Abstract

Title of Thesis:	HUMAN GAIT BASED RELATIVE FOOT SENSING FOR PERSONAL NAVIGATION
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Human gait dynamics were studied to aid the design of a robust personal navigation and tracking system for First Responders traversing a variety of GPS-denied environments. IMU packages comprised of accelerometers, gyroscopes, and magnetometer are positioned on each ankle. Difficulties in eliminating drift over time make inertial systems inaccurate. A novel concept for measuring relative foot distance via a network of RF Phase Modulation sensors is introduced to augment the accuracy of inertial systems. The relative foot sensor should be capable of accurately measuring distances between each node, allowing for the geometric derivation of a drift-free heading and distance. A simulation to design and verify the algorithms was developed for five subjects in different gait modes using gait data from a VICON motion capture system as input. These algorithms were used to predict the distance traveled up to 75 feet, with resulting errors on the order of one percent.

HUMAN GAIT BASED RELATIVE FOOT SENSING FOR PERSONAL NAVIGATION

by

Timofey Spiridonov

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Timofey Spiridonov
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Nomenclature

a_1 – Linear scaling factor in human gait model

b_1 – Offset in human gait model

λ – Relative foot sensor distance

ω – Stride frequency

s – foot separation

L – forward component of stride length

ϕ – heading

ψ – foot orientation angle

r – range measurement between given set of nodes

p – local right foot orientation distance

q – local left foot orientation distance

DGPS – Differential Global Positioning System

DHS – Department of Homeland Security

EMD – Empirical Mode Decomposition

GLANSER – Geospatial Location Accountability and Navigation System for Emergency Responders

GPS – Global Positioning System

IMU – Inertial Measurement Unit

RF – Radio Frequency

TOF – Time of Flight

Chapter 1

Introduction

1.1 Problem Statement

According to the United States Fire Association, on average, nearly 110 firefighters have lost their lives yearly in active service over the past decade. Many of these deaths are preventable, provided that the location and condition of the firefighter are known to the incident commander. The program objective is to produce a proof of concept for a system capable of tracking a First Responder as they travel through a GPS-denied environment. The navigation system must function without the use of GPS tracking (in GPS-denied environments) and with zero pre-installed infrastructure for tracking, while ensuring accuracy over time to within 1 meter of the actual physical position of the first responder. The navigation system must be capable of performing in a variety of harsh physical environments, including limited and no-visibility, and high heat while accurately capturing any physical motion that the first responder may undergo. The performance must be evaluated in a variety of locations, such as single-family homes, commercial high-rises, underground tunnels or wooded terrain.

The majority of motions performed by first responders within a burning building are on their hands and knees due to limited visibility. Thus, it is crucial for the system to be capable of evaluating and accurately tracking any human motion, including, but not limited to: walking, crawling, shuffling, and climbing. In addition to the standard inertial and dynamic approaches using a package comprised of accelerometers and gyroscopes, a human kinematics and dynamics study was conducted to evaluate the performance of a gait-based approach. A future goal of the program is to integrate a complete monitoring tool, capable of evaluating the physiological status of the subject, as well as accurately tracking their attitude in space.

This work was partially funded by investment from the Department of Homeland Security (DHS). A fundamental goal of the DHS program is to consolidate the lessons learned by the First Responder community regarding personal navigation, to avoid the loss of previous experience, and therefore also avoid repeating historically learned tragic lessons. As recently as January 2009, the DHS had released a set of requirements for their GLANSER (Geospatial Location Accountability and Navigation System for Emergency Responders) program, which accepted proposals and entered the first stage of development shortly after [1]. The GLANSER program is poised to set the industry standard for personal navigation research and development in the technical community. Numerous government agencies and significant portions of the private sector have a vested interest in the development of similar technology. The National Aeronautics and Space Administration developed comparable requirements for planetary surface (celestial) navigation technology and continue to pursue and fund similar projects. Countless military and special ops applications exist within each branch of the armed forces, including the popular “Future Soldier” initiative.

1.2 Previous Work

1.2.1 Inertial and Integrated Navigation Systems

The use of inertial sensors for personal dead reckoning is an aged concept that has been under considerable development over the past decade. While a variety of unique approaches have been taken to solve the problem, the fundamental issue with the inertial-based solutions stems from the drift of such packages over time, which rapidly leads to the build up of an unacceptable decay in accuracy. Accelerometer and gyro drift is particularly pronounced in use with moving parts that are subject to shock and temperature changes. To minimize unnecessary motion, many navigation sensor packages are designed for use as close to the subject’s center of mass as possible [2, 3]. In just a matter of minutes, the necessary double integration of the raw sensor data accumulates an ever-growing error term, which is unacceptable for the purposes of location and tracking. A successful navigation system must be capable of locating the subject within a one to three meter radius.

Several additional constraints on the technology exist simply because of a limit on the expense of the final product. Low-cost inertial sensors come with a performance tradeoff and their accuracy suffers more over time than “high-end” industrial grade accelerometer packages. High-performance accelerometer packages have a tradeoff between physical size and expense. Thus, what is available for use in a personal navigation system is a series of lower performance and smaller size inertial packages. The demand for miniature accurate inertial packages has spurred significant development in the areas. Companies such as Intersense Inc. have shifted focus to commercializing a new standard of accelerometer technology, coining the term of “industrial grade accelerometers” with their latest technology. However, even with expensive technology additional assumptions must be introduced to successfully decrease the error terms or incrementally re-zero the sensor drift errors.

A sample technique for dealing with drift errors was introduced by Dr. Johann Borenstein of the University of Michigan in the Personal Dead Reckoning (PDR) system [4]. In addition to the widely practiced “zero-velocity updates” concept which allows the re-zeroing of accelerometer drift every time a heel strike is detected in an IMU package, the University of Michigan team introduced the use of a straight-line walking assumption. By assuming straight-line trajectories in the majority of movement modes, until a drastic heading change is detected, the University of Michigan team was able to obtain accuracies to within several meters, under certain traveling conditions. A straight line assumption is so successful, because the majority of the error term stems directly from the rapid declination of the calculated heading from the true heading. Unfortunately, the straight line assumption cannot be made under all traveling conditions, and gradual turns are commonly found in outdoor applications.

Multiple inertial approaches have been marketed over the course of the last several years from representative companies such as TRX Systems, Q-Track and Honeywell. These solutions are based on fusions of sensor packages, and have led the charge in creating more accurate sensors, better processing algorithms, and new approaches to the problem. TRX Systems developed a design concept with some obvious limitations in functionality, as it accurately functions only in the most stable of gait modes, such as walking. Honeywell focused on designing a complimentary inertial system that couples with an existing GPS signal, relying on GPS-updates near windows. Honeywell approached the problem with focus on developing better and more expensive IMU hardware, where the algorithm design would follow suit. While some of these companies have successfully determined the right combination of hardware necessary to produce desired results under controlled circumstances (such as simple walking), it is clear that an auxiliary system is required to augment the IMU approach, if a standalone system is to be capable and robust enough to solve the entire problem.

1.2.2 RF Navigation

Radio frequency based solutions to the problem of personal navigation require an existing or deployable infrastructure around the incident area, which is directly contradicting to the program requirement mandated by the DHS. Such a requirement is a steep price to pay, and is often enough of a discouragement away from an RF based approach. Emergency situational responses for understaffed first responders would rarely have the luxury for additional setup and system calibration time and manpower. These systems have the benefit of functioning in an “absolute” reference frame, rather than a part of an estimate based on a dead reckoning system. Despite all of these considerations, a deployable system was developed and produced as part of an initiative by the Worcester Polytechnic Institute [5]. The Precision Personnel Locator Project resulted in the design and construction of a rapid deployment antenna and transactional RF Fusion system. This system is capable of achieving meter-level accuracies in single-family homes and even some multi-floor commercial buildings, but is ultimately inapplicable to large capture volumes, tall buildings, underground tunnels, or celestial navigation due to the necessary deployable infrastructure [6]. A new RF-based time of flight sensor and methodology will be introduced in this work to augment existing IMU technology.

1.2.3 Alternate technologies

A wide assortment of capable technology exists for communicating on demand information to first responders. Such technology has been in development for many decades, but lacks the maturity due to its inherent expense, and the lack of a viable supply-demand market [2]. While much of this information can be extremely useful for detection and relation of critical mission data, it is difficult to integrate into the requirements of the overall navigational package. One such example is a Remote Casualty Location Assessment Device (RCLAD) by L3 Communications and CyTerra, a Doppler Radar technology that is capable of detecting and measuring the distance to moving and near-stationary personnel through walls [2]. Integrating such information within the overall framework of a personal navigation system would serve as a great addition to many rescue initiatives. However, the practical integration to a personal navigation system is unlikely in the near future.

An additional technology produced by Q-track uses Near-field Electromagnetic Ranging and is capable of determining via its processing algorithms how a signal correlates to a particular path[2]. In essence, the technology correlates a live signal to previously stored signals sent by equipment located on the personnel, and can thus direct a rescuer along the previous path of a downed firefighter. This method also requires deployment of pre-existing infrastructure around the operating area and has similar limitations to the RF techniques described in the previous section.

1.2.4 Human Gait Analysis in Navigation

Human gait is the popular study of human locomotion and is often used in a kinesiology setting for injury evaluation and for the advancement of robotic locomotion. Human gait properties are very unique and variable between subjects due to the incredibly large number of degrees of freedom, yet these properties follow the same fundamental physical principles in all subjects [7].

Applying fundamental human gait principles in an engineering setting can help deduce a physical foundation for algorithms and sensor packages.

Applying the principle that “the body travels wherever the feet go” it is possible to glean some information about the location and state of the subject. A review of existing research into human gait properties was conducted, focused specifically on interactions involving the feet. It was concluded that only two fundamental human gait properties involving the feet were truly deterministic: the subject’s stride length and stride frequency [8]. The deterministic nature of these quantities allows the construction of individualized gait models for different subjects, using the fundamental relationship between stride length and frequency. It is important to note that the uniqueness of human gait properties between subjects also translates into large variability in gait model characteristics. This variability is sensitive to many factors, including footwear, type of gait mode, physical boundaries, and payloads. This prompts the question of accuracy of human gait models. It is clear that human gait modeling is simply a technique of first order accuracy, capable of augmenting existing systems and functioning as a form of “sanity check” and akin to simple pedometer concepts that are widespread in exercise distance estimation.

1.3 Objective of Current Work

The program objective is the study of human kinematics and dynamics to aid in the design of a robust personal navigation and tracking system for a variety of physical environments. An important aspect of the program was to develop a system by determining an appropriate suite of sensors and signal processing algorithms that can determine the user’s position inside of a building or structure without GPS or UWB to the accuracy of a meter. This work approaches the problem of personal navigation from a physical perspective and tries to gain important engineering insight from human gait characteristics. The modeling and study of First Responder (human) kinematics are imperative to the design of an optimal system for an emergency environment. The evaluation of the accuracy and performance of such a system in emergency environments was also a goal. The development of the personal navigation was sponsored by the Department of Homeland security and thus adhered to a set of requirements developed by the DHS. The difference between location (navigation) and tracking must also be considered in an overall design setting.

1.4 Thesis Outline

This work is comprised of a set of five chapters and a set of appendices.

The first Chapter outlines the problem statement, provides a historical overview of the work conducted in the field, the different approaches taken to solving the problem, and describes the current objectives of this research.

The second Chapter delves into the details of human biomechanics, as these principles are applied to different modes of human locomotion. This chapter also examines the unique characteristics and applications of human gait to the problem at hand, beginning with the investigation of simple pedometer concepts, and the expansion of these applications to an inertial system.

The third Chapter discusses a novel approach to determining the step size and heading of a human subject via a relative foot-sensor measurement. The proposed development of the relative foot sensor concept is outlined, the modeling of the sensor performance using both 2-D and 3-D simulations is presented, and the expected capability of the sensor is offered along with both its shortcomings and advantages.

The fourth Chapter describes the experimental approach taken toward validating the algorithms put forth in the previous Relative Foot Sensing Chapter. The algorithms presented in the previous chapter are evaluated using VICON motion capture data from a variety of subjects as input. An assortment of gait modes was investigated and the results are presented.

The final Chapter presents a summary of the results in this thesis and proposes future work for improving the quality of Personal Navigation packages and the accuracy of the gait modeled approach.

Appendix A evaluates the merit of using a differential GPS sensor as a platform for testing relative foot sensing concepts, and provides an estimate for the potential accuracy of the sensor.

Appendix B provides additional data captured throughout this work.

Chapter 2

Human Biomechanics of Walking

2.1 Modeling of Walking Biomechanics

Modeling and mathematical expression of human biomechanics has been a major focus of kinesiology and robotics research over the course of several decades. The evaluation of subjects and construction of kinematic models is far from a new phenomenon, yet for many years the goal of such models has been the analysis and prediction of forces and moments for injury analysis or robotic mimicry, rather than predictive capability of distance traveled. Breaking gait modeling down into individual, localized variables is a valid approach, and many existing models focus on highly specific properties of human gait. The approach described in this chapter is a simplification of the entire system and attempts to establish fundamental relationships found in the locomotive system in its entirety, rather than modeling each degree of freedom separately. This approach attempts to characterize deterministic properties of human gait including the stride length, stride frequency, and cumulative distance. A VICON motion capture system was used to record subjects walking on a treadmill and ground to model their stride length vs. frequency [Figure 1]. Firefighter boots were used for each walking test. It is clear from comparisons to regular walking and existing pedometry research that boots alter the natural gait in a complicated relationship that limits ankle movement and affects the acceleration and deceleration regions of the curve at higher frequencies [9].

It is possible to measure the instantaneous stride frequency of an individual using the accelerometer spikes from a synchronized inertial-based system. Given a model of stride length vs. frequency, it is then possible to calculate an estimated stride length of an individual using the instantaneous frequency information from the inertial measurements. This information allows the system to verify, to first order, the level of accuracy produced by the inertial sensor package. This approach can, in essence, be regarded as an advanced pedometer concept.

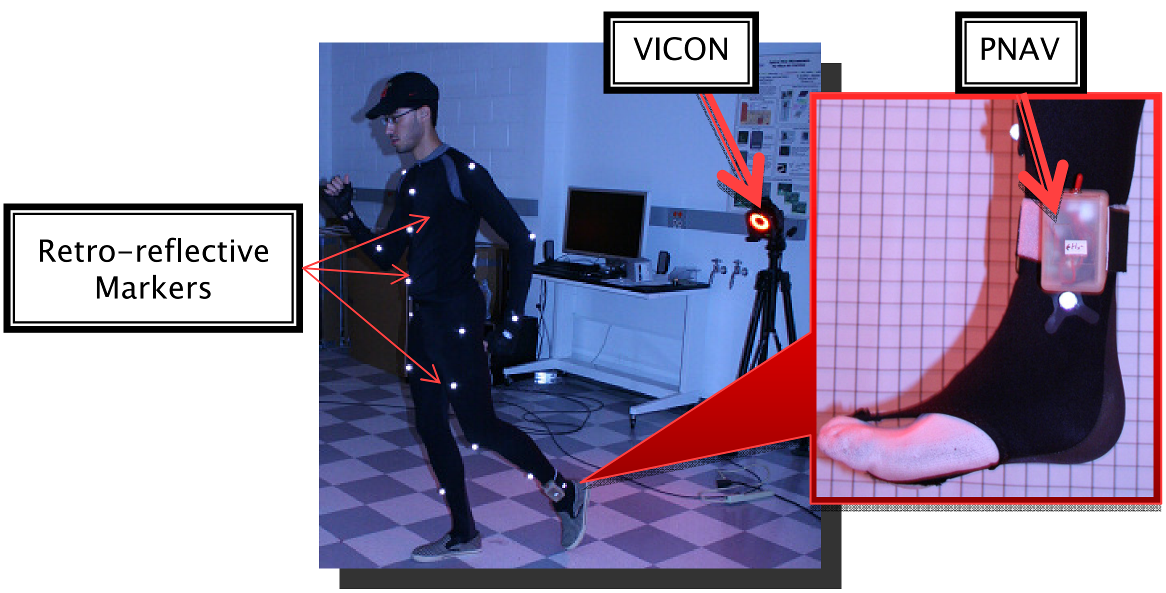

Figure 1: VICON Data Collection in Motion Capture Area

Motion capture technology allows precise tracking of markers in an absolute coordinate frame in space. This technology is extremely popular for obtaining experimental gait data, but quickly becomes expensive for use in large capture volumes. Thus, the use of treadmills for gait analysis has been popularized with the advent of motion capture technology, as it allows the investigation of gait for extended periods of time and distances, while eliminating the requirement for a large capture volume [10]. It is well documented that there are significant differences between human gait on a treadmill and gait over level ground. Of specific interest is the statistically significant difference in stride frequency on treadmills from the natural stride frequency over level ground. From the present analysis by Riley et al [11], it is clear that analysis of locomotion on treadmills often decreases the natural step size and increases the frequency of locomotion. Thus, in order to accurately create a model of natural gait, level ground locomotion should be analyzed. It is worth noting that human gait can also be affected by the addition of payloads and the introduction of low-visibility environments.

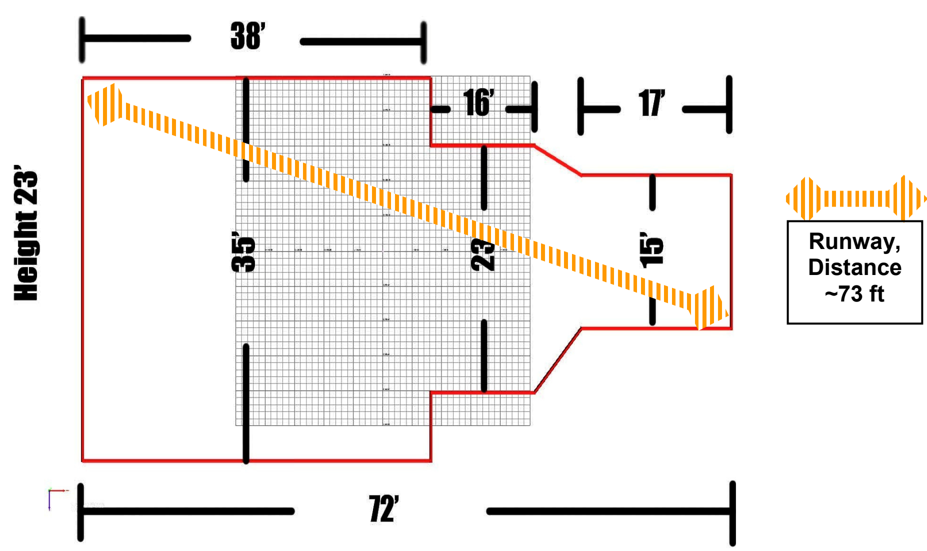

Figure 2: VICON House of Moves Capture Area

Gait models were constructed using VICON motion capture data of five different human subjects. The VICON motion capture data for five separate subjects was obtained by outside professional contractors at the House of Moves VICON studio in Los Angeles, California [Figure 2, Table 2]. Each subject wore Fireman boots in each gait mode trial. The data was transferred to the University of Maryland for processing and analysis. No personalized information about the subjects is available with the exception of key properties that characterize their gait such as height, gender, and weight [Table 1].

Table 1: House of Moves Subject Characteristics

Subject	Gender	Shoe size	Height	Weight
1	Female	7.5	5'9''	115 lbs
2	Male	11	6'1''	165 lbs
3	Female	5	5'9''	110 lbs
4	Female	7.5	5'7''	115 lbs
5	Male	14	6'7''	220 lbs

Each different mode of human locomotion must be modeled separately, and thus five unique modes were investigated: normal walking, backwards walking, forward shuffling, and crawling on hands and knees, and the army crawl on hands and elbows. In order to construct gait models, simple walking was investigated first at a range of speeds. This investigation validated basic kinesiology principles regarding the acceleration, natural, and deceleration sections of human gait, and allowed the focus of research to modeling natural gait properties, as they most accurately represent the average tendencies of the subjects over time. Using the treadmill data, a sample gait model of stride frequency vs. stride length was produced [Figure 3, Figure 4].

Table 2: Test Matrix at LA House of Moves

Gait Modality	Title	Description	Number Of Trials
1	Forward Walk	Regular walk along a straight line for a distance of 75 feet.	15
2	Backward Walk	Walking backward along a straight line for a distance of 75 feet.	15
3	Forward Shuffle	Shuffling forward without lifting up heel off of the ground for a distance of 75 feet.	15
4	Forward Crawl	Crawling on hands and knees for a distance of 75 feet.	10
5	Army Crawl	Crawling on stomach, elbows, and knees for a distance of 25 feet.	10

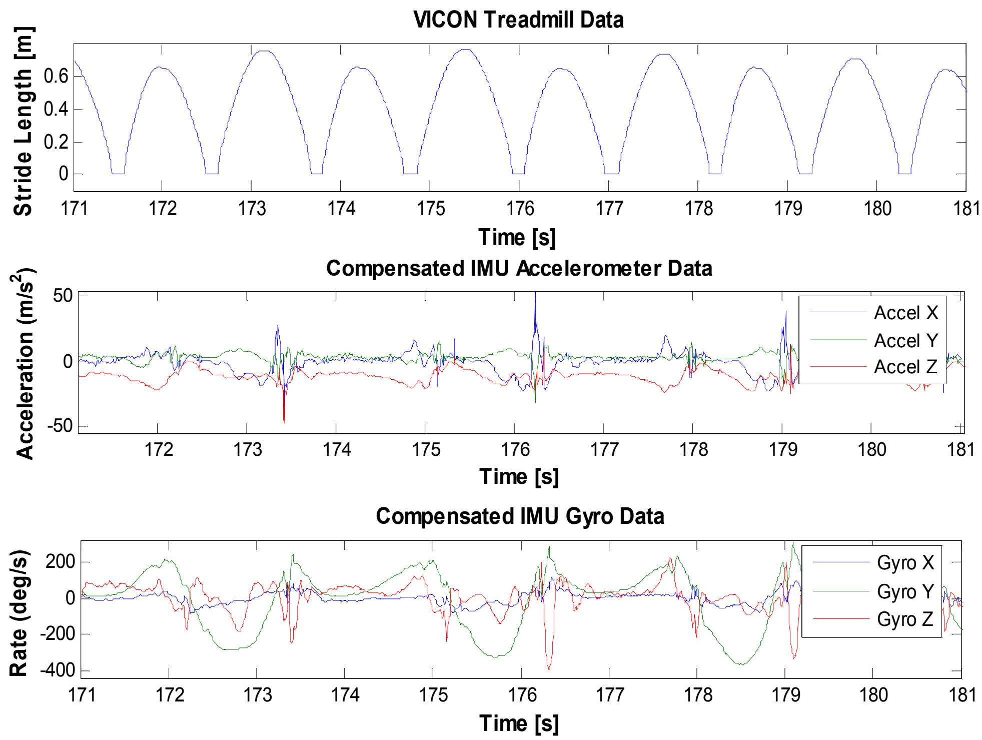

Figure 3: Treadmill Walking

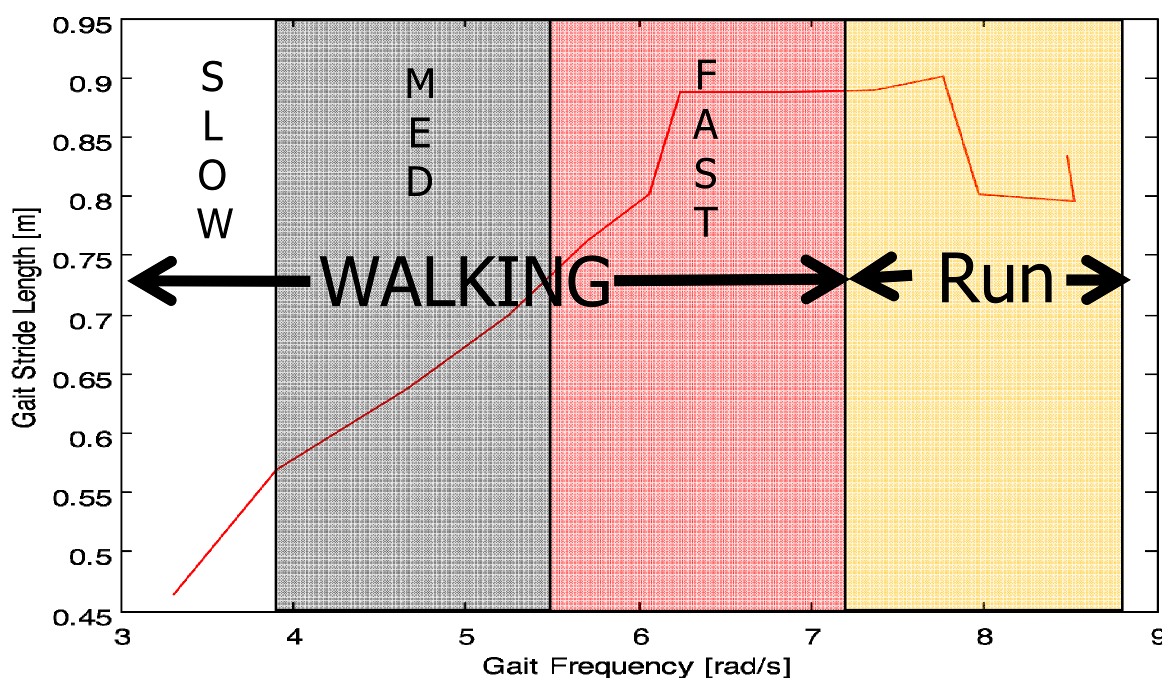

Figure 4: Treadmill Gait Model

It was determined through experimental testing and review of existing literature that the treadmill gait model was not entirely representative of the physical parameters of walking, as the treadmill dictated the frequency of the walking behavior, and did not allow the subject to enter their natural gait regime. The reasons for this are discussed at length by Riley et al. Treadmill walking can produce frequencies that are higher than the natural over ground frequencies at the same speeds by an average of 5-10%, to compensate, the corresponding stride length is lower by 3-7% [11, 12, 13].

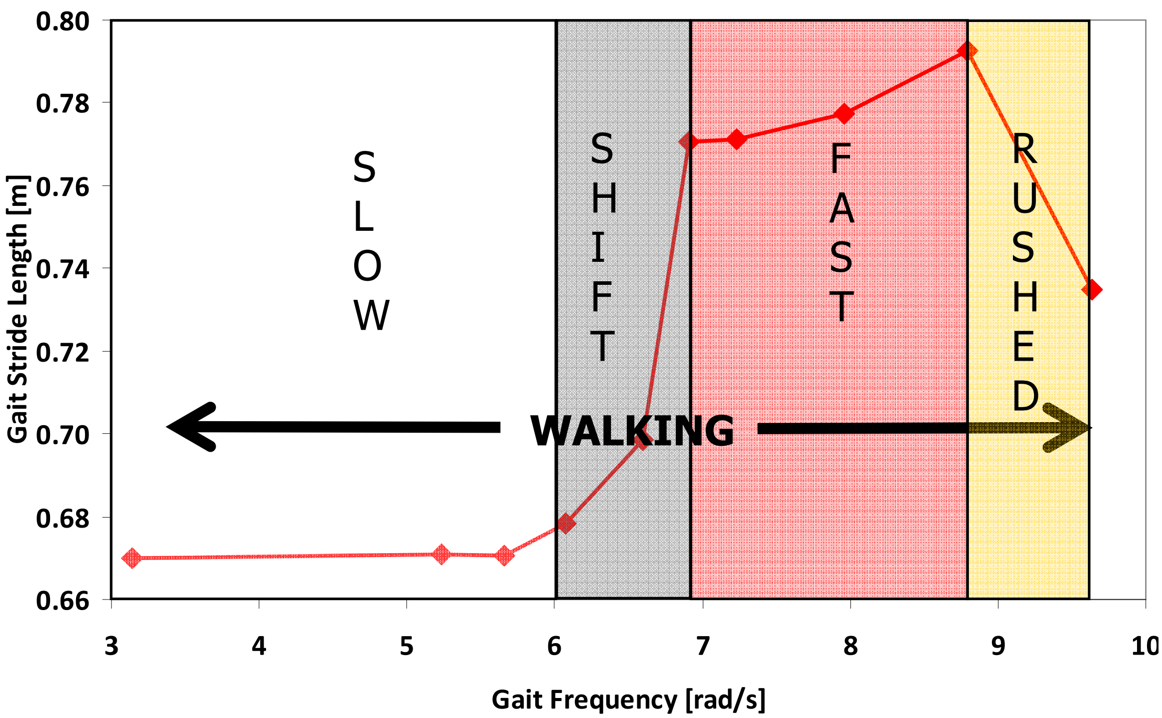

Figure 5: Ground Gait Model

To address these concerns, an additional investigation was conducted ground, in which the subject walked at different speeds over ground. This model was found to more accurately represent the distance traveled [Figure 5].

The gait model described above is used to estimate the total distance traveled and thereby provides a point of comparison to accelerometer outputs. To evaluate the error solely due to the distance calculation, straight line walking trials were analyzed for a variety of truth distances and at different walking speeds. Using an ideal step detection assumption (that each step is detected), it is possible to conclude that a gait model consistently determines the distance to within 5% of the true distance traveled. This is a substantial improvement over even existing advanced pedometer technology.

While the most obvious cause of most pedometer and gait-related errors is miscounted steps, the second leading cause is the misrepresentation of the acceleration and deceleration regimes. Simply put, as is evident in both Figure 4 and Figure 5, there is a non-linear acceleration and non-linear deceleration phase in the human gait. In order to account for that phase, a human gait model as found above may be used. The non-linear acceleration phase is uniquely defined by a large increase in stride frequency and is generally limited to the first three steps in normal walking modes. These steps are one half to one third of the natural gait stride length. The non-linear deceleration range is similarly expressed to the acceleration phase, but with a distinct drop in stride frequency. The natural gait regime can potentially be modeled very accurately, and serves as the foundation of pedometer technology.

This line of thinking naturally yields a comparison to existing simple pedometer technology.

2.2 Pedometers

Gauging distance traveled in units of strides, paces, or feet is a historically proven foundation for a measurement system, dating back to the ages of the Roman Empire [14]. Provided that the number of strides taken and the length of the strides are known, there is sufficient information to accurately determine the distance that was traversed. Most pedometers function on this principle, by counting steps as they are taken, and multiplying by an averaged stride length. The idea of mechanical pedometers was first conceived by the thought of inventors like Leonardo DaVinci and mechanically implemented by Thomas Jefferson [15]. These innovations were driven by a military demand and application toward mapping technology.

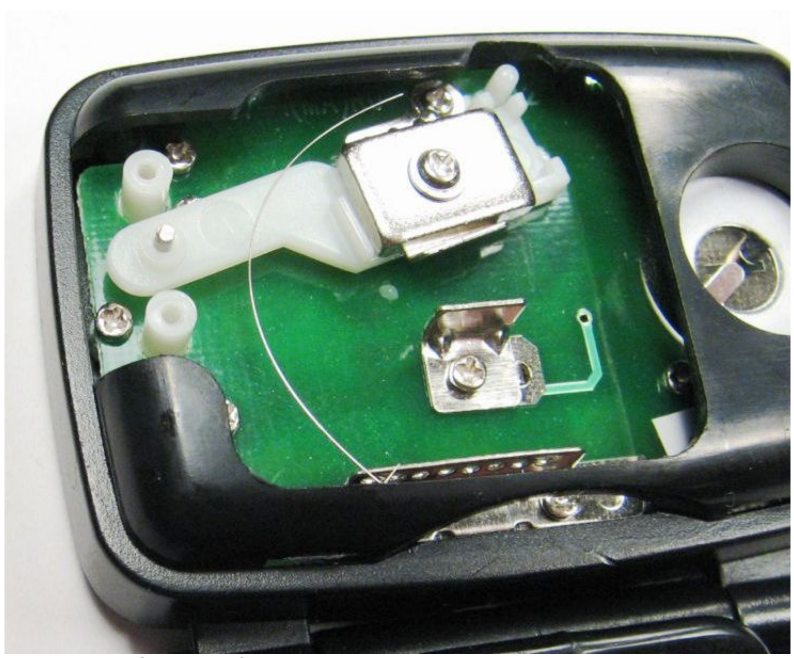

Photo Courtesy of Lenore M. Edman, www.evilmadscientist.com [16].

Figure 6: Modern Mechanical Pedometer

Mechanical pedometers count the number of steps via a pendulum or other inertial mechanism. These pedometers are prone to miscounting steps due to separate tendencies to over count in active regimes and under count in passive ones. Simple mechanical pedometers count only the number of steps and multiply this number by an “average human stride length”, generally close to 76 centimeters in length [17]. An example of a simple pendulum in a modern pedometer that closes an electric circuit to count a step is shown in Figure 6.

Advanced digital pedometers use two-axis and three-axis accelerometers to measure spikes in acceleration, and software to process the signal via predetermined algorithms to decide whether a step has been taken, and the length of each step. These pedometers are even capable of personalized calibration to individual gait parameters for increased accuracy; however, the biggest errors still accumulate due to missing steps. Coupled software systems and the advent of software focusing on cadence is moving toward becoming a standard – and yet this software does not yet include fully adaptive gait models [18]. Even with modern technology, slower walking has always presented a more difficult problem to solve, due to the smaller amount of available information for detecting a step in the presence of less distinct peaks in accelerometer spikes and rhythmic gait patterns.

Accuracy of mechanical and modern pedometer technology has been thoroughly evaluated by the research community. The study performed by Vincent et al. [19] makes the claim that consistent accuracy in step detection is possible by modern pedometer technology to within 5%. In order to compare the developed gait models to existing technology, a Tech4O Accelerator RM1 watch and a mechanical waistband Yamax Digiwalker SW700 pedometer were used. The Tech4O Accelerator watch contains a three-axis accelerometer and claims accuracy above 95%. This particular pedometer has the unique attribute of differentiating between running and walking gait, and using separate stride lengths to estimate each. The watch was calibrated to the individual gait attributes of the subject prior to testing. A walking test was performed on a distance of approximately 40 meters at slow, natural, and fast walking speeds.

A long straight hallway of 40 meters was traversed, and the resulting data was analyzed using pedometers, two ankle IMUs, and the ground model described in Section 2.1. At a natural (moderate) walking speed, on average, the subject traversed the hallway in a total of 59 steps.

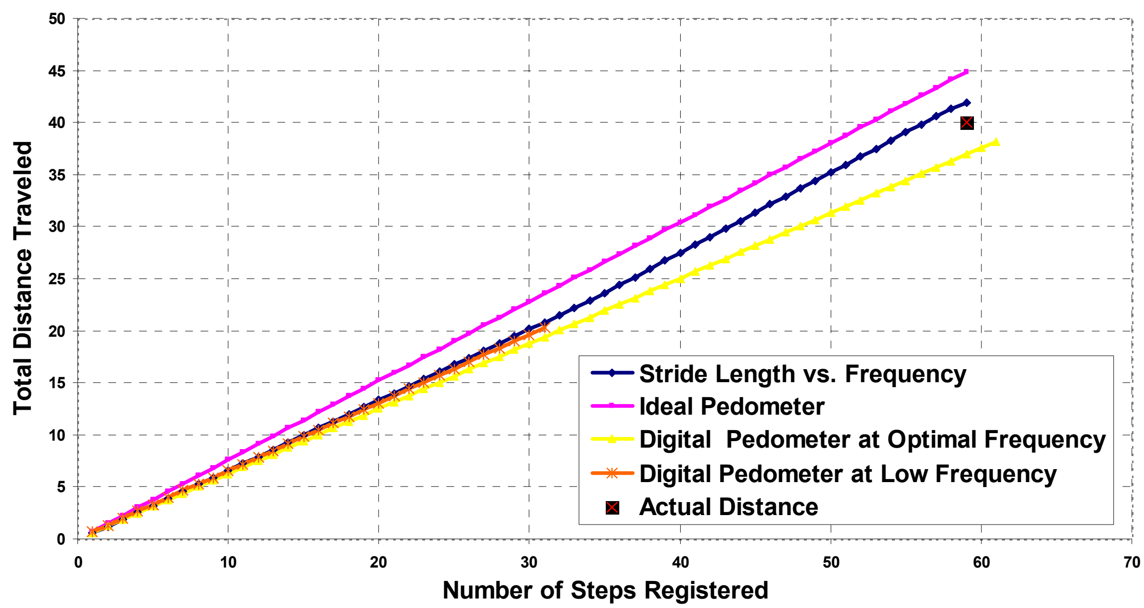

Figure 7: 40 Meter Walk Distance Deviation

An ideal mechanical pedometer with 59 steps would therefore yield a total traversed distance of 44.84 meters, and an error of 12.1%. A digital pedometer yielded an error range between 5% and 40%, depending on stride frequency. Running the acquired data through a stride-length vs. frequency model repeatedly generated accuracies near 5%, the best run yielded a traversed distance of 41.4 meters (3.5% error). It is important to conclude, therefore, that dead-reckoning systems with expensive sensor packages yield accuracies between 3% and 5% [20].

The results found in [Table 3: 40m Walk Prediction Error] for a natural (moderate) walking speed conclusively demonstrate that the gait model performed better than both mechanical and advanced digital pedometers for all walking speeds, assuming that the same number of steps were "missed" due to accelerometer insufficiency. However, using peak detection and the relative foot sensor concept described in Chapter 3 with the human gait model should eliminate a large portion of the accumulated error due to missed steps, and further increase the potential system accuracy and robustness.

Table 3: 40m Walk Prediction Error

Type of Model	Total Distance Error (m)	Percent Error
Simple Stride Length vs. Frequency Model	1.888	4.72%
Ideal Pedometer	4.84	12.1%
Digital Pedometer at Optimal Frequency	-1.83	4.57%
Digital Pedometer at Low Frequency	-19.71	49.29%

It is important to consider that human gait models must be individualized to the subject, and their validity can change due to the addition of payloads and the physical surroundings. Thus, there are a number of issues that can arise with subject base-lining, and the use of gait models alone to represent the distance traveled. Thus, the concept of human gait modeling can only be considered as an addition to an existing inertial system.

2.3 Inertial Measurement Systems

The University of Maryland's "Maryland Avionics Package" (MAP) was used as the foundation for the personal navigation inertial system. A suite of necessary sensors for complete dead-reckoning were selected from the avionics package to form the personal navigation system (PNAV), complete with three accelerometers, gyros, and magnetometer. The Maryland Avionics Package was described and developed in Conroy et al. [21]. The larger and more cumbersome PNAV package was later upgraded with the aid of Advanced Medical Electronics Corporation and the use of their miniaturization technology. Paul Gibson lead the project as primary investigator of "A Wireless Wearable System to Measure Adherence to Mind-Body Study Protocols", funded by the National Institutes of Health, and produced some of the necessary technology that was used over the course of this project by the AME Corp.

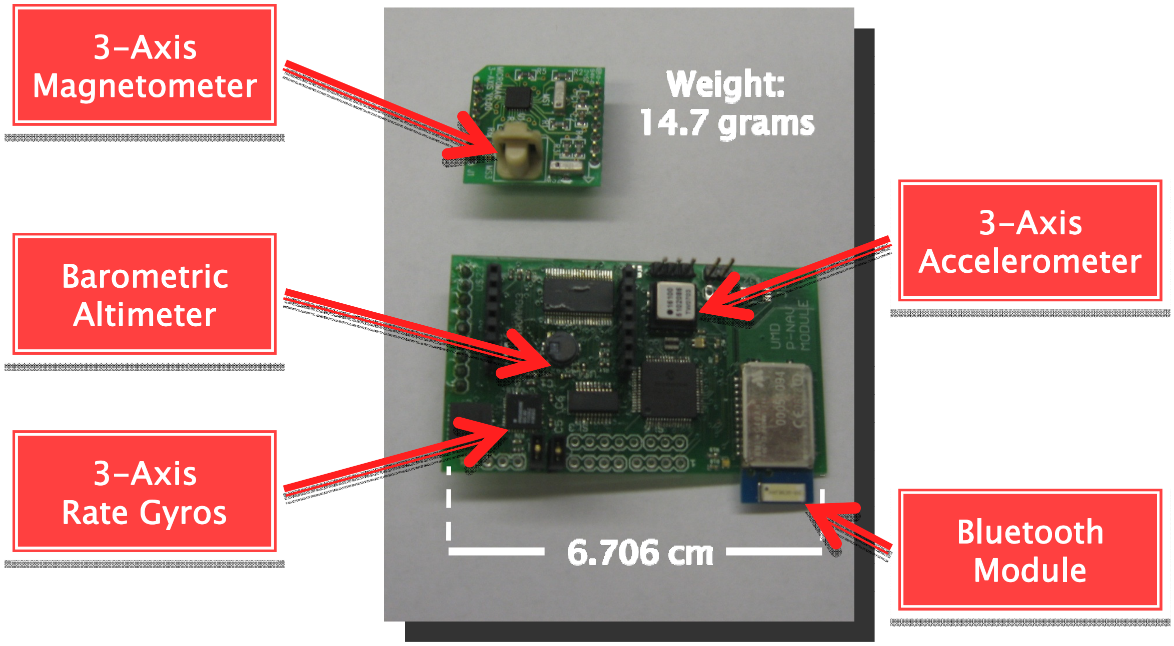

Figure 8: PNAV Circuit Board

The development of dead-reckoning systems has been well documented, and most notably IMU packages fall in ranges similar to Honeywell and its DRM class systems. Honeywell claims approximately 2-5% errors for the Honeywell DRM 4000 without GPS fix [20]. Thus, in order to be competitive with the industry systems, the PNAV system needed to be capable of similar accuracy and precision, after the addition of notable filtering and error re-zeroing techniques.

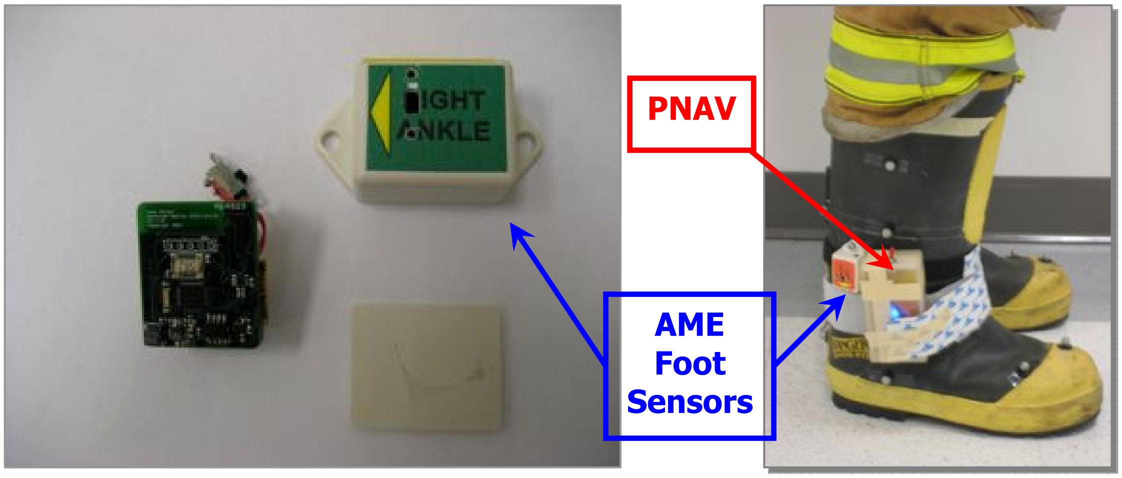

Figure 9: PNAV and AME Corp Inertial Sensor Suite

The PNAV and AME inertial systems were calibrated through a process of bias and scale factor determination on accelerometers, gyroscopes, and magnetometer sensors. The resulting data was then used in processing the signal and integrating the signals for distance and heading information.

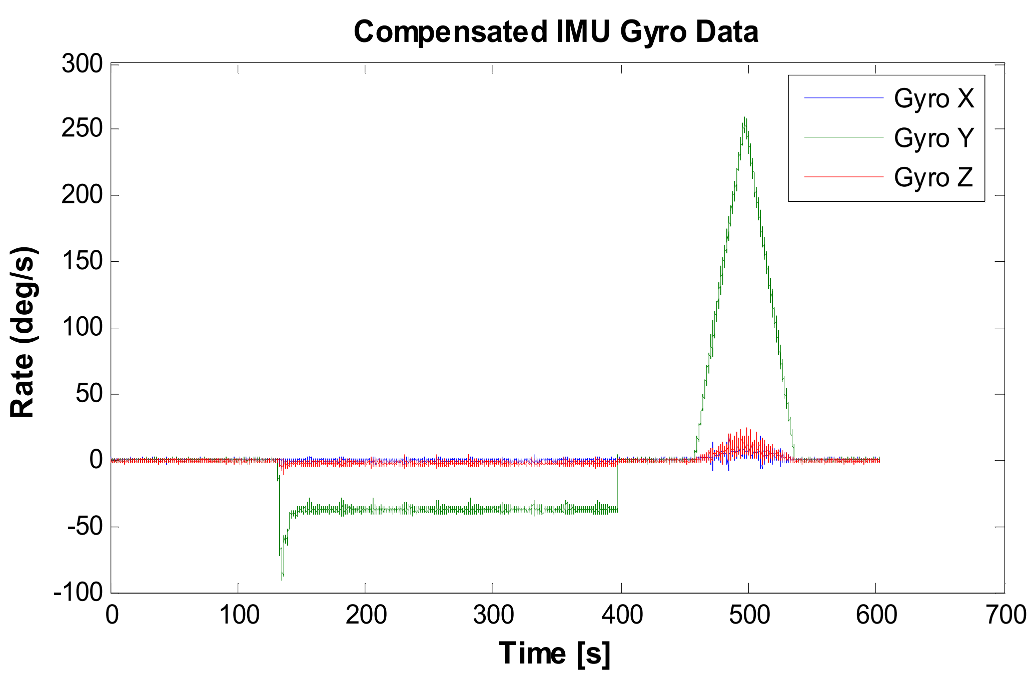

Figure 10: Gyroscope Calibration

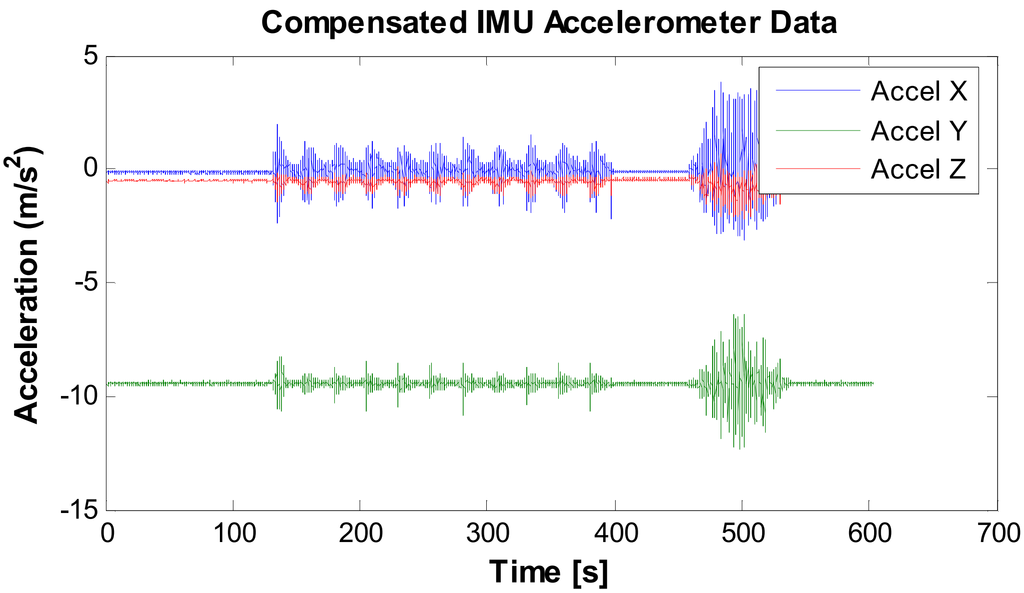

Figure 11: Accelerometer Calibration

A rate table setup, as shown in Figure 12, was used to calibrate the sensor suite. The noise characteristics were also sampled to estimate potential error and aid in the effective construction of filter techniques. While an onboard filtering technique was never implemented with the inertial solution, an alternate technology was pursued for development including the analysis of zero-velocity updates [22]. Some automatic filtering techniques were briefly investigated in the post-processing scheme, to estimate the order of magnitude of the error due to drift from the use of an inertial solution alone. It was established that within fifteen minutes of operation, the accelerometer and gyro solution would significantly degenerate from the true location, when applied to simple walking, in a range of 6-15% error.

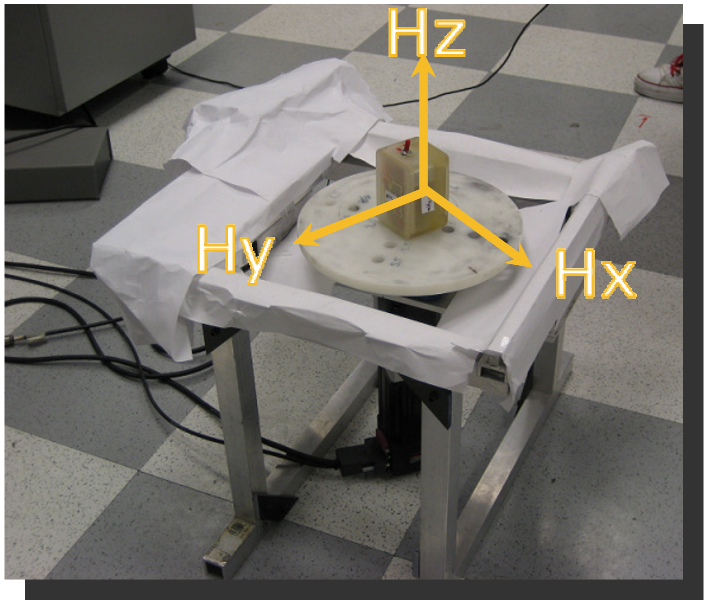

Figure 12: PNAV on Rate Table

Integrating unfiltered three-dimensional results of an extended indoor walk, combined with stair climbing and multiple direction changes produced an overall error close to 15% over 15 minutes. By adding a re-zero velocity update technique, the error range could be decreased to 5-7%. The new AME sensors were then used as a second generation PNAV board, with an updated sensor suite that communicated through Bluetooth with a main station (personal computer) that collected the data and produced similar error ranges to the first generation PNAV board. It is clear that an inertial solution alone is not sufficient to accurately solve the GPS-denied navigation problem.

2.4 Summary

Successful gait modeling can provide higher order of accuracy and a first order validation to inertial based systems. On a straight line walk, 5% error in distance from a gait-based model was determined, as shown in Table 3. This result is an improvement upon regular pedometer techniques, and can have a wide range of applications. Figure 4 and Figure 5 show the range and development of a stride length vs. frequency model. These figures exhibit a large vertical spike in stride length at a certain frequency, this frequency is very near 1Hz, or 6 radians/s. Inaccuracies in frequency measurements in this range can significantly increase the accumulated error. This regime requires a higher resolution of the behavior and more testing, as this falls into the category of non-linear gait behavior.

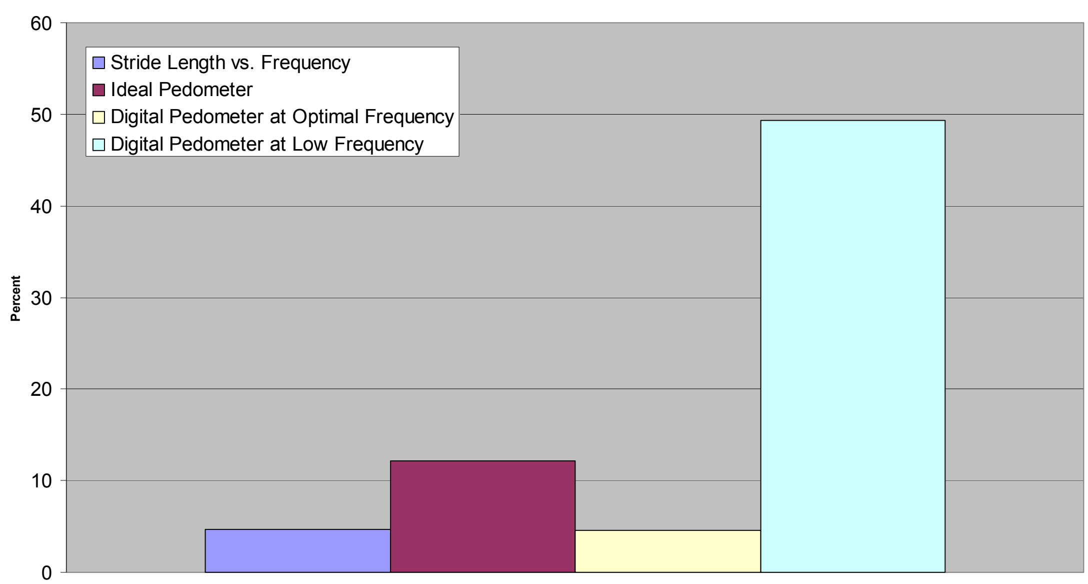

Figure 13: Distance Error for Different Methods Over 40m Walk

The greatest error in pedometer technology still stems from miscounting of the numbers of steps taken. Novel gait model analysis techniques can aid in the detection of steps with the use of a peak detection algorithm. A real-time peak detection algorithm, when synchronized with an inertial system, can help determine the likelihood of a certain mode. In order for this to be accomplished, future fuzzy logic algorithms must be developed.

There are drawbacks to gait-modeling, including the need for time-consuming personalized calibration and privacy concerns regarding the collection of personal data from first responders. Some potential scalability applications of the human gait models may exist, but require a more statistically sound analysis of gait properties in relation to specific body types, in a search for universal relationships between height, in-seam length, and stride length [23]. Stride parameters (stride length and cadence) are functions of body height, weight, and gender. Previous work has demonstrated effective use of such biometrics for identification and verification of people [24].

In order to characterize the gait mode that a subject is traveling in and more accurately count the number of steps taken, a distance calculating relative-foot sensor was conceived. Thinking of the gait models expressed in terms of stride length, it is natural to expand the principle to attempt measuring the distance between the feet in real time. This idea leads directly to the introduction of the relative foot sensor. Overall, the human gait model approach has the strong potential to aid the accuracy of personal navigation systems, and gives birth to a new type of pedometry concept.

Chapter 3

Relative Foot Sensing

3.1 Overview

The research presented in the first two chapters highlights several issues with existing sensor concepts and their application to emergency environments. Current sensors only infer number of step and coarsely measure the heading, and very few sensors produce exactly what is needed. Additional issues arise from the kinds of motions that emergency personnel must undergo, for instance, the shuffling of feet or side-stepping can easily be interpreted as a full step by inertial systems. Crawling motions on knees and belly present an even more challenging problem for existing sensor packages. Walking up stairs and climbing ladders presents a height informational challenge, as vertical rung steps can be interpreted as forward steps. Baro-altimeters are insufficient, as they are adversely affected by temperature and pressure in fire environments. The error associated with such motions grows rapidly. While gyros and accelerometers can be used to determine the proper orientation of the subject, the distance traveled becomes difficult to measure. A true dead reckoning sensor that can provide true distance and direction information is necessary for an elegant solution to the personal navigation problem. This chapter outlines the concept of relative foot sensing and details the algorithms necessary to process its accuracy and potential output data to achieve desired Personal Navigation results.

A new sensor to detect accurate stride lengths and incremental headings can be designed through the use of a network of wireless sensors in boots, that measure distances between each node. Simply demonstrated, Figure 14 shows the concept of measuring distance between different locations on the foot. This sensor can solve gait estimation and magnetometer deviation issues. The use of RF techniques for distance measurement via time of flight has been extensively investigated [25].

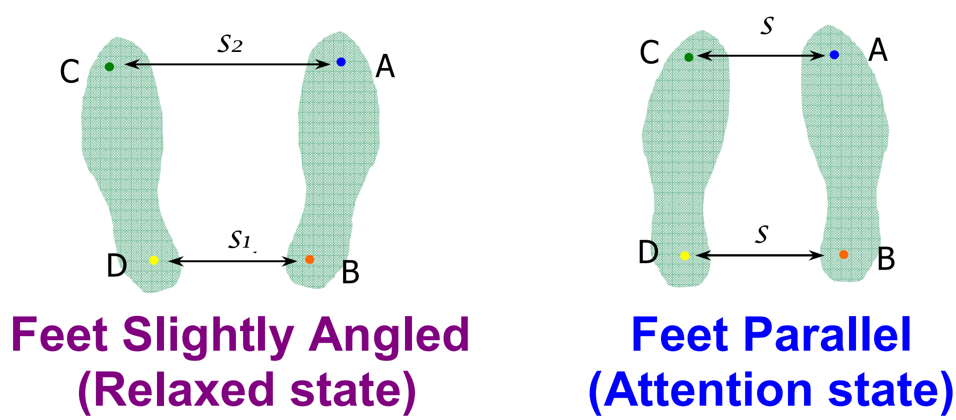

Figure 14: Simple Relative Foot Sensor Concept

Attaching multiple sensors on each foot provides the ability to determine the distance between each sensor node, such as $r_{AB} = r_{BA}$, $r_{CD} = r_{DC}$. These distances were assumed to be constant, due to the rigid body assumption for the sole of the boot. This assumption does not have to be a limitation of the method, as with a large number of nodes, the assumption can be disregarded. The determination of heading and stride length turns into a geometric problem. There are multiple options for range determination methods, such as Signal Time of Flight (TOF), Magnetic Intensity, or RF Phase Modulation [26]. The most practical solution is the positioning of RF receivers and transmitters plus processing board in the sole of the boot [Figure 15]. Using unique node identifiers, the carrier wave phase is processed for an accurate distance determination between two nodes.

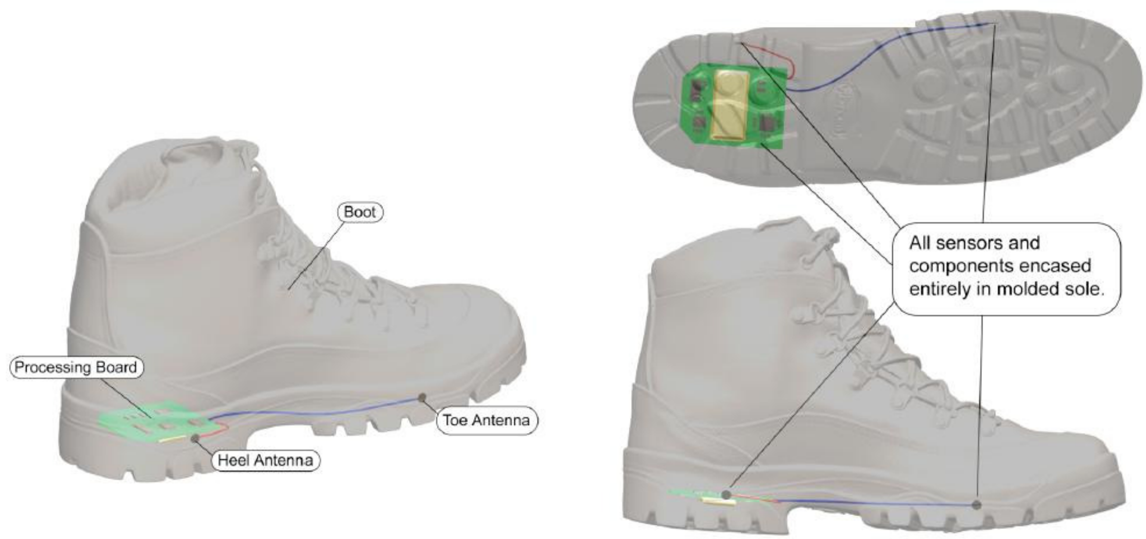

Figure 15: Relative Foot Sensor Boot Layout Concept

The VICON motion capture system provides absolute coordinates of markers located on First Responder boots, as they move through space, while the First Responders undergo basic gait motions such as walking, crawling, shuffling, etc. It is clear that from the location of these markers it is possible to calculate the distance between these markers, and therefore simulate the calculation of an incremental heading and stride length as a function of time. A geometric stride length is defined as the distance between the two feet when they are both on the ground. This method cannot be applied to running, when both feet may be in the air for some period of time [27]. The VICON motion capture system is not noise-free, and is capable of tracking its markers to millimeter accuracy [28]. Running a simple accuracy analysis for the required radio frequency of 2.4 GHz on a simple stride case [Figure 16]:

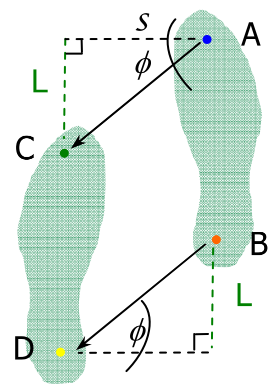

Figure 16: Simple Stride

$$L = \sqrt{r_{AC}^{\ 2} - s^2} \tag{3.1}$$

$$\partial L = \frac{r_{AC}}{\sqrt{r_{AC}^{\ 2} - s^2}} \partial r_{AC} \tag{3.2}$$

The assumption is made that foot separation does not change. In addition, some simple suppositions about the basic level of step accuracy and stride lengths estimates are made to calculate the sensor requirements.

$$\begin{aligned} s &= 0.5m & \partial s &= 0 \\ r_{AC} &= 0.75m & \partial r_{AC} &= 0.5mm \end{aligned} \tag{3.3}$$

Substituting (3.3) into (3.2), an accuracy determination on the order of 1mm is made in (3.4).

$$\partial L = \frac{0.75}{\sqrt{0.75^2 - 0.5^2}} 0.0005 = 0.67mm \cong 1mm \qquad (3.4)$$

If a 2.4 GHz radio frequency is assumed:

$$\frac{\partial r_{AC}}{v} = \frac{0.0005m}{0.125m} = \frac{1}{250} cycle \qquad (3.5)$$

Thus, measuring 1/250 of the radio wavelength would allow each stride length measurement to be accurate within 1 mm. Thus, VICON motion capture data taken for subjects in the professional LA House of Moves studio can be used to simulate the performance of the Relative Foot Sensor concept. Using this information, an elaboration on the algorithms was made to simulate the behavior of the system in a two dimensional environment with Random Gaussian Noise, the results of this simulation will be further discussed in the next section.

3.2 2-D Modeling

The sensor would be responsible for measuring distances $\boldsymbol{r}_{AC}$, $\boldsymbol{r}_{BD}$, $\boldsymbol{r}_{AB}$, $\boldsymbol{r}_{BC}$, $\boldsymbol{r}_{AD}$, and $\boldsymbol{r}_{CD}$, thus they are assumed to be known at each step**.** The variables that require calculation or estimation are denoted with a tilda (~) on the top. A set of initial conditions or information from the previous step must be assumed to solve the set of linear equations for a full 2-D step, described below in Figure 17.

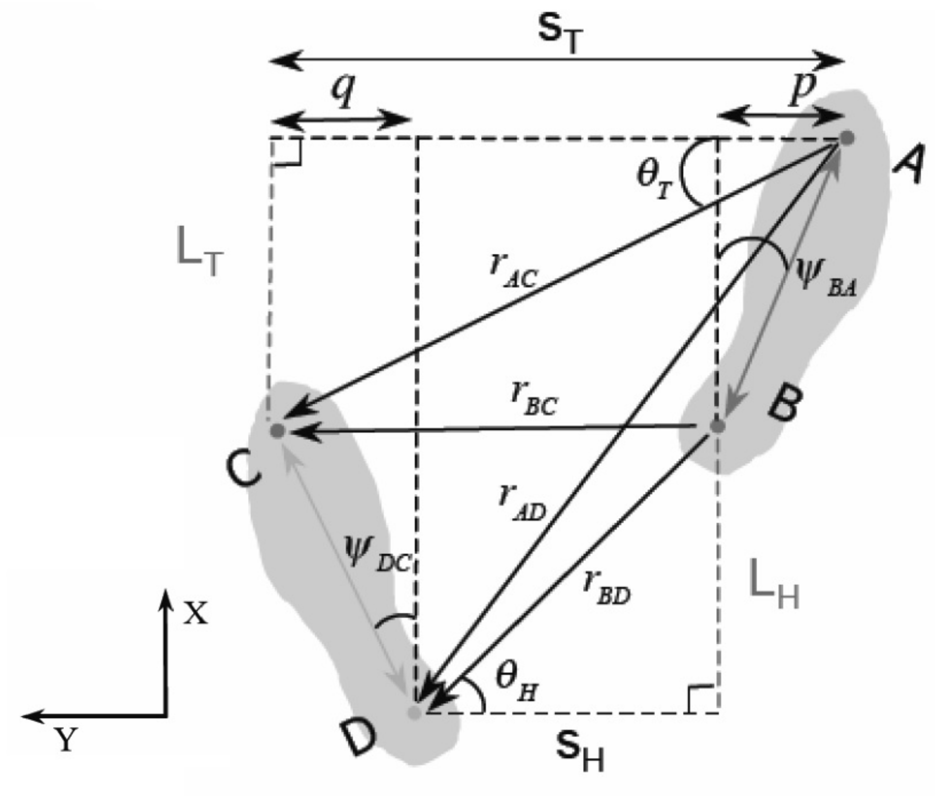

Figure 17: Full Geometry of 2-D Step

The stride length and foot separation entities are estimated as simple geometric properties of the step:

$$\tilde{L}_2 = \sin(\tilde{\phi}_2) r_{BD} \quad (3.6a)$$

$$\tilde{s}_2 = \cos(\tilde{\phi}_2) r_{BD} \quad (3.6b)$$

This can in turn be expanded to an expression. And a series of non-linear equations in 3.8 can be constructed for the system.

$$r_{BC}{}^2 = r_{CD}{}^2 + r_{BD}{}^2 - 2 r_{CD} r_{BD} \cos(90° - \tilde{\phi}_2) \quad (3.7)$$

$$\psi_{BA}(t_k) + \theta_T(t_k) + \theta_{CAB}(t_k) - 90° = 0 \qquad (3.8a)$$

$$\theta_{CDB}(t_k) - \psi_{DC}(t_{k-1}) + \theta_H(t_k) - 90° = 0 \qquad (3.8b)$$

$$\psi_{DC}(t_{k-1}) + \theta_{ACD}(t_k) - \theta_T(t_k) - 90° = 0 \qquad (3.8c)$$

$$\theta_{ABD}(t_k) - \psi_{BA}(t_k) - \theta_H(t_k) - 90° = 0 \qquad (3.8d)$$

Using the law of cosines: θ_{CAB}, θ_{CDB}, θ_{ACD}, and θ_{ABD} are found:

$$\theta_{ABD} = \arccos\left[\frac{r_{BA}^2 + r_{BD}^2 - r_{AD}^2}{2r_{BD}r_{BA}}\right] \qquad (3.9)$$

Since the heading from the previous step is always known, this system of equations can be solved for the next step stride length L_H and separation distance S_H

$$L_H = r_{BD}\sin(\theta_H) \qquad (3.10a)$$

$$s_H = r_{BD}\cos(\theta_H) \qquad (3.10b)$$

Integrating these quantities over time in turn produces the desired x and y location with respect to the starting point.

Using the past time step estimates provides a good initial guess to the next time step solution, to solve the non-linear system of equations that can be expressed in the following terms:

$$r_{BD}^2 = s_H^2 + L_H^2 \tag{3.11a}$$

$$r_{AD}^2 = (s_H + r_{BA}\sin\psi_{BA})^2 + (L_H + r_{BA}\cos\psi_{BA})^2 \tag{3.11b}$$

$$r_{AD}^2 = (s_H + r_{DC}\sin\psi_{DC} + r_{BA}\sin\psi_{BA})^2 + (L_H - r_{DC}\sin\psi_{DC} + r_{BA}\cos\psi_{BA})^2 \tag{3.11c}$$

$$r_{AD}^2 = (s_H + r_{DC}\sin\psi_{DC})^2 + (L_H - r_{DC}\cos\psi_{DC})^2 \tag{3.11d}$$

It is important to consider the limitations of this approach. The relative foot sensor alone is not capable of differentiating between forward and backward motion, or rightward and leftward motion, the integration of an inertial solution for directional addition is vital.

A simple transformation of reference frames can also be used to approach the problem from an “incremental” heading and stride length point of view. It is also important to note that the derivations above use a different frame of reference than the collected VICON data, and the entirety of the processing was conducted in the VICON xyz coordinate frame.

3.3 3-D Modeling

The two dimensional model can be expanded to three dimensions with the use of nodes A, B, C, D placed on the ankle or calf of the boot, in the Y-Z plane. A similar technique to the one described in Section 3.2 can then be used to determine the position of the feet in the vertical direction. Using the same derivation pattern as in the previous section, the two solutions can be combined for an X-Z and a Y-Z plane. By combining the X-Y solutions, and the X-Z/Y-Z solution, a full three-dimensional solution can be obtained.

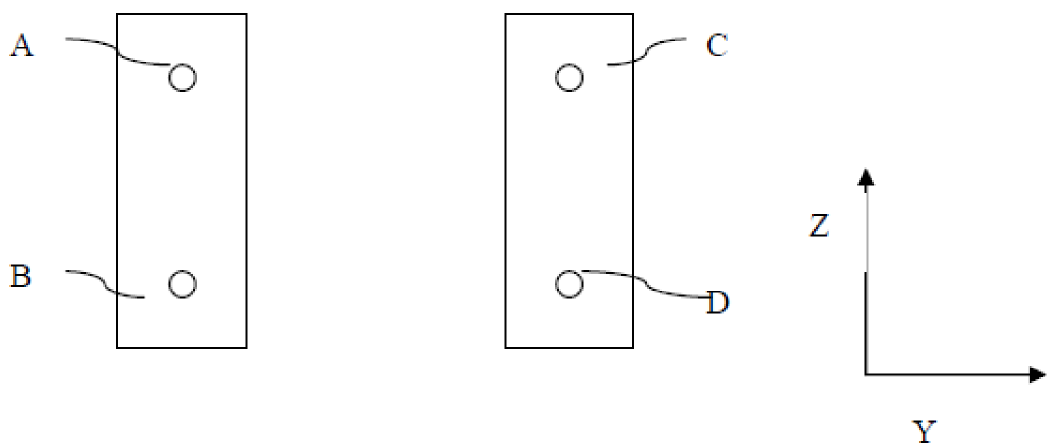

Figure 18: Additional Node Locations for 3-D Solution

The full three dimensional solution has immense benefits, as it eliminates the necessity for a magnetometer to successfully determine stair-climbing and ladder climbing.

3.4 Predictions

Using these concepts a simple 2-D simulation was coded in Matlab to test the effect of random inputted noise on a 4 node system, as described above. The simulation was run for ranges of 50-500 randomly varying steps, with an average step size of 50 centimeters, and repeated for a range of random error magnitudes to determine the necessary accuracy of the sensors. A sample error range for a path comprised of 250 steps, and a total truth distance of 125 meters is shown in Table 4. The relative foot sensor nodes must communicate with an accuracy of at least 1mm to achieve the desired accuracy for personal navigation. The relative foot sensor level of accuracy can significantly reduce the error associated with heading changes and completely eliminate certain errors due to the inability to differentiate between steps, as new peak detection algorithms can solve those issues.

Table 4: 2-D Simulation Error Range

Noise Magnitude	Percent Error Range	Distance Error
0.001 mm	± 10^{-4} %	0.000125 m
0.01 mm	± 10^{-3} %	0.00125 m
0.1 mm	± 10^{-2} %	0.0125 m
1 mm	± 10^{-1} %	0.125 m
1 cm	± 1 %	1.25 m
10 cm	± 10 %	12.5 m
1 m	± 100 %	125 m

A further study of the accuracy of these algorithms with the use of the relative foot sensor conecpt will be detailed in conjunction with the VICON data in the next Chapter. VICON data represents the exact human motion with an addition of a variety of noise characteristics, which makes it ideal for the evaluation of the algorithms, including alternate modes of gait such as crawling.

3.5 Summary

The relative foot sensor concept is groundbreaking in its approach to human gait and personal navigation, as it provides the ability to accurately determine the incremental heading and stride length of the subject with each step. Two-dimensional algorithms for finding the stride length and local heading angle are presented. The expansion to a three dimensional system is discussed by addition of vertical nodes and a similar approach as described in 2-D. A qualitative analysis on the expected error term in distance is evaluated. Coupled with an inertial approach to personal navigation, this sensor may be able to provide an elegant solution for issues in determining heading.

There are multiple challenges to successfully implementing this sensor as a solution, from a hardware standpoint. There must be common time synchronization across all of the sensor nodes, as well as with the inertial navigation framework. The sensor must also be small in size, low in weight, and have low power usage for any practical applicability.

A good proof of concept test is the use of differential GPS, which can be used to emulate a wireless signal between two nodes. This approach will be briefly discussed in Appendix A. The relative foot sensor also provides a new, previously unstudied metric of “distance between feet” that can be applied in kinesiology toward injury assessment. This metric can also be used for pattern recognition and many other applications.

Chapter 4

Experimental Testing and Validation of Relative Foot Measurements

4.1 Peak Detection Overview

In order to analyze the VICON motion capture data for the simulation of the relative foot sensor, a determination must be made on how to pre-process measurement data with the system limitations of power, computer processing throughput, and memory size. One approach is to only analyze peaks in the relative foot sensor data. When the maximum and minimum separation distances between nodes occur, some conclusions can be made about the state of the subject. For instance, when the foot separation is at a maximum between heel nodes, that distance is likely to correspond well to the subject's stride length in the regular walking mode. While this is not an exact measurement due to unique tendencies in subject's gait, it is a fair estimate in the absence of a time-synchronized inertial system.

Thus, for processing relative foot sensor data, a decision must be made whether peak amplitude of relative foot distance (discrete) or continuous data processing is the best approach. Each approach has distinct advantages and disadvantages. Continuous Processing requires significant processer power, but should be capable of much greater robustness, accuracy, and complexity of algorithms, since it provides “up to the second” information. Peak detection provides only distance information at freeze frames, similar to the way that distance and tracking information can be measured from foot-steps in the snow. A peak detection system would need to operate at least two steps behind real-time for successful peak detection and implementation. However, the overall navigation system would be simpler and more cost-efficient, while providing a first order level of accuracy. Due to the relative simplicity of its algorithms, peak detection was investigated first. The challenge in this algorithm, much like other pedometer concepts, remains in figuring out how to detect a step or a peak.

As stated previously, VICON data contains a relatively small magnitude of noise, which is expected to be on the same order as the noise characterized by the relative-foot sensor. Excessive noise prevents easy peak detection and must be filtered, but noise filtering requires processing power and proper design to maintain accuracy. A variety of cases were recorded and examined for the relative foot sensor algorithms: walking, crawling, ladder-climbing, shuffling, etc. A variety of filter strategies could be designed or applied to the motion capture data (low-pass, Kalman, Chebyshev, etc). It is important to note that unique filtering parameters would be necessary for the data of the actual relative foot sensor, as opposed to the filtering technique presented here for the VICON data. A vast amount of audio and imaging software exists, featuring built-in, well designed filtering capability. Rather than design and test a variety of filters in the initial stages of the research, the VICON data was uploaded into an open-source audio editor “Audacity” [29]. This software allowed the simple design, testing, and visualization of filtered data, represented as a sound wave in “.wav” format. The data was first processed with a low-pass filter and in the majority of trials it was found that a single low-pass filter with a threshold of 355 Hz was sufficient for achieving the desired results, by eliminating spurious peaks. In the cases where spurious peaks prevailed, more information was necessary to determine the type of movement that the subject was making in order to make the judgment on which peak had physical meaning. If the type of motion that the subject is making can be constrained to walking, crawling, shuffling, etc., it is possible to account for, and eliminate all spurious peaks in a processing algorithm. In addition, when an inertial system is time-synchronized with the relative foot sensor, step detection becomes significantly simpler. However, the design of a navigation system based purely on a relative foot sensor requires the use of fuzzy logic for locomotion mode detection, which will be the subject of future research.

The most telling case, due to its intuitive nature, remains the straight-line walk. This case will be analyzed and presented in-depth, with the use the heel node as the “primary” node for presented analysis.

4.2 Peak Detection in Linear Walking

The initial walking trials were conducted for a distance of 11 feet (3.3528m). The overall distance was limited due to the VICON motion capture setup and the constrained capture volume for imaging. In the trial presented below, the subject took 8 steps to cover that distance. The preliminary walking distances were then used to analyze the gait patterns highlighted by the relative foot sensor and the filtering techniques that could be successfully applied to the data set, as described in Section 4.1 [Figure 19]. This figure also demonstrates the potential to break the relative foot sensor data into x, y, and z components in a local inertial frame. This is simply possible when using the VICON data, but it is also possible using simple geometric properties for the relative foot sensor, given a minimum number of four nodes on each foot for full 3-D resolution. This set of information is invaluable for gait pattern recognition and will be discussed in more detail in a later section.

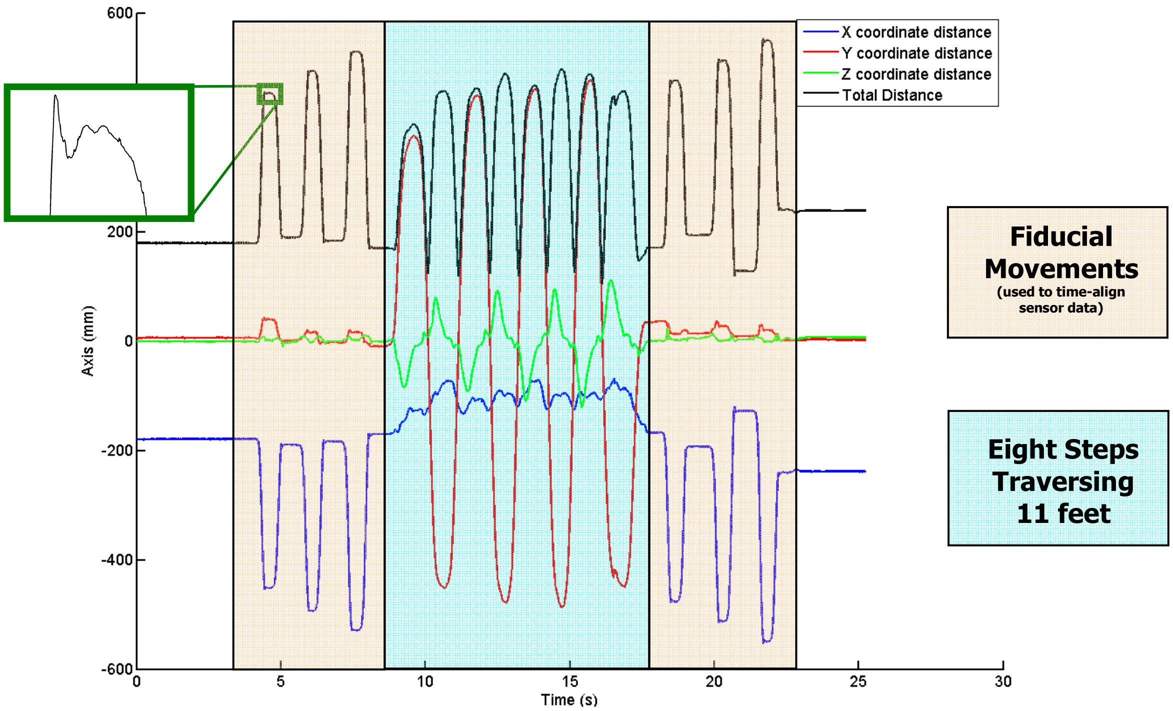

Figure 19: Unfiltered Relative Foot Distance for 11 ft Walk

The subject wore both inertial sensors and VICON markers when walking this trial. Figure 19 shows the types of issues that arise without data filtering. For simple post-processing and synchronization of these different sensor packages, the subject performed fiducial movements prior to the beginning of the trial, and at the end of the trial, by moving his feet in the VICON X-Z plane (where the Z axis represents the vertical direction and the Y axis is the primary axis of motion). The syncrhonization of these packages helped verify that the actual detected peaks from VICON data corresponded to the accelerometer spikes featured in the inerial package. Applying the same filtering techniques as described above to the data, Figure 20 shows a reduction in the presence of spurrious peaks. A difference between true stride length values and peak detection values displayed an error of approximately 1-2% for a variety of walking trials.

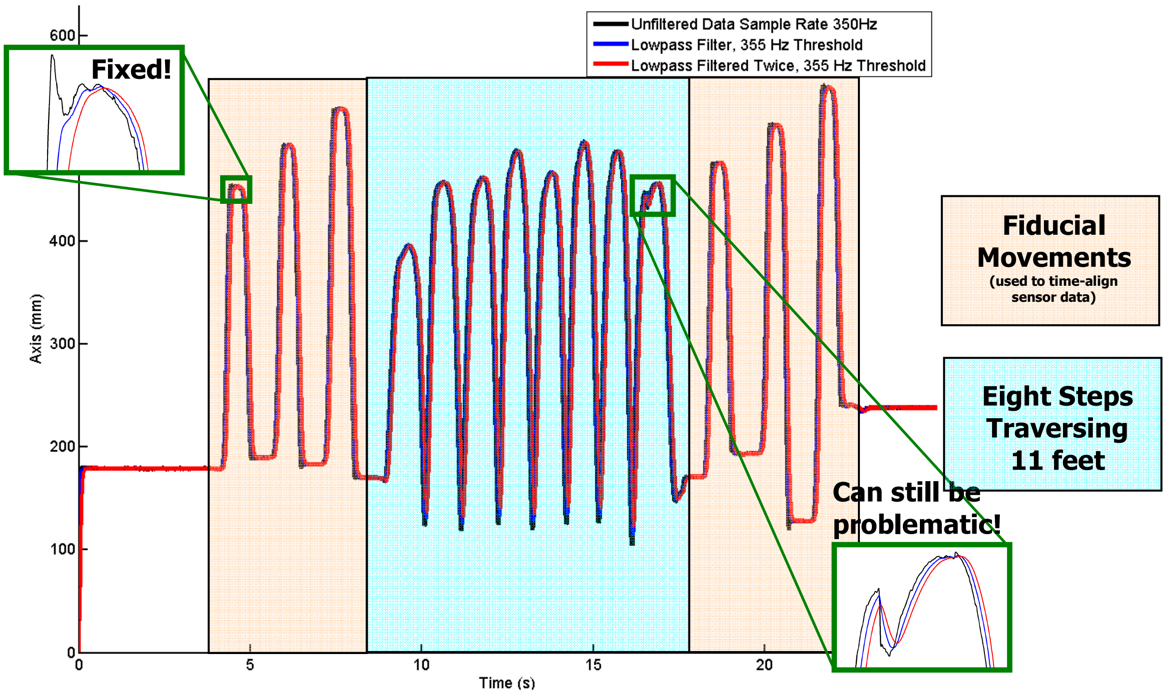

Figure 20: Filtered Relative Foot Distances for 11 ft Walk

Transforming the VICON relative foot sensor data into a more manageable peak detection algorithm allows the simple verification of distance traveled via a summation of the peaks. Summing the detected peaks of filtered data in the aforementioned trial, a traveled distance of 10.68 ft was calculated with the peak detection algorithm. The resulting error of 2.9% is a massive improvement on the constant stride length pedometer model, which would estimate a total distance travelled of (.76 meters) * 8 steps = 6.08 meters resulting in errors over 40%. This figure is valid provided a one dimensional assumption is made, and that the peak motion is directly in the Y-direction, and does not undergo any heading change. In reality, there is a small amount of heading change due to the imperfect nature of human gait, and therefore the addition of a heading term should improve this simple model. This addition and results will be discussed in a further section. Additional improvements are expected with the accurate determination of when a step is taken through synchronization of combined sensor packages. Since at least 4 nodes will be positioned on each of the subject's feet, the accuracy will also improve from the averaged communication of each node to one another.

A more detailed analysis of linear walking was conducted using data from the five subjects that were sampled by the LA House of Moves facility, as described in Chapter 2. This analysis allowed the construction of more detailed human gait models than the previous stride length vs. frequency models covered in Chapter 2. While these models can be constructed for all modes, only walking and crawling were investigated.

4.3 Peak Detection in Turning and Curved Walking

In order to make a change in direction, human mechanics of locomotion dictate that a shorter step is generally taken with the leg closer toward the inner radius of the turn, and a longer step is taken with the leg on the outer radius of the turn. This is evident in Figure 21, as this concept can also be expressed in terms stride lengths measured from one footprint to the next, as described in the previous sections of this work, thus the first stride length is shortened, and the second stride is elongated.

Figure 21: A Gradual Turn

Humans tend to slow down when approaching a turn, shortening their average stride length and altering their frequency away from natural [8]. This behavior corresponds to a drop in stride length, associated with a decrease in frequency. There are two types of turns encountered in buildings: a rounded or gradual turn, which requires three or more steps to complete, and a sharp corner 90° turn, which only requires 2 steps to accomplish the full change of direction. A gradual turn exhibits similar behavior. To test the effect of this behavior on personal navigation systems, basic testing was conducted.

A 90° right angle turn was performed at 3 different frequencies with an approach distance of 4.5 meters (or approximately 6 steps). The first stride going into the turn decreases slightly (by 5-10%), to an average length of 0.72m (compared to model values between .75 and .78m) at investigated frequencies between 66 and 80bpm (1.1-1.3 Hz). The investigation also yielded that even though the subject was asked to walk to a beat, to simulate a certain frequency. The subject naturally slowed their gait frequency prior to making the turn and increased the frequency back to nominal after completing change in heading. The second stride of the turn returns to a normal frequency stride or even elongates slightly. The resulting stride lengths at 90° turns were statistically consistent with the previously determined model. Note that in these cases, the stride length is measured from the impact location of the previous foot.

Table 5: Peak Detection Results for 90° Turn

Run Scenario	Distance Subject Instructed to Move	Peak Computed Distance	Error
90° Right Turn	14 ft	4.41 m =14.46 ft	3.29%
90° Right Turn (2)	14 ft	4.34 m =14.25 ft	1.79%
90° Left Turn	14 ft	4.39 m = 14.40 ft	2.85%
90° Left Turn (2)	14 ft	4.39 m = 14.40 ft	2.85%

Thus, it is possible to numerically account for the primary human turning mechanism with a shortened first step and a corresponding elongated step in the human gait model. The difficulty lies in detection of the turning mechanism with a combination of the inertial sensor and relative foot sensor. In addition, this mechanism has a very small effect on the average stride length vs. frequency model developed previously. The stride vs. frequency model should be capable of providing accurate distance information even when the subject makes walking turns without losing too much velocity. Stationary turning cannot be modeled with the same certainty, and relies on the incorporation of the inertial system for accurate motion analysis.

4.4 Relative Foot Distance for Gait Modeling

The linear walking data was processed for all five subjects, and new relationships were established between the novel metric of relative foot sensor distance and previously studied stride frequency. The 2-D algorithms for relative foot sensor that were developed in Section 4.1 were applied to the data and the total distance results can be found in Table 6.

Table 6: Sample 2-D Walking Analysis of Trial for Subject 2

Trial	Predicted Distance (ft)	Actual Distance (ft)	Percent Error	Distance Error (ft)
1	72.14	72.36	0.30	0.22
2	70.66	72.29	2.25	1.63
3	70.65	71.12	0.66	0.47
4	70.66	71.29	0.88	0.62
5	70.74	72.02	1.78	1.28
6	70.32	71.86	2.14	1.54
7	70.77	71.49	1.01	0.72
8	71.80	71.96	0.22	0.16
9	71.11	71.48	0.52	0.37
10	70.99	71.74	1.04	0.75
11	70.90	71.80	1.26	0.90
12	71.93	71.81	-0.17	-0.12
13	72.10	72.42	0.44	0.32
14	71.92	72.07	0.20	0.15
15	71.88	72.47	0.81	0.59
Average	**71.24**	**71.88**	**0.89**	**0.64**

The results in Table 6 demonstrates that for a traveled distance of 72 feet, the average error over 15 trials was less than one percent in linear walking, modeled in two dimensions. A linear model was constructed in post-processing to account for the residual difference between average stride length and actual stride length. The resulting gait model was used extensively in testing and validating the concept of the relative foot sensor. This technique was applied to all gait modes and subjects.

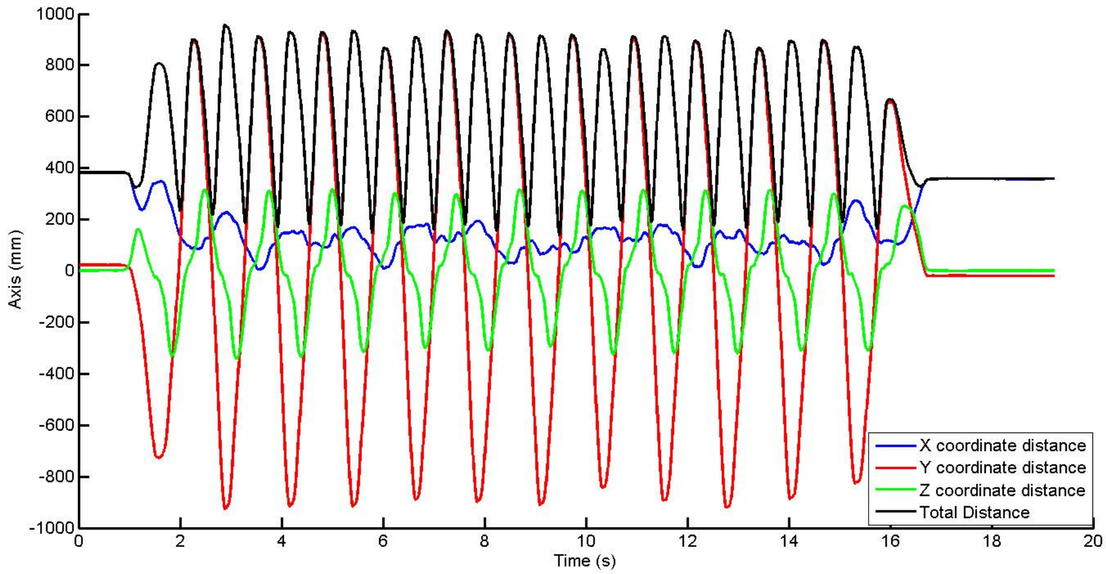

Figure 22: Relative Foot Distance for 75 ft Walking Trial by Subject 2

For reference, a sample trial by Subject 2 is investigated in more depth in this section. Specifically this is of greater interest because the two dimensional algorithms use angular data that has not been investigated in previous work. The heading angle (ϕ, defined in Figure 17) can be monitored continuously, similar to the relative foot distance relationship shown in Figure 22. The heading angle data has good correlation to two dimensional ideal values that were calculated using the aligned VICON axes along which the subject performed walking trials [Figure 23]. The VICON approximation requires the use of a straight line walking approximation. This result shows that walking can be considered in two dimensions and still produce accurate answers in distance traveled. The exact accuracy is discussed further in later portions of this chapter.

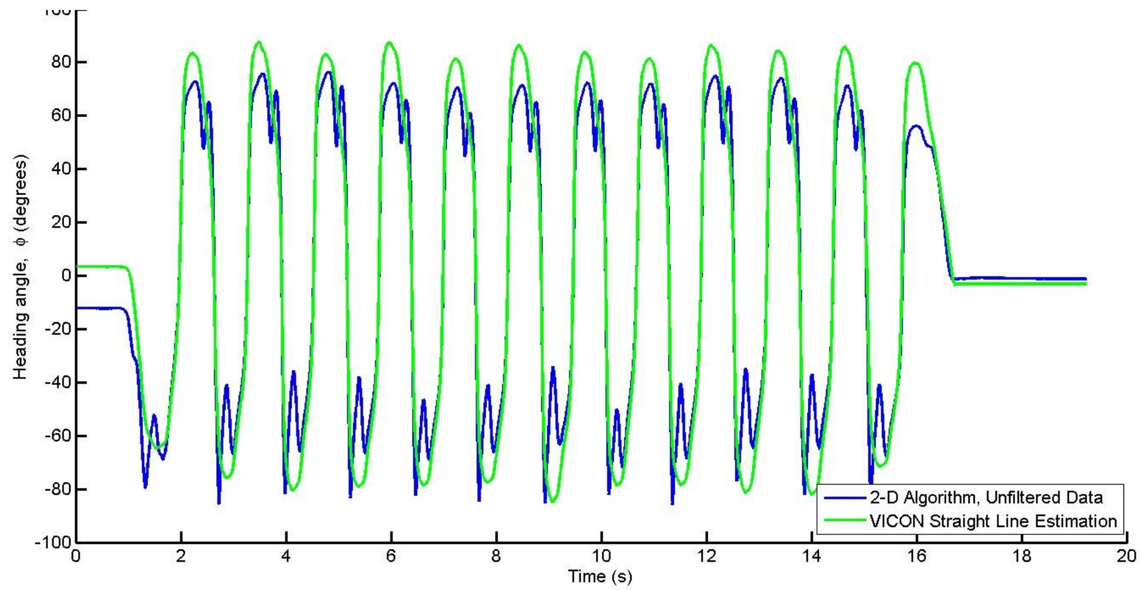

Figure 23: Heading Angle for Sample 75 ft Walking Trial by Subject 2

The relationship between relative foot sensor measurements and the frequency of walking is portrayed in Figure 24. This relationship plainly demonstrates the concepts described in the previous gait modeling section (Section 2.1), with a clearly defined “natural” gait relationship. As long as the subject traveled in the natural state, and not in the deceleration or acceleration phases, the relationship was linearly deterministic and can be used to successfully build a model between the two variables. The modeling of acceleration and deceleration phases is a much more complicated and non-linear process, and will be the subject of future investigations. The difficulty and accumulation of error with the application of these models would manifest itself in periods of transition between different phases, and extended periods of exposure to non-linear phases.

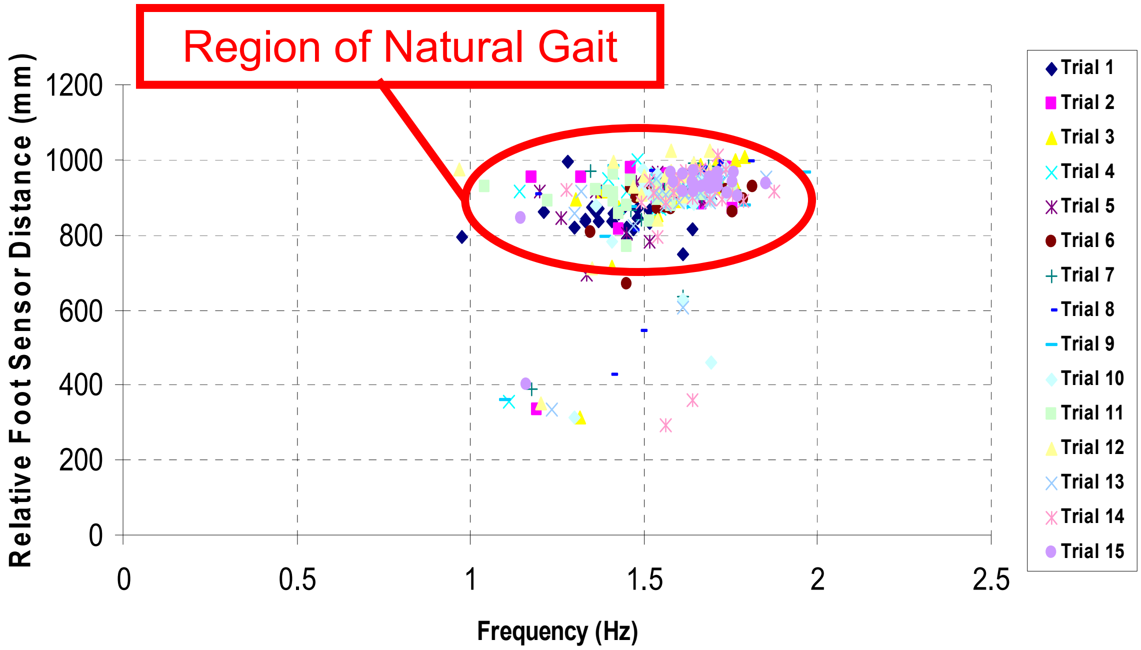

Figure 24: Foot Separation vs. Frequency Distribution for Male Subject 2

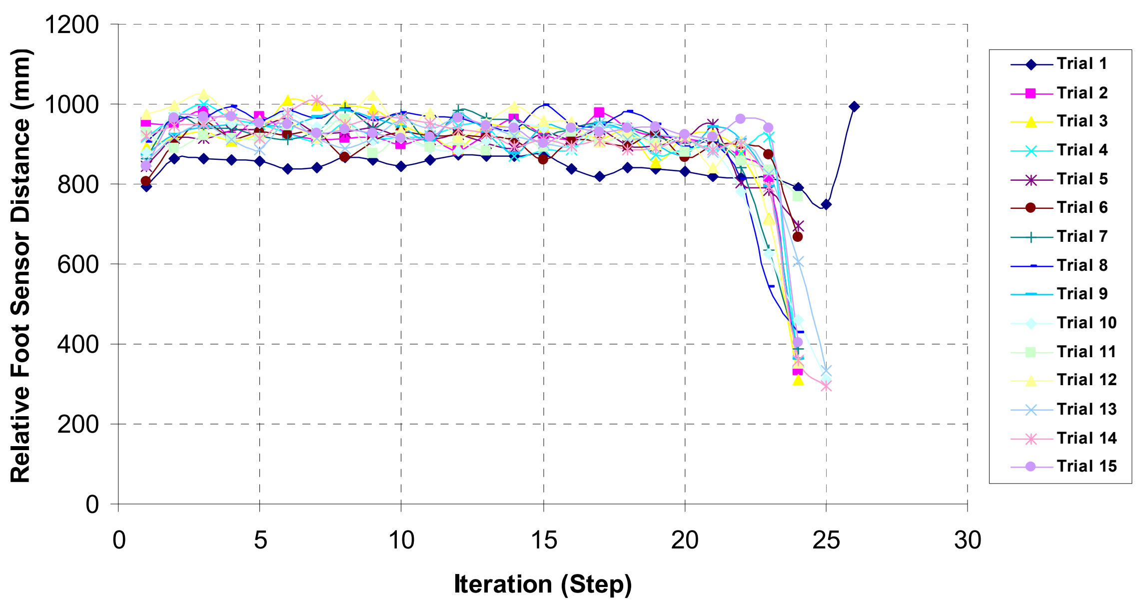

Figure 25: Gait Models by Trial for Male Subject 2

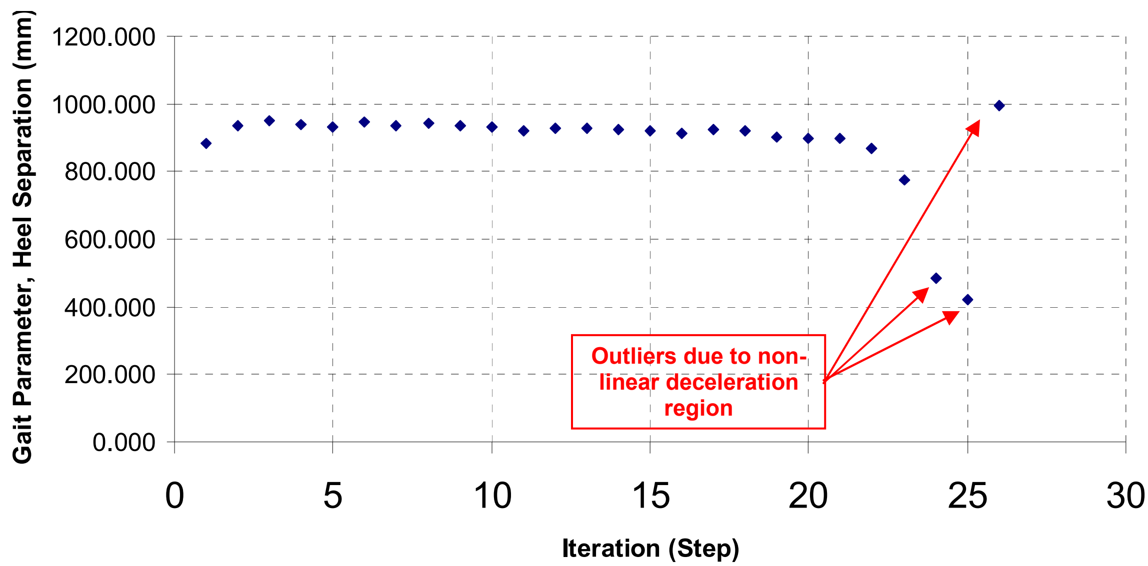

Figure 26: Averaged Gait Model for Male Subject

Figure 25 depicts the individual gait models for each trial that were then averaged into the gait model by step number. When subjects naturally walked a linear distance their behavior was able to be modeled and predictable.

It is important to note that the walking algorithms for the gait model successfully detected almost every step in all of Subject 2's trials, resulting in such strong correlations. The algorithms only miscounted a total of two steps over the course of more than 350 steps, for a sub one percent error. Figure 26 visually demonstrates that there is a linear region of stride length that is unique for each subject. This linear region represents the area of interest that was successfully modeled. Figure 27 shows the comparison in stride length models for the relative foot sensor between different subjects. It is evident that the relationships are unique from subject to subject, and an individual base-lining or evaluation is required to produce an accurate system.

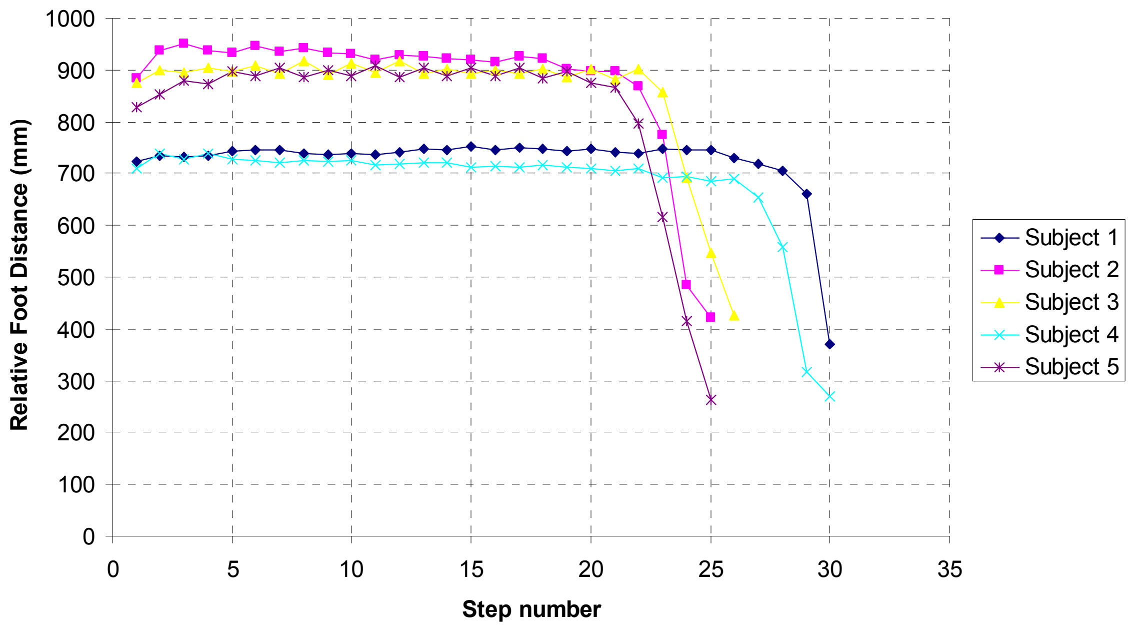

Figure 27: Gait Model Comparisons for Different Subjects

As a formal example, the process of constructing the residual term for the gait model for Subject 2 is demonstrated below. The overall average relative foot sensor distance for Subject 2 was determined to be $\lambda_{average}$ = 897.27 mm, from 15 different walking trials pictured in Table 6. The linear scaling factor a_1 was found to be 186.52 and the offset b_1 = -273.96.

Table 7: Linear Walking Gait Models

Subject	Average Relative Foot Distance $\lambda_{average}$ (mm)	Average Frequency ω (Hz)	Linear Scaling Factor a_1	Offset b_1
1	740	1.61	550.95	-892.65
2	897	1.56	186.52	-273.96
3	857	1.76	594.66	-1044.66
4	718	1.72	296.75	-461.44
5	828	1.63	104.55	-103.96

Quantifying the linear relationship between λ_{actual} and frequency ω, the linear gait region can found and is best described by the following formula; the specific numeric characteristics for the walking mode can be found in Table 7:

$$\lambda_{linear\ model} = \lambda_{average} + a_1 * \omega_{step} + b_1 \qquad (4.1)$$

It was also determined that individually generated simple peak-detection human gait models were capable of producing distance estimates with errors below 5% for all subjects, and the linear relative foot sensor gait model added notable improvements. The relatively higher percent errors for Subjects 3 and 4 can be directly attributed to the miscounting or detection of steps with the peak detection algorithms. There should be improvement to this error term with the addition of a synchronized inertial system in the walking modes.

Table 8: Pedometry Model vs. Linear Gait Model Results for Walking

Subject	Simple Pedometry Gait Model Error	Linear Relative Foot Sensor Gait Model Error
1	2.29 %	0.58%
2	2.75 %	0.82%
3	3.11 %	1.01%
4	4.31 %	1.13%
5	3.20 %	1.17%

An alternate way of expressing the gait results is through a display of instantaneous speed at each step vs. step number expression, as shown in Figure 28. This specific depiction shows that the actual speed of walking varies directly with right and left foot for certain subjects. In particular, Subject #5, the

6’7’’ male, had a very distinct variation in his stride speed. This can be attributed to a variety of possibilities, including a difference in leg length or previous injury. Unfortunately, this information is unavailable due to privacy concerns and the motion capture studio policy. It is also evident that each subject was walking in a unique way and at a unique speed.

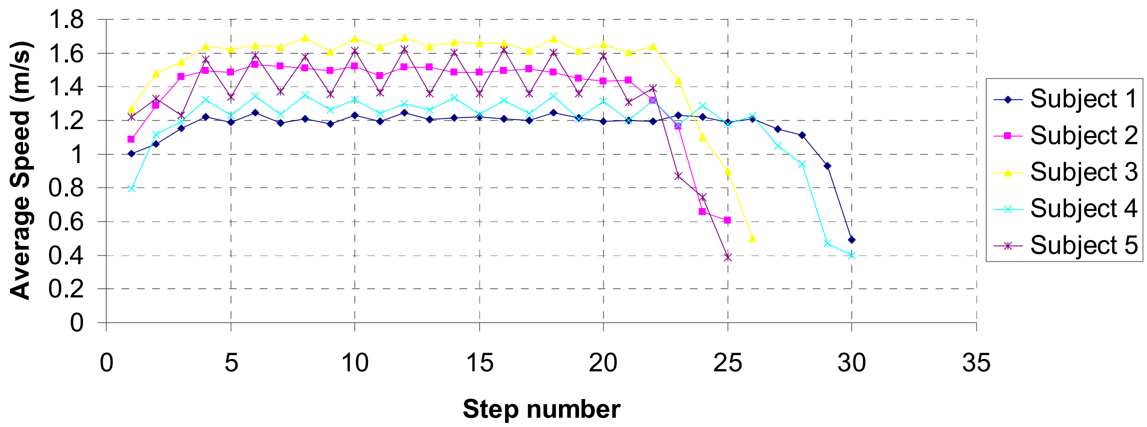

Figure 28: Walking Gait Model Average Speed Comparison

While investigating these relationships in two dimensions is useful for simulating level ground walking, it does not give the complete picture for more complex scenarios involving stair walking, and other irregular gait behaviors. Three-dimensional motion is specifically vital for the recognition of less regular and deterministic modes of human gait, such as crawling, as will be discussed in the next section. The full expansion and analysis of these methods to three dimensions will be the subject of future work.

4.5 Peak Detection in Crawling and Other Modes

Applying the two dimensional relative foot sensor gait modeling technique described above to the analysis of more complicated modes is not a trivial task, and several simplifying assumptions about each behavior must be made. The step detection algorithm for crawling modes is currently less robust than the walking algorithm, because the crawling mode exhibits more variation in behavior and different peak patterns. More research must be conducted in order to achieve the necessary level of accuracy with the step detection algorithms and pattern detection techniques.

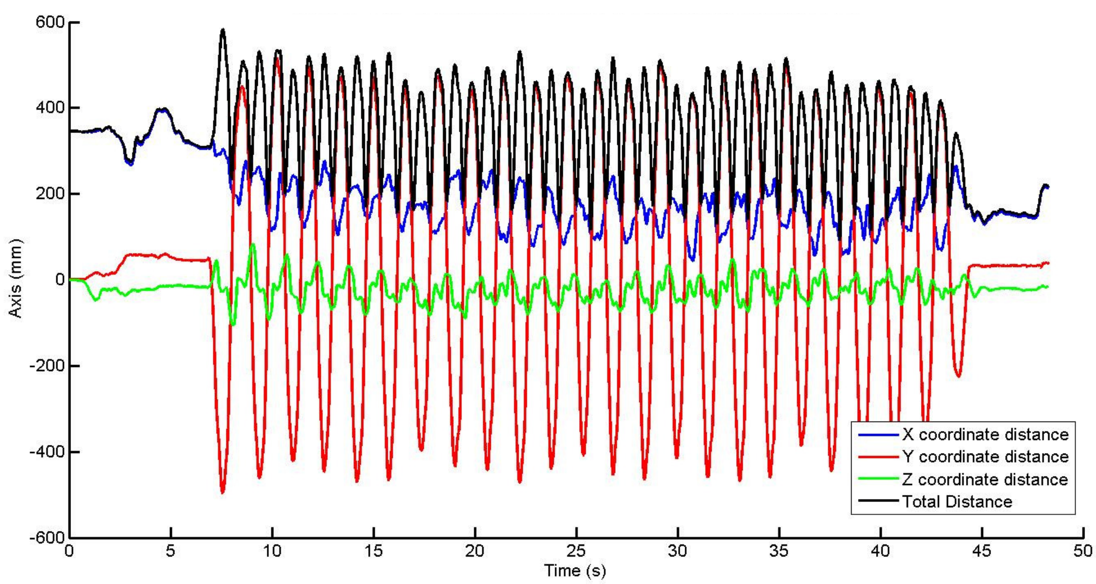

Figure 29: Relative Distances for 75 ft Forward Crawl by Subject 2

The simplest crawling case that was investigated was the baby crawl, or crawling on the hands and knees, this mode is referred to as the “forward crawl” throughout this work. Figure 29 demonstrates the relative foot sensor time history for a 75 ft forward crawl. It can be noted in this figure that the forward crawl has a significantly different pattern of peaks in the VICON x, y, and z axes. This mode also exhibits unique accelerometer spikes due to the impact of the knees and feet on the ground. The different orientation of the feet with the toes pointed into the ground into the VICON y-x plane or inertial x-y plane, allows for a simpler recognition of a crawling mode using the inertial sensor package. The fundamental difference in three-dimensional behavior of the mode is also evident in Figure 30, where the heading angular data is presented for a crawling mode. The heading angles no longer accurately represent the true behavior.

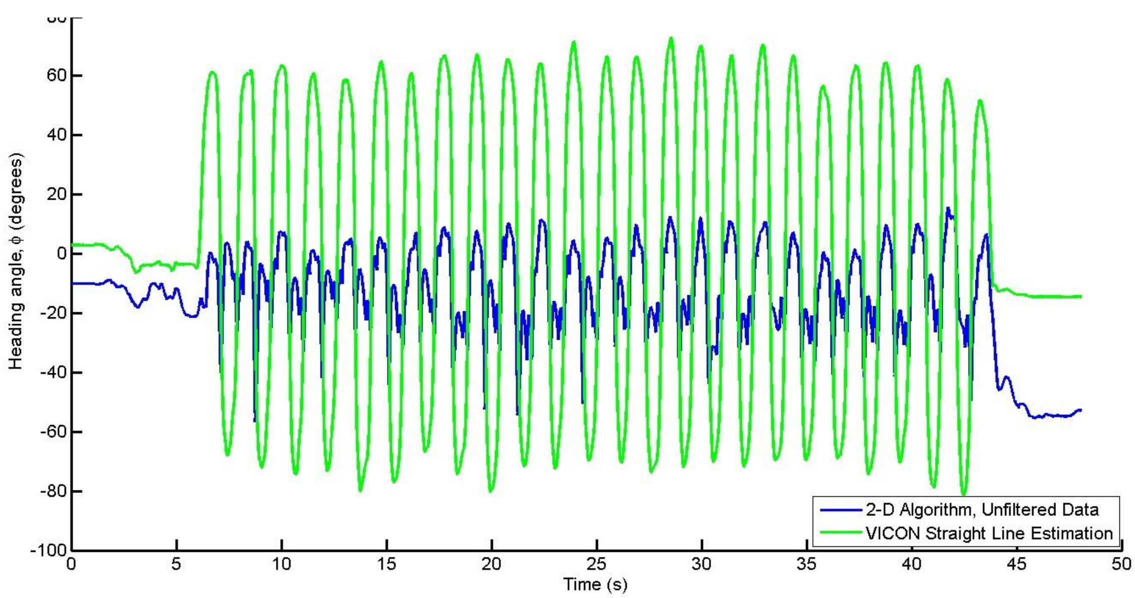

Figure 30: Heading Angle for Sample 75 ft Forward Crawl by Subject 2

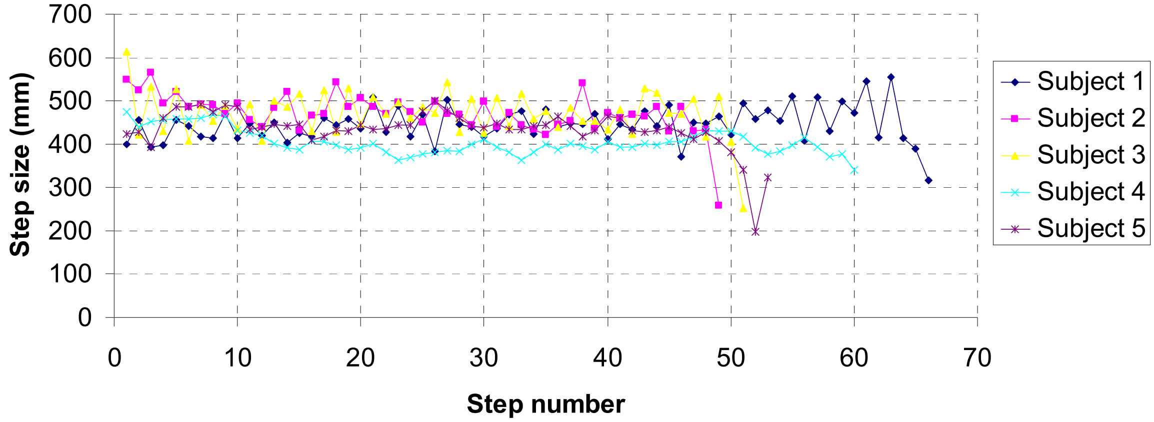

Figure 31: Crawling Gait Model Relative Distance Comparison

A crawling gait model comparison was conducted between subjects in a similar fashion to the walking gait model described in the previous section. The results can be found in Figure 27. Here it is determined that there is significantly more variation in crawling stride length between steps. The relationship is not as well established and therefore results in greater accumulation of error in the long term. This error is partially due to the three dimensional nature of crawling that is not accounted for in the 2-D algorithms used to process the gait model.

Table 9: Subject 2 Simulated Gait Model Errors

Run Scenario	Runway Distance	Model Computed Distance	Error
Straight Line Walk	72 ft	72.51 ft	0.71%
Backward Walk	72 ft	72.95 ft	1.32%
Forward Shuffle	74 ft	72.48 ft	2.05%
Backward Shuffle	74 ft	73.40 ft	0.81%
Forward Crawl	72 ft	68.12 ft	5.39%
Army Crawl	25 ft	23.18 ft	7.28%

Representing the average quantities of stride length and frequency in terms of speed, Figure 28 shows that the average crawling speed for all subjects is in fact very similar, yet there is a significant variation in the parameters that determine the way that the subjects crawl. Table 9 shows the unsurprising conclusion that crawling occurs at a smaller stride length and lower frequency than regular walking.

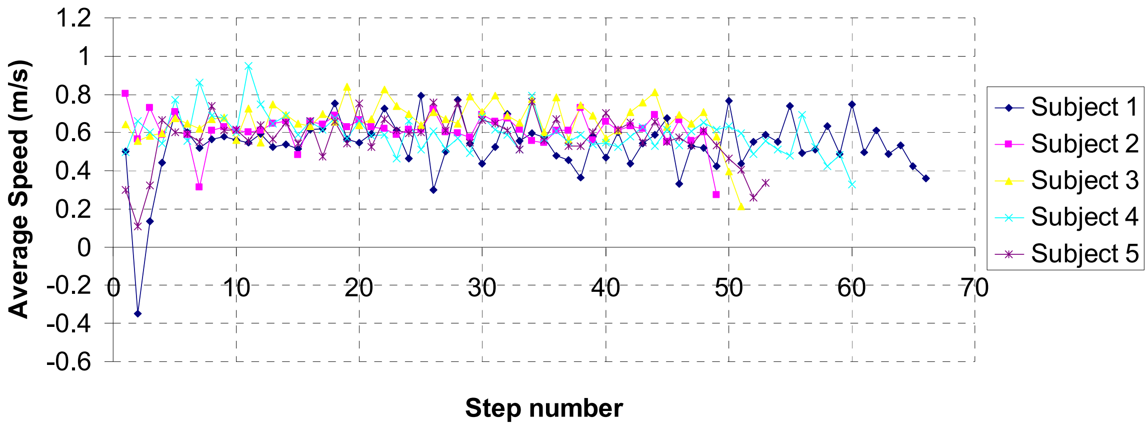

Figure 32: Crawling Gait Model Average Speed Comparison

Table 10: Crawling Gait Model Average Quantities

Subject	Average Stride Length $\lambda_{average}$ (mm)	Average Frequency ω (Hz)
1	446	1.197
2	472	1.302
3	470	1.407
4	407	1.473
5	435	1.313

Backward walking was explored and was concluded to be nearly identical in step detection and accuracy to regular walking. In fact, with the exception of certain subjects' ability to walk in a linear fashion, this mode was not significantly different from a relative foot distance stand point. The issue with modeling backward walking relates to the fact that this mode is never used in its natural form in first responder scenarios. This mode is generally used in limited visibility conditions and constrained spaces, and therefore would produce different results than a pre-set runway with no obstructions or changes in direction.

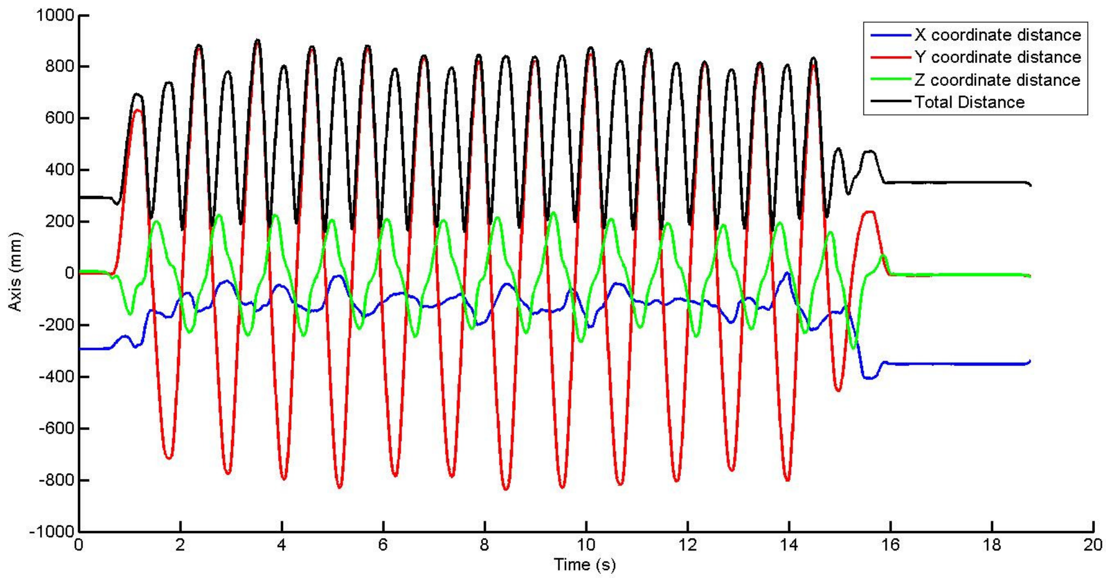

Figure 33: Relative Foot Distances for 75 ft Backward Walk by Subject 2

Figure 33 shows the relative foot sensor data and the rhythmic peaks of similar magnitude. Of particular interest are the z-axis peaks, as they exhibit a closer similarity to the dynamic of forward walking, and would result in the same mode of detection. It is therefore no surprise that the gait modeling accuracy is similar to that of forward walking. The backward walking heading information is also accurate as found in Figure 34, this heading calculation shows accuracy of the same order as the forward walk.

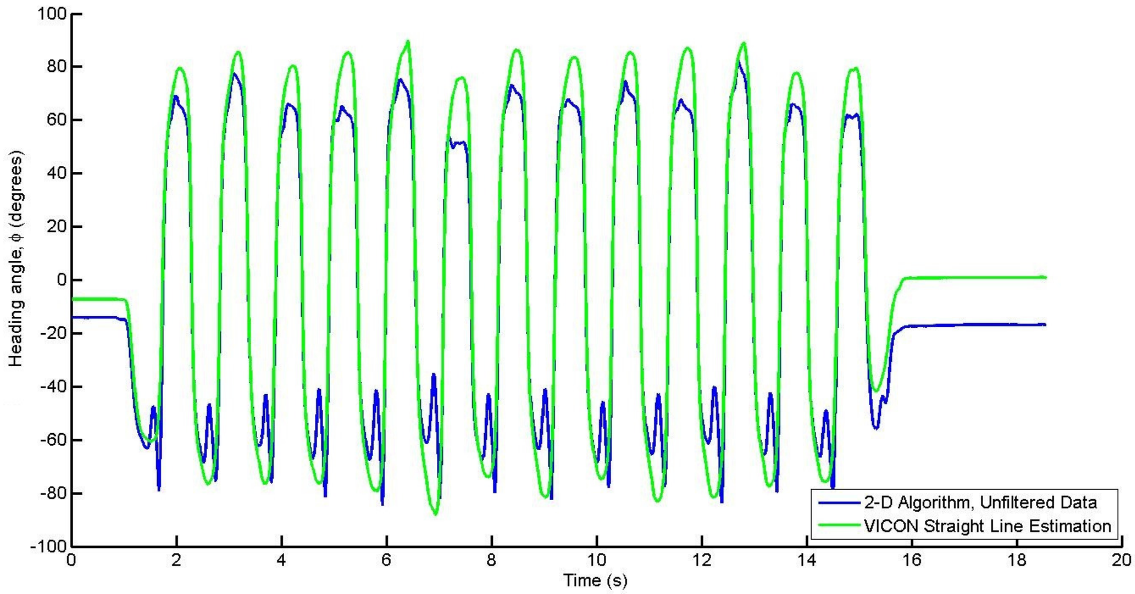

Figure 34: Heading Angle for Sample 75 ft Backward Walk by Subject 2

The more complex army crawl mode was also considered, this mode is unique in that it is conducted on the elbows and feet, with the stomach close to the ground, and the feet continuously swinging and transitioning between different planes of motion. This mode exhibits an even more complex three dimensional motion of the feet than the forward crawl [Figure 35]. It is no surprise that this mode also results in the greatest error when analyzed with the two dimensional methods described in the previous chapter. This mode also can contain double-peaks in the distance detection, as is apparent from the figure below. In this case, unlike the previous gait modes, the trials presented in Figure 35 and Figure 36 are in fact different trials, to better portray the characteristic features of the mode. The angular information in Figure 36 demonstrates the insufficiency of the two dimensional methods. This mode also provides an added challenge for step detection algorithms.

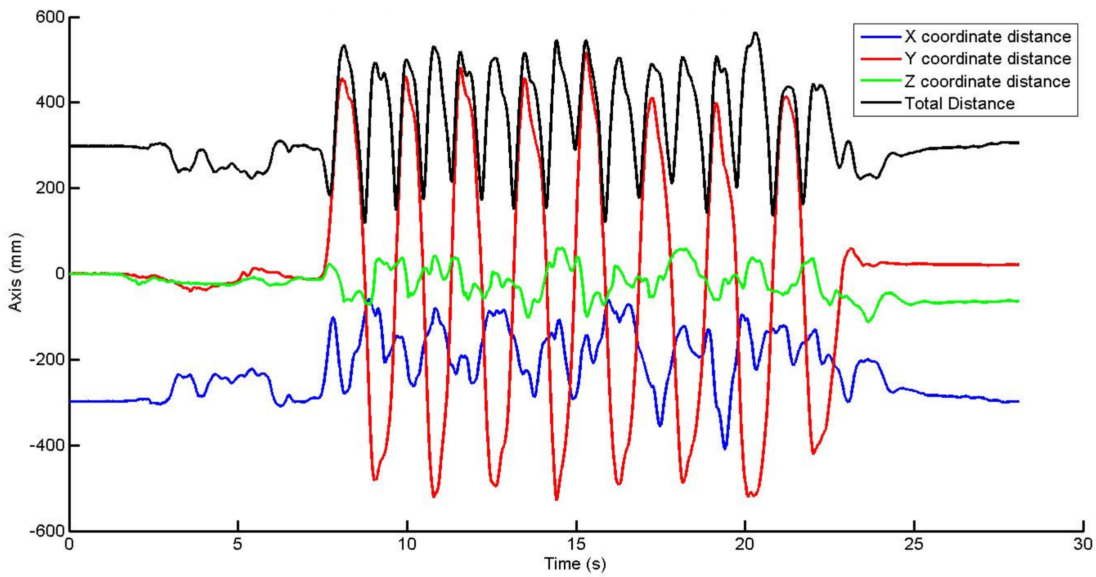

Figure 35: Relative Foot Distances for 25 ft Army Crawl by Subject 2

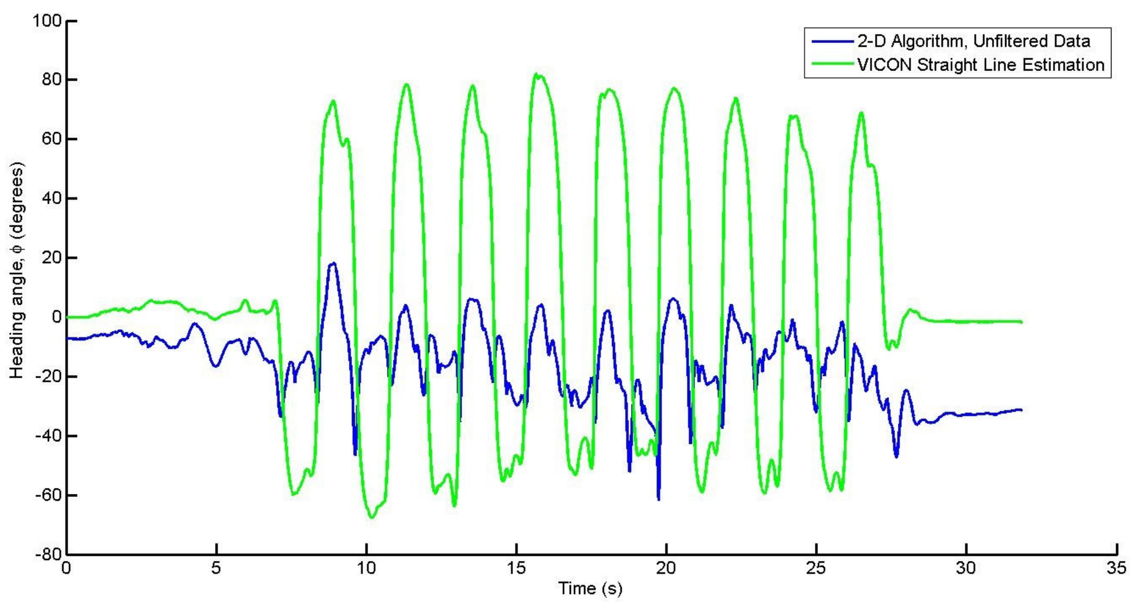

Figure 36: Heading Angle for Sample 25 ft Army Crawl Trial by Subject 2

Shuffling is a form of walking where the foot drags along the ground, avoiding the distinct impact that characterizes each walking step in the inertial frame. This motion is associated with slightly shorter steps in most cases, with the heel staying nearly fixed along the ground the entire time. However, Subject #1 displayed an elongated stride in the shuffle scenarios, similar to the way a person would ski or ice skate along the ground. The shuffling mode is closest to a truly 2-D form of locomotion, as it minimizes vertical motion (z-axis), as can be noted from Figure 37. Multiple types of shuffles were investigated with forward motion, backward motion, and side to side motion in a small capture volume limiting to a distance of 11 ft. The multi-directional shuffle analysis was used only to determine that the relative foot sensor could successfully determine accurate distance information in those cases. Additional inertial information is required to aid the relative foot sensor to determine which direction the motion occurs.

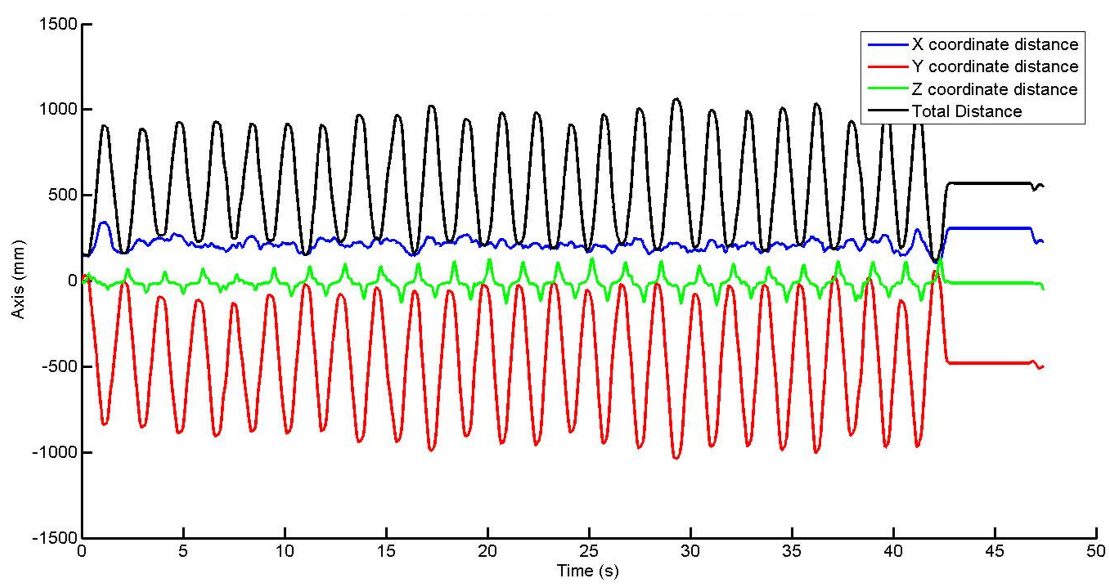

Figure 37: Relative Foot Distances for 75 ft Shuffle by Subject 2

Shuffle was determined to be the most stable mode that was analyzed by the relative foot sensor motion in Subject 2, as this subject had a particularly linear shuffle mode, and did not exhibit much lateral motion. Other subjects exhibited a sort of “ice skating effect”, where their strides extended laterally to the side, as well as forward, resulting in slightly longer strides that had to be corrected by the heading angle. This mode would also pose the most difficulty for a purely inertial system from the perspective of accurately detecting steps. However, this mode was most successful in capturing accurate heading information, due to its 2-D nature [Figure 38]. As in the crawl and unlike the walking gait modes, Figure 37 and Figure 38 refer to different trials, to capture the characteristic features of the mode.

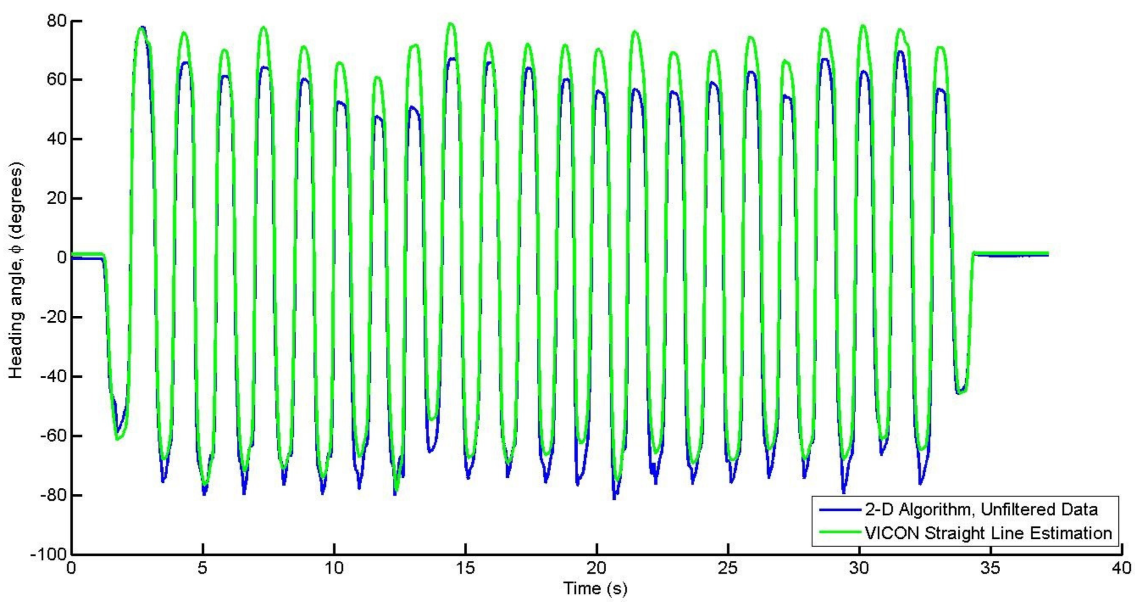

Figure 38: Heading Angle for Sample 75 ft Shuffle by Subject 2

A large amount of gait data was received from the VICON motion capture studio, due to the scope and limitations of this work only Subject 2 was presented in this section in the necessary detail and analyzed in all modes of gait. The results from this analysis demonstrate some difficulties in creating unique algorithms for complex gait modes, as well as elegant solutions to others. Other sample results for the rest of the Subjects can be found in the Appendix.

4.6 Summary

Peak detection algorithms for a relative foot sensor were presented and evaluated with great accuracies for fundamentally two-dimensional motion. These algorithms use the peak in distance measurement between nodes to determine when a step is taken. Filtering techniques were investigated and a low-pass filter with a threshold frequency of 355Hz was successful in eliminating noise characteristics in VICON data. Linear walking was investigated in detail for all five subjects. Gait models were constructed and enhanced for each subject, resulting in distance errors close to 1% for walking 75 feet, in the cases where step detection functioned properly. Subjects that were prone to step detection miscounts were still producing errors near 5% for simple walking. Peak detection algorithms of relative foot distances are very successful in the developed two-dimensional motions such as linear walking, backward walking, and shuffling.

The five modalities of movement that were investigated in depth at the VICON House of Moves studio allowed a summation of each subject's human gait properties. These properties are summarized in this section and the histogram figures associated with it. Each mode is presented for all five subjects.

While these properties demonstrate significant subject to subject variability, there are similar patterns in frequency and relative foot distance across different subjects that can be used for the creation of successful mode detection algorithms, as will be discussed below.

Linear walking behavior was analyzed using the relative foot sensor algorithms in this chapter, and human gait models were constructed for each subject. These models demonstrate consistent accuracy on the range of 1-3% in evaluating a distance of 75 feet in each subject.

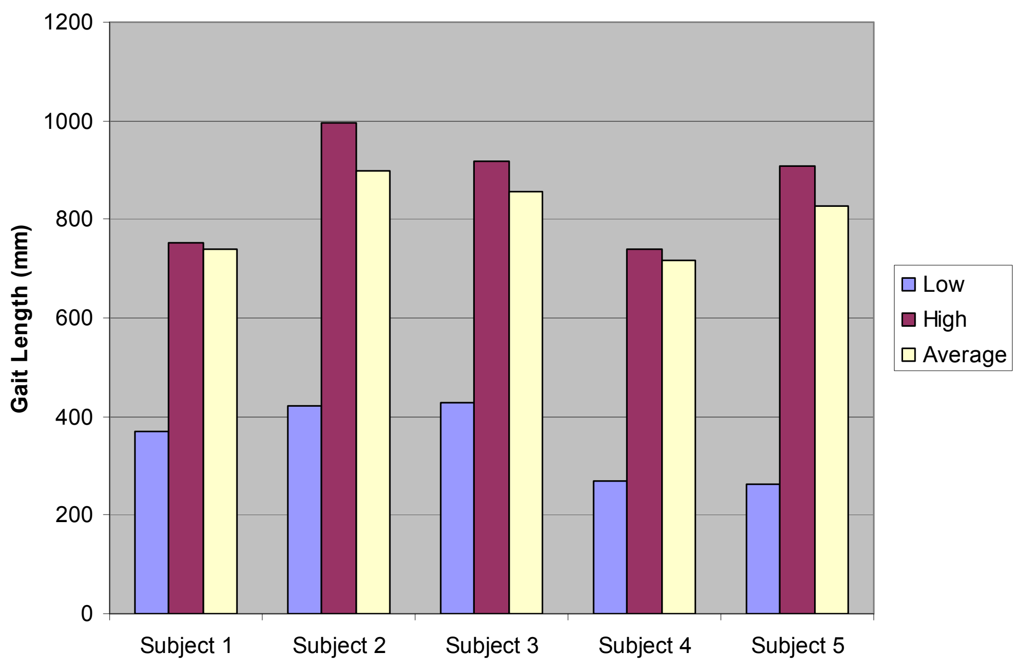

Figure 39: Forward Walking Relative Foot Distance

The simple forward walking cases are summarized first. The primary fundamental property investigated in this work is the relative foot distance, or the gait length property as demonstrated in Figure 39. The variance demonstrates that in this case the average stride length was fairly constant for the natural regime, and only deviated in the acceleration and deceleration stages. The frequency result is very similar to the relative foot distance, as a prevalent frequency regime dominates natural walking speeds.

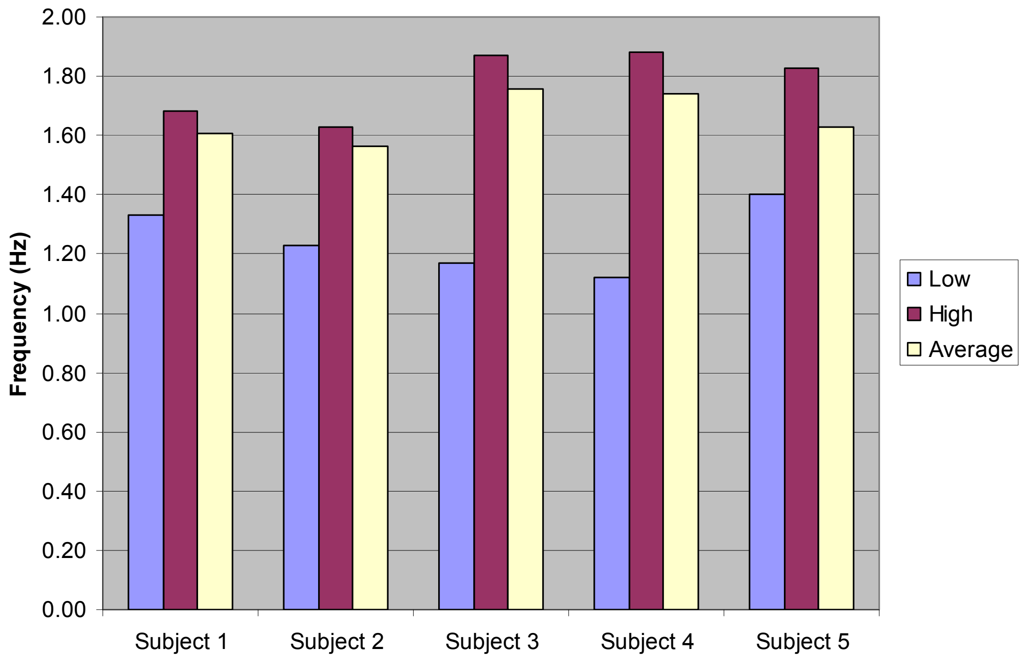

Figure 40: Forward Walking Frequency

Displaying averaged forward walking speed in Figure 41, for all five subjects demonstrates speeds near 3 mi/hr with a small amount of variation. It can be concluded from all of these results that walking is a consistent and repeatable mode. Finally, the overall percentage of error is summarized in Figure 42. Some clear outliers exist from the average error of approximately 1%, however, the largest values of error can be attributed due to miscounting of steps, and can therefore be eliminated in the future with better 3-D algorithms.

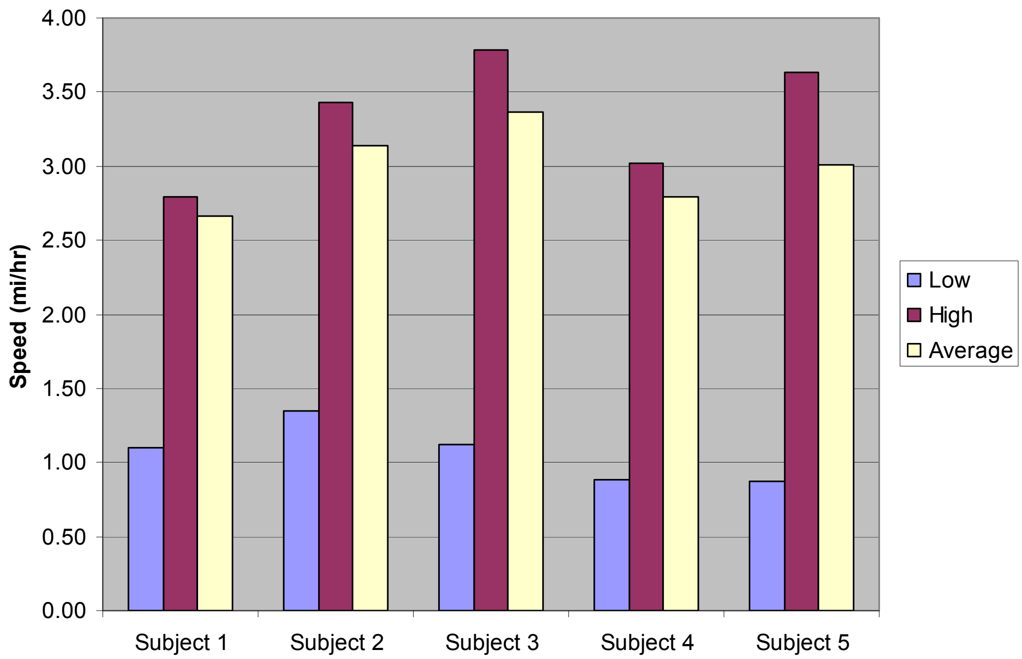

Figure 41: Forward Walking Speed

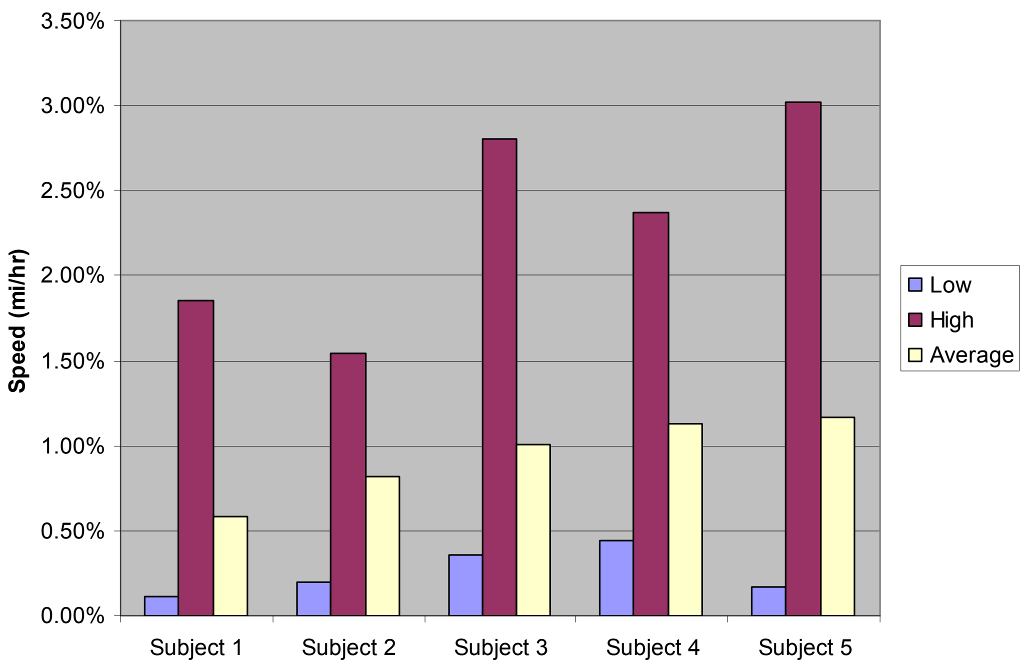

Figure 42: Forward Walking Percent Error

Forward crawling on hands and knees, as well as other fundamentally three-dimensional motions, are also evaluated. The crawling motions require further expansion of current two dimensional algorithms to three dimensions to ensure proper accuracy. This is apparent due to the larger percent error of the method, as evident in Figure 46. Simple forward crawling trials for a distance of 75 feet are evaluated and the summary is presented below, providing an overview of the accuracy and error terms across subjects and investigated unique gait modality properties. The main error term for crawling modes accumulates from miscounted steps and the two dimensional algorithm of heading calculation.

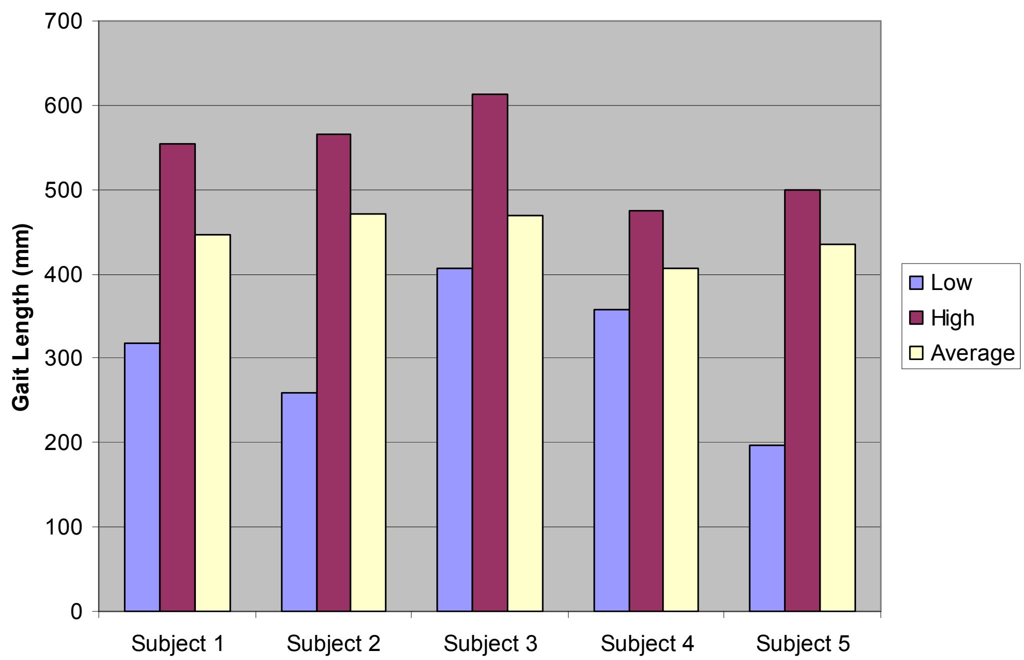

Figure 43: Forward Crawl Relative Foot Distance

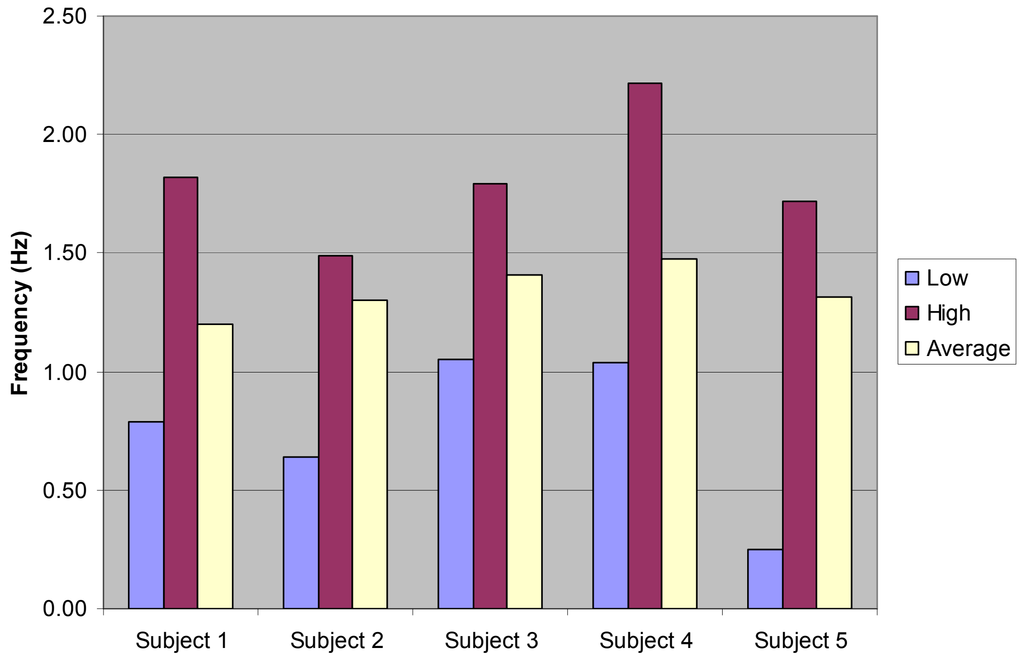

Figure 44: Forward Crawl Frequency

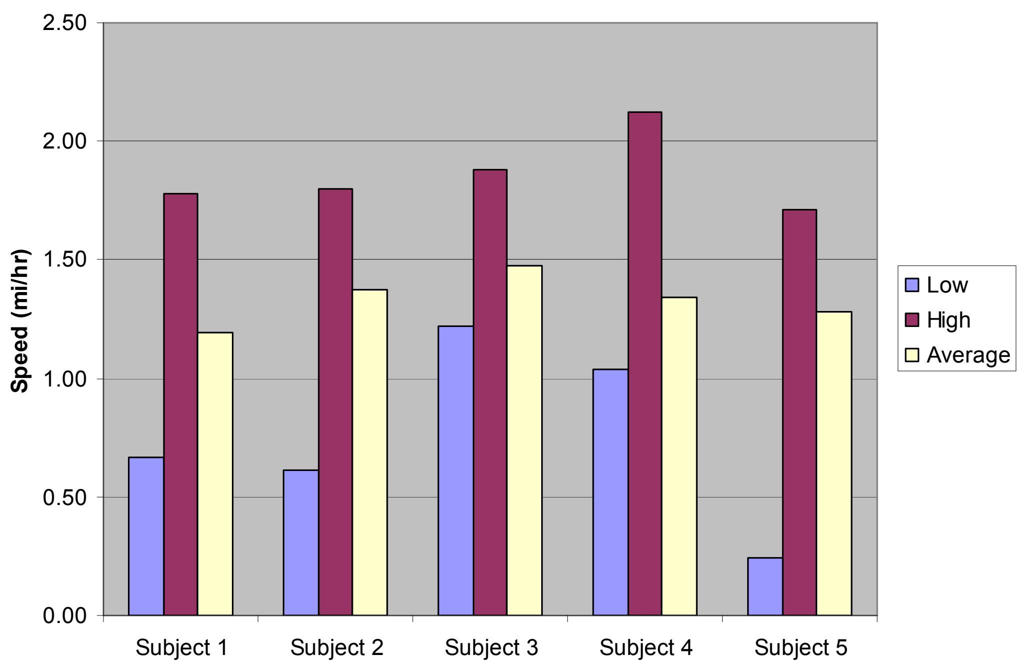

Figure 45: Forward Crawl Speed

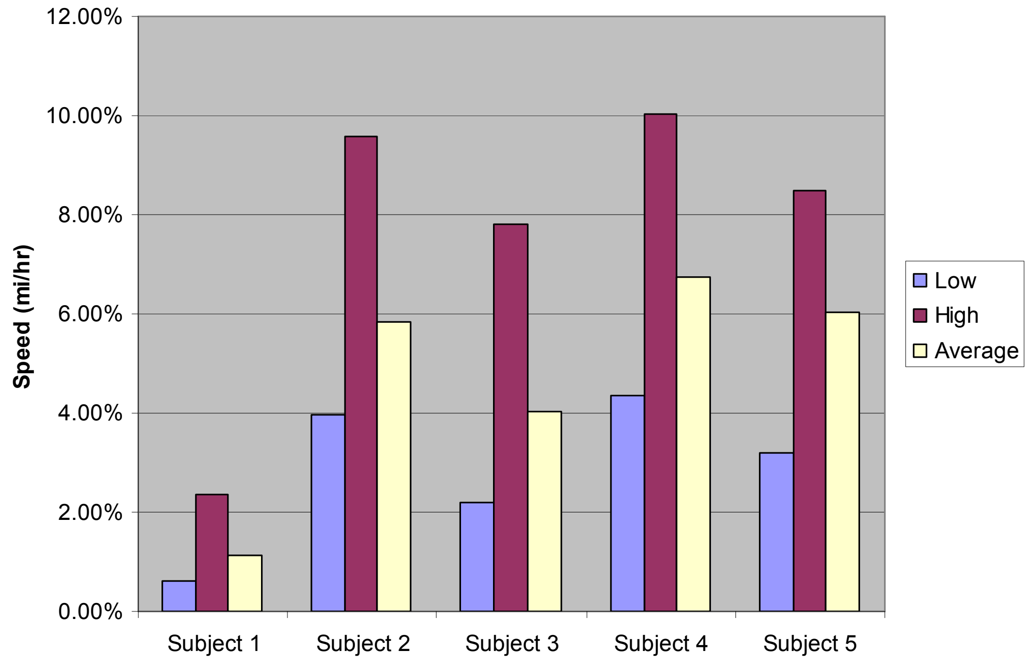

Figure 46: Forward Crawl Percent Error

The forward crawl exhibits the same promise with respect to the application of relative foot sensing algorithms. Unique deterministic properties of stride length [Figure 43] and frequency [Figure 44] can be used for mode detection of individual gait modes.

Please refer to Appendix B.1 for Tables summarizing the results found above for each gait modality. Additional gait data for discussion on the backward walking mode can be found in Appendix B.2., shuffling mode in Appendix B.3, and the army crawl mode in Appendix B.4.

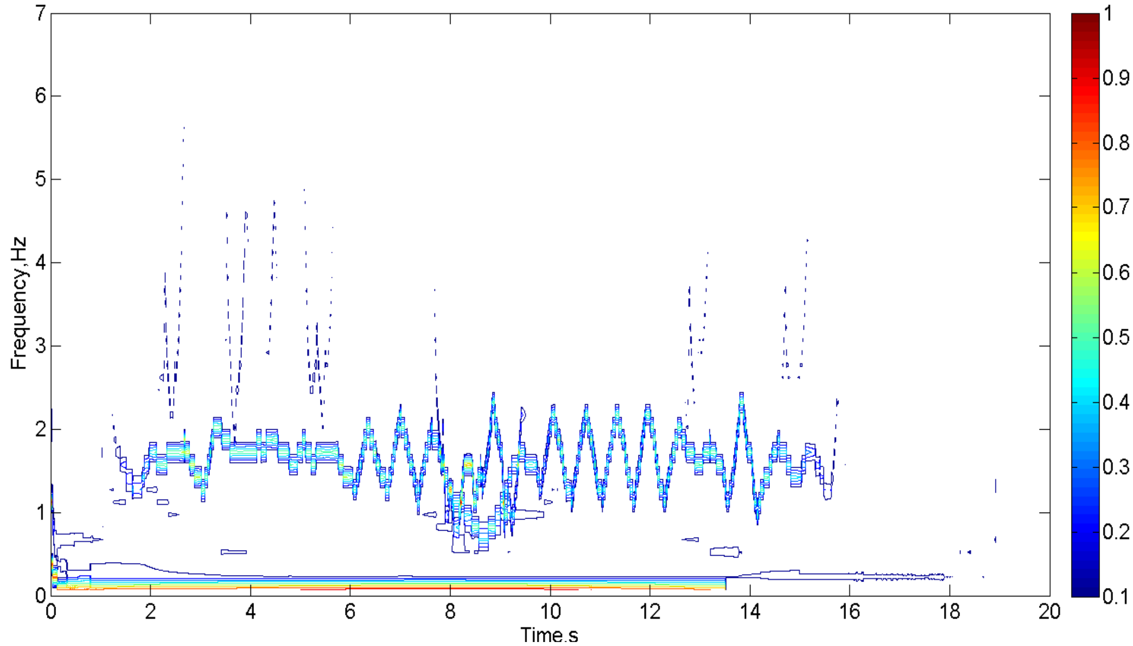

Figure 47: Hilbert-Huang Spectrum of Walking Trial for Subject 2

Empirical mode decomposition can be used to search for patterns in linear gait data. A sample walking trial can be broken into its intrinsic mode functions to analyze instantaneous frequency information. Using a walking trial for Subject 2, the methodology is demonstrated to produce a Hilbert spectrum, as seen in Figure 47. This spectrum is produced using an iterative method coded by Gabriel Rilling of Ecole Normale Supérieure de Lyon, France [30]. It is evident from the spectrum that there is a range of "natural frequency" found in natural gait for each Subject. The range is between one and two Hertz for Subject 2. Using the instantaneous frequency information, decisions can be made to determine what mode the subject is traveling in, provided some base-lining tests can be conducted on the subject [31].

A sample trial of backward walking was also analyzed using EMD. It is apparent from Figure 48, that the instantaneous frequency information in this mode of walking is even more distinguishable than the natural walking phase, in a wider frequency range than regular walking.

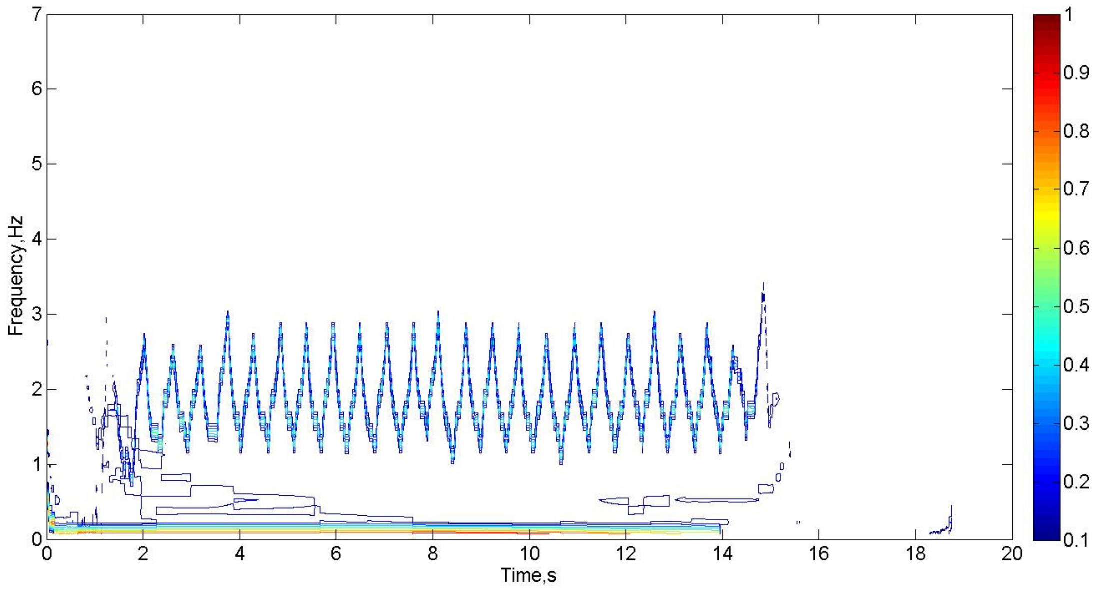

Figure 48: Hilbert-Huang Spectrum of Backward Walking Trial for Subject 2

The human gait mechanism of turning was discussed, specifically as the dynamics fit into peak detection algorithms. It is shown that the physical act of turning slightly decreases the accuracy of peak detection methods. This effect can be countered with the use of two dimensional relative foot sensor algorithms developed for multiple nodes to calculate incremental heading. It was also demonstrated that crawling and more complicated modes require the use of the three dimensional algorithms.

Human gait is a unique form of locomotion that is dependent on a variety of individualized variables, such as subject height [24]. Some of these dependencies are difficult to account for numerically. However, the properties of stride length and frequency are deterministic and can be used to enhance the accuracy of existing navigation sensor packages.

Chapter 5

Conclusion

5.1 Summary

Avoidable casualties occur in the line of First Responder duty on a regular basis. The knowledge of a downed firefighter's accurate location is an absolute necessity during search and rescue missions or even the course of routine service. A number of proposed solutions have historically been attempted, and most have been incomplete at best. RF Navigation is limited by the necessary setup and infrastructure, while inertial-based navigation systems have to deal with accumulated heading errors over time.

This work attempts to provide a proof of concept for an enhancement to the accuracy of an inertial based GPS-denied personal navigation system. A simple pedometry approach using human gait characteristics has merit due to its simplicity and ability to provide a first order verification of the inertial solution. It is possible to create models that correspond to human gait characteristics. Human gait data was analyzed for 5 subjects from a motion capture studio. Stride length vs. frequency models are designed using data from a VICON motion capture system. The stride length vs. frequency models exhibit distance errors near 5%

and serve as an improvement to existing inertial technology. This work then expands the line of thinking on a pedometry centered approach to personal navigation with the concept of the relative foot sensor.

The relative foot sensor concept proposes the construction of a network of wireless nodes that function as RF receivers and transmitters located in the sole of the boot [Figure 15]. Millimeter accuracy in determining distance between nodes is expected from carrier wave phase processing. A method for determining the location of the feet is derived using geometric properties produced by the relative foot sensor concept. This method allows the computing of a stride length, heading, and separation distance between the first and second feet based on the determined distances; and computing a location for personal responders based on the computed stride length, heading, and separation distance. Most importantly, the previously accumulating heading error term no longer dominates the location computation over time.

5.2 Future Work and Applications

Though the simple gait models using peak detection and the relative foot sensor metric were capable of reasonably predicting the distance traveled in the simple gait modes like walking and shuffling through the use of 2-D algorithms solving for incremental heading angles, the overall performance of the navigation system is incomplete. There remains a significant amount of work and analysis to be undertaken for advancing the human gait modeling and relative foot sensor technology to improve the accuracy of a personal navigation system.

The expansion and future work necessary to complete an accurate three dimensional and robust personal navigation system for harsh GPS-denied environments to single meter accuracy is detailed below.

- Expand the algorithms of the current human gait models to three dimensions to improve estimation accuracy at a variety of gait modes. Evaluate the three dimensional performance of the relative foot sensor concept with new algorithms.

- Develop the hardware suite for the relative foot sensor. The construction and calibration of the sensor must be undertaken in order to evaluate the exact, rather than potential, accuracy of the system.

- Synchronize and integrate the PNAV inertial system with the Relative Foot Sensor and a processing unit to analyze real-time performance, rather than post-processing performance. Analyze the performance of the combined system for potential improvements in accuracy. The expansion and integration of the relative foot sensor concept within the larger framework of a full inertial navigational system must be implemented and tested. Use the additional inertial information to determine direction of gait motion, as the relative foot algorithms alone cannot produce that result.

- Develop estimation models based on empirical data by conducting a more statistically representative study of a broad number of human subjects and modes, including mode transitions. Evaluate the potential for base-lining subjects using unique physical parameters. Specific focus should be directed toward the analysis and detection of different gait modes.

- The analysis of running gait has yet to be undertaken using the relative foot sensor. Running presents a unique challenge, as both feet are in the air for a certain period of time, invalidating a peak detection technique.

- Incorporate multiple redundant relative foot sensor nodes and investigate the resulting effect on accuracy.

- Study the applications of relative foot sensor to kinesiology and injury assessment via the pattern recognition of different modes.

- Develop a smart-centralized system that analyzes incoming data at a command center; integrate this software within a large framework of first responder efficiency.

Appendix A

DGPS Sensors for Relative Foot Sensing

A.1 Device Design and Development

This Appendix presents a sample system for determining relative distance, for reference as a proof of concept, constructed and tested by Asterlabs Inc. in Minnesota. The system employs differential techniques using GPS receivers to validate the approach of a relative foot sensor.

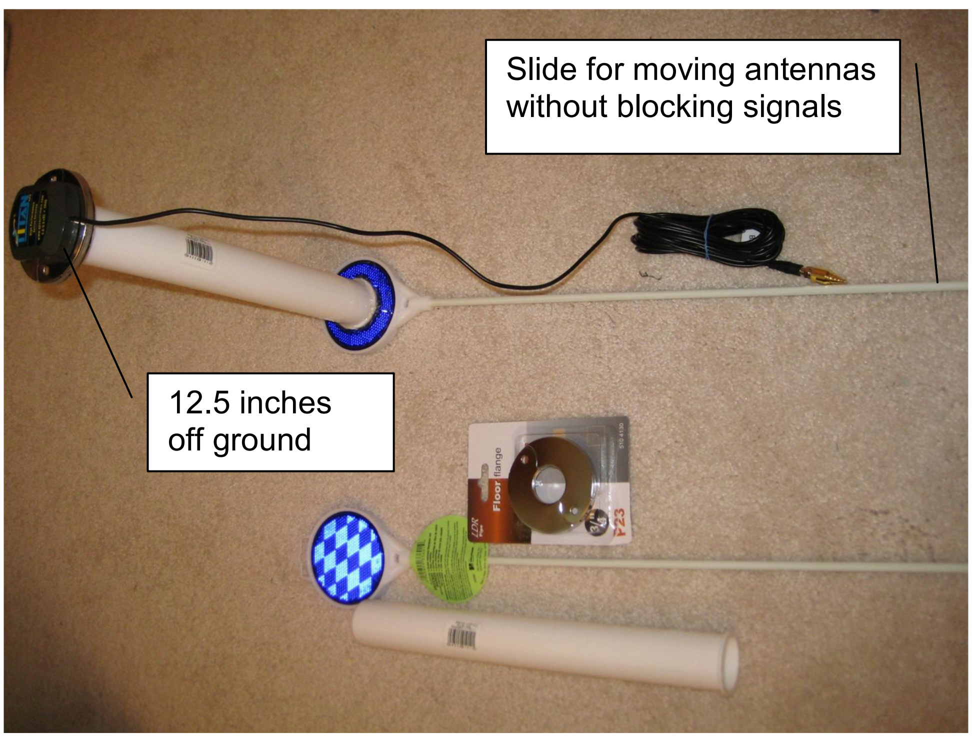

Figure 49: Elevated Antennas Platforms for Minimal Multipath Effects

Two antennas for receiving a GPS signal were used to simulate communicating nodes and experimentally determine the distance between them, effectively validating an RF approach to the relative foot sensor. The two antennas were elevated on platforms in order to increase the strength of the signal and minimize the effects of multipath (see Figure 49).

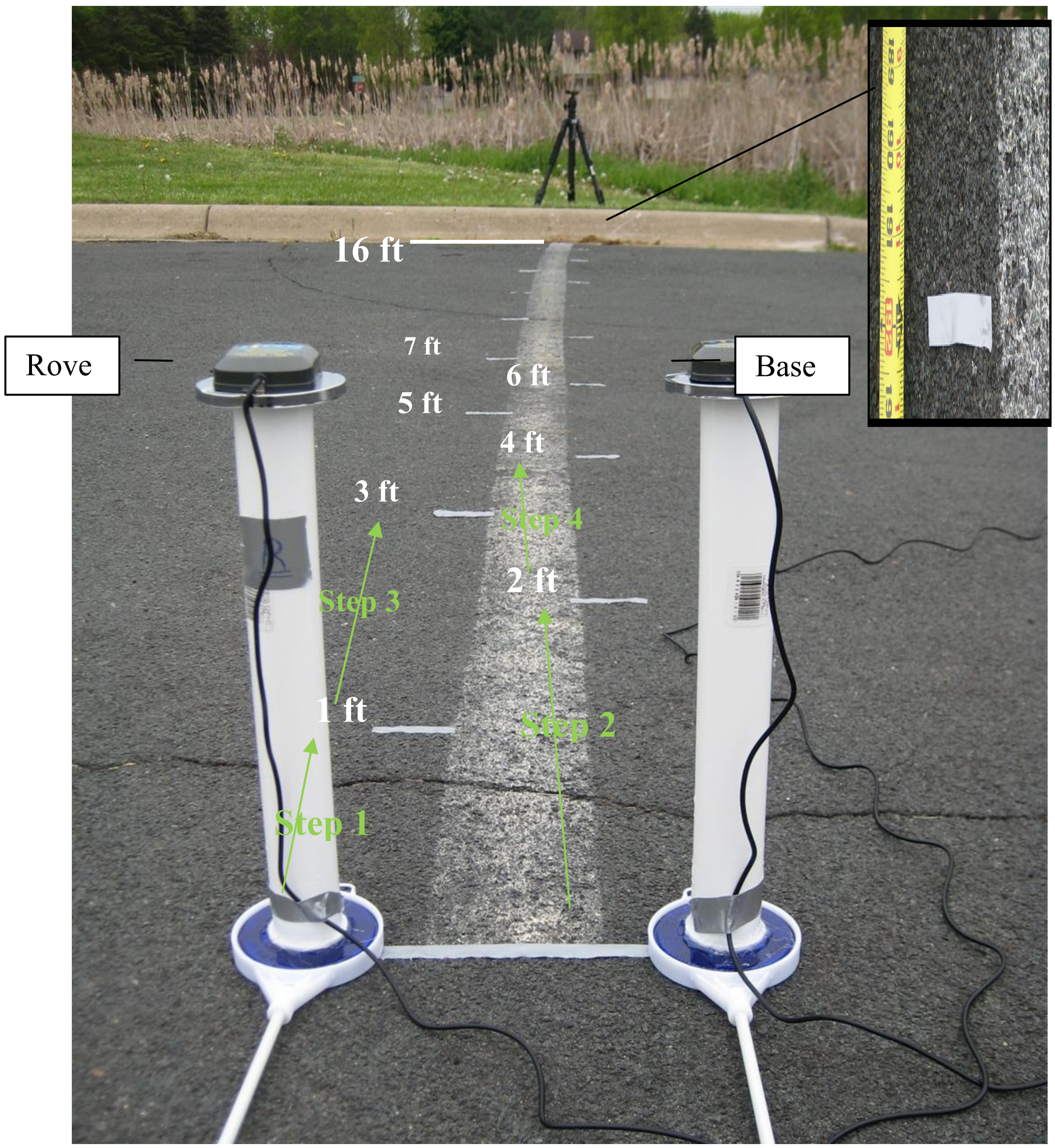

Figure 50: DGPS Test Layout

The test layout with is displayed in Figure 50, with an overview of the sample “steps” taken. The initial static baseline length was 9 inches and the final baseline length was 10.6 inches. A step consisted of sliding the antenna fixture across the ground from one marker to the next. Each step was followed with approximately a 10 second pause to sample the GPS signal. A total of 16 feet were "walked" with this method.

The first 10 minutes of the testing were used to measure a static 22.9 cm (9 inch) baseline for post-processing. The antenna sensors were “walked” along the ground by sliding on level ground. The following 6 minutes of simulated walking traversed a distance of 16 feet. The test was concluded with a 2 minute static test of a 27.0 cm (10.6 inch) baseline.

A.2 Experimental Testing and Results

Throughout the post-processing of results, the data from two incoming satellites were removed. It was discovered that data from satellite 13 was unusable due to cycle slip, and data from satellite 28 contained data drop. To fix the integers using the static periods of data, a MATLAB code was used for processing. The fixed integers were, in turn, used to playback the entirety of the data set.

The initial baseline length estimate was accurate to within 1 cm. Figure 51 shows the captured dynamic step behavior in addition to the 10 second pauses between steps. Additionally the “walking” characteristic decreases, coupled with an apparent increase in baseline length. The final baseline length was also accurate to within 1 cm.

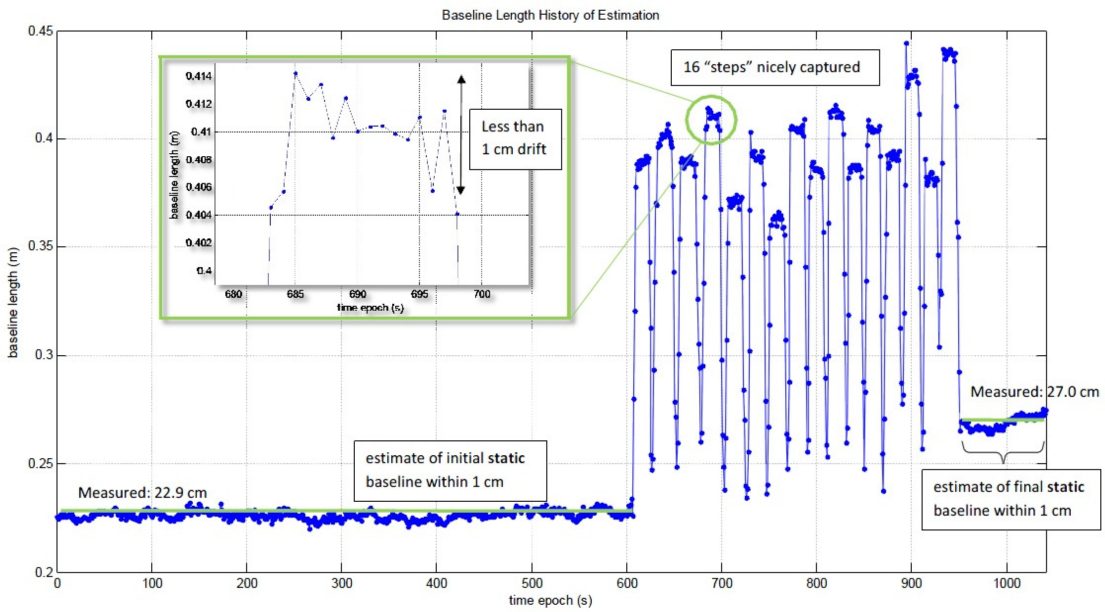

Figure 51: DGPS Time History

The main result for this single trial provides a good range values as the simulated nodes pass by each other and extend to maximum separation. The measurement errors within this system are shown to be on the order of ~1 cm, and that the errors of RFS solution are less than 0.5 inches from the first "step". This is well within the phase center accuracy of the GPS antennas and the "step" positioning estimate.

Appendix B

B.1 Summary of Gait Modality Results

Table 11: Summary of Modalities of Movement

	Modality	**Average Gait Length (mm)**	**Average Frequency (Hz)**	**Average Speed (mi/hr)**
Subject 1 Female 5’9”	Forward Walking	740	1.609	2.662
	Backward Walking	596	1.600	2.133
	Forward Shuffling	949	0.600	1.273
	Forward Crawl	446	1.197	1.194
	Army Crawl	434	1.093	1.061
Subject 2 Male 6’1”	Forward Walking	897	1.564	3.139
	Backward Walking	792	1.657	2.935
	Forward Shuffling	455	1.399	1.423
	Forward Crawl	472	1.302	1.375
	Army Crawl	433	.781	0.756
Subject 3 Female 5’9’	Forward Walking	857	1.757	3.367
	Backward Walking	640	1.482	2.121
	Forward Shuffling	534	0.978	1.168
	Forward Crawl	470	1.407	1.479
	Army Crawl	667	.627	0.936
Subject 4 Female 5’7”	Forward Walking	718	1.739	2.792
	Backward Walking	723	1.877	3.038
	Forward Shuffling	519	1.096	1.271
	Forward Crawl	407	1.473	1.341
	Army Crawl	581	0.762	0.990
Subject 5 Male 6’7”	Forward Walking	828	1.627	3.011
	Backward Walking	737	1.637	2.698
	Forward Shuffling	565	0.844	1.067
	Forward Crawl	435	1.313	1.278
	Army Crawl	635	0.777	1.103

Table 12: Summary of Errors for Modalities of Movement

	Modality	Average Predicted Distance (ft)	Average True Distance (ft)	Distance Error (ft)	Percent Error
Subject 1 Female 5'9''	Forward Walking	72.79	72.31	0.48	0.58%
	Backward Walking	73.53	72.04	1.49	2.06%
	Forward Shuffling	71.14	71.79	0.65	0.91%
	Forward Crawl	71.63	72.46	0.83	1.14%
	Army Crawl	27.01	25.63	1.38	5.38%
Subject 2 Male 6'1''	Forward Walking	72.05	72.65	0.6	0.82%
	Backward Walking	70.65	71.83	1.18	1.65%
	Forward Shuffling	70.62	71.62	1.00	1.39%
	Forward Crawl	75.05	70.9	4.15	5.85%
	Army Crawl	28.27	24.62	3.65	14.82%
Subject 3 Female 5'9'	Forward Walking	73.09	72.37	0.72	1.01%
	Backward Walking	71.85	70.63	1.22	1.73%
	Forward Shuffling	73.95	73.66	0.29	0.39%
	Forward Crawl	73.48	70.63	2.85	4.04%
	Army Crawl	26.26	23.28	2.98	12.80%
Subject 4 Female 5'7''	Forward Walking	71.64	72.46	0.82	1.13%
	Backward Walking	71.18	70.25	0.93	1.33%
	Forward Shuffling	72.01	72.33	0.32	0.46%
	Forward Crawl	74.99	70.25	4.74	6.74%
	Army Crawl	24.78	23.46	1.32	5.64%
Subject 5 Male 6'7''	Forward Walking	73.31	72.46	0.85	1.17%
	Backward Walking	71.73	71.32	0.41	0.58%
	Forward Shuffling	71.66	72.36	0.70	0.98%
	Forward Crawl	75.61	71.32	4.29	6.03%
	Army Crawl	28.18	23.22	4.96	21.38%

B.2 Backward Walking

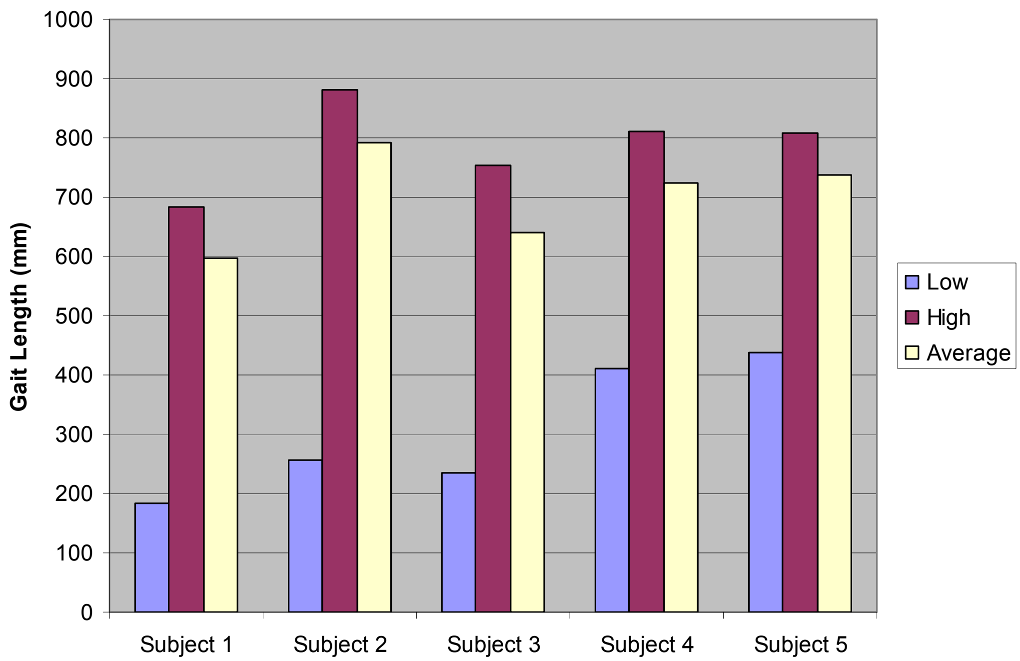

Figure 52: Backward Walking Relative Foot Distance Summary

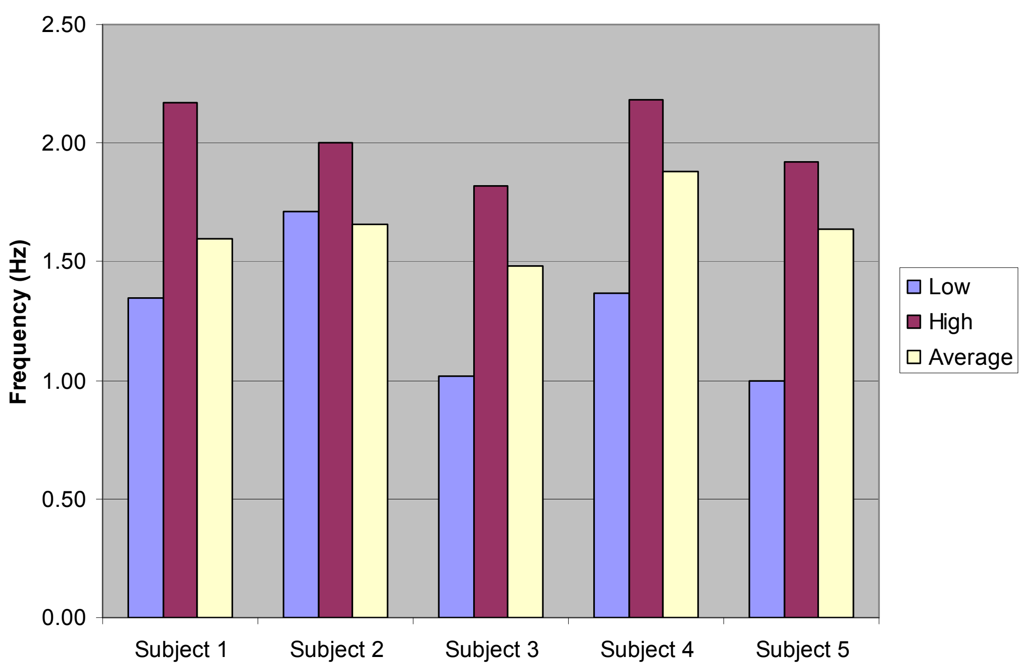

Figure 53: Backward Walking Frequency Summary

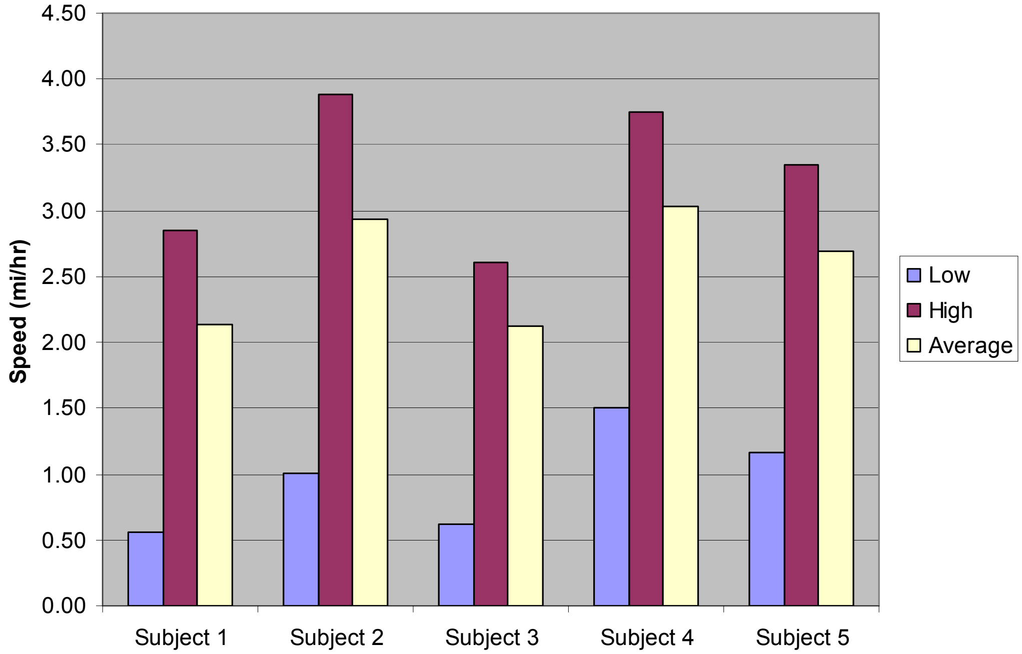

Figure 54: Backward Walking Speed Summary

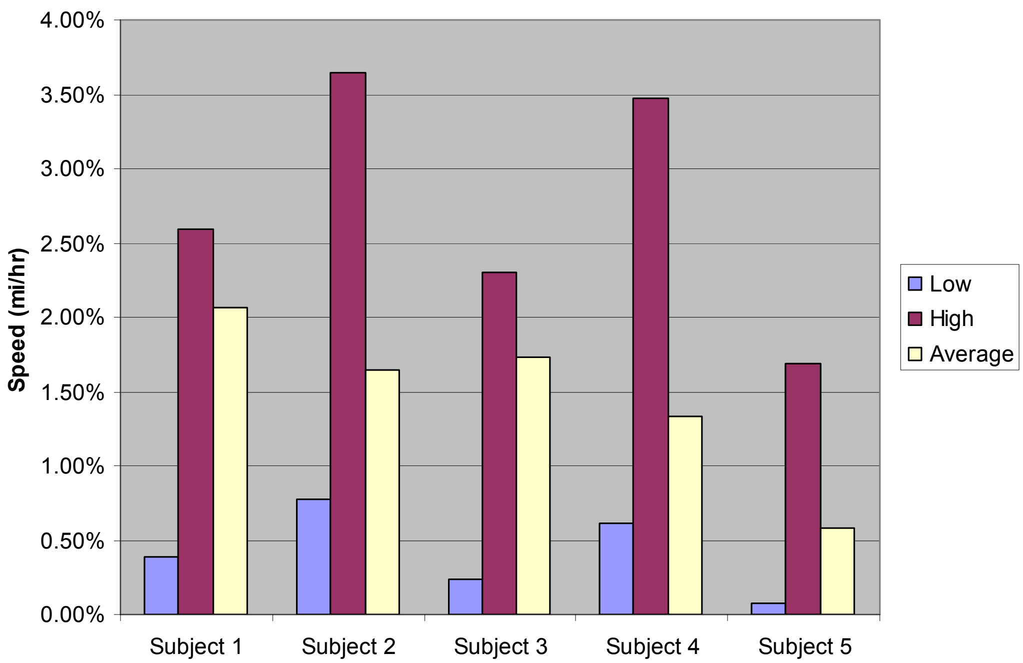

Figure 55: Backward Walking Percent Error Summary

B.3 Forward Shuffle

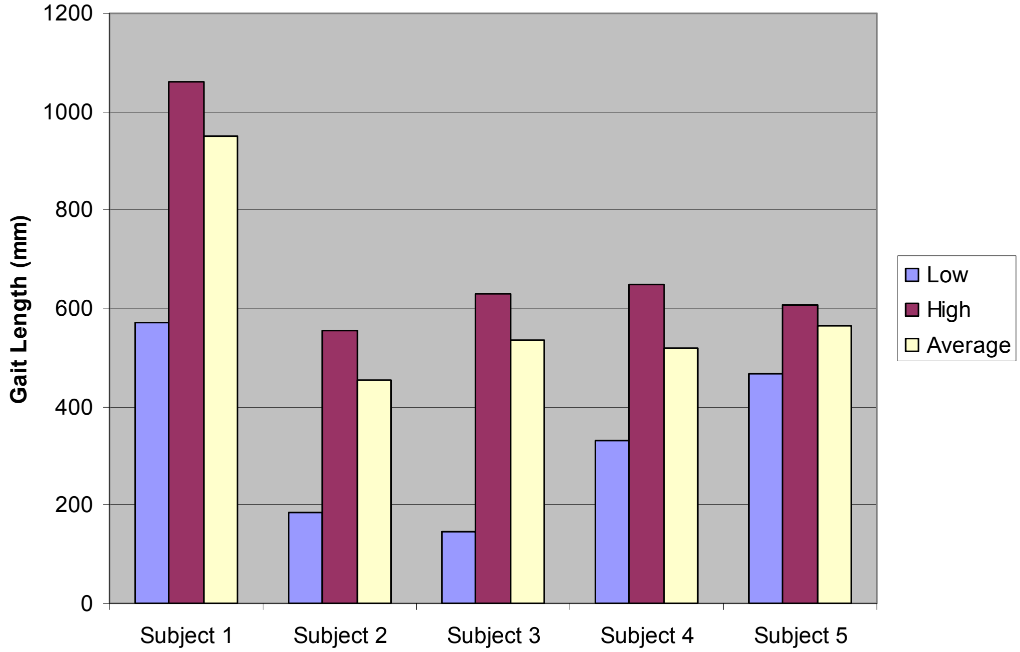

Figure 56: Forward Shuffle Relative Foot Distance Summary

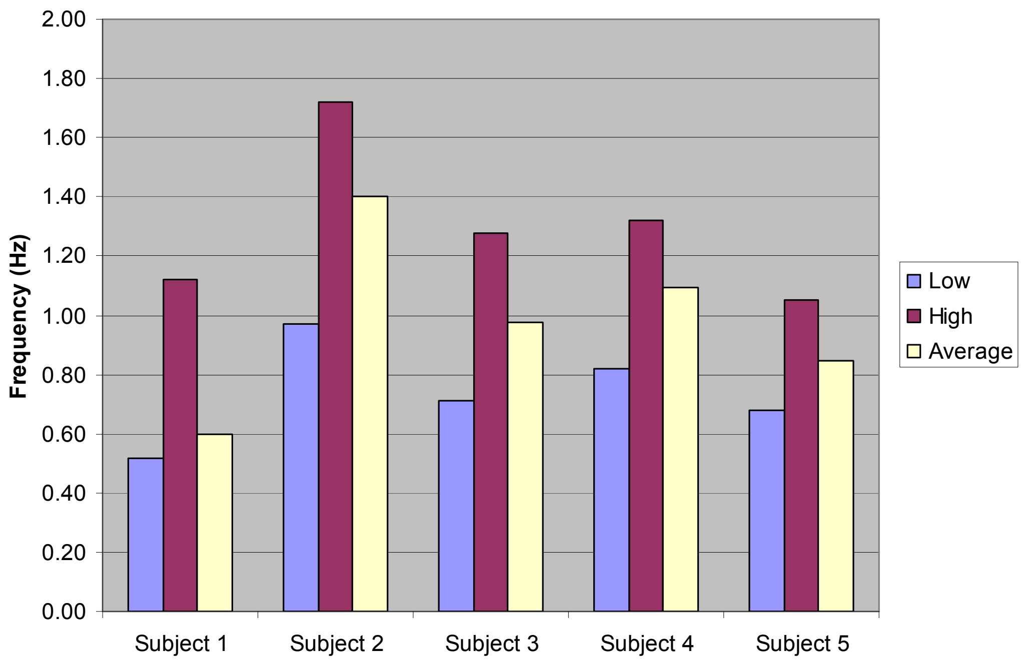

Figure 57: Forward Shuffle Frequency Summary

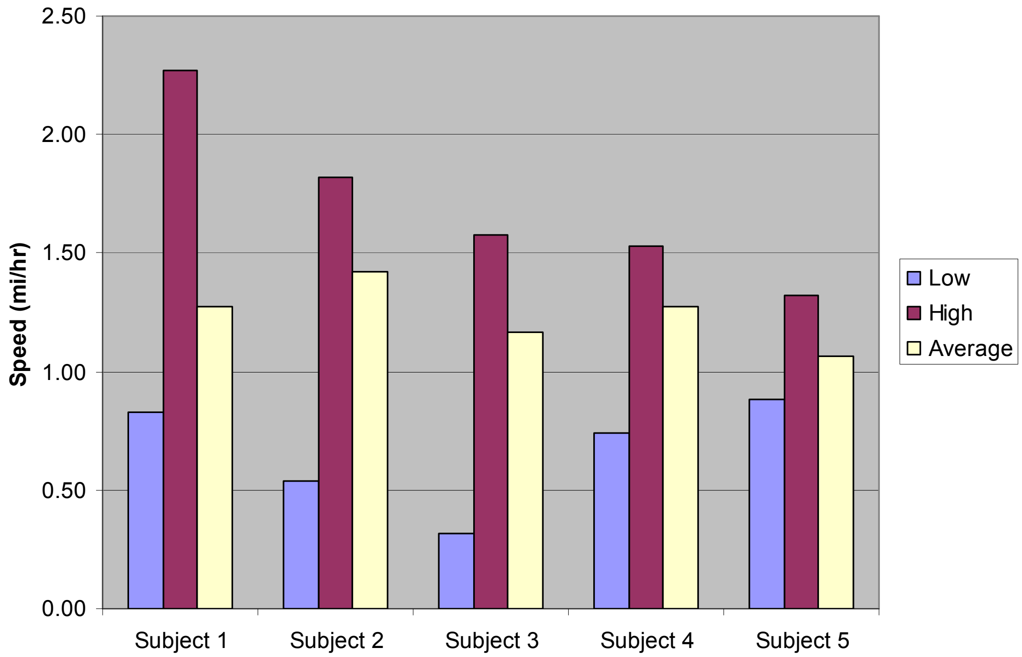

Figure 58: Forward Shuffle Speed Summary

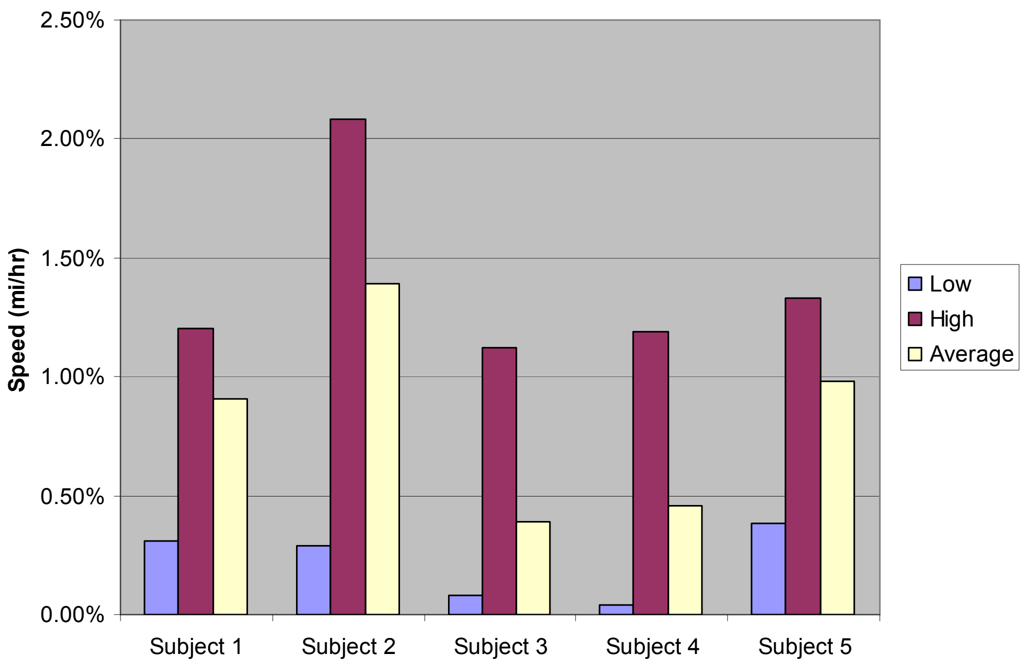

Figure 59: Forward Shuffle Percent Error Summary

B.4 Army Crawl

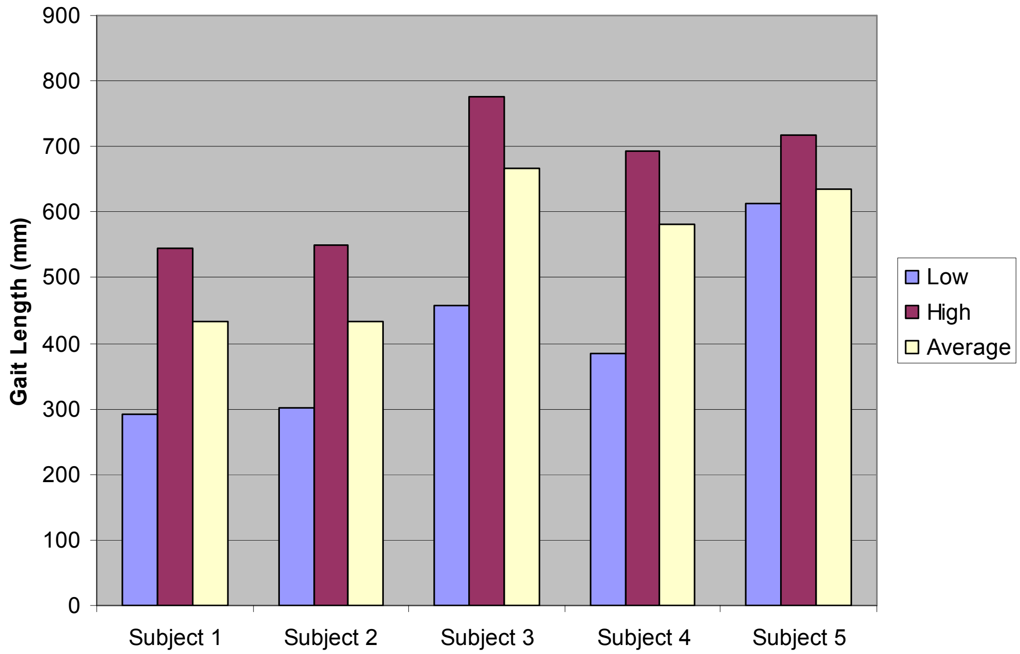

Figure 60: Army Crawl Relative Foot Distance Summary

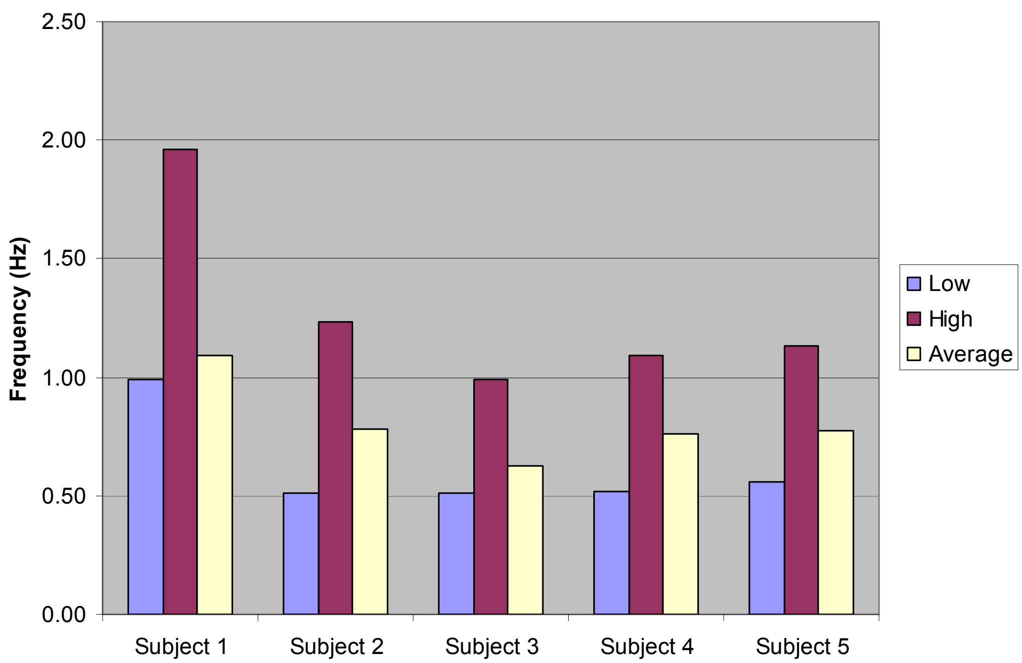

Figure 61: Army Crawl Frequency Summary

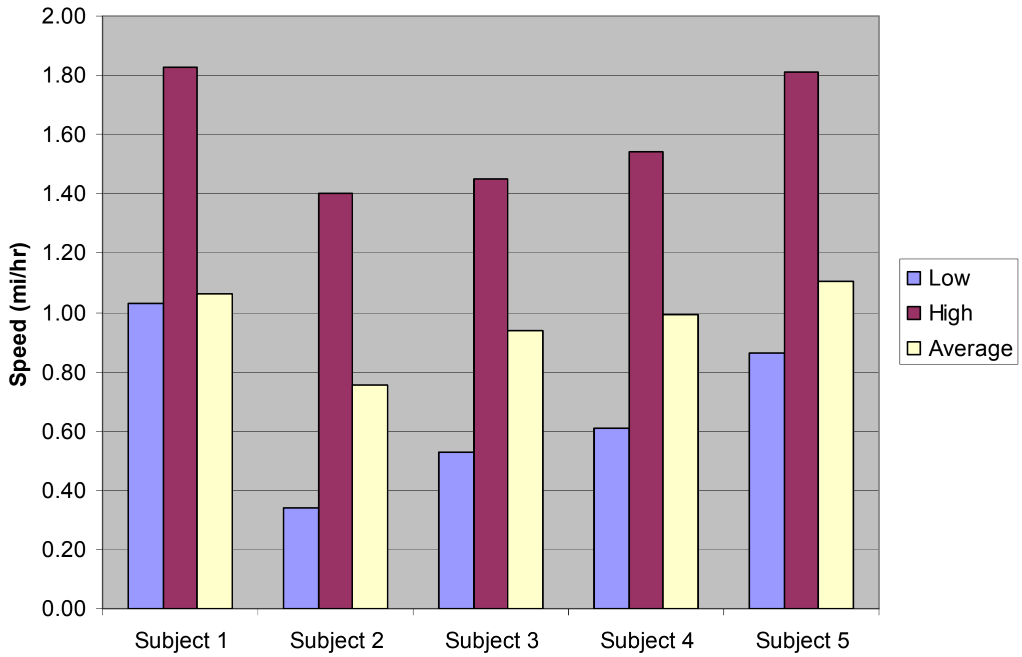

Figure 62: Army Crawl Speed Summary

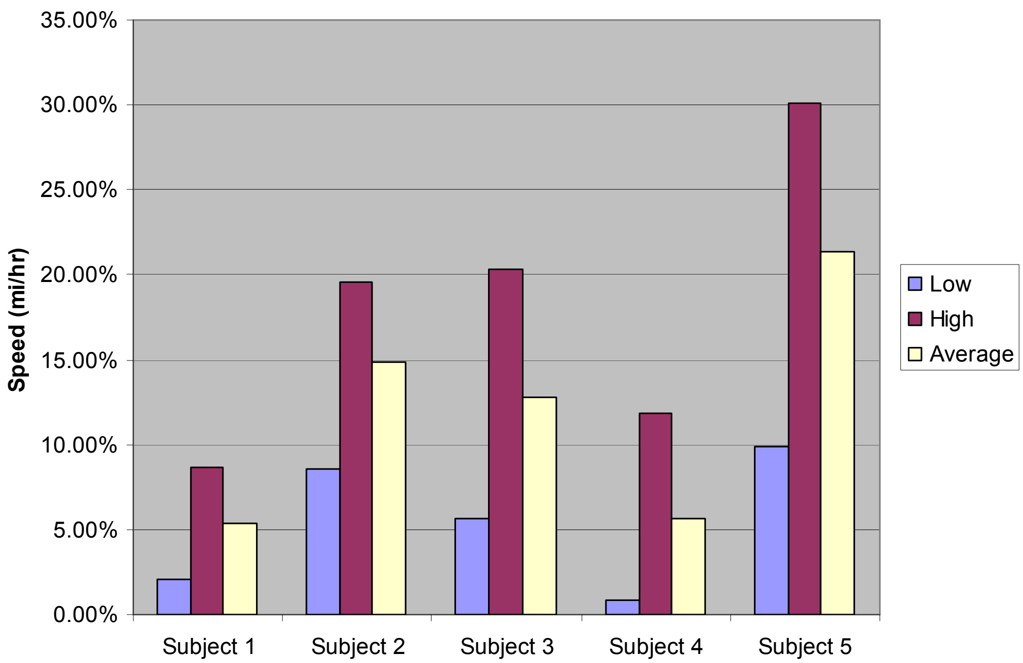

Figure 63: Army Crawl Percent Error Summary

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