INVESTIGATION OF MICROSCOPIC PEDESTRIAN WALKING BEHAVIOR

by

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Abstract

In sustainable urban planning, non-motorized active modes of travel such as walking are identified as a leading driver for a healthy, liveable, and resource-efficient environment. Walking is also an integral component of most trips. However, walking receives less attention in transportation engineering and planning compared to motorized modes. As the global society is becoming more aware of the benefits of active transportation, there is an increasing demand for designing and shaping the transportation system to put more emphasis on pedestrians. As such, standards and guidelines need to be developed in order to provide practitioners with the tools required to objectively evaluate pedestrian oriented facilities. However, the tools and methods developed and used for modeling pedestrian movement have not yet been developed to a level that can reliably measure pedestrian activity and behavior. To encourage walking, there is a need for a solid understanding of pedestrian walking behavior. This understanding is central to the evaluation of measures of walking conditions such as comfortability and efficiency. The aim of this thesis work is to gain an in-depth understanding of pedestrian walking behavior through the investigation of walking speed and the spatiotemporal gait parameters (step length and step frequency). This microscopic-level analysis provides insight into the pedestrian walking mechanisms and the effect of various attributes such as gender and age. The analysis relies on automated video-based data collection using computer vision techniques. This thesis makes several contributions which include: *i)* demonstrating the feasibility of using computer vision to capture pedestrian movement, *ii)* investigation of pedestrian speed variations with respect to design changes to intersection crossings, *iii)* investigation of the ability of individual pedestrians to change their walking speed as a response to pedestrian signal indications, *iv)* investigation of pedestrian gait parameters for various pedestrian and design attributes, and *v)* development of a methodology for classification of pedestrian age and gender using spatiotemporal gait parameters.

Preface

A version of chapter 3 has been presented. H. Hediyeh, T. Sayed, M. H. Zaki and K. Ismail, "Before and After Analysis of Pedestrian Crossing Speed Behavior at Scramble Phase Signalized Intersections," in *Transportation Research Board 91th Annual Meeting*, Washington, D.C., 2012. The video data were made available to UBC and pedestiran tracks were generated by Dr. Karim Ismail and also used in other studies.

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A version of chapter 4 (Case Study One) has been presented. H. Hediyeh, T. Sayed, M. H. Zaki and G. Mori, "Pedestrian Gait Analysis Using Automated Computer Vision Techniques," in *Canadian Society for Civil Engineering 9th International Transportation Specialty Conference*, Edmonton, AB, June 2012. The video data were recorded by UBC and pedestiran tracks were generated by Dr. Greg Mori and also used in other studies.

A version of chapter 4 (Case Study One) has been conditionally accepted for publication. H. Hediyeh, T. Sayed, M. H. Zaki and G. Mori, "Pedestrian Gait Analysis Using Automated Computer Vision Techniques," in *the journal of Transportmetrica,* 2012.

A version of chapter 4 (Case Study Two) has been submitted for publication. H. Hediyeh, T. Sayed and M. H. Zaki, "Automated Microscopic Analysis of Pedestrian Gait Parameters at Urban Signalized Intersections," 2013. Pedestiran tracks used are the same tracks used in chapter 3.

A version of chapter 5 has been submitted for publication. H. Hediyeh, T. Sayed and M. H. Zaki, "Automated Classification of Pedestrian Gender and Age using Spatiotemporal Parameters of Gait," 2013. Pedestiran tracks used are the same tracks used in chapters 3 and 4.

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Chapter One: Introduction

1.1 Background and Motivation

In sustainable urban planning, non-motorized active modes of travel such as walking are identified as a leading driver for a clean, healthy, liveable, and resource-efficient environment (Ismail, et al., 2009). Walking, or active transportation in general, has potential benefits such as reduced cardiovascular and respiratory disease from air pollution and reduced exposure to vehicular traffic injury risks and noise. Air pollution is estimated by Canadian Medical Association to cause 21,000 premature deaths as well as 92,000 visits to emergency rooms and 620,000 visits to doctor's office per year in Canada which translates into an annual economic cost of $8 Billion (CMA, 2008). Globally, the number of motorized vehicles driven on the earth is approximated to be more than one billion, which is expected to double in the next two decades (Sperling & Gordon, 2008). Worldwide, air pollution results in approximately 800,000 premature deaths (1.4% of all deaths) per year (OECD, 2008). Shifting from private motorized vehicle use to active transportation modes can help reduce the direct tailpipe emissions as well as the indirect emissions from vehicle manufacturing, fuel extraction and refining, and the construction and expansion of roadways (Hosking, et al., 2011) (Litman & Doherty, 2011). A transport system having a considerable portion of its mode share consisting of active transportation such as walking and cycling is also less vulnerable to future interruption in oil supplies (Hosking, et al., 2011).

Walking increases physical activity which results in prevention of heart disease, diabetes, obesity and cancer (Hosking, et al., 2011). Compared with improving vehicle and fuel efficiency, shifting from private motorized vehicles to active transportation and public mass transportation modes, in combination with improved land use, can have greater immediate health co-benefits (Hosking, et al., 2011). Increased physical activity has other health benefits such as weight control and helps maintain musculoskeletal and aerobic fitness which can eliminate or delay the onset of dependence, disability, and chronic disease (Morency, et al., 2007). Physical inactivity is identified to result in 3.2 million deaths per year, worldwide, which can be prevented by encouraging the adoption of active transportation (Mathers, et al., 2009). Walking which results in moderate increases in breathing and heart rates is known to significantly reduce mortality rate by 43% (Gregg, et al., 2003). Walking is also associated with lower mortality rates in adults with diabetes, and walking a minimum of 2 h/week is estimated to prevent one out of 61 deaths per year among diabetic adults (Gregg, et al., 2003). It is found that among wealthy countries, the rates of obesity are lower for those countries which have higher rates of walking and cycling as part of their transport system (Litman, 2011).

As communities are becoming increasingly aware of the benefits associated with active non-motorized modes of travel, pedestrian walking behavior research is receiving a growing attention from policy makers, researchers and practitioners. A better understanding of walking behavior is therefore central to the evaluation of measures of walking conditions such as comfortability and efficiency. Microscopic pedestrian data can be used to study pedestrian movement in order to solve well-entrenched problems in road user behavioral and safety analyses. Microscopic models of pedestrian movement increasingly incorporate detailed aspects of pedestrian behavior. A standard way in conducting such studies is to capture the movement of pedestrians as they use the transport system. Many researchers and practitioners have developed techniques for collecting pedestrian data to capture pedestrian movement in order to evaluate the characteristics of different facilities in terms of level-of-service, safety, etc. For example, there is a relatively large body of literature which investigates the walking speed of elderly pedestrians to ensure enough clearance time is provided at signalized intersections in order to reduce the potential conflicts between pedestrian and motor vehicle.

The standards and guidelines for design and operation of pedestrian facilities should take into account factors such as environmental and pedestrian characteristics to ensure acceptable site measures such as safety and level-of-service. For example, the elderly are found to have slower walking speeds compared to younger adults (Gates, et al., 2006) (Knoblauch, et al., 1996); therefore, their presence in pedestrian flow is found to have the potential to lower the facility's level-of-service, as a result (Galiza, et al., 2010) (Galiza, et al., 2011). The design level-of-service does not necessarily reflect the actual pedestrian experience if pedestrian diversity is not accounted for (Galiza & Ferreira, 2012). There is enough evidence to believe that the global population is aging in an increasing rate and the forecasts suggest that a greater population segment will be dedicate to elderly in a near future. It is estimated that in most Organization for Economic Co-operation and Development (OECD) countries, one in every four people will be aged 65 or older by 2030 and the population of elderly aged over 80 will triple by 2050 (OECD, 2001). According to the 2006 Census, an increase of 11.5% in the number of Canadians aged 65 and older was observed in the previous five years (Martel & Malenfant, 2007).

Many tools and methods have been developed for modeling vehicular traffic; however, methods and tools to model pedestrian activity have not yet been developed to a level to estimate measures such as accessibility, safety, and mobility for pedestrians (Pulugurtha & Repaka, 2008). As a result, despite the presence of demand for making cities more walkable, the policy makers and the planners do not have the required tools to conduct studies which objectively measure the costs and benefits of improvements or implementations of pedestrian facilities. Standards and guidelines need to be developed in order to provide practitioners with the tools required for evaluating the pedestrian oriented facilities (James & Walton, 2000). Pedestrian movement is usually captured and studied with the intention to discover the impact of pedestrian activity on motor-vehicle movement with less attention to the consideration and evaluation of walking as a separate means of traveling (James & Walton, 2000).

1.2 Pedestrian Data Collection

Even though non-motorized modes of transportations, especially walking, are receiving growing attention, these modes are not studied to the same extent as motorized modes. The lack of quality data is the main reason for the slow momentum in pedestrian research. The majority of pedestrian studies consider the movement of pedestrians at a macroscopic level which includes investigation of pedestrian crowd movement, pedestrian flow rate and density, platoon formation, pedestrian evacuation discharge rate at bottlenecks, etc. Few studies investigate the pedestrian movement at a microscopic level. To better understand the characteristics of macroscopic pedestrian flow such as dynamic lane formation and bottleneck capacity, detailed information on pedestrian flow can play an important role (Hoogendoorn, et al., 2004).

1.2.1 Microscopic Pedestrian Data

Detailed microscopic pedestrian data is required to calibrate pedestrian modeling tools such as micro-simulation suits so that the models better and more realistically represent the true movement of pedestrians. Examples of such movements and behaviors include pedestrian navigation around obstacles (Willis, et al., 2004) as well as pedestrian maneuvering and inter-person spacing (Kerridge & Chamberlain, 2005). Similar approach is followed in calibration of motor vehicle models to enhance movements and behavior such as lane changing and car following (Brackstone & McDonald, 1996) (Hoogendoorn, et al., 2004).

In addition, capturing microscopic pedestrian movement enables the evaluation of pedestrian facilities in terms of operations so that improvements to existing designs can be implemented. For example, capturing microscopic pedestrian movement enables the investigation of the ability of individual pedestrians to change their walking speed as a response to changes in pedestrian signal indications which may be a result of different perceptions of safety (Gates, et al., 2006) (Stollof, et al., 2007). This can, in return, enhance the safety and comfortability of pedestrians and be a driving factor for encouraging walking as a means of traveling.

Gait analysis is also a microscopic-level analysis which allows true estimates of objective walking measures such as step frequency and step length for different population segments. It can be used to translate walking distance into units such as number of steps or energy expenditure. Several applications are associated with gait analysis such as estimating the impact of trading personal vehicles for active transportation modes such as walking (Morency, et al., 2007). Gait analysis is also useful in demonstrating the walking costs to different groups of pedestrians such as the elderly and the obese, which allows the consideration of constraints on the movement ability of some pedestrians. Other direct applications are to provide feedback to standard guidelines for pedestrian movement such as crosswalk clearance times at intersections and the calibration of pedestrian micro simulation models. The goal of this microscopic-level analysis is to provide insight into pedestrian walking mechanisms and the effect of various attributes such as gender and age. As well, the analysis can help investigate the strategies of different pedestrians to control their walking speed.

1.2.2 Automatic Microscopic Pedestrian Data Collection using Video Sensors

One of the main challenges in conducting detailed analysis on pedestrian behavior is the lack of reliable data. This lack of reliable data can have a significant impact on several transportation engineering and planning aspects. The manual methods currently used in practice for the collection of pedestrian data lack the ability to capture microscopic changes in position and speed (Shi, et al., 2007). As well, the manual field observation of pedestrian data is labor-intensive, time consuming, and subject to high errors (Diogenes, et al., 2007) (Schneider, et al., 2005).

Data extracted from videos are rich in details and the costs associated with recording and storing the data are low (Ismail, et al., 2010). Therefore, the accurate pedestrian movement data such as speed measurement can greatly benefit from automatic tracking of the position of pedestrians in space and time (Saunier & Sayed, 2007). Automatic tracking requires computer recognition of the position of pedestrians in space with respect to time, and hence, the generation of a trajectory for each pedestrian. The benefits of automatic tracking of pedestrians include capturing the natural movement of pedestrians and minimizing the risk of disturbing the behavior of observed subjects, and the relatively higher accuracy and consistency in comparison to manual methods. Other benefits of automatic tracking include less resource requirement, and the availability of information about the microscopic behavior of pedestrians along the traveled distance. For example, microscopic data required for investigating the ability of individual pedestrians to change their walking speed as a response to pedestrian signal indication can be easily obtained with automatic tracking (Ismail, et al., 2009). Automatic tracking also enables the investigation of pedestrian gait analysis.

One reason the manual methods for pedestrian data collection are still preferred over automatic methods is that the automatic methods have not yet developed to a level that can recognize the diversity among pedestrians such as gender (Jones, et al., 2010). It is therefore of great value if additional information such as pedestrian gender and age can also be automatically captured by automatic data collection methods; this is one of the objectives of this thesis.

1.3 Problem Statement and Research Objective

1.3.1 Problem One: The Use of Computer Vision Techniques to Capture and Study Pedestrian Movement

Computer vision techniques are being widely used to detect and track pedestrians. It is of considerable interest to demonstrate the feasibility of using these techniques in capturing and studying pedestrian movement. As well, it is extremely important to check the accuracy of these techniques in capturing real pedestrian movement and to ensure meaningful conclusions are drawn from the studies using such techniques. This leads into the following research problem:

Demonstrate, using real world data, the feasibility and accuracy of using computer vision techniques to capture and study the pedestrian movement in open environments.

1.3.2 Problem Two: Pedestrian Walking Speed Behavior at Signalized Intersections

Pedestrian crossing speed at intersections is a characteristic of pedestrian flow which influences several intersection design features such as signal timings. To plan and design pedestrian facilities such as crosswalks at intersections, it is important to predict pedestrian movement under individual pedestrian attributes and different external circumstances. Little research has been conducted on the influence of the introduction of a scramble phase on pedestrian crossing speed. This study attempts to fill this gap with the aim to improve the understanding of pedestrian walking behavior at scramble phase signalized crossings. In addition, the effect of pedestrian signal indication on pedestrian walking speed behavior will also be investigated. For this purpose, the average crossing speed of pedestrians depending on the time they enter the crosswalk with respect to the start time of pedestrian signal indications (temporal effect) is studied. Similarly, the same speed behavior is analyzed through the first, second, third, and the fourth quarter of the crosswalk length.

To improve the understanding of pedestrian behavior at scramble phase signalized crossings by finding average pedestrian crossing speeds across different crosswalk legs, and to investigate the ability of individual pedestrians to change their walking speeds as a response to how far through the pedestrian signal phase (in terms of time), as well as how far through the crosswalk's length (in terms of position) they are.

1.3.3 Problem Three: Pedestrian Gait Analysis

Gait analysis is a microscopic-level analysis which allows true estimates of objective walking measures such as step frequency and step length for pedestrians. It is used to translate walking distance into units such as number of steps or energy expenditure. Several applications are associated with gait analysis such as estimating the impact of trading personal vehicles for active transportation modes such as walking. Gait analysis is also useful in demonstrating the walking costs to different groups of pedestrians such as the elderly and the obese. This allows the consideration of constraints on the movement ability of some pedestrians. Other direct applications are to provide feedback to standard guidelines for pedestrian movement such as crosswalk clearance times at intersections and the calibration of pedestrian micro simulation models.

To gain an in-depth understanding of pedestrian walking behavior through the investigation of the spatiotemporal gait parameters (step length and step frequency). This microscopic-level analysis provides insight into the pedestrian walking mechanisms and the effect of various attributes such as gender and age.

1.3.4 Problem Four: Demonstration of Conducting Before-After Pedestrian Behavior Studies

Before-After (BA) studies are conducted in order to evaluate the outcomes of engineering countermeasures. In this research, the changes in pedestrian crossing speed behavior following the implementation of a pedestrian scramble phase will be studied. The research problem is:

To demonstrate the feasibility of conducting a BA study by investigating the changes in pedestrian crossing speed behavior following the implementation of a pedestrian scramble phase.

1.3.5 Problem Five: Pedestrian Age and Gender Classification using Gait

Research shows that attributes such as age and gender have a significant effect on pedestrian behavior. Therefore, it is beneficial to have distributions for pedestrian attributes, in addition to simple measures such as exposure. For example, in order to ensure an adequate crossing time is provided for safe crossings at intersections, it is important to have an estimate for the percentage of pedestrians such as the elderly or children who are identified to have mobility constraints. Applications of gender and age classification include finding demographic characteristics for facilities such as schools, hospitals, shopping centers, and commercial and business districts. Other applications include security surveillance, shoppers' statistics, locomotion and healthcare monitoring, and allowing robots to perceive gender. This leads into the following problem statement:

To demonstrate the feasibility of automatic classification of pedestrian age and gender using two motion features: pedestrian step frequency and step length.

1.4 Thesis Structure

This chapter provides an introduction to this thesis which outlines the importance and the significance of this research to the rapidly developing field of active transportation, as well as the objectives and the problem statements with regards to this research work. A through literature review of the existing research regarding: the need for pedestrian data collection, automated techniques by the use of computer vision for the collection of pedestrian data, and pedestrian movement behavior studies, is presented in Chapter 2. Chapter 3 studies pedestrian movement in terms of walking speed at urban intersections. The chapter introduces the methodology used to automatically measure pedestrian walking speed. The effect of scramble phasing and pedestrian group size, as well as the effect of pedestrian signal indications on pedestrian walking speed, is also covered in Chapter 3. Chapter 4 studies the pedestrian movement behavior beyond the analysis of walking speed, in terms of spatiotemporal parameters of gait: step frequency and step length. The Chapter introduces the methodology for automatically extracting step frequency and step length and provides two case studies. In each case study, the distributions of pedestrian gait parameters (i.e., the walking speed, step frequency, and step length) are provided. Also, the effects of pedestrian attributes such as age, gender, and group size, as well as the effects of design attributes and pedestrian signal indications on gait parameters are investigated. In Chapter 5, the feasibility of using spatiotemporal parameters of gait for the purpose of pedestrian age and gender classification is introduced. Chapter 6 is the concluding chapter of this thesis.

Chapter Two: Literature Review

2.1 Background

As walking is receiving considerable attention from policy and transportation engineering officials for the purpose of sustainability and public health, there is an increasing effort being devoted to the study of pedestrian movements. This chapter includes a literature review of studies in transportation engineering and other fields which investigate the characteristics of pedestrian movement.

Walking is a major travel mode and the pedestrian is a key road user. Pedestrian studies improve the understanding of pedestrian as a major road user within the transport system. To study pedestrian behavior, data is required.

2.2 Pedestrian Data Collection

Walking speed has been identified in the literature to be a standard measure of pedestrian movement behavior. In other words, to determine the movement behavior of pedestrians against pedestrian or environmental attributes such as age, gender and weather, researchers mainly categorize attributes and measure and compare pedestrian walking speed within each category.

Data collection methods for counting or measuring the walking speeds of pedestrians can be categorized into manual field or video observations and automatic techniques. Semi-automatic methods are also employed for measurement of pedestrian walking speed. These techniques are briefly explained as follows.

2.2.1 Manual Field Observations

Manual data collection using field observations is conducted by observers standing on the side of a road or an intersection and recording pedestrian counts or measuring walking speed by marking on sheets or using clickers to record the number of pedestrian crossings or the time elapsed for pedestrian crossings. Manual field observation for pedestrian data collection is labor-intensive and limits the number of study sites due to high costs as these counts are typically done by two observers, or even three observers per site in cases of heavy traffic volumes (Schneider, et al., 2005). The costs associated with this type of data collection are too high that some communities do not even gather this information (Schneider, et al., 2005). Despite the high costs, manual field observations allow the observers to record additional information such as the behavior of pedestrians during intersection crossing. However, the accuracy of this technique can be potentially low depending on the complexity of the task. Diogenes et al (2007) conducted a study which compared the manual on-the-site pedestrian count using sheets and counters to manual counts using video cameras and found that the on-the-site manual methods underestimated pedestrian volumes, systematically, with the error rates ranging from 8 to 25%. In cases where pedestrian volume is low, manual on-the-site counts are found to be in agreement with manual video counts (Greene-Roesel, et al., 2008). In general, as complexity of the counting task increases, the accuracy is found to decrease (Greene-Roesel, et al., 2008). The error rates associated with the manual on-the-site pedestrian counts are identified to be greater at both beginning and end of the data collection period, which reflects the lack of observer's familiarity and experience with the task or fatigue (Diogenes, et al., 2007).

2.2.2 Manual and Semi-Automatic Video Observations

Manual video observations require the observer to view the taped video and count or measure walking speeds of pedestrians as they cross imaginary lines. Hui et al (2007) conducted a pedestrian study in which they extracted pedestrian data such as walking speed, step frequency, and step length, for a sample of over 1800 pedestrians by observing video files. This method is also labor-intensive, but potentially more accurate than manual field observations as the observer can view the recorded video multiple times if unsure about the counts or measurements.

Semi-automated methods are done by image processing tools to manually track walking pedestrians, as done in (Lam & Cheung, 2000) and (AlGadhi, et al., 2002), for example. The advantage of this technique over manual methods is that once the manual tracking is complete for each pedestrian, the data is then physical and can be saved and stored for future validation or used for other purposes. However, this method is still labor-intensive in cases where large sample sizes are desired.

2.2.3 Automatic Data Collection Methods

Special equipment is used in automatic data collection methods. Automatic methods can be used for long term monitoring of road users for the purpose of, for example, discovering the seasonal effect or rush hour effect on traffic volume or flow. The initial costs associated with automated data collection are generally higher than manual techniques due to equipment, implementation, and preparation costs. However, the labor costs and the effort associated with data collection using automatic methods are much lower, especially when large sample sizes are desired.

The technologies commonly used for automatic pedestrian data collection include infrared laser technology, ultrasonic sensors, doppler radar, and video imaging. Two types of infrared laser technologies to count pedestrians are passive and active infrared lasers. Passive infrared detects changes in thermal contrast, while active infrared detects obstructions in the laser beam to identify a passing object (Jones, et al., 2010). Passive infrared sensors are widely used for automatic pedestrian counting. However, they are found to consistently miss pedestrians walking in groups, and as a result, undercount pedestrians (Greene-Roesel, et al., 2008). A no-detection error rate of 12 to 48% is found for passive infrared counters (Jones, et al., 2010). Other shortcomings with this device are its inability to differentiate between bicyclists, pedestrians and strollers (Greene-Roesel, et al., 2008). On the other hand, active infrared sensors can distinguish between different road users such as pedestrians and bicyclists, and are therefore appropriate to be used for shared use pathways (Jones, et al., 2010) (Schneider, et al., 2005). The no-detection error rate for active infrared counters is found to be 15 to 21% (Jones, et al., 2010). Ultrasonic sensors emit an ultrasonic sound and sense the presence of an object (usually up to a distance of 9.1 meters) by listening to the echo bouncing off that object (Beckwith & Hunter-Zaworski, 1998). Doppler radars emit a radio wave and sense the presence of an object by analyzing the change in the frequency of the radio wave as it bounces back from a passing object (Beckwith & Hunter-Zaworski, 1998). Video imaging can detect a movement of an object by analyzing the change in pixels of a video image (Beckwith & Hunter-Zaworski, 1998). Beckwith and Hunter-Zaworski (1998) conducted a study in which they investigated the detection accuracy of ultrasonic sensor, passive infrared sensor, and doppler radar. They found detection rates of 47% and 89% for ultrasonic sensors installed at 7.6 and 4.3 meters from the passing pedestrian traffic, respectively. They also found detection rates for doppler radar and passive infrared to be 92% and 94%, respectively.

Video Sensors

Pedestrian data collection is also possible with the use of video sensors. Tsuchikawa et al (1995) proposed a method to automatically collect pedestrian count data from video files (with a top view camera) using background subtraction. Their method is robust against illumination level changes and its accuracy is reported to be as high as 90%.

2.3 Automatic Collection of Microscopic Pedestrian Data Using Computer Vision Techniques

Collecting reliable pedestrian data is often conducted by manual counts or measurements. However, the manual field observation of pedestrian data is labor-intensive, time consuming, and subject to high errors (Ismail, et al., 2009). Also, the manual methods currently used in practice for the collection of pedestrian data lack the ability to capture microscopic changes in position and speed (Shi, et al., 2007). Automated video analysis is becoming more popular as it overcomes the shortcomings present in the widely used manual methods. Automatic tracking of pedestrians in video scenes is possible with the help of computer vision techniques (Ismail, et al., 2009). For automatic tracking of pedestrian, moving road users must be detected and tracked frame-by-frame and classified into pedestrians and non-pedestrians (Ismail, et al., 2009). Data extracted from videos are rich in details and the costs associated with recording and storing the data are low (Ismail, et al., 2010). Common problems in this challenging task include global illumination variations, shadow handling, and multiple-object tracking (Forsyth, et al., 2005). Tracking of road users using computer vision is still an open problem and tracking of pedestrians is even more challenging than the tracking of other road users (Ismail, et al., 2009). Pedestrians are locally non-rigid, and have more variability in shapes and appearance compared to vehicles (Forsyth, et al., 2005).

2.3.1 The Tracking Algorithms

Two tracking algorithms are used in this thesis for detection of walking pedestrians: a feature-based tracking system; MM-Track algorithm.

Feature-based Tracking System

A Feature-based tracking system is a useful tool for the detection of pedestrians. The readers are encouraged to refer to (Saunier & Sayed, 2006) for more details about the algorithm. The tracking system was initially developed for vehicle detection and tracking as part of a larger system for automated road safety analysis. The tracking of features is done through the well-known Kanade-Lucas-Tomasi feature tracker. One advantage of feature-based tracking over other methods such as tracking using flow or tracking using probability is its ability to handle partial occlusion. For automatic traction, first, all features, whether stationary or moving, are detected. Then, stationary features or features with unrealistic motions are filtered out and the remaining features are kept. Next, the features that are recognized to belong to a specific object are grouped together;

cues such as spatial proximity and common motion are used for grouping features. Figure 2.1 shows a sample pedestrian tracking using feature-based tracking algorithm. This tracking algorithm was described and validated in a previous study (Ismail, et al., 2010). The accuracy of speed measurement from the automated system was reported to be acceptable. The root mean square error (RMSE) for comparison between automatic and manual speed calculation was reported to be 0.0725 m/s. Feature-based tracking and a computer vision system developed at the University of British Columbia were the core of the system for detection and tracking of pedestrians.

(a)	(b)

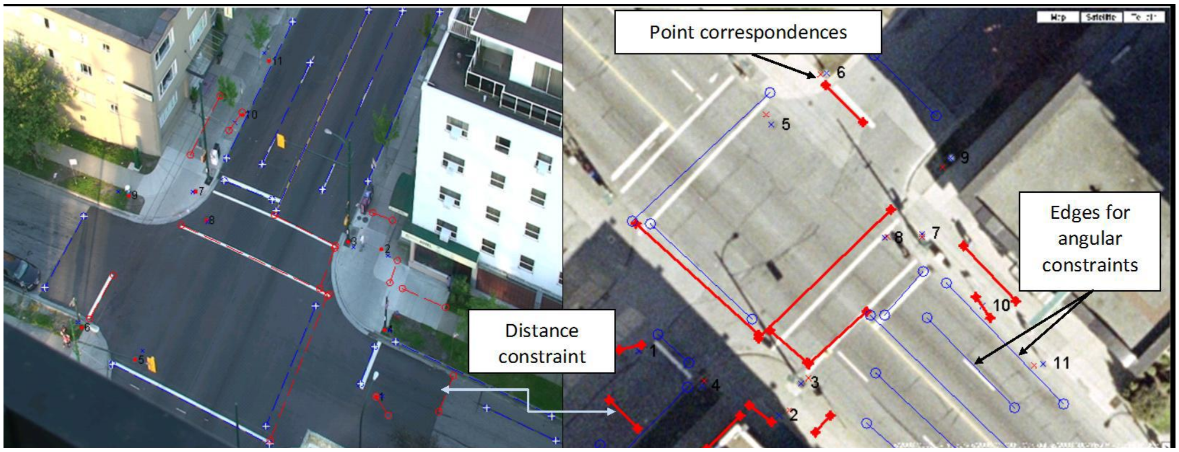
Figure 2.1 Sample Pedestrian Tracking using Feature-based Tracking. (a) represents the detection of moving features and (b) represents a pedestrian object after grouping the features

MM-Track Algorithm

Another tracking algorithm used for the generation of pedestrian trajectories is MM-Track Algorithm. For extraction of such trajectories from videos, all road users must be detected, recognized as pedestrians or other road users, and tracked frame-by-frame as they move. MM-Track algorithm is a cluster-based appearance modeling and online tracking approach algorithm used for detection of pedestrians (Khanloo, et al., 2012). The MM-Track is a hybrid single pedestrian tracking algorithm that puts together the advantages of descriptive and discriminative approaches for tracking. Readers can refer to (Khanloo, et al., 2012) for more detail about the algorithm.

2.3.2 Camera Calibration

Another important component of the system is to create a mapping from world coordinates to image plane coordinates using a homography matrix (a camera calibration process). This mapping enables the recovery of real-world coordinates of points that appear in the video. The matrix parameters specify the translation and orientation of the camera coordinates relative to the world coordinates. The parameters are obtained by minimizing the difference between the projection of geometric entities, e.g. points and lines, onto world or image plane spaces and the real-world measurements of these entities. The camera calibration process is described in detail in (Ismail, et al., 2010). To summarize, corresponding points in world and image spaces are annotated and the positions of the points on the world map are used to determine the real-world coordinates of those same points in the image space. As well, the true line segments lengths are measured from the orthographic image (either from Google map or from field measurements). The angular constraints are set by annotating pairs of parallel lines such as lane markings or light poles or perpendicular lines such as road markings in the image space. Figure 2.2 shows some of these steps. A reference grid is shown in Figure 2.3 “to visualize the accuracy of the estimated camera calibration parameters” (Ismail, et al., 2010).



(a) (b)

Figure 2.2 Calibration Data. (a) Image Space; (b) World Space. Source: (Ismail, et al., 2010)

(a) (b)

Figure 2.3 (a) Sample Grid on Image Space; and (b) Projected Sample Grid on World Space

2.4 Pedestrian Walking Behavior Studies

2.4.1 Pedestrian Crossing Speed

Pedestrian Crossing Speed (PCS) at intersections is a characteristic of pedestrian flow which influences several intersection design features such as signal timings. To plan and design pedestrian facilities such as crosswalks at intersections, it is important to predict pedestrian movement under individual pedestrian attributes and different external circumstances (Al-Azzawi & Raeside, 2007). Several studies have identified multiple characteristics which influence the PCS. Knoblauch et al (1996) investigated the effect of street width, timing of pedestrian signal phases, signal cycle length, and pedestrian group size on PCS. They found that pedestrians tend to have faster average crossing speed when the cycle length is long (probably because longer cycle lengths are used for wider streets) and that short Walk (W) intervals result in faster average crossing speed compared to moderate or long W intervals. Similar results were found for Don't Walk (DW) intervals. Also, pedestrians who start crossing the intersection on W indication continue walking with slower speeds than those who start on Flashing Don't Walk (FDW) or DW indications. They also found that pedestrians walking alone tend to have faster average crossing speed compared to those walking in pairs or larger groups. Other findings include faster average crossing speeds for wider streets compared to narrower streets. Gates et al (2006) conducted a study at eleven intersections in Madison and Milwaukee to identify the factors which influence crossing speeds of pedestrians. They found that the average crossing speed of pedestrians walking alone is higher than those walking in larger groups. They also found that pedestrians who start crossing the intersection during the FDW and DW indications walk faster than those who start crossing during the W indication. Tarawneh (2001) conducted a study investigating the mean and the 15th-percentile PCSs for intersections in Jordan. Factors such as street width and group size were found to significantly influence the average PCS. He found that pedestrians crossing wider streets tend to have higher average speeds. He also found that average crossing speeds of pedestrians walking in groups of 3 or more are slower than those walking alone or in pairs; however, he did not find the average PCS to be different between those walking alone and in pairs. Akcelik and Associates (2001) investigated pedestrian movement characteristics at actuated mid-block signalized crossings in Australia. They investigated the average walking speed of pedestrians through the first and the second half of the crosswalks, and reported a slower walking speed through the second half. Ishaque and Noland (2006) compared the average wait time and average travel time for pedestrians through the intersection between scramble pedestrian crossing and parallel-to-vehicle-phase crossing design using micro-simulation. The results showed that the average pedestrian wait time is higher in scramble crossing design, while the average pedestrian travel time is the same for both designs. The conflict between oncoming pedestrian platoons, referred to as bi-directional flow effect, is also found to have effects on PCS. Li et al (2010) investigated this effect and found that the increase in demand on both sides of crosswalk increases pedestrian crossing time as the opposing pedestrian flows interact. No studies were found that investigate the crossing speed of pedestrians at scramble phases or that compares the crossing speed before and after the introduction of a scramble phase. This study attempts to fill this gap.

It is important to note that the above-mentioned studies are based on manual speed measurements by field or video observations. None of the studies attempted to use computer vision techniques.

2.4.2 Pedestrian Gait

Gait Data Analysis

The Quantitative evaluation of Gait parameters has been traditionally undertaken manually. For example, Hui et al (2007) manually measured the gait parameters for 1882 pedestrians in China. The mean values for walking speed, step frequency, and step length were found to be 1.22 m/s, 1.91 Hz, and 0.64 m, respectively. A thorough review by Venuti and Bruno (2009) found that walking speed has a range of [1.08 to 1.60 m/s] +/- [0.15 – 0.63 m/s], step frequency has a range of [1.82 – 2.0 Hz] +/- [0.12 – 0.186 Hz], and step length has a range of [0.75 – 0.768 m] +/- [0.07 – 0.098 m].

Several studies investigated the relationship between gait parameters. Yamasaki et al (1991) observed that the relationship between stride length and walking speed is linear up to speeds of approximately 2.0 m/s for males and 1.83 m/s for females and deviates from linearity at higher walking speeds. Crowe et al (1996) found that stride frequency and length are both highly correlated with walking speed. Hui et al (2007) found walking speed, step length, and step frequency of a sample of 1882 Chinese pedestrians to follow normal distributions. They found walking speed to be correlated with both step frequency and length, but found no apparent relationship between the step length and the step frequency.

Several researchers investigated the effect of age on gait parameters. Older people were reported to have slower walking speeds and shorter step lengths compared to younger people (Elble, et al., 1991) (Judge, et al., 1996) (Crowe, et al., 1996) (Murray, et al., 1969) (Himann, et al., 1988) (Hageman & Blanke, 1986). Mixed results were reported on the relationship between age and the step frequency. Elble et al (1991) studied the effect of age on gait parameters for healthy young (30 years old mean age) and old (75 years old mean age) people and found that younger people walk faster by increasing their stride length rather than stride frequency during both natural and fast walking. Judge et al (1996) found older adults (79 years old) to have 10% shorter average step length compared to younger adults (26 years old) after correcting for leg length differences. Kirtley et al (1985) found decreasing stride length with increasing age in men aged 18 to 63. Zijlstra et al (2008) investigated whether the step length-frequency relationship of physically active community-dwelling older women between ages 54 and 85 changes with increasing age. They found that walking speed, stride length, and stride frequency decrease as age increases. However, they did not find systematic changes in the step length-frequency relationship (ratio of step length to step frequency) as a result of age increase, even in complex situations where subjects were given extra tasks to do in addition to walking. They concluded that the aging processes is not responsible for some older women to reduce step length or increase periods of double limb support in order to reduce the challenge of balance control during walking.

Factors such as gender (Crowe, et al., 1996) (Yamasaki, et al., 1991) (Hui, et al., 2007), race (Al-Obaidi, et al., 2003), weight (Hills & Parker, 1992), and walkway grade (Kawamura, et al., 1991) are also found to have effects on human gait during walking. Crowe et al (1996) investigated this effect and found that while walking speed does not significantly differ between males and females, females have shorter stride length and higher stride frequency compared to males. Yamasaki et al (1991) also investigated the difference in the walking patterns of males and females and found that, in comparison to males, females tend to increase their step frequency in order to speed up, and found that height influences this difference in the walking patterns of the two groups. They found that the average step length is significantly shorter for females while step frequency is significantly lower for males at speeds 1.5 m/s and greater. However, when accounted for height difference between the two groups, these differences were not significant at lower walking speeds than 2.17 m/s. Hui et al (2007) measured the gait parameters for 1882 pedestrians in China and found that, compared to males, females have slightly larger average step frequency, but shorter average step length (both significant). They conclude that due to a slightly smaller mean step frequency and a relatively larger mean step length and mean walking speed of males compared to females, step length is the main determinant of waking speed. They indicated, based on observational judgment, that the larger mean step length of males is a result of males being taller than females. Kawamura et al (1991) investigated the effect of grade on gait parameters of 17 healthy young men and found that the most conspicuous phenomena in upgrade walking to be in step frequency and the most conspicuous phenomena in downslope walking to be in step length, compared to level walking. They found step length to significantly decrease at 9 and 12 degree slopes in the downslope walking, and increase at 6 and 9 degree slopes in the upslope walking, compared to level walking. They found step frequency to significantly increase at 6 and 9 degree slopes in downslope direction compared to level walking.

Metabolic Energy Expenditure and Mechanics of Walking

The varying effects of factors on the gait parameters can be explained through the metabolic energy expenditure rate and the mechanical power requirements during waking. It is also an important element when evaluating the characteristics of walking conditions corresponding to measures such as comfortability and efficiency during walking. It is important to study the rate of energy expenditure across different pedestrian or infrastructure design attributes during walking, as well as the sensitivity of this rate to each step frequency and step length.

Humans have the ability to select walking patterns which minimize their metabolic energy expenditure (Holt, et al., 1995) and prefer to walk with a stride frequency at which the metabolic cost of walking is lowest (Umberger & Martin, 2007) (Donelan, et al., 2002) (Cavagna & Franzetti, 1986). Stride frequency is identified as a critical parameter which strongly influences metabolic cost of walking (O'Halloran, et al., 2010) (Donelan & Kuo, 2003) and that increasing or decreasing stride frequency above or below Preferred Stride Frequency (PSF) influences the metabolic cost of walking (Donelan & Kuo, 2003) (Russell & Hamill, 2007). When stride frequency is varied below and above the PSF, the metabolic energy expenditure forms a curve that has a U-shape with its minimum close to or at the PSF (Umberger & Martin, 2007) (O'Halloran, et al., 2010). O'Halloran et al (2010) studied the effect of changing stride frequency below and above PSF on the heart rate and ventilatory efficiency (by keeping the walking speed constant) and found that heart rate is lowest and ventilatory efficiency is greatest at the PSF. Donelan and Kuo (2003) investigated the effect of increasing step frequency above PSF by keeping the step length constant at 0.70 m, and found that a 60% increase in step frequency above PSF of 1.81Hz results in a 222% increase (2.3-7.3 W/kg) in the net metabolic power (net metabolic power is the power of standing still subtracted from the power of walking). The metabolic cost of walking is also found to change with varying stride length (Donelan, et al., 2002).

As well, there is a relationship between metabolic power expenditure and mechanical power requirements during waking. It is believed that the mechanical power during walking is also influenced by varying step frequency (Umberger & Martin, 2007) (Cavagna & Franzetti, 1986) and step length (Donelan, et al., 2002) and that a major determinant of the metabolic cost of walking is the mechanical work needed for step-to-step transitions to move and redirect the Body Center of Mass (BCM) during double support (Donelan, et al., 2002) (Neptune, et al., 2004) as well as to raise the BCM in single support (Neptune, et al., 2004). For the exchange of body's potential and kinetic energy during single limb support, little muscle work (Neptune, et al., 2004), and therefore, little metabolic energy expenditure is required. Umberger and Martin (2007) investigated the effect of varying step frequency (by keeping walking speed constant) on total mechanical power (based on the work done by lower limb joint moments) and efficiency during walking, and found that although the net metabolic energy expenditure is optimum at step frequency equal to PSF, the mechanical power is optimum at step frequency 11-12% lower than PSF, and the mechanical efficiency is optimum at step frequency 8% above PSF (Umberger & Martin, 2007). Cavagna and Franzetti (1986) investigated the effect of varying step frequency (at a constant walking speed) on the mechanical power spent to lift and accelerate the BCM (P_ext) and the mechanical power spent to accelerate the limbs relative to the BCM (P_int). They found P_ext to decrease and P_int to increase with increasing step frequency. They also found that the step frequency which results in the minimum total mechanical power (P_tot = P_ext + P_int) to be 20-30% lower than the freely chosen step frequency (i.e. PSF) at the same walking speed. Gordon et al (2009) found that decreasing or increasing vertical BCM movement below or above subjects' preferred range increases the metabolic cost of walking due to the increase in the mechanical work at the hip, knee, and ankle joints. Donelan et al (2002) investigated the effect of varying step length from 0.40 to 1.10 m on the mechanical power and the metabolic energy expenditure rate during walking at a constant step frequency of 1.80 Hz, and found that both mechanical work and metabolic rates increase with the fourth power of step length, and to a lesser extent, with step frequency. They found that, in order to increase their walking speeds, humans typically increase their step frequency and step length in almost equal proportion, and that, if the only determinants of the metabolic cost of walking were the step-to-step transitions (i.e. required mechanical work to redirect the BCM velocity), walking at high step frequencies and short step lengths would lower the metabolic cost (Donelan, et al., 2002).

During walking, BCM undergoes sinusoidal oscillations in vertical, horizontal, and lateral directions due to the external forces acting on the body to displace the BCM from a position to another (Crowe, et al., 1996). Crowe et al (1996) found the displacement of the BCM by double integration of the ground reaction forces. They found this oscillatory distance to be directly affected by the square of the period of the walking cycle (i.e. T^2 or $(\text{frequency})^{-2}$). This relationship highlights the strong effect of step frequency on the displacement of BCM as increasing frequency decreases the BCM oscillation amplitude. The lower BCM displacement associated with higher step frequency results in lower mechanical power requirement to lift and accelerate the BCM, but higher mechanical power requirement to accelerate the limb with respect to the BCM (Cavagna & Franzetti, 1986), which may increase or decrease the metabolic power depending on which mechanical power requirement change is larger.

Browning et al (2006) studied the effect of gender and obesity on energetic cost and preferred walking speed and found that both obesity and sex have influences on the net metabolic rate of walking. They found the net metabolic rate (W/kg) to be 10% higher (per kg) for obese individuals compared to normal-weight individuals, and 10% higher (per kg) for women compared to men. In an earlier study, Browning and Kram (2005) investigated the preferred walking speed and energetic cost of walking in obese women and found that obese women prefer to walk at speeds which minimize their energy cost per distance, even though this strategy requires a relatively higher aerobic effort compared to slower walking speeds. They recommend that obese women walk slower than their preferred walking speeds for weight management purposes; however, slower walking speeds can also be optimized based on step frequency and length combination selections which minimize the metabolic energy expenditure as was shown by (Zarrugh, et al., 1974). Zarrugh et al (1974) found that within normal walking speed range (up to about 2.4 m/s), for any given step length, there is a unique step frequency at which the required energy expenditure per unit distance is minimum. Browning et al (2005) found that, compared to normal-weight women, obese women have 11% higher average net metabolic rate (significant).

Browning & Kram (2007) found in a later study that knee-joint loads are larger in obese compared to normal-weight subjects and that peak sagittal-plane knee moments are reduced by 45% by decreasing walking speed from 1.5 to 1.0 m/s, and that the absolute peak sagittal-plane knee moments are equivalent between obese and normal-weight subjects at speeds 1.1 and 1.4 m/s, respectively. However, even at identical walking speeds, the two groups have the ability to select different stride length-stride frequency combinations which may affect the knee joint moments (Russell, et al., 2010) (Allet, et al., 2011) and plantar foot pressures and ankle joint moments (Allet, et al., 2011). Russell et al (2010) found that, for obese women walking at preferred walking speeds, decreasing stride length by 15% below preferred stride length (subsequently increasing stride frequency) results in significant reductions in the energy expenditure as well as the impulse of the external adduction moment; however, the peak shock during foot-ground impact, which may result in knee osteoarthritis, does not significantly decrease with this decrease in stride length. Allet et al (2011) found that by decreasing stride length by 20% while walking at constant speed results in a significant decrease in peak pressure under heel, mid-foot, and toes in normal-weight subjects.

Other Applications

Several applications can benefit from the gait analysis. Accurate pedestrian micro-simulation modeling relies on accurate characterizations of human movements. Micro-simulation models exist in which the movement of a pedestrian in each time step is decided based on the direction of movement and step size, with step size being a control parameter to ensure that the positions of two pedestrians in a close proximity do not overlap after a position update (Guo, et al., 2010). In such models different fractions of full step size are used with the full step size being the preferred option according to field experiments. Gait parameters are used to calibrate simulation parameters. For instance, simulation based on cellular automaton (Burstedde, et al., 2001) requires cell size setting. Each cell can be occupied by exactly one pedestrian at a single time step. This variability in cell size may be attributable to walking speed, and therefore, step size if a relationship between walking speed and step size exists (Chen, et al., 2008). There are empirical studies relating the longitudinal space requirements between pedestrians to walking speed, which show that a greater space is required with increasing walking speed due to the additional space requirement for taking a step (Daamen & Hoogendoorn, 2003).

2.4.3 Pedestrian Classification

There are several methods to classify human attributes. One method is to use the "pattern of movement" or gait. Gait is identified as a useful biometric for human recognition (Nixon, et al., 1999) (Nixon, et al., 2003) (Ekinci, 2006) (Stevenage, et al., 1999) (Boyle, et al., 2011). Pedestrians are recognized to have a unique rhythm during walking that is periodic and oscillatory (Mori, et al., 1994) (Yasutomi, et al., 1996) (Yoo, et al., 2006) (Nixon, et al., 1999) (Ekinci, 2006) (Crowe, et al., 1996) (BenAbdelkader, et al., 2002) (Makihara, et al., 2011) (Davis, 2001). The qualitative properties of walking patterns such as periodicity can be used for pedestrian detection and behavioral analysis. This unique rhythm (periodic oscillatory) can be used for automatic human recognition at a distance (BenAbdelkader, et al., 2002) (Nixon, et al., 2003) (Ekinci, 2006), discrimination of pedestrians form other moving objects such as bicycles or vehicles (Mori, et al., 1994) (Yasutomi, et al., 1996), or discrimination of human age (Davis, 2001) (Makihara, et al., 2011) and gender (Yoo, et al., 2006) (Makihara, et al., 2011) using computer vision techniques. It is possible to identify the class of humans from their gait, as step length and step frequency are functions of gender, body weight and height (BenAbdelkader, et al., 2002). In early gender classification research based on gait, Kozlowski and Cutting (1977) examined the gender classification of walker from moving light displays where human observers classified the gender of the walker. Their method resulted in 63% correct classification using full body joint markers. Mather and Murdoch (1994) showed in a later study that classification of gender can be improved by examining the frontal view of the subjects as males tend to swing their shoulders more than females and females tend to swing their hips more than males. Their classification method resulted in 79% correct gender classification. Davis and Gao (2004) introduced an automated method using an adoptive three mode PCA for feature extraction from point light displays, with a correct classification rate of 95.5%. Yu et al (2009) used human observer to classify gender based on human gait in controlled environment where they present a numerical analysis when considering different human components such as head and hair, chest, back and thigh and found these human components to be more discriminative than other components. Their correct classification rates are 94.35% based on upper body silhouettes, and around 67% based on lower body silhouettes. However, their method still suffers when there are view changes or with changes in clothing and footwear. Yoo et al (2006) proposed an automated system for gender classification of walking humans from video by utilizing a set of human gait data. They used Support Vector Machine classifier to discriminate human gender and their method resulted in 96% correct classification rate. The gait signature used in (Yoo, et al., 2006) was denoted by a sequential set of two-dimensional stick figures. BenAbdelkader et al (2002) used height as well as step length and frequency for automatic identification of people. Their method is view-invariant and results in a correct classification rate of 65% for non-fronto-parallel sequences. They showed that adding height as a feature in addition to the step frequency and length improves the performance of their classification method.

Gait has also been used for human age classification. Davis (2001) introduced a method for discriminating adults (30–52 years of age) from children (3-5 years of age) by comparison of the stride parameters using computer vision. They used six children and nine adults and computed their relative stride (stride length divided by stature) and stride frequency at different speeds from the trajectories of marked ankle and head positions. Their results showed strong distinction between the relative stride and stride frequency for the two groups and a correct classification rate of 93-95% was achieved using a trained two-class linear perceptron. Makihara et al (2011) introduced a video-based gait feature analysis for human age and gender classification using a large-scale multi-view gait database. They used arm swing, posture, and relative size of head for specific features for children, stride and body frame for specific features for adult males and females, and walking posture, body width, and arm swing for distinctive features of the elderly. They correctly classified children from adults at a rate of 74%, and males from females at a rate of 80%, and even higher when they limit the age range for adults.

Saunier et al (2011) proposed a method for discriminating pedestrians from vehicles by comparing the velocity profiles of each road user type. The difference in speed profile between a vehicle and a pedestrian was that a pedestrian speed profile had oscillatory shape from which step frequency and step length could be estimated, while a vehicle speed profile did not have a distinct shape. They estimate step frequency and step length of walking pedestrians from the oscillations in their speed profiles. They used computer vision techniques for tracking road users.

Chapter Three: Automated Analysis of Pedestrian Crossing Speed Behavior at Scramble-phase Signalized Intersections Using Computer Vision Techniques

3.1 Background

One of the important areas of pedestrian data collection is the average walking/crossing speed measurements. Many transportation applications require data of pedestrian walking speed, such as: developing pedestrian simulation models, planning and management of crowd movement, estimating facility level-of-service, and designing pedestrian signals (Ismail, et al., 2009). Pedestrian crossing speed at signalized intersections is an important engineering design parameter as it determines the time required for safe pedestrian crossing at the intersection (Tarawneh, 2001).

In this study, the change in crossing speed behavior of pedestrians following the implementation of a pedestrian scramble phase is investigated. Pedestrian scramble phasing is an exclusive pedestrian phase where pedestrian crossing is allowed in any direction across the intersection, during which no vehicle movement is allowed. The main benefit of the implementation of a scramble phase, as reported in the literature, is that it reduces pedestrian-vehicle conflicts, and therefore increases the safety of the intersection (Ismail, et al., 2010) (Bechtel & MacLeod, 2004) (Kattan, et al., 2009). However, both vehicles and pedestrians usually experience longer delays as a result of the increase in cycle length and the decrease in green ratios. Signal timing, as a design feature of an intersection, is influenced by the pedestrian walking speed to cross the intersection.

Pedestrian crossing speed is used to determine pedestrian clearance time. A walking speed of 1.22 m/s (4 ft/s) is recommended for traffic signal timing (MUTCD, Revision 1, 2003) (Dewarr, 1999) (HCM, 2000) (McShane, et al., 1998), regardless of the characteristics of the design of the intersection or the characteristics of the pedestrians crossing the intersection. However, research shows that pedestrian speed is influenced by factors such as the traffic, environmental, and pedestrian characteristics (Tarawneh, 2001) (Knoblauch, et al., 1996) (Gates, et al., 2006) (Akcelik_&_Associates, 2001) (Fitzpatrick, et al., 2006). Therefore, the recommended speed of 1.22 m/s for signal timing calculations may not provide adequate time for all pedestrians to make safe crossing maneuvers at signalized intersections. Characteristics such as age, gender, group size, pedestrian facility type, weather/season and vehicular traffic have been identified to influence pedestrian crossing speed. Little research has been conducted on the influence of the introduction of a scramble phase on pedestrian crossing speed. This study attempts to fill this gap with the aim to improve the understanding of pedestrian behavior at scramble phase signalized crossings.

The accurate pedestrian speed measurement can greatly benefit from automatic tracking of the position of pedestrians in space and time (Saunier & Sayed, 2007). The automatic tracking of pedestrians for crossing speed measurements requires less resource and also provides information about the microscopic behavior of pedestrians during the distance traveled. For example, microscopic data required for investigating the ability of individual pedestrians to change their walking speed as a response to pedestrian signal indication can be easily obtained with automatic tracking (Ismail, et al., 2009). The main source of the data in this chapter comes from video sensors. The data set used in this study was extracted and used in a previous study (Ismail, et al., 2010) for the automated analysis of pedestrian–vehicle conflicts for the same intersection.

3.2 Methodology

This section provides information about the characteristics of the studied site, the details of the methodology used for collecting data, and the methods and tools used for calculating pedestrian crossing speed and validation.

3.2.1 Site Characteristics

The study site is a busy downtown intersection located at 8th and Webster Streets, city of Oakland, California. 8th Street is a one-way, westbound street, with four traffic lanes. Webster Street is a one-way, southbound street, with also four traffic lanes. Pedestrian crosswalks are located on all four legs of the intersection, with two additional diagonally crossing bays in the scramble phase. The intersection layout and the lengths of the crosswalk legs are shown in Figure 3.1. The intersection was selected to demonstrate the feasibility of automated data collection for pedestrian walking speed in this study because of the availability of the video data (Ismail, et al., 2010). Pedestrian activity at this intersection is high (approximately 3,000 pedestrian crossings per leg, per hour, both directions at peak times) (Bechtel & MacLeod, 2004). Pedestrian movement in any direction is not allowed during the vehicle phase in the scramble phase (Bechtel & MacLeod, 2004). Similarly, vehicle movement is not allowed in any direction during the pedestrian phase in the scramble (Bechtel & MacLeod, 2004). In addition, vehicles are not allowed to make right-turns-on-red during the movement of the intersecting vehicle traffic (Bechtel & MacLeod, 2004). The pedestrian signal timing for both pre-scramble and scramble phases are provided in Table 3.1. The crossing legs were categorized into conventional and diagonal legs. Pre-scramble phase consists of four conventional crossing legs, and the scramble phase consists of two diagonal crossing legs in addition to the four conventional crossing legs present in pre-scramble.

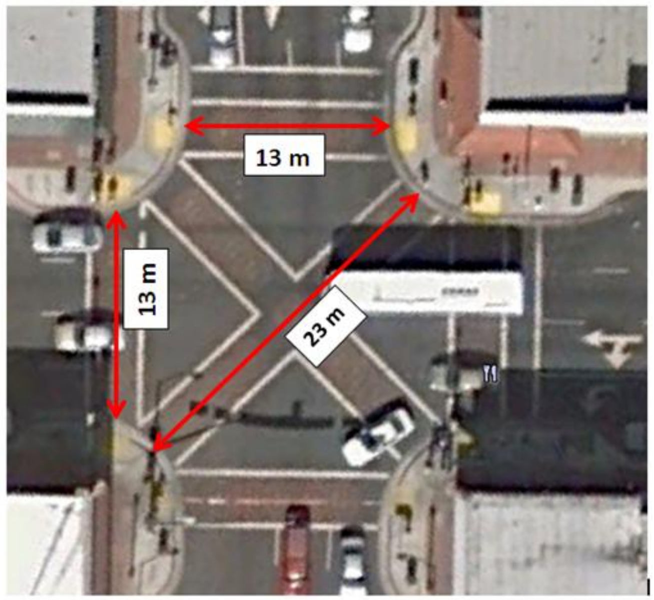


Figure 3.1 Case Study Intersection Layout

Table 3.1 Pedestrian Signal Timing for Pre-scramble and Scramble Phases (in seconds)

Phase	Parallel Approach	Walk (W)	Flash Don't Walk (FDW)	Don't Walk (DW)	Cycle Length
Pre-scramble Phase	8th St	7	8	6	45
	Webster St	10	9	5	
Scramble Phase		10	18	3	90

3.2.2 Data Collection

Computer vision techniques were used to generate pedestrian tracks. A feature-based tracking algorithm was used to detect pedestrians as explained in Chapter Two. Due to possible tracking interruptions, the pedestrian trajectory database included some short tracks that did not cover the majority of the crosswalk length. Including these short tracks in the analysis may introduce potential errors in the results and therefore it was decided not to use these tracks in the analysis. Another issue with tracking is over-segmentation where one pedestrian is tracked as more than one object. This can have influence on the results if over-segmentation is not consistent between all tracked pedestrians. Manual observations showed that the degree of over-segmentation was generally small and consistent across all crossing legs. Therefore, it was assumed that over-segmentation will not significantly affect the analysis and, for the rest of the paper, the term pedestrian is used to refer to pedestrian object. There were also a small number of instances where some pedestrians were not detected by the system; however, this is not problematic for speed calculations, but can affect pedestrian counting. Although the crossing speeds of pedestrian objects are obtained automatically, the system is not capable of determining the pedestrian group size for which the pedestrian object is detected in. Therefore, for each pedestrian object, the group size was recorded manually. The three pedestrian group sizes consist of one pedestrian, two pedestrians, and three or more pedestrians. Figure 3.2 shows a sample of the pedestrian tracks used in this study.

Figure 3.2 Sample Object Tracks in Scramble Phase with 8 Seconds or Longer Duration of Detection

Speed measurements were obtained using a script prepared in MATLAB 2010. To calculate the speed of each pedestrian object, two imaginary parallel lines (screens) are located across a selected section of each crosswalk leg of the intersection. Most tracks cross both screens and the speeds of those tracks are calculated based on the amount of time a track remains between the two screens, as illustrated in Figure 3.3. However, there are some tracks that are not long enough to cross both screens (even though they cover the majority of the crosswalk length) and only cross one of the two screens and it is important to measure speeds for such tracks. To measure the speed for a track that crosses one of the two screens, the shortest distance between the intersecting point of track with the crossed screen and the point coordinate of the point on the other end of the track between the two screens is used. This tool outputs one speed for each individual pedestrian object across a crosswalk leg. To find an average

Pedestrian Crossing Speed (PCS) through a crosswalk leg, all pedestrian object speeds are averaged and a mean speed is obtained.

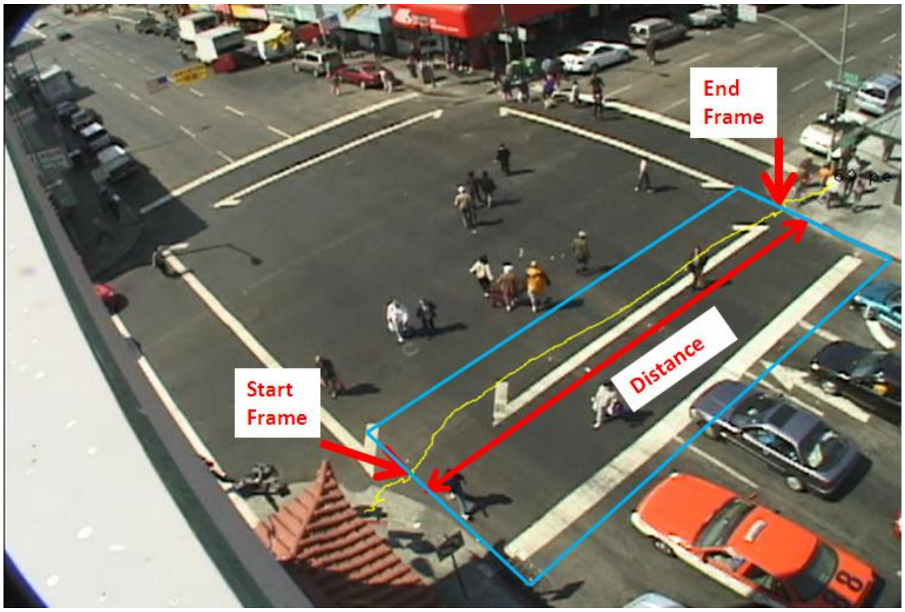


Figure 3.3 Walking Speed Measurement Method

3.2.3 Validation of Tracking Performance

It is important to ensure that the automatically measured speeds of the pedestrian objects represent the actual pedestrian speeds. To do so, a sample of 68 pedestrians was randomly selected and their speeds were manually measured and compared to the automatically measured speeds of the pedestrian objects. The results are shown in Figure 3.4. The Root Mean Square Error (RMSE) is found to be 0.07642 m/s, which is considered acceptable.

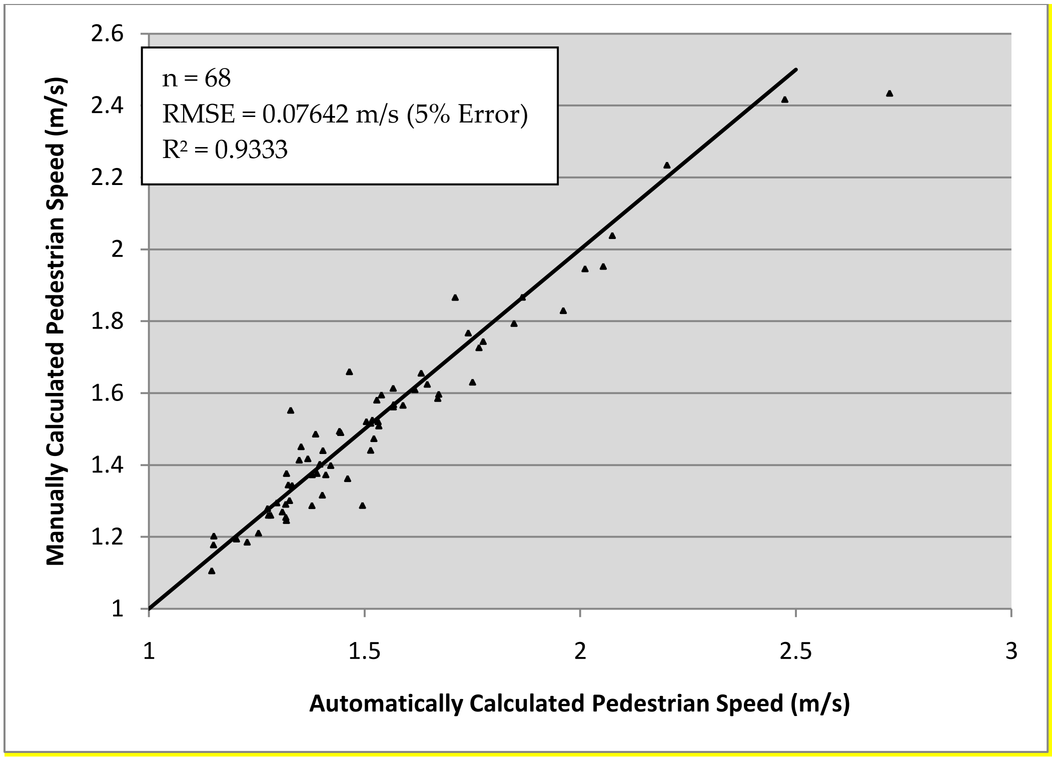


Figure 3.4 Comparison between Automatically and Manually Measured Walking Speeds in Scramble Phase

3.3 Analysis and Results

This section of the paper provides the results of the study. Manual pedestrian counts were conducted one hour in both before and after the scramble to determine the density changes through the crosswalks. The hourly pedestrian traffic flow rates through the entire intersection are 2176 ped/hr and 2228 ped/hr for pre-scramble and scramble phases, respectively. Therefore, the difference in pedestrian density will not have a significant impact on speed.

3.3.1 Comparison between Diagonal/Conventional Crossings before and after Scramble Phase

Table 3.2 shows the results of a comparison between PCS before and after the implementation of the scramble phase. Several conclusions can be made from the table:

- The average PCS for the conventional crossings before the scramble phase is 1.34 m/s. This value is consistent with the values reported in the literature. Tarawneh (2001) reported average PCS of 1.35 m/s for 14-16 m long crosswalk. Knoblauch et al (1996) reported 1.37 m/s average crossing speed for crosswalks 13.1 to 15.6 meters long (calculated from separate values for younger and older pedestrians)
- The average PCS for the conventional leg crossings after the scramble phase is 1.37 m/s. The difference between the PCS for conventional leg crossing between the pre and post scramble is statistically significant. This small difference could be the result of a decrease in pedestrian flow rate on the conventional legs in the scramble phase. Akcelik and Associates (2001) reported that the average and the 15th-percentile crossing speeds of pedestrians at mid-block signalized crosswalks decrease with increasing pedestrian flow rate.
- The average PCS for the scramble phase diagonal crossings is 1.51 m/s which is 10% higher compared to average PCS on conventional legs and is statistically significant. This is probably due to the longer lengths of the diagonal legs (40% longer). Researchers have shown that longer crosswalks result in larger average PCSs compared to shorter crosswalks (Tarawneh, 2001) (Knoblauch, et al., 1996).

- The average PCS for all crossing types after the scramble is 1.43 m/s, significantly higher than the 1.34 m/s before the scramble.

Table 3.2 Statistics for Pedestrian Crossing Speed before and after the Scramble Phase

Movement	No. Pedestrian Objects	Average (m/s)	Stan. Dev. (m/s)	P-value (difference in average PCS between column and row movement types)		
				Scramble (All Legs)	Scramble (Conventional Legs)	Scramble (Diagonal Legs)
Pre-scramble (All Legs)	1083	1.34	0.23	<0.0001	0.013	-
Scramble (All Legs)	1079	1.43	0.28	-	-	-
Scramble (Conventional Legs)	591	1.37	0.25	-	-	<0.0001
Scramble (Diagonal Legs)	488	1.51	0.29	-	-	-

Figure 3.5 shows the distribution of pedestrian crossing speeds. The 15th-percentile speeds, used for calculating the minimum pedestrian clearance time, are 1.25 m/s and 1.12 m/s for the diagonal legs (scramble) and conventional legs (pre and post scramble), respectively. According to Section 4E of Manual on Uniform Traffic Control Devices for Streets and Highways (Revision 1, 2003), the pedestrian clearance time should be long enough so that the pedestrians who just

stepped off the curb at the end of the W phase can make it, at a speed of 1.2 m/s, to at least the far side of the crosswalk or to a sufficient width median to wait for the next W phase. Based on the observed 15th-percentile speeds, and the clearance intervals provided in Table 3.1, longer clearance time is required for the intersection after the scramble (unless the DW phase is included in the clearance interval).

Figure 3.5 also shows that there are hardly any pedestrians using the diagonal leg crossings at speeds below 1.0 m/s. This may suggest that the slowest walking group who may consist of pedestrians with walking difficulties choose not to use the diagonal leg crossings.

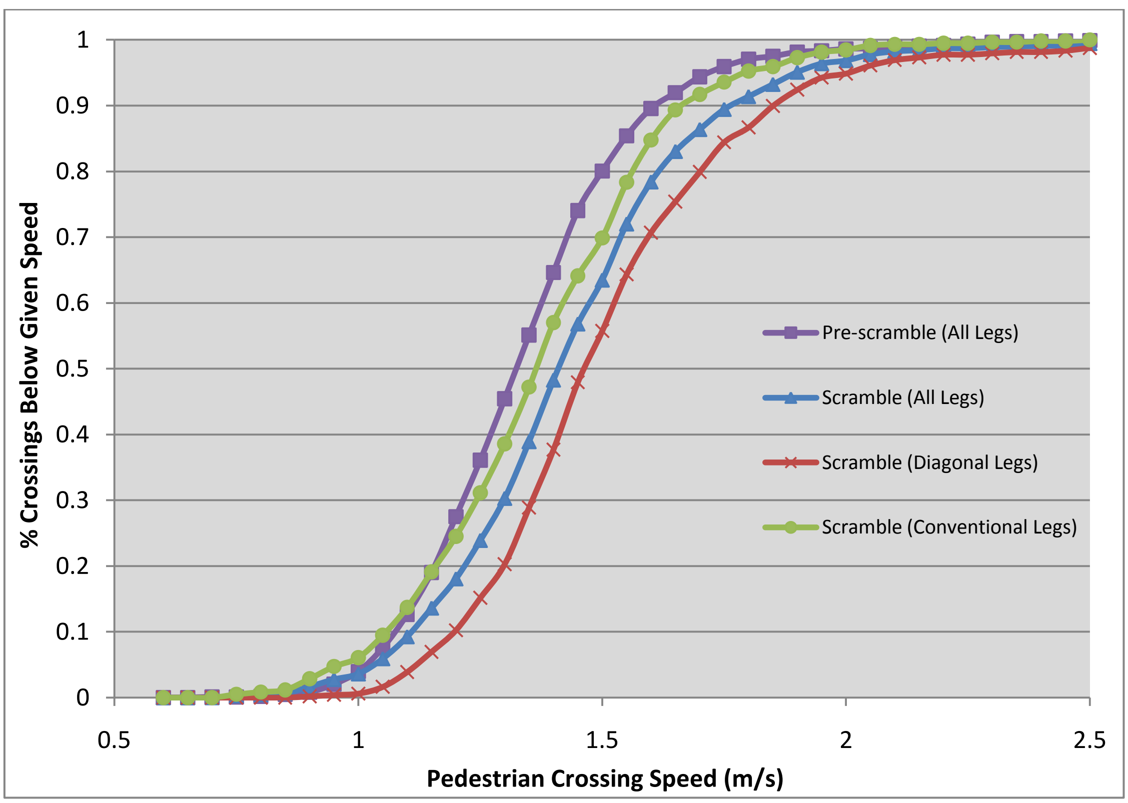


Figure 3.5 Percentage of Pedestrian Crossings below a Given Walking Speed

3.3.2 Effect of Group Size on Pedestrian Crossing Speed

The comparison results of the PCS before and after the implementation of the scramble phase is shown for different group sizes in Table 3.3 and Figure 3.6. Several conclusions can be made:

- Figure 3.6 shows that the average PCS decreases as group size increases in both pre-scramble and scramble phases.
- The average PCS for group sizes 1, 2, and greater than 2 for the pre-scramble are 1.35, 1.33, and 1.25 m/s, respectively. The difference in the mean PCS for the three group sizes is significant at the 5% level indicating that the group size has a significant impact on PCS. Similar results were found by Tarawneh (2001), Gates et al (2006) and Knoblauch et al (1996).
- The average PCS for group sizes 1, 2, and greater than 2 for the post-scramble are 1.46, 1.40 and1.29 m/s, respectively. The difference in the mean PCS for the three group sizes is significant at the 5% level.
- The average PCS for diagonally crossing pedestrians walking in groups of 1 or 2 pedestrians are significantly higher than the conventionally crossing pedestrians walking in same size groups. It is interesting to observe that the magnitude of the difference between the average speed decreases as group size increases (Figure 3.6).

Table 3.3 Effect of Group Size on Pedestrian Crossing Speed

Movement	Group Size	No. Pedestrian Objects	Average (m/s)	Stan. Dev. (m/s)	P-value (difference in average PCS between group sizes)
Pre-scramble (All Legs)	1	677	1.35	0.25	<0.0001
	2	356	1.33	0.19	
	>2	50	1.25	0.21	
Scramble (All Legs)	1	709	1.46	0.29	<0.0001
	2	302	1.40	0.24	
	>2	68	1.29	0.18	
Scramble (Diagonal Legs)	1	335	1.54	0.31	<0.0001
	2	139	1.46	0.23	
	>2	14	1.26	0.17	

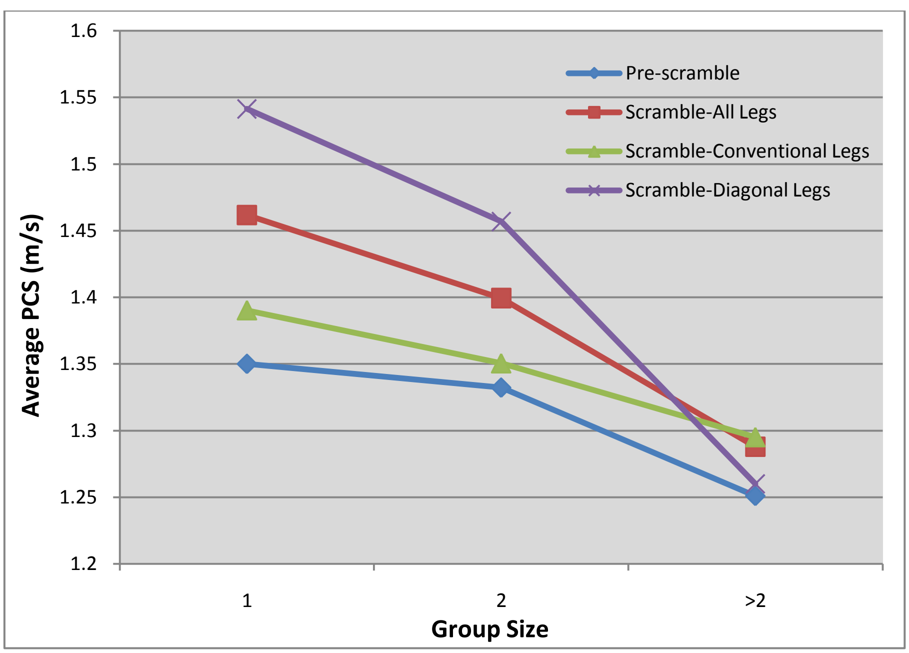


Figure 3.6 Before-After Average Pedestrian Crossing Speed for Pedestrians Walking in Different Group Sizes

3.3.3 Comparison between Complying/Non-Complying Pedestrian Crossings

Automatic tracking can provide useful information about the microscopic behavior of pedestrians during the distance traveled. This section investigates the walking behavior of pedestrians across time (temporal) and space (spatial). This is represented by the ability of individual pedestrians to change their walking speeds as a response to how far through the pedestrian signal phase (in terms of time), as well as how far through the crosswalk's length (in terms of position) they are. For this purpose, the average crossing speed of pedestrians depending on the time they enter the crosswalk with respect to the start time of pedestrian signal indications (temporal effect) is studied for both before and after the implementation of scramble phase. Similarly, the same speed behavior is analyzed through the first, second, third, and the fourth quarter of the crosswalk length. It is important to note that the magnitudes of the average pedestrian speeds reported in this section do not represent normal walking behavior; that is, the sample contains running pedestrians. The behavior of such pedestrians usually is not taken into consideration when determining a design pedestrian walking speed at an intersection. As a result, a larger average PCS is found compared to findings in Table 3.2.

Effect of Starting Time on Average Pedestrian Crossing Speed

The comparison results of the PCS before and after the implementation of the scramble phase are shown in Figure 3.7. Several conclusions can be made:

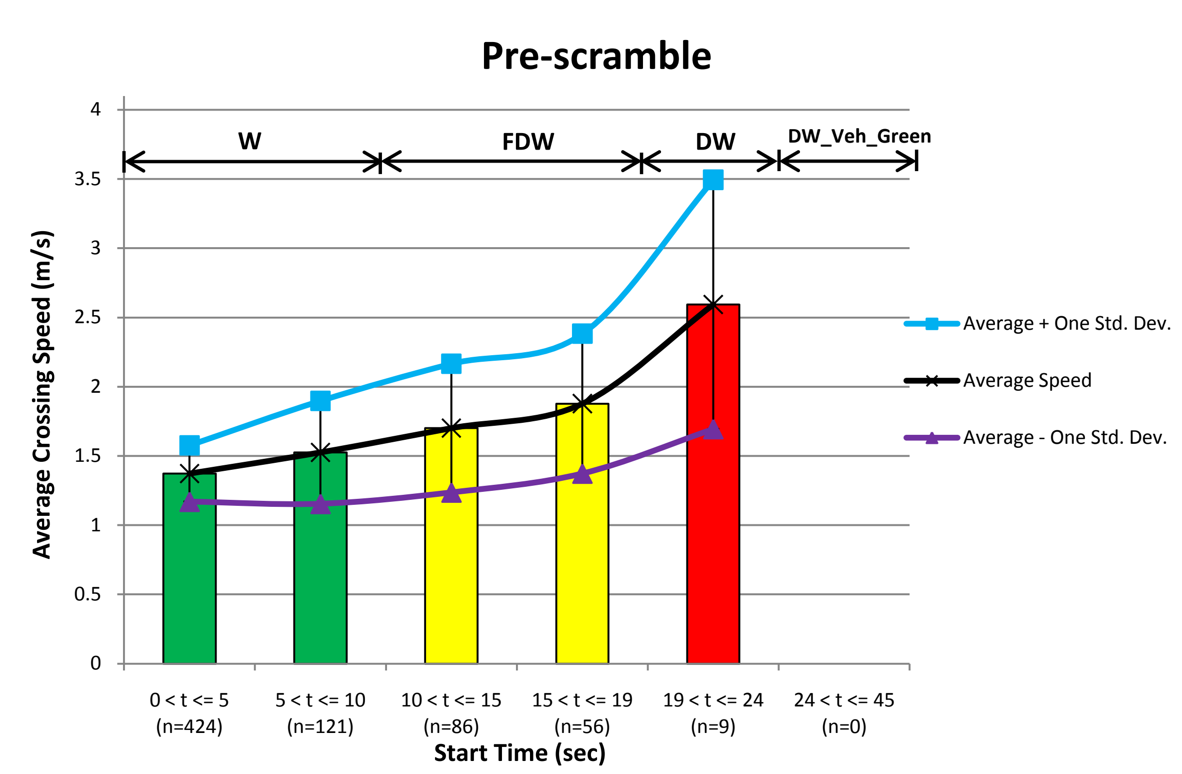
- The numbers of pedestrians who start crossing during W, FDW, and DW intervals before the implementation of the scramble are 545, 141, and 9 pedestrians, respectively. That is, 78% of pedestrians comply with the signal indications, while 22% do not. These results are generally consistent with the results reported in the literature. Akcelik and Associates (2001) reported that 87% of pedestrians started crossing mid-block crosswalks during the W indication, while the remaining started during the FDW or DW indications.

- The numbers of pedestrians who start crossing the intersection during W, FDW, DW, and DW-veh-green ("safe-side") intervals after the implementation of the scramble are 611, 178, 4, and 75 pedestrians, respectively. That is, 70% of pedestrians comply with the signal indications, while 30% do not (21% during FDW and DW). 29% of non-compliers are crossing during the DW-veh-green interval, which is close to the value (25%) Bechtel and MacLeod (2004) reported by manual observation of the same data. Pedestrian non-compliance to signal indications during FDW and DW intervals is similar in both before and after the scramble. The increase in the non-compliance in the scramble is mainly due to the crossings along the "safe-side" which may be the result of longer average delays (due to an increase in cycle length in the scramble phase) and/or unjustifiable DW phase along the "safe-side" where the opportunity for vehicle-pedestrian conflicts does not exist; the DW-veh-green ("safe-side") phase in the scramble was basically the only opportunity given to pedestrians in the pre-scramble phase to cross the intersection with a W indication.
- For both before and after the implementation of scramble, pedestrians who start crossing the intersection during W interval have considerably lower average speeds compared to those who start crossing during the

FDW interval. Knoblauch et al (1996) and Gates et al (2006) also found the average walking speed to be lower for pedestrians who start crossing during W interval compared to those who start crossing during the FDW interval. This difference in speed suggests that pedestrians entering the crosswalk during FDW may feel less safe and try to clear the intersection by increasing their walking speed. This difference is even larger in the after scramble, and this may be due to the longer diagonal crosswalks.

- The standard deviation of average speed is lower for pedestrians who enter the crosswalks during W interval compared to those who enter during FDW interval. This larger variability in walking speeds during FDW interval (especially towards the end) may reflect varying responses of pedestrians to the risk of not completing the crossing safely, with some pedestrians significantly increasing their speeds.

(a)



(b)

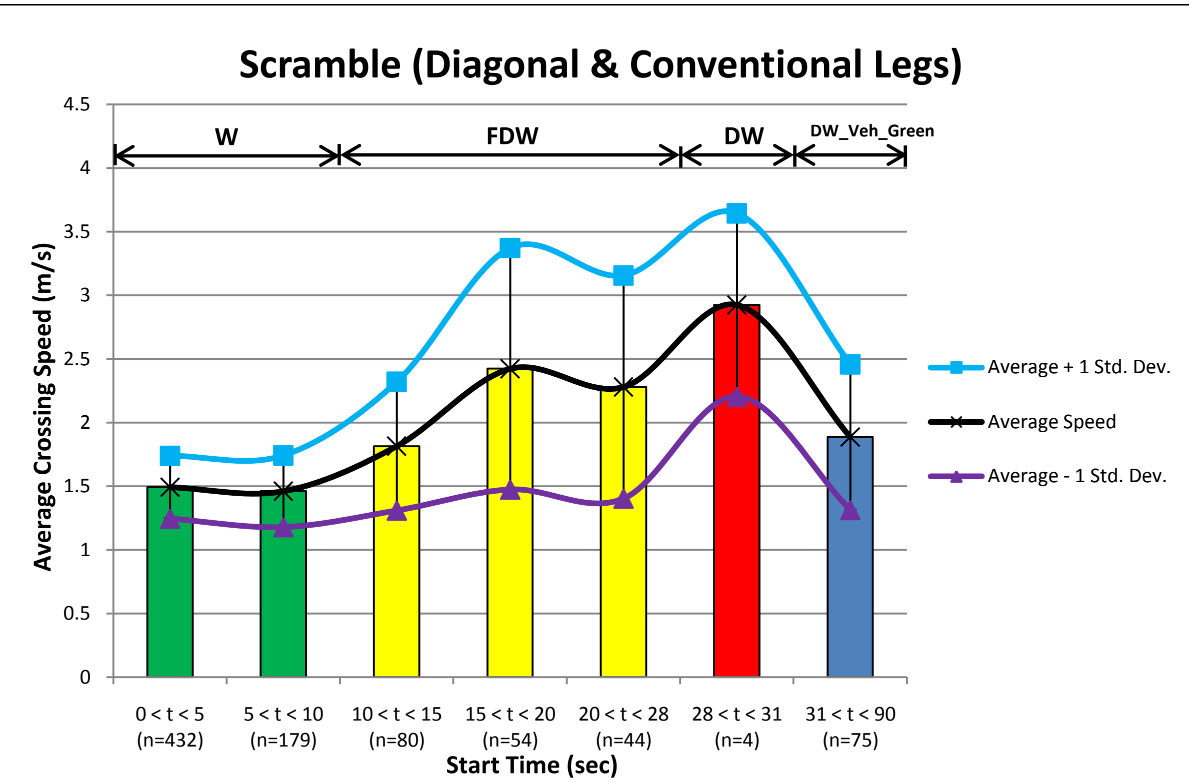
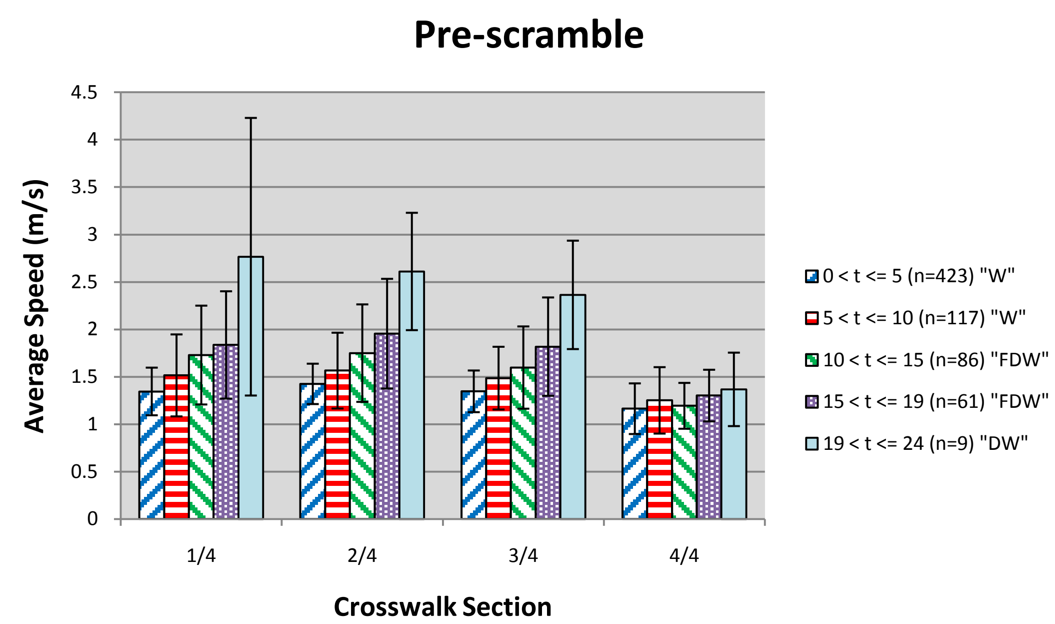


Figure 3.7 Pedestrian Walking Speed Behavior as a Response to Pedestrian Signal Indications

Spatial-temporal Effect on Average Pedestrian Crossing Speed

Figure 3.8 shows the average speed of pedestrians who start crossing at specific pedestrian signal indications (time) through different sections along the crosswalks in before and after the implementation of scramble phase. The figure shows that pedestrians slow down as they reach the end of the crosswalk in both before and after the scramble. This is consistent with the results reported by Akcelik and Associates (2001).

(a)



(b)

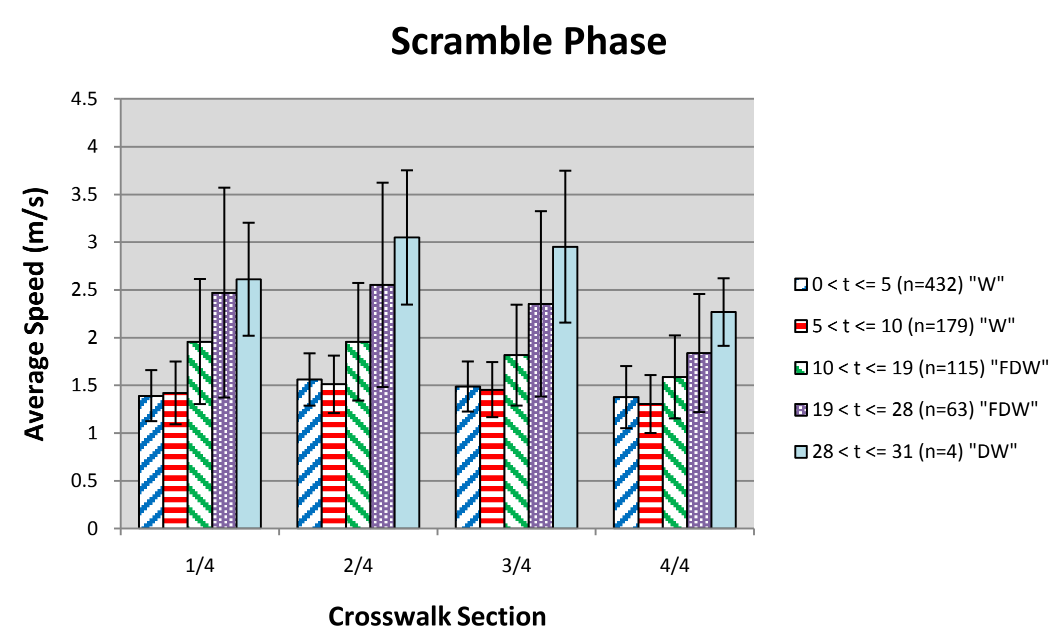


Figure 3.8 Spatial-Temporal Effect on Pedestrian Walking Speed

3.4 Conclusions

This chapter presented the results of a study conducting a general analysis on pedestrian crossing speed behavior using automatic collection of microscopic pedestrian data and to study pedestrian speed variations with respect to design changes to urban intersection crossings. The context of the study was to investigate the effect of scramble design characteristics on pedestrian average crossing speed. The ability of individual pedestrians to change their walking speeds as a response to how far through the crosswalk's length (in terms of position), as well as how far through the pedestrian signal phase (in terms of time) they are, was also studied.

The results showed that the implementation of a scramble phase at this location affects average PCS. The average PCS in scramble phase was determined to be significantly larger than the average PCS in pre-scramble phase when crossings through all, conventional, or diagonal legs of the scramble. However, there was a slight difference between PCS through conventional legs of the scramble and pre-scramble, and this slight difference is probably due to the decrease in pedestrian flow through the conventional legs of the scramble. It was also shown that the diagonally crossing pedestrians have significantly higher crossing speed than the conventionally crossing pedestrians in the scramble phase. The results also showed that the implementation of scramble influences group walking speeds as the average PCS for all group sizes were larger in scramble phase (all legs) compared to pre-scramble phase. The average PCS was also shown to be larger for diagonally crossing pedestrians compared to conventionally crossing pedestrians when walking alone or in pairs, within the scramble phase. It was also shown that the average PCS decreases as group size increases in both pre-scramble and scramble phases. Pedestrians who started crossing the intersection during W indication walked slower than those who started crossing during FDW indication. In addition, pedestrians had faster walking speeds through the first half of the crosswalk and slowed down as they approached the end of the crosswalk. Pedestrian non-compliance to signal indications during FDW and DW intervals is similar in both before and after the scramble. The increase in the non-compliance in the scramble is mainly due to the crossings along the “safe-side” which may be the result of longer average delays (due to an increase in cycle length in the scramble phase) and/or unjustifiable DW phase along the “safe-side” where the opportunity for vehicle-pedestrian conflicts does not exist.

The increasing emergence of sustainability in the transport system is encouraging new and innovative designs such as scramble and it is important to know how pedestrians react to these designs. There is a considerable need for collecting microscopic data to enable a better understanding of pedestrian behavior. The automated technique used in this paper can provide a useful tool to collect such data. Future research work can include investigating more microscopic details of pedestrian walking behavior such as the analysis of gait parameters (step frequency and length). As well, there is a need to investigate the impact of various pedestrian attributes (age, gender, height, etc.) on walking speed and the gait parameters.

Chapter Four: Pedestrian Gait Analysis Using Automated Computer Vision Techniques

4.1 Background

As communities are becoming increasingly aware of the benefits associated with active non-motorized modes of travel, pedestrian walking behavior research is receiving a growing attention from policy makers, researchers and practitioners. A better understanding of walking behavior is therefore central to the evaluation of measures of walking conditions such as comfortability and efficiency. Gait analysis is a microscopic-level analysis which allows true estimates of objective walking measures such as stride frequency and length for different population segments. It is used to translate walking distance into units such as number of steps or energy expenditure. Several applications are associated with gait analysis such as estimating the impact of trading personal vehicles for active transportation modes such as walking (Morency, et al., 2007). Gait analysis is also useful in demonstrating the walking costs to different groups of pedestrians such as the elderly and the obese. This allows the consideration of constraints on the movement ability of some pedestrians. Other direct applications are to provide feedback to standard guidelines for pedestrian movement such as crosswalk clearance times at intersections and the calibration of pedestrian micro simulation models.

The current study examines the spatiotemporal gait parameters (i.e., step length and step frequency) in order to improve the understanding of pedestrian walking behavior in outdoor urban environments. The goal of the microscopic-level analysis is to provide insight into pedestrian walking mechanisms and the effect of various attributes such as gender and age. The main source of the data in this study is collected from video sensors. Data extracted from videos are rich in details and the costs associated with recording and storing the data are relatively low (Ismail, et al., 2010). The analysis of walking speed, step frequency, and step length is performed by means of automated computer vision techniques. The benefits of automatic tracking include capturing the natural movement of pedestrians and minimizing the risk of disturbing the behavior of observed subjects and the relatively higher accuracy and consistency in comparison to manual methods. More specifically, gait parameters are computed and analyzed across pedestrian gender, age, height, group size, and crosswalk grade.

4.2 Methodology

This section provides information about the details of the methodology used for collecting data, and the methods and tools used for calculating pedestrian gait parameters and the validation of the technique. Two case studies are then followed to demonstrate the technique: Vancouver, BC and Oakland, California. In the Vancouver case study, a feature-based tracking algorithm, and in the Oakland case study, an MM-Track algorithm is used for the purpose of pedestrian detection.

4.2.1 Data Collection

A frame-by-frame detection of pedestrians in space and time using computer vision can be used to generate pedestrian speed profiles. Each pedestrian step is observed to introduce a periodic fluctuation in the speed profile, and therefore, the gait parameters such as step frequency and step length can be computed by analyzing the speed signal (Saunier, et al., 2011). Figure 4.1 below summarizes the methodology for gait parameters measurement and validation of automatic step frequency calculation.

As illustrated in Figure 4.1 and Figure 4.2, pedestrian trajectories generated by feature-based tracking or the MMTrack algorithms in terms of coordination of space with respect to time are analyzed and a speed profile is produced for each pedestrian object. Each pedestrian speed profile is used to compute an average step frequency for that pedestrian. It is Important to note that the walking speed profile shown in Figure 4.2 is normalized and smoothened. The position of each pedestrian across time is used to compute the average walking speed for that pedestrian. Average step length is then calculated, knowing that walking speed, step frequency, and step length are found to have the following fundamental linear relationship:

Walking Speed = Step Frequency × Step Length

Walking speed is defined as the change in the position of a pedestrian in a unit of time. The details of the pedestrian speed measurement method were described in detail in Chapter Three. To calculate the speed of each pedestrian object, two parallel screen lines are located across the selected study section of the crosswalk. The speed of a pedestrian object is calculated based on the time the pedestrian object remains between the two screens.

Step frequency is defined in this study as the number of times a foot touches the ground in a unit of time (i.e. vertical frequency). Stride frequency, however, is defined as the number of times the same foot touches the ground in a unit of time. Step frequency is therefore twice the stride frequency. Similarly, step length is half of stride length. It is assumed that each fluctuation in speed profiles is due to a pedestrian taking a step forward. This assumption was validated by visual inspection of pedestrians in videos against their speed profiles as the speed of pedestrian centroid is lowest at double support phase (with both feet in contact with ground) and highest at single support phase, in between the two double support phases. Under this assumption, each cycle represents one forward step and the reciprocal of the cycle period represents the estimated step frequency. An average step frequency is then the mean frequency of a few cycles.

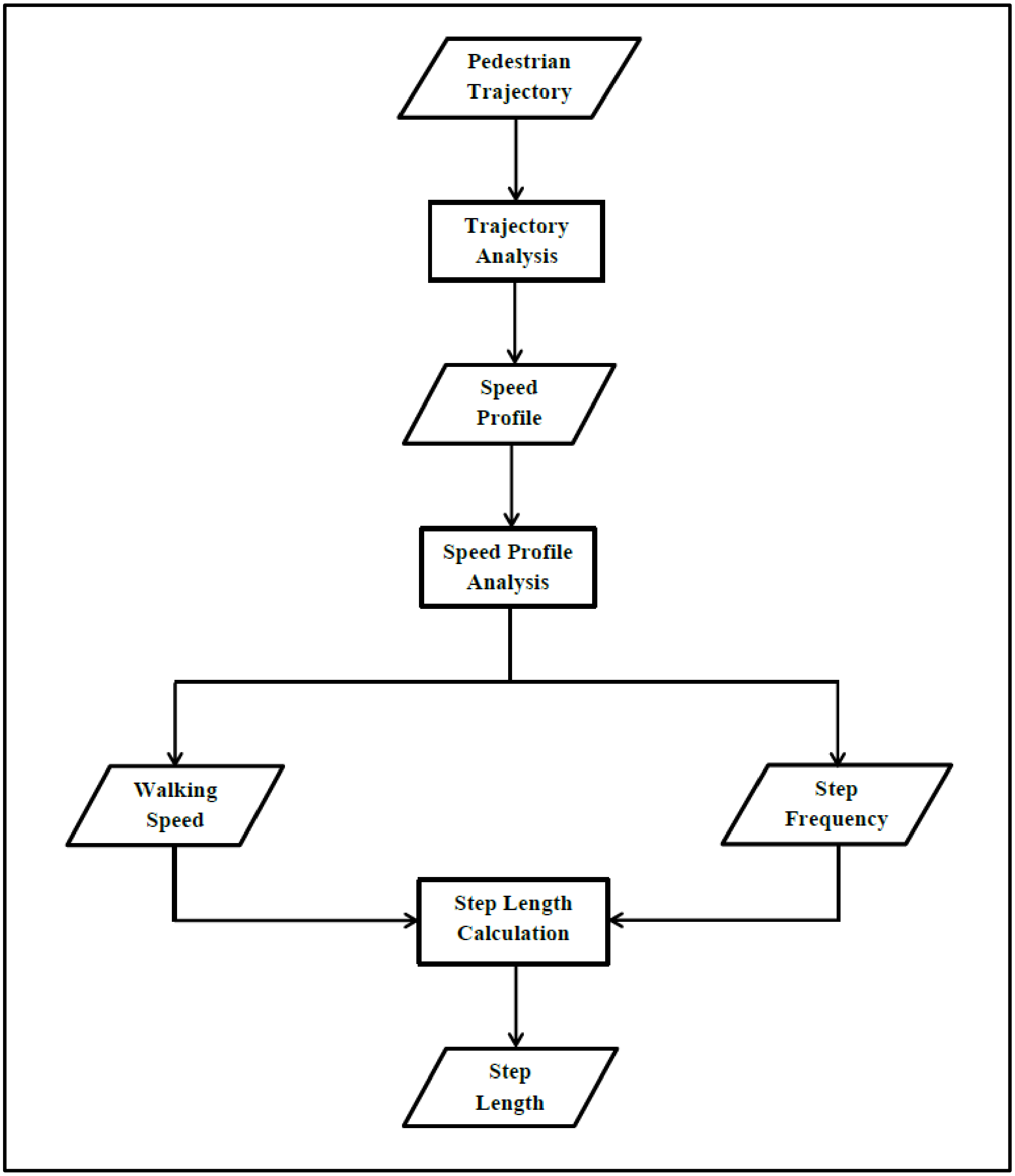


Figure 4.1 Pedestrian Gait Parameters Measurement Process

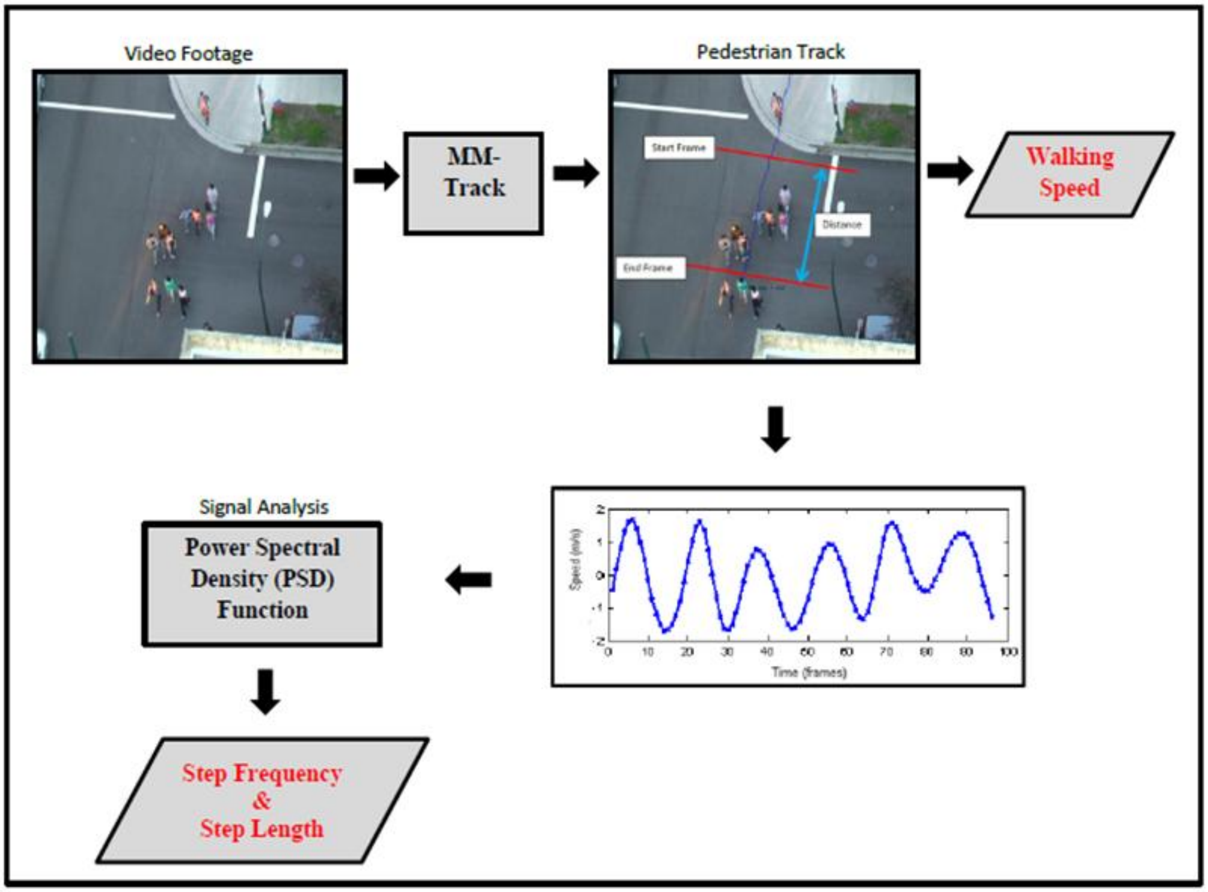


Figure 4.2 Pedestrian Gait Parameters Measurement Method

A road-users trajectory T is a finite set of tuples:

$$T=\{(x_1,y_1,vx_1,vy_1),\ldots,(x_i,y_i,vx_i,vy_i),\ldots,(x_n,y_n,vx_n,vy_n)\} \qquad (4.1)$$

With $i=\{1,\ldots,n\}$ a discrete temporal index, such that $T(i)$ will return a 4-tuple (x_i,y_i,vx_i,vy_i), with x and y are the spatial coordinates and vx and vy are the corresponding velocities. Associated with each road-user is a movement profile, describing the speed variations along the trajectory lifetime. The road users speed profiles are represented as time-series, which are obtained from the corresponding road-users trajectories. The speed profile ***S*** is defined as

S=*norm*(***Vx***,***Vy***), with ***Vx*** and ***Vy*** are the velocities vectors of length *n*, for the x and y coordinates, respectively. Identifying the walking step frequency corresponds to detecting the dominant periodicity in the noisy signal of the speed profile. This is reduced to the problem of evaluating the power spectral density (PSD) of the speed profile (Oppenheim & Schafer, 1999). PSD shows the strength of variations in terms of frequency. In its simplest form, PSD estimation corresponds to calculating the periodogram of the speed profile signal; i.e., mean square of the Discrete Fourier Transform of the signal. It is assumed that the sampling did not suffer from aliasing problem. Also, prior to generating the power spectrum, the speed signal is first smoothened and normalized (i.e. mean speed subtracted form instantaneous speed). Therefore, the power spectrum of S[n] is proportional to that of S(t) of the real pedestrian speed profile. In this case the PSD *P* estimate for each frequency f is given by:

$$P(f) = \frac{1}{F_s\, n} \left| \sum_{i=1}^{n} s_i e^{-\frac{-j(2\pi f)i}{F_s}} \right|^2 \qquad (4.2)$$

With F_s is the sampling frequency. A sample of pedestrian walking speed profiles (smoothened) in addition to their power spectrums are shown in Figure 4.3. Pedestrian walking speed profiles were also normalized (not shown) as required by the power spectral density function. Finally, step length is simply found by dividing the walking speed by step frequency. The sample data provided in Figure 4.3 were generated from tracks generated using MM-Track algorithm.

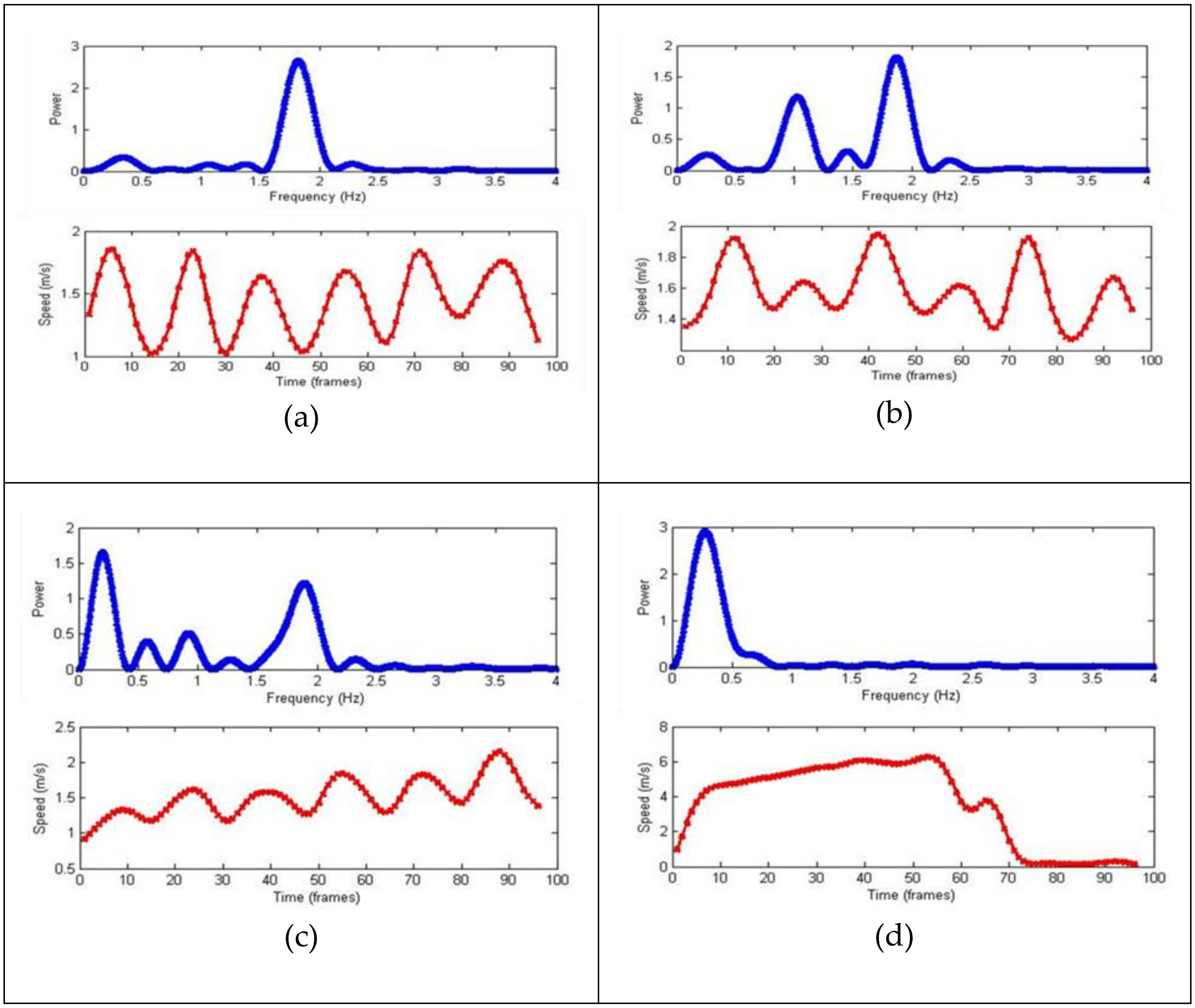


Figure 4.3 Smoothened Walking Speed Signal (Bottom); Power Spectrum (Top)

4.2.2 Validation of Tracking Performance

Due to the existence of noise and other factors in the speed signal, the frequency at which the power spectrum shows a maximum may or may not be a correct estimate of the step frequency. For example, in Figure 4.3 (c), the power spectrum has its maximum at a frequency of about 0.2 Hz which is probably due to the increasing trend in the speed profile, not due to pedestrian taking a step. In this case, the step frequency is best represented by the frequency which corresponds to the second largest power spectrum. Figure 4.3 (a and b) demonstrate the cases as the largest power spectrum represents the estimated step frequency. A similar technique used by Saunier et al in (2011) is employed for frequency selection. That is, any frequency outside a predefined range and/or of insufficient power density (with respect to maximum power density) is filtered out, and the frequency with the maximum power density (among the remaining frequencies) is selected to represent the pedestrian step frequency. The frequency estimation process is shown in Figure 4.4.

The sufficiency of the power density is defined by comparing the power density to a threshold ratio of maximum power ($\propto \in [0,1]$). Saunier et al (2011) considered averaging a number of different frequencies within the predefined range and of sufficient power, rather than only selecting the frequency with maximum power. This may have been related to the quality of tracking in their study. However, the tracking quality in this work resulted in one frequency of sufficient power for the majority of tracks and eliminated the need for considering the average of several values. To find an optimum value for α, 100 pedestrian objects (using MM-Track algorithm) were randomly selected and the α value which minimizes the Root Mean Squared Error (RMSE) of the estimated frequencies was calculated. The estimation of step frequency is sensitive to which section of the pedestrian body is detected and where the object centroid is located with respect to the pedestrian. If only a leg, a foot, an arm, or a hand is detected and identified as pedestrian centroid, then the estimated frequency is the stride frequency (half of step frequency), whereas if other sections of the pedestrian body such as head or chest are detected and identified as centroid, then the estimated frequency is a step frequency. A useful frequency range was selected across which the frequency represents only the step frequency. The range [1.4-2.6 Hz] was found to be a representative range of pedestrian step frequency during walking in (Saunier, et al., 2011). With constraining the frequency range, an alpha value of 0.5 was found to be optimum. Out of 100 pedestrian objects, the method identified 93 with calculable step frequencies. The range [1.0-3.0 Hz], however, is identified to represent the step frequency range for walking in (Niyogi & Adelson, 1994). To ensure that the range [1.4-2.6 Hz] is a representative range for pedestrian step frequency in this study, different frequency ranges were also tested with α set to 0.5. The method does not output an estimated step frequency for cases (Figure 4.3 (d), for example) where the maximum power within the predefined range does not exceed or equate the threshold α. An α value of 0.5 was used as the optimized value. Figure 4.5 summarizes the accuracy of the automatic step frequency estimation method after using the optimized parameter values. The RMSE is 0.061Hz which represents approximately 3.6% error (1.866 ± 0.068 Hz).

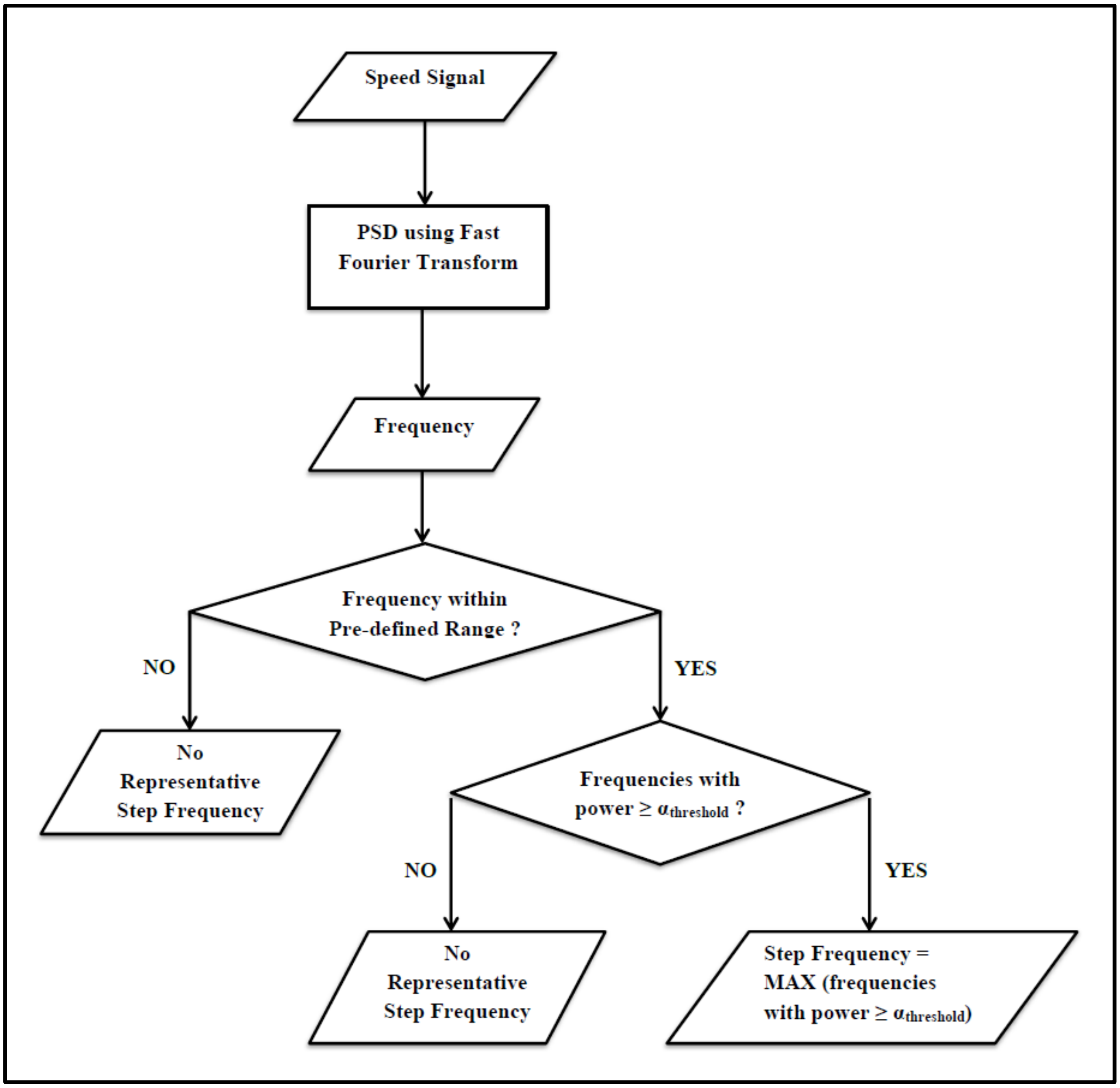


Figure 4.4 Walking Step Frequency Estimation Process

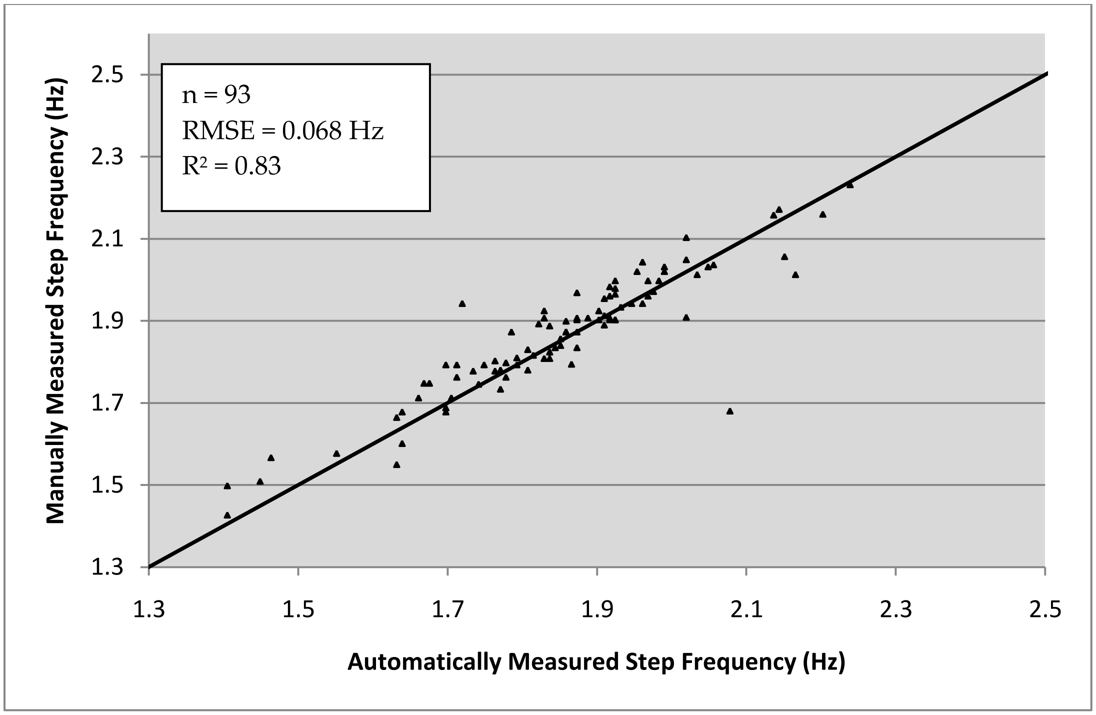
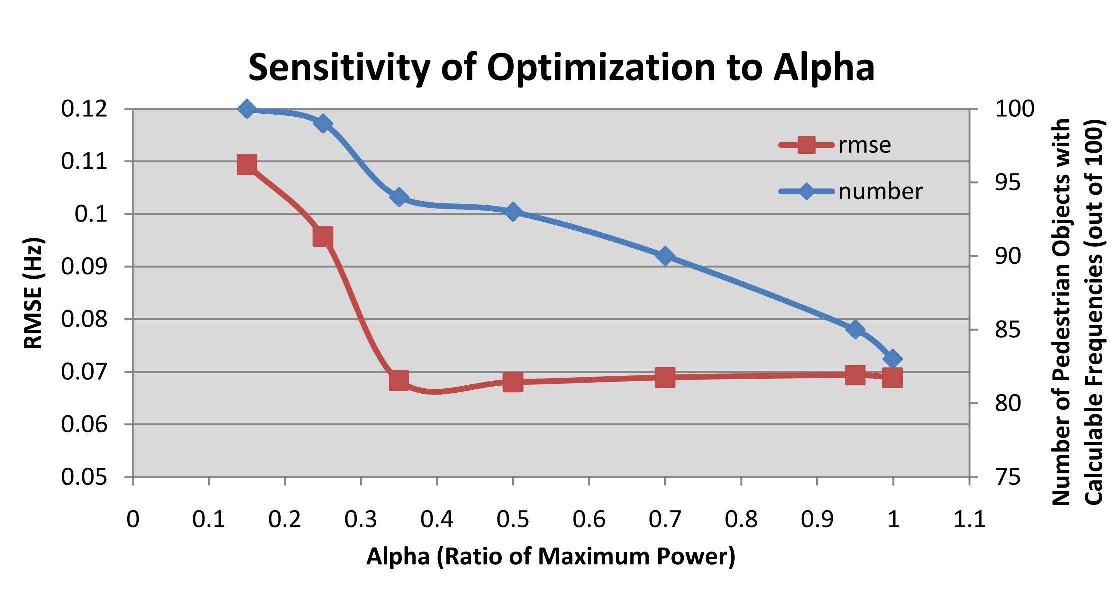


Figure 4.5. Comparison between Automatically and Manually Measured Pedestrian Step Frequencies

4.2.3 Sensitivity Analysis

Figure 4.6 shows the sensitivities of the RMSE and the number-of-pedestrian-objects-with calculable-frequencies to the value of α and the pre-defined frequency range. As illustrated in Figure 4.6 (a), the RMSE decreases substantially up to alpha value of 0.35 and remains relatively constant as alpha increases; however, the number of pedestrian objects with calculable frequencies decreases as alpha increases. Also, as illustrated in Figure 4.6 (b), the RMSE decreases substantially with decreasing the frequency range up to [1.4-2.6 Hz] range, and stays constant thereafter.

(a)



(b)

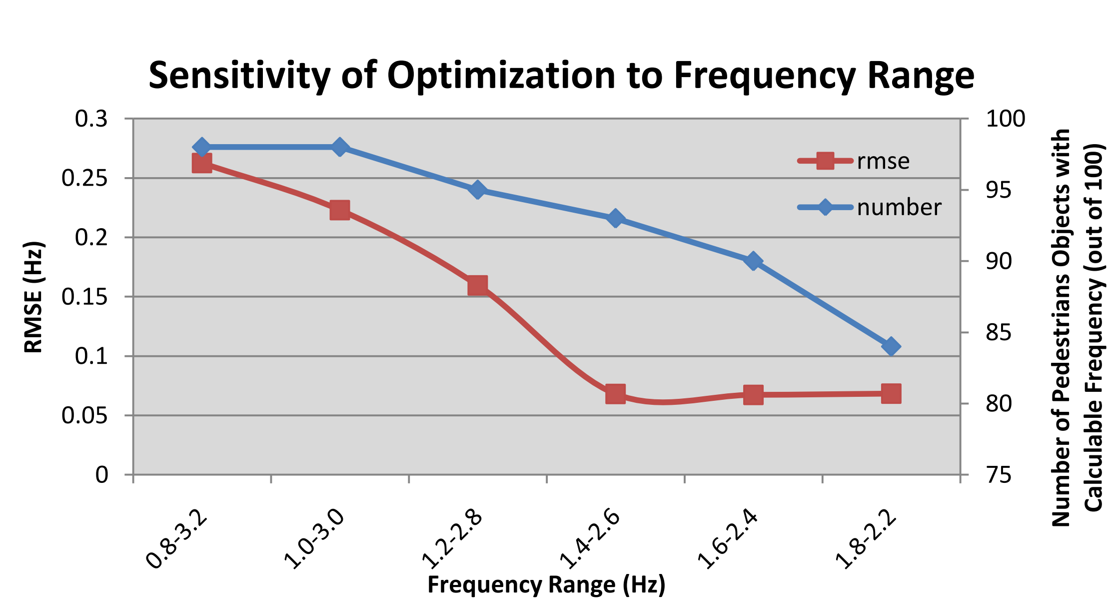


Figure 4.6 Sensitivity of Optimization to Alpha (a) and Step Frequency Range (b)

4.3 Case Study 1: Vancouver Case Study

4.3.1 Site Characteristics

The study location (Figure 4.7) is a busy downtown intersection located at Robson and Broughton Streets in downtown Vancouver, British Columbia. Robson Street is a northwest-southeast, two-way major street, with two lanes in each direction. Parking is permitted along the right lane in each direction with time restrictions; no parking is allowed during rush hours or special-event days. Broughton street is a northeast-southwest, two-way minor street, with one lane in each direction. Parking is allowed along the right side of the street in both directions. Vehicular flows are controlled by flashing-green signals along Robson Street, and by stop-signs along Broughton Street, with no turning restrictions on either approaches. Pedestrian crossing is allowed along all the four legs of the intersection, at any time across Broughton, and with actuated control across Robson. There is a downward grade in the northwest direction along Robson. This study will only focus on pedestrian movement along Robson Street (i.e. along northwest-southeast direction). MM-Track algorithm is used for detection of pedestrians in this case study.

Figure 4.7 Vancouver Case Study Intersection Layout and Sample Pedestrian Tracks

4.3.2 Relationship between Walking Speed and Gait Parameters

First, the relationship between the walking speed and the gait parameters is investigated. This can help explain pedestrian strategies to adjust their waking speeds in terms of the step length and frequency. Figure 4.8 shows the change of walking speed with both step frequency and step length. As shown in the figure, the step length seems to have a greater influence on walking speed than step frequency due to the larger slope of the best fit line. The regression coefficients for Pedestrian Speed vs. Step Frequency and Pedestrian Speed vs. Step Length are 0.56m and 1.67s^{-1}, respectively. This indicates that pedestrians usually control their walking speeds by adjusting their step length more than they adjust their step frequencies. Similar results were found in (Hui, et al., 2007) (Crowe, et al., 1996) which indicated that the walking speed is more sensitive to step length than to step frequency. Although not stated, the figures presented by Crowe et al in (Crowe, et al., 1996) and Hui et al in (Hui, et al., 2007) show a relatively higher sensitivity of walking speed to stride length than to stride frequency.

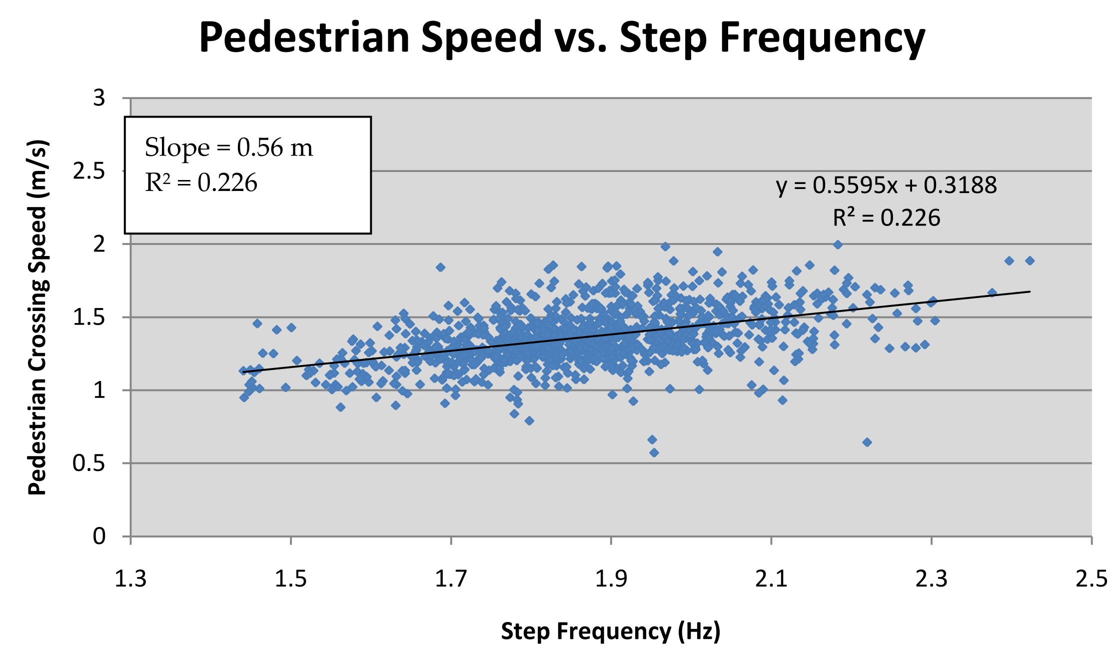
Standardized regression coefficients were also found using Equation 4.3 so that the magnitudes can be better compared between the two regressions in Figure 4.8. The standardized regression coefficients for Pedestrian Speed vs. Step Frequency and Pedestrian Speed vs. Step Length are 0.386 and 0.940, respectively (unitless).

$$x_i{}' = \frac{x_i - Min\,\{x_1,x_2,\ldots,x_n\}}{\mathrm{Max}\,\{x_1,x_2,\ldots,x_n\} - Min\,\{x_1,x_2,\ldots,x_n\}} \qquad (4.3)$$

Where, x is a gait parameter such as walking speed, step frequency, or step length, and x_i is the actual value of that gait parameter for pedestrian *i*, and $x_i{}'$ is the standardized value of that gait parameter for pedestrian *i*.

And, Max{} and Min{} are the maximum and minimum of the entire gait parameter arrays for the entire pedestrian population, respectively.

(a)



(b)

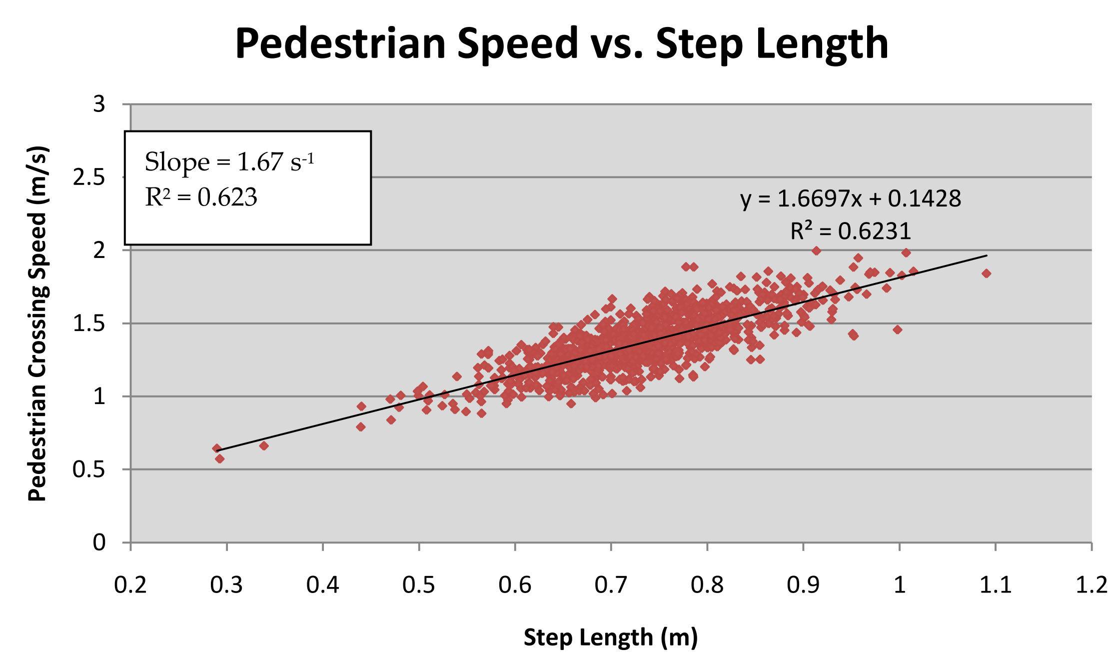


Figure 4.8 Effect of Pedestrian Step Frequency and Step Length on Walking Speed

4.3.3 Distributions of Pedestrian Gait Parameters

Pedestrian step frequency, step length and walking speed were found to generally follow the normal distribution (confirmed by the χ^2 test) as shown in Figure 4.9. The mean values and the standard deviations of walking speed, step frequency, and step length for 1090 pedestrians were found to be 1.36 ± 0.19 m/s, 1.87 ± 0.16 Hz, and 0.73 ± 0.09 m, respectively.

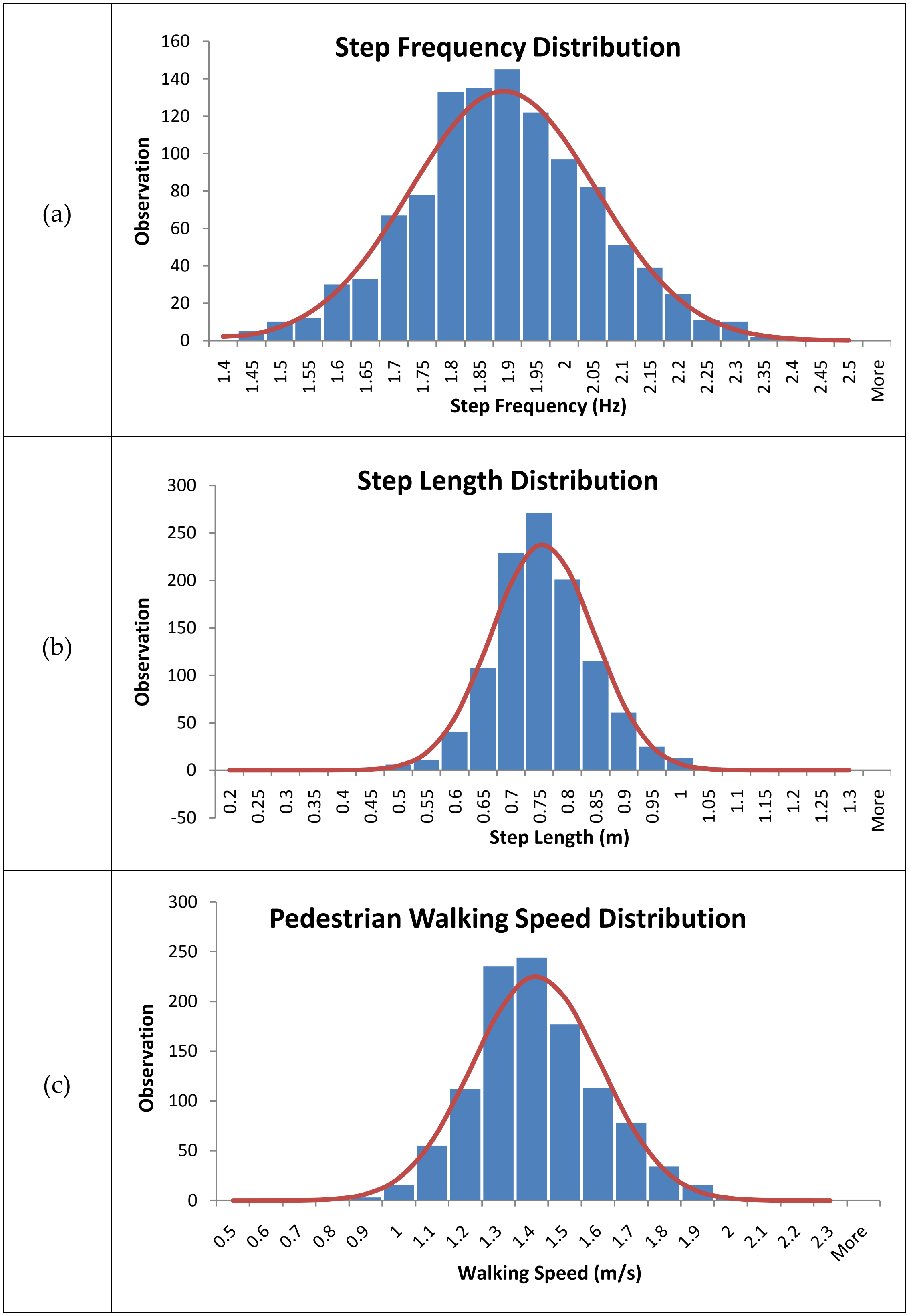


Figure 4.9 Distributions of Pedestrian Gait Parameters

As well, walking speed was categorized into small ranges, and step length vs step frequency plots were created for each speed category. As speed increases, the slope of l/f generally increases, suggesting that step length increases more than step frequency as pedestrians increase their walking speed. This is illustrated in Figure 4.10.

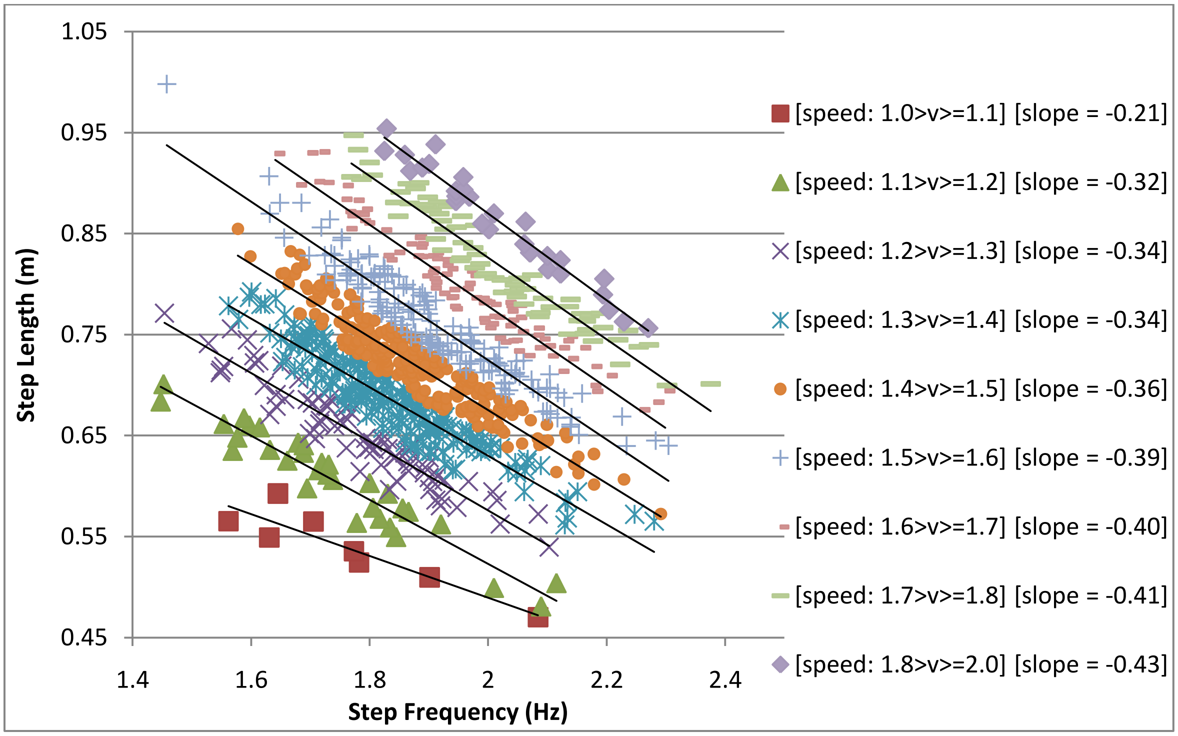


Figure 4.10 Step Length vs. Step Frequency at different Walking Speeds (Correlation for each walking speed is greater than 85%)

Average gait parameters were also calculated for 494 pedestrians walking on the sidewalk, just before the crosswalk. Average walking speed, step frequency, and step length were found for pedestrians walking on the sidewalk to be 1.20 m/s, 1.83 Hz, and 0.66 m, respectively; these values were significantly lower than the corresponding values of 1.36 m/s, 1.87 Hz, and 0.73 m found for pedestrians walking on the crosswalk. The increases in average walking speed, step frequency, and step length of pedestrians were 14%, 2%, and 11%, respectively, as they moved from sidewalk to crosswalk. A slightly higher average step frequency but a considerably higher average step length, along with a considerably higher average walking speed, for pedestrians on crosswalk compared to pedestrians on sidewalk suggests that pedestrians mainly use step length as a control parameter to adjust their walking speeds, or at least to cross the street.

4.3.4 Comparison between Gait Parameters across different Design and Pedestrians Attributes

Table 4.1 summarizes the gait parameter values studied in this paper. The highlighted cells indicate significance at the 5% level. There is an upgrade in the southeast direction which is found to significantly influence the pedestrian walking speed and step frequency. In order to evaluate the differences in the gait parameters across different pedestrian attributes, it was decided to focus on the pedestrians walking in one direction (northwest) to eliminate the effects of the grade on gait parameters. Several conclusions can be made from the table as follow.

Effect of Grade on Gait Parameters

The average step frequency and the average walking speed are significantly higher for pedestrians walking in the northwest direction (negative slope) compared to pedestrians walking in the southeast direction (positive slope), while average step length is not significantly different between the two directions. This shows that pedestrians mainly control their walking speeds by adjusting their step frequencies when negotiating such a grade. The results are consistent with findings of Kawamura et al (1991) in terms of increasing in step frequency in the downslope walking, but inconsistent in terms of increasing walking speed and non-changing step length in the downslope walking as they found that the most conspicuous phenomena in downslope walking to be in step length, compared to level walking. This inconsistency may be related to the steepness of the grade or the fact that they only studied the walking patterns of 17 young men.

Effect of Pedestrian Gender on Gait Parameters

Compared to males, females have a significantly lower average step length but a significantly higher average step frequency. Average walking speed is slightly, but significantly higher for males compared to females. These results are consistent with the findings of (Crowe, et al., 1996) (Yamasaki, et al., 1991) (Hui, et al., 2007) in terms of step length and step frequency. This can be attributed to the height difference between the two groups (Yamasaki, et al., 1991). Figure 4.11 shows each step frequency and step length as a function of walking speed, with walking speed being categorized in small segments. The results show significant differences in step frequencies between males and females at all speeds, and significant differences in step lengths between males and females at speeds greater than 1.2 m/s. The results suggest that, compared to males, females increase their step frequency to increase their walking speed.

Effect of Pedestrian Age on Gait Parameters

The average walking speed, step frequency and step length are significantly different between the four age groups. Average step frequency decreases as age increases. Pedestrians aged 16 or less have the largest average step frequency and shortest average step length compared to all other age groups. Pedestrians in this age group (mainly children) were observed in the majority of cases to walk with their parents who usually belong to the third age group (36-55). The equal average walking speeds between these two age groups suggest that children, who usually cannot increase their step lengths beyond certain limits due to their short heights, increase their step frequencies substantially in order to increase their walking speeds and "catch up" with their parents. Average walking speed increases between the first age group (16 or less) and the second age group (16-35), and decreases thereafter. Average walking speed is the lowest for the oldest age group (56+). The results of this study suggest that, compared to older pedestrians, younger pedestrians increase their walking speed by increasing their step frequency rather than their step length. This is opposite to the findings of Elble et al (1991); however, it should be noted that the oldest age group in this study consists of pedestrians with 56 years of age or older, with a small sample size (n=16). The sample size may not be adequate to make general conclusions regarding the gait selection of elderly pedestrians.

Effect of Pedestrian Height on Gait Parameters

As height increases, the average step frequency decreases and the average step length increases, with the differences being statistically significant. The average walking speed is not significantly different between different height groups.

These finding suggest that, in order to have the same "pace" in speed as other pedestrians, shorter pedestrians use faster step frequencies and tall pedestrians use longer step lengths. Average height pedestrians have step lengths and step frequencies between those of shorter and taller pedestrians. These findings are consistent with the findings of Yamasaki et al (1991).

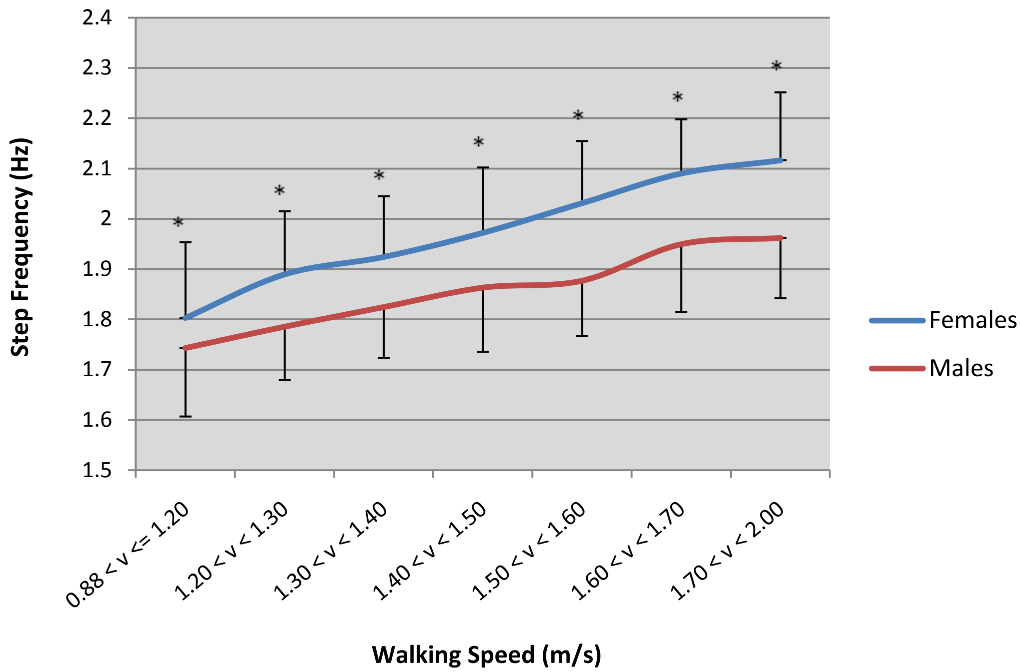
Effect of Pedestrian Group Size on Gait Parameters

The average step length decreases significantly as group size increases. The average step frequency also decreases with increasing group size, but the difference is not significant. The significant decrease in average walking speed with increasing group size is thus mainly the result of decreasing average step length. These findings suggest that step length may be the control parameter for people within a group to adjust their walking speeds in order to walk with the same "pace" as others within the same group.

Table 4.1 Pedestrian Gait Parameter Values

Attribute	Variable	Mean (Standard Deviation)				p-value		
		Count	*Frequency (Hz)*	*Length (m)*	*Speed (m/s)*	*Frequency (Hz)*	*Length (m)*	*Speed (m/s)*
Direction	*Northwest*	902	1.89 (0.15)	0.73 (0.08)	1.38 (0.18)	<0.0001	0.481285	<0.0001
	Southeast	188	1.78 (0.18)	0.73 (0.12)	1.29 (0.23)			
Gender (*Northwest*)	***Male***	458	1.84 (0.13)	0.76 (0.09)	1.39 (0.19)	<0.0001	<0.0001	0.0487
	Female	444	1.94 (0.15)	0.71 (0.07)	1.37 (0.17)			
Age (*Northwest*)	***<16***	30	2.00 (0.17)	0.67 (0.07)	1.34 (0.14)	<0.0001	<0.0001	<0.0001
	16-35	628	1.89 (0.15)	0.74 (0.09)	1.40 (0.18)			
	36-55	228	1.86 (0.15)	0.72 (0.07)	1.34 (0.16)			
	56+	16	1.79 (0.14)	0.73 (0.04)	1.32 (0.14)			
Height (*Northwest*)	***Short***	159	2.00 (0.16)	0.70 (0.07)	1.40 (0.17)	<0.0001	<0.0001	0.1593
	Average	613	1.87 (0.14)	0.73 (0.08)	1.37 (0.18)			
	Tall	130	1.80 (0.11)	0.77 (0.09)	1.39 (0.18)			
Group Size (*Northwest*)	***1***	162	1.90 (0.15)	0.77 (0.09)	1.46 (0.20)	0.1555	<0.0001	<0.0001
	2	497	1.89 (0.15)	0.73 (0.08)	1.37 (0.17)			
	3+	243	1.87 (0.14)	0.72 (0.08)	1.34 (0.15)			

(a)



(b)

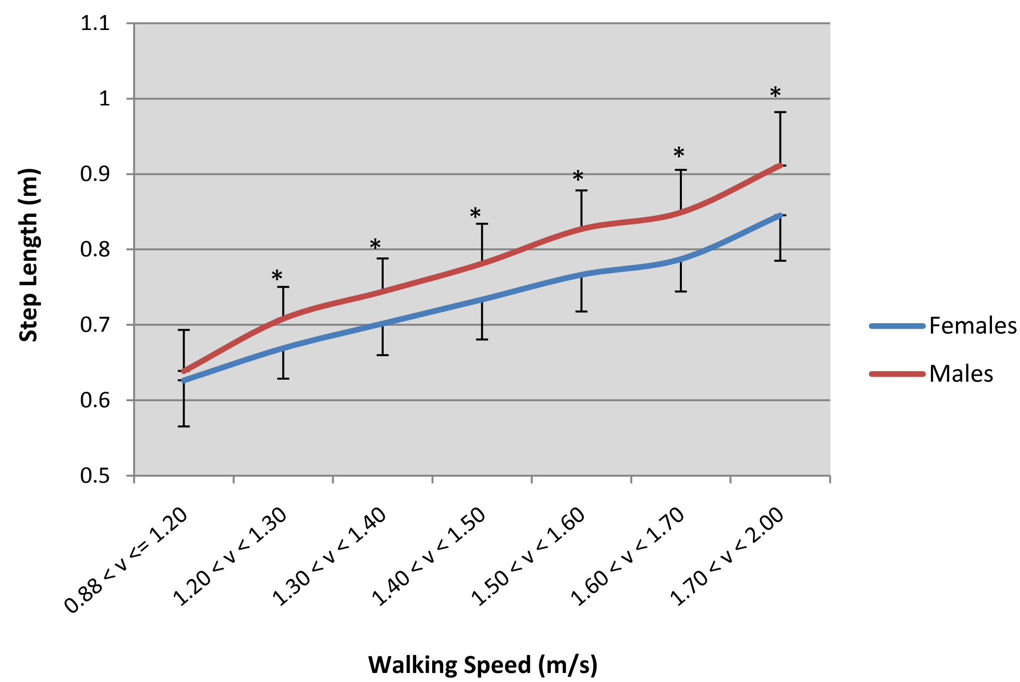


Figure 4.11 Step Frequency and Step Length of Males and Females as a Function of Walking Speed (* indicates statistical significance at 5% level)

4.4 Case Study 2: Oakland Case Study

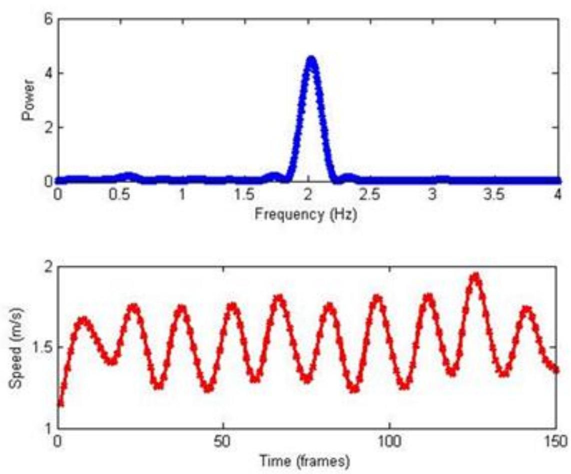
4.4.1 Site Characteristics

The study site is a busy downtown intersection located at 8th and Webster Streets, city of Oakland, California. The details of the site characteristics were discussed in Chapter Three. The crossing legs were categorized into conventional and diagonal legs. The same dataset used in Chapter Three are used in this case study to further study the pedestrian walking characteristics beyond the analysis of walking speed. Again, feature tracking was used for detection of pedestrians in this case study. Figure 4.12 shows the study site after the implementation of a scramble phase.

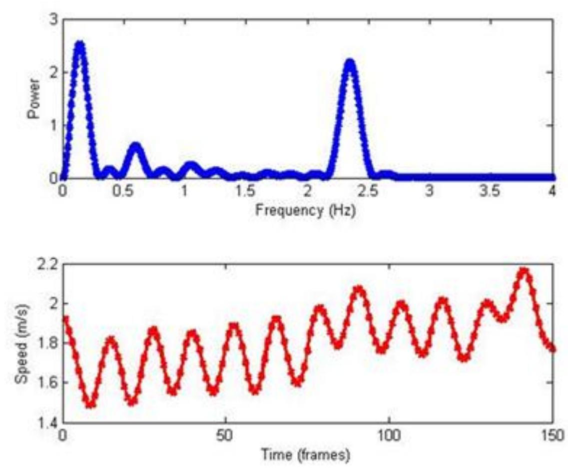
Figure 4.12 Study Site after Implementation of Scramble Phase with Sample Pedestrian Trajectories

4.4.2 Data Collection and Tracking Performance

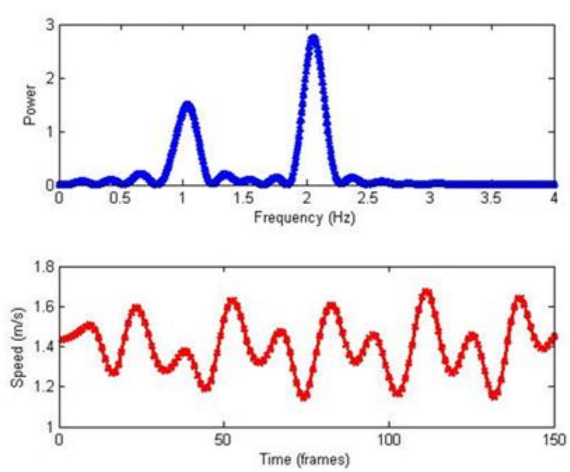
A sample of pedestrian speed profiles (smoothened and normalized) in addition to their power spectrums are shown in Figure 4.13. Step length is simply estimated by dividing the walking speed by step frequency.



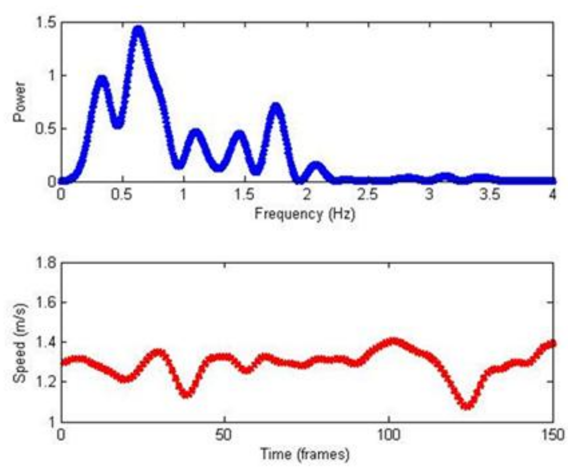
(a) Speed Signal with no Trend Effect



(b) Speed Signal with Trend Effect



(c) Speed Signal with no Trend Effect



(d) Speed Signal With Dominant Noise Components

Figure 4.13 Smoothened Pedestrian Walking Speed Signal (Bottom); Power Spectrum (Top)

Even though the accuracy of step frequency estimation on tracks generated using MM-Track was validated in Section 4.2, the validation of the estimation in this case study is important as the pedestrian tracks in this case study are generated using feature-based tracking algorithm. To do so, the step frequencies for a sample of 90 pedestrians were manually calculated and compared against automatically estimated values. Figure 4.14 demonstrates the comparison between manually and automatically calculated step frequencies. The root-mean-squared-error and correlation variable are found to be 0.0468 Hz and 0.899, respectively, which demonstrate a great agreement between the manual and automatic methods. The RMSE represents approximately 2.3% error (2.00 ± 0.0468 Hz).

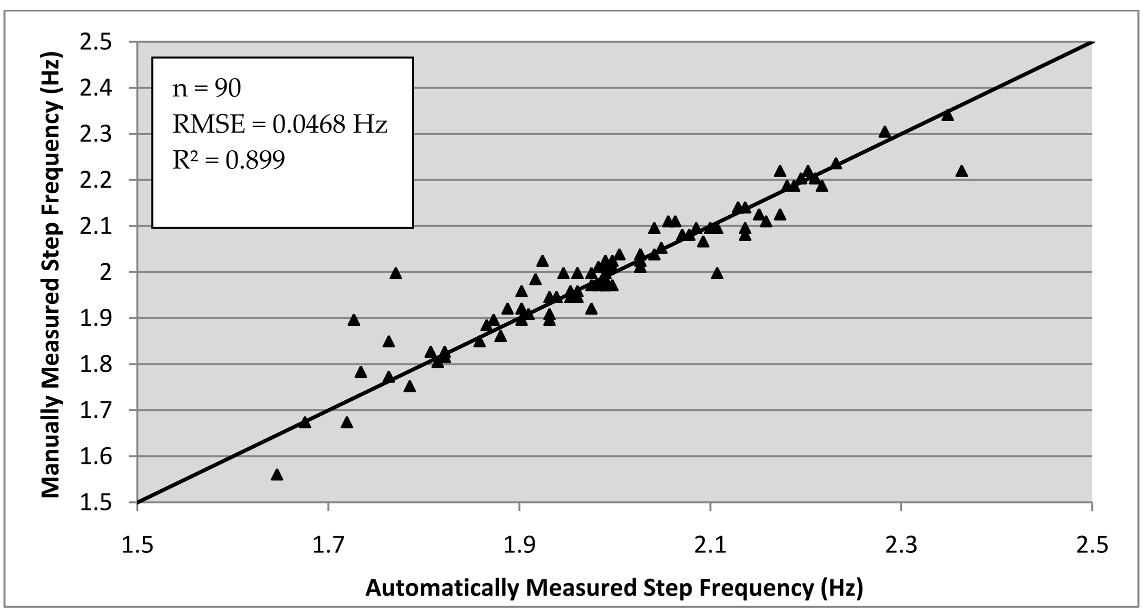


Figure 4.14 Comparison between Automatically and Manually Measured Pedestrian Step Frequencies

The following sections present the results of this case study which investigates the gait selection of pedestrians with respect to attributes such as pedestrian age, gender, group size, crosswalk type, and pedestrian signal indication.

4.4.3 Distributions of Pedestrian Gait Parameters

Gait parameter distributions were found for a sample pedestrian population in both before and after the implementation of scramble phasing; however, pedestrians walking through the diagonal legs of the intersection in the scramble phase were excluded and only the pedestrians walking through the conventional legs were considered to ensure the true investigation of each attribute. Pedestrian step frequency, step length and walking speed were found to follow the normal distribution as shown in Figure 4.15. The mean values and the standard deviations of walking speed, step frequency, and step length for 684 pedestrians were found to be 1.49 ± 0.21 m/s, 1.95 ± 0.17 Hz, and 0.76 ± 0.10 m, respectively.

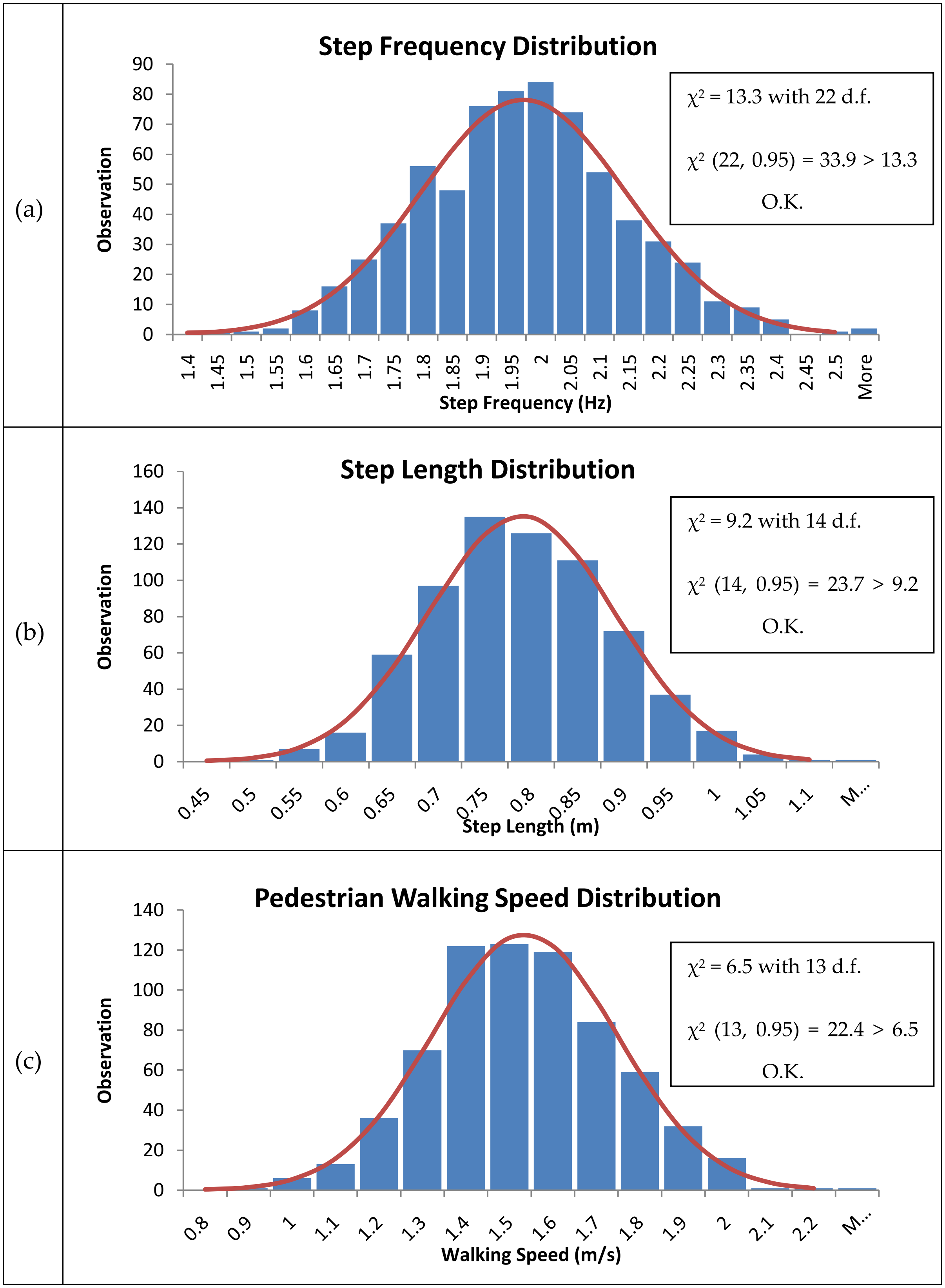


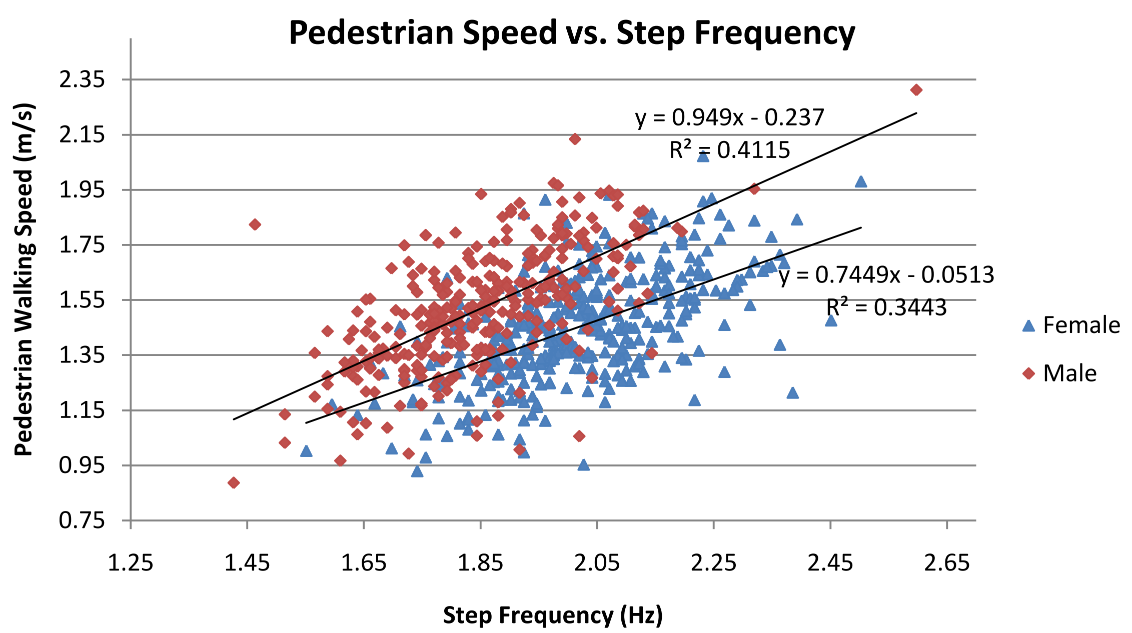
Figure 4.15 Distributions of Pedestrian Gait Parameters

4.4.4 Relationship between Walking Speed and Gait Parameters

The same sample population used in the previous section is considered here to investigate the effects of pedestrian step frequency and step length on pedestrian walking speed. Figure 4.16 illustrates the separate effects of step frequency and step length on pedestrian walking speed for female and male pedestrians. As it is shown in the figure, the effect of step length on walking speed is greater than the effect of step frequency on walking speed, explained by the slope of the best-fit-lines. This indicates that pedestrians usually control their walking speed by adjusting their step length more than step frequency. The higher correlation in Figure 4.16 (a) compared to Figure 4.16 (b) indicates that a higher variation in walking speed can be explained by changes in step length rather than changes in step frequency.

Standardized regression coefficients were also found using Equation 4.3 so that the magnitudes can be better compared between the two regressions in Figure 4.16. The standardized regression coefficients for Pedestrian Speed vs. Step Frequency and Pedestrian Speed vs. Step Length for female pedestrians are 0.612 and 1.123, respectively (unitless). The standardized regression coefficients for Pedestrian Speed vs. Step Frequency and Pedestrian Speed vs. Step Length for male pedestrians are 0.780 and 1.070, respectively (unitless).

(a)



(b)

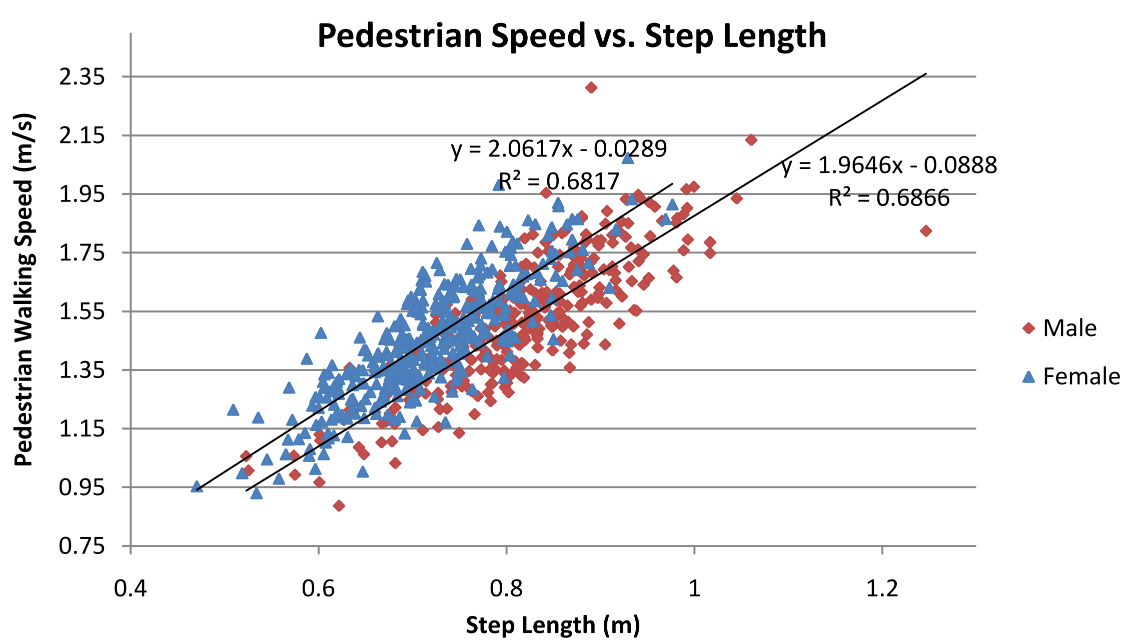


Figure 4.16 Effect of Pedestrian Step Frequency and Step Length on Walking Speed

4.4.5 Comparison between Gait Parameters across Pedestrian Group Size, Gender, and Age

In this section, only the behavior of pedestrians walking through the conventional crosswalks, in both before and after the implementation of scramble phase, is analyzed.

Table 4.2 summarizes the gait parameter values (step frequency, step length, and walking speed) across pedestrian gender and group size. The following observations can be made from the table:

- For all group sizes combined, as well as for pedestrians walking alone, females have statistically significant larger average step frequency, shorter average step length, and slower average walking speed compared to males. From this it can be concluded that, compared to males, females increase their walking speed by increasing their step frequency when walking alone.
- For pedestrians walking in pairs or larger groups, average walking speed is not statistically different between males and females, even though females have significantly larger average step frequency and shorter average step length compared to males. This similarity between the average walking speeds may suggest that the majority of the groups consist of both genders, and that when in groups, the different genders still select their step frequency-step length combination for controlling their walking speed as if they are walking alone.
- Female pedestrians have similar walking behavior when walking alone or in groups as none of their three average gait parameter values are significantly different across group size.

- Male pedestrians walking alone have different walking behavior than male pedestrians walking in groups as they have larger average step frequency and faster average walking speed. However, males have similar average step lengths across group size. This may suggest that male pedestrians control their walking speeds by adjusting their step frequencies rather than step lengths when walking in groups.
- For all genders combined, pedestrians walking in groups have lower average step frequency and slower average walking speed, but similar average step length, compared to pedestrians walking alone.

Table 4.3 summarizes the gait parameter values across pedestrian age. It can be observed from the table that the average step frequency, step length, and walking speed decrease significantly with increasing age. The decrease is larger in magnitude when considering pedestrians older than 55 years of age.

4.4.6 Effect of Scramble Phase on Pedestrian Gait Parameters

In this section, the sample population consists of pedestrians at the scramble intersection, across both conventional and diagonal crosswalks. Table 4.4 shows the three gait parameter values for pedestrians walking in the scramble phase. Even though slightly larger, the average step frequency for pedestrians walking through the diagonal legs of the scramble is not found to be significantly different than that through the conventional legs; however, both average step length and walking speed are significantly higher for diagonally crossing pedestrians. This may suggest that to increase their walking speed, pedestrians usually increase their step length more than step frequency when crossing a longer crosswalk.

4.4.7 Comparison of Gait Parameters between Temporally Complying and Non-complying Pedestrians

Table 4.5 summarizes the gait parameter values for temporally complying and non-complying pedestrians. The category of pedestrians using the conventional legs consists of pedestrians in both before and after the implementation of scramble phase, while the category using the diagonal legs consists only of pedestrians in the scramble as there were no diagonal legs present in the pre-scramble. Through the conventional legs, pedestrians who start crossing the intersection on Walk (W) indication (temporally complying pedestrians) have similar average step frequency, but significantly shorter average step length and slower average walking speed, compared to those who start during Flash Don't Walk (FDW) indication (temporally non-complying pedestrians). Through the diagonal legs, however, complying pedestrians have significantly lower average step frequency, in addition to significantly shorter average step length and slower average walking speed. This may suggests that non-complying pedestrians use different strategies to increase their walking speeds when using different length crosswalks (diagonal/conventional), and that the longer crosswalk length encourages the non-complying pedestrians to increase their step frequency in addition to increasing their step length in order to increase their walking speed and clear the intersection quickly.

Table 4.6 summarizes the results of pedestrian gait selection across pedestrian age, gender, and group size as a function of pedestrian compliance to pedestrian signal indications. The population consists of pedestrians walking through the conventional crosswalks, in both before and after the implementation of scramble phase. The following can be concluded from the table:

- When it comes to investigating the behavior of temporally non-complying pedestrians, young (16 to 35 years of age) and mid-age (35 to 55 years of age) pedestrians behave differently than old pedestrians (56 years of age or older). Among the three age groups, compared to the complying pedestrians, the non-complying young and mid-age pedestrians have significantly higher average step length and walking speed; however, the average step frequency does not significantly differ between complying and non-complying pedestrians between the young and mid-age groups. For old pedestrians, none of the three average gait parameters significantly differ between complying and non-complying pedestrians. From these findings, it can be concluded that both young and mid-age pedestrians increase their walking speeds by increasing their step lengths when they are in non-compliance mode, while old pedestrians do not change their walking behavior. It is interesting to note that among the young and old groups, compared to the compliers, the non-compliers have slightly lower average step frequencies and significantly higher average step lengths and walking speeds. This may indicate that when some pedestrians increase their step length to increase their walking speed, they tend to slightly decrease their step frequency.

- Compared to males, females increase their step length more than step frequency to increase their walking speeds when in non-compliance with the signal indications.
- Pedestrian group size is found to have no significant effect on pedestrian walking behavior during non-compliance, as all non-complying pedestrians, whether walking alone or in groups, increase their walking speeds by increasing their step length more than step frequency.

Table 4.2 Gait Parameter Values across Pedestrian Gender and Group Size

Group Size	Count			Step Frequency (Hz)			Step Length (m)			Walking Speed (m/s)		
	Female	*Male*	*All*	*Female*	*Male*	*All*	*Female*	*Male*	*All*	*Female*	*Male*	*All*
1	264	213	477	**2.03** (0.15)	***1.88** (0.15)	**1.96** (0.17)	**0.72** (0.08)	***0.83** (0.10)	**0.76** (0.10)	**1.45** (0.20)	***1.55** (0.23)	**1.50** (0.22)
2+	112	95	207	**2.00** (0.15)	***1.80**** (0.13)	**1.91**** (0.18)	**0.73** (0.07)	***0.81** (0.08)	**0.76** (0.09)	**1.46** (0.18)	**1.46**** (0.19)	**1.46**** (0.19)
All	376	308	684	**2.02** (0.15)	***1.85** (0.15)	**1.95** (0.17)	**0.72** (0.08)	***0.82** (0.09)	**0.76** (0.10)	**1.45** (0.20)	***1.52** (0.22)	**1.49** (0.21)

* indicates statistically significant difference (1%) compared to the cell directly to the left

** indicates statistically significant difference (5%) compared to the cell directly above

( ) values in brackets indicate the standard deviation

Table 4.3 Gait Parameter Values across Pedestrian Age

Age	Count	Step Frequency (Hz)	Step Length (m)	Walking Speed (m/s)
17 to 35	148	**2.01** (0.16)	**0.80** (0.10)	**1.60** (0.20)
36 to 55	447	***1.94** (0.17)	***0.77** (0.09)	***1.49** (0.19)
>55	87	***1.84** (0.15)	***0.69** (0.10)	***1.28** (0.17)

* indicates statistically significant difference (1%) compared to the cell directly above

( ) values in brackets indicate the standard deviation

Table 4.4 Gait Parameter Values for Pedestrians Walking in Scramble Phase

Crosswalk Leg	Count	Step Frequency (Hz)	Step Length (m)	Walking Speed (m/s)
Conventional	247	**1.97** (0.17)	**0.76** (0.11)	**1.49** (0.22)
Diagonal	213	**1.98** (0.18)	***0.79** (0.11)	***1.57** (0.25)

* indicates statistically significant difference (1%) compared to the cell directly above

( ) values in brackets indicate the standard deviation

Table 4.5 Gait Parameter Values for Complying and Non-Complying Pedestrians

Crosswalk Leg	Pedestrian Signal Phase	Count	Step Frequency (Hz)	Step Length (m)	Walking Speed (m/s)
Conventional	*W*	559	**1.94** (0.17)	**0.76** (0.10)	**1.47** (0.20)
	FDW	125	**1.96** (0.19)	***0.80** (0.10)	***1.57** (0.23)
Diagonal	*W*	193	**1.97** (0.18)	**0.79** (0.11)	**1.55** (0.24)
	FDW	20	***2.12** (0.17)	****0.85** (0.12)	***1.80** (0.22)

* indicates statistically significant difference (1%) compared to the cell directly above

** indicates statistically significant difference (5%) compared to the cell directly above

( ) values in brackets indicate the standard deviation

Table 4.6 Gait Parameter Values for Complying and Non-Complying Pedestrians across Age, Gender, and Group Size

Attribute	Attribute Range	Count		Step Frequency (Hz)		Step Length (m)		Walking Speed (m/s)	
		W	*FDW*	*W*	*FDW*	*W*	*FDW*	*W*	*FDW*
Age	*16 - 35*	122	26	**2.02** (0.16)	**1.98** (0.16)	**0.78** (0.09)	* **0.87** (0.11)	**1.57** (0.19)	* **1.71** (0.17)
	35 -55	361	86	**1.94** (0.17)	**1.97** (0.20)	**0.76** (0.09)	* **0.80** (0.09)	**1.47** (0.18)	* **1.57** (0.21)
	56+	75	12	**1.85** (0.15)	**1.83** (0.15)	**0.69** (0.10)	**0.70** (0.10)	**1.28** (0.17)	**1.27** (0.19)
Gender	*Female*	321	55	**2.02** (0.15)	**2.05** (0.15)	**0.71** (0.08)	* **0.76** (0.08)	**1.44** (0.19)	* **1.55** (0.20)
	Male	238	70	**1.84** (0.14)	** **1.89** (0.19)	**0.82** (0.09)	**0.84** (0.11)	**1.51** (0.21)	* **1.58** (0.25)
Group Size	*1*	389	88	**1.96** (0.17)	**1.97** (0.19)	**0.76** (0.10)	* **0.79** (0.11)	**1.48** (0.21)	* **1.56** (0.24)
	2+	170	37	**1.91** (0.17)	**1.92** (.018)	**0.75** (0.08)	* **0.82** (0.08)	**1.43** (0.18)	* **1.58** (0.19)

* indicates statistically significant difference (5%) compared to the cell directly to the left

** indicates statistically significant difference (10%) compared to the cell directly to the left

( ) values in brackets indicate the standard deviation

4.5 Conclusions

A solid understanding of pedestrian behavior is central to the evaluation of measures pertaining to walking conditions such as comfortability and efficiency. This chapter examined the spatiotemporal parameters of gait (step length and step frequency) in order to improve the understanding of pedestrian walking behavior across different characteristics such as pedestrian gender, age, group size, and pedestrian signal indication. The study used an automated technique to estimate the step frequency and step length based on oscillations in walking speed profile caused by pedestrian taking forward steps. Collecting reliable pedestrian data is often conducted by manual counts or measurements. However, the manual field observation of pedestrian data, especially microscopic data, is labor-intensive, time consuming, and subject to high errors. The use of computer vision techniques for measuring gait parameters has several advantages such as capturing the natural movement of pedestrians and minimizing the risk of disturbing the behavior of observed subjects, the richness of the data that can be extracted, and the relative higher accuracy and consistency.

In two case studies, walking speed was shown to be linearly correlated with both step length and step frequency. The analysis confirmed earlier studies which conjectured that, in order to increase the walking speed, pedestrians tend to increase their step lengths more than they increase their step frequencies. It was found in the Vancouver case study that, compared to males, females increase their step frequency more than step length to increase their walking speed during normal walking conditions without the presence of pedestrian signals.

Although similar results were found in the Oakland case study with the presence of pedestrian signals, it was found that, compared to males, females increase their step length more than step frequency to increase their walking speed when in non-compliance with signal indications. It was also found in the Oakland case study that older pedestrians do not significantly change their walking behavior when in non-compliance with signal indications as their gait parameters did not change significantly. This may indicate that the elderly have physical constraints which can limit their ability to react to unsafe conditions and improvements to the quality of the information provided to the pedestrian at intersections, in addition to pedestrian education, can reduce pedestrian non-compliance to signal indications and enhance the safety of elderly pedestrians. When walking in groups, the pedestrians in the Vancouver case study were found to control their walking speed by adjusting their step length, while the pedestrians in the Oakland case study were found to control their walking speed by adjusting the step frequency. This inconsistency in results between the two case studies when investigating the effect of group size on pedestrian gait selection may be due to the presence of pedestrian signal controls in the Oakland case study or the presence of a negative crosswalk slope in the Vancouver case study.

Finally, gait parameters were found to be influenced by pedestrian gender, age, group size, crosswalk type (length and grade), and pedestrian signal indication.

Chapter Five: Automated Classification of Pedestrian Gender and Age using Spatiotemporal Parameters of Gait

5.1 Background

There is considerable interest in encouraging sustainable modes of transportation such as walking. Therefore, a good understanding of walking behavior of various pedestrian groups (elderly, children, obese, etc.) is essential to allow for better planning and design of pedestrian facilities. Of particular importance is the good understanding of the strategies different pedestrians use for efficient and comfortable walking and to determine the population norms. Many studies have shown that attributes such as age and gender have a significant effect on pedestrian behavior. Therefore, it is beneficiary to have distributions for pedestrian attributes, in addition to simple measures such as exposure. For example, in order to ensure adequate crossing time is provided for safe crossings at intersections, it is important to have an estimate for the percentage of pedestrians such as the elderly or children who are identified to have mobility constraints. Applications of gender and age classification include finding demographic characteristics for facilities such as schools, hospitals, shopping centers, and commercial and business districts. Other applications include security surveillance, shoppers' statistics, locomotion and healthcare monitoring, and allowing robots to perceive gender.

Gender can be automatically classified by several methods such as recognition of voice (Harb & Chen, 2003), face (Golomb, et al., 1991), and gait (Li, et al., 2008). Gait recognition, among other methods, has been identified to be a good biometric for human recognition and has gained a considerable interest from researcher in many fields for human classification and recognition. Some earlier studies have shown that it is possible to use gait as a biometric to identify human age (Davis, 2001) and gender (Yoo, et al., 2006).

This study examines the performance of a k-NN classifier, a machine learning algorithm, for the purpose of the automated classification of the age and gender of walking pedestrians. The classification is based on two motion feature vectors, pedestrian step frequency and step length, which are automatically extracted from the speed profiles of walking pedestrians. This is a non-intrusive method and can be conducted at a distance. Computer vision techniques are used to automatically detect and track pedestrians in video scenes from an open (uncontrolled) environment.. Each pedestrian step is observed to introduce a periodic fluctuation in the speed profile, and therefore, the gait parameters such as step frequency and step length can be computed by analyzing the speed signal. The method has the advantage of only relying on the pedestrian speed profile and using a simple classification algorithm.

5.2 Methodology

In this section, the methodology used in the study for the classification of age and gender of walking pedestrians will be explained.

5.2.1 Computation of Feature Vectors

The feature vectors used in this study for classification of age and gender are two gait parameters: step frequency, and step length. Pedestrian walking speed is also considered as a third motion feature to improve the classification rates in some cases. The process steps used in this study to classify pedestrian age and gender are shown in Figure 5.1 and Figure 5.2. Automatic tracking of pedestrians in video scenes is possible with the help of computer vision techniques. Automatic tracking requires computer recognition of the position of pedestrians with respect to time, and hence, the generation of pedestrian trajectories. As shown in Figure 5.2, two tracking algorithms, namely Feature Tracking and MM-Track, are used for two different data sets to extract pedestrian tracks. The feature tracking and MM-Track algorithms were explained in Chapter Two. Another important component of the system is to create a mapping from world coordinates to image plane coordinates using a homography matrix (camera calibration) which was also explained in Chapter Two. This mapping, common for both tracking algorithms, enables the recovery of real-world coordinates of points that appear in the video. Pedestrian tracks, which contain information about the position of each pedestrian at every frame are then processed and instantaneous speeds and speed profiles are generated and the same technique used in Chapter Four are used to estimate pedestrian step frequency and length.

A sample of pedestrian speed profiles (smoothened) in addition to their power spectrums are shown in Figure 5.3. Walking speed, the third feature vector, was estimated by placing screens around the region of interest and measuring the amount of time it takes for the pedestrian track to cross this region as was explained in Chapter Three.

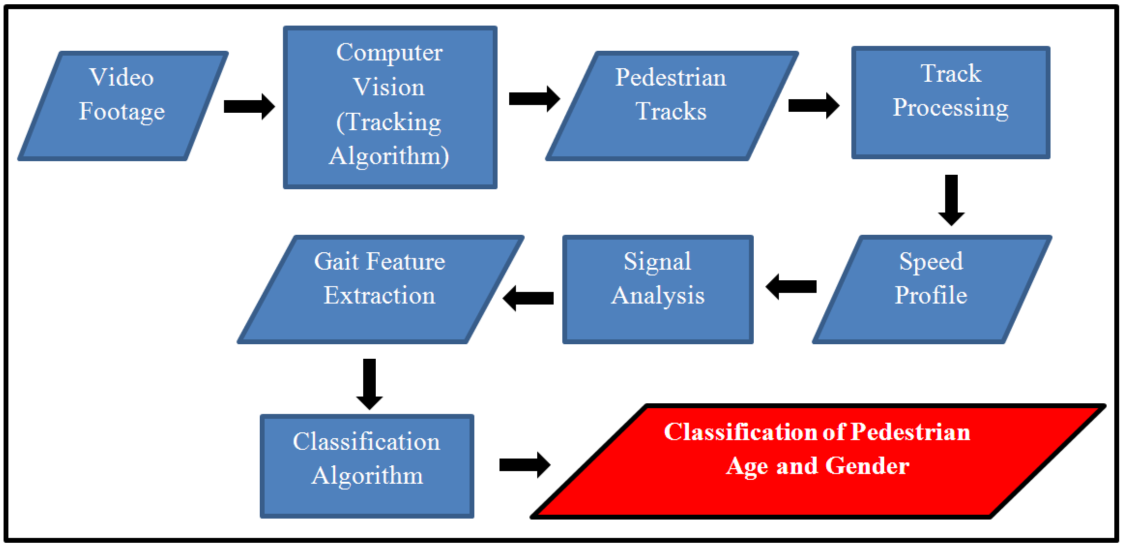


Figure 5.1 Pedestrian Age and Gender Classification Process

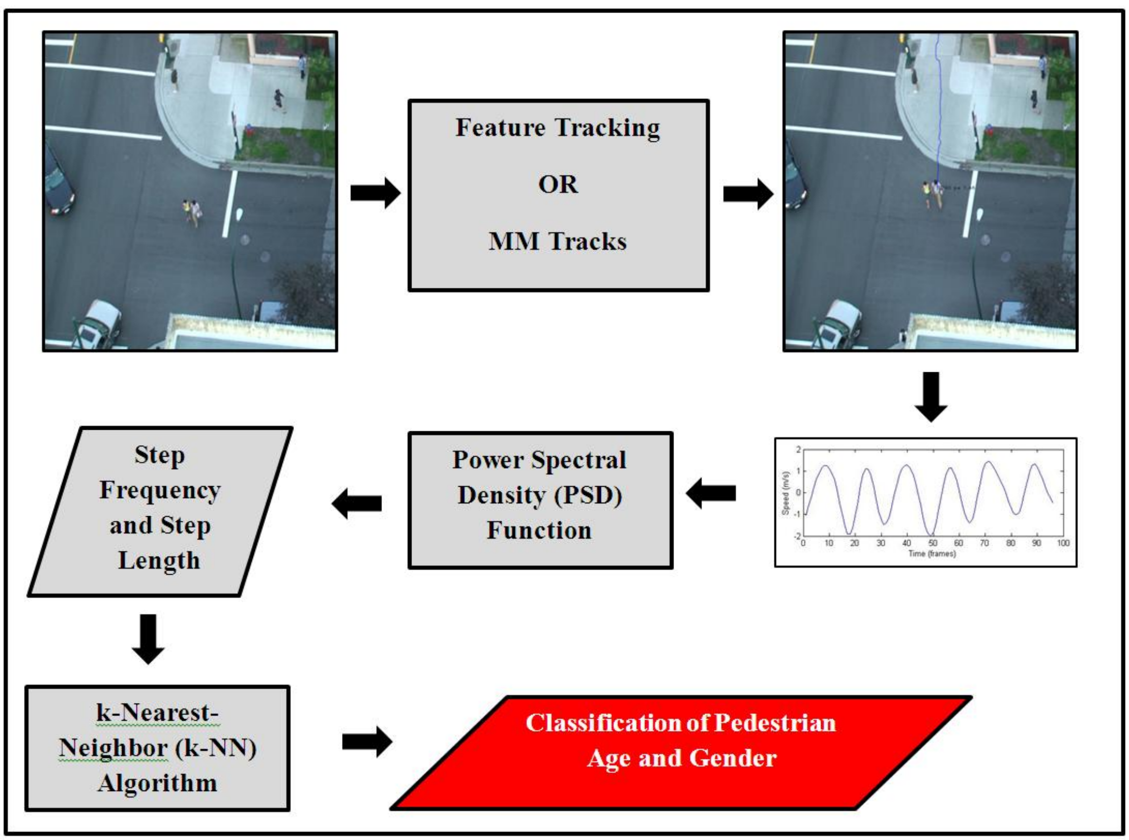


Figure 5.2 Pedestrian Age and Gender Classification Method

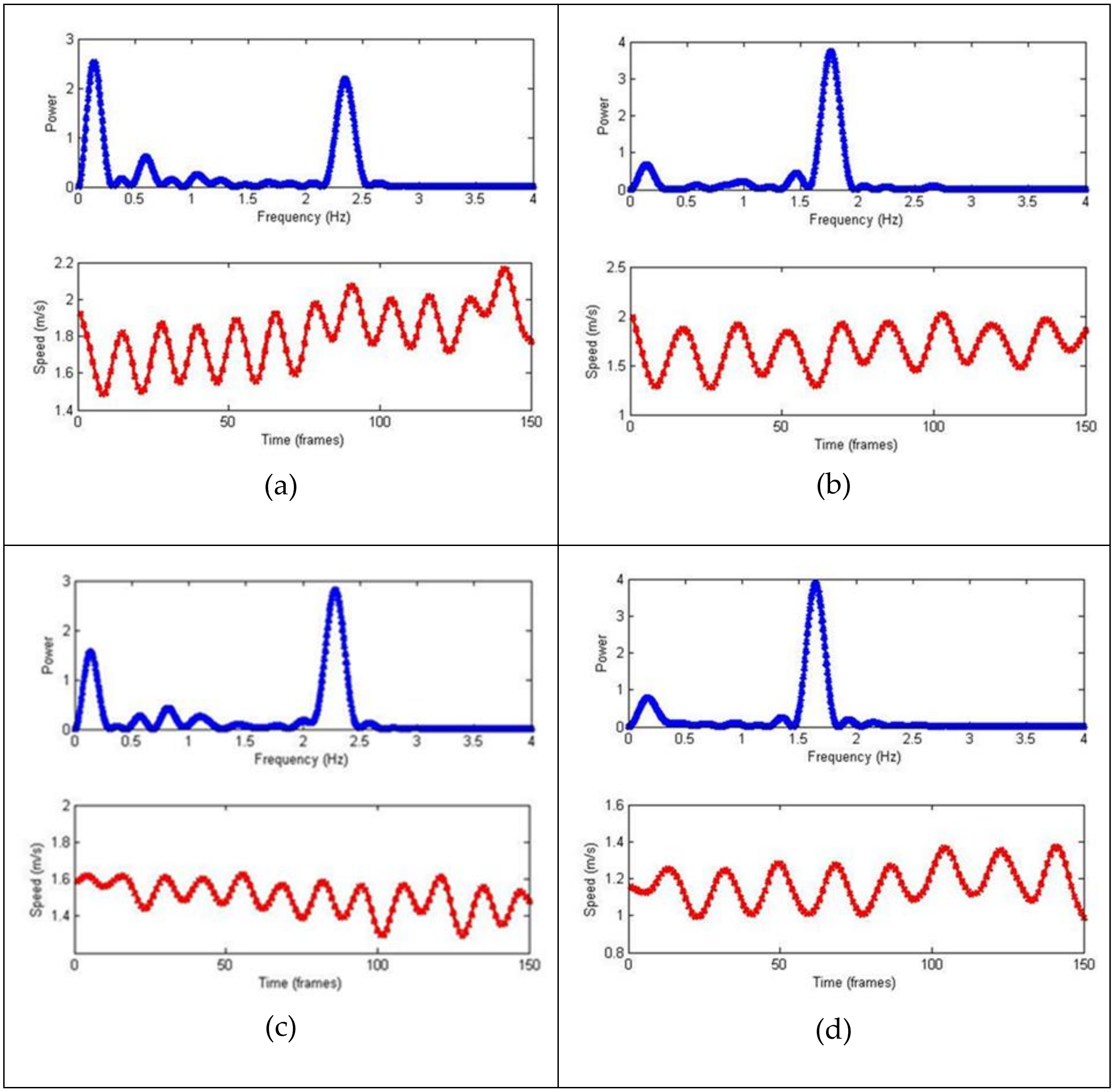


Figure 5.3 Pedestrian Step Frequency Estimation using Walking Speed Profile. (a) represents a Female subject aged between 36 and 55 with step frequency of 2.35 Hz; (b) represents a Male subject aged between 36 and 55 with step frequency of 1.76 Hz; (c) represents a Female subject aged between 17 and 35 with step frequency of 2.28 Hz; (d) represents a Female subject aged over 55 with step frequency of 1.65 Hz

5.2.2 The Classification Algorithm

The *k*-Nearest Neighbors (*k*-NN) algorithm is a suitable tool for binary classification. It is a simple machine learning algorithm used for object classification based on closest training samples in the feature space. It simply assigns a class to an object based on the majority votes of its *k* nearest neighbors, among the training data set of labeled objects. Cover and Hart (1967) were the first to introduce the idea of nearest neighbor patter classification in which an unclassified sample point is assigned a class based on its closeness to a collection of labeled points of known classes. The closeness of the neighbor objects to the unknown object is determined from a distance measure (e.g. Euclidean distance). An advantage of this instance-based or simple learning classifier is that it only approximates the function locally and defers the computation until classification. The parameter *k* is a positive integer and is usually set to a small. Mainly, the choice of *k* and the applied distance measure determine the performance of the k-NN classifier (Latourrette, 2000). It is shown in (Domeniconi, et al., 2002) that the value of *k* is difficult to predetermine in cases when the data is not uniformly distributed. Larger values of *k* are in general “more immune to the noise presented and make boundaries more smooth between classes”, and that “choosing the same (optimal) *k* becomes almost impossible for different applications” (Song, et al., 2007).

Up to three feature vectors are used for age and gender classification: walking speed, step frequency, and step length. The algorithm calculates the three-dimensional feature vectors of the unknown object and calculates the Euclidean distance metric from *k* closest feature vectors of the learning objects. The three gait parameters for all learning objects and unknown objects are first standardized, using Equation 4.3, in prior to feeding to the algorithm.

$$x_i{}' = \frac{x_i - Min\,\{x_1, x_2, \ldots, x_n\}}{\text{Max}\,\{x_1, x_2, \ldots, x_n\} - Min\,\{x_1, x_2, \ldots, x_n\}} \qquad \text{(4.3, repeated)}$$

Where, x is a feature such as step frequency or step length, and x_i is the actual value of that feature for pedestrian *i*, and $x_i{}'$ is the standardized value of that feature for pedestrian *i*.

And, Max{} and Min{} are the maximum and minimum of the entire feature arrays for the entire pedestrian population, respectively.

A majority vote of the k nearest feature vectors determines the probable type of any unknown data. This is shown in Figure 5.4.

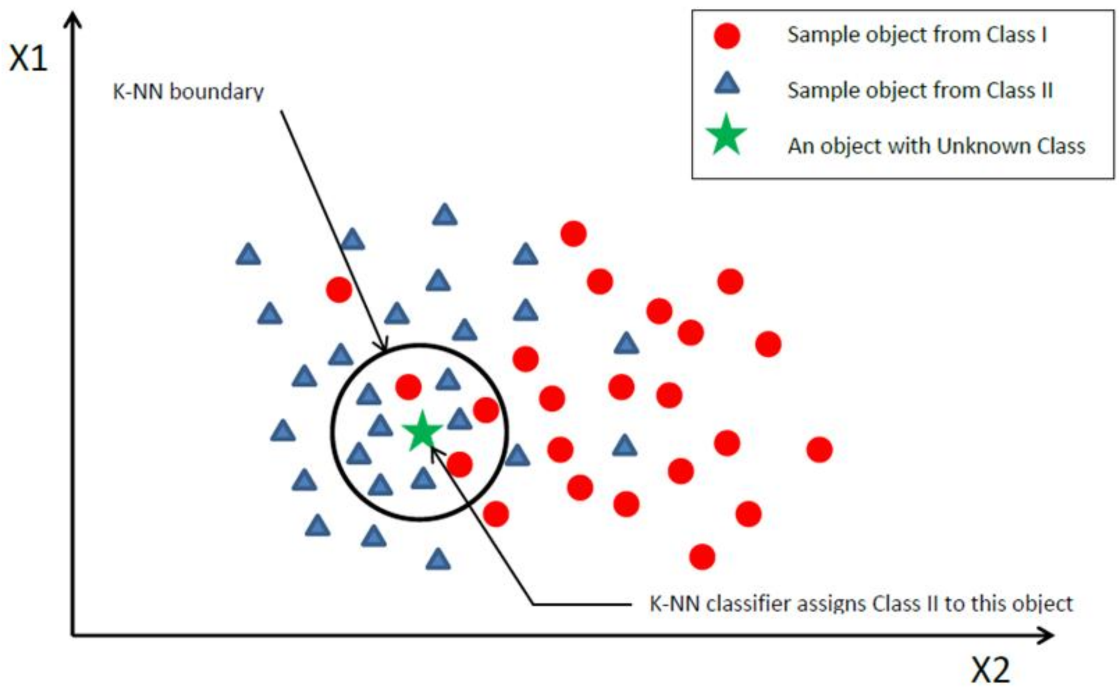


Figure 5.4 Binary Classification in a Two-dimensional Sample Space

Age and gender are each divided into two classes (i.e. Male or Female for gender, and Young or Old for age). The Young consists of pedestrians between the ages of 16 to 35, while the Old consists of pedestrians older than 55 years of age.

5.2.3 The Classification Performance

In this study two performance measures are used to evaluate the performance of the classification: Correct Classification Rate (CCR) and Cohen's kappa coefficient (κ). Kappa is a statistical tool used to measure the inter-rater agreement for categorical items (Strijbos, et al., 2006). The statistic corrects for the agreement expected by chance and gives a more robust measure of the agreement compared to simple percent correct classification. In this case, κ is used to test the significance of the classification results (CCR). Kappa takes values in the range of $\kappa \in [-1,1]$, with $\kappa = -1$ indicating perfectly incorrect classification, κ = 0 indicating true classification totally expected by chance, and κ = 1 indicating perfectly correct classification. In general, a κ of 0.6 is considered to be a minimum requirement (Landis & Koch, 1977), below which the likelihood of agreement by chance is considered significant.

The equation for κ is:

$$\kappa = \frac{\bar{P} - \overline{P_e}}{1 - \overline{P_e}} \tag{5.1}$$

where,

$\bar{P}$ is the CCR, and

$\overline{P_e}$ is the hypothetical probability of classification by chance.

The variance of kappa, Var(κ), is:

$$Var(\kappa) = \frac{1}{\mathrm{N}} \times \frac{\sum_1^2 p_i{}^2 - \left(\sum_1^2 p_i{}^2\right)^2}{\left(1 - \sum_1^2 p_i{}^2\right)^2} \tag{5.2}$$

where, *N* is the total number of objects to be classified, and p_i is the proportion of all assignments in the *i*th category.

Under the hypothesis of no correct classification beyond chance and using the central limit theorem, the value $\kappa/\sqrt{Var(\kappa)}$ may be approximately distributed as a standard normal variant (Fleiss, 1971). If $\kappa/\sqrt{Var(\kappa)}$ exceeds the critical Z value (Z = 2.32 at a significance level of 99%), then the CCR results are significant beyond what is expected by chance.

The method is demonstrated using two case studies. The first case study uses data from Vancouver, British Columbia and the second uses data from Oakland, California. Both locations are busy downtown intersections with high pedestrian activity. Gender classification was undertaken for both Oakland and Vancouver datasets while age classification was done only for the Oakland dataset due to limited sample size for old pedestrians in the Vancouver dataset. For gender classification in the Oakland dataset, only the pedestrians walking alone were taken into consideration while in Vancouver dataset, gender classification was conducted for all pedestrian group sizes due to a limited number of pedestrian samples walking alone. For age classification in the Oakland dataset, pedestrians walking alone or in groups are taken into consideration.

5.3 Case Study 1: Vancouver, British Columbia

5.3.1 Gender Classification

Figure 5.5 shows the gait of 801 labeled objects for the Vancouver dataset based on gender. The data consists of pedestrians walking alone or in groups. As shown, the gait parameters for males and females are concentrated in two different regions with some overlap between them. The data was split into labeled data (90%) and unlabeled data (10%). 89 unlabeled objects were fed into the k-NN algorithm to be assigned a binary classification of male or female. As illustrated in Table 5.1, a Correct Classification Rate (CCR) of 78% is achieved based on two feature vectors, step frequency and step length. Similarly, a CCR of 78% is achieved when all three feature vectors are used in classification. In both cases 69 out of 89 subjects are correctly classified as male or female subjects. It may be arguable that using walking speed as a feature vector along with step frequency and step length may not be a good practice as walking speed is simply the product of step frequency and step length.

The κ statistic was found to be 0.551 and $\kappa/\sqrt{Var(\kappa)}$ was found to be 5.19 regardless of whether two or three feature vectors were used. Even though κ = 0.551 is smaller than 0.6, the standard normal variant still shows a significant gender classification beyond chance (i.e., 5.19 > 2.32).

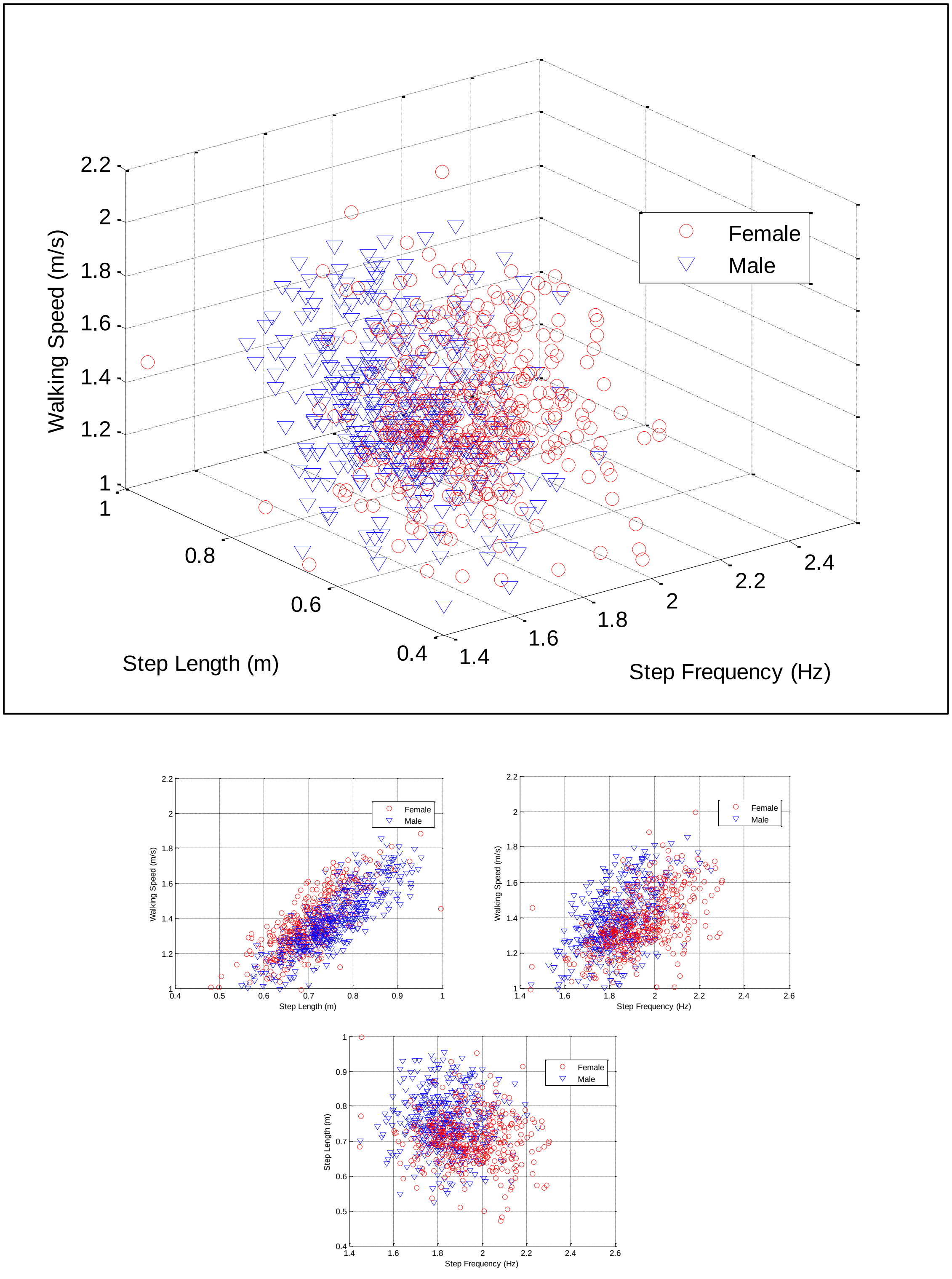


Figure 5.5 Labeled Objects Based on Gender (Vancouver Case Study)

Table 5.1 Pedestrian Gender Classification Results (Vancouver Case Study)

<table>
<tr><th>Feature Vector</th><th colspan="4">CCR (%) [k=18]</th></tr>
<tr><td>Step Frequency</td><td rowspan="3">77.53</td><td rowspan="2">77.53</td><td>70.79</td><td>-</td></tr>
<tr><td>Step Length</td><td>-</td><td>61.80</td></tr>
<tr><td>Walking Speed</td><td>-</td><td>-</td><td>-</td></tr>
</table>

Note: Results in this table are based on characteristics of pedestrians walking alone or in groups

5.4 Case Study 2: Oakland, California

5.4.1 Gender Classification

A greater separation between gender gait data is shown in Figure 5.6, compared to that in Figure 5.5. The gender gait data here consists only of pedestrians walking alone, and this could be the reason for greater separation of the gait data points as pedestrians may behave differently by coordinating their walking speed when walking in groups. Eighty subjects with unknown gender are compared against 272 labeled subjects and the classification rates are summarized in Table 5.2. A CCR of 81% is achieved when the two feature vectors, step frequency and step length, are used for classification, and a CCR of 85% is achieved when considering all three feature vectors. The CCRs are higher for Oakland dataset compared to those of Vancouver dataset.

The κ statistic was found to be 0.70 and $\kappa/\sqrt{Var(\kappa)}$ was found to be 6.26 when all three feature vectors were used. When two feature vectors were used the results were still significant (κ = 0.625 and $\kappa/\sqrt{Var(\kappa)}$ = 5.55). These results show that the CCRs of 85% and 81.25% for gender are significant beyond expectations by chance.

A better classification rate in this case study compared to the Vancouver case study is probably due to the fact that only the pedestrians waking alone are considered as there may be unobserved effects of group size on pedestrian walking behavior.

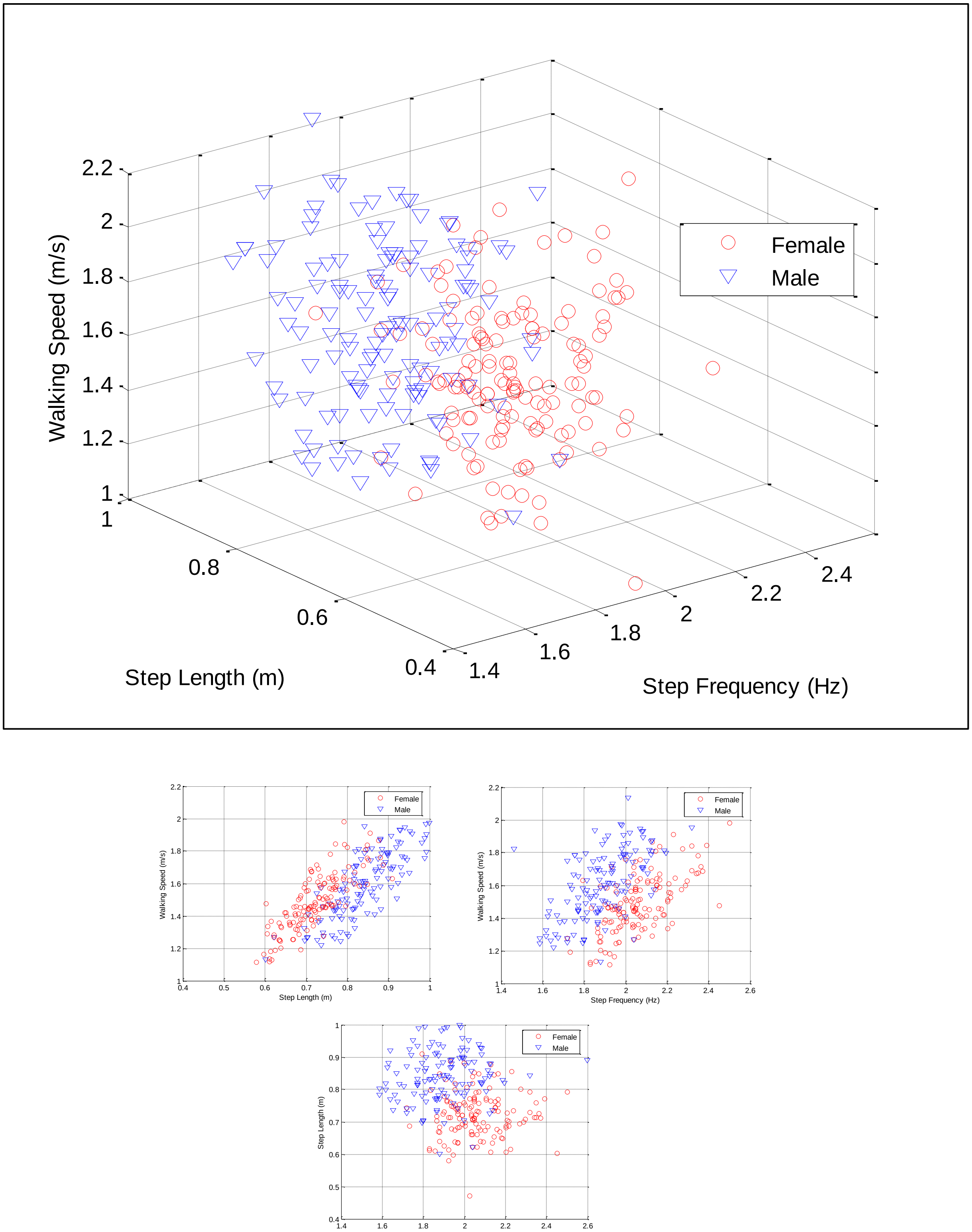


Figure 5.6 Labeled Objects Based on Gender (Oakland Case Study)

Table 5.2 Pedestrian Gender Classification Results (Oakland Case Study)

<table>
<tr><th>Feature Vector</th><th colspan="4">CCR (%) [k=26]</th></tr>
<tr><td>Step Frequency</td><td rowspan="3">85.00</td><td rowspan="2">81.25</td><td>67.50</td><td>-</td></tr>
<tr><td>Step Length</td><td>-</td><td>71.25</td></tr>
<tr><td>Walking Speed</td><td>-</td><td>-</td><td>-</td></tr>
</table>

Note: Results in this table are based on characteristics of pedestrians walking alone

5.4.2 Age Classification

Figure 5.7 shows the labeled gait data points for young (aged between 17 and 35) and old pedestrians (aged older than 55 years of age). A great separation of the gait data is obvious from the figure with minor overlap. 50 objects of unknown age class are to be classified using 178 labeled objects. The results of the classification are shown in Table 5.3. A CCR of 86% was achieved when using the two feature vectors, step frequency and step length. Similarly, a CCR of 86% is achieved when using all three feature vectors for classification. 43 out of 50 data points were correctly classified as young or old subjects when using two or three feature vectors for classification.

The κ statistic was found to be 0.72 and $\kappa/\sqrt{Var(\kappa)}$ was found to be 5.09 regardless of whether two or three feature vectors were used. These results show significant age classifications beyond expectations by chance.

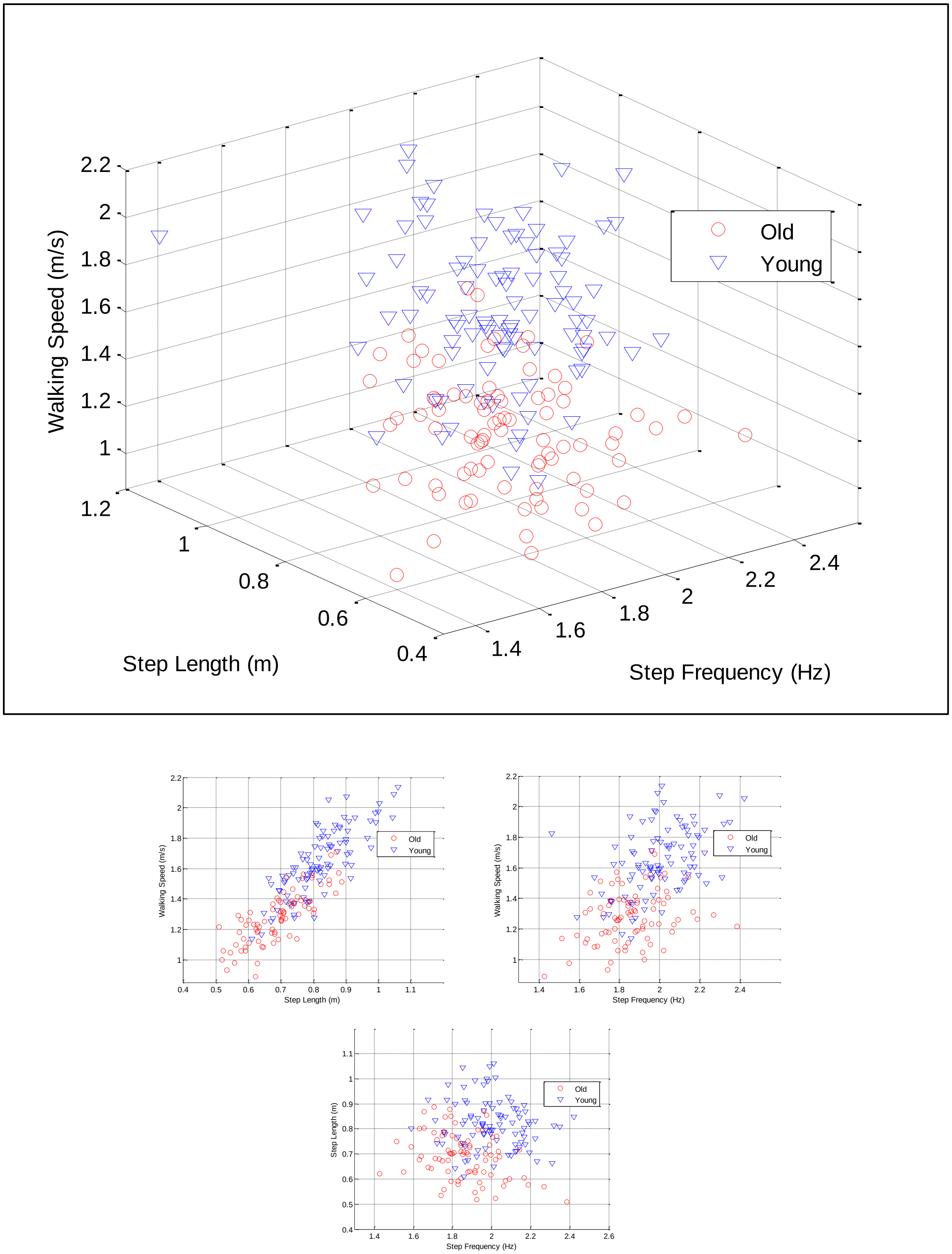


Figure 5.7 Labeled Objects Based on Age (Oakland Case Study). The Old group consists of pedestrians older than 55 years of age and the Young group consists of pedestrians aged between 17 and 35

Table 5.3 Pedestrian Age Classification Results (Oakland Case Study)

<table>
<tr><th>Feature Vector</th><th colspan="4">CCR (%) [k=26]</th></tr>
<tr><td>Step Frequency</td><td rowspan="3">86.00</td><td rowspan="2">86.00</td><td>76.00</td><td>-</td></tr>
<tr><td>Step Length</td><td>-</td><td>74.00</td></tr>
<tr><td>Walking Speed</td><td>-</td><td>-</td><td>-</td></tr>
</table>

Note: Results in this table are based on characteristics of pedestrians walking alone or in groups

5.5 Conclusions

In this paper, the feasibility of using the spatiotemporal parameters of gait (step frequency and step length) as cues to identify the gender and age of pedestrians was investigated in two case studies. Pedestrian walking speed profile was used to extract two motion features: step frequency and step length. These motion features were used to classify pedestrians according to their gender and age. Computer vision techniques were used for the automatic detection and tracking of pedestrians in open environment, from which pedestrian speed profile was generated. A k-Nearest Neighbors (k-NN) algorithm was used as a classification tool. Two performance measures were used to evaluate the performance of the classification: Correct Classification Rate (CCR) and Cohen's kappa coefficient (κ).

The results of the study showed statistically significant CCRs of 78% and 81% for gender classification in Vancouver and Oakland case studies, respectively, with Vancouver case study considering pedestrians walking alone or in groups and with Oakland case study only considering pedestrians walking alone. A better classification rate in the Oakland study is probably due to the fact that only the pedestrians waking alone were considered as there may be unobserved effects of group size on pedestrian walking behavior. The results also showed statistically significant CCR of 86% for age classification in Oakland case study where pedestrians walking alone or in groups were considered. The CCR for gender classification in Oakland case study was improved from 81% to 85% when walking speed was also considered as a classification feature, while it did not affect the age classification in the same case study or gender classification in the Vancouver case study.

The results are very encouraging, given that only the spatiotemporal gait parameters were used as motion features to discriminate between pedestrian age and gender. Future work includes exploring other motion features such as lateral movement of pedestrians during walking to further improve the classification results. This may require adjustments to the camera position and angle to better capture specific movements. The use of more advanced classification algorithms may also improve the results.

Chapter Six: Conclusions and Future Work

6.1 Summary and Conclusions

In this thesis, the importance of a need for building a sustainable transport system which places more attention towards encouraging non-motorized modes of transportation such as walking was introduced. This research can be used as a tool for developing objective measures and techniques for capturing and studying pedestrian movement. This can help in providing transportation planners and officials with the tools and standards required to evaluate pedestrian oriented facilities in order to enhance the service quality. This can effectively encourage walking as a means of travel.

A standard approach in conducting pedestrian studies is to capture the movement of pedestrians as they use the transport system. One of the main challenges in conducting detailed analysis on pedestrian behavior is the lack of reliable data. This lack of reliable data can have a significant impact on several transportation engineering and planning aspects. Conventionally, pedestrian movement is captured using human observers and data such as volume counts or walking speed measurements are measured and recorded using manual methods. The manual field observation of pedestrian data is labor-intensive, time consuming, and subject to high errors. The manual methods currently used in practice for the collection of pedestrian data also lack the ability to capture microscopic changes in position and speed.

The accurate pedestrian movement data can greatly benefit from automatic tracking of the position of pedestrians. Automatic tracking requires computer recognition of the position of pedestrians in space with respect to time, and hence, the generation of trajectories for each pedestrian. The benefits of automatic tracking identified in this thesis include capturing the natural movement of pedestrians and minimizing the risk of disturbing the behavior of observed subjects and the relatively higher accuracy and consistency in comparison to manual methods. Other benefits of automatic tracking include less resource requirement and information availability about the microscopic behavior of pedestrians during the distance traveled.

6.2 Research Contributions

6.2.1 The Use of Computer Vision Techniques to Capture and Study Pedestrian Movement

The feasibility and accuracy of using computer vision techniques for detecting and tracking pedestrians, and hence, collecting microscopic pedestrian data was demonstrated in Chapter 3 and Chapter 4. Microscopic pedestrian data can be used to capture and study pedestrian movement behavior in order to solve well-entrenched problems in road user behavioral and safety analyses. The microscopic data included pedestrian walking speed, step frequency, and step length.

6.2.2 Pedestrian Walking Speed Behavior at Signalized Intersections

Pedestrian crossing speed at intersections is a characteristic of pedestrian flow which influences several intersection design features such as signal timings. To plan and design pedestrian facilities such as crosswalks at intersections, it is important to predict pedestrian movement under individual pedestrian attributes and different external circumstances. In Chapter 3, an attempt was made to improve the understanding of pedestrian crossing behavior at signalized intersections. The ability of individual pedestrians to change their walking speeds as a response to how far through the crosswalk's length (in terms of position), as well as how far through the pedestrian signal phase (in terms of time) they are, was studied.

6.2.3 Pedestrian Gait Analysis

Gait analysis is a microscopic-level analysis which allows true estimates of objective walking measures such as stride frequency and length for pedestrians. An in-depth understanding of pedestrian walking behavior through the investigation of step length and step frequency was demonstrated in two case studies in Chapter 4, which can be used to provide insight into the pedestrian walking mechanisms and the effect of various attributes such as gender and age. Distributions for gait parameters were found for a sample pedestrian population in both case studies in Chapter 4. Also, the individual effects of step frequency and step length on walking speed were investigated. The behavior of pedestrians in terms of their selection of step frequency and length in order to change their walking speed while crossing the intersection was investigated. This investigation took place across pedestrian age, gender, group size, and crosswalk grade in the first case study and across pedestrian age, gender, group size, crosswalk type, and pedestrian signal indications in the second case study.

6.2.4 Demonstration of Conducting Before-After Pedestrian Behavior Studies

Before-After (BA) studies are conducted in order to evaluate the outcomes of engineering countermeasures. In Chapter 3, the changes in pedestrian crossing speed behavior following the implementation of a pedestrian scramble phase, was studied. In specific, the feasibility of conducting a BA study by investigating the changes in pedestrian crossing speed behavior following the implementation of a pedestrian scramble phase was investigated.

6.2.5 Pedestrian Age and Gender Classification using Gait

Research shows that attributes such as age and gender have a significant effect on pedestrian behavior. Therefore, it is beneficiary to have distributions for pedestrian attributes, in addition to simple measures such as exposure. In Chapter 5, the feasibility of automatic classification of pedestrian age and gender using two motion features (pedestrian step frequency and step length) was demonstrated. The results are encouraging.

6.3 Future Research

In the research presented, pedestrian walking behavior was studied across pedestrian or other attributes and the difference in behavior was compared across those attributes. Temporal violation was one of the attributes considered in this thesis. Spatial violation such as "j-walking" is another important attribute to consider when analyzing pedestrian behavior. From the walking behavior of pedestrians one may be able to determine the cause of such action, whether it is a result of poor design or pedestrian action. This research can be extended to analyzing pedestrian walking behavior and its relation to pedestrian safety. This can help determine how pedestrians react to unsafe traffic conditions such as when they are in traffic conflicts with motor vehicles.

In this thesis, a methodology for classification of pedestrian age and gender was introduced which solely relied on using two major motion features (step frequency and step length) to distinguish between pedestrian types. Finding additional motion features such as the amplitude of pedestrian lateral movement, can greatly improve the classification performance. Research into more robust classification algorithms can also improve pedestrian classification.

Other future research include studying pedestrian walking behavior at different pedestrian facilities such as roundabouts, sidewalks, parks, airports, and shopping malls and determining a walkability index for each facility. In addition, pedestrian gait analysis can be applied to determine the effect of pavement condition (such as uneven surface) on pedestrian gait selection. This can provide valuable information for redesigning roads and crosswalks to accommodate pedestrians with better walking conditions and to help make walking a more enjoyable mode of transport. This information can also be directly incorporated into pedestrian simulation models to make pedestrian movement more realistic with respect to the available conditions.

Cycling is another active transportation mode which is gaining considerable attention from the public. A similar approach to pedestrian behavior research introduced here can be applied to studying the behavior of bicyclists. In addition, pedestrian walking behavior can be studied in future research with varying pedestrian flow density as opposed to the free-flow (uninterrupted flow) scenario studied in this research. Finally, the accurate estimation of gait parameters can be very useful for quantifying the positive health impact of active modes of transportation such as walking as several researchers have shown that the varying effects of factors on the gait parameters can be explained through the metabolic energy expenditure rate and mechanical power requirements during waking.

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