HUMAN-SCALED PERSONAL MOBILITY DEVICE PERFORMACE CHARACTERISTICS

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To my wife and family.

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LIST OF ABBREVIATIONS

cc	Cubic Centimeters
GEM	General Electric Motors
GPS	Global Positioning System
IMS	Intelligent Mobility System
nSat	Number of Satellites
PDOP	Positional Dilution of Precision
PMD	Personal Mobility Device
SOV	Single-Occupant Vehicle
VMT	Vehicle Miles Traveled
V2V	Vehicle to Vehicle
V2I	Vehicle to Infrastructure

SUMMARY

Today, numerous alternative modes of mobility are emerging to provide a solution to the problems created by the automobile. This research envisions a future where transportation in urban areas will be dominated by small personal mobility devices (PMDs) instead of automobiles. This *Intelligent Mobility System* (IMS) would be a car-free zone where people travel by a shared-system of PMDs providing levels of mobility greater than walking but less than a car. This research effort focuses on the operational aspects of this future system by studying PMD performance characteristics as inputs for a computer simulation model of an IMS environment.

Therefore, the primary objective of this research is to evaluate the operations of PMDs that are currently used in a variety of settings. GPS recorders are used to log speed and location data each second of pedestrian, bicycle, Segway, and electric cart trips. From this data, typical speed and acceleration profiles are derived for later use in a simulation model. This research also analyzes the results of a Segway test where a group of six Georgia Tech researchers and a guide completed a Segway trip of approximately 8 miles in Atlanta. Segway speed and acceleration are analyzed using three factors, sidewalk width, surface quality, and pedestrian density to study their effect on Segway speed.

Pedestrians have the lowest mean speed and the most narrow speed distribution. Segways, bicycles and electric carts have increasingly faster mean speeds and wider speed distributions, respectively. Segways and bicycles were found to have similar acceleration distributions. Segways seem to provide a level of speed and mobility between that of pedestrians and cyclists, meaning that Segways might capture new users by providing a level of mobility and convenience previously unseen.

Narrow sidewalk widths, poor sidewalk quality, and heavy pedestrian density all decreased Segway speeds. Even if there was ample sidewalk space and the surface is of

excellent quality, speeds were still low if there are heavy pedestrian densities. Similarly, if there are no pedestrians but the surface is very rough, Segway speeds would likely be constrained. The researchers suspect that surface quality is likely an independent constraint for Segway speed and that sidewalk width and pedestrian density interact to limit Segway speeds under certain conditions. This research concludes that these external factors may affect PMD speed and should be considered when analyzing PMD mobility, especially in an IMS setting.

CHAPTER 1

INTRODUCTION

The transportation system in the United States and much of the developed world is car-centric. Today, numerous alternative modes of mobility are emerging to provide a solution to the problems (congestion, high resource consumption, safety, etc.) often associated with the automobile. Segways, scooters, micro-vehicles, electric carts, and even traditional bicycles are designed to efficiently move humans with little or no cargo and without the added bulk of traditional automobiles. Compact, light-weight, and powered by clean energy, these human-scaled personal mobility devices (PMDs) could provide one aspect of the solution to the challenges associated with traditional vehicle travel.

This research envisions a future where transportation in urban areas will be dominated by PMDs instead of automobiles. Researchers at Georgia Tech call this an *Intelligent Mobility System* (IMS). An IMS would be a car-free zone where people travel by a shared-system of PMDs with autonomous operation capabilities. Within the IMS zone, PMDs would provide levels of personal mobility greater than walking but less than that of a car. PMDs with autonomous operation capability are interconnected via wireless communications allowing them to independently pick up system users at their location and drop them off at their destination. Automobiles and transit can make connections at the car-free IMS zone boundary. Transit stations within or near the IMS zone boundary provide regional connections to home, work, airports, train, other IMS zones, or car parking. Ultimately, IMS zones may provide a solution to many of the problems caused by traditional automobiles while still providing a similar or better level of mobility.

This research in this thesis focuses on the operational aspects of this future system. If IMS zones were to exist, *how would the system operate*? Eventually, a computer simulation model would be the best way to evaluate the operation of this proposed system. In order to create this model, research is needed to analyze the performance characteristics of PMDs which will be needed as model inputs.

Therefore, the primary objective of this research is to evaluate the performance characteristics of PMDs that are currently used in a variety of settings. This is accomplished by placing Global Positioning System (GPS) data recorders on PMDs to log speed and location data each second of the trip. From this data, typical speed and acceleration profiles are derived for later use in a simulation model. This research analyzes the speed and acceleration characteristics of pedestrians, bicycles, Segways, and electric carts.

This research also analyzes the results of a Segway test where a group of six Georgia Tech researchers and a guide completed a Segway trip of approximately 8 miles in the city of Atlanta. Segway speed was analyzed using three factors, sidewalk width, surface quality, and pedestrian density to evaluate their effect on Segway speed.

As society pursues more sustainable modes of transportation in the future, it will be important to understand PMD operations and behavior as well as the factors that influence them. While this research has many limitations, it is a first step towards *Intelligent Mobility Systems*, a sustainable transportation solution for the future.

CHAPTER 2

BACKGROUND

This chapter describes the underlying concepts and factors pertinent to this project. This chapter first describes the current state of our car-centric transportation system, and outlines a possible alternative in the form of a future transportation system populated by masses of human-scaled personal mobility devices (PMDs). The chapter goes on to discuss PMDs in detail, investigates current simulation models, and describes the data that would be needed to create a model populated by PMDs.

2.1 Our Car-Centric World

There are strong arguments for decreasing car use in favor of safer, more sustainable and more equitable modes. Today, there are over one billion cars on Earth (Sperling, 2009). Over 52 million cars were produced in 2009. Currently three new cars are built every two seconds, one for every three babies born. Worldwide motor vehicle accidents killed 1.2 million people in 2009 and injured 50 million more (Richards, 2010). Automobile emissions increasingly create air quality problems in urban areas and are responsible for more than 25% of all greenhouse gas emissions in the United States (EPA, 2006). Wide boulevards and freeways sever communities by inhibiting social interactions and pedestrian travel, and while few of the very poor own vehicles throughout the world, they often receive the brunt of the negative impacts of increased car ownership and travel (Wright, 2005).

Traditionally, the approach to mitigate the adverse effects of mass car use in the United States has been to increase automobile fuel efficiency, improve emission controls, and attempt to decrease travel demand. While this has greatly reduced emissions per vehicle, national vehicle-miles traveled (VMT) has not decreased dramatically. Strategies such as traffic calming, carpooling, virtual commuting, and others are "approaching their limits of efficacy (Reutter & Reutter, 1996)." A potential alternative to address these challenges is to reduce car use by either removing them from parts of the transportation system and/or by replacing car trips with more sustainable modes of transportation.

2.1.1 Thinking Car-free

There are many benefits to removing cars from a central business district (CBD) or other types of urban environments. One of the most obvious benefits of car-free zones is the increase in pedestrian safety. Without the presence of vehicles, the only accidents that could occur are between pedestrians and low-speed vehicles like bicycles. These incidents are far less frequent and much less severe (Shaheen & Rodier, 2008). With the creation of a walkable environment free from cars, the people living, working, or shopping in the car-free area walk more and children are safer in or near the street. Walkability, noise reduction, air quality improvements, and safe streets are some of the strongest attractions of car-free zones (Nobis, 2003).

Reductions in road capacity and the implementation of car restrictions in neighborhoods have shown to be effective ways of reducing car trips and VMT (Goodwin, 1998; Nobis, 2003). Reductions in VMT directly should increase energy security by decreasing reliance on foreign oil. With fewer automobiles operating in urban centers, the local air quality would greatly improve. VMT reductions typically result in carbon-dioxide and ozone reductions throughout the area influenced by the car-free zone, and the reductions in fine particulate emissions immediately within the car-free zone would be substantial. Also, car-free households have substantially lower environmental impacts from their ground transportation and energy use in general (Ornetzeder et al., 2008).

2.1.2 Getting Back to the Human Scale

Until recent history, humans have never moved much faster than walking speed. Presently, cars have increased human mobility beyond the speed limits of human ability to perceive and react to the natural environment. Therefore, complex structured human environments have been created around the car to safely accommodate increased human mobility. Freeways, arterials, and their surrounding environment are made for drivers to navigate them at high-speed, often neglecting the pedestrian or cyclist (Vanderbilt, 2008).

Mobility

Even though most of our cities have been constructed around car use, the average vehicular speeds on these roads are often equal to or less than other alternative modes in heavily congested cities. A study of a bike-share program in Lyon, France showed that the average origin to destination bicycle trip speed was 13.5 km/h (8 mph) while average car speeds in downtown European cities vary between 10 km/h (6 mph) and 15 km/h (9 mph). The Lyon study also found that bicycle trips were often shorter than car trips because bicyclists could take shorter routes using bicycle or pedestrian infrastructure (Jensen et al., 2010). Previously, Liu and Parthasarathy (2003) analyzed regional travel-household survey data from the New York Metropolitan Transportation Council and estimated that 27% of trips within Manhattan were suitable for Segway use based on trip lengths and travel time. All of this means that a significant portion of urban car trips could be replaced by low-speed modes that are more energy and space efficient while maintaining a similar or better level of personal mobility, especially when appropriate infrastructure is available.

Energy

Vehicles are designed for a myriad trip purposes, but most vehicle trips are single-occupant vehicle (SOV) trips with little or no cargo. In 2000, over 75% of vehicle trips were SOV trips and this figure has likely only rose since then (Pisarski, 2006). The average automobile weighs over 4000 lbs and the average American person weighs approximately 180 lbs; hence, over 95% of the energy used during a SOV trip is used to move the automobile itself and less than 5% of the energy is used to move the actual person (EPA, 2009; Ogden et al., 2004). This means that 95% of the energy of SOV trips is spent moving the vehicle weight rather that the person, in comparison to only 37% of the energy used in a Segway trip is spent moving the Segway. Table 1 shows transportation vehicles, their average weight, and the percentage of wasted energy considering a single passenger weighting 180 lbs.

Table 1. Wasted Energy per Mode

Mode	Weight[lbs]	Dead Weight	Source
Car	4000	96%	(EPA, 2009)
Micro-vehicle	1000	85%	(MIT, 2012)
Scooter (50cc)	220	55%	(Lance Powersports, 2012)
Segway	105	37%	(Segway, 2012)
Bicycle	30	17%	Estimate

*Note: Each vehicle type is defined and discussed in Section 2.3

Urban Space

Many would agree that much of our nation's urban space is occupied by parking and roadways, but little is actually known regarding the true percentage. In 2005, Manville and Shoup, the author of the popular book "The High Cost of Free Parking," analyzed the effects of parking and parking regulations on the urban form. Using Los Angeles as their case study for a car-dependent urban area, Manville and Shoup traced claims about the amount of land in Los Angeles dedicated to the car back to a 1966 study prepared for a large number of urban areas in which the study concluded that 35% of land area was dedicated to streets and 24% was dedicated to parking (Wilbur Smith & Associates, 1966; Manville, 2005). Southworth and Ben-Joseph (2003) subsequently concluded that the automobile consumes close to half of the land area of U.S. cities, and in Los Angeles the figure may approach two-thirds. Davis and her colleagues recently studied the parking lot footprint of the Great Lakes Region. Using a sample of 30 zip codes across four states, Davis estimated that there were more than 2.5 parking spaces per registered vehicle (Davis, Pijanowski, Robinson, & Kidwell, 2010).

With all the urban space currently dedicated to vehicles, PMDs have a tremendous potential to reduce the footprint of the transportation system, especially through parking demands. Researchers at MIT estimate that the savings in parking space for the MIT CityCar, a micro-vehicle (see Section 2.3.4), could free up entire blocks of parking (MIT, 2012). Figure 1 shows a typical car parking lot and the space required for the same number of parking spaces for the MIT CityCar. Other researchers have estimated that three Segways could travel side-by-side within a single car lane (Liu & Parthasarathy, 2003). Therefore, using smaller, human-scaled modes of transportation would alleviate traffic congestion and improve urban spaces.

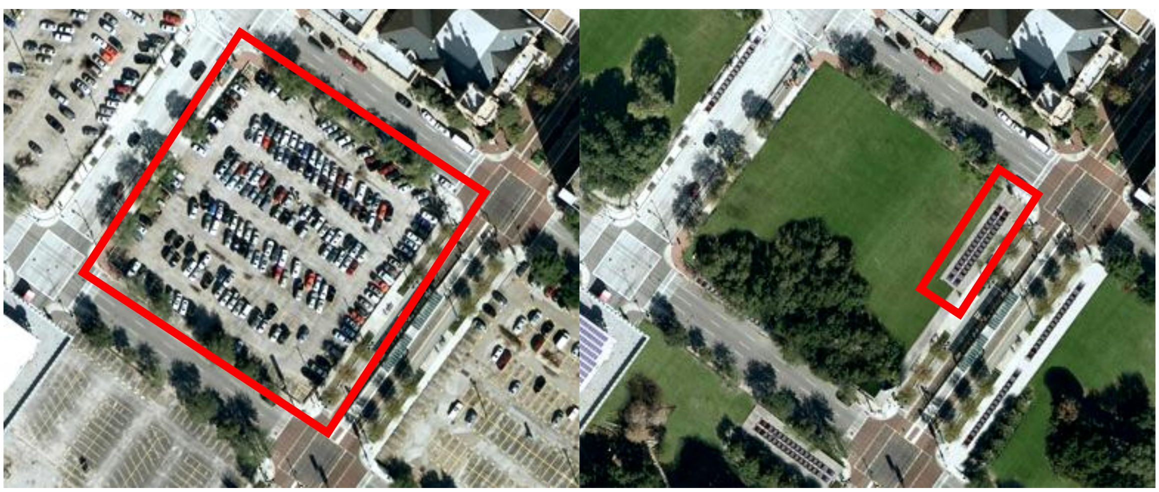


Figure 1. A Typical Car Parking Lot (Left) vs. Parking for the MIT CityCar (right) (MIT, 2012)

2.2 Intelligent Mobility Systems

Removing cars from the transportation system in favor of lighter, smaller, more efficient, human-scaled personal mobility devices (PMDs) powered by clean energy would provide the solution to many of the aforementioned problems caused by traditional automobiles. Combining PMDs with mass transit (potentially capable of accommodating PMDs) or traditional vehicle-based facilities (for longer trips) would allow PMDs to provide a similar or better level of mobility to that of cars in many situations. In order to provide society with a sustainable transportation system, this research envisions a future transportation system full of PMDs instead of traditional vehicles. This system that researchers at Georgia Tech call an *Intelligent Mobility System* (IMS) would be a car-free zone where people travel by a shared system of autonomously operable PMDs. IMS zones have four key elements as shown in Figure 2.

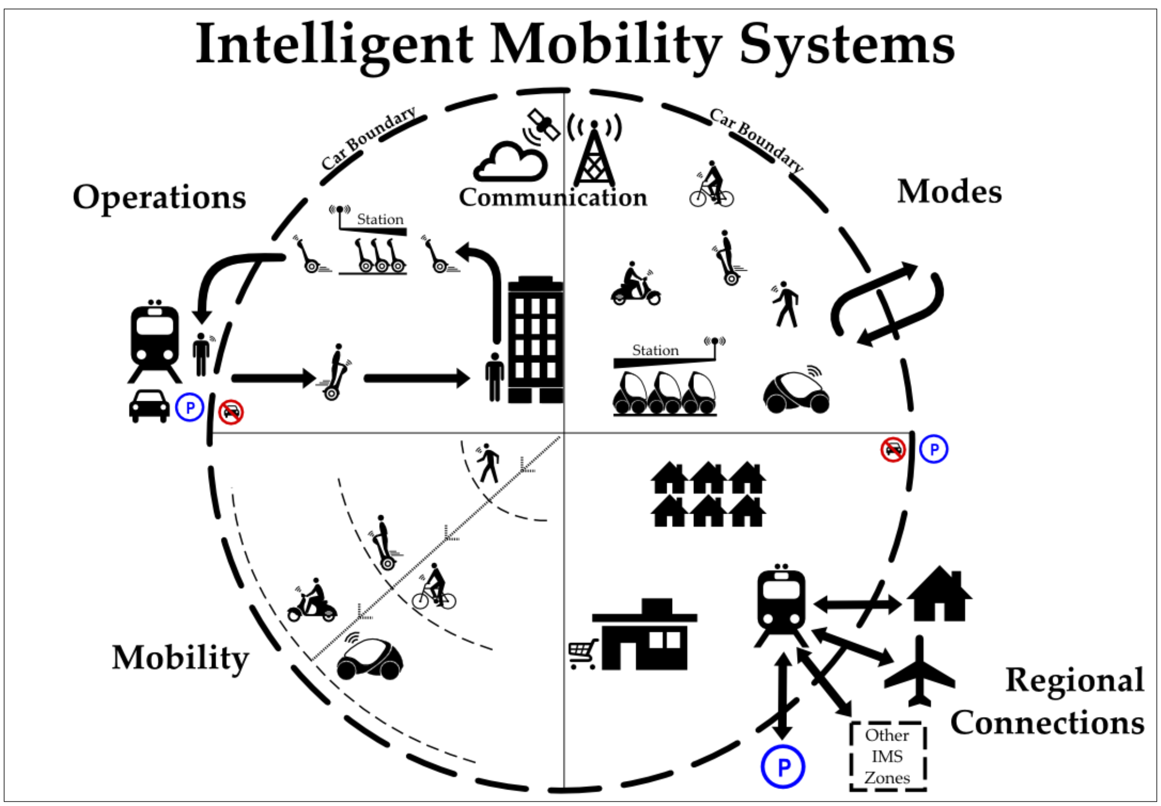


Figure 2. An Overview of IMS Elements

The four key elements of IMS are Mobility, Operations, Modes, and Regional Connections. They are described in more detail in the following:

- **Mobility** – Human-scaled PMDs provide levels of mobility greater than walking but less than that of a car. Low-speed, human-scaled mobility allows safer interaction between vehicles and pedestrians while still providing mobility and access necessary to meet travel demands within and around the IMS zone.
- **Operations** – Automobiles and transit can make connections at the car-free IMS zone boundary. PMDs with autonomous operation capability are interconnected via wireless communications allowing them to pick up system users at their location. After completing the trip, the PMD can return to a station to await the next trip.
- **Modes** – IMS zones will support only the use of PMDs within the car-free zone. PMDs could be bicycles, scooters, Segways, micro-vehicles, or any of the types of devices described in Section 2.3, and PMDs could operate in and around an IMS zone. These PMDs can be a part of the automated shared-use system or individuals can use their own PMD devices not integrated into the automated shared-use system.
- **Regional Connections** – Transit stations within or near the IMS zone boundary provide regional connections to home, work, airports, train stations, other IMS zones, or car parking.

Ultimately this research effort focuses on the operational aspects of this future system. Analysis of potential benefits requires an understanding of how an IMS zone would operate. Eventually, a computer simulation model would be the best way to evaluate the operation of this proposed system. In order to create this model, research is needed to analyze the performance characteristics of PMDs as model inputs.

2.3 Human-scaled Personal Mobility Devices

Human-scaled personal mobility devices (PMDs) are transportation alternatives to the car that are designed to efficiently carry one or two humans with little or no cargo, provide increased mobility to that of a pedestrian, maneuver easily among other devices and pedestrians in an undefined traffic stream, and safely interact with a myriad of other transportation modes including pedestrians. While the Segway is the current PMD most fitting of this IMS vision, this section discusses bicycles (Section 2.3.1), scooters (Section 2.3.2), Segways (Section 2.3.3), micro-vehicles (Section 2.3.4), electric carts (Section 2.3.5), and other PMDs (Section 2.3.6).

2.3.1 Bicycles

Other than walking, the bicycle is the most notable mobility alternative to the car. However, only 1% of all trips in the United States are made via bicycle, among the lowest rates in the industrialized world (Pucher, 2008). Compared to some European countries where cycling rates are high (e.g. The Netherlands has 25% bicycle mode share), Americans see cycling as inconvenient, unprofessional, and an unsafe mode of transportation (Pucher, 2008). Also, bicycles are often difficult if not impossible for the elderly, disabled, or small child to ride as a means of transportation. If PMDs can provide similar mobility options to bicycles without their perceived inconvenience, the likelihood of IMS zones being a success in the United States would increase greatly.

The American Association of State Highway Transportation Officials (AASHTO) publication, *Guide to the Development of Bicycle Facilities*, contains operational characteristics of bicycles for the purpose of infrastructure design. AASHTO defines parameters for several Design Bicycles. This research will focus on the most common, Design Bicycle A, which is the typical upright adult bicycle. The bicycle is typically 70 inches in length and requires a horizontal lane width of at least 48 inches (60 inches is preferred). Cyclist speed varies based on age, skill, infrastructure, and weather conditions. Typical adult cyclist speeds range from 8-15 mph on paved level terrain while experienced physically fit riders can exceed speeds of 30 mph under ideal cycling conditions while travelling downhill. AASHTO states that a design speed of at least 18 mph should be sufficient for use on relatively level terrain. AASHTO also specifies typical cyclist acceleration and deceleration rates of 1.5 - 5 ft/s^2 (1 – 3.4 mph/s) and 16.0 ft/s^2 (11 mph/s), respectively. Deceleration rates for wet conditions are 8.0 – 10.0 ft/s^2 (5.5 – 6.8 mph/s) (AASHTO, 2012) While the *Guide to the Development of Bicycle Facilities* devotes a chapter to shared use trails that are free from cars, much of the book is focused around orienting car-centric infrastructure around the bicycle as the exception.

In 2004, the Federal Highway Administration (FHWA) studied the characteristics of emerging road and trail users. Using 21 data collection stations at three shared-use paths across the United States, FHWA studied the physical dimensions and operational characteristics of non-motorized trail and roadway devices including:

- Bicycles
- Electric bicycles
- In-line skates
- Scooters
- Skateboards
- Segways

This study found that only one percent of bicyclists actually exceeded the 20 mph design speed that is often used per AASHTO’s 1999 recommendation and that the 85th percentile speed for bicyclists was 14 mph. The study found that the mean and 85th percentile deceleration rate to be 2.3 m/s^2 (5.1 mph/s) and 3.3 m/s^2 (7.4 mph/s) respectively (Landis et al., 2004).

2.3.2 Scooters

The term scooter can refer to a number of two-wheeled devices ridden by one or two people, and steered using handlebars. Scooters can be motorized or non-motorized, and even non-motorized scooters can have small motors added for propulsion.

<u>Non-motorized Scooters</u>

Non-motorized scooters, also called "kick scooters," consist of a small platform on which the user stands between two small wheels. The user then kicks one foot on the ground while keeping the other on the scooter to propel forward. A vertical bar rising up from the front wheels to a pair of handle bars at the user's waist is used for steering (see Figure 3).

Figure 3. Non-motorized Scooters (Belize Bicycle, 2012)

During the Emerging Trail Users Study, FHWA found the mean travel speed to be 12 km/hr (7.5 mph) and the 85th percentile and 15th percentile speeds to be 15 km/h (9 mph) and 9 km/h (5.5 mph) respectively. The study also found kick scooters to have a mean deceleration rate of 2.4 m/s^2 (5.4 mph/s) and an 85th percentile deceleration rate of 2.6 m/s^2 (5.8 mph/s). The mean and 85th percentile braking distances were 4.9 m (16 ft) and 8.9 m (29 ft) respectively (Landis et al., 2004).

Motorized Scooters

Motorized scooters are designed to have the driver sitting with their legs directly in front of them and feet flat on the floor of the scooter body rather than straddling like a motorcycle. Scooters also have much smaller wheels than motorcycles. Traditionally, mopeds are motorized bicycles that can be powered using either a motor or pedals for propulsion.

Laws regarding the use of scooters are written and enforced at the state government level in the United States. For most states, if the scooter has an engine less than 50 cc in size and travels no more than 30-35 mph, it is considered a “moped” by law. This means that no special license is required for operation and, often, vehicle registration is not necessary. However, “moped” use is typically limited to roadways with speed limits of 35 mph or less. Scooters with engines 50 cc or greater in size are usually subject to the same laws as motorcycles (DMV.org, 2012). Figure 4 shows examples of a moped and a motor scooter.

Figure 4. Examples of a Moped (left) and a Motor Scooter (right)

(Lance Powersports, 2012; MRA, 2012)

Scooters are essentially motorcycles with smaller wheels and a slightly different body. Therefore, they operate similarly to motorcycles. Scooters also operate in the same traffic stream as automobiles. Thus their operational characteristics are likely similar up to a certain speed. Mopeds and small scooters may operate more like bicycles at low speeds, displaying similar maneuverability. Unfortunately, this thesis was unable to collect speed or acceleration data from scooters. However, scooters are worth mentioning here because they would likely have a large mode share in future IMS settings.

2.3.3 The Segway

Segway Personal Transporter (PT) is by far the most popular innovative PMD, excluding the traditional bicycle or scooter. Invented by Dean Kamen, the Segway PT is designed to “look, act, and feel like a pedestrian” (Heilemann, 2001). The original Segway Human Transporter (HT), introduced in 2001, has been replaced by the new model Segway PTs. For simplicity, this paper will refer to both Segway HTs and Segway PTs as a “Segway.”

The Segway is a two-wheeled, battery-powered device that is operated by the user who stands on a platform between the two wheels. The Segway uses a sophisticated system of sensors and controls that self-balances the device. While the user stands on the platform between the two wheels, the Segway balances itself by moving either forward or backward to compensate for the movement of the user. This enables the user to control the device by shifting their body weight and leaning slightly forward or backward. If the user leans forward, the device accelerates in the forward direction. If the user leans backward, the device accelerates in the reverse direction. To turn, the Segway has a set of handlebars that project upward in front of the user. These handlebars pivot at the base of the platform on which the user stands. The user simply shifts the handlebars to the left or right to turn in the desired direction.

There are two product models offered by Segway, the i2 and the x2. Each is customizable with accessories for various applications. The i2 is the Segway designed for the urban/suburban domain and meant to be driven primarily on paved surfaces. The x2 has a more rugged frame with wider wheel base, larger tires and greater ground clearance since it is designed for off-road terrain. Since this research focuses on IMS zones, the i2 is the most applicable Segway model for further discussion. Figure 5 shows a rider on a Segway i2.

Figure 5. Rider on a Segway i2 (Photo Credit: Lance Ballard)

The i2 footprint is 19 inches by 25 inches, weighs 105 lbs, and has a zero-degree turning radius, meaning that it can turn in place. The i2 can travel 24 miles or up to 480 city blocks on a single charge with a total load capacity of 260 lbs. It has a top speed of

12.5 mph, but has an additional setting that can limit speeds to 8 mph for beginner use (Segway, 2012).

Currently, 44 states have passed legislation legalizing and defining the operation of Segways and similar devices while the other six states have no law addressing Segway use (GHSA, 2012). Segways are used by hundreds of police forces and numerous warehouses and industrial sites. Many tourism companies offer Segway tours of popular tour destinations across the globe. While the use of Segways is still fairly novel, it is the current PMD which most fits the vision for this research and offers the mobility, range, and size necessary for the demands of this research. Therefore, Segways are the primary PMD used in this study.

Previous Studies

There have been a number of previous studies about Segway operational characteristics and behavioral uses. Liu and Parthasarathy (2003) explored the potential benefits and challenges to Segway use. Due to the small size of the device relative to the car, they speculate that three Segway lanes could be built in a typical 12 ft traffic lane. This creates great potential to alleviate traffic congestion through mass Segway use. Liu and Parthasarathy also state that Segway use would reduce the consumption of gasoline and decrease the amount of pollutants emitted into the atmosphere. Liu and Parthasarathy go on to argue that Segways could provide a connectivity solution for intermodal transportation. They also claim that if Segways were utilized to their full potential in the urban setting, the result will be an increase in mixed-use, high-density neighborhoods. However, the cost of a Segway is significantly more than a bicycle (Segway PT retail price is over $6,000), making it an expensive alternative.

Shaheen and Rodier (2008) studied the use of Segways as a "first and last mile connectivity solution" around a Bay Area Rapid Transit (BART) station in the San Francisco Bay area. The project introduced shared-use electric bicycles, non-motorized bicycles, and Segways to employment centers in and around BART stations. Unexpectedly, the Segways were used more often for short day trips (e.g. lunch, business meetings, errands) than as part of commutes, and of day trips. Segways had the highest program mode share (52%) relative to the electric bicycle (36%) and bicycle (12%) modes. The results of the study also indicated a net reduction in vehicle travel among participants. The authors also conducted qualitative surveys of bystanders on a multi-use trail that often encountered the Segway users. Of the 109 respondents, the greatest concern was accidents, but only 20% indicated they would use the trail less if the Segway or electric bike were commonly used on the trail. When asked about what Segway users should be required to do, the most common response (25%) was that Segway users should be required to follow the same rules as bicycles. Many respondents indicated that special lanes should be provided for the Segways (32%), and some also reported that these modes should be allowed on mixed-use trails (23%), streets (18%), and sidewalks (15%). Overall, this study showed that Segways could provide a solution to transit's "last-mile problem" and that the general public is open to the assimilation of Segways into the transportation system.

As a part of the FHWA *Characteristics of Emerging Road and Trail Users* study, Segway riders were videotaped as they rode through a defined course. The results of the Segway user performance are presented in Table 2. Speed was defined as the normal cruising speed of users on a flat, smooth section of a shared-use facility. The perception-reaction time was defined as the duration between the researchers commencement of the stop signal until the initiation of the braking action by the user. The study also found that the highest acceleration rates for Segways were 3 ft/s^2 (2 mph/s) (Landis et al., 2004).

Table 2. Segway HT Characteristics (Landis et al., 2004)

Characteristics	Mean	85th Percentile
Length (inches)	22.00	22.00
Width (inches)	25.00	25.00
Sweep width (ft)	3.44	3.49
Three-point turn (inches)	38.70	39.40
Eye height (inches)	73.90	70.60
Speed (mph)	9.46	10.29
Response time (seconds)	1.06	1.52
Braking distance (ft)	8.80	10.20

In June 2010, FHWA published a new report discussing the results of research conducted using the Segway HT, the predecessor to the i2, on a closed course under controlled conditions. The researchers found the following results (Miller et al., 2010):

- Experienced riders traveled at a mean speed of 7.71 mph and 11.2 mph for the 8 mph and 12 mph speed keys respectively.
- Novice and experienced riders approached obstacles at speeds ranging from 2.7 mph to 6.8 mph with a mean of 4.5 mph.
- Experienced riders passed obstacles faster than novice riders by an average of 1.9 mph.
- Novice and experienced riders passed moving pedestrians at an average speed of 5 mph and average clearance of 36 inches.
- Novice and experienced riders passed obstacles by 0.5 mph slower and 18 inches closer on narrow sidewalks (4.4 ft wide) as opposed to wide sidewalks (10.2 ft wide).
- Experienced riders made planned stops in a mean time of about 2.4 seconds and a mean distance ranging from 6 ft to 15 ft with a mean of 10 ft.

- Experienced riders' mean response time for unplanned stops was 0.52 seconds with a mean stopping sight distance of 14.5 ft, taking a total of 2.31 seconds including response time.
- Experienced riders stopped at a mean distance of 8.7 ft and 14.7 ft for each speed key.
- Novice and experienced riders passed objects with a mean clearance of 14.5 inches with a range from 3.3 to 43.2 inches.

Unfortunately, there have been no studies about the operation of Segways within an unrestricted environment filled with pedestrians, bicycles, and other modes of transportation. More research is needed to understand how Segways and their users interact with dynamic surroundings and Segway performance characteristics in a real-world setting. In part, this study aims to help fill this need in Chapter 4.

2.3.4 Micro-Vehicles

While cars create numerous problems for society, many of these problems are attributed to vehicle size, speed, fuel, and emissions. Currently, alternatives to the traditional car are being developed to maintain the comfort and mobility of a car while making them smaller and safer to operate in a complex urban environment. There are numerous types of small car alternatives in development and production. For simplicity, this research refers to these PMDs as "micro-vehicles."

Micro-vehicles are usually electrically powered and designed to carry one or two passengers with small cargo (25-35 mile range and 20-30 mph top speeds). These devices all have lower top speeds (10-20 mph) and ranges (20-30 miles) than that of a traditional automobile. This section presents a few examples of the most prominent micro-vehicles currently in development.

GM EN-V

In a joint venture, General Motors (GM) and Segway Inc. developed a project named PUMA (Personal Urban Mobility and Accessibility). The PUMA project resulted in the creation of a prototype micro-vehicle that could carry two passengers using the Segway PT base and battery powered propulsion system. Using the same self-balancing technology, this PUMA vehicle operates on two wheels. It can travel between 25 and 35 mph with a range of approximately 30 miles on one charge. Progressing with this concept, GM unveiled the EN-V concept vehicle in 2010. The GM EN-V (Electric Networked-Vehicle) uses the PUMA powertrain and chassis but boasts the capability of being operated at varying levels of autonomy using GPS, sophisticated sensory technology, vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) communication (GM, 2010).

Figure 6. Segway PUMA (left) and GM EN-V (right)

(Segway, 2012; GM, 2010)

MIT CityCar

In 2003, researchers at the Massachusetts Institute of Technology (MIT) began developing a new concept car designed for urban mobility, called the CityCar. Designed around the idea of moving people efficiently within an urban environment, the CityCar is electrically powered, highly maneuverable, and folds up to save space when parked. Four independently controlled “Robot Wheels” give the CityCar a zero-degree turning-radius. When extended for driving, the CityCar is a little over 8 ft in length, but folds to a length of 5 ft when parked. Considering the average parking space is 20 ft long in the United States, four CityCars could fit into the length of a single parking space. The CityCar has a top speed of 50 km/hr (30 mph), a range of 120 km (75 miles), and can be fast-charged in 15 minutes (Clancy, 2010).

Figure 7. MIT CityCar in Both Driving (left) and Parked (right) Configurations (MIT, 2012)

In early 2012, Hikiro Driving Mobility, a Spanish company, announced the beginning of production on the Hikiro *Fold*, a small electric vehicle based on the MIT CityCar. Scheduled to go on sale in 2013 for the price of $16,000, Hikiro plans to promote the cars in European car-sharing programs (MIT, 2012).

2.3.5 Electric Carts

Electric carts are used for a variety of purposes. The two most popular uses are as golf carts and small utility vehicles. Electric carts can be designed to carry two to six people and can have a cargo bed allowing for the transport of equipment or other cargo. While some can be gasoline powered, this study will focus on electric carts because they operate at a lower speed and better fit this research’s vision of a PMD.

Small electric carts are most commonly used for recreation and utility purposes. Golf courses use electric carts for the players to travel the course during play. Electric carts are also used as utility vehicles to transport maintenance personnel, tools, and equipment around large properties and facilities. Figure 8 shows an example of a common electric cart used for recreational use.

Figure 8. A Common Electric Cart (Club Car, 2012)

While small electric carts are typically not “street-legal,” recently, Global Electric Motors (GEM), a subsidiary of Polaris Industries, has produced a line of “street-legal” electric carts. GEM makes numerous models of its electric carts for various purposes. The GEM e2 is designed to carry two passengers and can have a small cargo attachment in the rear (Figure 9). The GEM e2 has two speed modes, low and high, with top speeds of 15 mph and 25 mph respectively. With a wheel base of 72 inches, the GEM e2 has a turning radius of 12 feet. The GEM batteries provide a range of up to 30 miles at 72°F. At lower temperatures, the range could be as low as 12-15 miles. The actual range varies depending on road conditions, terrain, weather, and driving habits (GEM, 2011).

Figure 9. GEM Car (GEM, 2012)

Some communities use electric carts as a primary mode of transportation for short trips. Peachtree City, Georgia is such an example. Peachtree City has a large system of paved shared-use paths on which electric carts are permitted to operate. Often running parallel to city streets, these paths allow community members to travel form home to school, work, stores, and other locations within the city using electric carts as opposed to a car (see Figure 10). Peachtree City requires drivers of electric carts on to have an automobile driver’s license (Hollis, 2008).

Figure 10. Peachtree City Electric Cart on Separated Path (Hollis, 2008)

There has been no research about electric cart performance characteristics, and GEM cars and other types of electric carts are the PMDs that most resemble micro-vehicles. Therefore, electric carts are included in this study. While micro-vehicles will likely operate differently within an IMS zone than they do currently on roadways and shared-use paths, the speed and acceleration characteristics of electric carts in this study should closely resemble those expected of a micro-vehicle.

2.3.6 Other PMDs

There are many other human-scaled PMDs that are not mentioned or studied in this research. Some notable exclusions are motorcycles and disability scooters/powered wheel-chairs. Motorcycles travel at speeds exceeding the limitations for safe operation within IMS zones and would likely be restricted from the IMS zones along with cars. While components of any IMS zone disability scooters or powered wheel-chairs, extremely important and vital for the mobility of their users, these devices are unlikely candidates for mass scale IMS zone operations. The following section describes a few of the other more notable PMDs that are currently in use.

T3 – Electric Stand-up Vehicle

An alternative that is similar to the Segway PT is the T3 Electric Stand-up Vehicle. Currently marketed exclusively to law enforcement, security, and government agencies, the T3 is a three wheeled vehicle that resembles a chariot. The T3 has a capacity of 450 lbs, a top speed ranging from 12 mph to 25 mph, and a range of 15 – 75 miles per charge depending on the battery option chosen. It recharges in 3-4 hours. Compared to the Segway PT, the T3 is much larger, heavier, and more expensive (T3Motion, 2012).

Figure 11. T3 Electric Stand-up Vehicle (T3Motion, 2012)

RYNO Micro-Cycle

The RYNO Micro-Cycle is a one-wheeled motorcycle powered by battery. It stabilizes itself during use, but does not stand upright under its own power when stationary. The RYNO propulsion is very similar to a Segway™ but steers like a motorcycle with handlebars and lateral weight shift of the rider. The RYNO can travel at speeds up to 20 mph for a range of 30 miles on one charge (RYNO Motors, 2012).

Figure 12. RYNO Micro-cycle (RYNOmotors, 2012)

YikeBike

In 2009, an inventor in New Zealand developed the YikeBike. The YikeBike is an unconventional bicycle that is battery powered and can be folded down into a compact form that is easily carried. Resembling the old penny farthing style bicycles with a large wheel in the front followed by a much smaller trailing wheel used for steering in the rear, the YikeBike is little like a conventional bicycle. However, the YikeBike has a range varying from 6 to 18 miles depending on the battery pack and a top speed of nearly 15 mph. The YikeBike costs between $2,000 and $4,000 depending on model (YikeBike, 2012).

Figure 13. YikeBike (YikeBike, 2012)

2.4 Simulation Modeling of IMS

The goal of this research is to provide the performance characteristics necessary to populate a simulation model with human-scaled personal mobility devices. There are two types of simulation models commonly used in traffic operations: *link-based models* and *agent-based models.* While *link-based models* are ideal for simulating automobile traffic, pedestrians are often better represented using *agent-based models*. Without further analysis, it is unclear which, or if either, model is well suited for simulating human-scaled personal mobility device operations. Therefore, both types of models are discussed in this section.

2.4.1 Link-Based Models

Most automobile traffic simulation models are essentially link-based models. VISSIM, Paramic, and SimTraffic are a few of the most commonly used traffic simulation models of this type. Link-based models consist of a fixed-infrastructure environment (i.e. roadways, intersections, interchanges, etc.) where simulated vehicles can travel in pre-defined lanes and directions. Vehicles are typically generated at the model boundaries or internal sources and sinks. They travel through the model either according to assigned routing decisions or a decision process at each intersection. Traffic flow models may be fairly simple to rather complicated algorithms attempting to accurately capture the car-following nature of vehicles. In stochastic models vehicles are assigned values for characteristics such as, car following parameters, acceleration capabilities, desired speed, driver aggressiveness, desirable and max deceleration, etc. Models tend to have varying levels of calibration capabilities.

For example, most simulation models use proprietary car-following models (Olstam & Tapani, 2004). Generally, if there are no other vehicles immediately in front of a vehicle within the simulation, the simulated vehicle travels at its assigned desired speed. Once the simulated vehicle approaches the rear of a slower traveling automobile, it then travels differently according to a predefined *car-following model.* The car-following model specifies how the car reacts to the car it is following. Taking into account reaction time, travel speed, and acceleration characteristics of each vehicle, the car-following model defines the distance and speed a car will travel when following another slower-moving car.

One way to model an IMS zone may be to use a following-based model and populate it with human-scaled personal mobility devices as separate vehicle types. By defining a new vehicle type for each type or class of PMD, the speed and acceleration characteristics can be changed to match those documented by this study. Then, a simulation model could be populated with PMDs.

However, PMDs do not currently, nor will they likely, operate under the same set of operational rules and standards as automobiles do today. The strictly defined rules of the road allow for the simulation of automobile traffic using following-based models, but PMDs can accelerate quickly both in terms of speed and direction. Also, PMDs are not confined to fixed routes or lanes like automobiles, and attempting to model the complex, dynamic proposed IMS environment using a network model would be difficult.

2.4.2 Agent-Based Models

Agent-based models may provide a better solution for simulating the operations of PMDs. Agent-based models are a more directly capability of simulating an environment open for free maneuvering with user defined boundaries. Each agent occupies a "cell" or block of space within the operating environment (Dijkstra et al., 2000). The agent then makes its own travel decisions to move to any adjacent cell based on user-defined agent characteristics and movement constraints. This includes interactions with other pedestrians and obstacles within the simulated environment (Kukla et al., 2001; Ronald, 2007). Agent-based models provide the flexibility to better simulate the complex movements and behaviors of pedestrians.

The PMD operating task is likely more similar to that of pedestrian wayfinding and behavior than that of the driving task because of the high maneuverability of PMDs and their dynamic interaction with a non-uniform environment. In order to simulate PMDs within an agent-based model, among many areas, research is needed to define typical speed and acceleration distributions and how the range of possible accelerations and turning movements vary with speed.

2.5 Vehicle Performance Characteristics

A future simulation model of an IMS zone, regardless of being a link based or agent based nature, would require PMD operational constraints. One of the main operational characteristics is possible speed and accelerations for each type of PMD. This range of possible speed and accelerations is easily obtained from manufacturer specifications or simple data collection procedures. However, the simulation model would also require joint probability distributions of likely speeds and accelerations for each type of PMD. Typically, vehicle performance characteristics are analyzed graphically using three-dimensional Watson plots (Milkins, 1983). This thesis uses a modified two-dimensional representation of a Watson plot that allows for plotting multiple groups of data at the same time.

CHAPTER 3

METHODOLOGY

This chapter outlines the research objectives of this project and describes the methodology used to achieve those objectives. To evaluate human-scaled PMD performance characteristics, the research team first validated the accuracy of the GPS recorders used to observe PMD operations. GPS recorders were then used to collect speed and acceleration data from pedestrians, Segways, bicycles, and electric carts. The research team also conducted a Segway test route to become more familiar with PMD operations and analyze the effect of external factors on PMD operation.

3.1 Objective

To enable future research about IMS, this research aimed to *evaluate human-scaled PMD performance characteristics*. More knowledge is needed about the operation of PMDs. Acceleration characteristics, typical travel speeds, functional capabilities, ranges, and behavioral characteristics must be more completely understood to successfully model simulated PMD operations and to incorporate these devices into the transportation system. Therefore, the objective of this research is to evaluate these performance characteristics with the goal of creating model inputs for simulating IMS environments. This was accomplished by collecting speed and location data from PMD trips using GPS recorders.

3.2 Data Collection Method

A low-cost and accurate means of measuring PMD speed was required to collect PMD speed and acceleration data. This section describes the data collection equipment used for this study and the data filtering process.

3.2.1 GPS Data Recorders

Global Positioning Systems (GPS) use a combination of satellites and receivers to triangulate their location on the surface of the Earth. When the GPS receiver is moving, it will read a slightly different signal frequency from the satellite due to the Doppler Effect. This difference between the known satellite signal frequency and the frequency observed by the GPS receiver is known as Doppler shift, and it is directly proportional to the relative velocity between the signal source and receiver. This same concept is used by RADAR and LIDAR guns to detect velocity of cars traveling down the road or a baseball pitch. Using multiple satellites, the GPS receiver can estimate both its position, velocity and heading (Chalco, 2007).

For this study, the research team used QSTARZ BT-Q100XT and BT-Q100EX data logging GPS receivers. Both have similar technology, accuracy, and operation. For simplicity, any data logging GPS receiver used in this study will be referred to as a "GPS recorder." Figure 14 shows a photograph of one of the GPS recorders used in this study. These small, low-cost GPS recorders are capable of logging data at user-specified time intervals. They have a battery life of approximately 48 hours with a good signal-lock (QSTARZ, 2012).

Figure 14. GPS Recorder (QSTARZ, 2012)

3.2.2 GPS Data Filtering and Smoothing

GPS recorders are prone to errors like every instrument. The manufacturer specifies the GPS recorders to be accurate within 3 m for location and 0.1 m/s for speed respectively (QSTARZ, 2012). However, the GPS recorders are still prone to random errors due to poor satellite lock or coverage, obstruction of the satellite signal, or other factors. So, the GPS recorders use proprietary algorithms to filter and smooth the data points that exceed expected variances based on past and current conditions (Ogle et al., 2002; Ogle, 2005). While this mechanism within the device works to correct the data, random errors still exist in the GPS recorder output.

Previously, Jun & Guensler observed that the accuracy of GPS speed and location measurements were affected by the number of satellites (nSat) used for the measurement. This also affects the Positional Dilution of Precision (PDOP). They found that measurements with nSat less than four and PDOP greater than eight were erroneous and needed to be filtered differently than other data with "good" GPS fix. Jun & Guensler then developed a modified version of a popular mathematical filter to smooth GPS data (Jun et al., 2006). This filter and the modified version of this filter are described in the following.

<u>The Kalman Filter</u>

The Kalman Filter was originally developed by Kalman in 1960. The Kalman filter is a recursive mathematical process that estimates the state of a system or process in a way that minimizes the mean of the squared error (Welch & Bishop, 2001). This method of filtering data involves two steps. The first step, known as the *Prediction Process*, uses the current and previous measurements to predict the next measurement. The second step, the *Correction Process*, corrects this predicted measurement based on the actual observed measurement (Kalman, 1960). This process is shown in Figure 15.

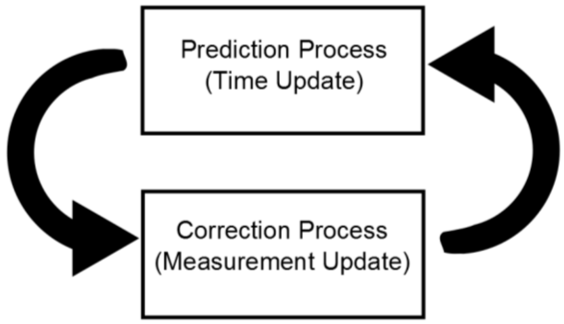


Figure 15. The Kalman Filter Cycle

The time update equations for the Prediction Process are

$$x_k^- = Ax_{k-1} + Bu_k$$

$$P_k^- = AP_{k-1}A^T + W$$

Where k is the time step, x_{k-1} and P_{k-1} are the initial predictor and the initial error noise, respectively, u_k is an additional known-input parameter, W is the prediction error variance, and A and B are the time transition matrices for the prediction process (Simon, 2001; Welch & Bishop, 2001).

The measurement update equations are

$$K_k = P_k^- H^T (HP_k^- H^T + V)^{-1}$$

$$x_k = x_k^- + K_k(z_k - Hx_k^-)$$

$$P_k = (I - K_k H)P_k^-$$

Where K is the Kalman gain matrix, H is the time transition matrix for the observation process, z is the observed data, P is the modified error variance in the Kalman filter, and V is the measurement error variance (Simon, 2001; Welch & Bishop, 2001).

The Modified Kalman Filter

Previously, a research team at Georgia Tech developed a modified version of the Kalman Filter specifically for GPS speed and location data from automobile trips (Jun et al., 2006). This Modified Kalman Filter was a Kalman Filter that smoothed "bad" GPS data differently than "good" GPS data based on the number of satellites (nSat) and Position Dilution of Precision (PDOP). Any data point with nSat less than four or PDOP greater than eight was considered "bad." The researchers modified the conventional discrete Kalman filter by using two measurement errors based on the GPS quality criteria, one for good GPS data and one for bad GPS data.

In that previous study, the Georgia Tech research team compared three smoothing methods designed to minimize the impact of GPS random error on travel distance, speed, and acceleration profile estimates. They found that the Modified Kalman Filter was the most effective smoothing method and recommended the use of the Modified Kalman Filter for smoothing GPS speed and location data (Jun et al., 2006).

Previous studies suggest using the square of the mean error from the GPS recorder specifications for the Kalman filter measurement noise (Simon, 2001; Welch & Bishop, 2001). Process noise is simply the data capture rate multiplied by the measurement noise. Therefore, when data are collected at a rate of 1 Hz, the process noise is the same as the measurement noise (Jun et al., 2006).

Filtering PMD Data

All of the GPS data for this study were smoothed using the modified version of the Kalman Filter. This filter was used to remove random errors that still exist in the data even after the proprietary GPS filter. For this study, GPS location and speed data were collected at a rate of 1 Hz which is one measurement per second. Therefore, the time transition matrix, *A*, is one second. Also, this application of the Kalman filter is one dimensional since the location and speed data are filtered separately. This means that u_k becomes zero, simplifying the time update equations to

$$x_k^- = x_{k-1}$$

$$P_k^- = P_{k-1} + W$$

Similarly, the measurement update equations also reduce to:

$$K_k = P_k^- (P_k^- + V)^{-1}$$

$$x_k = x_k^- + K_k(z_k - x_k^-)$$

$$P_k = (I - K_k)P_k^-$$

where K is the Kalman gain matrix, x_k is the corrected measurement, z_k is the original measurement, and P_k is the modified error variance used for the next step of the filter process.

Previously, researchers at Georgia Tech using this modified Kalman filter derived a GPS measurement error of 0.25 mph based on previous mean delta speeds. This research used the same value. Since the data capture rate for the GPS recorder was 1 Hz, both the process noise and measurement noise were $0.5(1^2$ second x 0.5^2 mph) (Jun et al., 2006).

Accelerations were not observed directly from the GPS recorders. Rather, the acceleration for each second of the trips was calculated based on the filtered speeds for each device and the time difference between each filtered speed data point.

Trip Parsing

The software used with the GPS recorders (QTravel) automatically parsed each trip. However, this research was not interested in the speed and acceleration data when the PMD was idle, even during the trip, because the goal was to analyze performance characteristics, specifically speed and acceleration. Therefore, to separate the idle data from the mobile part of each trip, any segment of data where the speed was less than two miles per hour for at least 10 seconds was labeled as idle. Two miles per hour was used in order to remove any residual GPS noise that was not removed during the Kalman filtering process. The resulting datasets then contained only speed and acceleration data from when the PMD was moving so that speed and acceleration distributions were not skewed by observations that occurred while idling.

3.3 Data Collection Method Validation Testing

This research used GPS recorders to collect location, speed, and heading data from PMD trips. However, the low-cost GPS recorders used in this study needed to be verified for accuracy and reliability at low speeds. An augmented data-logging cyclometer was used as ground truth to compare speeds and accelerations during low-speed PMD trips observed by the GPS data recorders.

Ideally, these tests would have been conducted on Segways. However, due to limited Segway availability, the research team conducted three tests on a bicycle that recorded speed using both the cyclometer and a GPS recorder. The first test (*Lab Test*) was conducted on a straight-line, marked path of a known length that is visible in aerial photography, thus visible to GPS satellites. The second test (*Field Test*) consisted of five bicycle trips under real-world conditions. Finally, the third test (*Hard Acceleration Test*) used hard accelerations and decelerations to observe the ability of the GPS recorders to accurately capture extreme acceleration events. Each of the three validation tests used the same bicycle, cyclometer, and rider.

3.3.1 Cyclometer

A cyclometer is a device that most often is used to monitor the speed of a bicycle by measuring the time it takes per wheel revolution. A cyclometer consists of three components: a computer, a reed switch, and a magnet. The magnet is placed on the wheel of the bicycle and the reed switch is placed on the fork of the bicycle such that the magnet passes across the reed switch once every wheel revolution. The computer sends a small direct current (DC) signal to the reed switch. When there is no magnet present, the reed switch is open, and no current passes through the switch back to the computer. When the magnet passes in front of the reed switch, the reed switch closes allowing current to pass through the switch and back to the computer. This change in current and voltage is recognized by the computer as the completion of one wheel revolution.

Knowing the circumference of the wheel, the computer can calculate the velocity of the device based on the time between two contact/switch closures. Figure 16 shows the inside of a reed switch, and Figure 17 shows the reed switch and computer unit of the cyclometer used in this study, and Figure 18 shows a diagram of a cyclometer installed on a bicycle.

Figure 16. A Reed Switch (Wikipedia, 2012)

Figure 17. Cyclometer Reed Switch (left) and Computer Unit (right)

(Sigma Sport, 2012)

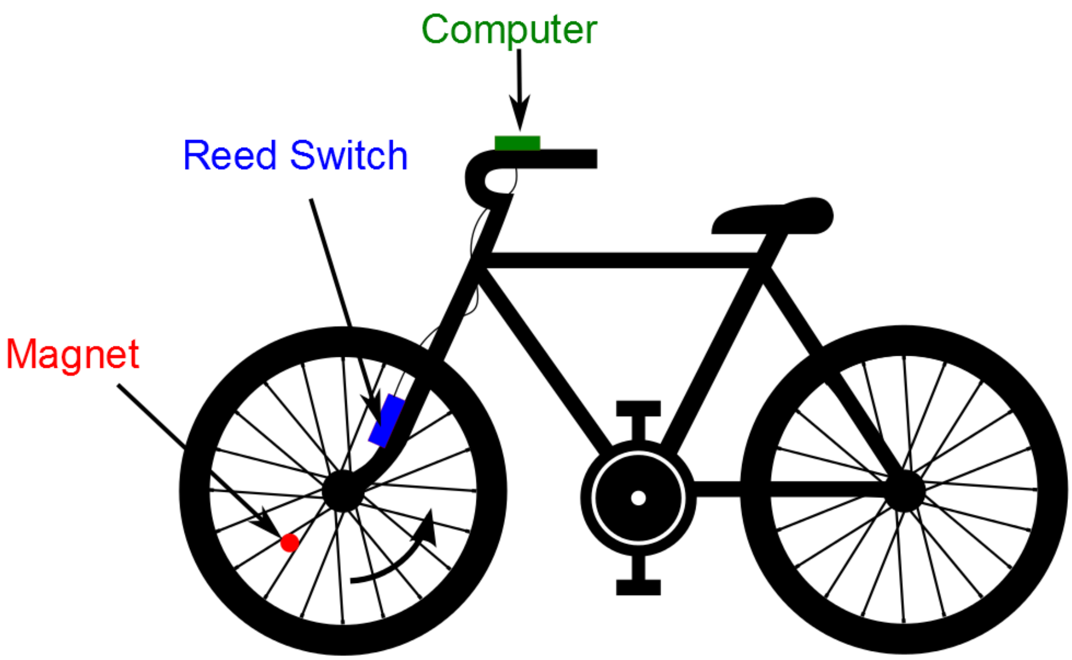


Figure 18. Diagram of Cyclometer Installed on a Bicycle (Credit: Lance Ballard)

<u>Previous Studies</u>

In 2004, Witte and Wilson used a cyclometer to analyze the accuracy of low-cost GPS recorders to record speed under real-world conditions. Their research was interested in GPS recorders to observe the speed of horses as they traveled over ground. For their study, they used a bicycle with a cyclometer and GPS recorder to record speed during trips around a cycle track and along a straight path. The cyclist rode at speeds ranging from 15 – 35 km/h (9.3 – 21.7 mph).

The low-cost GPS recorder used by Witte and Wilson was accurate within 0.2 m/s (0.45 mph) of the true speed measured for 45% of the values and within 0.4 m/s (0.9 mph) for 64% of the values. The effect of PDOP on speed accuracy was not significant. Although the speed error increased when the number of satellites used decreased, the median absolute error was less than 0.5 m/s (1.12 mph) even when only three satellites were used. While the GPS data followed acceleration and deceleration reasonably well, it lagged behind during transitions from acceleration to deceleration, effectively smoothing the acceleration curves. The study concluded that low-cost GPS recorders were sufficiently accurate to record speed over ground even at lower speeds (Witte & Wilson, 2004).

Bicycle and Augmented Data-Logging Cyclometer

The bicycle used for this testing was a men's mountain bike with 26 inch diameter wheels and tires (Figure 19). With a top speed upwards of 25 mph, the maximum wheel revolutions per second that would need to be recorded by the cyclometer would be 2.5.

Figure 19. Bicycle Used for Validation Testing (Trek, 2012)

Unfortunately, there are no cyclometers on the market that will log each wheel turn or log speed at a rate adequate for this validation test (1 Hz). Another option was to use a DC voltage event data logger in conjunction with the cyclometer to record the time of each wheel turn, but the team was unable to find a DC voltage event data logger that recorded at a rate sufficient to capture each wheel turn (2.5 Hz or more).

DC voltage event counter data loggers, however, are able to count DC voltage events at a higher rate than it can record time-stamps for each event (100 Hz vs. 1 Hz). Therefore, this research used a DC voltage event counter data logger to record the number of wheel revolutions each second. Rather than recording the time of each wheel turn, the DC voltage event counter stored the number of voltage events that occur within a user-specified time increment. By attaching multiple magnets equidistance around the wheel, each voltage event represented a certain degree of wheel rotation. The number of DC voltage events per second then provided the degree of rotation that occurred within that second. This was then translated into ground speed based on the circumference of the wheel. By increasing the number of magnets on the wheel, the precision of each measurement was increased, provided that no magnet passes went undetected. For this research, eight magnets were attached to the front wheel of the test bicycle adjacent to the reed switch such that they triggered the reed switch with each pass (see Figure 20).

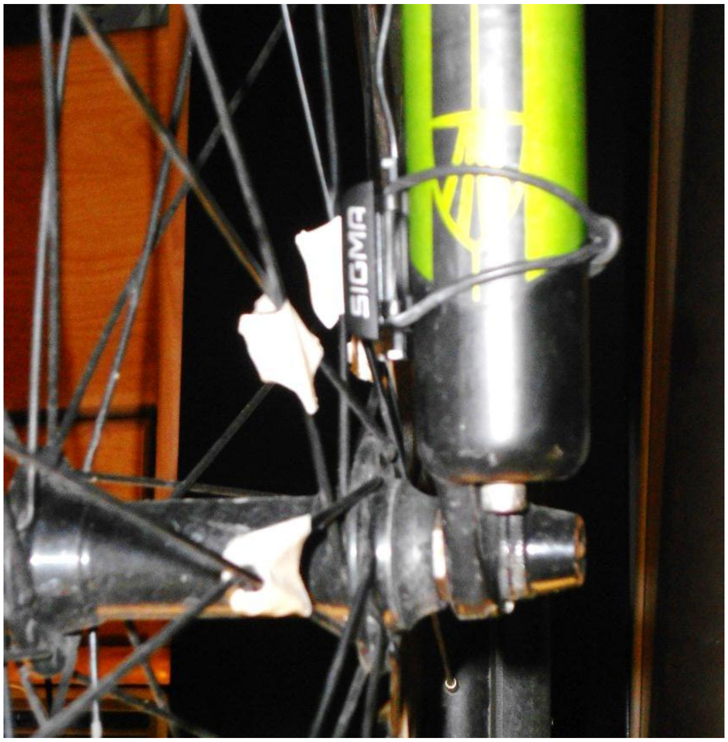


Figure 20. Magnets and Cyclometer Reed Switch Installation

(Credit: Lance Ballard)

Before and after each trip, the cyclometer calibration was checked by rotating the bicycle wheel 10 times to ensure that the data logger counted 80 events (8 magnets/rev x 10 rev = 80 events). The data logger clock synchs with the computer clock every time it is connected to the computer. The computer clock was set to the same UTM time that the GPS recorders use to match the times of data recording as closely as possible.

During analysis, the team realized the clock within the augmented cyclometer produced time-stamp errors within the data. These were corrected using a linear correction factor for each trip that was calibrated graphically. The linear correction factor varied among trips. Therefore, it was adjusted manually for each trip to match major trip events . An example of the clock error for a test bicycle trip and the corrected data for the same trip are shown in Figure 21 and Figure 22, respectively. All of the cyclometer data for the Data Collection Method Validation Testing was corrected in this fashion.

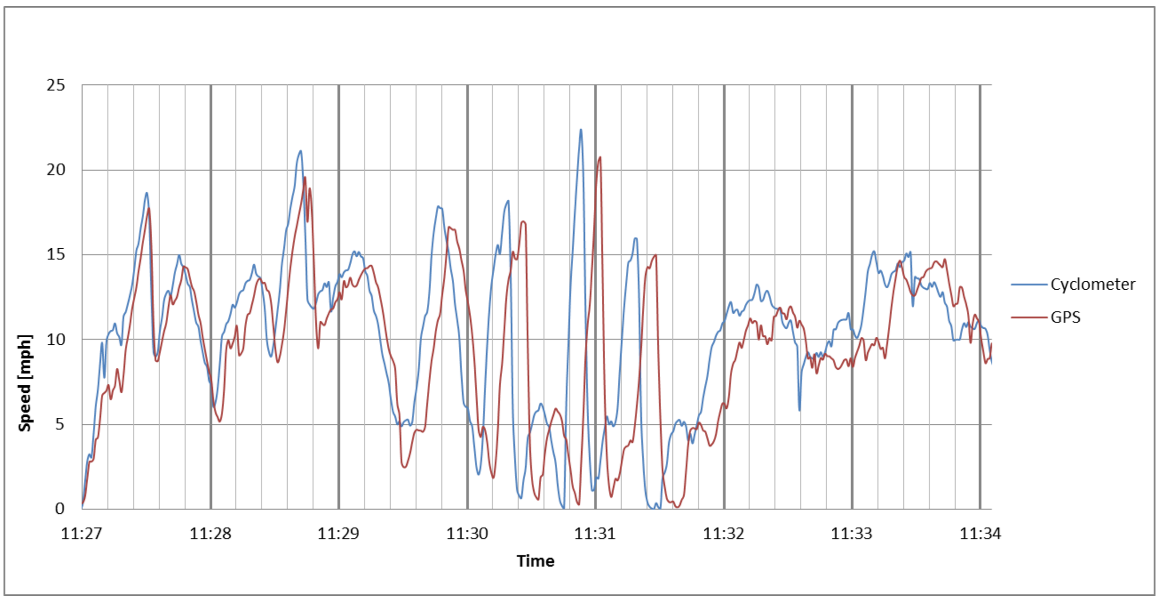


Figure 21. Example of Cyclometer Speed with Clock Error

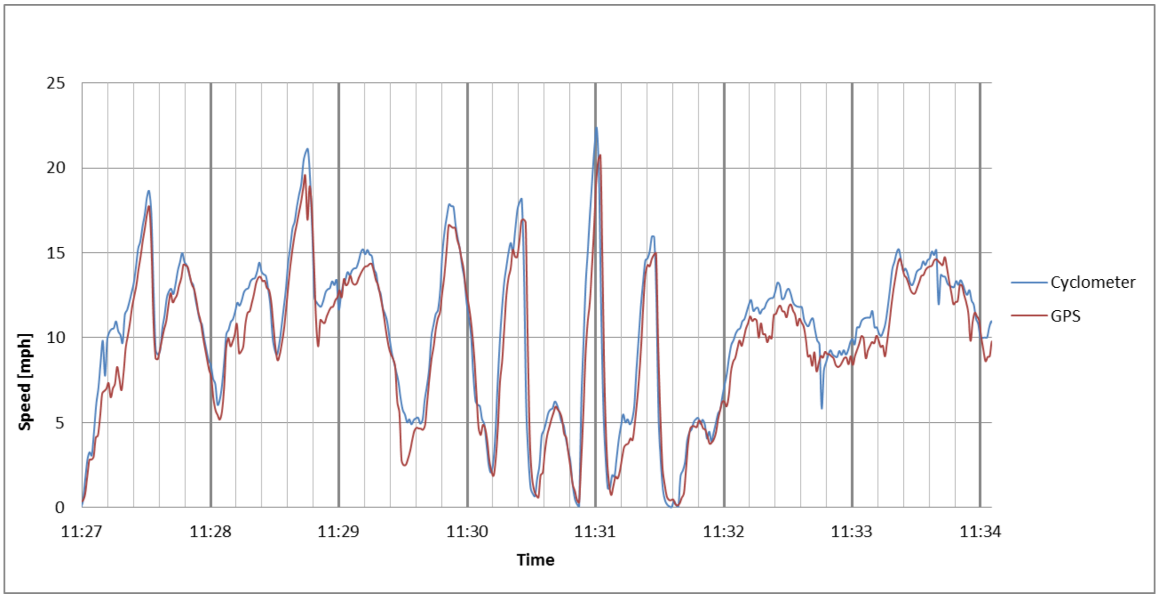


Figure 22. Example of Cyclometer Speed with Clock Corrected

3.3.2 Lab Testing

The first round of data collection method validation testing analyzed the speed and acceleration accuracy of the GPS recorders under controlled conditions. The bicycle equipped with the augmented cyclometer and a GPS recorder traveled along a straight, flat path visible in aerial photographs and thus visible to GPS satellites. The test route is shown in Figure 23. The path was field measured and found to be a distance of 614 ft.

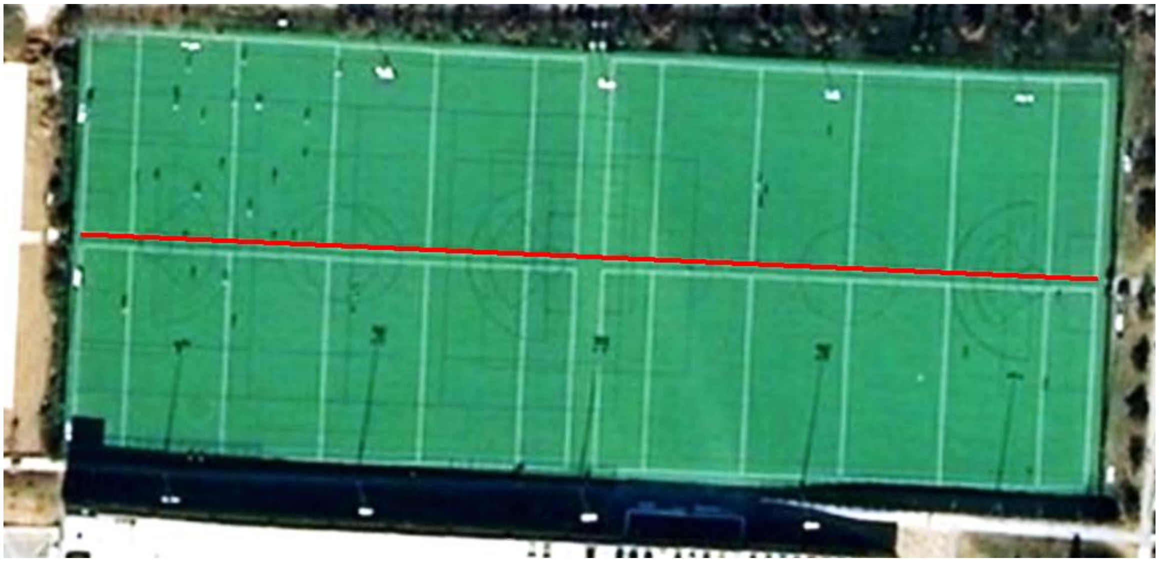


Figure 23. Data Collection Method Validation Test Route (Credit: Google Earth)

The lab testing consisted of 30 trips, 10 at each of three speed categories: walking (4 mph), coasting (8 mph), and pedaling (15-25 mph). After testing, the GPS speed and acceleration was compared to the cyclometer speed and acceleration on a second-by-second basis.

Results

Figure 24, Figure 25, and Figure 26 show the speed and acceleration results for an example run from walk, coast, and pedal runs, respectively. The bottom part of the graph shows the speed which is marked on the left axis. The top part of the graph shows the acceleration for the trip using the axis on the right side of the graph. The graphs for all thirty Lab Tests can be found in Appendix B.

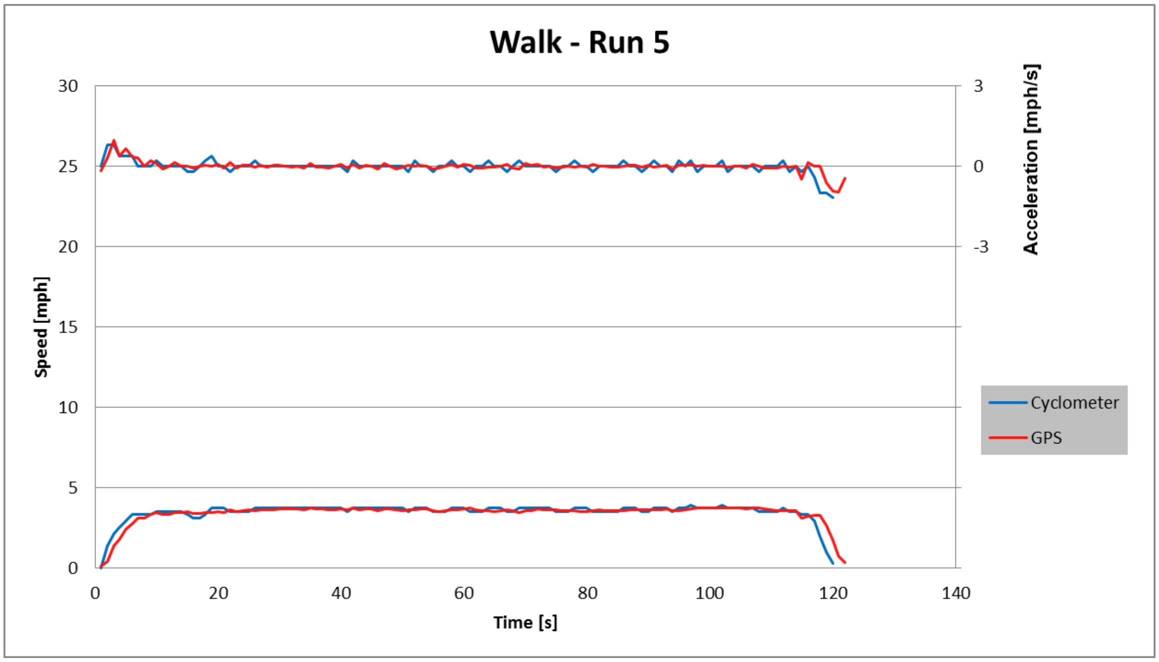


Figure 24. Lab Test – Walking Speed – Run 5

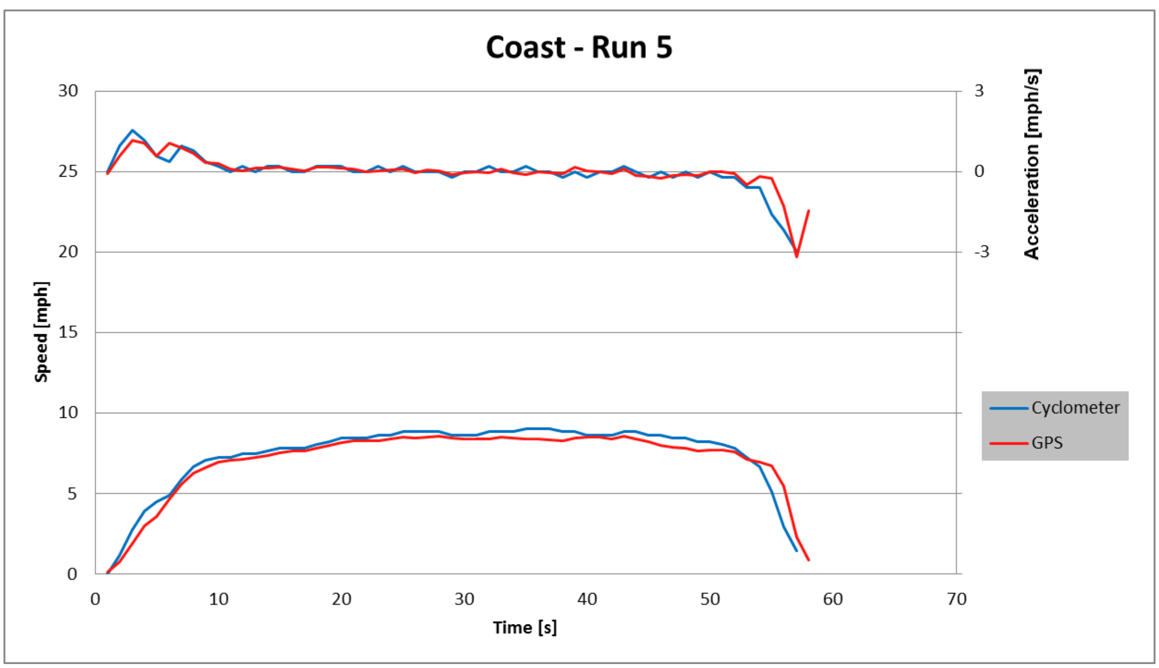


Figure 25. Lab Test – Coasting Speed – Run 5

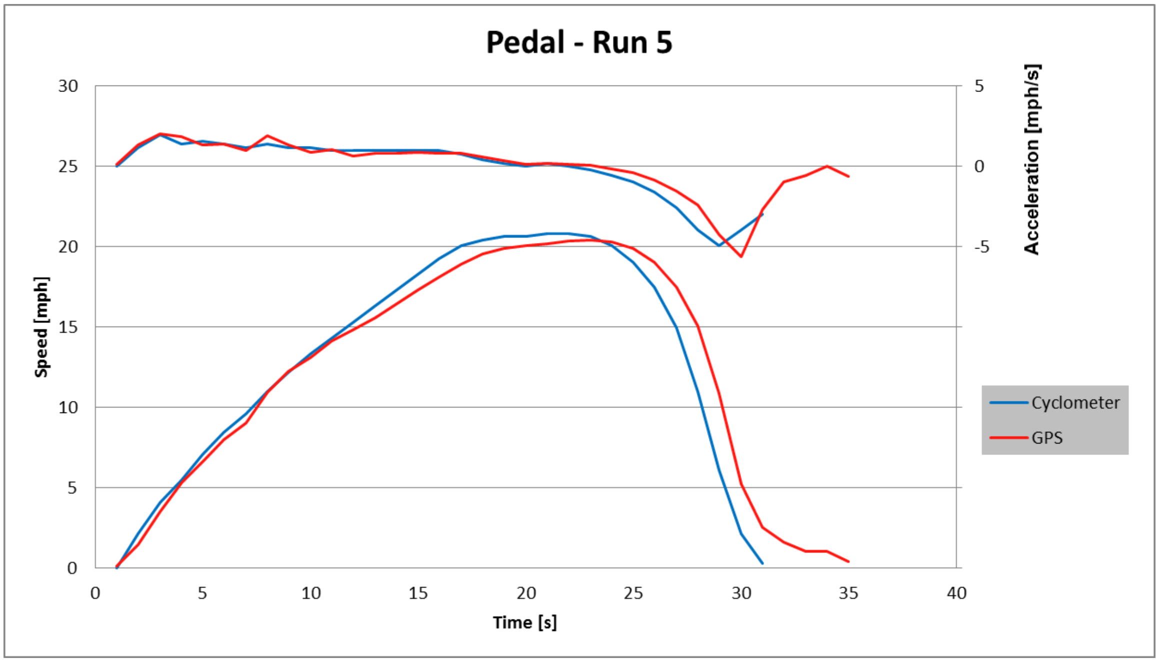


Figure 26. Lab Test – Pedal Speed – Run 5

The GPS recorders appear to measure speed very similarly to the cyclometer for each of the three speed categories tested. Differences between each concurrent speed observation were calculated by taking the absolute difference between the GPS recorded speed and the corrected cyclometer speed. This absolute value difference was calculated for speed and acceleration for each second of each trip. Table 3, Table 4, and Table 5 report the mean and standard deviation for both absolute speed and absolute acceleration differences for each of the three Lab Test categories.

Table 3. Lab Test GPS/Cyclometer Difference - Walking

Walk	Speed Difference [mph]	Acceleration Difference [mph/s]
Mean	0.14	0.12
Std. Dev.	0.20	0.13

Table 4. Lab Test GPS/Cyclometer Difference - Coasting

Coast	Speed Difference [mph]	Acceleration Difference [mph/s]
Mean	0.46	0.22
Std. Dev.	0.55	0.32

Table 5. Lab Test GPS/Cyclometer Difference - Pedaling

Pedal	Speed Difference [mph]	Acceleration Difference [mph/s]
Mean	1.10	0.37
Std. Dev.	1.03	0.41

As the speed increases, the mean and standard deviations for absolute speed difference and absolute acceleration difference increase as well. However, the largest mean speed difference is only 1.1 mph.

3.3.3 Field Testing

The field testing collected data from the GPS and cyclometer during five trips under real-world conditions. These were bicycle commute trips in the City of Atlanta over a three day period on the bicycle equipped with the cyclometer. The routes consisted of streets, bike lanes, sidewalks, and shared-use paths free from cars. A map of the five trips can be seen in Figure 27.

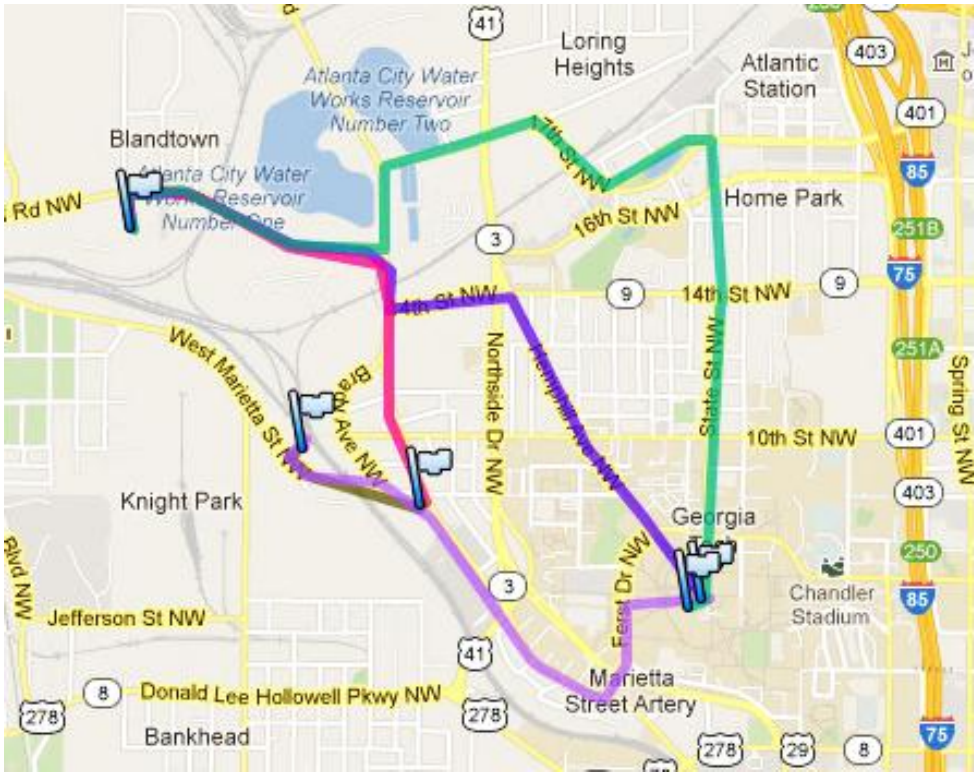


Figure 27. Map of Validation Bicycle Field Test Trips (Credit: QTravel)

The data from the field test trips were analyzed similarly to the lab test trips by comparing the GPS speed and acceleration to the cyclometer recorded speed and acceleration on a second-by-second basis.

Results

Figure 28 shows a speed and acceleration plot from one of these trips (see Appendix B for all five trips). Table 6 shows the results of the statistical analysis for the five trips.

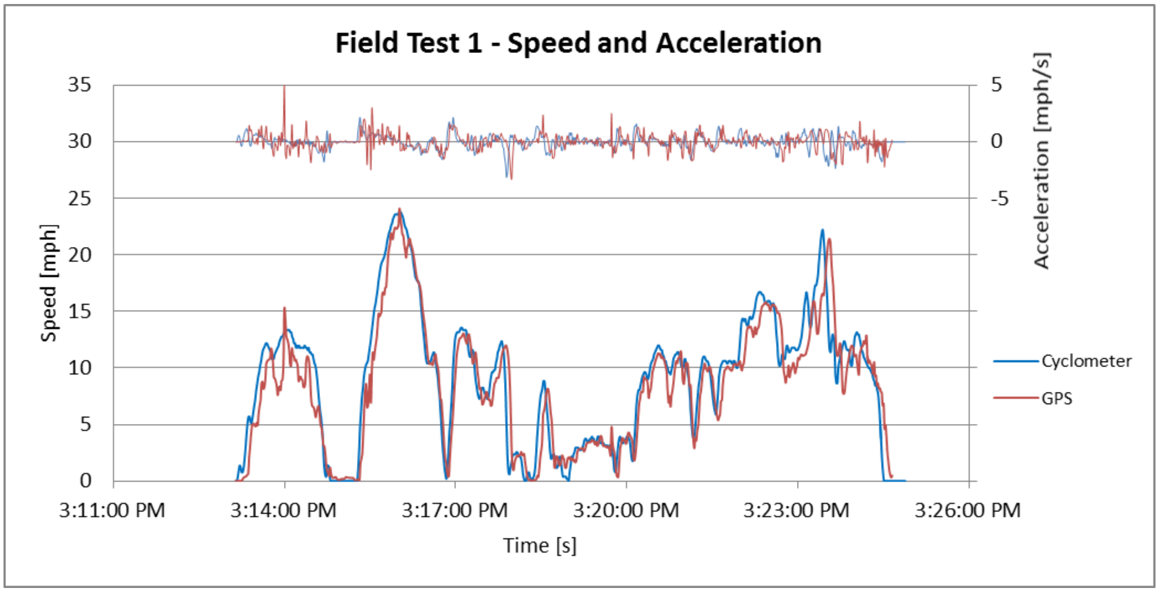


Figure 28. Data Collection Method Validation Field Test 1 Speed and Acceleration

Table 6. Field Test GPS/Cyclometer Difference

	Speed Difference [mph]	Acceleration Difference [mph/s]
Mean	1.18	0.58
Std. Dev.	1.48	0.99

The Field Tests provide evidence that the GPS recorders are capable of accurately report speed and acceleration within the range of expected PMD operations. The mean absolute speed and acceleration differences for the Field Tests are 1.18 mph and 0.58 mph/s, respectively.

3.3.4 Hard-Acceleration Test

The final validation test consisted of a single bicycle trip. During this trip, the rider accelerated and decelerated as quickly as possible while maintaining safety and making sure the front wheel equipped with the cyclometer did not skid or slip. The purpose of this hard-acceleration test was to observe the ability of the GPS recorders to accurately capture extreme acceleration events. The test used two locations with sag vertical curves to increase the ability to accelerate and decelerate quickly on the downhill and uphill parts of the curve respectively. Figure 29 shows the entire trip, and the two locations used for hard-acceleration testing.

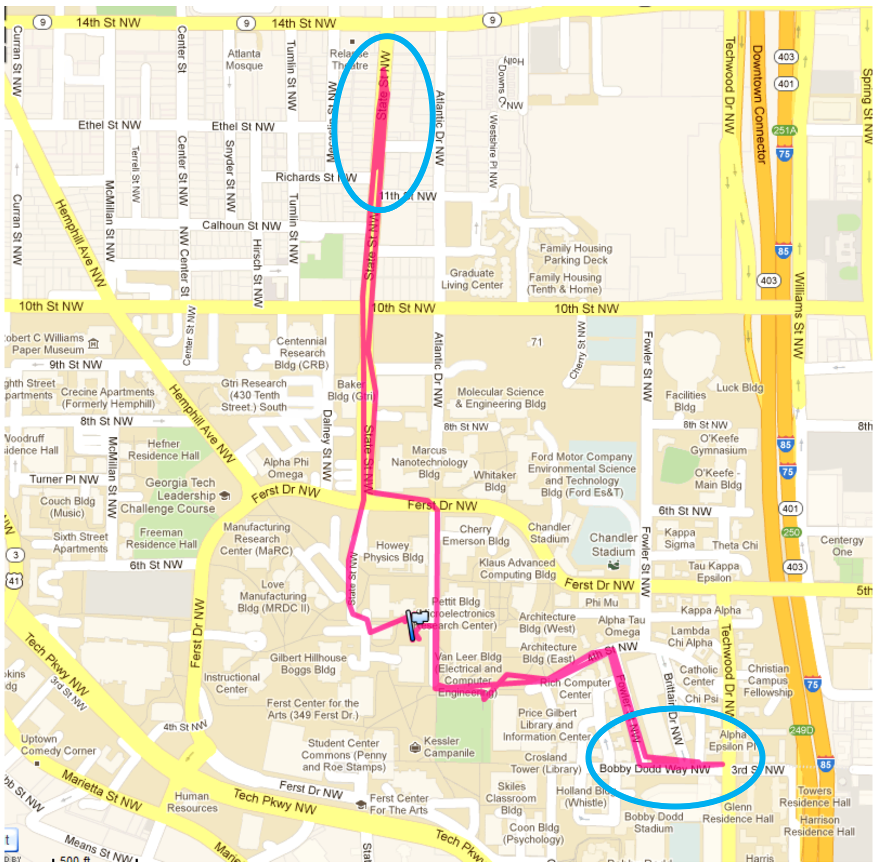


Figure 29. Hard Acceleration Validation Test Trip and Locations (Credit: QTravel)

The Hard Acceleration Test was analyzed by comparing the GPS recorded speed and acceleration to the cyclometer speed and acceleration on a second-by-second basis, especially focusing on the most extreme acceleration events.

Results

Figure 30 shows both GPS and cyclometer Segway speed and acceleration for the entirety of the Hard Acceleration Test. Figure 31 shows a smaller portion of the trip that is designated by the shaded box in Figure 30.

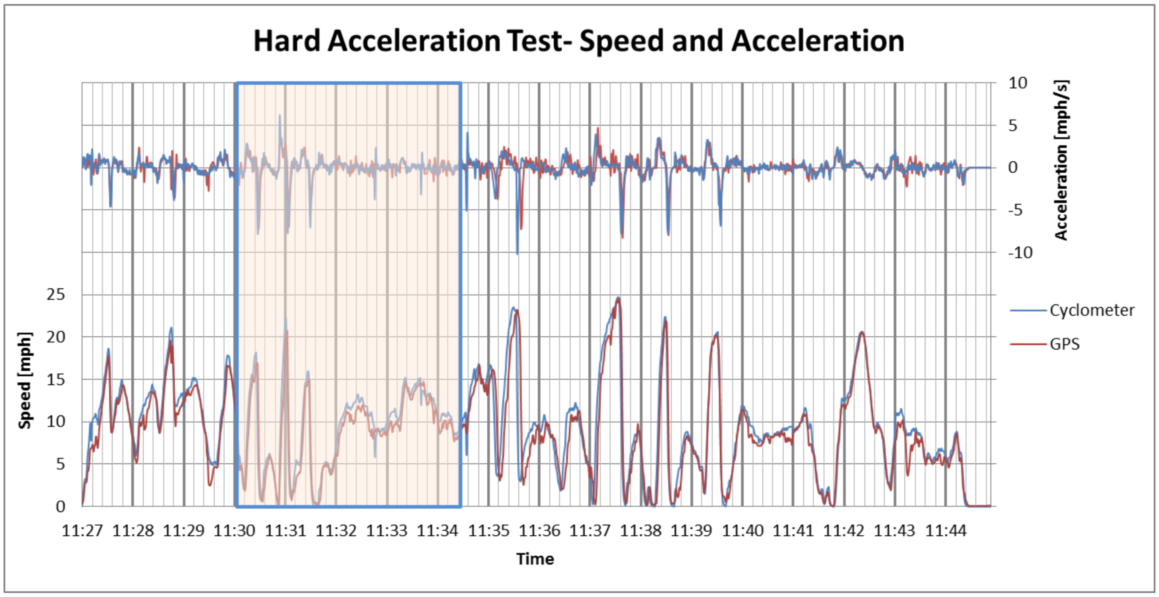


Figure 30. Hard Acceleration Test 1

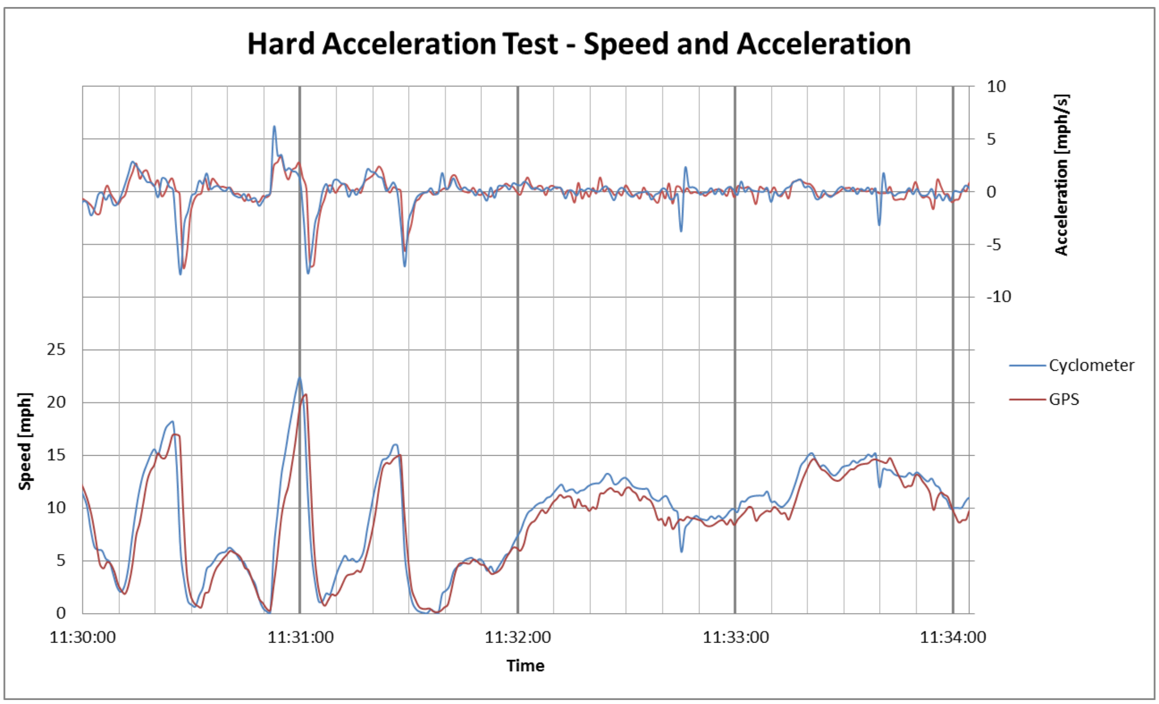


Figure 31. Hard Acceleration Test 2

Even under the most extreme accelerations capable by the bicycle rider, the GPS recorder adequately captured all the acceleration events and accurately recorded speed throughout the course of the trip. Throughout the entirety of the trip, the mean absolute speed and acceleration difference is 1.3 mph and 0.61 mph/s, respectively. This is slightly greater than the previous tests but still relatively small when considering the magnitude of speeds.

Table 7. Hard Acceleration Test GPS/Cyclometer Difference

	Speed Difference [mph]	Acceleration Difference [mph/s]
Mean	1.30	0.61
Std. Dev.	1.72	0.90

3.3.5 Data Collection Method Validation Test Conclusion

To validate the data collection method, second by second data collected simultaneously by both a cyclometer and a GPS recorder were compared. This research used the cyclometer as a "ground truth" because the cyclometer is far less fallible than the GPS recorder and the cyclometer could be calibrated before and after each test run. If the GPS recorder observed the same data as the cyclometer, the data collection method would be viewed as acceptable for this thesis. For each second of the trip, the absolute difference between the cyclometer and GPS speed and acceleration were calculated and analyzed. Although the cyclometer clock error made it difficult to pair the two datasets for each second of every trip, the statistical analysis shows that the average speed and acceleration differences between the cyclometer and GPS recorder data were 1.3 mph and 0.61 mph/s in the worst cases. However, the graphical comparison shows that the GPS recorders measured speed and acceleration practically the same as the cyclometer. Therefore, the GPS recorders are adequate for PMD speed and acceleration data collection.

3.4 PMD Data Collection

To accomplish the objectives of this research, the research team collected location, speed, and heading data from PMD trips using GPS data recorders. This section describes the data sources, the data collection procedures, and the expected results of the data collection effort.

3.4.1 Data Sources

PMDs are used by a variety of organizations and individuals. For this data collection, the research team recruited public agencies, private companies, and other types of organizations that use fleets of PMDs. Bicycle-share programs allow users to use bicycles without having to own and store one, and they are becoming increasingly popular in major cities. Segways are often used by law enforcement for patrols, by tourism agencies for city and attraction tours, and by companies for transportation around large commercial or industrial sites. Golf courses use electric carts for the players to travel the course during play. Electric carts are also used as utility vehicles to transport maintenance personnel, tools, and equipment around large properties and facilities.

Data were collected from four types of PMDs. Data from pedestrian trips were collected from two students walking to, from, and within the Georgia Tech campus. Bike trips from three Georgia Tech students and faculty members were also collected. Segway data were collected from one Segway tour agency and two security agencies that use Segways for patrolling in addition to the data collected from the Segway test trips. Finally, the team collected data from electric carts used by various departments at Georgia Tech.

3.4.2 Data Collection Procedure

After recruiting the participating agency or individual via phone or email, GPS recorders were installed on their devices by the research team using a plastic Zip-tie, Velcro, or tape. Figure 32 shows one GPS recorder attachment configuration for a Segway. The participant then turned on the GPS recorder for the duration of each trip to record location and speed at a rate of 1 Hz. The participant recorded trips for one week or until the GPS battery or storage was exhausted. Finally, the participants returned the GPS recorders and the *Info Sheet* to the research team for data processing (see Appendix C).

Figure 32. GPS recorder Instrumented on Segway

Once returned to the research team, the GPS data were retrieved using the QTravel software, and the raw data were exported to excel files coded by data source, mode, trip purpose, and trip number.

3.5 Analysis of Performance Characteristics

After filtering, the performance characteristics were analyzed for each PMD. Speed and acceleration data were compared across modes and also within each mode by participant, trip, trip purpose, conditions, and other factors. The primary analysis was in the form of speed and acceleration scatter plots and density plots. The speed and acceleration density plots were important because they can be used as simulation model inputs for each PMD.

3.5.1 Statistical Analysis

To analyze the differences between speeds and accelerations between modes or resulting from various factors, the research team used the Kolmogorov-Smirnov (KS) Test. The KS Test is a non-parametric test that analyzes the difference between the distributions of two datasets. The KS test measures the distance (D) between the cumulative distribution function (CDF) of each distribution and returns a p-value test statistic. A small p-value of nearly zero means to reject the null hypothesis that the two distributions are the same. This research used a p-value of 0.05 for selection criteria to accept or reject the null hypothesis.

3.6 Segway Testing

The final portion of this research was a first-hand Segway Test by the research team. On August 10, 2012, the research team consisting of three Georgia Tech faculty and three graduate research students tested six Segways by traveling approximately eight miles in the City of Atlanta (see Figure 33). The Segways were rented through City Segway Tours of Atlanta, and the group was accompanied by a trained Segway guide, making seven Segway trips in all. The goal of the testing was, to travel as one would when commuting from one location to another, to observe interactions between Segways and pedestrians, and to experience Segway operations first hand. Each of the seven

Segways was instrumented with a GPS recorder for the entirety of the trip recording at rate of 1 Hz. The map of the trip route is shown in Figure 34.

Figure 33. Research Team during Segway Testing (Credit: Lance Ballard)

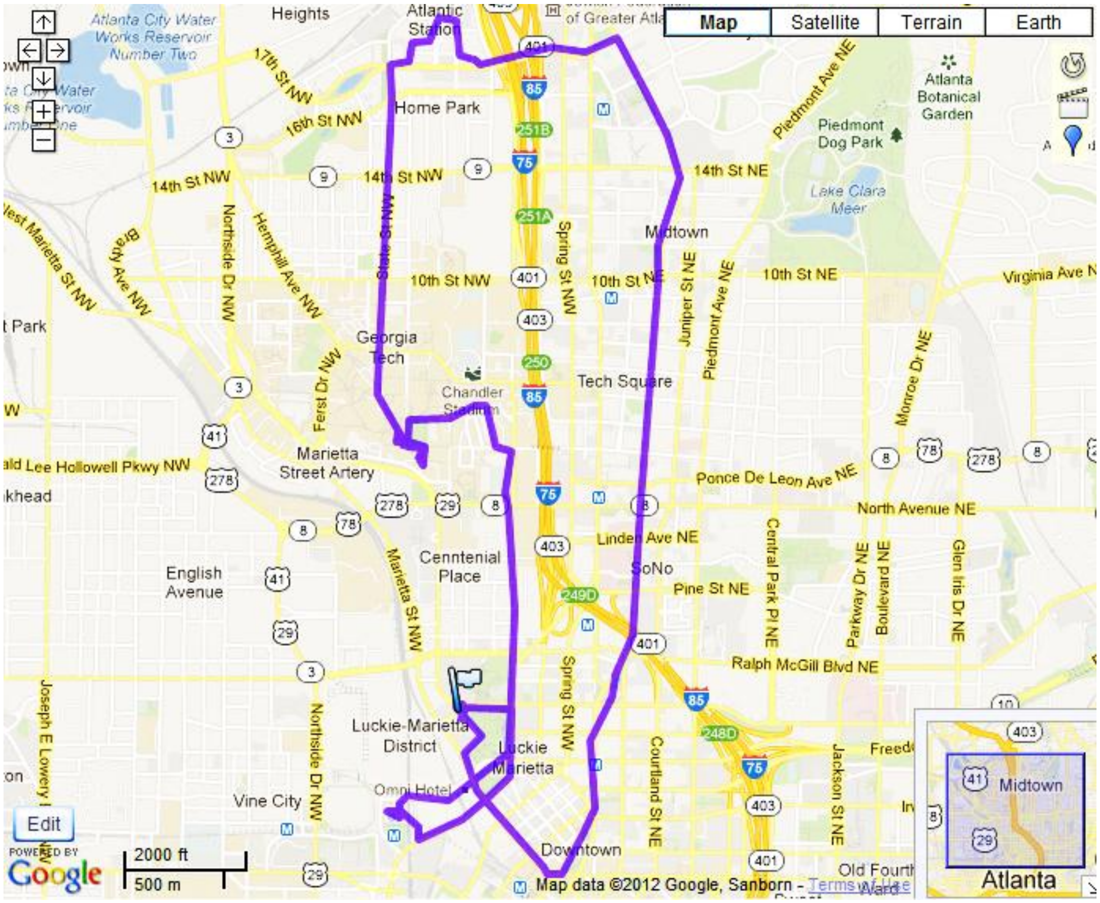


Figure 34. Map of Segway Testing in Atlanta (Credit: QTravel)

During the Segway Test trips, the participants noticed that their speed tended to vary in relation to infrastructure and the surrounding environment. To examine how these factors influenced Segway operations, the Segway test route was separated into seven segments based on three criteria: Sidewalk Width, Surface Quality, and Pedestrian Density. Each criterion consisted of a three-level categorical ranking system. Sidewalk width was described as narrow, medium, or wide. A segment was ranked as narrow if the majority of the segment had sidewalks of approximately four feet in width, medium for approximately six to eight feet in width, and wide if greater than 10 feet. However, this ranking was made subjectively without quantitative measures for each segment. Most of the route was on sidewalks, but the sections that were on a roadway or in a bike lane were rated as having a wide sidewalk width. Surface quality described the quality of the sidewalk or street and its roughness. Surface quality was categorized as poor, medium, or excellent based on the number of cracks or seams in the pavement surface and on the roughness experienced by the Segway users during the trip. Pedestrian density represented the amount of pedestrians that could potentially obstruct the Segway path within each segment, and it was rated as light, medium, or heavy. This ranking was very subjective and difficult to make since pedestrian density is continually in flux and non-uniform throughout the segments. Figure 35 shows the map of each of the seven segments and Table 8 shows how each segment was rated. Appendix A shows photographic examples of the rankings for each criterion.

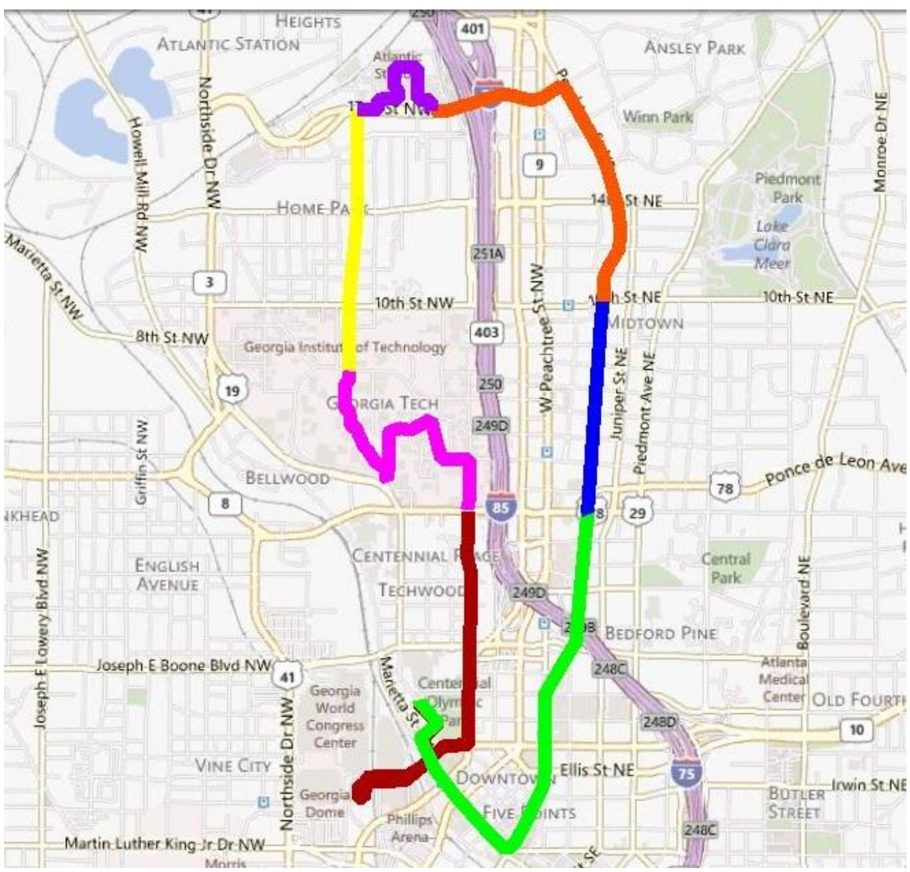


Figure 35. Segway Test Route Segments (Credit: Google Earth & Bing Maps)

Table 8. Segway Test Segment Characteristics

Segment	Color	Sidewalk Width	Surface Quality	Pedestrian Density
1	Green	narrow	bad	heavy
2	Blue	narrow	medium	medium
3	Red	wide	excellent	medium
4	Purple	wide	excellent	heavy
5	Yellow	wide	excellent	light
6	Pink	wide	excellent	heavy
7	Maroon	medium	medium	medium

Segment one started at the beginning of the route and continues through downtown Atlanta until reaching the intersection of North Avenue and Peachtree Street. However, the small period of time at the very beginning of the route where the team used the lowest speed key with a maximum speed of 8 mph was removed for analysis since it occurred using a different speed key, and the team was still familiarizing themselves with the Segways. The first segment had the narrowest sidewalks, poor surface quality due to inconsistent pavement and construction in many areas, and heavy pedestrian traffic. The second segment continued up Peachtree Street from North Avenue to 10th Street where pavement conditions improved to medium, but the pedestrian density was still heavy. The third segment was also on Peachtree Street from 10th Street to 17th Street where the path turned west and traveled down 17th Street to the Atlantic Station area. This segment was ranked as having wide sidewalks, medium surface quality, and medium pedestrian density. A small portion of this segment actually occurred on the roadway when crossing the 17th Street Bridge where the team road in the bike lane to experience mixed traffic. Segment four was entirely within Atlantic Station, a high-density, mixed-use development with wide sidewalks, excellent surface quality, and heavy pedestrian traffic. From Atlantic Station, Segment five headed south on State Street from 17th Street to Ferst Drive at the Georgia Tech campus. The team operated on the street for the entirety of the fifth segment. Therefore, the sidewalk width was rated as wide, surface quality as excellent and pedestrian density as light. The sixth segment was entirely within the Georgia Tech campus where sidewalk width was always wide and surface quality was excellent. Pedestrian density varied throughout the time spent on campus travelling segment six, ranging from very dense to medium at times. However, the segment was ranked as heavy pedestrian density because of the frequency of pedestrian encounters for the majority of the segment. The final segment travelled down Centennial Olympic Parkway south away from campus and returned to the starting point. This seventh segment had medium sidewalk widths, medium surface quality, and medium pedestrian density.

CHAPTER 4

RESULTS & DISCUSSION

This chapter reports the results of the analysis performed in Chapter 3 and discusses the implications of these analyses. First, this section discusses the results for each type of PMD. Then, speed and acceleration data from each mode are compared. Next, the results of the Segway Test are analyzed and discussed. Finally, the effects of external factors on PMD speed and acceleration are analyzed.

4.1 Data Collection Results

After confirming the ability of the GPS recorders to accurately record PMD speed and acceleration, GPS recorders were used to observe pedestrian, Segway, bicycle, and electric cart trips. Table 9 shows the results from the PMD data collection. Observations were taken at one second intervals for all of the trips.

Table 9. PMD Data Collection Results Summary by Mode

Mode	Total Participants	Total Trips	Trip Length [mi]			Non-Idle Observations
			Min	Max	Avg	
Pedestrian	2	8	0.38	2.38	1.18	15,342
Segway	3 agencies	48	0.69	12.25	6.92	249,284
Bicycle	3	26	0.32	9.75	2.32	33,761
Electric Cart	3	3	1.75	5.32	3.75	3,158

The vast majority of observations come from Segway trips because, as mentioned in Section 2.3, Segways are the PMD most representative of the vision for IMS operations. A similar number of pedestrian and bicycle observations were recorded. Electric carts have the smallest amount of mobile observations.

4.2 Speed and Acceleration Results by Mode

4.2.1 Pedestrian

The data collection resulted in a total of over 15,000 non-idle observations (4 hours) of pedestrian trip speeds and acceleration. Figure 36 shows a plot of the paired speed and acceleration data. Each point in the bottom-left graph represents the speed and acceleration for one second of a pedestrian trip and shows the relationship between trip speed and acceleration events. Each point is semi-transparent to show the point density for paired speeds and accelerations. The top plot is the density plot of all of the non-idle speed data from pedestrian trips, and the plot on the far right shows the density plot for trip accelerations.

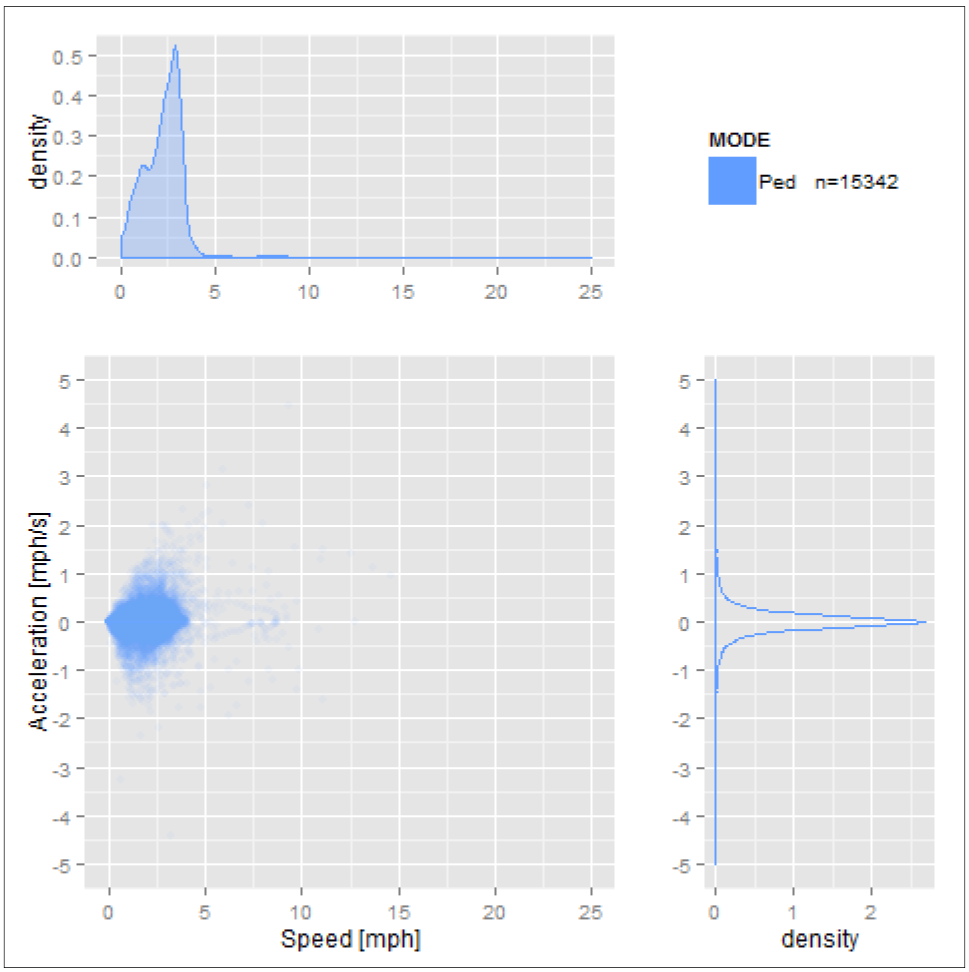


Figure 36. Pedestrian Speed and Acceleration

The pedestrian trips are as expected with a max speed approaching 5 mph, a mean speed of 2.2 mph and a mode at approximately 2.9 mph. The acceleration density plot also shows that the majority of pedestrian accelerations are less than 1 mph/s. The pedestrian acceleration distribution is expected since even though pedestrians can accelerate from standing still to walking quickly, walking speed is relatively slow in comparison to other modes. There are some observations above 5 mph that could be either the result of a pedestrian increasing speed for some reason, crossing the street for example, or the result of residual GPS errors.

4.2.2 Segway

Using almost 250,000 observations (almost 70 hours) of Segway speeds and accelerations, Figure 37 is the same combination plot for Segway trips. The mean and mode for Segways are 4.6 mph & 2.4 mph, respectively. The speed density plot is skewed with a strong tail to the right towards the upper end of the Segway speed threshold of 12.5 mph. Almost all of the Segway accelerations fall within the bounds of -2 mph to 2 mph, and the largest accelerations occur when travelling between 3 and 8 mph.

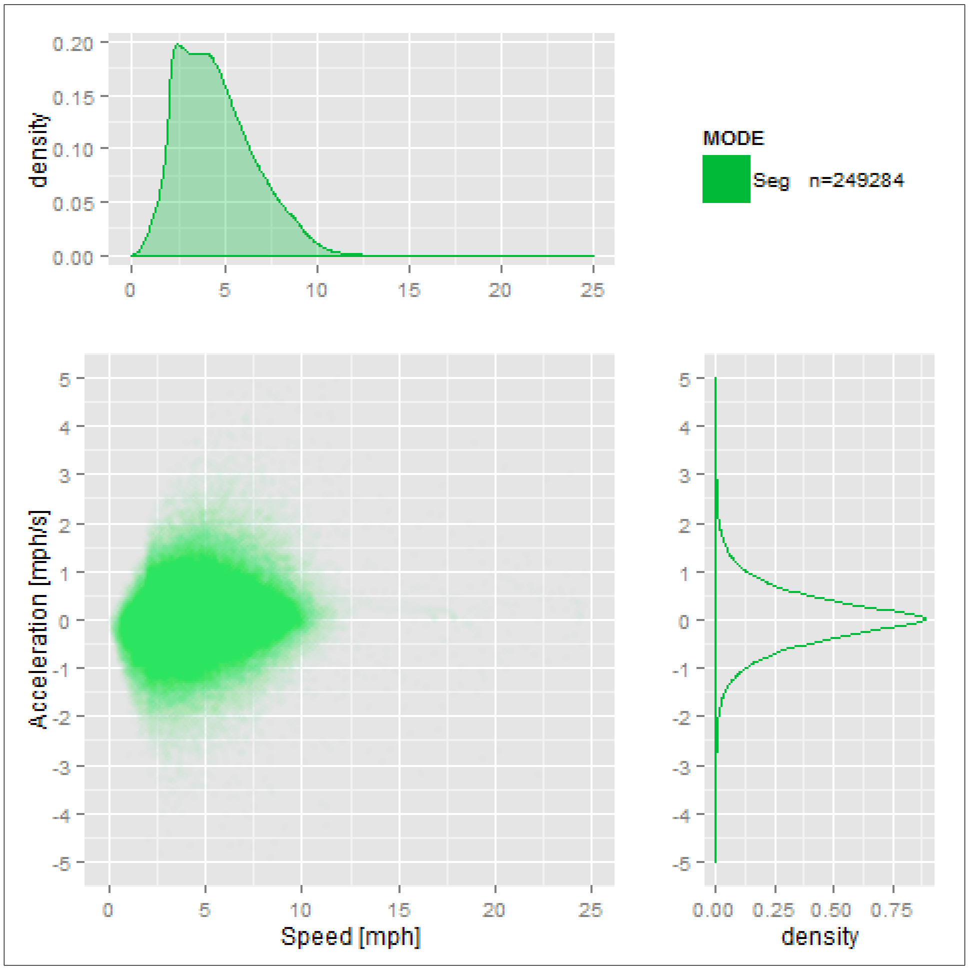


Figure 37. Segway Speed and Acceleration

Although Segways have a top speed of 12.5 mph, Segways rarely achieved speeds greater than 10 mph, and the majority of speed observations were below 5 mph. This could imply that Segways do not offer significantly increased mobility over walking. However, this is likely due to fact that the Segway trips observed during this study were from patrol or tour agencies, and these trips are not commute trips. Commute trips on Segways would likely have faster speed distributions. Later in this report, data will be presented for just the Segway test trips taken on August 10, 2012 as part of the data collection intended to be more representative of commute conditions.

4.2.3 Bicycle

There were 33,761 observations over 9 hours of bicycle speeds and accelerations are shown in Figure 38. While bicycle speeds reached upwards of 25 mph for brief periods, the majority of trips occur at a speed of 5 – 15 mph. The mean speed was 9.7 mph. The distribution of bicycle accelerations is focused between -2 and 2 mph/s with the greatest accelerations extending to -5 and 5 mph/s.

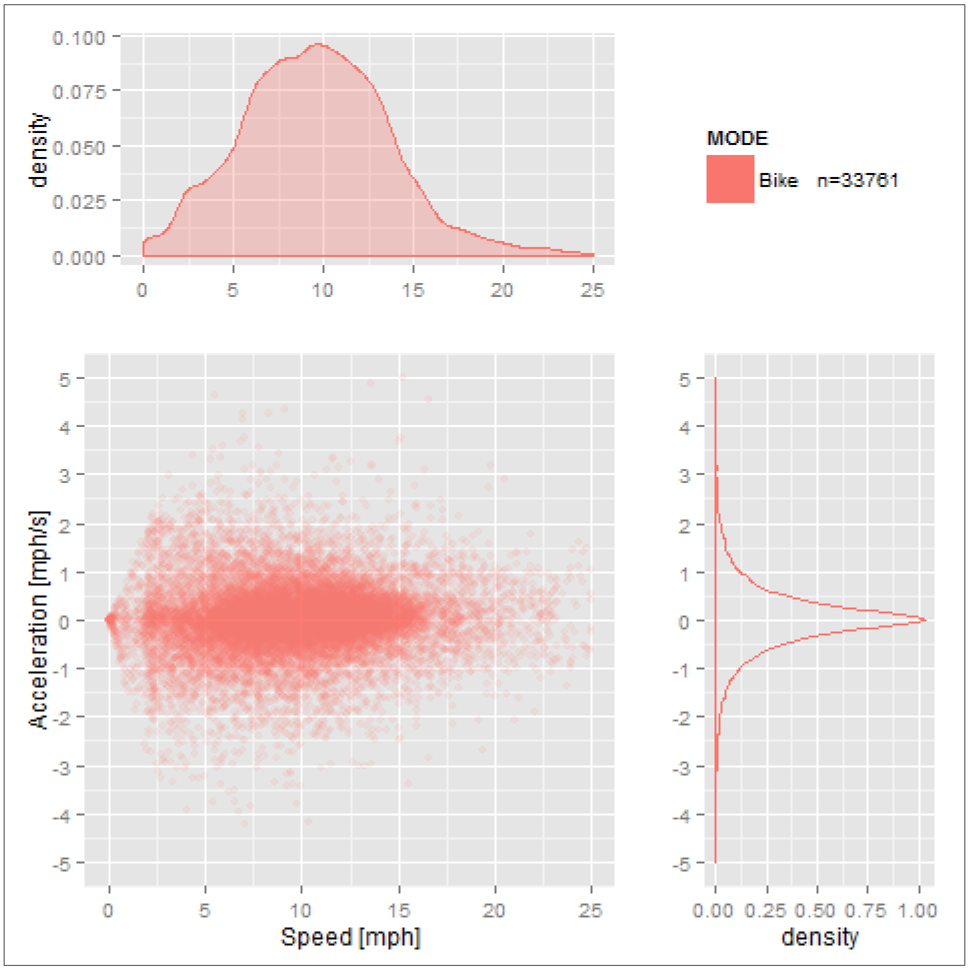


Figure 38. Bicycle Speed and Acceleration

All of the data shown in Figure 38 are from bicycle commuter trips and show that bicycles offer a potential available speed advantage over pedestrians and Segways. However, the average speed for these bicycle commute trips was 9.7 mph, well within the range of Segway operations. Unfortunately, these findings are based on only three bicycle participants. Data from a much larger group of cyclists and commute based Segway trips is necessary for a detailed mobility comparison between these PMDs.

4.2.4 Electric Cart

All of the electric cart data were collected from GEM cars. GPS recorder limitations, infrequent and inconsistent electric car use, and time constraints limited the electric cart data to only three electric cart trips on the Georgia Tech campus. However, the research team expects the data to be representative of future IMS zone electric car operation because the purpose of each trip was to travel from one location on the Georgia Tech campus to another and the trip occurred on campus in the midst of pedestrian, bicycle, and other modes of traffic.

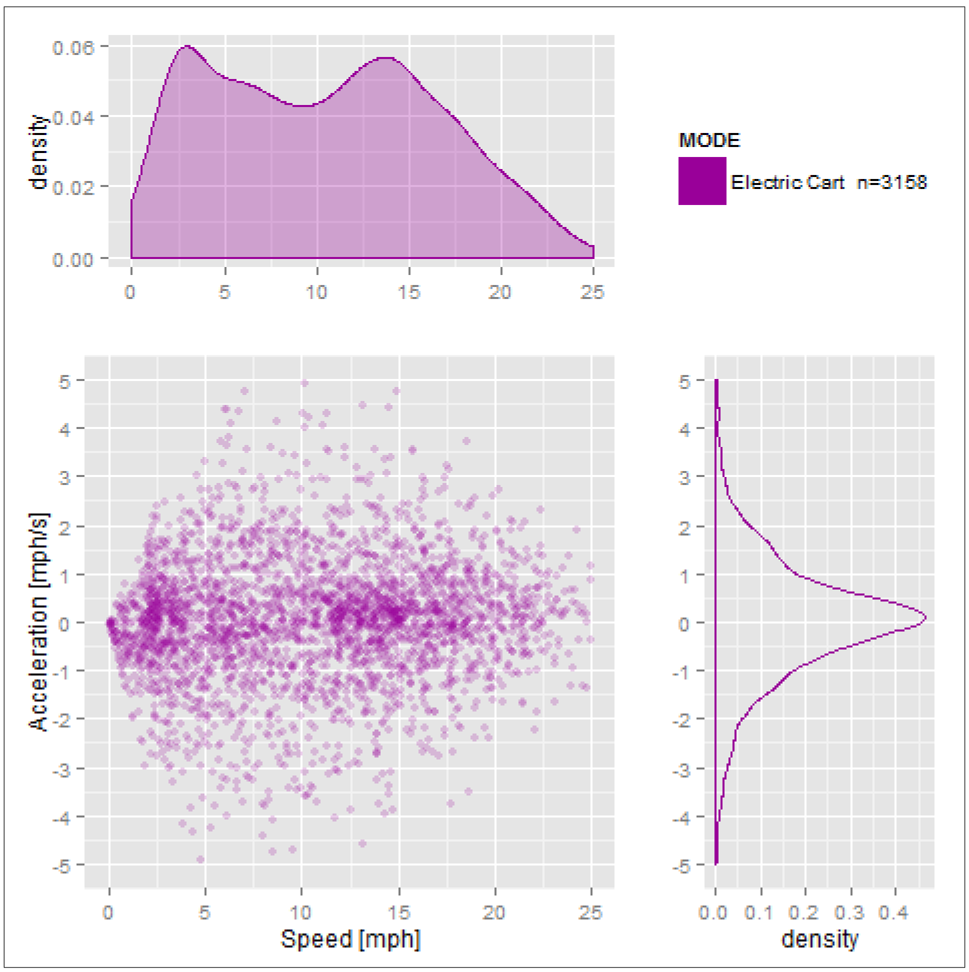


Figure 39. Electric Cart Speed and Acceleration

The average speed for electric car trips is 10.7 mph. Figure 39 shows that the electric cart speed data is bi-modal with a mode of 3 mph and 14 mph and some observations of greater than 25 mph. The first mode peak is likely due to parts of the electric cart trips that occurred on the sidewalk or other areas with pedestrian traffic. When electric carts travel on the sidewalk, there are no right-of-way rules, and often, electric carts are forced to travel at walking speed behind pedestrians until there is sufficient clearance to pass safely. The second peak is likely from travel on sidewalks free of pedestrians or small campus streets with limited or restricted car access. Under these conditions, electric carts are able to travel at higher speeds. However, due to the level of pedestrian activity in the campus environment, it would still be unsafe for the electric carts to travel at full speed. The electric carts are street legal and often operate on campus streets within car traffic. Yet, even on the street, speed limits on campus are limited to 25 mph and cars often travel at even lower speeds due to the presence of many pedestrians and cyclists.

4.3 Comparison of Modes

Figure 40 compares the speed and accelerating distributions for each of the four modes observed in this research. Pedestrians have the lowest mean speed and the smallest range of both speed and acceleration. Segways have slightly greater speeds and a slightly greater range of speeds and accelerations than pedestrians. Next, bikes have greater speeds than Segways (for those measured) and a greater range of speeds. However, bicycles and Segways seem to have similar acceleration distributions. Electric carts have the highest speed and also the greatest range of speeds of all the PMDs observed. Electric carts also have the greatest range of accelerations. Table 10 shows basic statistics for the speed distributions for each mode.

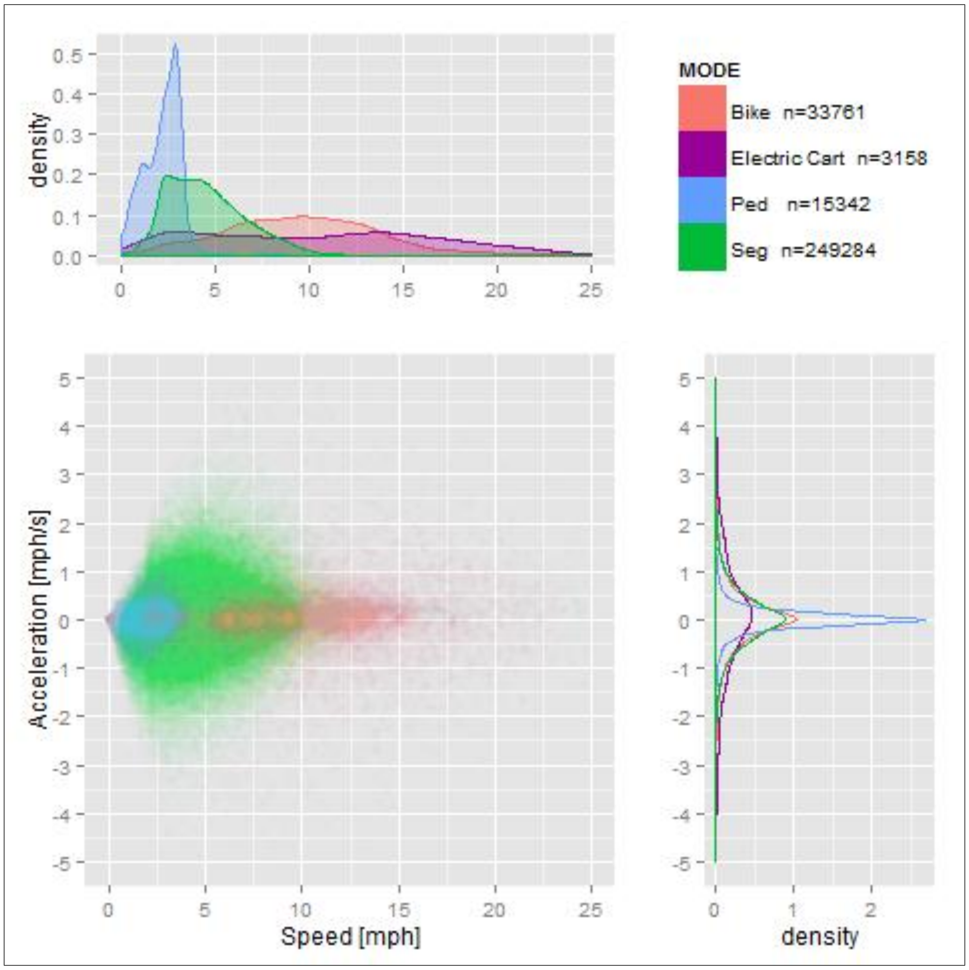


Figure 40. Modal Comparison of Speed and Acceleration

Table 10. Speed Distribution Statistics by Mode [mph]

Mode	Mean	Peak Density	Std Dev
Pedestrian	2.23	2.89	1.03
Segway	4.56	2.43	0.80
Bicycle	9.66	9.67	4.27
Electric Cart	10.72	3.02/14	6.45

Each of these four modes spans four distinct levels of speed. Bicycles were expected to have a speed range slower than electric carts. However, the distribution of Segway speeds seems to fill the gap between pedestrians and bicycles. Since mobility is typically directly related to speed, this could mean that Segways provide a level of mobility that is greater than pedestrian mobility but less than bicycles.

Pedestrians have the most dense acceleration distributions. Segways and bicycles have very similar acceleration distributions, and electric carts have the widest range of accelerations of all the modes.

Results from the KS tests were used to compare speed and acceleration distributions by mode are shown in Table 11 and Table 12. A p-value of less than 0.05 for the KS test indicates that there is evidence to suggest that the two distributions are not the same. Conversely, if the p-value for either test is greater than 0.05, there is not sufficient evidence to say that the distributions are different. In this chapter, these values, indicating there is not enough evidence to suggest that the distributions or means are different, are highlighted in red. Please note that the lowest possible value reported by the ks.test() command within R is 2.2E-16. Whenever "<2.2e-16" is reported, this means that the number is, for all practical purposes, nearly zero.

Table 11. KS Test for Mode Speeds

KS - p	Pedestrian	Segway	Bicycle	Electric Cart
Pedestrian		< 2.2e-16	< 2.2e-16	< 2.2e-16
Segway	< 2.2e-16		< 2.2e-16	< 2.2e-16
Bicycle	< 2.2e-16	< 2.2e-16		< 2.2e-16
Electric Cart	< 2.2e-16	< 2.2e-16	< 2.2e-16	

Table 12. KS Test for Mode Accelerations

KS - p	Pedestrian	Segway	Bicycle	Electric Cart
Pedestrian		< 2.2e-16	< 2.2e-16	< 2.2e-16
Segway	< 2.2e-16		4.656E-10	< 2.2e-16
Bicycle	< 2.2e-16	4.656E-10		< 2.2e-16
Electric Cart	< 2.2e-16	< 2.2e-16	< 2.2e-16	

The KS tests in Table 11 and Table 12 show that all of the modes have significantly different speed and acceleration distributions. With such a large number of observations for each mode, the KS test could suggest significant differences between the distributions even if they were practically similar. However, it is clear from Figure 40 that the speed distributions for each mode are significantly different. The acceleration distributions for bicycles and Segways are the only distributions that are not practically different. The KS test for acceleration in Table 12 returned the highest p-value for the Segway to bicycle comparison. However, it was still very small and resulted in a rejection of the null hypothesis that Segway and bicycle acceleration distributions are the same. Therefore, this research concludes that each of the four modes have significantly different speed and acceleration distributions, but bicycle and Segway accelerations may be similar.

4.3.1 IMS Implications of Modal Speed and Acceleration Comparison

Many types of PMDs are expected to operate within IMS zones. Therefore, it is important to not only understand the performance characteristics of each type of PMD but also how they compare in relation to one another. This information will be valuable in future research predicting future mode share and trip capture of PMD types within IMS zones.

One of the most interesting results of the modal comparison is the speed distribution for Segways. In most instances, speed is directly related to mobility, greater speed equals greater mobility. In an IMS environment, Segways may be able to fill a gap in mobility between walking and biking.

Although electric carts and bicycles did not have significantly different mean speeds, their respective speed distributions show that electric carts can provide a level of mobility greater than bicycles. However, the electric cart speed distribution also shows that electric cart operations are likely different (mainly slower) under heavy pedestrian traffic conditions. This hypothesis is partially explored in Section 4.5 by analyzing Segway speed in relation to pedestrian density and other external factors.

Overall, given the proposed IMS environment described in Section 2.2, the results from the modal comparison imply that IMS zones could use a diverse population of PMDs to provide multiple levels of mobility to the public.

4.4 Segway Test

As described in Section 3.6, Segway operations were tested by the research team during an 8 mile Segway Test trip. Analysis from the seven Segway Test trips shows little difference in the speed and acceleration distributions between participants (Figure 41). Each participant traveled the same path at the same time. The Segway tour guide had slightly higher density of very low or zero accelerations. This could be due to the guide's experience with the Segway leading to more "smooth" travel with less extreme accelerations compounded by the possibility of slightly erratic use by the inexperienced participants due to the novelty of using a Segway for the first time.

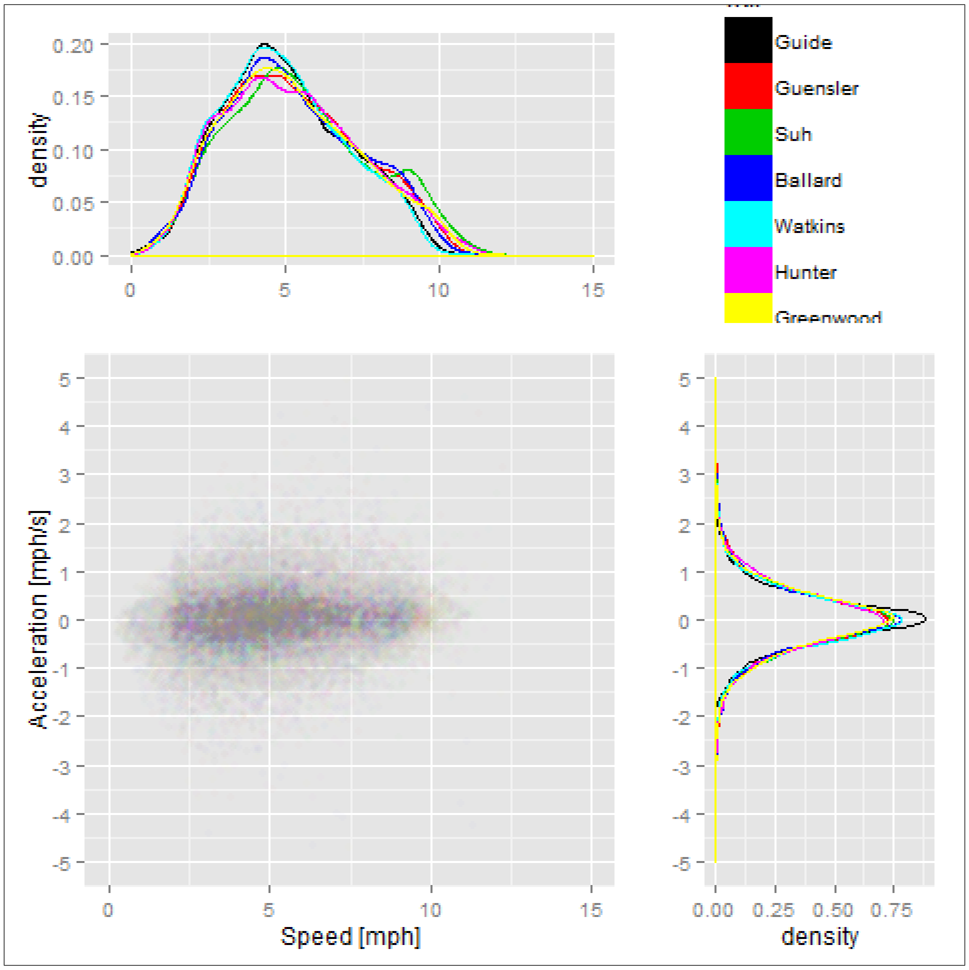


Figure 41. Segway Test Speed and Acceleration

A statistical comparison of the speed distributions for each participant reports that only a few of the speed distributions are actually statistically similar (Table 13). In all practicality, however, all of the speed and acceleration distributions are similar (Table 14).

Table 13. KS Test for Segway Test Speed by Participant

KS - p	Guide	Guensler	Suh	Ballard	Watkins	Hunter	Greenwood
Guide		0.000135	2.56E-11	0.001555	0.1439	1.56E-07	0.001969
Guensler	0.000135		6.50E-05	0.8509	1.14E-08	0.002421	0.613
Suh	2.56E-11	6.50E-05		1.56E-05	5.55E-16	3.28E-07	2.64E-06
Ballard	0.001555	0.8509	1.56E-05		2.78E-07	0.001359	0.3899
Watkins	0.1439	1.14E-08	5.55E-16	2.78E-07		6.73E-12	1.92E-07
Hunter	1.56E-07	0.002421	3.28E-07	0.001359	6.73E-12		0.003027
Greenwood	0.001969	0.613	2.64E-06	0.3899	1.92E-07	0.003027	

Table 14. KS Test for Segway Test Acceleration by Participant

KS - p	Guide	Guensler	Suh	Ballard	Watkins	Hunter	Greenwood
Guide		1.79E-05	0.002172	0.00245	0.000902	3.47E-05	0.000161
Guensler	1.79E-05		0.2474	0.2739	0.118	0.6775	0.126
Suh	0.002172	0.2474		0.4732	0.4523	0.05028	0.1827
Ballard	0.00245	0.2739	0.4732		0.07093	0.4545	0.6867
Watkins	0.000902	0.118	0.4523	0.07093		0.00868	0.01929
Hunter	3.47E-05	0.6775	0.05028	0.4545	0.00868		0.414
Greenwood	0.000161	0.126	0.1827	0.6867	0.01929	0.414	

The data from the guide is the most different form the group. This may suggest that Segway operational behavior varies based on user experience. However, while there a many observations, there were only seven Segway Test trips. A much broader study of Segway users is needed to confirm this theory.

4.4.1 Observations from Segway Test

During the Segway test, the research team observed a number of operational and behavioral characteristics of Segway use in urban areas. It is important to note that all of these observations are anecdotal. First, Segway operation is rather intuitive. Brief instruction and only a few minutes of practice were needed to familiarize each participant with Segway controls and operations. After that, little thought or effort is needed to steer and control the device. Second, Segways are extremely maneuverable. They can turn, accelerate, and decelerate almost as quickly as a pedestrian.

Portions of the trip utilized a bike lane next to car traffic or were on the street where car traffic volumes were small. Due to the height at which one stands on a Segway, the vehicular traffic was not as intimidating as anticipated. While the difference in speed could create safety concerns when mixing with car traffic, Segway users might be expected to comfortably operate their device within an IMS environment where micro-cars were also operating.

The team also noticed that when the Segways were in the large group, many pedestrians moved out of the path of the Segways voluntarily. This could be due to the size of the group or the novelty of encountering a Segway. At one point during the trip, the team split up on the Georgia Tech campus to see how pedestrians responded to a single Segway in their path. While it seemed that pedestrians were less likely change their behavior due to a single Segway than a group of Segways, the Segway test did not provide enough experience or evidence to conclude if pedestrians responded to a single Segway differently than a group of Segways.

When traveling on a Segway, maintaining constant speed is relatively easy and does not require much effort. However, accelerating and decelerating seem to require more thought and physical exertion than when traveling at a constant speed. This may suggest that Segway users have added incentive to smooth their Segway speeds and accelerations as to not accelerate or decelerate abruptly.

An important observation from the Segway test was that Segway trip speed seemed to be influenced by a number of external factors, namely sidewalk or path width, surface quality, and pedestrian density. When sidewalks were very narrow, the team seemed to travel slower in order to safely negotiate the path while when the sidewalk was wide or the Segways were on a roadway, the team tended to travel at top speed. Surface quality and pedestrian density seemed to affect Segway speed similarly.

4.5 Effects of External Factors

During the Segway Test trips, the participants noticed that their speed tended to vary in relation to infrastructure and the surrounding environment. To examine how these factors influenced Segway operations, the team chose three factors for further analysis: sidewalk width, surface quality, and pedestrian density. Each criterion consisted of a three-level categorical ranking system. Sidewalk width was described as narrow, medium, or wide. Surface quality described the quality of the sidewalk or street and its roughness. Surface quality was categorized as poor, medium, or excellent. Pedestrian density represented the amount of pedestrians that could potentially obstruct the Segway path within each segment, and it was rated as light, medium, or heavy.

For this analysis, the small portion of the Segway Test trip that occurred using the lower speed key was excluded. Not only was this portion of the trip skewed due to speed limitations, it was also a "warm-up" period for the participants as they became familiar with Segway operations for the first time.

4.5.1 Sidewalk Width

Sidewalk width is ranked as narrow, typical, or wide. Figure 42 is a spatial representation of trip speed for one of the Segway Test participants. The width of the grey line represents the sidewalk width ranking of narrow, medium, and wide for each part of the route. The colored points create the line of the actual Segway path, and the color of those points symbolizes the speed at that location with red being the slowest and green being the fastest.

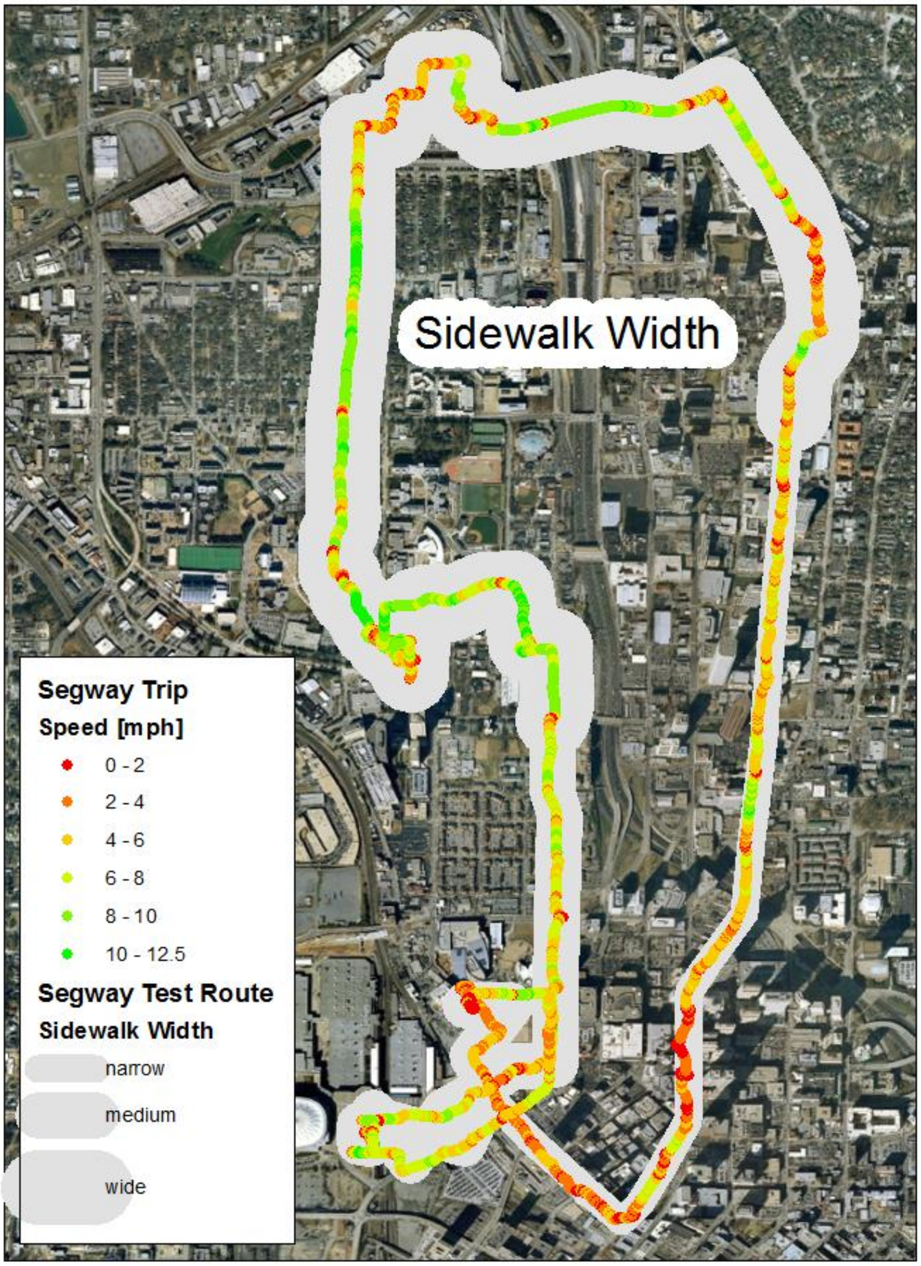


Figure 42. Map of Segway Test Trip Speed by Sidewalk Width

Since each section has periods with low and high Segway speeds, it is difficult to spatially distinguish how much sidewalk width truly affects Segway speed. Figure 43 is a graphical representation of Segway speeds and accelerations for all of the Segway Test trips categorized by the sidewalk width rankings. Narrow sidewalks have the slowest mean speed and the distribution with the smallest range. Sections with typical sidewalk widths have the next highest mean speed and a slightly wider distribution. The wide sections of sidewalk have the greatest mean speed and the widest distribution of all. The speed distribution of wide sidewalks is flat with no distinctive peak. Figure 43 and Table 15 also shows that while speed is clearly affected by sidewalk width, the distributions of accelerations for each ranking are very similar across all sidewalk widths.

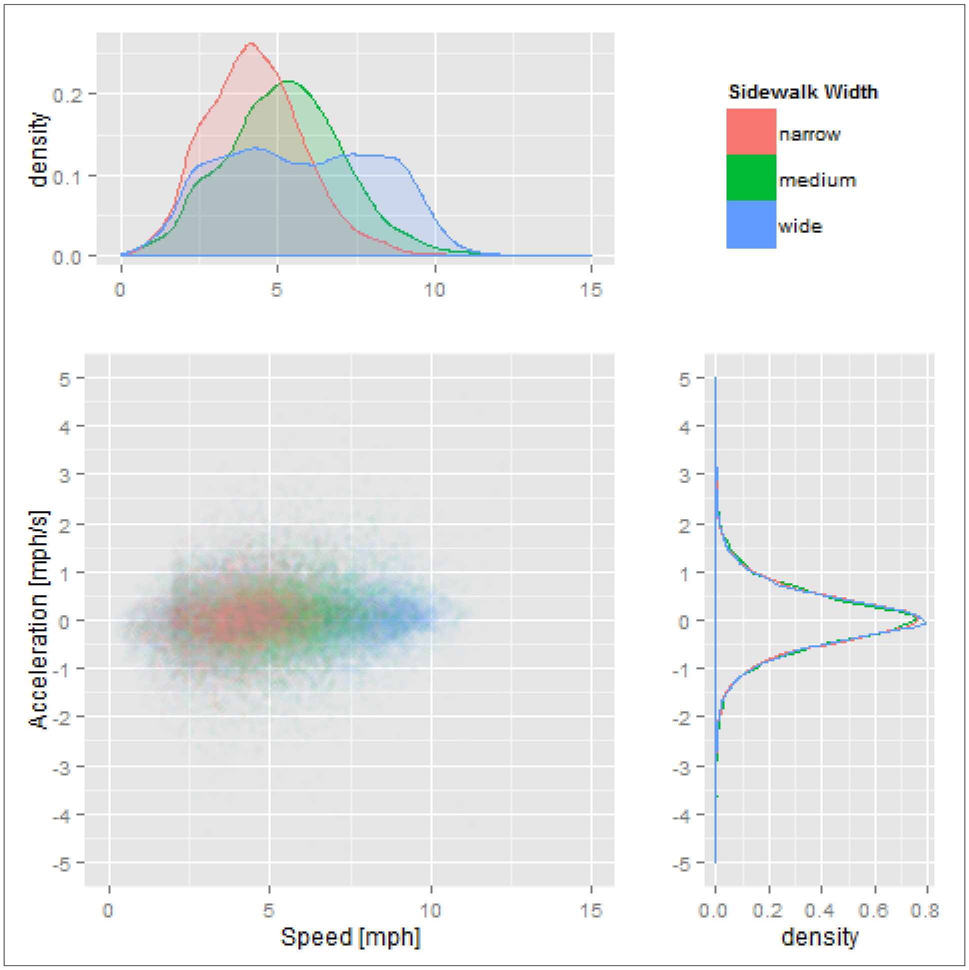


Figure 43. Effect of Sidewalk Width on Segway Speed and Acceleration

Table 15. Sidewalk Width Speed Statistics

Sidewalk Width	Mean [mph]	Peak Density [mph]	Standard Deviation [mph]
narrow	4.28	4.15	1.54
medium	5.21	5.34	1.83
wide	5.75	4.25	2.46

A KS test for differences among sidewalk width Segway speed distributions show that sidewalk width has a very significant effect on Segway speed between each ranking level since each of the p-values is less than 0.05 (Table 16).

Table 16. KS Test for Segway Speed by Sidewalk Width

KS - p	narrow	typical	wide
narrow		< 2.2e-16	< 2.2e-16
typical	< 2.2e-16		< 2.2e-16
wide	< 2.2e-16	< 2.2e-16	

Table 17 suggests that sidewalk width also has a significant effect on Segway acceleration. However, while these differences may be statistically significant because of the very large sample size for each distribution, these differences do not appear to be practically different when viewing Figure 43. Although statistically significant, sidewalk width doesn't practically effect Segway accelerations.

Table 17. KS Test for Segway Acceleration by Sidewalk Width

KS - p	narrow	typical	wide
narrow		0.0002479	0.008265
typical	0.0002479		0.03092
wide	0.008265	0.03092	

4.5.2 Surface Quality

Surface quality was the next factor analyzed. Surface quality describes the "smoothness" or "roughness" of the paved surface for each segment. Broken and cracked sidewalks were ranked poor, while road surfaces or sidewalks in exceptional condition were ranked excellent. Similar to sidewalk width, the effect of surface quality on Segway speeds can be seen both spatially (Figure 44) and graphically (Figure 45).

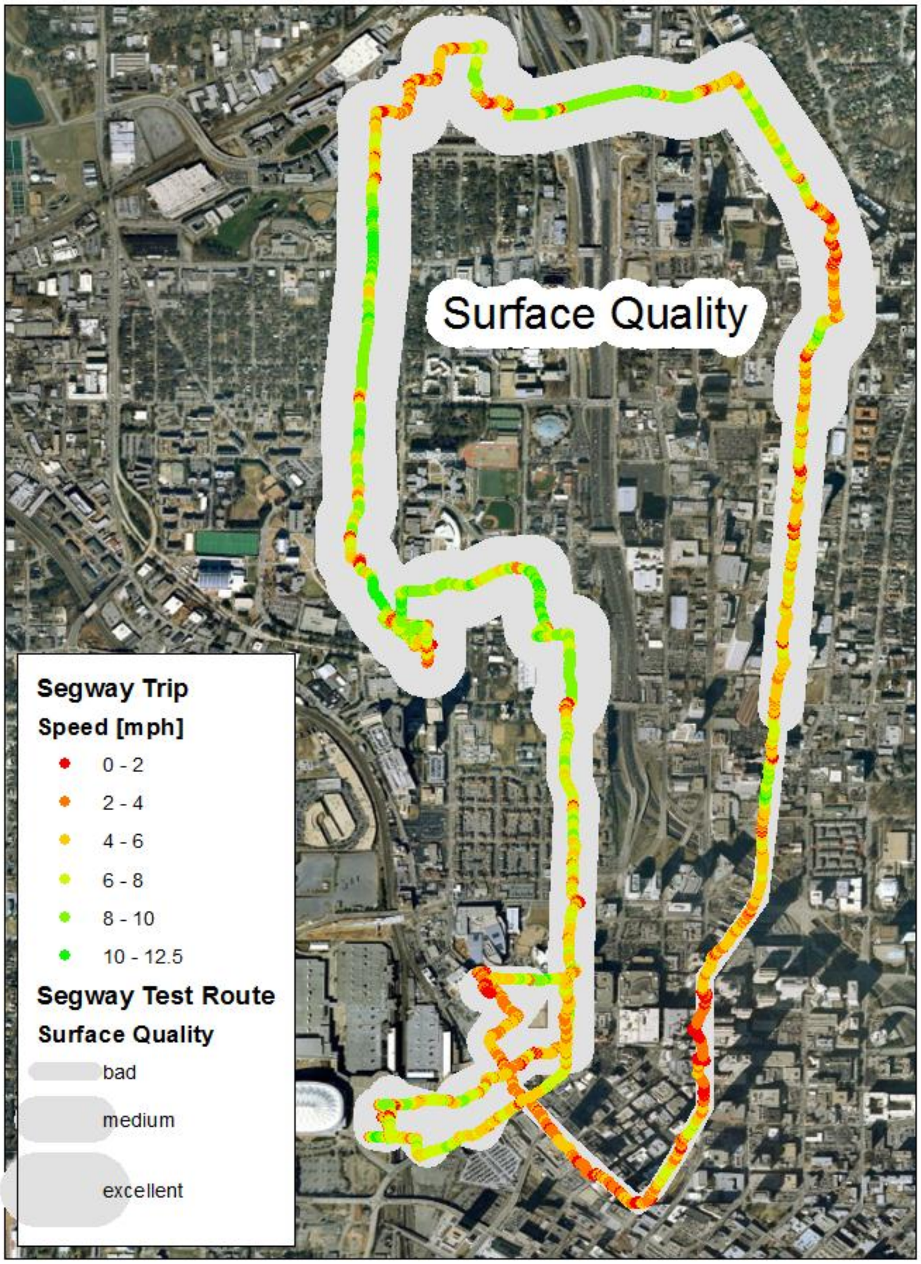


Figure 44. Map of Segway Test Trip Speed by Surface Quality

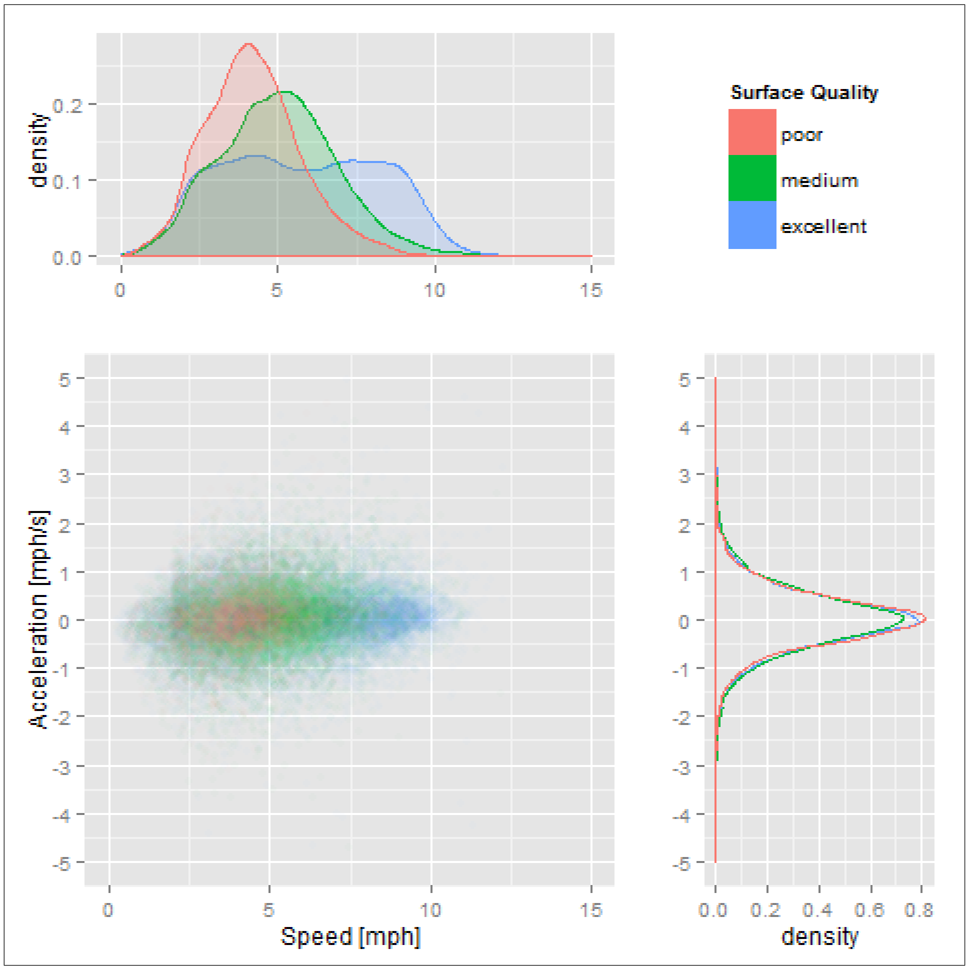


Figure 45. Effect of Surface Quality on Segway Speed and Acceleration

The effect of surface quality on Segway speed and acceleration is nearly identical to that of sidewalk width. The poorest surface quality resulted in the slowest speed while the best surface quality has the greatest speed and widest distribution (Table 18). Also, there is little visible difference between the acceleration distributions for each sidewalk quality rank.

Table 18. Surface Quality Speed Statistics

Surface Quality	Mean [mph]	Peak Density [mph]	Standard Deviation [mph]
poor	4.21	4.06	1.50
medium	5.00	5.13	1.81
excellent	5.75	4.25	2.46

The KS test (Table 19) for Segway speed reveals that the distribution for Segway speed differed significantly between the surface quality rankings, meaning that surface quality significantly affected Segway speed. Also like sidewalk width, the KS test for acceleration distribution (Table 20) shows that there are statistical differences between each of the distributions. However, Figure 45 shows that there is no practical difference between the acceleration distributions based on surface quality.

Table 19. KS Test for Segway Speed by Surface Quality

KS - p	poor	typical	excellent
poor		< 2.2e-16	< 2.2e-16
typical	< 2.2e-16		< 2.2e-16
excellent	< 2.2e-16	< 2.2e-16	

Table 20. KS Test for Segway Acceleration by Surface Quality

KS - p	poor	typical	excellent
poor		1.10E-11	2.74E-06
typical	1.10E-11		0.001798
excellent	2.74E-06	0.001798	

Overall, there is evidence to suggest that surface quality may affect Segway speed but not acceleration. Poor quality surfaces or pavements are likely to inhibit Segways from traveling at top speeds because the Segway device has no suspension and is very sensitive to disconformities in the pavement surface.

4.5.3 Pedestrian Density

The final category for Segway speed and acceleration analysis was pedestrian density. Just like the two prior categories, Figure 46 and Figure 47 depict the spatial and graphical distribution of Segway speed and acceleration, respectively.

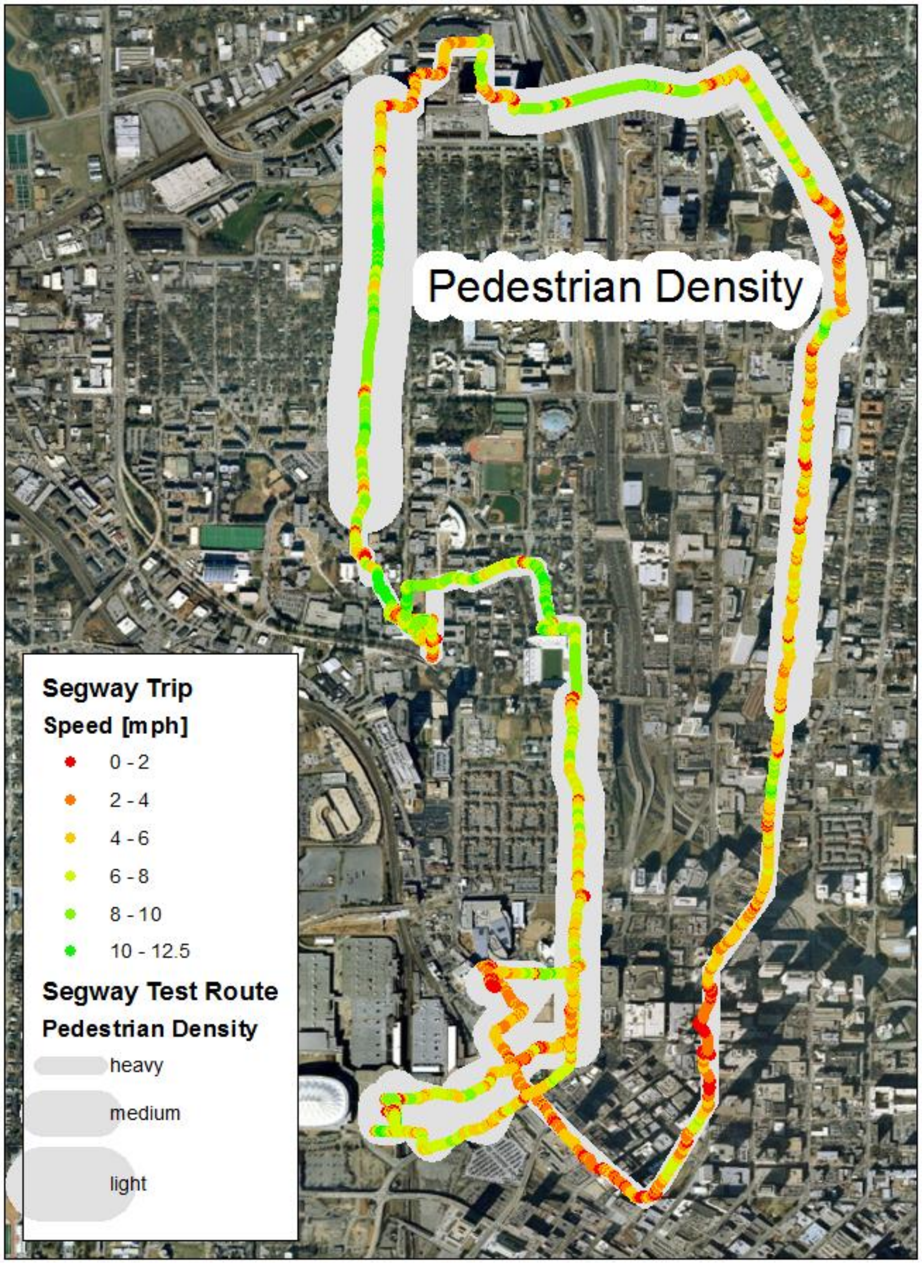


Figure 46. Map of Segway Test Trip Speed by Pedestrian Density

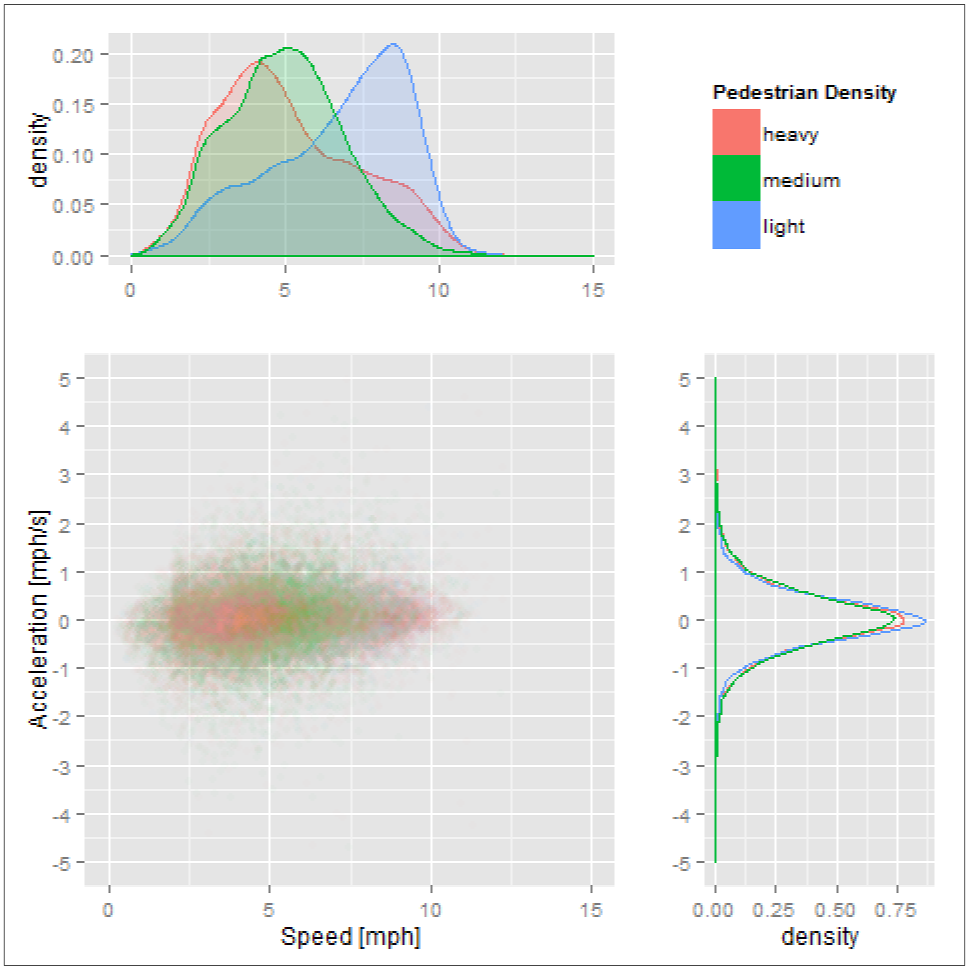


Figure 47. Effect of Pedestrian Density on Segway Speed and Acceleration

Pedestrian density appears to affect Segway speed slightly differently than the previous categories. Heavy and medium pedestrian densities produce similar Segway speeds with means of approximately 5 mph. Although the peak density for medium Pedestrian Density is 1 mph greater than that of heavy pedestrian density (Table 21), both speed distributions have similar densities for those peaks and similar tails for higher speeds. Light pedestrian density has the greatest mean speed and a very different distribution. The peak density speed is 8.5 mph (Table 21) and the distribution has a tail trailing to lower speeds rather than higher. This suggests that in light pedestrian density, Segways are able to operate at a free-flow rate of speed.

Table 21. Pedestrian Density Speed Statistics

Pedestrian Density	Mean [mph]	Peak Density [mph]	Standard Deviation [mph]
heavy	5.122	4.094	2.293
medium	4.977	5.044	1.882
light	6.721	8.515	2.224

Again, the KS tests (Table 22 and Table 23) for Segway speed and acceleration show that there are significant differences between the distributions for each rank. Also once again, the distributions of Segway accelerations were practically the same even though Table 23 shows that the KS test for acceleration resulted in statistical differences between the distributions.

Table 22. KS Test for Segway Speed by Pedestrian Density

KS - p	heavy	moderate	light
heavy		< 2.2e-16	< 2.2e-16
moderate	< 2.2e-16		< 2.2e-16
light	< 2.2e-16	< 2.2e-16	

Table 23. KS Test for Segway Acceleration by Pedestrian Density

KS - p	heavy	moderate	light
heavy		9.18E-05	0.03425
moderate	9.18E-05		5.54E-05
light	0.03425	5.54E-05	

Sidewalk width and surface quality seem to affect Segway speed very similarly or may be correlated, and while the trend is similar for pedestrian density, the speed distribution for each of the pedestrian density ranks is very different from sidewalk width and surface quality. As sidewalk width and surface quality conditions become more favorable for higher speeds, the speed distributions for each category become more flattened. However, as pedestrian density becomes lighter, the speed distributions do not become more flat but retain a similar peak that is at a higher speed. This may imply that pedestrian density has the greatest influence on Segway speed of these three categories.

4.5.4 External Factors Interaction

Given that there are three categories of external factors and three ranks for each category, a total of 27 combinations of external factor ranks are possible. Unfortunately, the segment selection and ranking for the Segway Test were post hoc, and only six unique combinations of external factor rankings are available. Therefore, only a small number of interaction scenarios can be tested. Table 24 shows the external factor rankings for each segment of the Segway Test

Table 24. Segway Test Segment External Factor Characteristics

Segment	Color	Sidewalk Width	Surface Quality	Pedestrian Density
1	Green	narrow	bad	heavy
2	Blue	narrow	medium	medium
3	Red	wide	excellent	medium
4	Purple	wide	excellent	heavy
5	Yellow	wide	excellent	light
6	Pink	wide	excellent	heavy
7	Maroon	medium	medium	medium

Unfortunately, most of the segments had wide sidewalk width and excellent surface quality. However, across those segments, pedestrian density varied. Figure 48 shows the speed and acceleration plots for pedestrian density when sidewalk width is wide and surface quality is excellent. Once again, acceleration is not affected. Speed is affected by pedestrian density when on wide sidewalks with excellent pavement. In this case, the speed distributions for heavy and medium pedestrian density are similar while the light pedestrian density has much higher speeds.

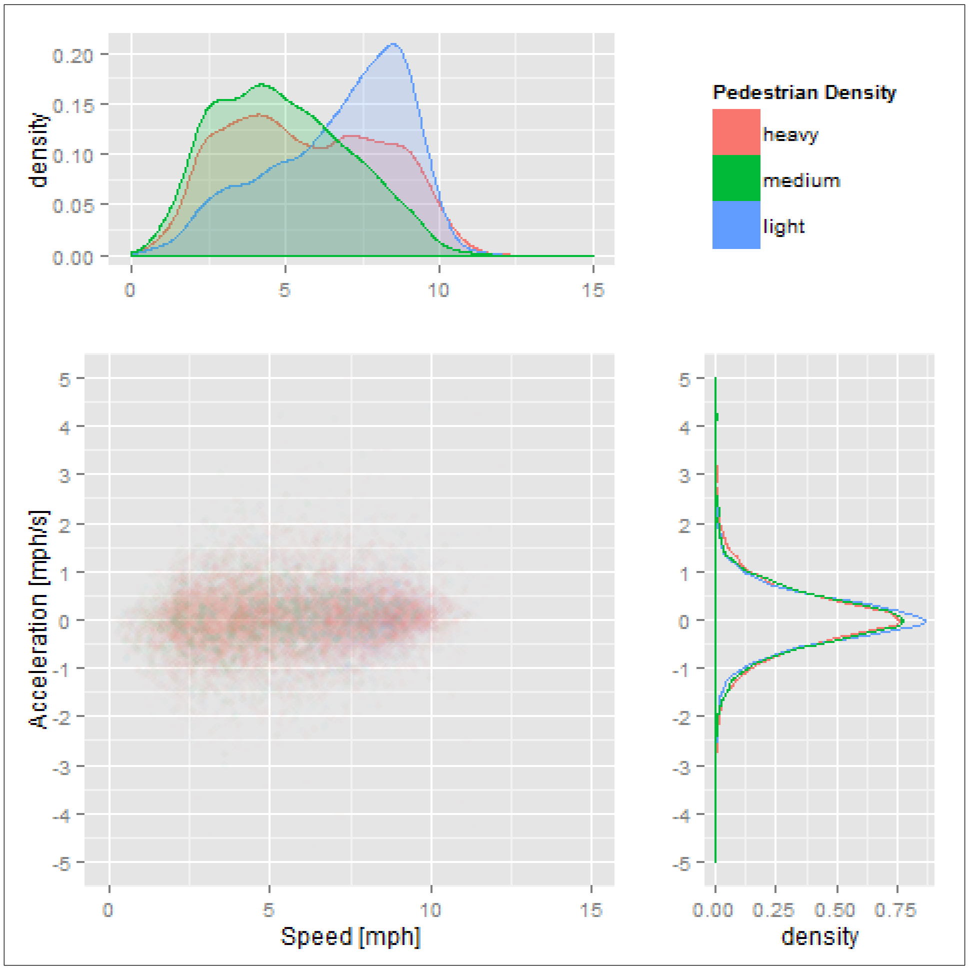


Figure 48. Segway Test Speed and Acceleration by Pedestrian Density on Wide Sidewalk with Excellent Surface Quality

When sidewalks are narrow, there is little difference between speed distributions for heavy and medium pedestrian densities (Figure 49). This is not surprising since just one pedestrian on a narrow sidewalk can block the path of a Segway, slowing it down significantly. Unfortunately no data is available for light pedestrians on a narrow sidewalk, allow for not evaluate of the interaction between these parameters.

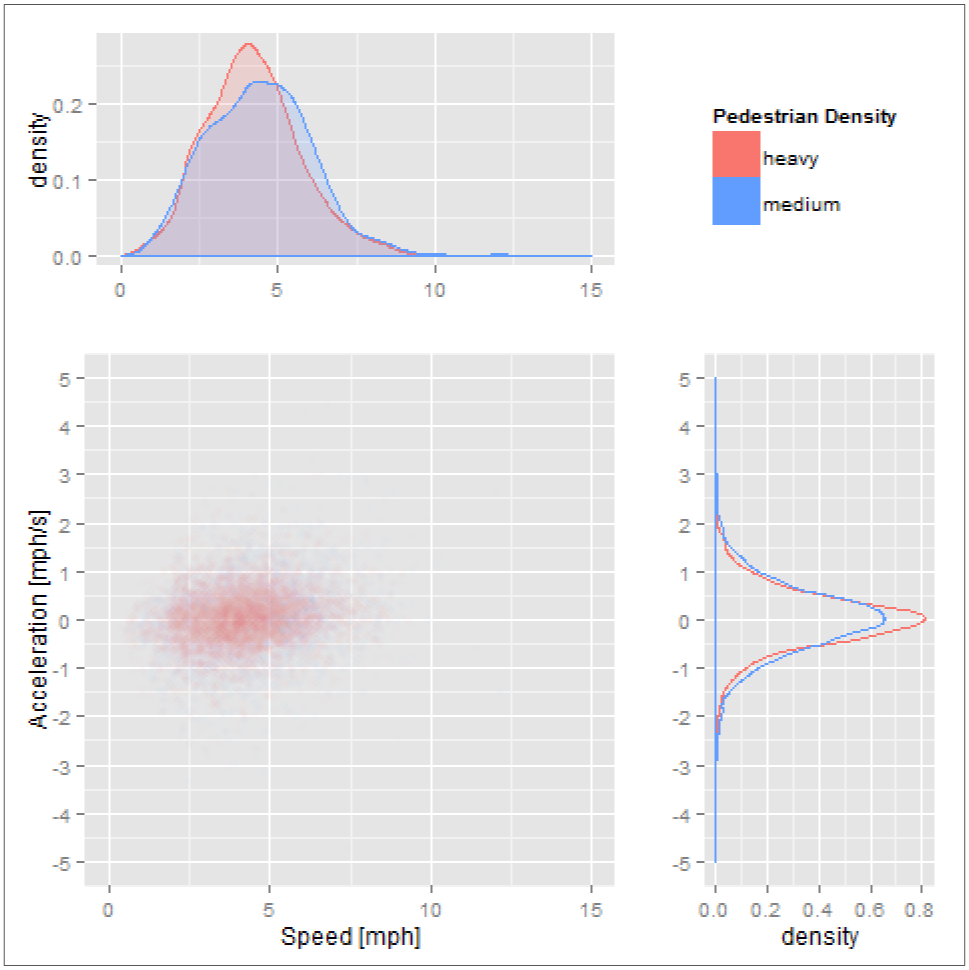


Figure 49. Segway Test Speed and Acceleration by Pedestrian Density on Narrow Sidewalk

The final interaction analysis compares the speed and acceleration distributions for sidewalk width when pedestrian density is heavy. Figure 50 shows that the combination of many pedestrians and narrow sidewalks results in low speeds while wide sidewalks produce a wide range of speeds when many pedestrians are present. This suggests that where the sidewalk or path is wide enough, Segways can maneuver around crowds and maintain higher speeds in places but may still be slowed by very large crowds.

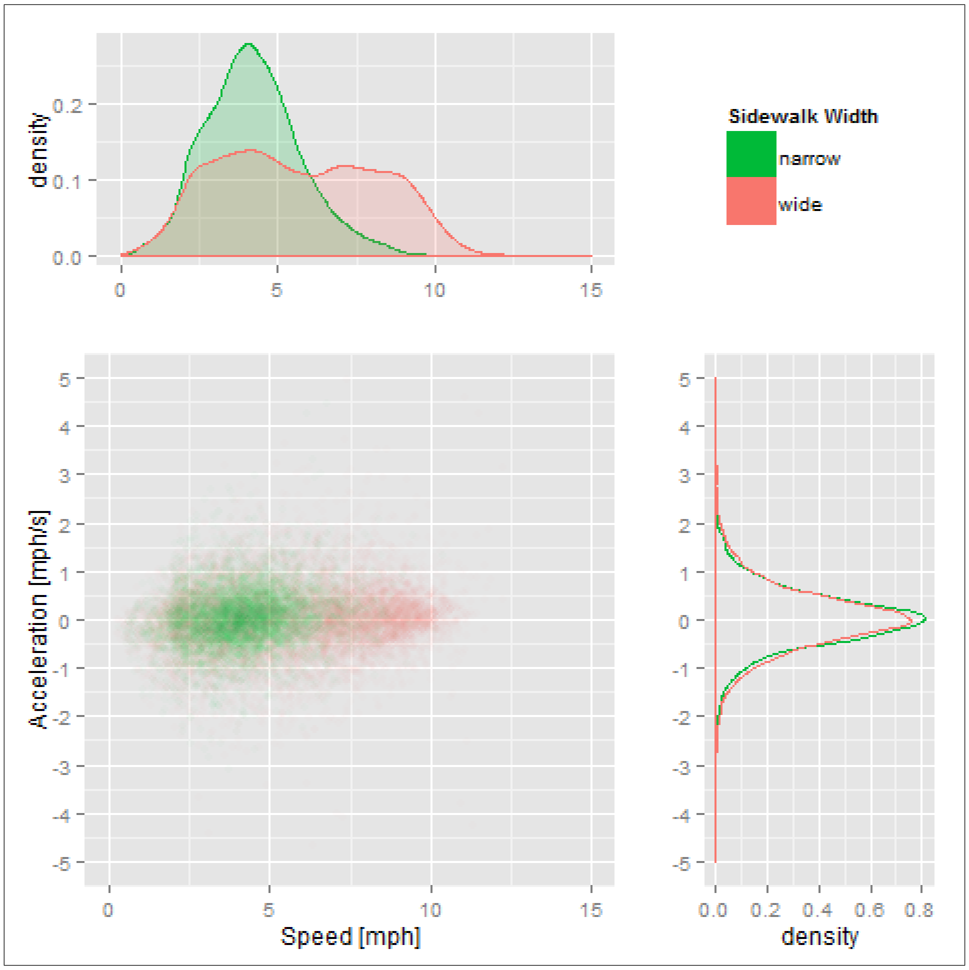


Figure 50. Segway Test Speed and Acceleration by Sidewalk Width with Heavy Pedestrian Density

4.5.5 IMS Implications of External Factors

Each of the categories appears to significantly influence Segway speed. Wide sidewalks, excellent pavements, and light pedestrian densities result in the highest Segway speeds. While there is likely some interaction between these three factors, this research was unable to test for all of them. However, the research team suspects that even if there is ample sidewalk space and the surface is of excellent quality, speeds will likely still be low if there are heavy pedestrian densities. Similarly, if there are no pedestrians but the surface is very rough, Segway speeds will likely be constrained. The researchers suspect that surface quality is likely an independent constraint for Segway speed and that sidewalk width and pedestrian density interact to limit Segway speeds under certain conditions although additional data is clearly necessary to fully explore these parameters.

Segway acceleration characteristics appear independent of external factors. This means that Segway users accelerate and decelerate similarly despite these external factors and that Segway users experience a similar number of acceleration events regardless of the external situation. Segway users likely smooth their speed to a desirable level given the external factors so that they are required to accelerate or decelerate as infrequently as possible. For example, if a surface is rough with many bumps or cracks, the Segway user may slow to a speed sufficiently slow for the surface characteristics rather than travel faster between bumps or cracks and then slow abruptly at each of them. Similarly, when in a large crowd of pedestrians, Segway users may travel at speeds similar to pedestrians to avoid speeding up and slowing down excessively when navigating through the crowd. Sidewalk Width seems to affect Segway speed, but the speed reduction may be related to obstructions along the path. Theoretically, narrow sidewalks with no obstructions should not greatly impede Segway speed. However, when encountering an obstruction such as a large pavement crack or some pedestrians, a narrow sidewalk would force the Segway to slow down or even stop to navigate around or over the obstruction. Similarly, wide sidewalks or paths provide greater space to maneuver, requiring a greater number of obstructions to significantly influence Segway speed.

CHAPTER 5

CONCLUSIONS, LIMITATIONS, & FUTURE RESEARCH

5.1 Conclusions

The purpose of this study was to explore PMD operations and analyze PMD performance characteristics for use as inputs in future simulation modeling. GPS recorders were used to observe speed and acceleration data from four transportation modes that would likely be used in an IMS system: pedestrians, Segways, bicycles, and electric carts. The data were then filtered to smooth the data and remove random GPS errors. Idle observations were excluded so as to analyze only the performance characteristics during mobile operations.

Pedestrians had the lowest mean speed and the most narrow speed distribution. Segways had the next lowest mean speed followed by bicycles and then electric carts. As the mean speed increased with each mode, so did the range and standard deviation. Electric carts had a bimodal speed distribution that likely occurred due to a large number of both unobstructed free flow speeds when driving on a roadway and other observations from parts of the trips that occurred on mixed-use paths among a large number of pedestrians that exhibited much slower speeds. Pedestrians had the smallest range of accelerations while electric carts had the widest. Segways and bicycles had very similar acceleration distributions.

Another important finding from the modal comparison is that Segways seem to provide a level of speed and mobility between that of pedestrians and cyclists. During the Segway testing, the research team also found that Segways are maneuverable and easy to use. All of this could mean that Segways could capture new users by providing a level of mobility and convenience previously unseen.

The Segway trip speed seemed to be influenced by a number of external factors, namely sidewalk width, surface quality, and pedestrian density. Analysis showed that each of these factors appear to influence Segway speed. Narrow sidewalk widths, poor sidewalk quality, and heavy pedestrian density all decreased Segway speeds. Unfortunately, the segments of the Segway Test were ranked by these three categories after the test was completed and only six of 27 possible ranking combinations were analyzed. However, the research team suspects that even if there is ample sidewalk space and the surface is of excellent quality, speeds will likely still be low if there are heavy pedestrian densities. Similarly, if there are no pedestrians but the surface is very rough, Segway speeds may be constrained. The researchers suspect that surface quality is likely an independent constraint for Segway speed and that sidewalk width and pedestrian density interact to limit Segway speeds under certain conditions. There may also be interaction between sidewalk width and surface quality.

Ultimately, this research will help create a simulation model of PMDs in an IMS environment. The speed and acceleration distributions for each PMD mode can be used to create probability density functions for desired speed and acceleration assignment within agent-based models. However, more study will be needed to create new behavior models for each type of PMD.

5.2 Limitations

Since there are currently no IMS zones in existence, none of the data collected is a perfect representation of PMD operations within the IMS context. PMDs and pedestrians may behave and operate differently under IMS conditions than in the observations from this research. However, since much of the PMD speed and acceleration data were collected on or near the Georgia Tech Campus or dense urban areas in Atlanta, it is likely many of the results are transferrable.

Another limitation of this research is that there are a limited number of PMD trips and users for all modes, especially electric cart. Since it is unclear if PMD operational behavior is uniform across the user population, a larger sample of users is necessary to validate the findings in this research. Also, although there are a large number of Segway observations, they are all from tour or patrol trips. Segway commute trips, especially in dense urban areas, would be more representative of the vision of IMS zone operations in this research.

The external factor testing is limited by three things: 1) the segments were selected and ranked after the trips were already completed, 2) the segments were ranked qualitatively and subjectively rather than quantitatively, and 3) only six of the 27 possible combinations of external factor rankings were tested, greatly reducing the ability to test for interactions between the factors. Despite these limitations, the analysis shows that the three external factors examined here, sidewalk width, surface quality, and pedestrian density, may impact PMD operations and performance. Additional data for a more varied range of conditions and individuals and more quantitative approach to studying the effect of external factors on PMD operations is important to better understand these relationships in the future.

Other factors, such as weight and weather conditions, were not considered in this analysis although they may also be important factors influencing PMD operation. More importantly, PMD use was not studied from a behavioral perspective. Although PMD use and IMS zones may be feasible in terms of operation, this research did not study user behavior.

5.3 Future Research

Ultimately, the success of IMS zones will rely on their ability to provide society with a level of mobility for short and medium range trips equal to or greater than that currently achieved by cars. Therefore, it is imperative that researchers and transportation planners understand PMD operations and performance characteristics, PMD user behavior, and the effects that external factors have on PMD speed and mobility.

First, more PMDs need to be studied to analyze the differences in their operations and performance characteristics. IMS zones will support a variety of transportation, and to operate such a complex system will require very detailed and very accurate information about the operational capabilities of each device.

There are few ways to further study how external factors influence PMD operations. First, PMDs need to be tested under more controlled and quantitatively documented circumstances. For this study, external factors were selected and ranked qualitatively for large segments. More analysis is needed at a finer resolution. Also, multiple types of PMDs need to be tested as well. Finally, testing more combinations of external factors should provide analysis for all of the possible interactions between these factors. All of this would help researchers better understand how external factors will impact PMD operations, mobility, and user behavior, thus yielding more substantive expectations about IMS feasibility in the future.

Since many of the PMDs expected for use in IMS zones are still novel or rarely used for personal commutes, further research is needed about user behavior. Two studies could achieve this goal. First, a detailed study of PMD operational behavior within an IMS type of environment would document PMD following behavior, turning movements, and navigation in a dynamic environment. This research could then be the basis for the development of new PMD operational behavior models for simulation purposes.

Lastly, another study would analyze PMD user trip behavior. A Segway or other type of PMD could be given to a participant for their use over a number of weeks. The user could complete a trip journal about their PMD trips. This would give researchers valuable information about when and why people would use PMDs instead of other modes. All of this information, in conjunction with the other recommended research, could be used to create a simulation model of an IMS environment.

Ultimately, this thesis serves as a starting point for IMS research. IMS environments may one day provide a sustainable transportation system. Much more research and knowledge will be required to achieve successful PMD integration and IMS implementation. Maybe one day people will leave their homes and travel to work via micro-vehicles or some PMD yet to be invented. May this be a small step towards a more sustainable future in human mobility.

APPENDIX A

EXAMPLES OF EXTERNAL FACTORS INFLUENCING SEGWAY OPERATIONS

Figure 51. Heavy Pedestrian Density, Wide Sidewalk, and Excellent Surface Quality

Figure 52. Medium Pedestrian Density, Wide Sidewalk, and Excellent Surface Quality

Figure 53. Light Pedestrian Density, Excellent Surface Quality

Figure 54. Medium Pedestrian Density, Narrow Sidewalk Width, Medium Surface Quality

Figure 55. Medium Pedestrian Density, Narrow Sidewalk Width

Figure 56. Poor Sidewalk Quality

APPENDIX B

RESULTS OF DATA COLLECTION METHOD VALIDATION TESTING

B.1 Lab Test

Walk

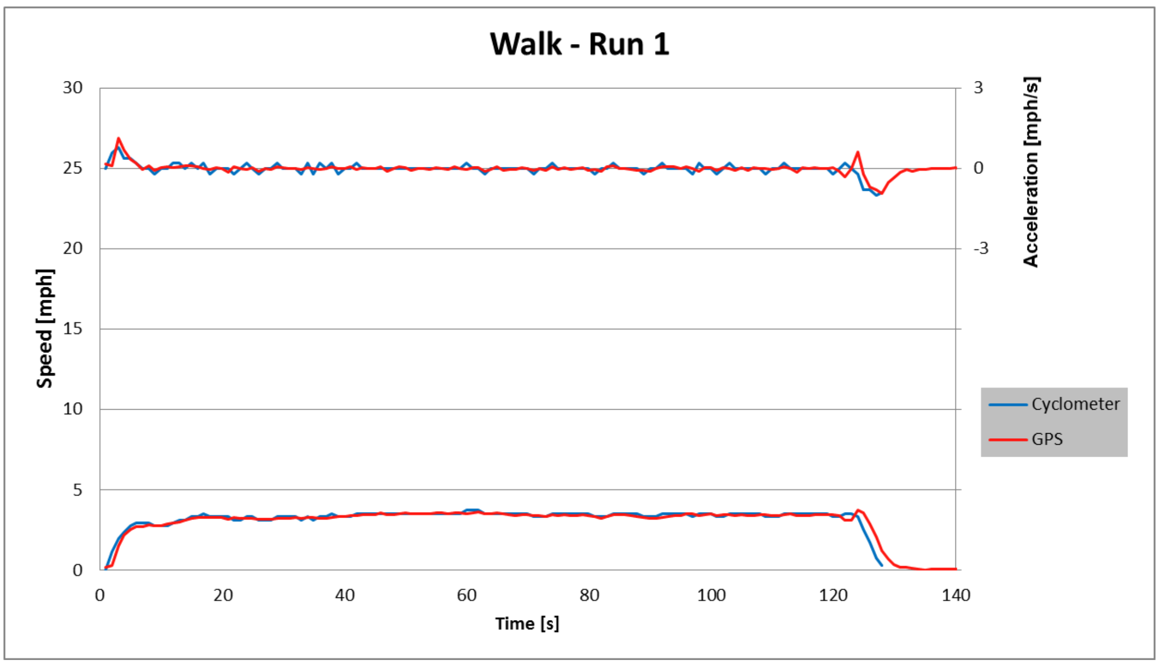


Figure 57. Lab Test Speed and Acceleration – Walk 1

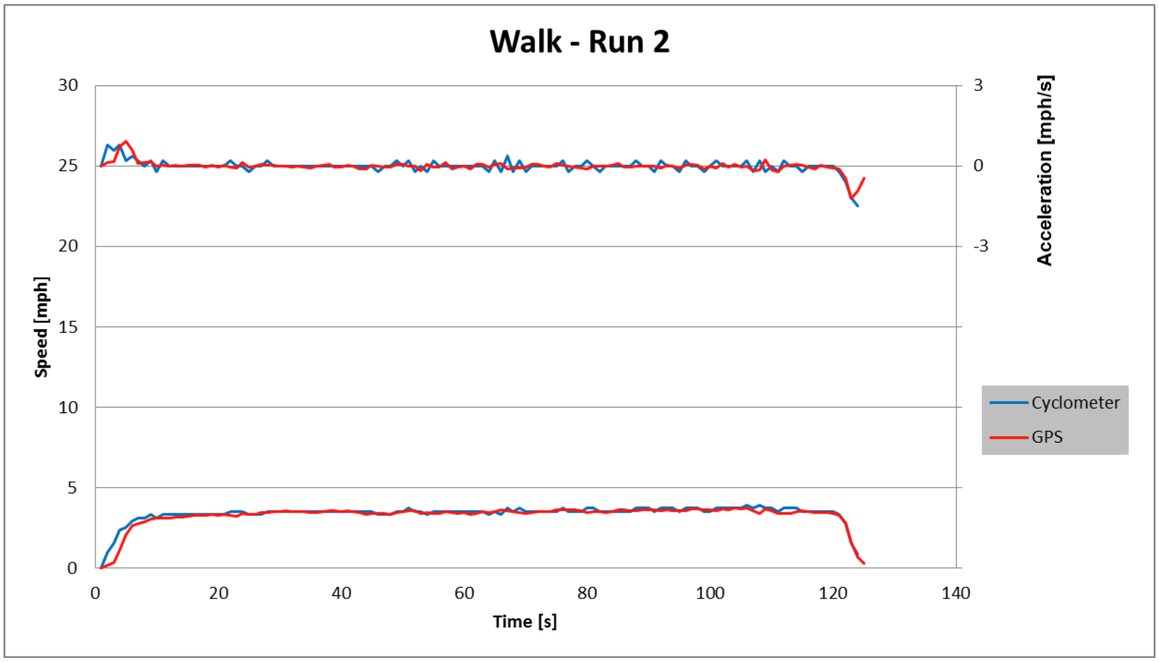


Figure 58. Lab Test Speed and Acceleration – Walk 2

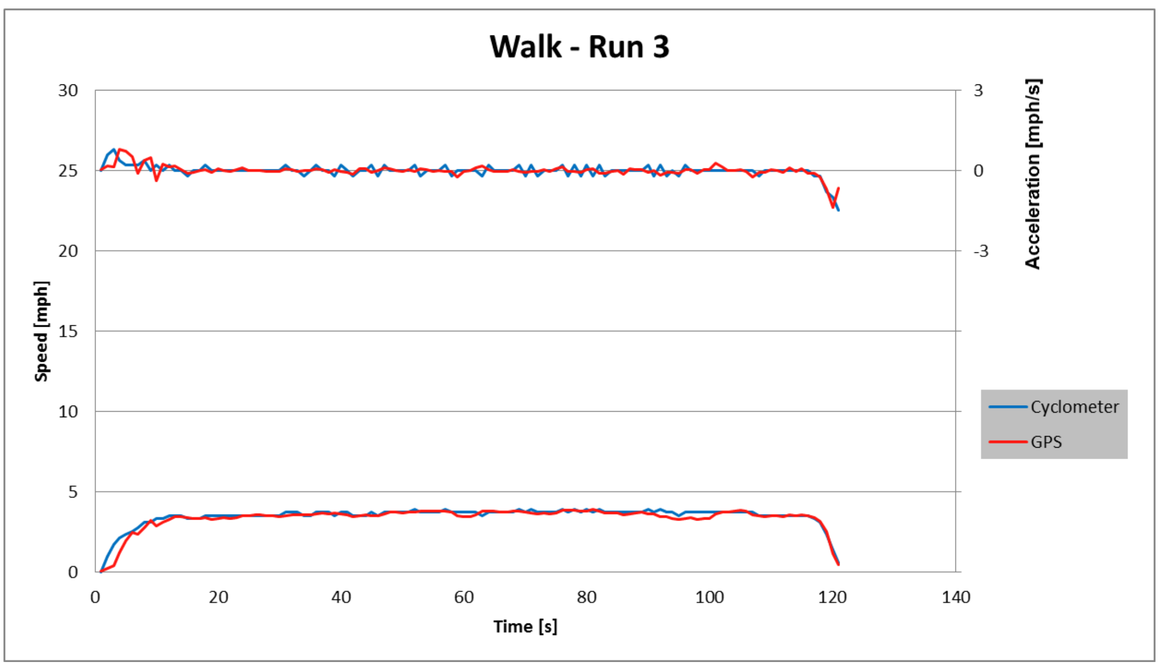


Figure 59. Lab Test Speed and Acceleration – Walk 2

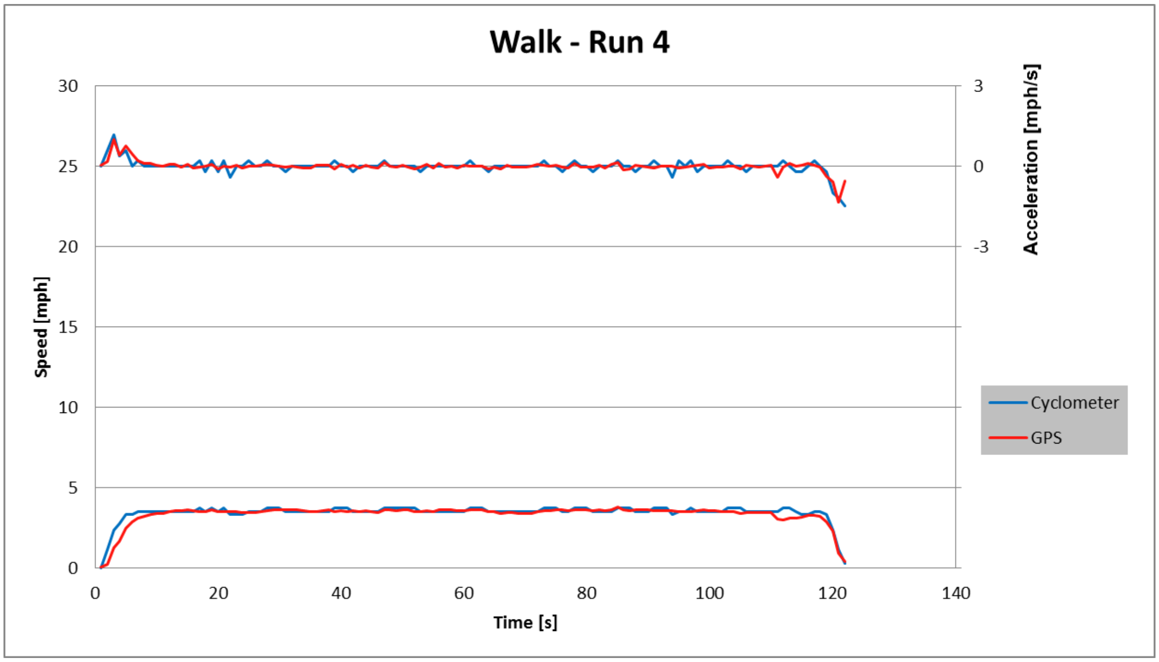


Figure 60. Lab Test Speed and Acceleration – Walk 4

Figure 61. Lab Test Speed and Acceleration – Walk 5

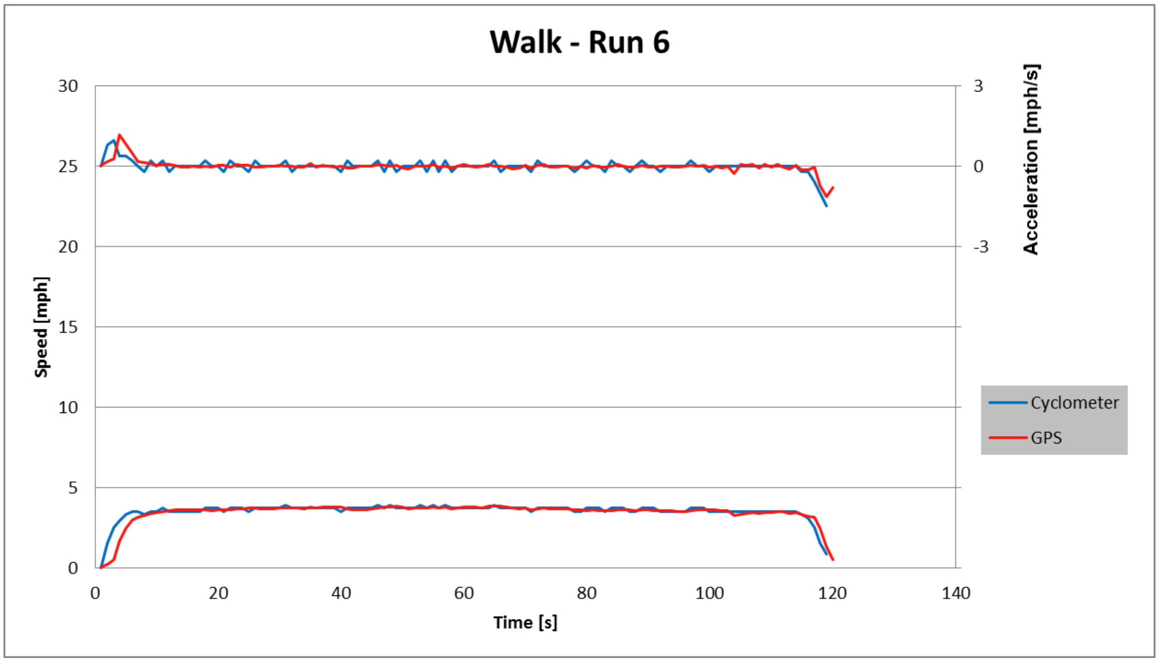


Figure 62. Lab Test Speed and Acceleration – Walk 6

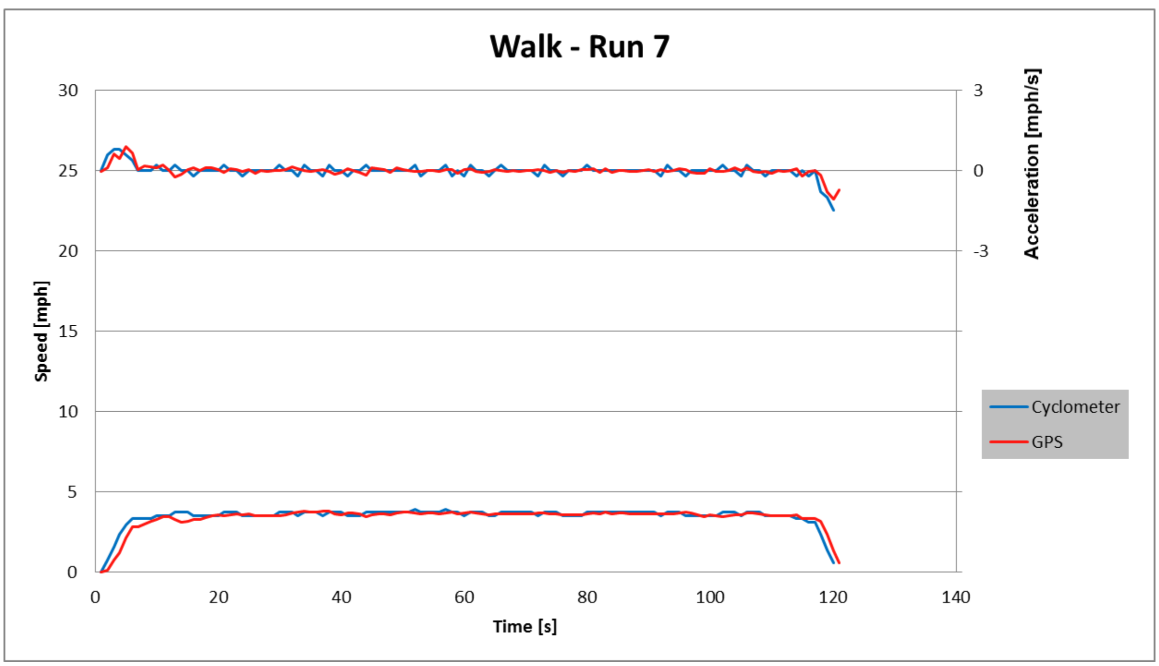


Figure 63. Lab Test Speed and Acceleration – Walk 7

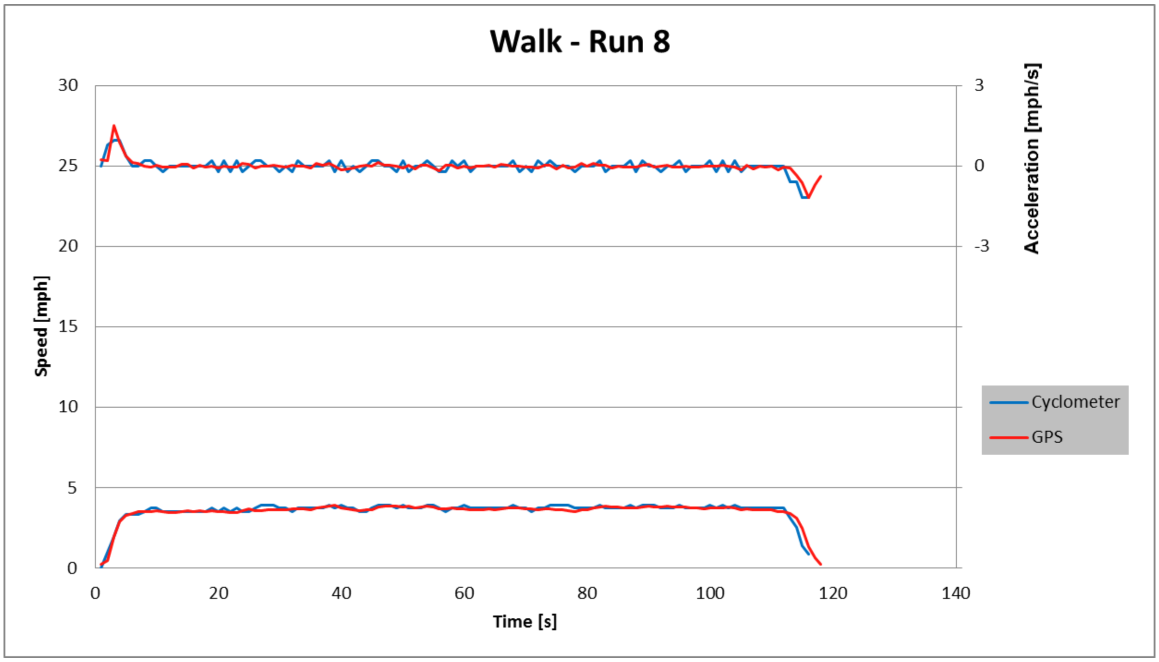


Figure 64. Lab Test Speed and Acceleration – Walk 8

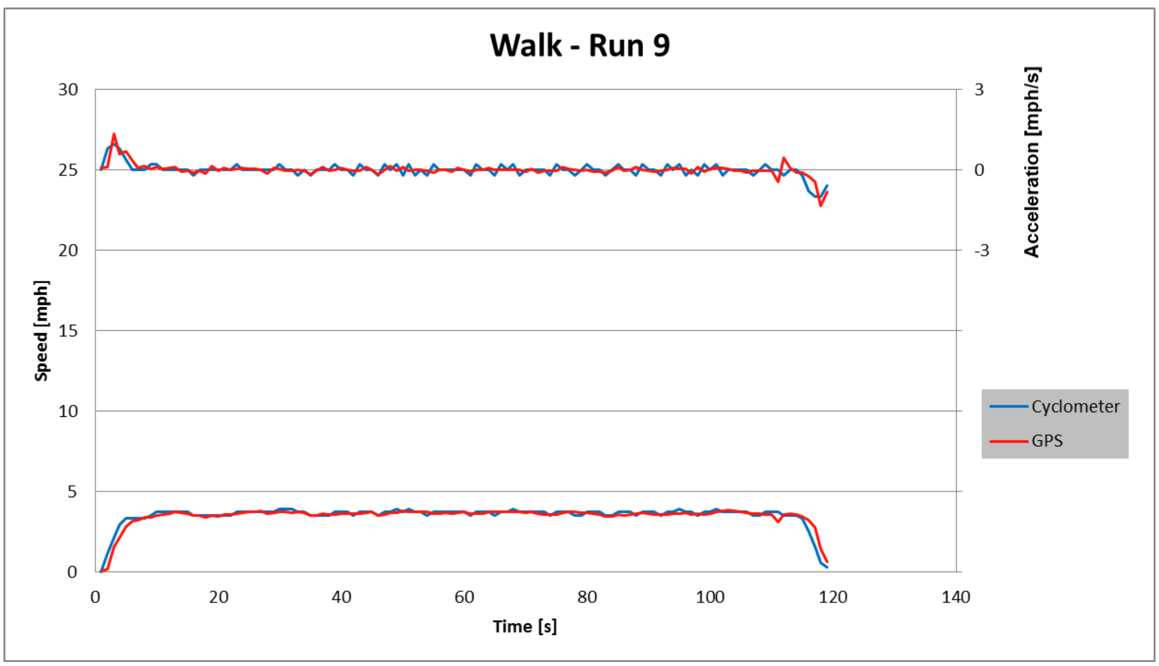


Figure 65. Lab Test Speed and Acceleration – Walk 9

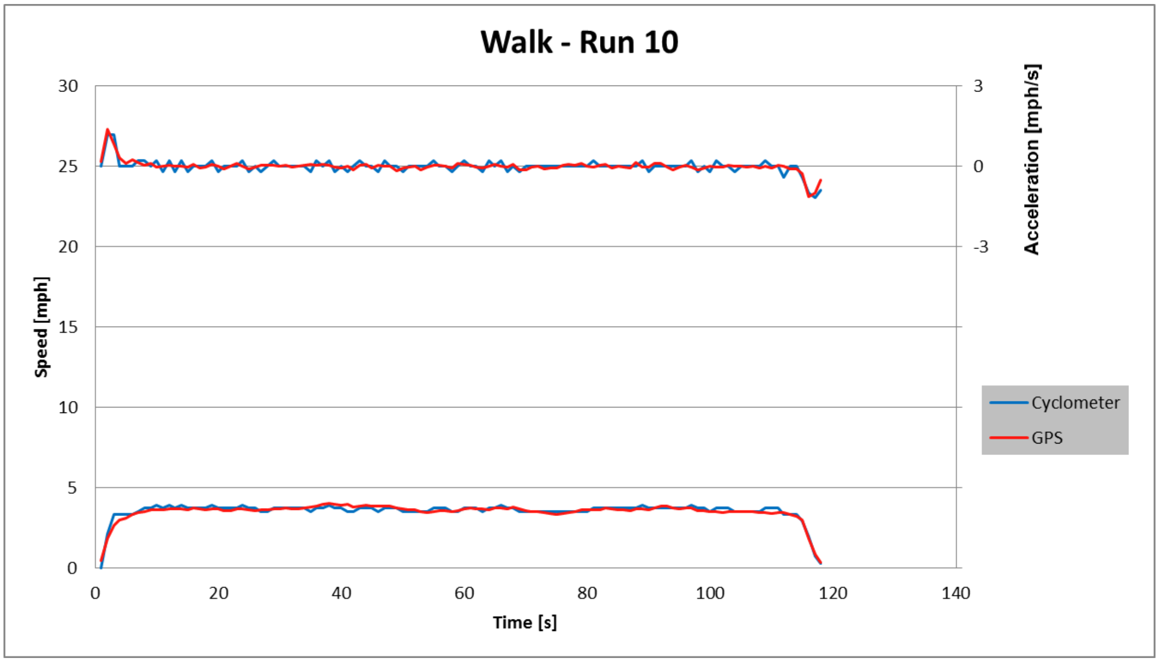


Figure 66. Lab Test Speed and Acceleration – Walk 10

Coast

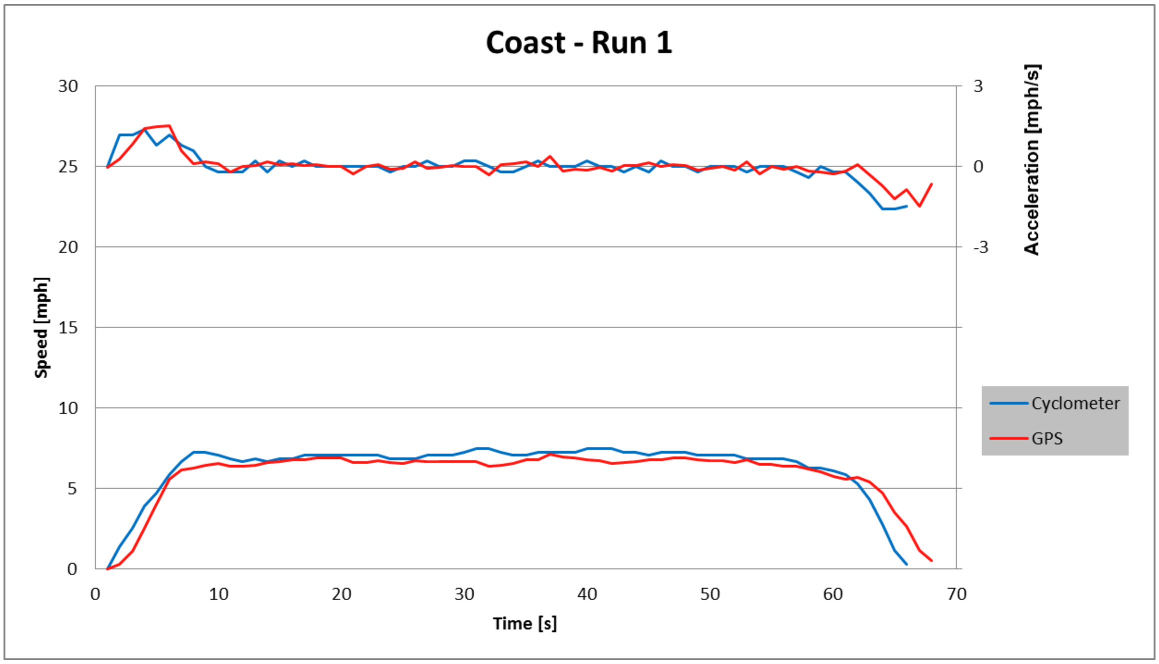


Figure 67. Lab Test Speed and Acceleration – Coast 1

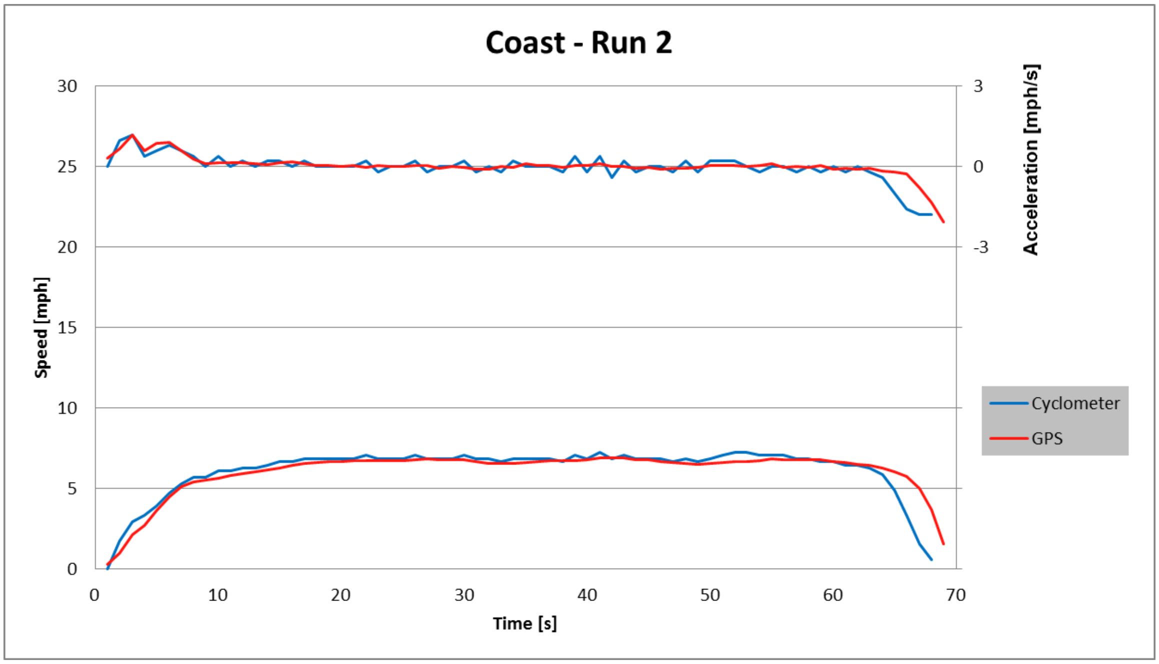


Figure 68. Lab Test Speed and Acceleration – Coast 2

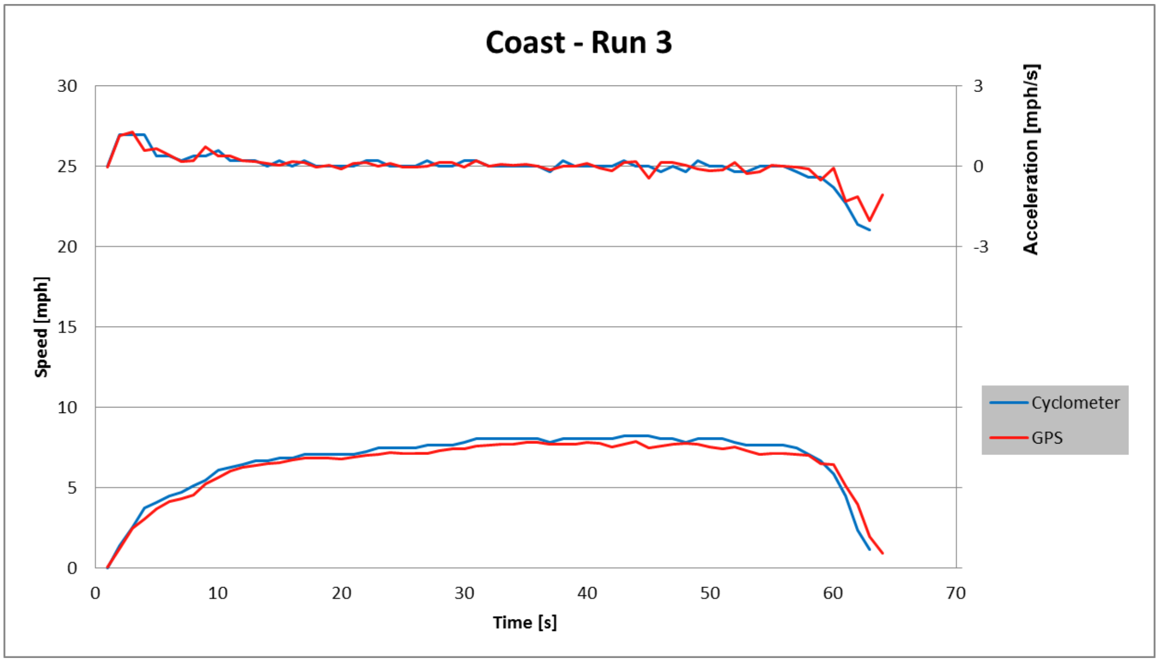


Figure 69. Lab Test Speed and Acceleration – Coast 3

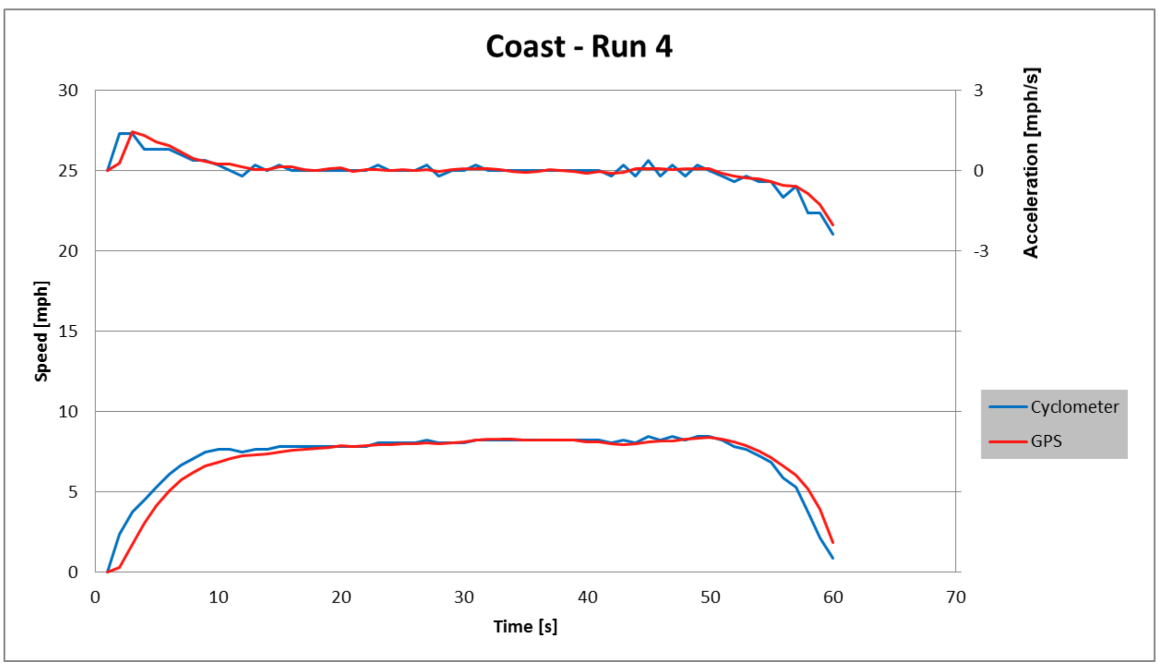


Figure 70. Lab Test Speed and Acceleration – Coast 4

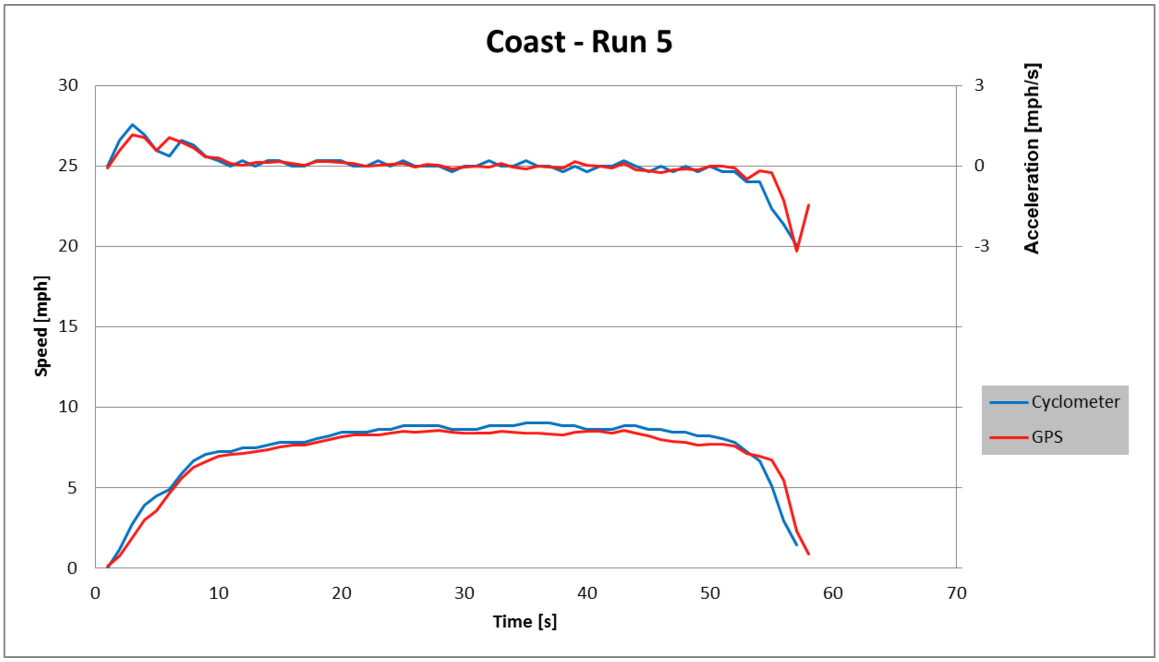


Figure 71. Lab Test Speed and Acceleration – Coast 5

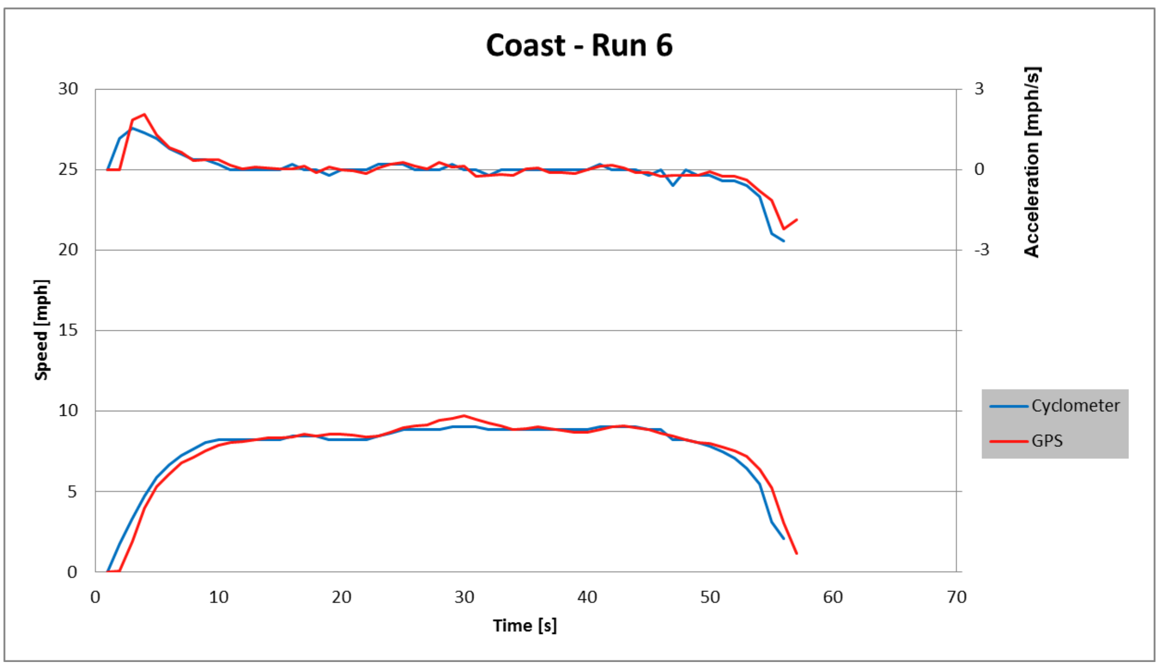


Figure 72. Lab Test Speed and Acceleration – Coast 6

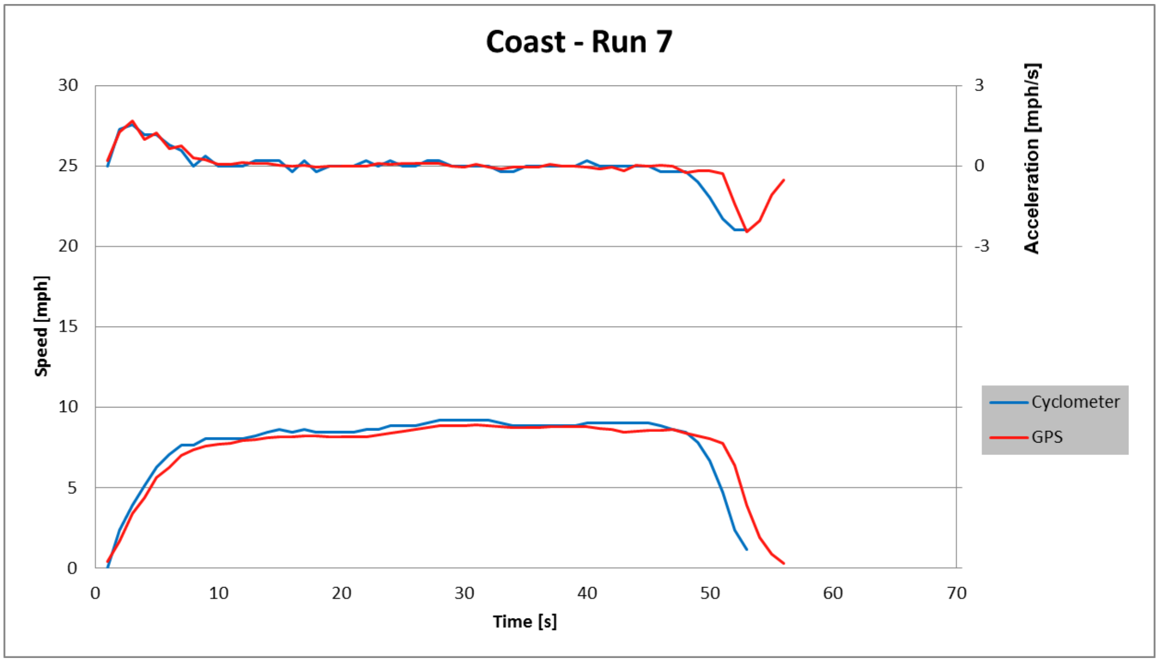


Figure 73 Lab Test Speed and Acceleration – Coast 7

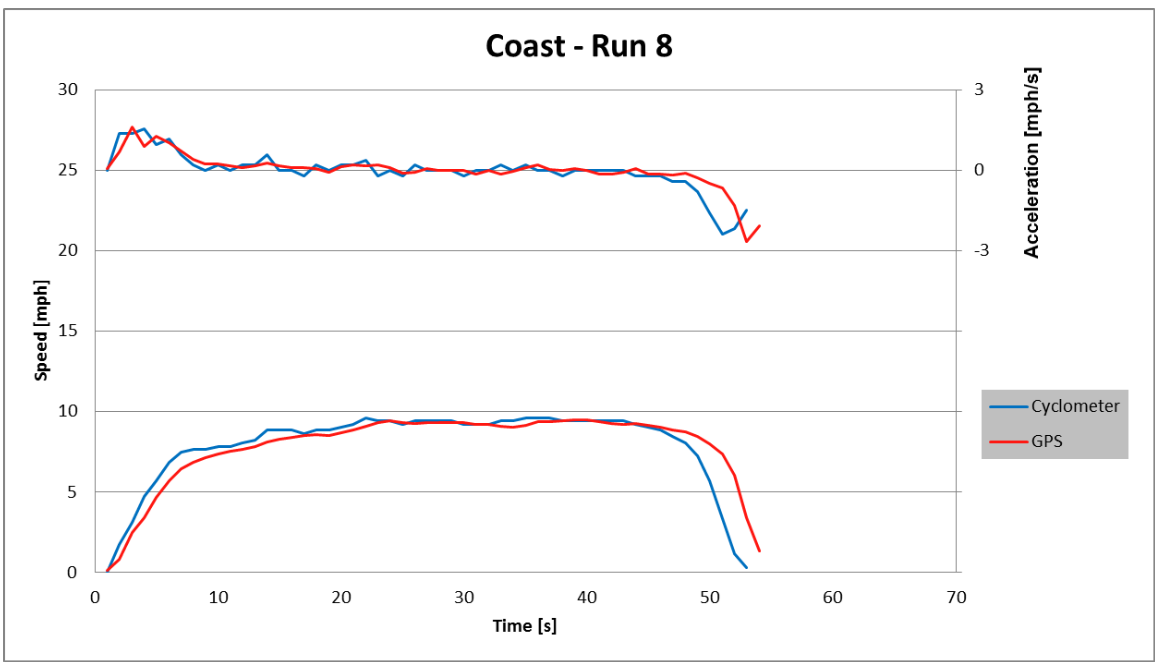


Figure 74. Lab Test Speed and Acceleration – Coast 8

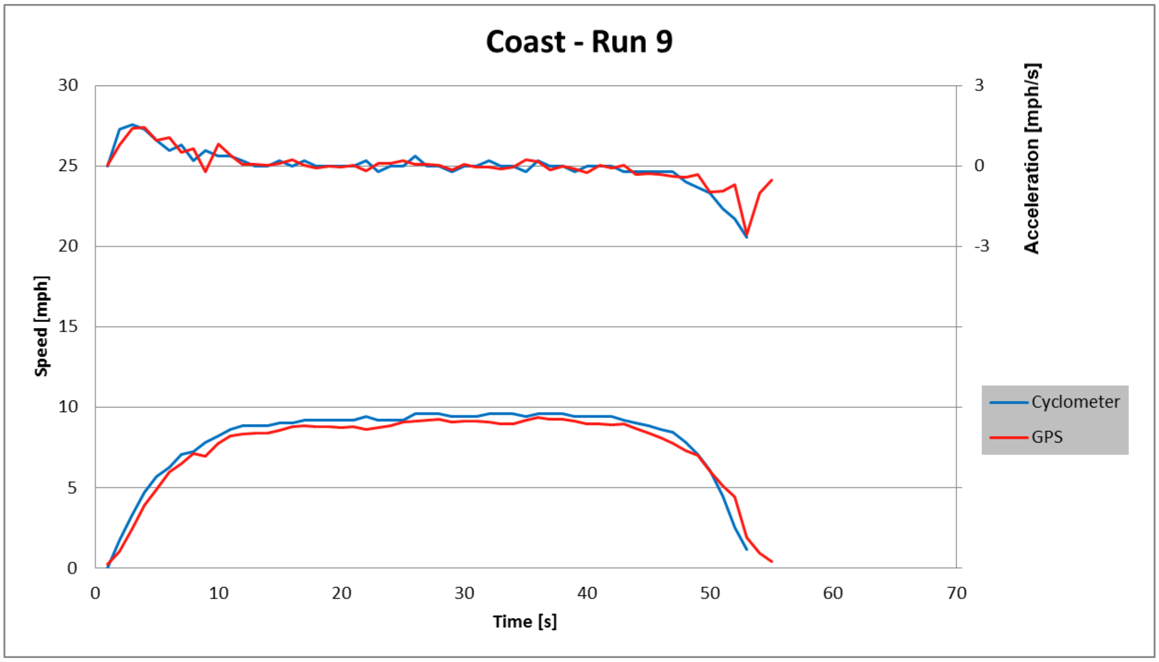


Figure 75. Lab Test Speed and Acceleration – Coast 9

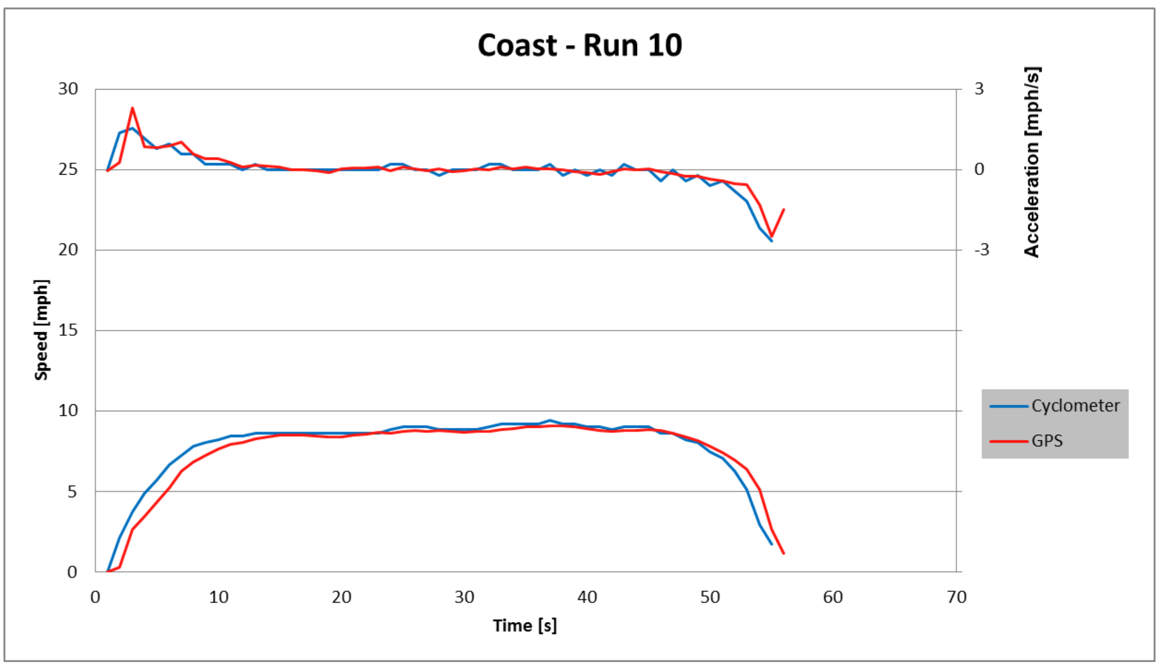


Figure 76. Lab Test Speed and Acceleration – Coast 10

Pedal

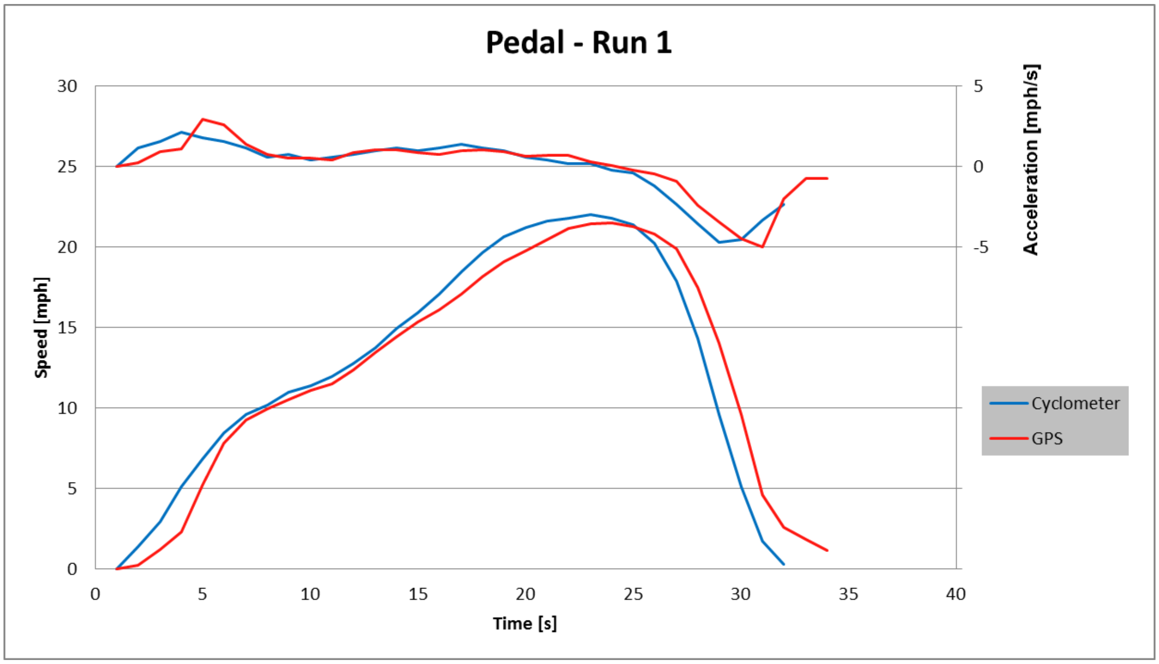


Figure 77. Lab Test Speed and Acceleration – Pedal 1

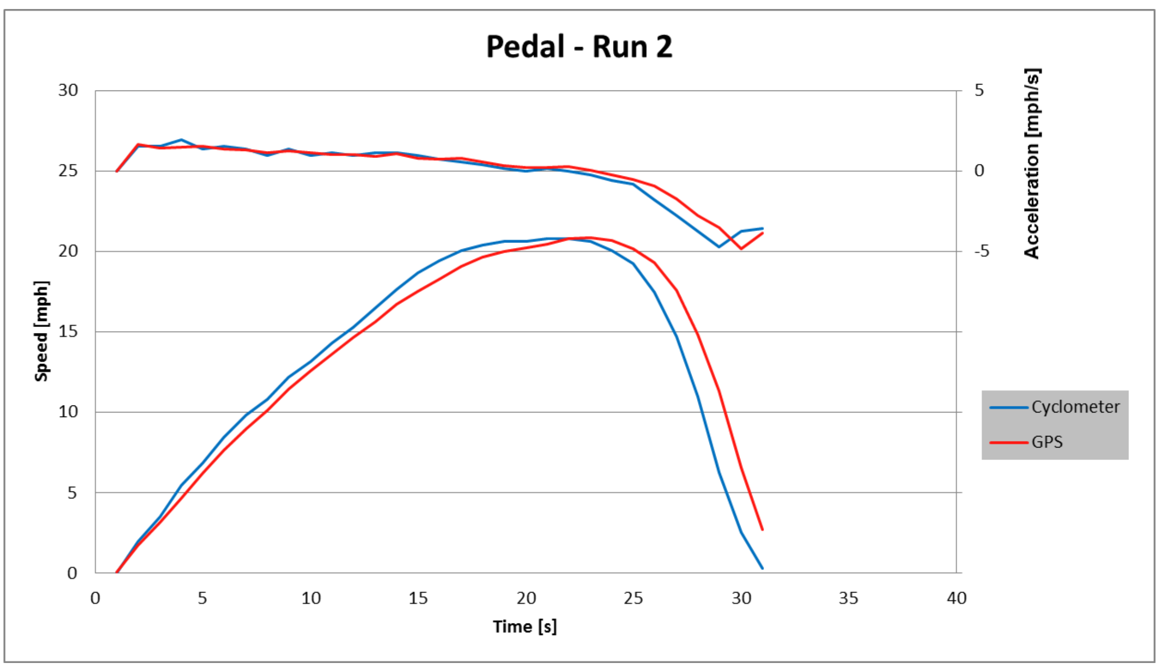


Figure 78. Lab Test Speed and Acceleration – Pedal 2

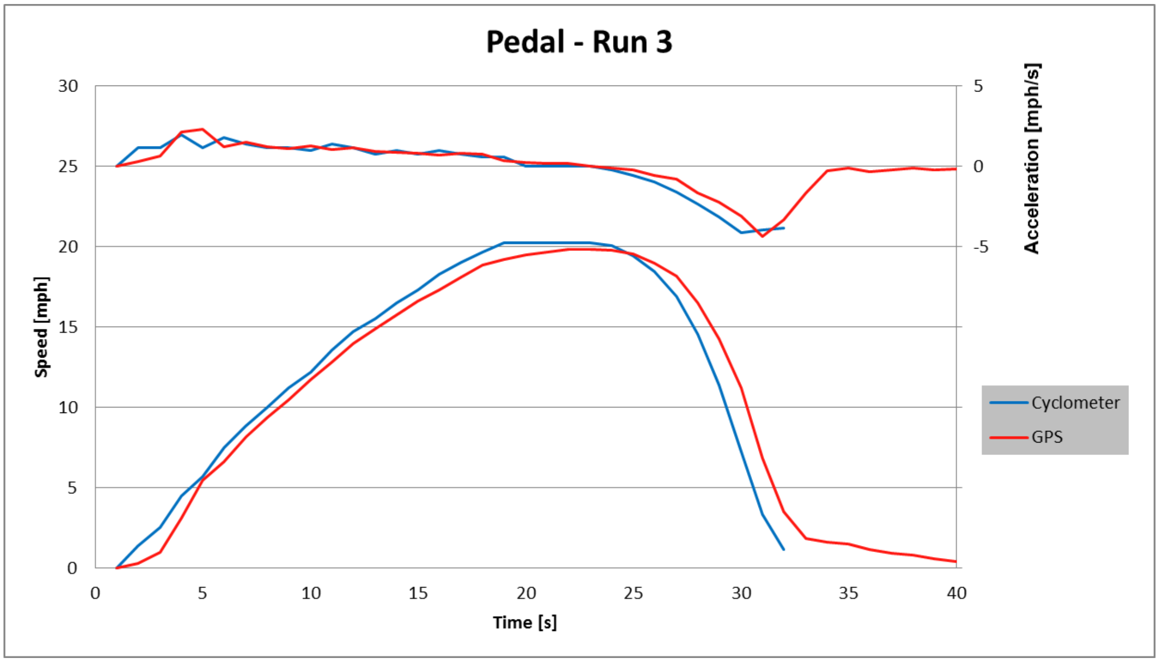


Figure 79. Lab Test Speed and Acceleration – Pedal 3

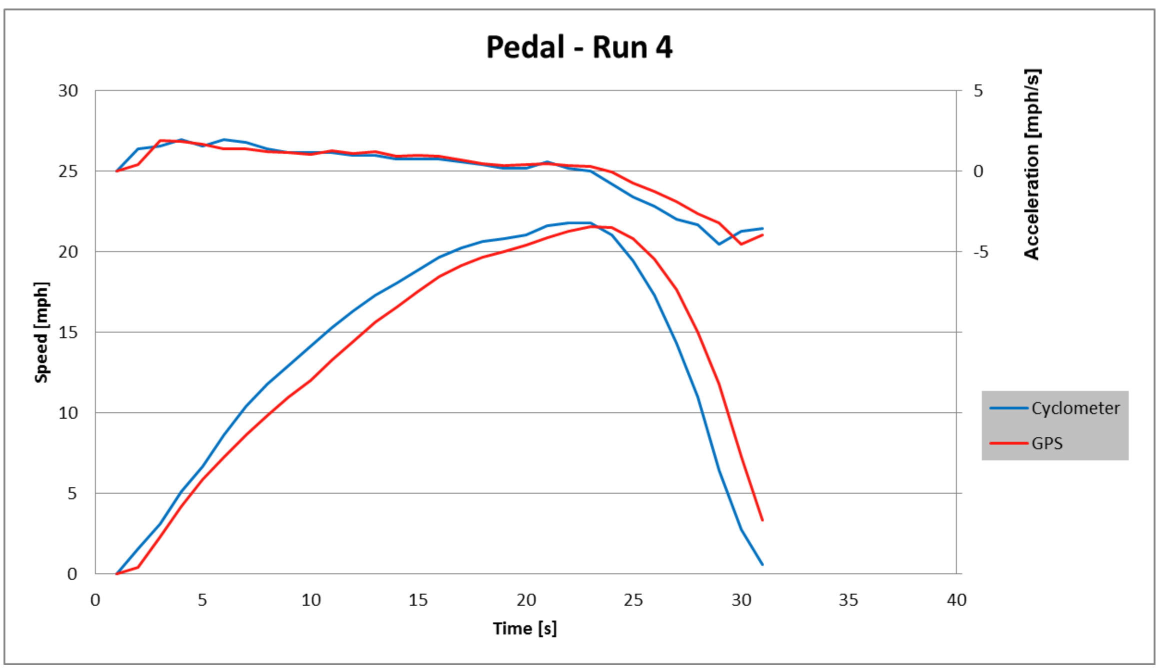


Figure 80. Lab Test Speed and Acceleration – Pedal 4

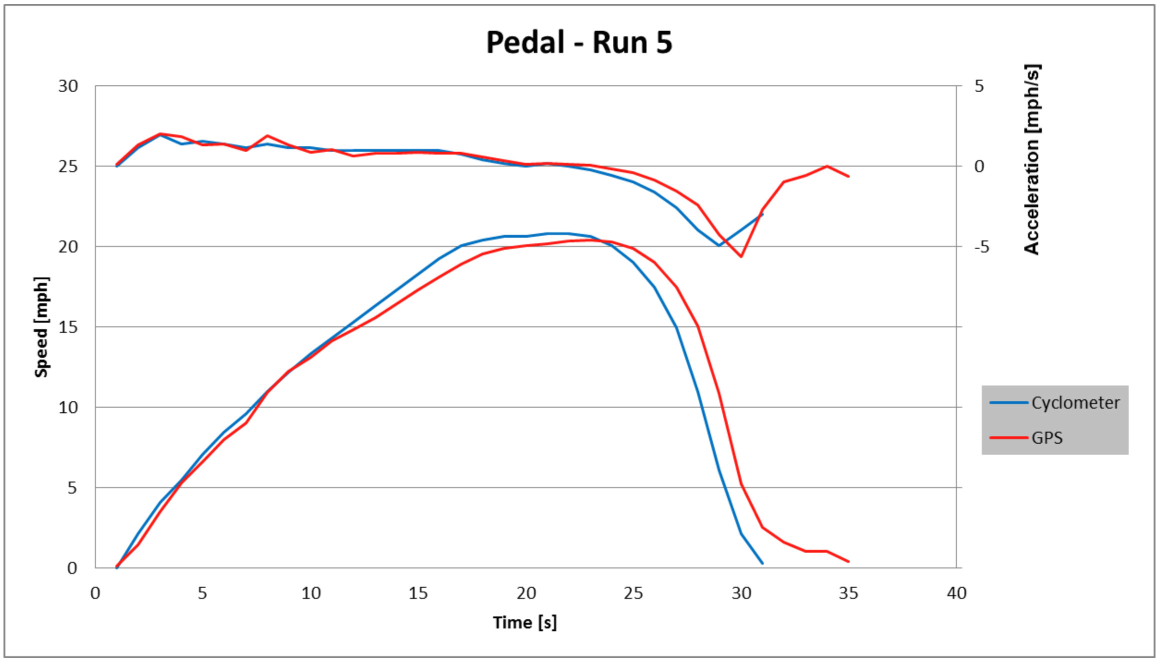


Figure 81. Lab Test Speed and Acceleration – Pedal 5

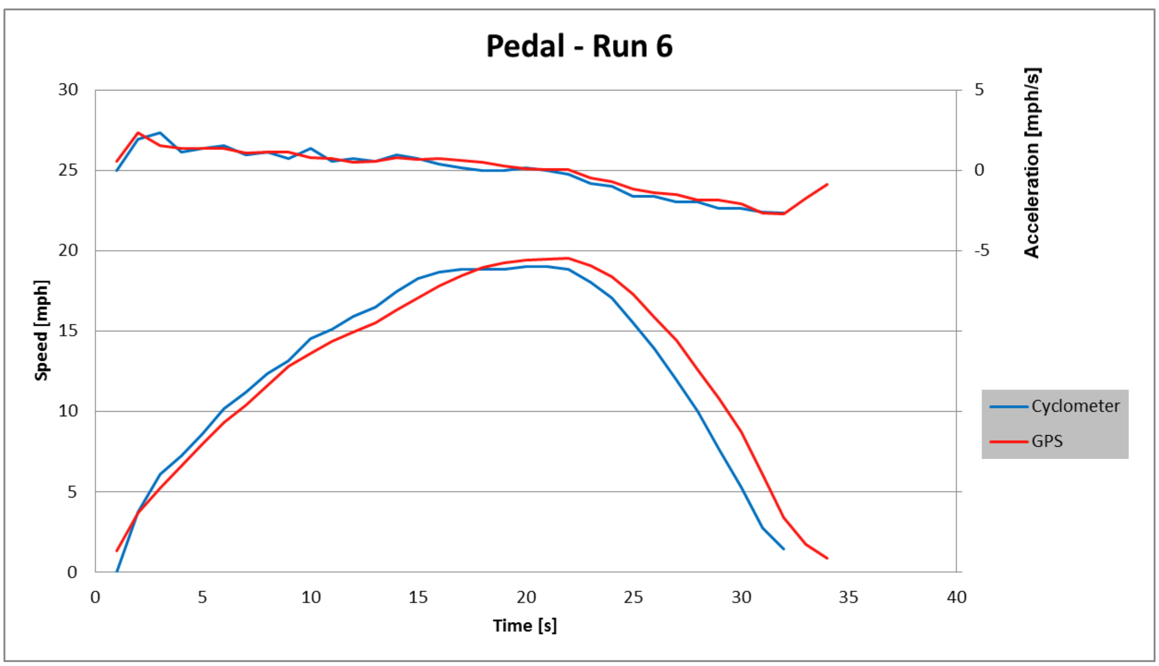


Figure 82. Lab Test Speed and Acceleration – Pedal 6

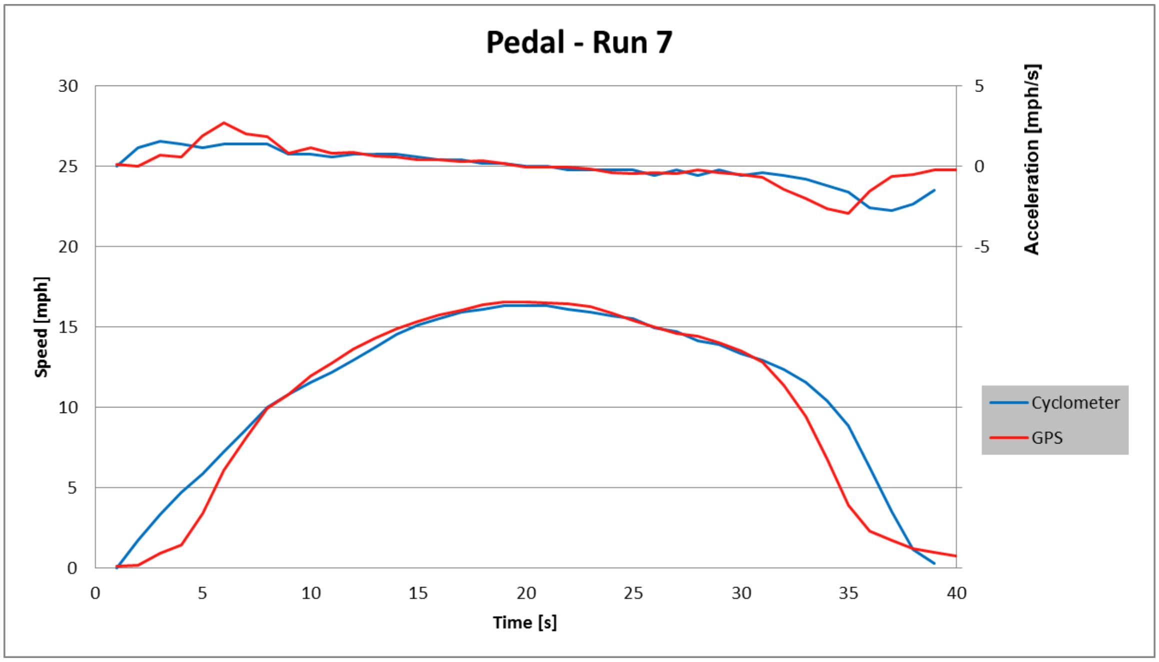


Figure 83. Lab Test Speed and Acceleration – Pedal 7

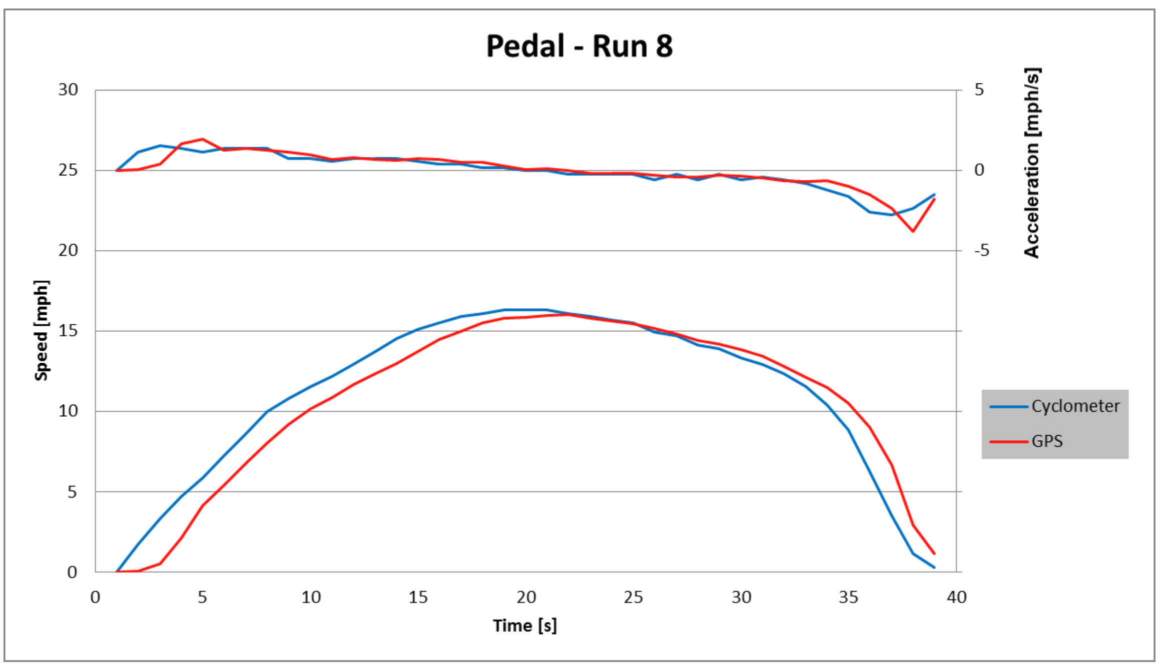


Figure 84. Lab Test Speed and Acceleration – Pedal 8

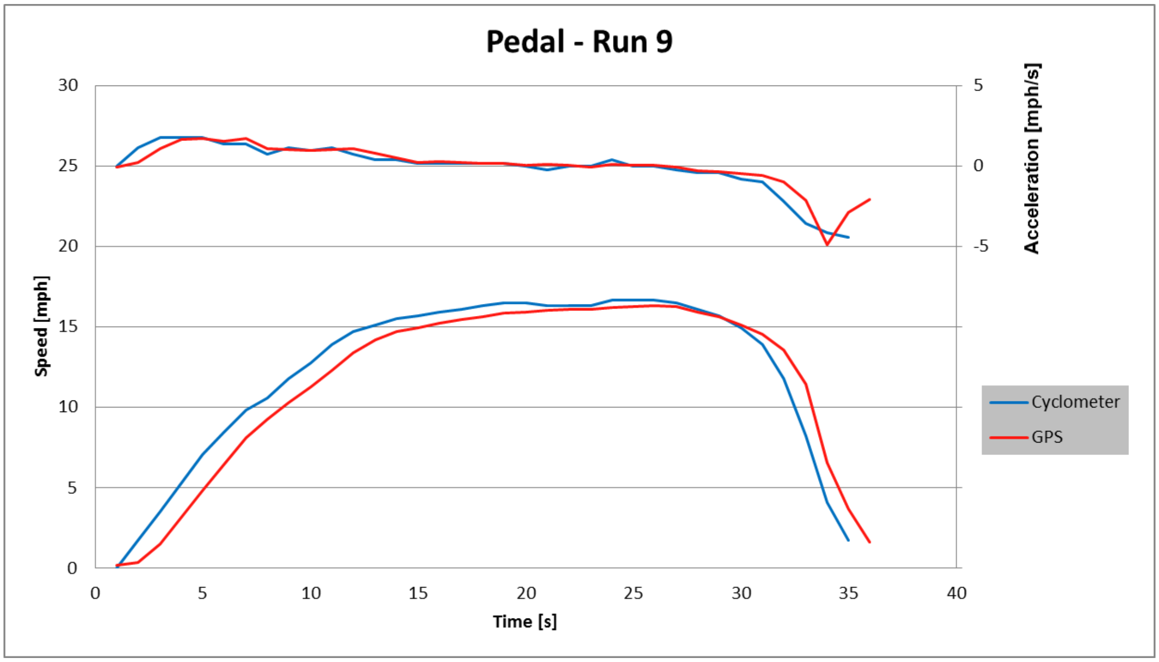


Figure 85. Lab Test Speed and Acceleration – Pedal 9

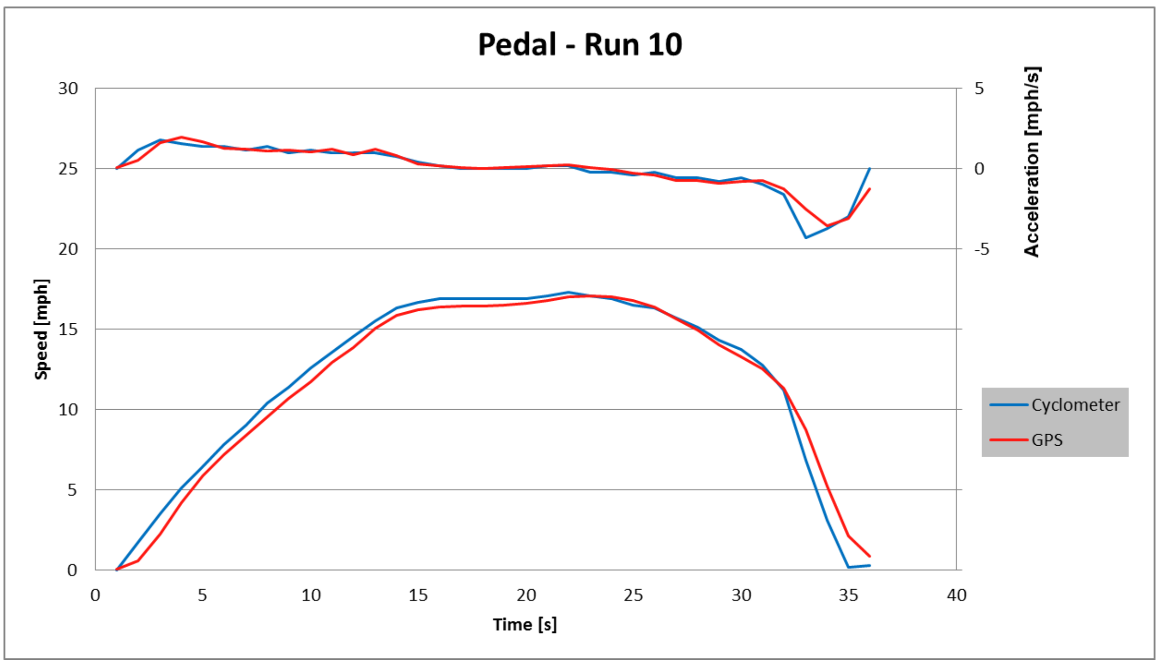


Figure 86. Lab Test Speed and Acceleration – Pedal 10

B.2 Field Test

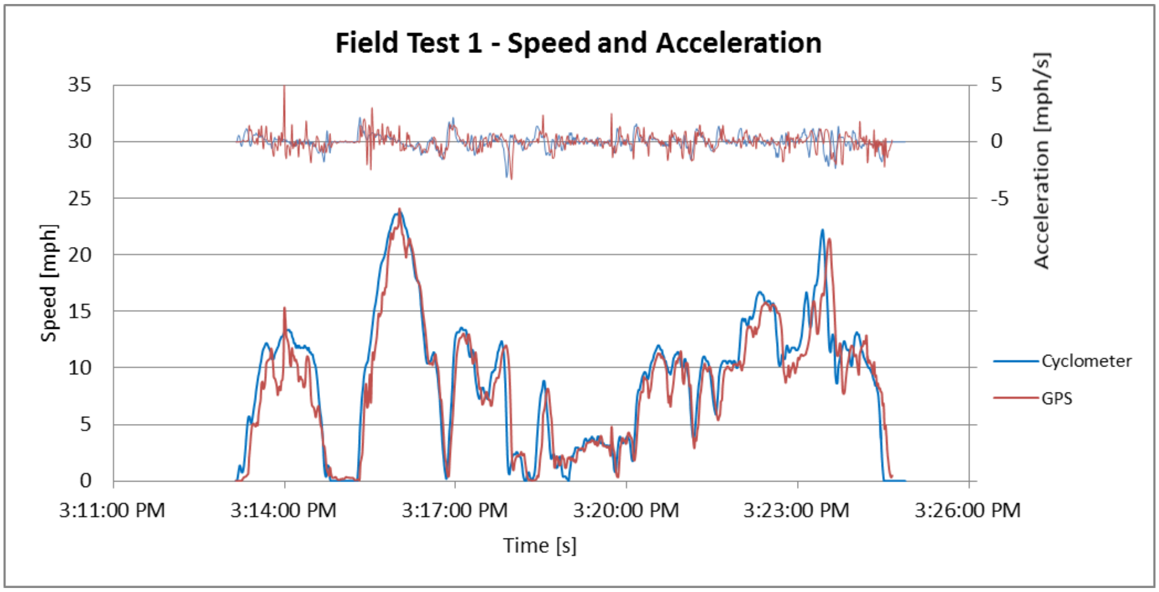


Figure 87. Field Test Speed and Acceleration 1

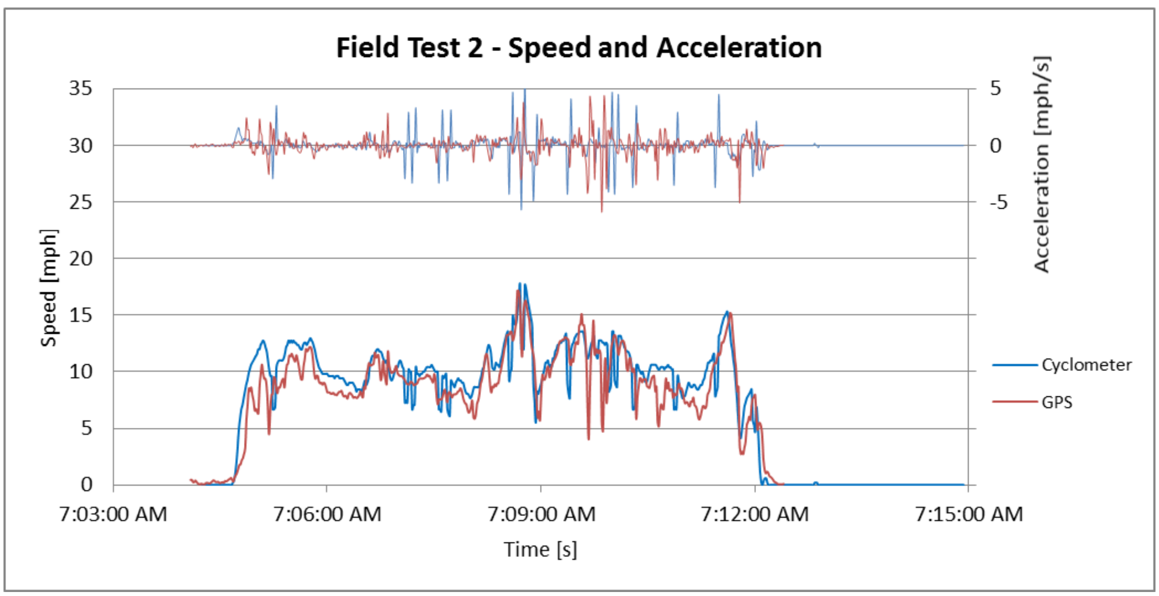


Figure 88. Field Test Speed and Acceleration 2

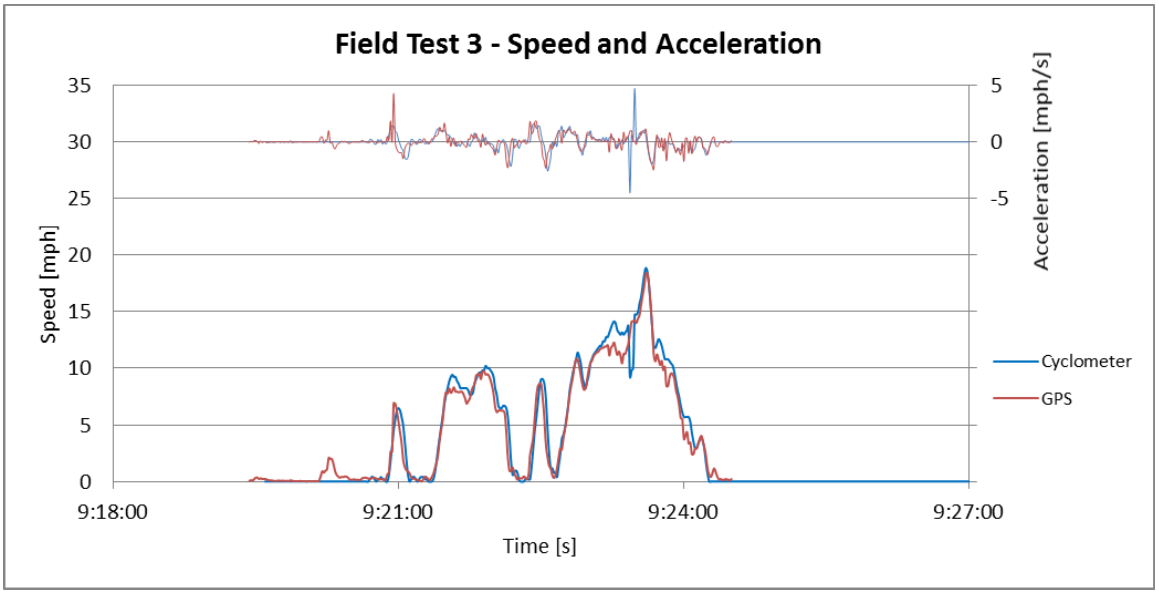


Figure 89. Field Test Speed and Acceleration 3

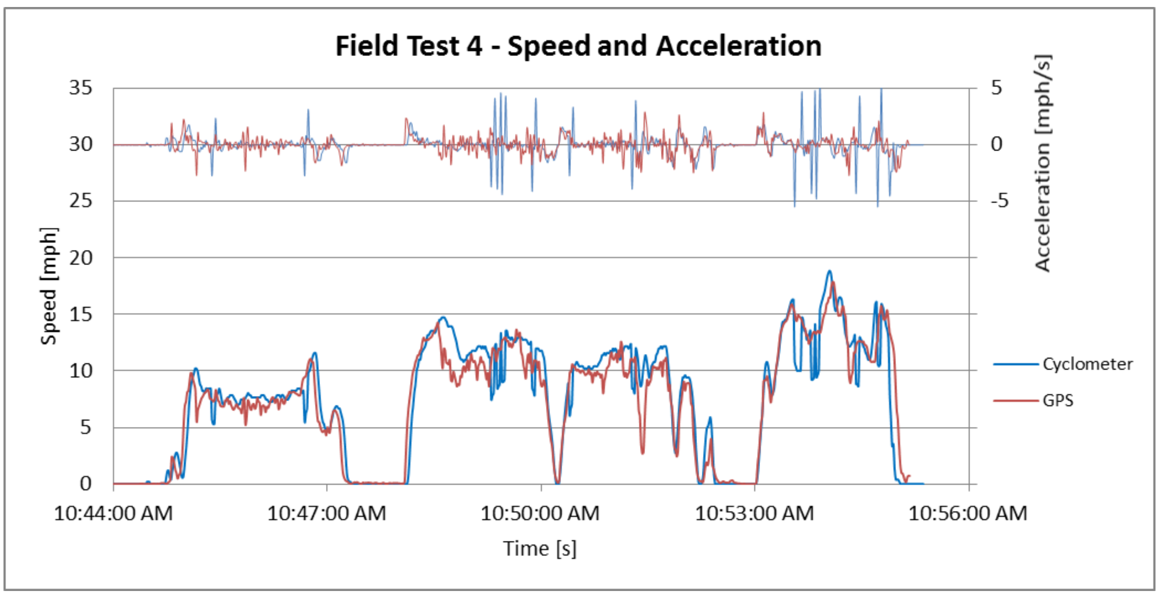


Figure 90. Field Test Speed and Acceleration 4

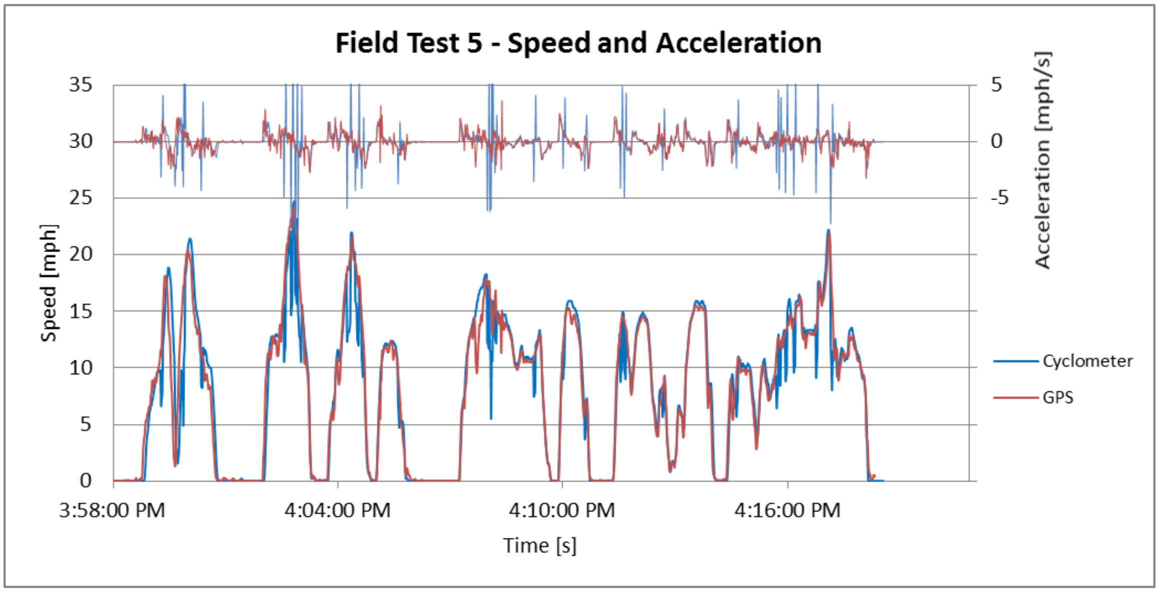


Figure 91. Field Test Speed and Acceleration 5

B.3 Hard Acceleration Test

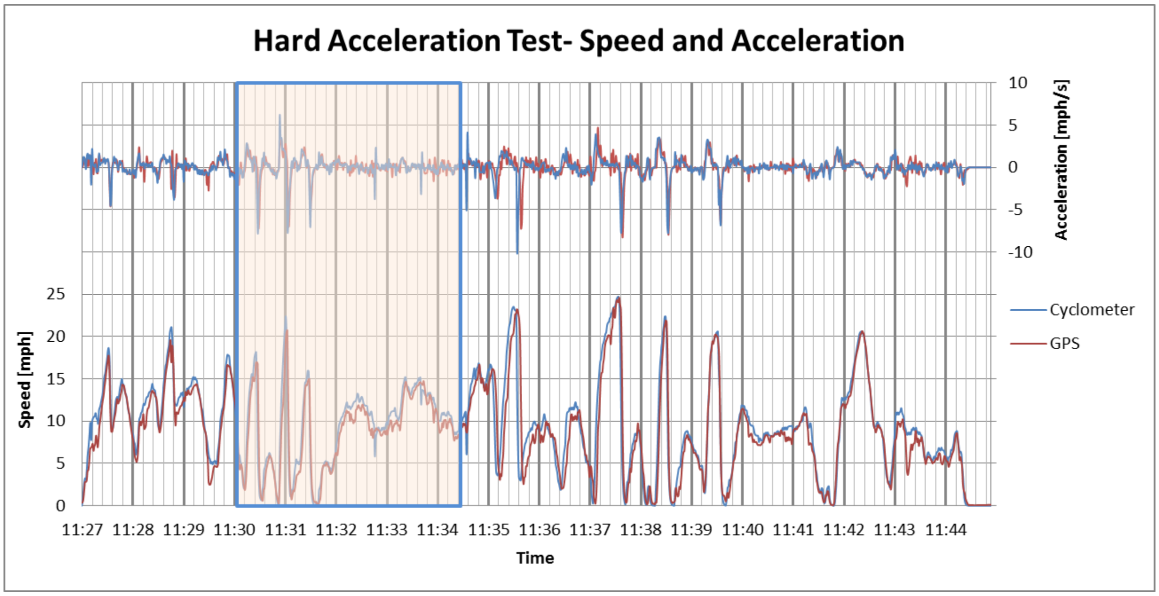


Figure 92. Hard Acceleration Test 1

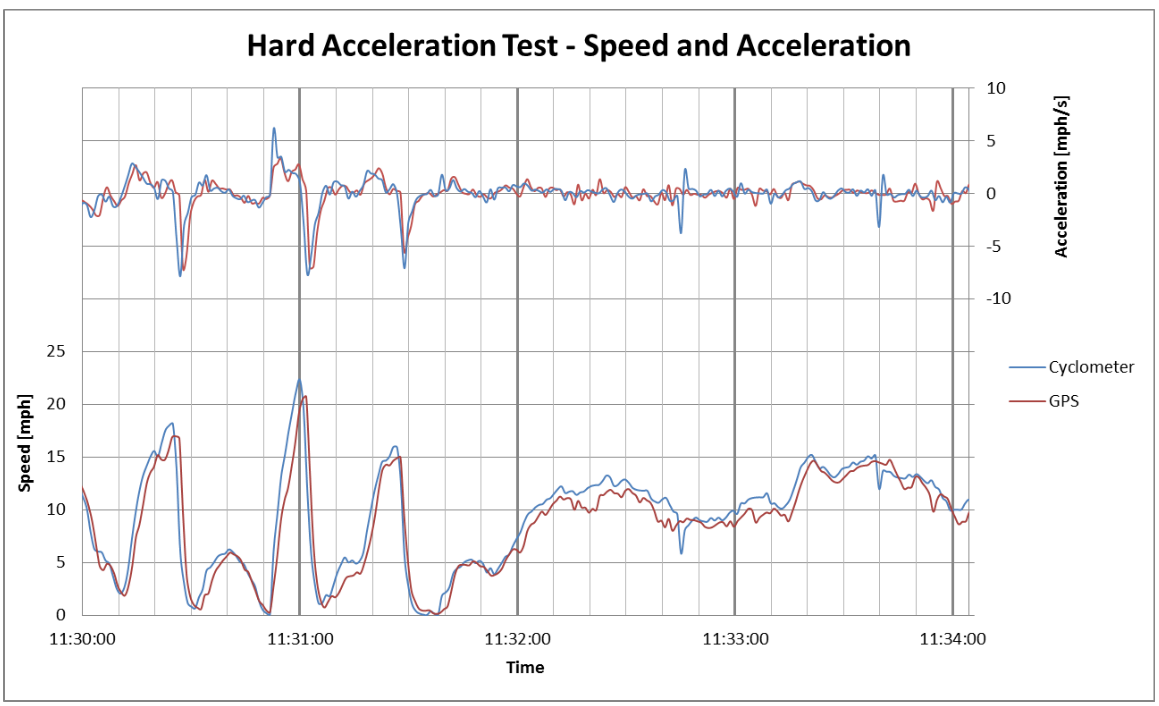


Figure 93. Hard Acceleration Test 1

APPENDIX C

DATA COLLECTION SHEETS

Georgia Institute of Technology

School of Civil and Environmental Engineering

<Participant Name>
<Address>

<Date>

Dear <Participant Name>,

I am Dr. Michael Hunter, a transportation engineering professor and researcher at the Georgia Institute of Technology. We are conducting research on the potential for a transportation system where small personal mobility devices, much like the <device>, are used to transport people from place to place. To analyze this possibility, we need to better understand how people currently operate these devices.

We hope that you can help us with this effort by letting us collect data from your <device>(s) via GPS data recorders. The GPS data recorders log speed and location data from your trips. No personal data will be collected.

A few days after you receive this letter we will call you to determine if you are interested in participating or if you have any questions. If you agree to help with our research, we would mail or deliver the GPS recorders to you at our expense. They are easy to temporarily attach or carry on your device. We would provide instructions to attach the GPS recorders. All you would have to do is turn them on to record information about your trips.

After completing the data collection, we would ask you to answer a few questions about your experiences with your <device>(s) and details about the data collection procedure. This will take no more than 5 minutes. You will then place the GPS data recorders back in the box and mail it back to us, free of charge, using the shipping label we will supply. We will make a follow up call to you to answer any questions, or receive any comments, you may have.

If you have any questions, please contact me using the information provided below. Your time and assistance are greatly appreciated.

Sincerely,

Dr. Michael P. Hunter

Associate Professor
Director Georgia Transportation Institute
Associate Professor
School of Civil and Environmental Engineering
Georgia Institute of Technology
Phone: 404-385-1243
Email: michael.hunter@ce.gatech.edu

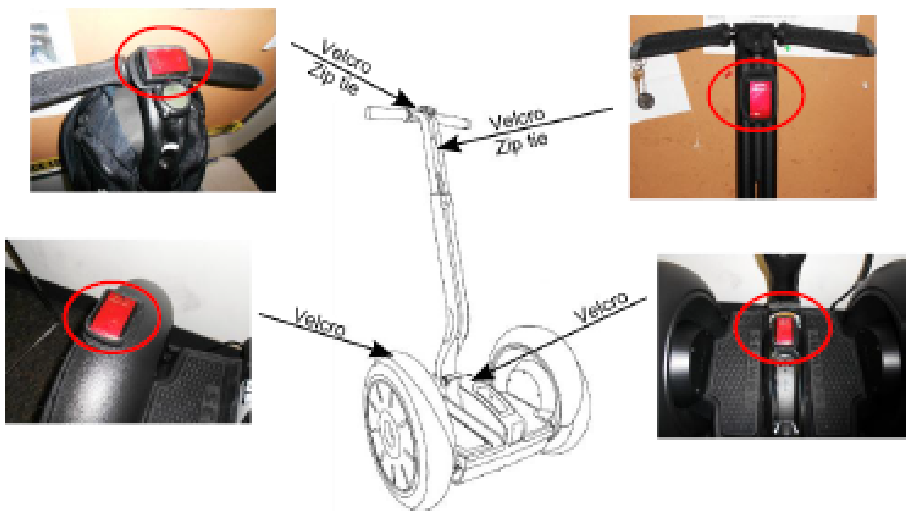
School of Civil and Environmental Engineering
Atlanta, GA 30332-0355 U.S.A.
Phone 404-894-2201
Fax 404-894-2278

GPS DATA COLLECTION INSTRUCTIONS

STEP 1: GPS RECORDER INSTALLATION

The steps below are recommended to help you install the GPS recorder on your device.

1. Keep the GPS recorder inside its protective sleeve.
2. Ensure that the GPS recorder will have an unobstructed view of the sky.
3. Orient the GPS recorder face-up or face-out. **DO NOT** install it face-down.
4. Use either the plastic zip tie or the adhesive Velcro strip to attach a single GPS recorder to each device. For the Segway, choose between four recommended locations: on the main tube below the info key, on the handle bars above the info key, on top of the fender, or on the console between the rider's feet.



STEP 2: GPS RECORDER OPERATION

At least 30 seconds prior to beginning your trip, turn the GPS recorder to the **LOG** setting by moving the switch on the bottom left side of the GPS recorder all the way up to the second click as shown below. This can be done while the GPS recorder is still within the protective sleeve. A solid orange light in the middle of the device indicates the GPS recorder is searching for satellites. A blinking orange light means the GPS recorder has a satellite lock and is ready for use. Please wait for the light to begin blinking before beginning your trip.

After the completion of each trip, turn the GPS recorder off to conserve battery. Remember to turn it back on prior to beginning your next trip. If you use your personal mobility device(s) very frequently (more than 5 times per day), you may let the device run continually until the battery has been exhausted.

The GPS recorder(s) are fully charged. No charging is required. Once the battery has been exhausted (no lights come on the front of the GPS recorder when turned on), you are ready to return the GPS recorder(s).

STEP 3: DOCUMENTATION

Complete the *Info Sheet* making sure to fill out the information for each GPS recorder used. The GPS unit number is the number written in marker on the front of the GPS recorder.

STEP 4: RETURN GPS RECORDERS

After completing the data collection process, return all of the GPS recorders and the *Info Sheet* to the box. Close and tape the box and use the provided shipping label to mail the GPS recorders back to Georgia Tech.

INFO SHEET

Device Type (i2, x2, HT):____

Type(s) of use (tour, personal, patrol, etc.):__________________________________

Please list the conditions for each trip in the table below.
Each line is meant to represent an individual trip. However, if a single GPS device is used for multiple trips by a single user or a single type of user in one day, they may be combined in a single row.

Segway #	**GPS unit #**	**User Level: Experienced or Beginner**	**Speed key used**	**Date(s) of trip(s)**	**Weather Conditions**

The following questions are about your experiences with your Segway.

What is a typical range/battery life for your device (in hours or miles)? ____________________

What voltage do you use to recharge your device? __________________________________

How many hours does it take to make a full recharge (from empty to full)? __________________

APPENDIX D

CODES AND SCRIPTS USED FOR ANALYSIS

Modified Kalman Filter – MATLAB

```
%Kalman Filter  - GPS

%This script takes the standard QSTARZ GPS log output and runs the speed,
acceleration
%and coordinate data through the Kalman filter and smoothing algorithm
%below.  This consists of a forward pass predicting the next value and then
%correcting the prediction based on the actual recorded value for the next
%time step.
%This program reads from an .xls file, calculates the corrected data, and
%then populates new columns in the same .xls file with the corrected data.

clear
%file and sheet names!
rawfile = 'C:\rawfile.xlsx';
sheetname = 'sheetname';
newfile = 'C:\newfile.xlsx';

%read GPS data from .xls file and define vectors
a=xlsread(rawfile,sheetname);
GPS_time = a(:,7);
GPS_dT = a(:,8);
X_coor_raw = a(:,27);
Y_coor_raw = a(:,26);
Speed_raw = a(:,28);
Acc_raw = a(:,29);
nSat = a(:,30);
PDOP = a(:,20);
heading = a(:,17);

%INITIAL INPUTS
Speed_PN = 0.5^2; %GPS speed error 0.1 m/s = 0.224 mph (Process noise)
Speed_MN = 0.5^2; %GPS speed error 0.1 m/s = 0.224 mph (Measurement noise)
Bad_GPS_Speed_MN = 3^2; %Max variation (threshold) of GPS speed for poor GPS
signal condition
X_PN = 0.00295; %GPS X coordinates error: 0.00295 degree = 100 m (Process noise)
Y_PN = 0.00352; %GPS Y coordinates error: 0.00352 degree = 100 m (Process noise)
X_MN = 0.00295; %GPS X coordinates error: 0.00295 degree = 100 m (Measurement
noise)
```

Y_MN = 0.00352; %GPS Y coordinates error: 0.00352 degree = 100 m (Measurement noise)
Bad_GPS_X_MN = 10^2; %set up max variation (threshold of X for poor GPS signal points: 10 degree)
Bad_GPS_Y_MN = 10^2; %set up max variation (threshold of Y for poor GPS signal points: 10 degree)
Speed_init_Pmin = 5; %Initial variance of speed error for the first speed point: 5 mph
X_init_Pmin = 0.000002; %Initial variance of X error for the first X point
Y_init_Pmin = 0.000002; %Initial variance of Y error for the first Y point

%SPEED - first calc
Speed_Xhat_min(1,1) = Speed_raw(1,1); %Speed(1,1) indicates the first real GPS speed. After reading this value, put it to the Speed_Xhat_min for the first prediciton process in the Kalman filter.
Speed_Pmin(1,1) = Speed_init_Pmin + Speed_PN; %Create the Kalman error variance matrix
Speed_K_Gain(1,1) = Speed_Pmin(1,1)/(Speed_Pmin(1,1) + Speed_MN); %Create the Kalman gain matrix
Speed_Xhat(1) = Speed_Xhat_min(1,1) + Speed_K_Gain(1,1)*(Speed_raw(1,1) - Speed_Xhat_min(1,1)); %Correct the speed with the Kalman gain matrix and the difference between the estimated and the measured speeds. At this time, we will get hte filtered GPS speed
Speed_P(1,1) = (1-Speed_K_Gain(1,1))*Speed_Pmin(1,1); %Update the Kalman error variacne matrix for the next second speed

%COORDINATES - first calc
X_Xhat_min(1,1) = X_coor_raw(1,1); %X_coor(1,1) is the first real GPS X coordinates point collected from our box.
X_Pmin(1,1) = X_init_Pmin + X_PN;
X_K_Gain(1,1) = X_Pmin(1,1)/(X_Pmin(1,1) + X_MN);
X_Xhat(1) = X_Xhat_min(1,1) + X_K_Gain(1,1)*(X_coor_raw(1,1) - X_Xhat_min(1,1)); %At this time, we will get the filtered GPS X coordinates
X_P(1,1) = (1-X_K_Gain(1,1))*X_Pmin(1,1); %Update the Kalman error variance matrix for the next X value

Y_Xhat_min(1,1) = Y_coor_raw(1,1);
Y_Pmin(1,1) = Y_init_Pmin + Y_PN;
Y_K_Gain(1,1) = Y_Pmin(1,1)/(Y_Pmin(1,1) + Y_MN);
Y_Xhat(1) = Y_Xhat_min(1,1) + Y_K_Gain(1,1)*(Y_coor_raw(1,1) - Y_Xhat_min(1,1)); %At this time, we will get the filtered GPS Y coordinates
Y_P(1,1) = (1-Y_K_Gain(1,1))*Y_Pmin(1,1); %Update the Kalman error variance matrix for the next Y value

%SPEED LOOP
for i=2:length(Speed_raw)

```
    if nSat(i,1) > 4 && PDOP(i,1) < 8  %GPS signal is good (nsat>4,PDOP<9)
        Speed_Xhat_min(i,1) = Speed_Xhat(i-1,1); %This is the second speed value, so “i”
is 2, then Speed_Xhat(i-1,1) is Speed_Xhat(2-1,1) = Speed_Xhat(1,1), which we already
had as the first filtered speed value.Thus, we don’t have to worry about the number of
“i”. You can just use the previous speed value filtered by Kalman for the
“Speed_Xhat_min(i,1)”. Ignore the “i” here
        Speed_Pmin(i,1) = Speed_P(i-1,1) + Speed_PN; %The “Speed_PN” is the initial
set-up value that we already know. The “Speed_P(i-1,1)” is also the value that we know
for the previous filtering process. We can easily calculate the “Speed_Pmin(i,1)”
        Speed_K_Gain(i,1) = Speed_Pmin(i,1)/(Speed_Pmin(i,1) + Speed_MN); %You will
use the GPS signal condition at this time. Based on the signal condition, you will choose
one from two speed measurement error values, which we initially set up before.
        Speed_Xhat(i,1) = Speed_Xhat_min(i,1) + Speed_K_Gain(i,1)*(Speed_raw(i,1) -
Speed_Xhat_min(i,1)); %Based on the equation above, you will have the second filtered
speed data.
        Speed_P(i,1) = (1-Speed_K_Gain(i,1))*Speed_Pmin(i,1); %Update the kalman error
matrix for the next GPS speed
    else  % When GPS signal is bad
        Speed_Xhat_min(i,1) = Speed_Xhat(i-1,1);
        Speed_Pmin(i,1) = Speed_P(i-1,1) + Speed_PN;
        Speed_K_Gain(i,1) = Speed_Pmin(i,1)/(Speed_Pmin(i,1) + Bad_GPS_Speed_MN);
        Speed_Xhat(i,1) = Speed_Xhat_min(i,1) + Speed_K_Gain(i,1)*(Speed_raw(i,1) -
Speed_Xhat_min(i,1));
        Speed_P(i,1) = (1-Speed_K_Gain(i,1))*Speed_Pmin(i,1);
    end
end

%ACCELERATION LOOP
for i=2:length(Speed_raw)
    Acc_smooth(i,1) = (Speed_Xhat(i,1)-Speed_Xhat(i-1,1)) / GPS_dT(i,1);
end


%COORDINATES LOOP
for i=2:length(X_coor_raw)
    if nSat(i,1) > 4 && PDOP(i,1) < 8  %GPS signal is good (nsat>4,PDOP<9)
        X_Xhat_min(i,1) = X_Xhat(i-1,1); % For X coordinates
        X_Pmin(i,1) = X_P(i-1,1) + X_PN ;
        X_K_Gain(i,1) = X_Pmin(i,1)/(X_Pmin(i,1) + Bad_GPS_X_MN);
        X_Xhat(i,1) = X_Xhat_min(i,1) + X_K_Gain(i,1)*(X_coor_raw(i,1) -
X_Xhat_min(i,1));
        X_P(i,1) = (1-X_K_Gain(i,1))*X_Pmin(i,1);
        Y_Xhat_min(i,1) = Y_Xhat(i-1,1); % For Y coordinates
        Y_Pmin(i,1) = Y_P(i-1,1) + Y_PN ;
        Y_K_Gain(i,1) = Y_Pmin(i,1)/(Y_Pmin(i,1) + Bad_GPS_Y_MN);
```

```
        Y_Xhat(i,1) = Y_Xhat_min(i,1) + Y_K_Gain(i,1)*(Y_coor_raw(i,1) -
Y_Xhat_min(i,1));
        Y_P(i,1) = (1-Y_K_Gain(i,1))*Y_Pmin(i,1);
    else %GPS signal is bad
        X_Xhat_min(i,1) = X_Xhat(i-1,1); % For X coordinates
        X_Pmin(i,1) = X_P(i-1,1) + X_PN ;
        X_K_Gain(i,1) = X_Pmin(i,1)/(X_Pmin(i,1) + X_MN);
        X_Xhat(i,1) = X_Xhat_min(i,1) + X_K_Gain(i,1)*(X_coor_raw(i,1) -
X_Xhat_min(i,1));
        X_P(i,1) = (1-X_K_Gain(i,1))*X_Pmin(i,1);
        Y_Xhat_min(i,1) = Y_Xhat(i-1,1); % For Y coordinates
        Y_Pmin(i,1) = Y_P(i-1,1) + Y_PN ;
        Y_K_Gain(i,1) = Y_Pmin(i,1)/(Y_Pmin(i,1) + Y_MN);
        Y_Xhat(i,1) = Y_Xhat_min(i,1) + Y_K_Gain(i,1)*(Y_coor_raw(i,1) -
Y_Xhat_min(i,1));
        Y_P(i,1) = (1-Y_K_Gain(i,1))*Y_Pmin(i,1);
    end
end

%write filtered data to new excel file
headers = {'GPS Time','GPS dT','Heading','nSat','PDOP','Lat','Lon','Speed','Acc'};
xlswrite(newfile,headers,sheetname,'A1:I1');
xlswrite(newfile,GPS_time,sheetname,'A2');
xlswrite(newfile,GPS_dT,sheetname,'B2');
xlswrite(newfile,heading,sheetname,'C2');
xlswrite(newfile,nSat,sheetname,'D2');
xlswrite(newfile,PDOP,sheetname,'E2');
xlswrite(newfile,X_Xhat,sheetname,'F2');
xlswrite(newfile,Y_Xhat,sheetname,'G2');
xlswrite(newfile,Speed_Xhat,sheetname,'H2');
xlswrite(newfile,Acc_smooth,sheetname,'I2');

clear
```

Typical Speed and Acceleration Plot – R (ggplot2)

```
###MODAL COMPARISON###
rm(list=ls(all=TRUE))

#Load Required Packages
setwd("folder_path/")
library("gdata")
library("rJava")
library("gplots")
library("ggplot2")
library("aws")
library("rgl")
library("xts")
library("lattice")
library("foreign")
library(gridExtra)
library(sqldf)

#READ DATA
mode <- read.dbf("MODE2.dbf")
bymode <- sqldf('SELECT * FROM mode ORDER BY MODE desc')

#PLOT
p <- ggplot(bymode,aes(x=SPEED,y=ACC,colour=MODE))+
  scale_x_continuous(limits=c(0,25)) +
  scale_y_continuous(limits=c(-5,5),breaks=c(-5:5)) +
  xlab("Speed [mph]")+ylab("Acceleration [mph/s]")+
  geom_point(alpha="0.01") +
  scale_fill_manual(values=c("#F8766D","#990099","#619CFF","#00BA38")) +
  scale_colour_manual(values=c("#F8766D","#990099","#619CFF","#00BA38"))

p1 <- p + theme(legend.position = "None")

g_legend<-function(a.gplot){
  tmp <- ggplot_gtable(ggplot_build(a.gplot))
  leg <- which(sapply(tmp$grobs, function(x) x$name) == "guide-box")
  legend <- tmp$grobs[[leg]]
  legend
}
p_legend <- ggplot(bymode,aes(x=SPEED,colour=MODE,fill=MODE))+

geom_bar()+scale_fill_manual(values=c("#F8766D","#990099","#619CFF","#00BA38")
,
                        labels=c("Bike  n=33761",
```

```
                                    "Electric Cart  n=3158",
                                    "Ped   n=15342",
                                    "Seg  n=249284")) +
  scale_colour_manual(values=c("#F8766D","#990099","#619CFF","#00BA38"),
                    labels=c("Bike  n=33761",
                             "Electric Cart  n=3158",
                             "Ped   n=15342",
                             "Seg  n=249284"))
legend <- g_legend(p_legend)

p2 <- ggplot(bymode,aes(x=SPEED,colour=MODE)) +
  geom_density(aes(fill=MODE),alpha=0.3) + xlim(range=c(0,25)) +
  theme(legend.position = "none", axis.title.x=element_blank()) +
  scale_colour_manual(values=c("#F8766D","#990099","#619CFF","#00BA38")) +
  scale_fill_manual(values=c("#F8766D","#990099","#619CFF","#00BA38"))


p3 <- ggplot(bymode,aes(x=ACC,colour=MODE)) +
  geom_density() + coord_flip() +
  theme(legend.position ="none", axis.title.y=element_blank()) +
  scale_colour_manual(values=c("#F8766D","#990099","#619CFF","#00BA38")) +
  scale_x_continuous(limits=c(-5,5),breaks=c(-5:5))

#Print & Save Plots
png("mode2.png")
grid.arrange(p2,legend,p1,p3,ncol=2, nrow=2,
             widths=c(2,1), heights=c(1,2))
dev.off()

pdf("mode2.pdf")
grid.arrange(p2,legend,p1,p3,ncol=2, nrow=2,
             widths=c(2,1), heights=c(1,2))
dev.off()
```

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