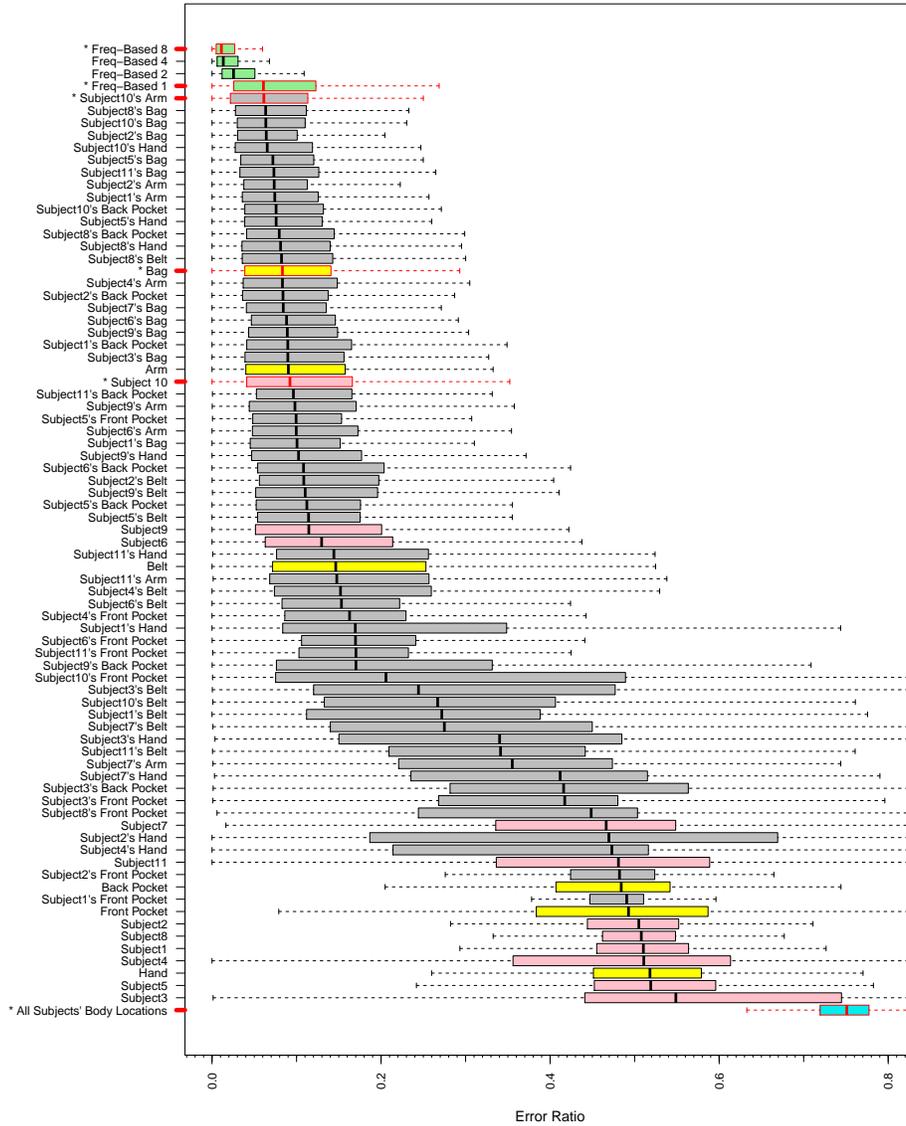
Figure 3.4: Error Ratio, ordered by median, of (a: green) 4 window sizes of RRACE (first four) and time-based algorithm trained on: (b: cyan) all subjects' body locations (last one), (c: pink) all body locations of each single subject, (d: yellow) one body location of all subjects, and (e: grey) single body location of one subject.

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Table 3.5: Unpaired Z-test comparison of error ratios of the best and the worst versions of the frequency-based algorithm and the best of each category of time-based algorithm. Algorithm variants are ordered by increasing *ER* mean.

Algorithm	ER	8-Sec RRACE	Subject10's Arm	1-Sec RRACE	Bag	Subject10
		Difference with				
8-Sec Window RRACE (a)	0.058	-	-	-	-	-
Subject10's Arm (e)	0.078	0.012	-	-	-	-
1-Sec Window RRACE (a)	0.115	0.054	0.029	-	-	-
Bag (d)	0.119	0.055	0.032	not sig	-	-
Subject10 (c)	0.179	0.102	0.081	0.046	0.040	-
All Subjects' Body Locations (b)	0.735	0.675	0.650	0.618	0.609	0.537

Thus, the single "fair" comparison is between either version of RRACE (colour green in Figure 3.4), and the time-based algorithm trained on *all* subjects and *all* body locations (colour cyan in Figure 3.4). Table 3.5 summarizes these comparisons. Unlike Figure 3.4 where entries are ordered by median, the algorithm variants here are ordered based on mean, therefore subject10's *arm* which came after the 1-second RRACE comes before it in this table.

3.4 Discussion

The goal of this research was to develop a cadence measurement algorithm for mobile phones equipped with accelerometers that is robust and works out-of-the-box with an Error Ratio of 5% or less (comparable to Yang et al.'s *waist-mounted* cadence measurement device [67] and *MPTrain* of Oliver & Flores-Mangas [47]). First, we will review the nature of RRACE's error, its performance on different body locations and robustness to subject differences, and compare it with the time-based algorithm. Then we will examine its main weakness, and finally we will discuss the best choice for window size.

3.4.1 The nature of RRACE's Error

Our data shows that very few outliers with extremely large or small values are responsible for some of the error in RRACE's readings. We believe there are two types of outliers: (a) random readings as a result of irregularities in the signal, and (b) harmonic readings which happen when the main frequency component gets smaller than its harmonics. These outliers may be avoided by filtering the outcome of RRACE. The rest of the error is caused by hardware measurement error and delay from the 4 second window.

3.4.2 RRACE Performs Best with the Arm, Bag, Belt, and Front Pocket Locations

Based on our experiment, four body locations contain enough information for RRACE to make accurate cadence estimations: *arm*, *bag*, *belt*, and *front pocket*, with Error Ratios ranging from 3%-5%. By this criteria, RRACE works (*i.e.*, can access sufficiently consistent motion to meet this *ER*) at four out of six body locations, with negligible difference among these. Front pocket was the body location most robust to speed change. Note that, even though RRACE performs poorly with *back pocket* and *hand*, it still performs better than the time-based algorithm did at these locations.

In contrast, the time-based algorithm was highly sensitive to body location. It was almost impossible to tune the time-based algorithm for three of the body locations, *front pocket* among them. That is, for three body locations (*front pocket*, *back pocket*, and *hand*), the time-based algorithm could *not be tuned* to perform well; for the other three (*arm*, *bag*, and *belt*), the time-based algorithm can perform well (with a lowest *ER* of 11.5%), but requires knowledge of and tuning for the particular location. The body location with the lowest *ER* is *bag*, but its *ER* of 11.5% is still almost double the Error Ratio of the 8-second and 4-second window RRACE.

3.4.3 RRACE is Robust to Subject Differences

As discussed in 3.3.2, the time-based algorithm was very sensitive to subject differences; it could not be trained to work on all body locations of all subjects, and

when trained on single body locations $ER = 12\%$ was the best result which could only be achieved for *bag*. RRACE worked for all of our subjects with no prior tuning to compensate for subject differences with much lower *ER*.

3.4.4 RRACE Window Length of 4 seconds is Best:

Our results showed that highest accuracy (lower error ratio) is achieved at larger window sizes. The difference in Error Ratio is substantial for 1 vs 2-second windows, and for 2 vs 4-second windows, but not for 4 vs 8-second windows. A 4-second window size seems the ideal length among our candidates as a compromise between responsiveness and accuracy.

3.4.5 RRACE is Sensitive to Very Slow Speeds

Our outdoor validation results showed that, like other pedometers, RRACE is sensitive to speed. The highest Error Ratio belongs to the slowest speed with $ER = 6.3\%$. We attribute this worsened performance to two possible causes:

(a) At lower speeds, walking cycles take longer and fewer cycles are captured in a fixed window size. This weakens RRACE. Mitigation requires use of a larger window size, *e.g.*, by dynamically changing the window size to fit the speed.

(b) The kind of walking performed by our subjects becomes less autonomous and more irregular when they are asked to walk at very low speeds, especially because users can easily choose to walk as slowly and irregular as they want, while at high speeds step interval is bounded by subject's physique.

The time-based algorithm is less affected by walking speed because it just detects single steps, no matter how irregular or distant from each other they are. Thus one practical approach might be to shift to a time-based algorithm when low speeds are detected.

3.5 Conclusion and Future Work

In this paper we introduced a new algorithm for measuring cadence from accelerometer data from smart phones, called RRACE. We also presented an experiment design for verification of our algorithm. Our validation study showed that RRACE performs well under different speed conditions, providing 5% or lower

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error for four of the six common body locations examined: *front pocket*, *bag*, *arm* and *belt*, consistent with previous work in a single location [67]. Our algorithm was also robust to orientation and subject differences, and thus can be said to work 'out of the box', without requiring calibration or parameter tuning. RRACE's primary weakness is a drop in performance for slow and irregular walking.

We compared RRACE with a state-of-the-art published time-based algorithm which we tuned in every way possible. Our highly conservative comparisons show that RRACE is substantially more accurate than the time-based algorithm tuned for any subset of the data. Our data suggests that RRACE is also superior to the time-based algorithm in terms of independence from body location and robustness to user differences. The exception is for very low and/or irregular speeds; these are situations which may not be considered walking in most applications of a cadence detection method.

As well, our algorithm provides general guidelines for window size and robust spectral analysis. This information can be used to inform solutions to more complex real-time gait analysis problems, such as activity detection for fitness or rehabilitation applications, or individual gait identification for mobile security. A discussion of its use for these purposes is available in Chapter 5.

Our algorithm can be improved in several respects: (a) Reduce estimation outliers by using smart filters which will increase the accuracy of our algorithm even more; (b) Insert an algorithmic step that adjusts window size based on current cadence, to optimize the accuracy/responsiveness tradeoff; (c) Employ cadence to measure other useful information about gait such as stride length and type of gait. As well, one limitation of our analysis is the comparison with a threshold-based time-domain algorithm, which does not consider autocorrelation-based algorithms; future work is planned to compare RRACE with this approach.

Chapter 4

Gait Classification Data Collection

> *Well sir, I have a silly walk and I'd like to obtain a Government grant*
> *to help me develop it.*
> — Eric Idle, Monty Python's Flying Circus

Cadence estimation provides a promising means for exercise and fitness applications, but it is only one aspect of gait. Previous work with pedometers shows that a single gait parameter is not enough for applications encouraging physical activity [9]. Inferring higher-level activities and gaits lends itself to a host of new applications, including fitness journals and novel interaction modalities for exergames.

In this chapter, we describe the gait data collection methodology and summary results, to be used for a gait classification algorithm described in Chapter 5. First, in Section 4.1, we report our methodology for selecting a set of gaits suitable for this study and the established application space, described in Table 4.1. We then describe the Android-based data collection application, GaitLogger, in Section 4.2, and our study procedure in Section 4.3. Finally, we summarize the collected data, including demographics and data quality, in Section 4.4.

4.1 Gait Selection

In order to inform gait as input for mobile exercise applications and exercise games, we wanted to explore a wide variety of gaits. Previous work, surveyed in Section 2.2.2, has investigated 2 to 6 distinguishable gaits, often relevant for context-aware applications. We had four primary goals: (a) to push boundaries for context-aware applications, investigating gaits that were similar (such as distinguishing jogging from running); (b) to explore novel gaits suitable for exercise applications, by involving different muscle groups; (c) to explore novel gaits that could be easily linked by metaphor to a child-friendly exercise game, such as marching like a soldier or walking on a tight rope; and (d) to connect modes of travel involving varying levels of physical activity, such as cycling or rollerblading. These four goals informed the generation of our gaits; as such, our target gaits were divided into four *gaitsets*, sets of gaits grouped by their relationship to our four goals. Because of this emphasis on unorthodox gaits, we wanted data to be collectible in a quick and practical manner, both in our data collection and in target application spaces. We hope to support iterative development and experimentation in games or other interactive applications; this has the added benefit of facilitating personalization of our algorithms.

With this in mind, we developed a set of gaits suitable for an exercise or context-aware game or application. After piloting, we retained 15 gaits organized into three gaitsets (*Pedestrian*, *Exercise,* and *Game*) corresponding to our first three goals; for scope and logistical reasons, our fourth goal of travel methods (the would-be *Locomotion* gaitset) was considered but left to future work. Exploring 15 gaits allowed us to collect 30 seconds of each gait easily within 20 to 30 minutes, without exertion being a problem for participants (some gaits, such as twofoothop, can be physically demanding when maintained for 30 seconds). To limit scope, all gaits had to involve directional movement and be bipedal - that is, we did not allow in-place activities like jumping jacks or walking on hands and knees. Our gaits are described in Table 4.1.

The final list of 15 gaits were refined during piloting from a longer list of brainstormed gaits. We discovered during initial brainstorming that some gaits were consistently interpreted by participants (*e.g.*, walking on heels, walking like a pen-

Category	Label	Verbal description
Pedestrian	walk	Walk normally
	fastwalk	Walk quickly
	jog	Jog, *if asked for clarification:* slow run
	run	Run, not necessarily a flat out sprint, but a run
	ascendstairs	Walk up the stairs as you normally would until you reach the top
	descendstairs	Walk down the stairs as you normally would until you reach the bottom
Exercise	toes	Walk on your toes
	heels	Walk on your heels
	liftknees	Walk while lifting your knees high in the air
	kickingbum	Walk while kicking your bum. You don't actually have to hit it, but do that motion
Game	twofoothop	Hop with two feet
	penguin	Walk like a penguin
	narrow	Walk as if on something narrow, like a tightrope
	walkbackwards	Walk backwards
	walksideways	Walk sideways

Table 4.1: Gaits and descriptions used in our data collection study

guin) but others were not (*e.g.*, skipping, walking like a zombie). To facilitate our user study and allow for a robust application, we decided to only use gaits that were consistently interpreted by a simple verbal or written description. That is, a user could read an instruction from a smartphone application and understand the movement. We are thus directly measuring participants' interpretation of several gaits, important for a game or application to be distributed to a wide audience. This would also reduce any bias from the experimenter demonstrating a gait, and avoided logistical and possibly biased approaches of giving diagrams or videos of each gait. To accomplish this, many gaits were combined, dropped, or had their description refined through iterative piloting. A longer list of explored gaits, including our gaitset descriptions used during brainstorming and piloting, follows. This list includes the would-be Locomotion gaitset that was dropped after brain-

storming.

- "Pedestrian" - Everyday walking suitable for context-aware applications. These would be suitable for supporting interior GPS or casual exercise applications. In this gait subset we stressed a gradient of similar gaits to expand upon previous work on context-aware applications. "Pedestrian" gaits include:

  - Walking
  - Walking quickly
  - Jogging/slow run
  - Running
  - Ascending stairs
  - Descending stairs

- "Exercise" - Gaits that exercise different leg muscle groups, inspired by plyometrics, warmups, and stretches. Because numerous exercise movements exist, we chose ones that would exercise different muscle groups, and heavily used our scoping criteria of bipedal, directional movement."Exercise" gaits include:

  - Walking on toes
  - Walking on heels
  - Walking while lifting knees high in the air
  - Walking while kicking bum
  - Squat walk
  - Lunges
  - Walking sideways (either grapevine or shuffle)

- "Game" - Gaits that are exciting for kids and suitable for exercise games. These might resemble iconic characters such as zombies, gaits already associated with children's games such as skipping, or abstract motions for which

metaphors are easily developed such as hopping (can easily be tied to being an animal, such as a frog or kangaroo). "Game" gaits include:

- Hopping on two feet
- Walking backwards
- Walking like a zombie
- Walking or marching like a soldier
- Skipping
- Tip toeing or sneaking
- Walking on a tightrope
- Walking on something narrow

As well, we developed one category of gaits that are not necessarily bipedal, but important to our application area:

- "Locomotion" - Not necessarily bipedal, but in the same spirit, locomotion gaits are methods of movement that involve vehicles or other devices. These gaits are also closely related to context-aware applications and previous work. "Locomotion" gaits include:

  - Cycling
  - Riding a skateboard
  - Rollerblading
  - Riding on a bus
  - Driving or riding in a car

During the study, we were careful to stick to the developed descriptions. When the participant asked if they were doing the gait correctly, we responded with a "Yes" regardless of what they were actually doing. Inquiries about misunderstood words (such as asking whether the heel was the front or the back of the foot) were answered concisely. On one occasion, a participant understood "jog" to be the same as "walking quickly". This was the only situation in which we asked them to repeat the gait; in this case, asking them to do a "slow run". The same researcher ran all participants.

4.2 GaitLogger

Figure 4.1: GaitLogger main screen
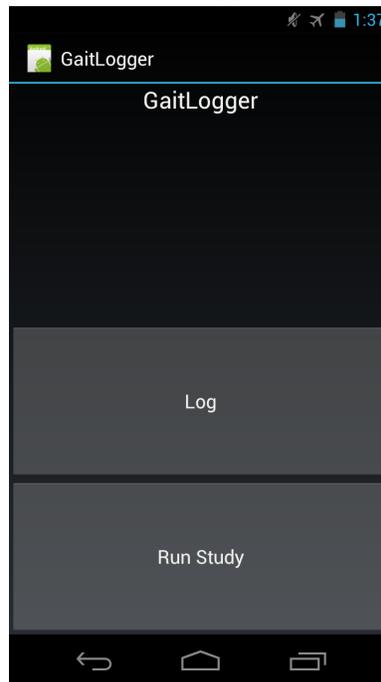
To collect data, we developed an Android application, GaitLogger (Figure 4.1). GaitLogger was developed in Java 1.6 using the Software Development Kit (SDK) for Android 4.0.

GaitLogger Modes

GaitLogger has two modes: *Study Runner* mode (Figure 4.2), which is used to run the experiment, and *Log* mode (Figure 4.3), used to record gait.

GaitLogger's Study Runner mode, used by the experimenter, writes participant information to a Comma Separated Value (CSV) file. This includes the participant number, time stamps used in the synchronization process (described below), and time stamps for the beginning and end of each trial, where one gait is recorded. Study Runner mode also allows randomization of gait order to facilitate data logging.

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Figure 4.2: GaitLogger study runner mode
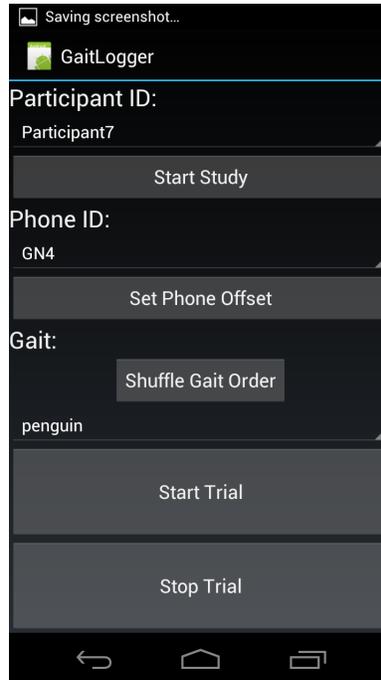
GaitLogger's Log mode allows the researcher to enter phone information required for the study, connects to the accelerometer or gyroscope, and logs the raw sensor data to a file. The phone information is saved in a CSV file, and includes the participant ID, the phone's location-on-person (LOP), and the phone ID. Log mode also allows selection of which sensor to access: accelerometer, gyroscope, or both. Due to issues described in Section 4.4.2, we only sampled from the accelerometer in our study.

GaitLogger Implementation Details

When logging data, GaitLogger creates a Service object [1], which informs the Android operating system that it is to operate in the background. This Service, GaitLoggerService, has native code section written in the C programming language. This native code section connects to the accelerometer and/or gyroscope to sample data at the fastest possible sampling rate, which is determined by the

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Figure 4.3: GaitLogger log mode

(a) Logging (b) Not Logging
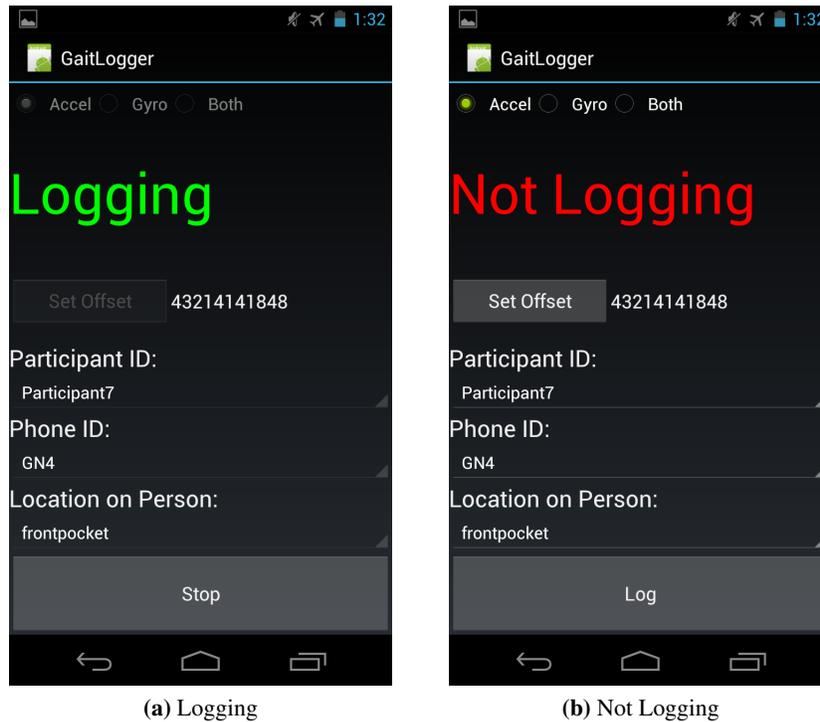
operating system; our empirically measured sampling rates are reported in Section 4.4.2. Data is buffered to reduce bottlenecking from input/output (I/O) operations when saving to the file. GaitLogger connects to this native code section using the Java Native Interface (JNI). Sensor data is also saved to a CSV file, which can be collected after the study.

GaitLogger Use In Study

Seven Samsung Galaxy Nexus smartphones were used in the experiment, each loaded with GaitLogger. Six were placed on the participant using the same locations as in our cadence estimate study (see Chapter 3): front pocket, back pocket, hip, hand, arm, and backpack. These six phones were in Log mode. The final phone was held by the experimenter, and was in Study Runner mode. The experimenter entered participant ID on all seven phones. One by one, each of the six logging

phones was synchronized with the experimenter's phone by pressing a button on the the logging phone and the experimenter's phone simultaneously. This method of synchronization is only as exact as the experimenter's motor control, but this is close enough for our purposes: each trial lasts 30 seconds, and synchronization has an error rate of a fraction of a second. During the study, the experimenter logged beginning and end times for each gait on the *Study Runner* phone.

4.3 Study Design

Our study followed the overall structure described below:

1. Participant Recruitment, described in Section 4.3.1.

2. Setup and Participant Briefing, described in Section 4.3.2.

3. Data Collection, described in Section 4.3.3.

4. Study Conclusion, described in Section 4.3.4.

In the following subsections, we elaborate on the study design.

4.3.1 Participant Recruitment

Participants were recruited through email lists to University student pools, commonly used for this purpose. Emails linked to an online Doodle (cite) poll, which offered a number of sign-up times. Please see Section A.2.2 for email and advertising details.

4.3.2 Setup and Participant Briefing

Before participants arrived, each phone was charged and had GaitLogger installed and running (Section 4.2). One phone was put into Study Runner Mode (Figure 4.2), into which the anonymous participant identification number (hereafter referred to as "participant ID") was entered. The other six phones were then put into Log mode. The experimenter then synchronized all the phones' clocks using GaitLogger, entered location-on-person and participant ID, and started logging the accelerometer data. Phones were placed in any necessary cases; for example, the

phone going on the participant's arm was slipped into a commercially available exercise arm band, and the phone placed in the backpack location was placed loose in a backpack.

Once participants arrived, they were given consent forms (Section A.2.1) to read and sign, then given a copy for their records. After this, participants filled out demographic information (Section A.2.3). Participants were then read a briefing from a script and given time to ask questions. Phones were then given to the participant to be placed in the appropriate locations. The "arm" phone was placed on the participant's self-reported non-dominant arm. The "hand" phone was held in the dominant hand, although this was not strictly enforced during the study when it would interfere with their normal walking gait (*e.g.*, the participant might use their dominant hand to hold a railing when walking up or down stairs). Participants were instructed to place pocket or belt phones where they would normally be placed, and to adjust the backpack so that it was comfortable. See Figure 4.4 for a picture of the participant apparatus.

4.3.3 Data Collection

Once the phones were in place, we collected accelerometer data (and for four participants, gyroscope data; see Section 4.4.2) using GaitLogger to record the sensor signals. Aside from Ascend Stairs and Descend Stairs, participants performed each gait described in Table 4.1 for exactly 30 seconds each in an outside, paved, relatively level and straight location. Ascend Stairs and Descend Stairs were performed on a square spiraling indoor staircase, with participants instructed to either walk all three floors to the top of the stairs or all three floors to the bottom. Because Ascend Stairs and Descend Stairs were limited by the height of the staircase, these gaits were not necessarily performed for 30 seconds each. However, typical time to travel up or down the stairs exceeded 30 seconds. Outside gaits were performed in a random order. For logistical reasons, Ascend Stairs and Descend Stairs were performed either at the beginning or end of the trial; this was counterbalanced by participants, as was the order of Ascend Stairs and Descend Stairs.

(a) Front

(b) Back

(c) Arm

(d) Belt

Figure 4.4: Participant apparatus

4.3.4 Study Conclusion

After the study, phones were retrieved from participants, and the purpose behind the gaits was explained. Participants received $10 in compensation for participating in the study.

4.4 Data Summary

In this section we summarize the collected data for our study. Specifically, we describe our participants (Section 4.4.1) and the data collected (Section 4.4.2). Data logs were used in gait classification algorithm development, described in Chapter 5.

4.4.1 Participants

12 people (6 female) participated in the study. All were right-handed. Self-reported age, weight, and height were gathered during the study using a basic questionnaire (Section A.2.3). Summary statistics can be found in Table 4.2.

4.4.2 Data Quality

Overall, collected accelerometer data were very consistent. Mean sample period was 16.95 ms, corresponding to 59.00 Hz, with a mean of 1901.76 data points per participant/location/gait trial. Unfortunately, due to occasional gaps in data collection, the result of recording data on a smartphone with the operating system in control of sampling events, 6 trials had total recorded time less than 30 seconds. This may have been caused by background processes interfering with the data recording; however, this was isolated to only a few trials. A summary of the overall accelerometer data can be found in Table 4.3. A summary of accelerometer

	Age (years)	Height (cm)	Weight (kg)
Minimum	21	155	46
Median	26	171.5	69.5
Mean	25.3	171.5	68
Standard Deviation	2.96	9.71	14.14
Maximum	31	183	86

Table 4.2: Self-reported statistics from 12 participants

	Observations present per data cell	Recorded Time Span (seconds)
Minimum	74	28.04
Median	1 662	31.26
Mean	1 901.76	32.45
Standard Deviation	731.78	3.87
Maximum	6 932	56.22

Table 4.3: Summary of recorded accelerometer data

Participant ID	Location	Gait	Observations present per data cell	Recorded Time Span (seconds)
Participant 8	backpocket	jog	89	28.22451
Participant 8	backpocket	kickingbum	74	29.26617
Participant 8	backpocket	toes	104	29.04672
Participant 8	backpocket	walkbackwards	111	28.95335
Participant 8	backpocket	walksideways	86	28.04027
Participant 10	frontpocket	descendstairs	685	29.53482

Table 4.4: Summary of low-quality accelerometer data

trials with less than 30 seconds of recorded time can be found in Table 4.4. Sample periods for both accelerometer and gyroscope can be found in Table 4.5.

Gyroscope data were also collected for participants 6, 9, 10, and 12 by repeating the experiment after the accelerometer-recording experiment, in order to determine relative data quality and informativeness for our purposes. We found that the gyroscope data were not as consistent as accelerometer data. Gyroscope data had a mean sample period of 80.05 ms, corresponding to 12Hz, and had a mean of 378 data points per trial. In fact, 3 trials had absolutely no data. Because of this poor performance, possibly related to the onboard sensor chip's caching scheme, we decided to only analyze accelerometer data in Chapter 5. A summary of the recorded gyroscope data can be found in Table 4.6. A summary of accelerometer trials with less than 30 seconds of recorded time can be found in Table 4.7.

	Accelerometer (ms)	Gyroscope (ms)
n	6 756 537	405 945
Minimum	0	0
Median	8.3	35.95
Mean	16.95	80.05
Standard Deviation	28.75	101.6
Maximum	7 389.38	16 284.8

Table 4.5: Summary of GaitLogger sample period over all recorded data (including between trials)

	Observations present per data cell	Observations present per non-empty data cell	Recorded Time Span (seconds)	Recorded Time Span, non-empty (seconds)
Minimum	0	8	0.00	0.35
Median	378	379	31.18	31.18
Mean	399.87	403.23	31.84	32.1
Standard Deviation	133.35	128.74	5.64	4.84
Maximum	1169	1169	54.59	54.59

Table 4.6: Summary of recorded gyroscope data

Participant ID	Location	Gait	Observations present per data cell	Recorded Time Span (seconds)
Participant 12	backpocket	walk	396	16.40
Participant 12	frontpocket	walk	8	0.349761962
Participant 12	hand	walk	0	0
Participant 6	hand	descendstairs	0	0
Participant 6	backpack	descendstairs	0	0

Table 4.7: Summary of low-quality gyroscope data

Chapter 5

Gait Classification Algorithm Development

He followed in his father's footsteps, but his gait was somewhat
erratic.
— Nicolas Bentley

In Chapter 4, we described the collection of raw accelerometer logs from 12 participants performing 15 gaits in 6 locations. In this chapter, we describe our analyses for developing a gait classification algorithm using the collected accelerometer logs. We begin by describing our feature extraction method, including window size, handling of orientation through different vectorizations of accelerometer data (referred to in this chapter as "axis sets"), and statistical features in Section 5.1. We then describe a preliminary analysis to compare window size, axis, and machine learning classification techniques in Section 5.2, by examining their effect on a single location and gaitset. Finally, we present two analyses with the best performing algorithm to examine the influence of location and gaitset in Section 5.3.

5.1 Feature Extraction

In this section, we describe our methods for extracting features for classification. We investigate two window sizes and three methods of generating sets of axes.

Statistical features are taken from an axis set on a single window, and thus each generated window corresponds to a single observation for machine learning algorithms.

5.1.1 Window Sizes

Because we only collected 30 seconds of data and both 2 and 4 second windows performed well in our cadence experiment (see Chapter 3), we separated our data in 2 second windows with 1 second (50%) overlap, and 4 second windows with 2 second (50%) overlap. Overlapping windows allowed us to generate more observations, at the expense of having some correlation between observations. We examined the effect of window size in Section 5.2.

5.1.2 Axis Sets

For each set of features, we had to choose a set of axis projections, created out of our original 3 accelerometer vectors. We examined three axis sets:

XYZ Using the original x, y, and z sensor data from the triaxial accelerometer.

VH Calculating the gravity vector by taking the mean of the x, y, and z axes, and separating these axes into a vertical component and a horizontal component (as in [68], but with our 2 or 4 second window rather than 10 seconds).

MAG Using the magnitude (Euclidean or ℓ-2 norm) of the x, y, and z axes to have a rotationally-invariant feature set (as in our cadence detection algorithm; see Chapter 3).

These axis sets explore the tradeoff between robustness to orientation and information: XYZ provides all captured information, but is sensitive to differences in orientation, while VH and MAG give robustness by reducing the amount of orientation information captured.

5.1.3 Features

Features are extracted using the Python programming language, drawing upon the Scipy software package [29]. Features were chosen to represent a large number of

basic statistical observations of both time and frequency domain data: our gaits can have subtle differences, and we wanted to capture as much information as possible. The spectral domain of each window is calculated using the Fast Lombe-Scargle Periodogram (FASPER) algorithm [49], as in our cadence estimation algorithm RRACE (described in Chapter 3).

- For each axis in a specified axis set, we take the following features:

  - Minimum value

  - Maximum value

  - Mean value

  - Variance

  - Skewness

  - Kurtosis

  - 25th percentile

  - Median (50th percentile)

  - 75th percentile

  - A ten-bin histogram, normalized to have the proportion of each value in each bin

  - The most powerful spectral frequency (cadence as estimated by RRACE)

  - The weakest spectral frequency

  - A weighted average of spectral frequencies by spectral power

  - Spectral variance

  - Spectral entropy

  - A ten-bin histogram of spectral powers, normalized to have the proportion of each value in each bin

- In addition, we look at basic correlations between the original three axes:

  - Pearson correlation coefficient for the x-axis and the y-axis

  - Pearson correlation coefficient for the x-axis and the z-axis

- Pearson correlation coefficient for the y-axis and the z-axis

- P-value for the Pearson correlation coefficient for the x-axis and the y-axis

- P-value for the Pearson correlation coefficient for the x-axis and the z-axis

- P-value for the Pearson correlation coefficient for the y-axis and the z-axis

- Finally, we take the signal magnitude area (sum of the Euclidean or ℓ-2 norm of every x,y,z tuple).

5.2 Algorithm Selection

With our features chosen in Section 5.1, we had to choose the right parameters for our algorithm. Specifically, we needed to decide on window size, the axis set to be used, and which classifier is the most successful at handling our data.

We examined the window sizes and axis sets described in Section 5.1.3. We also examined 6 commonly used classification algorithms, all with implementations in Weka [24]:

ZeroR A baseline classifier. ZeroR finds the class with the greatest number of instances. This is equivalent to accuracy due to chance when instances are balanced.

- Referred to as "ZeroR" in analysis.

Naïve Bayes A common classifier, employing Bayes' Rule to construct an estimate of prior probability (probability of a class given the observed features) from a collection of posterior probabilities (probability of a set of features given a class).

- Referred to as "NB" in analysis.

J48 A Java implementation of the C4.5 decision tree algorithm [24]. A C4.5 decision tree is constructed by iteratively selecting a feature that gives the highest information gain, and splitting on that feature.

- Referred to as "J48" in analysis.

Multilayer Perceptron A commonly used neural network algorithm.

- Referred to as "MP" in analysis.

Random Forest An algorithm that uses *bagging* to randomly select smaller sets of a features, constructing a decision tree for each one. Decisions are made by majority response of these trees. In this implementation, we try two variations by manipulating the number of trees constructed. As the number of trees approaches infinity, the accuracy of a Random Forest classifier converges [5]. Through piloting we found accuracy converged between 100 and 500 trees. We thus try those two parameters:

- Random Forest with 100 trees (Referred to as "RF100" in in analysis)
- Random Forest with 500 trees ("RF500")

Support Vector Machine (SVM) An algorithm that constructs a number of hyperplanes in a high-dimensional feature space to divide the space into regions corresponding to each class. Because SVM is a commonly used algorithm for gait recognition, we combine it with Principal Components Analysis (PCA) to reduce the feature set. We examine four variations of SVM:

- SVM without PCA (Referred to as "S" in analysis)
- SVM with PCA tuned to explain 95% of the variance ("S+P")
- SVM with PCA tuned to explain 95% of the variance but with a maximum of 15 features ("S+P15"). We chose this because it is a rule-of-thumb to have 10 times the number of observations
- SVM with PCA tuned to explain 95% of the variance but with a maximum of 30 features ("S+P30")
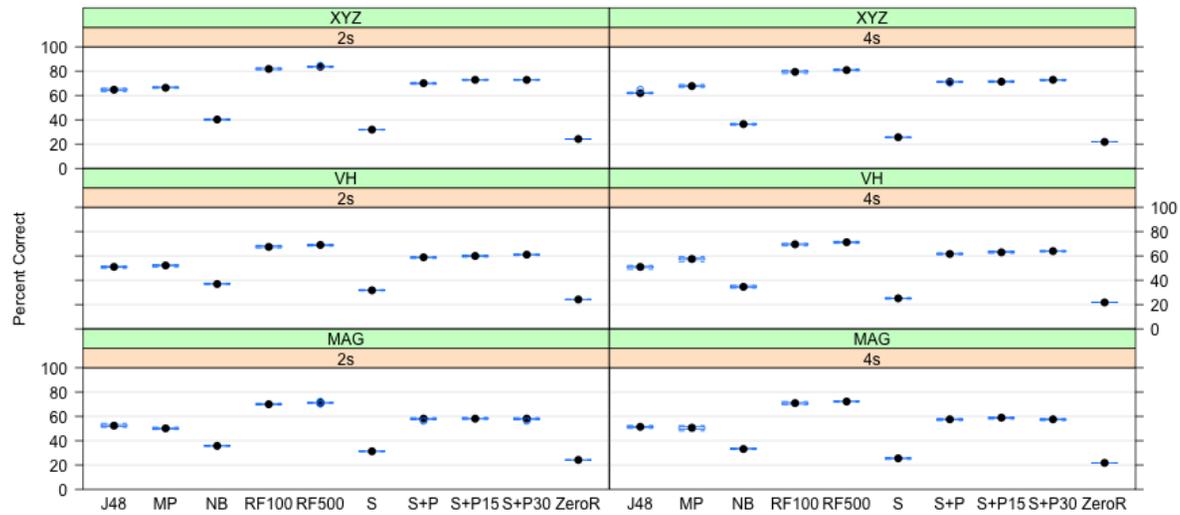
Figure 5.1: Bar-and-whiskers plot of the algorithm selection study. In this work, bar-and-whiskers plots report on *quantiles*; that is, the bar in the middle represents the median, the box represents the 25th percentile to the 75th percentile, and the ends of the whiskers represent the extremes of the dataset's range excluding outliers. All bar-and-whiskers plots were produced using the R statistical programming language's `bwplot` function in the `lattice` library.

Table 5.1: Violations of normality in the results.

Axis	Window	Algorithm	Shapiro-Wilk *W*	Shapiro-Wilk P-Value
XYZ	4s	J48	0.65	0.00023
MAG	4s	NB	0.81	0.012
MAG	2s	ZeroR	0.63	0.00012
VH	2s	ZeroR	0.63	0.00012
XYZ	2s	ZeroR	0.63	0.00012
MAG	4s	ZeroR	0.64	0.00017
VH	4s	ZeroR	0.64	0.00017
XYZ	4s	ZeroR	0.64	0.00017

Note that though these classifiers can require significant time to train, we are primarily concerned with their computational costs during evaluation (so that they can run in real-time on a smartphone). With this in mind, all the classifiers are expected to run in real-time on smartphones. ZeroR runs in constant time (as it always outputs the same class). J48, Random Forests, and Multilayer Perceptron are all tree- or graph-based; classification corresponds to traversing these structures. Naïve Bayes as well is relatively efficient, as we did not use a kernel estimator; for each feature/class pair there is a normal distribution describing estimated posterior probability, from which probabilities for each class can be easily calculated. SVM is expected to be efficient because it only involves the calculation of an exponential kernel function. This must be repeated for each class or pair of classes (as SVM is a binary classifier), but is still expected to be tractable on a smartphone.

An analysis was carried out looking at these three factors, using the collected accelerometer data (described in Chapter 4). Datasets for each axis size and window size were generated with a program written in the Python programming language, using the Scipy software package for statistical features [29]. The generated datasets were stored in the ARFF file format, the standard file format for Weka datasets. For each axis set, window size, and classifier combination, we conducted 10 iterations of 10-fold cross validation. We aggregated results for each cross-validation, resulting in 10 estimates of mean axis set/window/classifier accuracy. Results follow. To make this computationally tractable and to focus on

Table 5.2: Top 20 algorithms ranked by mean percent correct. All results shown are the mean value of 10 iterations of 10-fold cross-validation. Analysis was conducted on data from all participants but limited to the Front Pocket location and the Pedestrian gaitset.

Axis	Window	Algorithm	Mean percent correct
XYZ	2s	RF500	83.70
XYZ	2s	RF100	81.85
XYZ	4s	RF500	80.95
XYZ	4s	RF100	79.50
XYZ	2s	S+P15	72.84
XYZ	2s	S+P30	72.83
XYZ	4s	S+P30	72.79
MAG	4s	RF500	72.28
XYZ	4s	S+P15	71.39
VH	4s	RF500	71.21
MAG	2s	RF500	71.20
XYZ	4s	S+P	71.14
MAG	4s	RF100	70.80
MAG	2s	RF100	69.99
XYZ	2s	S+P	69.93
VH	4s	RF100	69.48
VH	2s	RF500	68.91
XYZ	4s	MP	67.76
VH	2s	RF100	67.58
XYZ	2s	MP	66.47

interpretable results, we used a single location (Front Pocket) and a single gaitset (Pedestrian), described in Chapter 4. The location and gaitset were chosen *a priori*, and because they were the most similar to locations and gaits used in previous work. The Pedestrian gaitset is expected to be the most difficult to classify, as it has the most gaits (6) and was designed around subtle differences between gaits (*e.g.*, walking and walking quickly, jogging and running).

We thus had 10 observations in each of the $3 \times 2 \times 10 = 60$ datasets, generated with Pedestrian/Front Pocket data from all 12 participants. Results are visible in Figure 5.1.

We planned an Analysis of Variance to compare the different factors. However, the Shapiro-Wilk test of normality failed on the residuals of 8 data cells at the 5% level of significance (see Table 5.1). We thus were unable to detect statistical effects for each of the three factors (axis set, window size, and classifier), and could not conduct analysis through planned contrasts. Instead, because we hoped to choose a single best algorithm for our subsequent analysis on gaitset and location, we took the highest-ranking algorithm: XYZ/2s/RF500. See Table 5.2 for the ranked accuracy of the top 20 tested algorithms. Further analysis of these different classification parameterizations is left to future work; possible approaches to achieve normality include larger sample sizes (*i.e.*, a greater number of iterations of 10-fold cross-validation), non-parametric analysis (such as bootstrap methods), and transformations of the response variables.

5.3   Location And Gait

After choosing our algorithm in Section 5.2, we conducted our main algorithm analysis with location, gaitsets, and participants as factors, in that we examine the benefit of knowledge of these different factors by training classifiers that assume specific levels (such as an algorithm that is trained only on Exercise gaits with Front Pocket as the location). We report our analysis design in Section 5.3.1, and our results in Section 5.3.3 and Section 5.3.4. Discussion of these results can be found in Chapter 6.

5.3.1   Analysis Design

A second analysis was carried out, in which we compared the effects of carrying location, gaitset (one of Pedestrian, Exercise, Game, or All), and participant, using the same dataset as in Section 5.2 (fully described in Chapter 4). We used the best performing algorithm in our Algorithm Selection experiment (Section 5.2): we used a 2 second window on the raw X/Y/Z signals with 50% (or 1 second) overlap, extracting features as described in Section 5.1, using a Random Forest classifier with 500 trees implemented in Weka [24].

We conduct this analysis twice, once training and testing on all 12 participants ("All Participants", Section 5.3.3), and once training and testing on each participant

("By-Participant", Section 5.3.4). For each location, gaitset, and (for by-participant analysis) participant, we conducted 10 iterations of a 10-fold cross-validation. Our results analyze the mean of each cross validation, giving 10 data points for each location/gaitset(/participant) combination.

5.3.2 Computational Setup and Performance

These analyses were conducted on a Macbook Pro laptop with a 2.7 GHz Intel i7 processor and 8 GB of RAM. Training the All Locations/All Gaits/All Participants data cell with the RF500 algorithm exceeded the 8GB memory capacity of the laptop. We should note that these computational costs are only present when training the algorithm, and that the RF500 algorithm, once trained, can perform efficiently on mobile devices. All other datasets were analyzed on this laptop, although conducting 10 10-fold cross-validations can take several hours depending on the dataset.

5.3.3 Results - All Participants

Results of the cross-validation experiment over all participants suggests a trend in gaitset, but potential interactions between gaitset and carrying location; see Figure 5.2 for results grouped by gaitset, Figure 5.3 for results grouped by carrying location, and Table 5.3 for mean classification rates. Unfortunately, due to a lack of computing power, the All Locations/All Gaits data cell could not be generated.

Confusion matrices have been produced for all gaits, and gaits grouped by gaitset, over all locations and all participants. As the All Locations/All Gaits/All Participants data cell could not be computed with RF500, we used RF100 as a substitute in the confusion matrix, presented in Figure 5.4. Major patterns in the all gaits confusion matrix follow, using "→" to indicate mis-classification. Note that mis-classification is not necessarily bidirectional; when it is, we use "↔".

- many gaits → *ascendstairs* and *descendstairs*

- many gaits → *narrow* and *walkbackwards*, although not as strongly as with *ascendstairs* and *descendstairs*.

- Major confusions between two gaits are:

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- *walk → fastwalk*

- *walk → ascendstairs*

- *jog → fastwalk*

- *ascendstairs → descendstairs*

- *fastwalk → descendstairs*

- *toes → narrow*

- *walksideways → narrow*

- *walkbackwards → kickingbum*

Major patterns in the confusion matrices by gaitset are:

- Pedestrian shows a number of confusions. As in the all gaits confusion matrix (Figure 5.4), many gaits were mis-classified as *ascendstairs*, and several were mis-classified as *jog*. Both of the stairs were often correctly distinguished from *jog* and *run*. Few gaits were confused with *run* and *walk*. Major individual confusions include:

  - *run → jog*

  - To a lesser extent, *walk ↔ fastwalk*

  - To a lesser extent, *jog ↔ fastwalk*

- Exercise demonstrates few standout confusions between its gaits. The most confused gait was *heels*, in that it has the darkest column excluding the diagonal element, followed by *liftknees*. The strongest individual confusion is *liftknees → heels*. *Toes* and *kickingbum* were confused with each other more than with the other two gaits.

- Game demonstrates many confusions; several gaits were classified as *narrow*. Strong individual confusions are:

  - *walksideways → narrow*

  - *walksideways → walkbackwards*

  - *walkbackwards → narrow*

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- *penguin → walkbackwards*

- To a lesser extent, *walkbackwards → walksideways*

- To a lesser extent, *penguin → twofoothop*

As in Section 5.2, we planned an Analysis of Variance to compare the different factors. However, like Section 5.2, the Shapiro-Wilk test of normality failed on the Exercise/Arm data cell residuals at the 5% level of significance (W=0.83, p=0.037). We thus were unable to detect statistical effects for each of the two factors (location and gaitset), and could not conduct analysis through planned contrasts. Again, further analysis of these different classification parameterizations is left to future work.

Table 5.3: Mean gaitset/location accuracy rate over all participants. All results shown are the mean value of 10 iterations of 10-fold cross-validation. Analysis was conducted using XYZ/2s/RF500.

Gaitset	Location	Mean percent correct
Exercise	Back Pocket	87.2
Exercise	Front Pocket	86.6
Exercise	Arm	85.3
Game	Front Pocket	85.0
Exercise	Belt	84.8
Exercise	Backpack	84.6
Game	Back Pocket	84.5
Pedestrian	Front Pocket	83.7
Exercise	Hand	83.4
Pedestrian	Back Pocket	82.6
Game	Arm	81.7
All Gaits	Front Pocket	80.1
Game	Backpack	79.9
All Gaits	Back Pocket	79.8
Game	Belt	79.6
Pedestrian	Belt	79.5
Game	Hand	78.9
Pedestrian	Backpack	78.9
Pedestrian	Arm	78.4
Pedestrian	Hand	77.2
All Gaits	Arm	74.5
All Gaits	Belt	74.4
All Gaits	Backpack	74.3
All Gaits	Hand	73.5
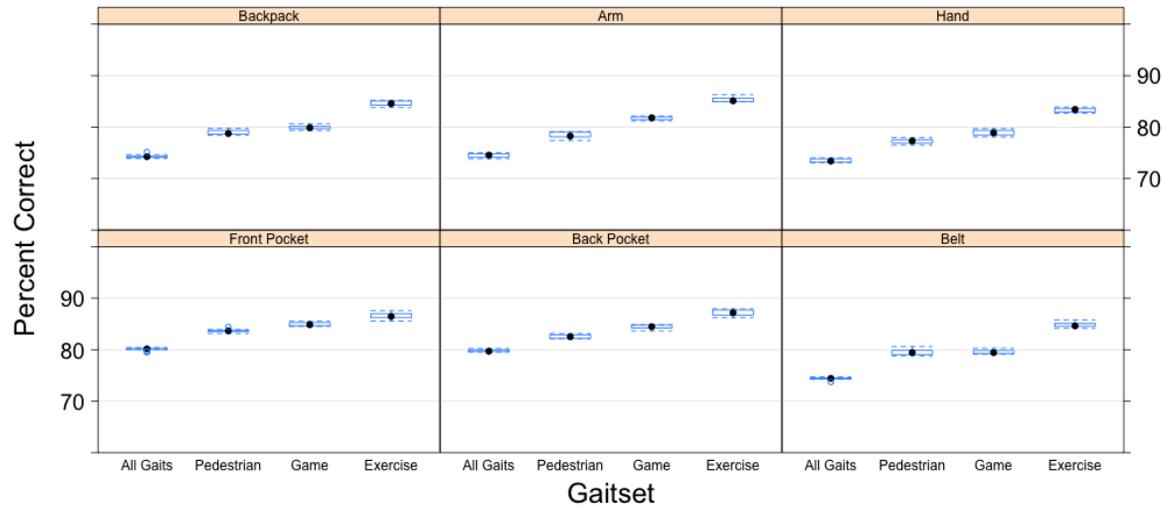
Figure 5.2: Bar-and-whiskers plot of 10 means of 10-fold cross-validation results of the XYZ/2s/RF500 algorithm trained on all participants by carrying location and gaitset, arranged to highlight differences in gaitset.
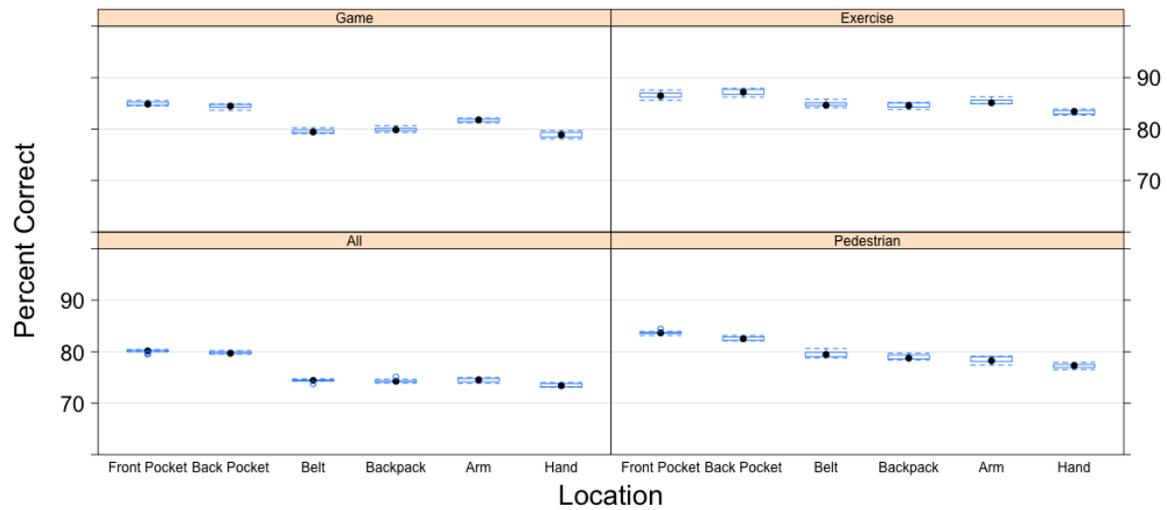
Figure 5.3: Bar-and-whiskers plot of 10 means of 10-fold cross-validation results of the XYZ/2s/RF500 algorithm trained on all participants by carrying location and gaitset, arranged to highlight differences in carrying location.

Actual \ Classified as	liftknees	toes	run	fastwalk	twofoothop	ascendstairs	walksideways	walk	kickingbum	descendstairs	jog	heels	narrow	walkbackwards	penguin
liftknees	70	0.9	1.4	2.1	1.6	4.7	1.1	2.4	2.7	2.4	1.6	1.8	3.7	2.3	1.3
toes	2.2	67.3	1.3	2.1	2.3	4	1.5	2.4	1.7	2.8	2.1	1.8	5	2.2	1.3
run	2.7	2	66.3	1.6	1.9	5.6	1.7	1.9	1.3	3.8	2.6	2	3.2	2.2	1.3
fastwalk	2.4	2.2	2	59.2	1.9	9	3	2.6	1.2	5.8	2.5	1	2.4	3.2	1.7
twofoothop	2.2	1.4	1.4	2.3	69.7	4.9	1.9	2	1.8	2.7	1.9	2	3.3	1.3	1.4
ascendstairs	1.8	0.7	1.9	1.6	1.2	75.6	1.5	1.5	0.7	5.4	1.2	0.8	2.4	2.2	1.6
walksideways	2.3	3.5	1.5	2.3	1.4	7.4	56.9	2.5	3.7	3.8	2.6	1.9	4.5	3.9	1.9
walk	2.6	2.3	2.5	4.2	2.4	9.1	2.9	55.3	0.9	4.8	2.8	1.8	2.7	3.1	2.6
kickingbum	3.6	2.7	2.1	1.6	1.8	5.5	3.5	1.1	62.1	3.6	1.2	2.8	3.5	4.1	0.9
descendstairs	1.7	0.8	0.7	1.1	1.5	5.6	1.3	1	0.7	79.3	1.2	1	2.3	1.1	0.7
jog	1.7	2.5	1.6	4.1	1.5	5	1.6	1.5	1.2	3.9	67.4	1.4	3.5	1.6	1.5
heels	2.3	2.5	1.8	1.7	3.6	4	1	2	2	3.6	2.4	65.8	2.7	3	1.7
narrow	2.9	3.5	2.1	1.2	1.9	3.6	1.3	1.7	1.7	2.3	1.8	2.5	68.1	2.9	2.5
walkbackwards	1.7	3.2	1.5	1.8	1.6	5.2	2.6	1.6	3.6	3.8	2.1	1.9	4.6	62.5	2.4
penguin	1	0.9	2	1	3	5	1.5	1.9	1.1	3.9	2.1	1.5	2.5	3.3	69.5

Figure 5.4: Confusion matrix for a 10-fold cross validation of the chosen algorithm (XYZ/2s/RF500) trained on all participants, all gaits, and all carrying locations. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

(a) Pedestrian

(b) Exercise

(c) Game
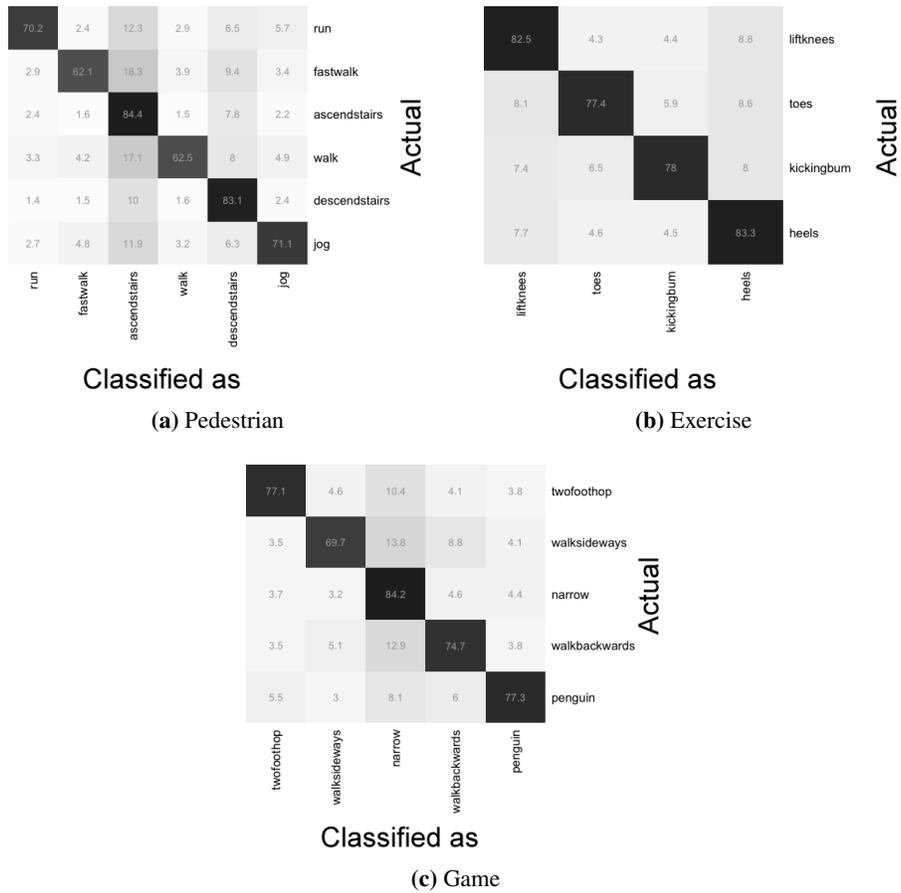
Figure 5.5: Confusion matrices for a 10-fold cross validation of the chosen algorithm (XYZ/2s/RF500) trained on all participants and all carrying locations for each gaitset. The algorithm thus attempts to distinguish only between gaits in the gaitset. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

5.3.4 Results - By-Participant

Analysis of all participants gives some insight, but training the XYZ/2s/RF500 algorithm on each participant might improve results with the short data collection time of 30s per gait and location, and reveals variability in individual differences; see Figure 5.7, Figure 5.8, and Figure 5.9 for graphs of the effect of participants by gaitset and location, and Figure 5.10 for a graph involving only the effect of participants. Top performing mean data classification rate was 100.0%, present in three data cells (involving two participants): Game/Front Pocket/P3, Game/Backpack/P9, and Exercise/Backpack/P3. The worst performing mean data classification rate was All Gaits/All Locations/P10 with a mean of 63.2% classification rate. See Table 5.5 and Table 5.6 for the top 20 and bottom 20 ranked datasets, respectively. Confusion matrices for the four worst ranked data cells are presented in Figure 5.11, Figure 5.12, Figure 5.13, and Figure 5.14.

As with Section 5.2 and Section 5.3.3, we planned an Analysis of Variance to compare the different factors. However, as before, the Shapiro-Wilk test of normality failed on 55 of 336 data cell residuals at the 5% level of significance. We thus were unable to detect statistical effects for each of the three factors (location, gaitset, and participant), and could not conduct analysis through planned contrasts. Further analysis of these different classification parameterizations is again left to future work.
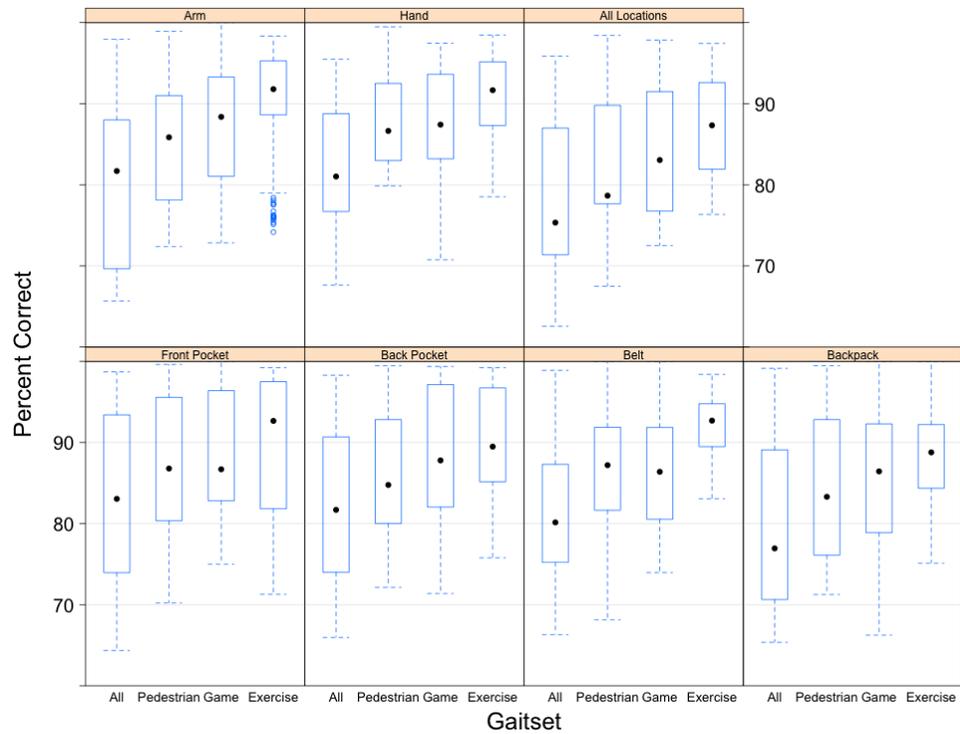
Figure 5.6: Bar-and-whiskers plot of the Location-Gaitset-Participant Analysis, aggregated by Location and Gaitset.

Table 5.4: Mean gaitset/location accuracy rate, by-participant. All results shown are the mean value of 10 iterations of 10-fold cross-validation for every participant. Analysis was conducted using XYZ/2s/RF500.

Gaitset	Location	Mean percent correct
Exercise	Belt	92.2
Exercise	Hand	91.0
Exercise	Arm	90.1
Exercise	Back Pocket	89.8
Exercise	Front Pocket	89.7
Exercise	Backpack	88.7
Game	Back Pocket	88.6
Game	Front Pocket	88.2
Pedestrian	Hand	87.9
Game	Hand	87.5
Game	Arm	87.4
Exercise	All Locations	87.3
Pedestrian	Front Pocket	87.0
Game	Belt	87.0
Pedestrian	Belt	86.7
Game	Backpack	86.3
Pedestrian	Back Pocket	86.0
Pedestrian	Arm	85.6
Pedestrian	Backpack	84.7
Game	All Locations	84.1
All	Front Pocket	83.0
Pedestrian	All Locations	82.7
All	Hand	82.3
All	Back Pocket	82.1
All	Belt	81.6
All	Arm	80.7
All	Backpack	80.1
All	All Locations	78.1
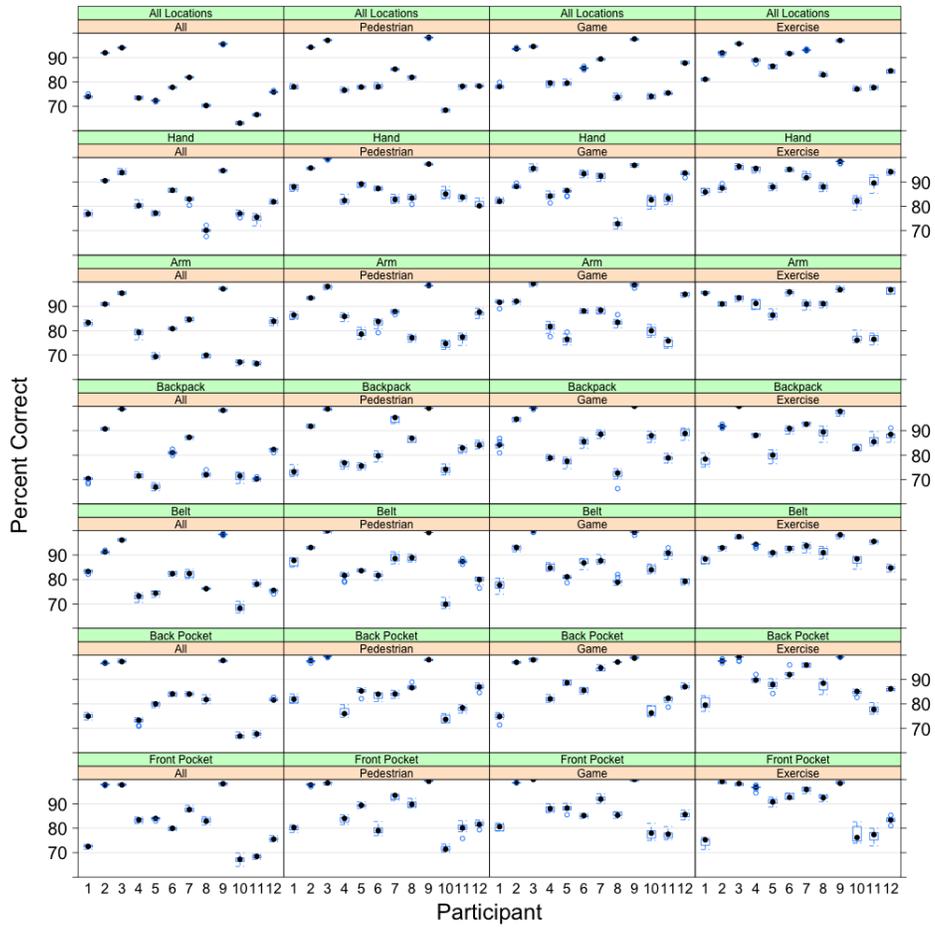
Figure 5.7: Bar-and-whiskers plot of the Location-Gaitset Analysis. By-participant analyses are presented by gaitset and location.
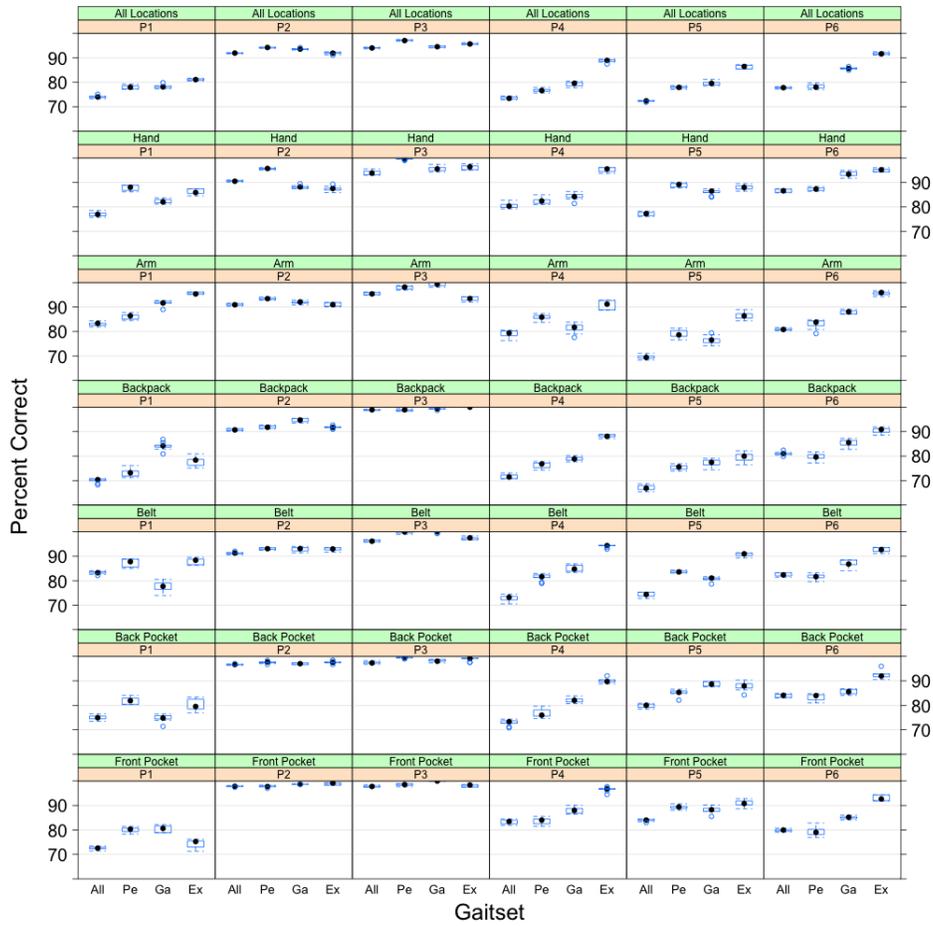
Figure 5.8: Bar-and-whiskers plot of the Location-Gaitset Analysis, to highlight gaitset performance for each of participants 1 through 6. Notice that participants tend to consistently perform well or poorly *independent of* gaitset/location conditions. This graph is continued in Figure 5.9.
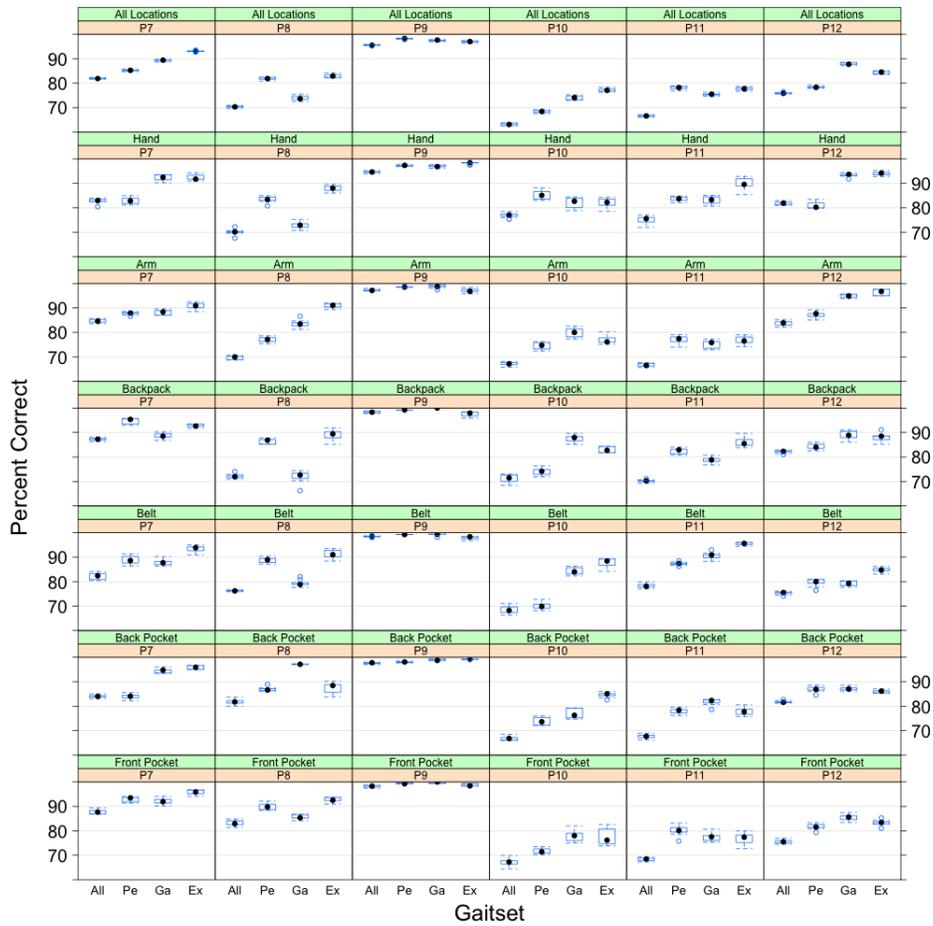
Figure 5.9: Bar-and-whiskers plot of the Location-Gaitset Analysis, to high-light gaitset performance for each of participants 7 through 12. This graph is a continuation from Figure 5.8.
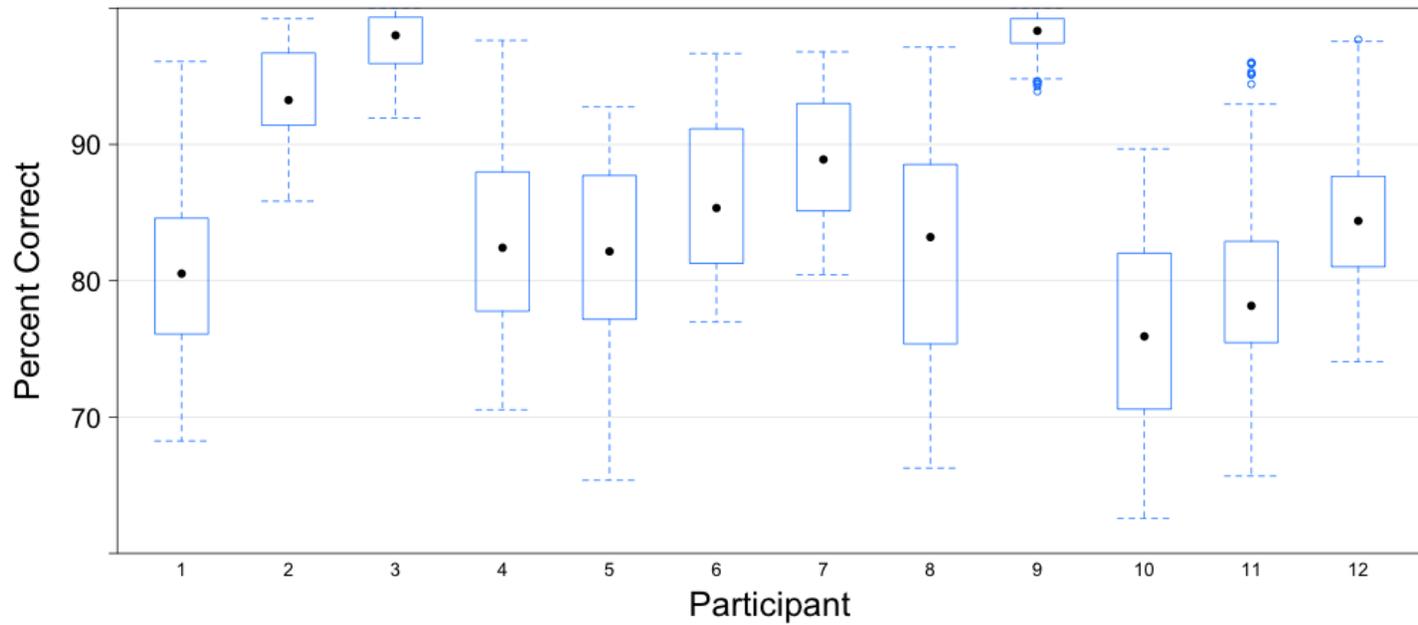
Figure 5.10: Bar-and-whiskers plot of the Location-Gaitset Analysis. By-participant analyses are presented without any other factors.

Table 5.5: Top 20 of 336 gaitset/location/participant data cells by mean percent correct. All results shown are the mean value of 10 iterations of 10-fold cross-validation. Analysis was conducted using XYZ/2s/RF500. Three participants are present in this group.

Gaitset	Location	Participant	Mean percent correct
Game	Front Pocket	P3	100.0
Game	Backpack	P9	100.0
Exercise	Backpack	P3	100.0
Game	Belt	P3	99.9
Pedestrian	Belt	P3	99.7
Game	Front Pocket	P9	99.7
Pedestrian	Hand	P3	99.4
Game	Belt	P9	99.4
Pedestrian	Back Pocket	P3	99.4
Pedestrian	Front Pocket	P9	99.4
Game	Backpack	P3	99.3
Game	Arm	P3	99.3
Pedestrian	Belt	P9	99.2
Pedestrian	Backpack	P9	99.2
Exercise	Back Pocket	P9	99.2
Game	Back Pocket	P9	99.0
All Gaits	Backpack	P3	98.9
Exercise	Back Pocket	P3	98.9
Exercise	Front Pocket	P2	98.8
Game	Arm	P9	98.8

Actual \ Classified as	liftknees	toes	run	fastwalk	twofoothop	ascendstairs	walksideways	walk	kickingbum	descendstairs	jog	heels	narrow	walkbackwards	penguin
liftknees	64	3.4	0	0	7.9	7.3	1.1	2.2	4.5	0	0	5.1	1.1	0.6	2.8
toes	0.6	69.1	1.1	4.6	0	8	0.6	1.7	0	1.1	1.1	1.7	2.3	1.7	6.3
run	0	1.1	77.2	0	1.1	1.7	0	0.6	0	3.3	2.8	0.6	8.3	0	3.3
fastwalk	1.1	3.8	4.4	54.6	2.7	2.7	1.1	3.3	1.1	0.5	10.4	0	5.5	3.8	4.9
twofoothop	4.3	1.1	1.6	0	75.8	5.4	0.5	1.1	0	1.1	1.1	2.2	1.1	0.5	4.3
ascendstairs	1.3	0.4	3.3	0.8	0	76.2	0	1.7	0	6.7	0.4	3.3	1.7	0.8	3.3
walksideways	9.6	11.4	12.6	1.2	0	5.4	40.1	1.2	5.4	2.4	0	0.6	6.6	0.6	3
walk	9.5	2.2	5	0	0	6.1	2.8	61.5	3.4	1.1	0	2.2	3.4	1.7	1.1
kickingbum	8.8	1.8	3.5	0	0	10	2.4	2.4	51.8	0.6	0	12.4	2.9	0.6	2.9
descendstairs	3.7	5.5	9.2	1.2	2.5	19	0	0.6	0	33.1	0.6	2.5	11.7	3.1	7.4
jog	2.2	6	3.8	3.3	0	2.2	0.5	1.1	0	2.2	65.4	1.1	1.6	2.7	7.7
heels	0.6	3.5	0	0.6	0.6	5.3	1.2	11.8	0	0.6	0.6	67.1	0.6	1.2	6.5
narrow	0	2.4	14.2	0	0.6	7.1	0	1.2	0	3	0	0	66.3	0.6	4.7
walkbackwards	1.1	1.7	6.3	0.6	0	5.2	0	0.6	1.1	1.1	0	0	3.4	70.7	8
penguin	0.6	1.1	2.8	0	13.6	6.2	0	1.1	0	2.3	0	0	1.7	14.1	56.5

Figure 5.11: Confusion matrix for the worst-performing gaitset/location/participant combination using XYZ/2s/RF500: All Locations/All Gaits/P10. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

	liftknees	toes	run	fastwalk	twofoothop	ascendstairs	walksideways	walk	kickingbum	descendstairs	jog	heels	narrow	walkbackwards	penguin
liftknees	48	5.8	1.2	0.6	1.7	0.6	0.6	23.3	1.2	6.9	0	2.3	2.9	2.3	2.3
toes	4	69	2.9	0	5.2	2.3	1.1	0	0	4	1.1	4.6	2.9	2.9	0
run	0.5	3.8	71.6	0.5	2.7	2.2	1.1	0	1.6	4.4	3.3	6	0.5	1.6	0
fastwalk	0	1.1	2.2	76.3	1.1	2.7	4.3	0	2.2	2.7	1.6	2.2	1.6	2.2	0
twofoothop	0	2.8	0	0	75.7	1.7	0	0	0	4.4	0.6	4.4	8.8	0.6	1.1
ascendstairs	0.5	4.5	1	0.5	1.5	55.1	1.5	1.5	0.5	22.2	1	1.5	2.5	1.5	4.5
walksideways	0	5.9	4.8	17.7	2.7	4.3	34.9	0.5	2.7	6.5	11.3	3.2	1.1	3.8	0.5
walk	1.6	0	0	0	1.6	1.1	0	71	1.1	4.9	2.2	4.9	1.6	1.1	8.7
kickingbum	0.5	3.8	5.4	3.2	1.6	1.6	2.7	0	55.4	1.1	0	7.5	4.3	11.8	1.1
descendstairs	0.3	0.8	1.1	0.3	0.5	1.6	0	0.3	0.5	84.1	2.4	4.8	1.3	1.6	0.3
jog	0.5	1.6	1.1	0.5	0	1.1	2.7	2.7	1.1	10.2	72	2.7	0	0.5	3.2
heels	0.5	3.2	2.2	1.1	5.9	0	0	1.6	3.2	7	0.5	73.7	0	1.1	0
narrow	1.1	3.8	0.5	0.5	5.4	4.8	0	0	1.1	4.8	3.2	1.1	69.4	1.1	3.2
walkbackwards	1.1	8.6	8.1	0.5	1.6	2.7	0.5	0	7.5	4.8	0	3.2	0.5	57	3.8
penguin	0.5	1.1	1.1	0	2.2	0.5	0	2.2	1.6	2.2	2.2	4.3	1.1	7	74.2

Classified as / Actual

Figure 5.12: Confusion matrix for the second worst-performing gaitset/location/participant combination using XYZ/2s/RF500: All Locations/All Gaits/P11. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

Actual \ Classified as	liftknees	toes	run	fastwalk	twofoothop	ascendstairs	walksideways	walk	kickingbum	descendstairs	jog	heels	narrow	walkbackwards	penguin
liftknees	51.6	9.7	3.2	0	0	0	0	19.4	0	12.9	0	3.2	0	0	0
toes	0	54.8	6.5	0	3.2	3.2	0	0	0	0	0	19.4	12.9	0	0
run	0	0	80.6	0	6.5	0	3.2	0	0	0	6.5	0	3.2	0	0
fastwalk	0	0	0	77.4	0	9.7	6.5	0	0	3.2	0	0	3.2	0	0
twofoothop	0	3.2	3.2	0	77.4	3.2	0	3.2	0	0	3.2	3.2	3.2	0	0
ascendstairs	6.1	0	6.1	0	0	39.4	0	9.1	0	18.2	0	0	12.1	0	9.1
walksideways	0	0	12.9	19.4	9.7	3.2	29	3.2	6.5	6.5	6.5	0	3.2	0	0
walk	3.2	0	3.2	0	3.2	3.2	0	71	0	12.9	0	0	0	0	3.2
kickingbum	0	3.2	6.5	3.2	0	0	0	0	71	3.2	0	3.2	0	9.7	0
descendstairs	3.2	0	1.6	0	0	1.6	0	0	1.6	82.3	1.6	1.6	0	4.8	1.6
jog	3.2	0	3.2	0	0	0	0	0	0	12.9	71	0	0	3.2	6.5
heels	0	6.5	3.2	0	0	0	3.2	3.2	3.2	0	0	71	6.5	3.2	0
narrow	0	6.5	3.2	6.5	0	3.2	0	0	0	16.1	0	3.2	61.3	0	0
walkbackwards	0	3.2	3.2	0	0	3.2	3.2	0	9.7	9.7	0	3.2	0	61.3	3.2
penguin	0	3.2	3.2	0	3.2	3.2	0	0	0	3.2	0	3.2	0	0	80.6

Figure 5.13: Confusion matrix for the third worst-performing gaitset/location/participant combination using XYZ/2s/RF500: Arm/All Gaits/P11. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

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Actual \ Classified as	liftknees	toes	run	fastwalk	twofoothop	ascendstairs	walksideways	walk	kickingbum	descendstairs	jog	heels	narrow	walkbackwards	penguin
liftknees	80	6.7	0	0	10	0	0	0	0	0	0	3.3	0	0	0
toes	0	80.6	3.2	6.5	0	0	0	0	0	6.5	0	3.2	0	0	0
run	3.3	0	66.7	0	3.3	6.7	0	0	0	6.7	0	0	13.3	0	0
fastwalk	6.5	6.5	0	64.5	0	3.2	3.2	0	0	6.5	9.7	0	0	0	0
twofoothop	6.5	0	0	0	71	6.5	0	3.2	0	6.5	0	0	3.2	0	3.2
ascendstairs	0	2.4	9.8	0	0	78	0	0	0	9.8	0	0	0	0	0
walksideways	3.3		3.3	3.3	0	0	53.3	0	3.3	0	0	0	6.7	0	0
walk	9.7	3.2	6.5	6.5	3.2	0	6.5	58.1	3.2	0	0	0	3.2	0	0
kickingbum	3.3	6.7	6.7	0	0	3.3	6.7	0	63.3	3.3	0	6.7	0	0	0
descendstairs	3.2	6.5	9.7	0	0	6.5	0	0	0	64.5	0	0	9.7	0	0
jog	6.5	6.5	6.5	0	3.2	0	0	0	0	3.2	71	0	3.2	0	0
heels	0	6.7	0	0	0	3.3	0	10	3.3	0	0	76.7	0	0	0
narrow	0	6.2	12.5	0	0	0	0	0	0	3.1	0	0	78.1	0	0
walkbackwards	0	0	0	0	0	0	0	0	0	0	0	0	0	87.1	12.9
penguin	0	0	0	0	0	0	0	0	0	0	0	0	0	0	100

Figure 5.14: Confusion matrix for the fourth worst-performing gaitset/location/participant combination using XYZ/2s/RF500: Backpack/All Gaits/P10. Darker squares represent a higher classification rate. Numbers presented are percents of classification rates for each actual gait (that is, rows sum to 100%).

Table 5.6: Worst 20 of 336 gaitset/location/participant data cells ranked by mean percent correct. All results shown are the mean value of 10 iterations of 10-fold cross-validation. Analysis was conducted using XYZ/2s/RF500. Five participants are present in this group.
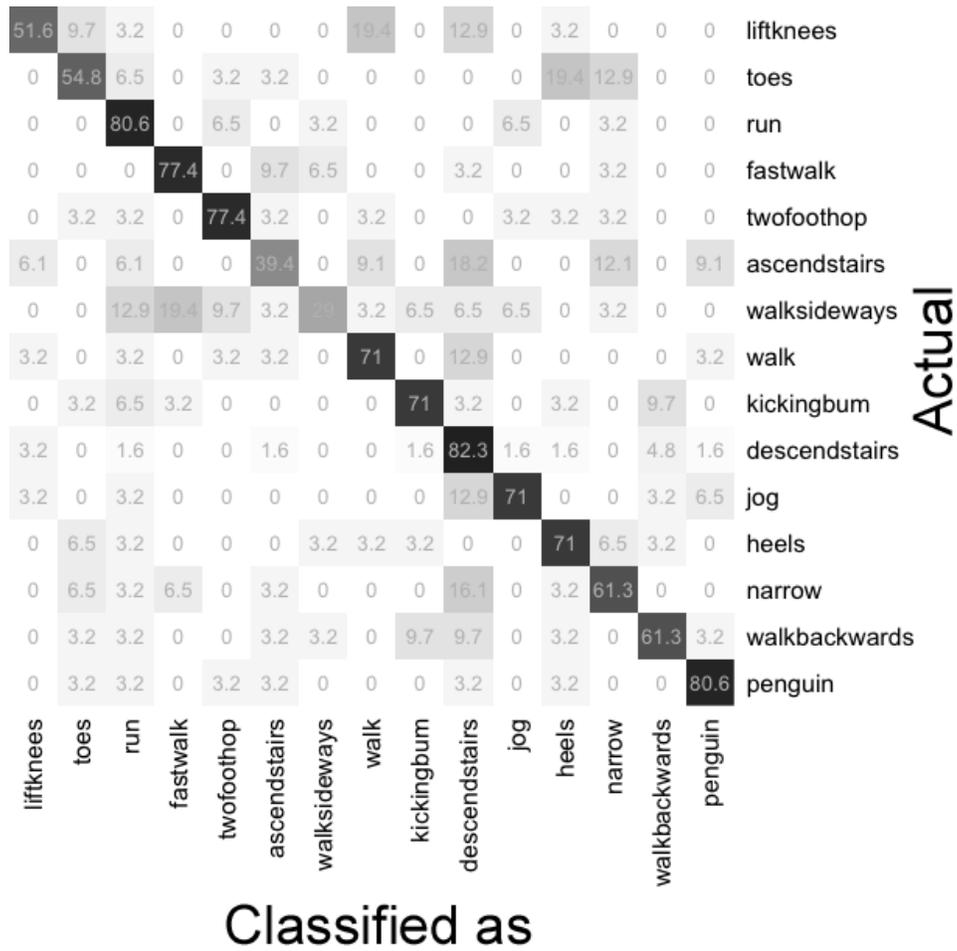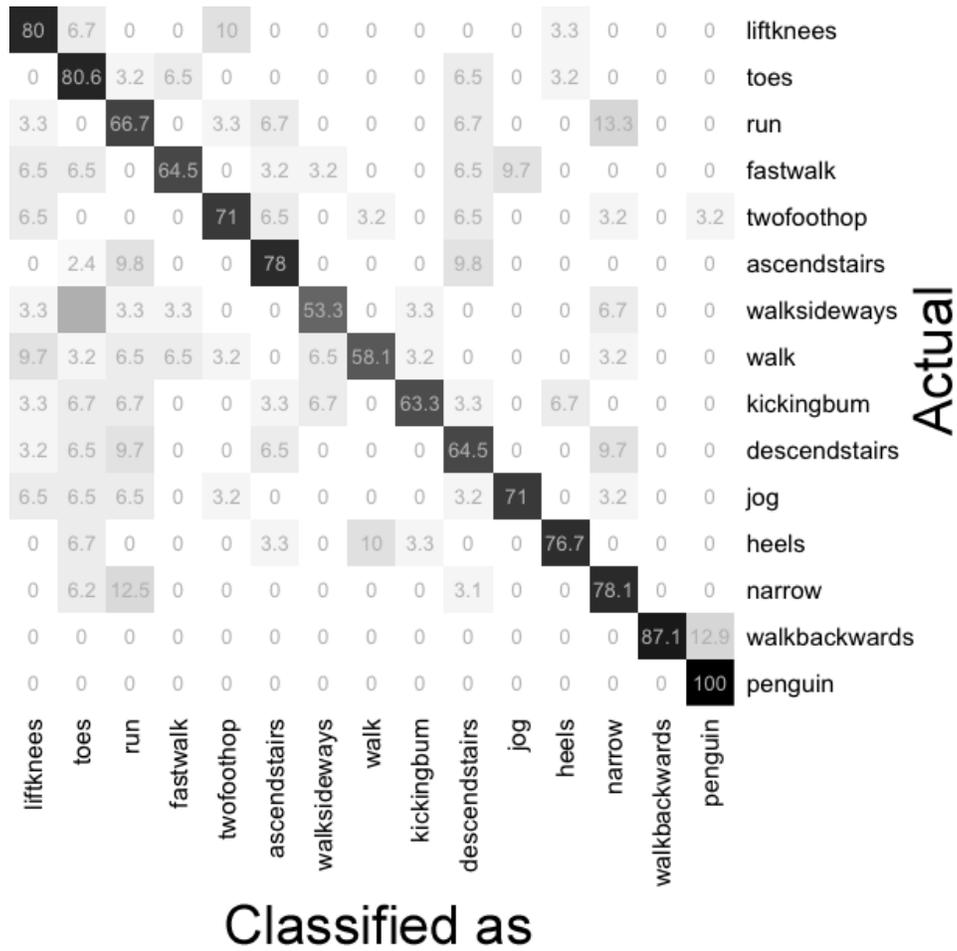
Gaitset	Location	Participant	Mean percent correct
All Gaits	Backpack	P4	71.7
All Gaits	Backpack	P10	71.1
All Gaits	All Locations	P8	70.3
All Gaits	Backpack	P11	70.2
All Gaits	Hand	P8	70.1
All Gaits	Backpack	P1	70.1
Pedestrian	Belt	P10	70.1
All Gaits	Arm	P8	69.7
All Gaits	Arm	P5	69.5
All Gaits	Belt	P10	68.6
Pedestrian	All Locations	P10	68.4
All Gaits	Front Pocket	P11	68.3
All Gaits	Back Pocket	P11	67.6
All Gaits	Front Pocket	P10	67.3
All Gaits	Arm	P10	67.1
All Gaits	Backpack	P5	67.0
All Gaits	Back Pocket	P10	66.9
All Gaits	Arm	P11	66.7
All Gaits	All Locations	P11	66.6
All Gaits	All Locations	P10	63.2

Chapter 6

Gait Classification Discussion

Everywhere is walking distance if you have the time.
— Steven Wright

In this chapter, we discuss the findings of the Gait Classification algorithm developed in Chapter 5: a Random Forest classifier with 500 trees extracting features from the original x, y, and z axes in 2 second windows. Our major findings include: overall success of classification in Section 6.1, a discussion of the complex interplay between location and gaitset in Section 6.2, and an examination of the effects of individual differences in Section 6.3. Finally, we discuss the limitations of our study in Section 6.4.

6.1 Overall Success

Overall, the classification scheme performed well, with a varying range of success. Before we begin our discussion, we should note that comparisons to previous work are difficult due to differences in application areas and methodology (such as the number of subjects, the amount of recorded data, and the types and numbers of gaits). Despite this, we still make an effort to compare our results with previous work whenever possible.

When trained and tested over all participants, accuracy ranged from 73.5% (All Gaits/Hand) to 87.2% (Exercise/Back Pocket), although we unfortunately and notably exclude All Gaits/All Locations (due to limitations of computational power;

see Section 5.3.2 for more details), which is expected to be the worst performer. All are larger than chance, which ranges from $6.6\bar{6}\%$ (All Gaits) to 25% (Exercise) depending on gaitset. See Table 5.3 for details.

As we only collected 30 seconds for each gait/participant/location section, we also investigated the improvement when the classifier is trained upon participant-specific data. Overall, accuracy improved by about 5%, although due to non-normality of the data we cannot verify that this difference is statistically significant. However, it suggests that a short personalization session might improve classifications rates. Even with personalization, though, there was a great deal of variation in accuracy: mean classification rates ranged from 63.2% to 100.0%. We attribute this large range of success to differences in gaitset, carrying location, and participant, and discuss these factors in detail in Section 6.2 and Section 6.3. The lowest mean classification rate, 63.2%, is well above chance ($6.6\bar{6}\%$ for all 15 gaits). Indeed, for all locations and all gaits, after training on an individual for 30 seconds for each gait, the mean classification rate across all 12 participants was 78.1%.

For non-real-time analysis we expect that both personalized and non-personalized algorithms (that is, trained on the user's data or not) could be sufficient for extremely high classification rates: Kunze et al. used a majority vote of several 1 second windows with 82% classification rate in 1 or more minute sequences to achieve 100% classification rate of walking vs not walking [36]. For real-time applications, a classification rate of 78.1% could be used with novel application design or game mechanics to improve perceived recognition rates. We also note that many of our gaits are very similar, and that careful pruning of the selection of gait can also improve performance: our Exercise gaitset had a mean classification rate of 87.3% over all body locations when personalized, and achieved a mean classification rate of 92.2% when it was known to be mounted on the user's belt. Thus, our results are promising for robust classification of a wide variety of gaits.

6.2 Gait is a Complex Ecosystem Involving Gaitset and Location

We have several main conclusions about gaitset and location. Altogether, they paint a picture of subtle interactions involving many different factors. We comment

upon our main findings in this section, and explore what patterns emerge while respecting the complexity of these factors.

There is no clear cut ranking of gaitset performance

As our results demonstrate, the success rate of gait recognition depends upon a variety of features, ranging from 73.5% (All Gaits/Hand) to 87.2% (Exercise/Back Pocket) with non-personalized algorithms, and from 63.2% (All Gaits/All Locations/P10) to 100.0% (three different data cells) for personalized algorithms (trained on the individual). Drawing from Figure 5.6, we see that this wide variation does not distinguish a clear ranking of locations or gaitsets in terms of accuracy. Even if there were statistically significant differences between the presented factors, interactions between the factors are present between gaitset and location: Game has a higher median than Pedestrian in some locations (such as Back Pocket or Arm), and a lower median in others (such as Belt and Front Pocket).

In aggregate, Exercise performs best and All Gaits performs worst

However, we can still draw some conclusions about the relative performance of the different gaitsets. In general, the best performing gaitset tended to be Exercise, and the worst performing gaitset was the expected worst performer, All Gaits. In the all participant analysis, the top three performing data cells are Exercise data sets, and the worst 4 performing data cells are All Gaits data sets (Table 5.3). In the by-participant analysis, the top 6 performing algorithms are Exercise data sets, and the worst 6 performing algorithms are All Gaits data sets (Table 5.4). In both all participant and by-participant analyses, the best performer for every location was Exercise, and the worst performer for every location was All Gaits. Although we do not yet have statistical analysis to support this claim, the small ranges of our data sets (visible in the bar-and-whiskers plot of Figure 5.2) make a promising case. A close look at the by-participant results (Figure 5.8 and Figure 5.9) shows that these results might change dramatically depending on the user when the algorithm is personalized. We elaborate on this effect of individual differences in Section 6.3.

Gait similarity in a gaitset tends to affect classification performance

Though there could be several reasons for the difference in performance of different gaitsets, such as the number of gaits within each gaitset, our findings suggest that the *types* of gaits chosen within each gaitset are an important factor. As we can

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see in Figure 5.5, Exercise's gaits have fewer standout confusions with each other than the gaits in Pedestrian and Game, which is not surprising considering that Exercise is the best performing gaitset. Pedestrian has a number of confusions that suggest differences between these gaits are quite subtle, such as *walk → fastwalk* and *jog → fastwalk*.[1] This is an expected result, and is consistent with the design of the Pedestrian gaitset to include very similar gaits (see Section 4.1). For the Pedestrian gaitset, then, we note that distinguishing between different categories of interpreted speeds of walking is challenging, and it may be best to only classify walking and jogging or running, or refer to cadence directly in applications.

In the Game gaitset, most gaits were mis-classified as *narrow*, especially *walksideways* and *walkbackwards*. The *least* confused gaits were *narrow → walksideways*, and *penguin → walksideways*. We thus suggest that *narrow*, *walksideways*, and *walkbackwards* are similar, but different from *twofoothop* and *penguin* (which, unexpectedly, had a strong confusion with *penguin → twofoothop*). Ultimately, many of these gaits are similar to normal walking, and those that differ were more easily recognizable.

The effect of carrying method is subtle

The smartphone's carrying location has a subtler effect on classification performance. Looking at all participants analysis (Figure 5.3), we can see that Front Pocket and Back Pocket tend to perform better than other locations for the Pedestrian, Game, and All Gaits gaitsets; this could also be the case in Exercise, but if so the effect is less clear. However, once we look at the by-participant bar-and-whiskers plots (Figure 5.8 and Figure 5.9), we find that this varies strongly with individuals. In several cases (such as P1/All Locations and P1/Arm) Exercise performs best and All Locations performs worst, as they do in aggregate, but in several cases (such as P1/Hand or P1/Front Pocket) we no can no longer draw the same conclusions. This effect of individual differences is quite prominent, and is discussed next in Section 6.3.

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[1] Recall that "→" signifies mis-classification; thus, "*walk → fastwalk*" signifies that *walk* was frequently mis-classified as *fastwalk*.

6.3 Individual Differences Have a Strong Influence on Gait Recognition

Individual differences add an important dimension to the relationship between location and gaitset. Looking at Figure 5.7, we see that that adding participant as a factor diminishes the range of each set of results. This suggests that participant, location, and gaitset all contribute to the success or failure of training an algorithm. This is especially remarkable given that in this analysis, each algorithm was *trained upon the participant, location, and gaitset combination.* Furthermore, the confusion matrices for the four worst performing participant/location/gaitset data cells (Figure 5.11, Figure 5.12, Figure 5.13, and Figure 5.14) show wide variation. This suggests that individual differences are a major factor in the recognizability of these gaits. This could be due to a number of confounded variables, from gait interpretation to the clothing worn by a participant (see Section 6.4 for a longer discussion of confounding variables).

Finally, looking at participants as a single factor in Figure 5.10 suggests that individual differences do not account for all variability; ranges are quite large. However, we note that three participants seem to perform considerably better than others: P2, P3, and P9; in fact, the 18 best performing data cells were from P3 and P9. No distinguishing demographic features stand out for these three participants: both sexes are represented, heights and weights vary (155-183cm and 51-64kg respectively), and no notable behaviours were observed during the study. This suggests that these gaits may work very effectively for certain individuals with minimal personalization (30 seconds per gait and location). If this is from gait interpretation, then it is possible that, with instruction for users, a wide variety of gaits could be effectively classified.

This wide variation in individual differences for activity recognition is consistent with literature (Zhang et al. report 69% to 95.3% with their best classifier [70], Kunze et al. report 72% to 93% with a binary classifier [36]), but we are not aware of any previous work that has commented on or explored individual differences and their impact on gait. Furthermore, previous work has used a non-personalized algorithm for all participants; we demonstrate this effect even when it is personalized via training on each participant, location, and gaitset, suggesting that it is not

merely error from the classifier, but an intrinsic component of each participant's gaits that must be considered in future gait analysis.

We thus suggest that future work attempting gait classification with gaits that might be susceptible to individual differences, such as the interpretation of unusual gaits or gaits with subtle differences must accomodate these differences. We aim to pursue this in our future work; see Section 7.2 for more details.

6.4 Limitations

There are several limitations to our study that must be considered for interpretation and future work. Major limitations involve the amount of data collected, confounds in experimental factors, and the selected algorithm for analysis.

Data collection

When collecting data, we only collected 30 seconds per gait/participant/location data cell in order to satisfy a compromise between covering a large number of gaits and an adequate number of samples per gait. Although our results suggest that this can be very successful for some users with a limited amount of data collection, other participants did not perform as well. Overall, we expect that more data will lead to better collection rates. In fact, previous work has often collected more data and used larger window sizes than 2-seconds. We therefore have shown a lower-bound, but not explored the effect of increasing data size.

Because of this limitation, we used 50% overlap in our windows, which may bias our results (as data points are not all independent). However, this is also representative of our target application - we plan on using an overlapping window for possible exercise applications or games using this classification algorithm.

As well, our results and conclusions may not generalize to all populations. Although our 12 participants have a range of heights, weights, and ages (Table 4.2), they were all younger adults without any medical conditions that would affect their gaits. The influence of age (such as gaits performed by children or the elderly) and effects of medical conditions (such as a limp) were not considered, and must be left to future work.

Additional considerations include using a single commercially-available phone, and not including handbags or purses as a carrying location in data collection.

Confounds

There are some confounds found in our experimental factors. First, we only collected data once from each participant. Therefore, individual differences in participants are involved with many different factors, including but not limited to: interpretation of gait description, physical gait characteristics, clothing, and phone orientation in its location-on-person. Our goal was to develop an algorithm that is robust to many of these factors, but given the effect of individual differences on classification rates, we recommend that future work investigate these confounding factors.

Another major confound is that the gaitsets do not have a consistent number of gaits: Pedestrian has 6 gaits, Game has 5, and Exercise has 4. We thus have not investigated the role of number of gaits compared with the types of gaits in a gaitset. Further analysis is planned but left to future work.

Selected Algorithm

We selected a single algorithm, which used the original x, y, and z axes, a 2 second window, and a Random Forest classifier with 500 trees (see Section 5.2). It is possible that the gait classification ecosystem is even *more* complicated, in that difference classification schemes could be more or less effective depending on different gaitsets, locations, and individuals. This could be contingent on axis set, window size, classification algorithm, or any combination of the three factors.

Chapter 7

Conclusion

Meandering leads to perfection.
— Lao Tzu

Mobile exercise applications and games show great promise to encourage exercise and fitness, increasingly important in our modern world. Modern mobile devices come with a wealth of sensors, including accelerometers, to support these applications. However, to truly manage ubiquitous gait sensing, one must take into account a variety of factors, including the carrying location of the device as well as the individual differences of the gait itself. Cadence estimation, a simple gait analysis task, is achievable through accelerometers on smartphones in a manner robust to these factors. However, gait classification remains a more challenging task that, though achievable, is heavily influenced by carrying location and individual differences.

In this chapter, we summarize and conclude our research. First, in Section 7.1, we review our major findings from these two types of sensing. We then layout future directions in Section 7.2.

7.1 Conclusions

In this section, we review the overall results from our two main studies.

Our cadence estimation study, presented in Chapter 3, demonstrated that we can robustly estimate a simple gait parameter, cadence, in real-time on mobile de-

vices. We present the algorithm to do this, RRACE: Robust Real-time Algorithm for Cadence Estimation, which uses a frequency-domain analysis of the accelerometer signal, transformed to be orientation-invariant. We demonstrate that RRACE is robust to carrying location, individual differences, and moderate to fast speeds, although it is sensitive to slow speeds (where our participants' walking becomes erratic). Overall, it was able to estimate cadence with 5% or lower error rate.

We also compared RRACE to the most accurate published time-based cadence estimation algorithm. We found that this time-based algorithm is extremely sensitive to carrying location and individual differences. Though some algorithms are affected by these factors, it is possible to overcome these differences using robust sensing techniques.

Our gait classification study, presented in Chapter 4, Chapter 5, and Chapter 6, demonstrated similar themes in the more challenging problem of classifying user gait. First, we presented 15 different gaits that, in general, were consistently interpreted during piloting. We also provide 3 gait sets suitable for different purposes: Pedestrian gaits, indicative of common context-aware gaits; Game gaits, with simple metaphors that are suitable for an exercise game (especially for kids); and Exercise gaits, gaits that involve different muscle groups in the legs. We found that it was feasible to classify gait with quick personalization (30 seconds of recording per location and gait): our worst-case scenario, classifying gait over all carrying locations and 15 different gaits, had a mean personalized performance of 78.1%. This improved when the carrying location was known and the set of gaits was reduced, achieving a mean best score of 92.2% with the Exercise gaitset located at the belt. These results were accomplished using a Random Forest classifier with 500 trees analyzing the original x, y, and z signal axes using a 2 second window, and can be computed on a smartphone in real time. This algorithm was determined by a study of different classification algorithm parameterizations.

During analysis of the classification algorithm, we found that carrying location, gaitset, and individual differences all influence gait classification success, even when considered in training. This reflects our findings with the time-based algorithm in the cadence estimation study; ultimately, gait is a complex entity, and sensing with smartphone accelerometers in a variety of locations is a difficult problem. However, we have been able to draw major conclusions. First, that the se-

lection of a set of gaits influences classification rates, with many similar gaits being confused by the classifier. With this in mind, the Exercise gaitset tends to perform best in general, and attempting to classify all 15 gaits is in general the most challenging problem. We have presented details of which gaits were mis-classified as other gaits, to provide guidelines for future design with gait classification. Carrying location has a subtler effect than gait selection, but in general suggests front and back pockets to be the best carrying locations for gait classification; this is strongly affected by each participant's individual differences. Finally, and on that note, we found that while classification rates per individuals were in general promising, some individuals had extremely high classification rates regardless of location or gaitset, suggesting that individual differences might be the most influential factor in gait classification. We encourage others to investigate this phenomenon with further exploration.

7.2 Future Work

Given our findings, we have several possible directions for future work, including improvements for both algorithms, and an expansion into different application areas.

We believe that our cadence estimation algorithm, RRACE, can be improved through harmonic analysis. At this time, RRACE only analyzes the most powerful frequency observed; by examining more than this, the algorithm might be able to become even more accurate. As well, RRACE does not perform well at lower speeds. An adaptive algorithm, such as switching to a step detection technique when speed or cadence is reduced, could remedy this flaw. Finally, smoothing filters could be applied to improve the cadence estimation.

For gait classification, we find that the question of individual differences to be unanswered but important. We plan on investigating individual differences in a number of ways: investigating the role of instruction for gaits, to see whether simple verbal descriptions of gaits are sufficient; examining whether the performance of the gait itself is the problem, or the carrying locations or clothing has an impact; and investigating whether these individual differences can be characterized and understood. Improvements to the algorithm itself might be accomplished

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by developing a more intelligent classification model (*e.g.*, using a Markov-model approach to consider previous classifications, or Bayes-net-like approach using different classifiers in tandem to make a more accurate classification of gait, carrying location, and user).

Finally, we hope to expand this work into other application areas beyond supporting fitness and exercise. Examining subtler gait characteristics, such as asymmetry or limping, could be beneficial as an early warning system for those who might suffer debilitating diseases, or for remote monitoring of rehabilitation. Using individual differences to recognize the user of a mobile device could be useful for security or context-aware applications. Finally, a better understanding of the role of location could help us develop context-aware applications, such as recognizing when a user is carrying the phone in his or her pocket; for example, by turning the ringer volume up when the phone is in a pocket to improve detection rate.

Ultimately, there is great potential for accelerometer sensing in mobile devices, with applications ranging from health and fitness to simple interactive context-aware applications. This work has provided valuable information about some of the factors that influence gait analysis in real-time on a mobile smartphone, including carrying location and individual differences. We hope to transform gait sensing to be ubiquitous and robust, to help improve fitness, health, and other applications in the world.

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Appendix A

Supporting Materials

A.1 Cadence Estimation Study Forms

A.1.1 Consent Forms

Department of Computer Science
2366 Main Mall
Vancouver, B.C. Canada V6T 1Z4
tel: (604) 822-3061
fax: (604) 822-4231

Project Title: Gait Measurement Algorithm Verification
(UBC Ethics #H01-80470)
Principal Investigator: Karon MacLean, Professor, Dept. of Computer Science, 604-822-8169
Co-Investigator: Idin Karuei, PhD Candidate, Dept. of Computer Science, 604-827-3982
Oliver Schneider, M.Sc. Student, Dept. of Computer Science
Michelle Chuang, B.Sc. Student, Dept. of Computer Science

The purpose of this experiment is to test the gait measurement algorithm that we have developed on android phones.

In this experiment, you will be asked to walk on a sidewalk at different speeds ranging from very slow to brisk walking. You will be asked to carry android phones in your front and back pocket and a backpack provided by us, attached to your arm and belt, and held in one of your hands.

REIMBURSEMENT: We are very grateful for your participation. However, you will not receive compensation of any kind for participating in this project.

TIME COMMITMENT: 1 × 30 minute session
CONFIDENTIALITY: *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenters will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

Department of Computer Science
2366 Main Mall
Vancouver, B.C. Canada V6T 1Z4
tel: (604) 822-3061
fax: (604) 822-4231

RESEARCHER'S COPY
CONSENT FORM

Project Title: Gait Measurement Algorithm Verification
(UBC Ethics #H01-80470)

Principal Investigator: Karon MacLean, Professor, Dept. of Computer Science, 604-822-8169
Co-Investigator: Idin Karuei, PhD Candidate, Dept. of Computer Science, 604-827-3982
Oliver Schneider, M.Sc. Student, Dept. of Computer Science
Michelle Chuang, B.Sc. Student, Dept. of Computer Science

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                        accessible only to the experimenters.

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Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

You hereby CONSENT to participate and acknowledge RECEIPT of a copy of the consent form:

PRINTED NAME _____ DATE _____

SIGNATURE _____

A.2 Gait Classification Study Forms

A.2.1 Consent Forms

Project Title: Gait Classification Algorithm Development
(UBC Ethics #H01-80470)
Principal Investigator: Karon MacLean, Professor, Dept. of Computer Science, 604-822-8169
Co-Investigators: Oliver Schneider, M.Sc. Student, Dept. of Computer Science
Idin Karuei, PhD Candidate, Dept. of Computer Science, 604-827-3982

The purpose of this experiment is to gather data for a gait classification algorithm that we are developing on android phones.

In this experiment, you will be invited to perform several gaits, such as walking, jogging, running, ascending or descending stairs, or riding a bicycle or bus. If uncomfortable with any requested gait(s) or activities, you may choose to omit it/them and it will not affect your reimbursement. You will be asked to carry several android phones in these locations, which we will be using to measure parameters of your motion: in your front and back pocket, in a backpack provided by us, attached to your arm and belt, and held in one of your hands when safe to do so.

REIMBURSEMENT: We are very grateful for your participation. You will receive monetary compensation of $10 for this session.

TIME COMMITMENT: 1 × 45 minute session
CONFIDENTIALITY: *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

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Project Title: Gait Classification Algorithm Development
(UBC Ethics #H01-80470)

Principal Investigator: Karon MacLean, Professor, Dept. of Computer Science, 604-822-8169
Co-Investigators: Oliver Schneider, M.Sc. Student, Dept. of Computer Science
Idin Karuei, PhD Candidate, Dept. of Computer Science, 604-827-3982

The purpose of this experiment is to gather data for a gait classification algorithm that we are developing on android phones.

In this experiment, you will be invited to perform several gaits, such as walking, jogging, running, ascending or descending stairs, or riding a bicycle or bus. If uncomfortable with any requested gait(s) or activities, you may choose to omit it/them and it will not affect your reimbursement. You will be asked to carry several android phones in these locations, which we will be using to measure parameters of your motion: in your front and back pocket, in a backpack provided by us, attached to your arm and belt, and held in one of your hands when safe to do so.

REIMBURSEMENT: We are very grateful for your participation. You will receive monetary compensation of $10 for this session.

TIME COMMITMENT: 1 × 45 minute session
CONFIDENTIALITY: *You will not be identified by name in any study reports. Data gathered from this experiment will be stored in a secure Computer Science account accessible only to the experimenters.*

You understand that the experimenter will ANSWER ANY QUESTIONS you have about the instructions or the procedures of this study. After participating, the experimenter will answer any other questions you have about this study.

Your participation in this study is entirely voluntary and you may refuse to participate or withdraw from the study at any time without jeopardy. Your signature below indicates that you have received a copy of this consent form for your own records, and consent to participate in this study.

If you have any concerns about your treatment or rights as a research subject, you may contact the Research Subject Info Line in the UBC Office of Research Services at 604-822-8598.

You hereby CONSENT to participate and acknowledge RECEIPT of a copy of the consent form:

PRINTED NAME _____ DATE _____

SIGNATURE _____

A.2.2 Recruitment Email

Department of Computer Science
201-2366 Main Mall
Vancouver, B.C. Canada V6T 1Z4
tel: (604) 822-3061
fax: (604) 822-4231

Human Gait Classification with Smart Phones

Principal Investigator: Karon MacLean, Professor, Dept. of Computer Science, 604-822-8169
Co-Investigator: Oliver Schneider, MSc Student, Dept. of Computer Science
Idin Karuei, PhD Candidate, Dept. of Computer Science, 604-827-3982
Version 1.0 / 22 December, 2011

The following message will be used to recruit participants for our study. We will distribute this message using either or both of the following methods:

- Emailing the recruitment message to mailing lists maintained by the Computer Science department or our research group, such as a list of department graduate students (often used for this kind of purpose) and a list of persons who have expressed an interest in being study participants.
- Uploading the recruitment message to an online forum posting, such as craigslist.ca.

From: Oliver Schneider and Idin Karuei
Subject: Call for Study Participants - $10 for Human Gait Classification with Smart Phones

The SPIN Research Group in the UBC Dept. of Computer Science is looking for participants for a study recognizing user gait. You will be compensated $10 for your participation in a single 45-minute session.

We will place Android phones in your front and back pocket, a bag or knapsack, on your hip, on your arm, and in your hand, and measure parameters of your movement during several types of typical activities. You will be asked to move freely outdoors in a safe place, such as an otherwise unused running track, and asked to do several different gaits for a few minutes each, such as walking, jogging, running, ascending and descending stairs. You may be asked to ride a bicycle (safety equipment will be provided) or a bus.

Please visit <URL> to sign-up for the experiment.
You can contact me if you have any questions.

Oliver Schneider
MSc Student, UBC Computer Science
oschneid@cs.ubc.ca

A.2.3   Demographic Information Form

Date: _____

ID: _____   Checklist: Frontpocket

Height: _____   Backpocket

Weight: _____   Backpack

Age: _____   Belt

Sex: _____   Arm

Dominant Hand: _____   Hand

Order: A (stairs first, up then down) Water

         B (stairs first, down then up) Whistle/Stopwatch

         C (stairs last, up then down)

         D (stairs last, down then up)

Date: _____

ID: _____   Checklist: Frontpocket

Height: _____   Backpocket

Weight: _____   Backpack

Age: _____   Belt

Sex: _____   Arm

Dominant Hand: _____   Hand

Order: A (stairs first, up then down) Water

         B (stairs first, down then up) Whistle/Stopwatch

         C (stairs last, up then down)

         D (stairs last, down then up)

A.3 Other Forms

A.3.1 Participant Reimbursement Form

Experiment Name: _____

BREB Ethics Approval # _____

Date	Name	Number	Paid	Signature	Email

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revised 7/23/2012