Design and Implementation of a Smartphone Application for Estimating Foot Clearance during Walking

by

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Ethics Statement

The author, whose name appears on the title page of this work, has obtained, for the research described in this work, either:

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Abstract

Maximum Foot Clearance (MaxFC) is the maximal foot height during the swing phase relative to the ground, and is a gait variable that is highly associated with tripping and falling. An iPhone mobile application is designed to analyze the MaxFC in real time using the iPhone's built-in accelerometer and gyroscope to collect data when the phone is attached to the shank of the leg. Our method is based on double integration and drift cancellation of foot acceleration signals. An optical motion capture system was used as gold standard, and the results show the mean error over all strides is less than 10.3%. The findings illustrate the feasibility of using an iPhone application to estimate MaxFC. The application is designed and implemented to display the foot clearance results conveniently. A user study was conducted and feedbacks indicate that this application can be suitable to self-monitor risk of falls to prevent falling.

Keywords: Mobile Health application, Smartphone Foot Clearance, Accelerometer, Gyroscope, Fall Prevention

Dedication

The success of this research would not have been possible without conscientious corroboration, endurance, tolerance and support from different people, at their official and individual capacities. Due to the fact that it is difficult to mention each by name the author is hereby indebted to convey a cordial thanks to them.

I am also genuinely grateful to my kind husband, Dr. Atabak Sarrafan, who gave me guidance to start, complete and finish my Master degree and whose happiness, love and cooperativeness clearly directed my way. Thank you for all unrelenting, vigorous and endeavouring love.

I am furthermore indebted to my family, my Father Mr. Mohammad Taghi Yousefian, whose endless encouragement keeps me motivated and my mother, Ms. Akram Saeedian, whose love and patience supports my success during life.

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Chapter 1.

Introduction

1.1. Background

Falls in the elderly are a major public health issue due to associated mortality rates and social cost [1]. One of the most important factors that have adverse consequence in seniors' quality of life is falling [2], [3]. It is reported that among seniors, one third fall each year [4], mostly tripping while walking. The negative impact of falling among seniors is significant and its consequences are both physical and psychological damage. Moreover, the relative injuries after falling increase the senior's dependency on others to perform daily routines, consequently decreasing the quality of life.

One of the recent and promising approaches in fall prevention research and assessing associated risk is the wearable sensor-based method that helps early detection of risk through *gait analysis* to ensure appropriate interventions. Gait analysis is the study of human locomotion in terms of gait parameters such as walking cadence, velocity, step/stride length, step duration and foot clearance (FC). A persons' walking pattern can be assessed by gait analysis to determine abnormalities as well as any significant variation in gait parameters and potential consequences of those abnormal patterns [5]. It has been reported that variability of gait parameters such as stride length, walking speed and FC are correlated with the risk of falls during walking [6], [7]. FC is defined as the foot's height during the swing phase (i.e., when the foot is above the ground) [8] as shown in Figure 1.1 [9].

Figure 1.1. Foot Clearance – Blue line shows the vertical displacement curve of the heel, red line shows the vertical displacement curve of the toe during normal walking and green line shows one stride signal and walking phases on gyroscope z-axis

For years, the quantitative analysis of gait patterns was studied in gait laboratories equipped with many complicated measurement and analysis devices. However, the use of such facilities requires specialized personnel, laboratory environment, expensive equipment and cumbersome data acquisition procedures [1], [10], [11]. A system is needed during daily activity to monitor the foot trajectory and gait characteristics to assess the risk of falling. Recently, inertial measurement unit (IMU) sensors have become convenient alternative devices and are being used widely for important gait analysis [8], [9], [12]–[14]. Many researchers have utilized accelerometer and gyroscope to estimate the stride length and stride time [15], [16]. Others have used accelerometer and gyroscope to evaluate the walking speed, running speed and distance travelled [17], [18]. Moreover, recent studies have looked at accelerometer and gyroscope to estimate heal and toe clearance, FC, stride length, stride velocity and turning angles [4], [9].

Even more recently, the advent and widespread use of smartphones has offered an alternative to these specific commercial devices for studying gait patterns. Although smartphones collect data at lower frequencies than IMUs, smartphones can do more computational analysis to the sensor readings on the device, and can process the data by specific algorithms [19]. In particular, smartphones are lightweight and can be easily worn using sport armbands directly on the user's shank or above the ankle thus minimizing interference with normal gait conditions. Therefore, it is beneficial to design mobile health applications that can allow individuals to self-monitor their gait, independent of clinical practices and expensive laboratory equipment.

1.2. Goal of this Research

The goal of this research is to investigate the initial validation and design of our new iPhone mobile application called *FootClearance*, that detects Maximum Foot Clearance (MaxFC) and serves as a fall risk assessment tool with long-term monitoring by the user. Since many smartphones equip users with rapid access to the Internet, sensors, data and location information, these mobile devices can be a perfect tool for self-monitoring and diagnostic, preventive and educational tasks for patients and clinicians.

1.3. Research Questions

To the best of our knowledge, we are the first to use the built-in sensors of the iPhone to estimate MaxFC. Our major contributions are as follows:

- Introducing a new approach to calculate the MaxFC through use of iPhone sensors.
- Designing and implementing a novel iPhone application to estimate and track the MaxFC during ground walking for early detection of risk of falls and monitoring rehabilitation progress.
- Performing an initial validation of the system that shows this application can serve as a viable self-monitoring tool to estimate users' MaxFC independently, without the clinician's help, in their natural environment with real time processing the walking data.

1.4. Thesis Overview

Chapter 2 reviews the literature on important gait parameters and their various methods of calculation, the importance of foot clearance and its estimation, iPhone platform and its technical specifications. Chapter 3 states computational details and proposed algorithm. Moreover, in this chapter the design and implementation of our application is discussed. Chapter 4 is the experiment chapter that features a report on the results of the project experiments, data collection and validation. In addition, this chapter reviews the user study on our iPhone prototype application and how we iterated on the user interface design. Chapter 5 covers the discussion and conclusion, limitation and future work of this study.

Chapter 2.

Literature Review

2.1. Important Gait Parameters

Gait analysis is able to provide useful information in various areas such as health care, therapy, sports training, and characteristic recognition [20]. Commonly used gait parameters are defined based on the detection of gait events. Stride velocity (SV) is considered as the mean value of foot velocity in ground plane (XY) during each gait cycle [9]. Step length (SL) is defined as the distance measured between two successive foot-flat positions of the foot [9]. Cadence is the number of steps the person walks per second [5]. Foot clearance (FC) is defined as the maximal foot height during swing phase relative to the height at foot-flat [8] (see the blue line in Figure 1.1). Turning Angle (TA) is defined as the relative change in azimuth (i.e. the projection of orientation in ground plane (XY)) between the beginning and the end of gait cycle [9].

2.2. M-Health Applications to Estimate Gait Parameters

Advances in smartphone technology in recent years and their wide usage among people have enhanced many aspects of medical practice. Recently many researches have focused on utilising smartphone to improve senior's independence through the design and implementation of various mobile health applications. A current and recent trend has seen the deployment of accelerometers and gyroscope embedded in smartphones for analysis and measurements of gait parameters [19]–[27]. Therefore, it is possible to explore designs of mobile health applications that can allow individuals to self-monitor their gait.

Majumder et al. [23] designed and implemented an application called *iPrevention* that uses the built-in accelerometer and gyroscope of the smartphone to identify abnormal walking patterns in users to prevent falls. Through this system, the raw data were collected from the built-in sensors while the user is walking to calculate the acceleration and orientation. Their algorithm classified the user's walking pattern as either normal or abnormal. If a person walks in an abnormal pattern, the system detects a high-risk pattern and warns the user using a message and vibration to alert them about an imminent fall. The difference between this system and our model is that they classified user's gaits rather than make a quantitative estimation.

Pierleoni et al. [24] used a smartphone as a fall detection tool. They collected data from the accelerometer and magnetometer, and then classified events either as fall events or non-fall events by a machine learning method. In addition, the cellular network of the device was used to send notifications and alerts to relatives in case of falls. This system is beneficial for fallen patients who have been left immobilized for a period of time, but it cannot directly prevent falls.

Raknim et al. [25] used a smartphone as a diagnostic tool. They monitored and recorded patients' gait characteristics to identify those who are in their early stage of neurological disease, as these groups are high potential fallers. The results of their work show the possibility of applying smartphone accelerometer and gyroscope data to provide early warnings to potential Parkinson disease (PD) patients and encourage them to seek medical assistance and diagnose this disease earlier.

Cheng et al. [19] used a smartphone as self-monitoring tool. They designed a smartphone application called *GaitTrack* that is a self-health monitoring method used to do activity recognition and differentiate between walking and non-walking activities, recording only during walking. This system enables the phone to be carried normally for health monitoring for continuous tracking.

Capela et al. [26] used a smartphone as a rehabilitation tool. They proposed an algorithm to examine the 6MWT (six-minute walking test, a simple physical capacity test) on a smartphone application that uses the device accelerometer and gyroscope data to report the step length, step timing, gait symmetry, and walking changes over time. In this study, they tried to estimate just parameters that are necessary to evaluate the 6MWT.

Kim et al. [28] presented a simple wearable smartphone camera-based system called *SmartGait*, for measurement of step length, step width, step time and gait speed. The findings show that *SmartGait* provides many advantages and is a strong alternative wearable system for laboratory and community-based gait assessment.

Qin et al. [20] measured gait parameters such as velocity, step length, and cadence by designing a smart-phone based gait monitor system, which worked by detecting current rate of acceleration using multi-axes accelerometer and rotational attributes using multi-axis gyroscope.

Zhu et al. [27] have developed an iOS-based Rhythmic Auditory Cueing Evaluation called *iRACE* to assess step time and step length during walking by the device's built-in tri-axial accelerometer and gyroscope. Results reveal that *iRACE* is a potentially useful clinical tool.

2.3. Estimation of Gait Parameters by Inertial Measurement Unit sensors

An overview of research using IMU sensors to calculate various gait parameters is given in Table 2.1. Although assessing the gait parameters by IMUs is more convenient than laboratory equipment, the need for a clinician’s help for offline processing of raw data is a significant disadvantage for this technique, as these inertial sensors can take raw data at high frequencies but lack the capability to do computational tasks on the device.

Table 2.1. Systematic Reviews of IMU sensors to calculate Gait Parameters

Authors	Sample Size	Gait type	Sensor Location	Parameter Outcome	Results
Milosevic et al. [29]	40 Healthy subjects	Single vertical jumps and repetitive four jumps	Sensors: Acc[1] & Gyro[2] & Magnet[3] Attached to: the waist of the user	Jump height	Mean difference of 0.7 cm (max.1.9 cm) for single vertical jumps and 0.6 cm (max. 2.1cm) for the repetitive four jumps.
Rampp et al. [15]	101 old patients	Normal walking with and without a wheeled walker	Sensors: Acc & Gyro Attached to: below ankle joint	Stride Length Stride Time	The absolute error of stride length was 6.26 cm on normal walking test.
Boutaayamou et al. [30]	7Healthy subjects	Self-selected speed	Sensors: Two Acc Attached to: shoes, one at heel and one at forefoot	Event of walking: HS[4], TS[5], HO[6], and TO[7]	MAP: 1.3ms ± 7.2ms /HS -4.2ms ± 10.9ms /TS -3.7ms ± 14.5ms /HO -1.8ms ± 11.8ms /TO
Sijobert et al. [16]	10 Healthy subjects and 12 PD[8]	Normal walking, fast walking and comfort speed	Sensors: Acc & Gyro Attached to: shank	Stride Length	Mean error over all the strides was less than 6% for healthy group and 10.3% for PD group.
Mariani et al. [4]	12-Healthy adults	Short walking trials/ self-selected, slow and fast walking speed	Sensors: Acc & Gyro Attached to: upper part of the foot	Heal and Toe clearance estimation	MAP[9]: 4.1 ± 2.3 cm for maximal heel clearance and 1.3±0.9 cm for minimal toe clearance
Yang et al. [18]	7-Healthy subjects	Run at five different treadmill speeds	Sensors: Acc & Gyro Attached to: lateral side of shank	Running speed	%RMSE: 4.10%.
Li et al. [17]	8-Healthy subjects	Run at different treadmill speeds	Sensors: Acc & Gyro Attached to: lateral side of shank	Walking speed and distance travelled	RMS[10]: %7 for speed estimation. RMS: 4% for travel distance estimation

[1] Acc: Accelerometer
[2] Gyro: Gyroscope
[3] Magnet: Magnetometer
[4] HS: heel strike
[5] TS: toe strike
[6] HO: heel-off
[7] TO: toe-off
[8] Parkinson Disease
[9] Mean accuracy and precision
[10] RMS: Root Mean Square

2.4. Foot Clearance

Falls in older adults are a major public health concern and attracts many researchers to focus on designing and implementing fall prevention tools. Tripping during walking is the predominant cause of falls in elderly and has been reported to account for up to 53% of falls [2]. The ultimate goal of research on tripping is to understand the factors that contribute to a trip so that individuals at risk of tripping can be identified and trip prevention strategies implemented. FC, defined as the foot elevation during the stride phase, is an important indicator of trip and fall in subjects [2], [8]. Minimum foot clearance (MinFC) is the minimum vertical distance between the lowest point of the foot of the swing leg and the walking surface during mid-swing in the gait cycle [2]. Maximum foot clearance (MaxFC) is the maximal foot height during swing phase relative to the height at foot-flat [8]. During walking, insufficiency or fluctuations of FC could lead directly to tripping, a major cause of fall in older people [4]. FC variability is the most discriminative parameter between young and elderly subjects, hence can be an important new gait parameter to estimate risk of fall in elderly [1], [2], [8], [9]. Any significant decrease in either MinFC or MaxFC, and an increase in their variation will put the subject at the risk of falls. Gait deviations due to the MinFC increase the risk of trips and subsequent falls because of foot-ground contact [1], [2], [11] and deviations due to the MaxFC cause trips and subsequent falls over obstacles (since it shows the ability of the subject to pass the obstacle without tripping over it) [14].

In this research, we estimate the MaxFC. Previous studies suggested that the best part of the body to place sensors for calculating the MinFC is the foot dorsum, because the MinFC is estimated by tracking the movement of the toe of the swing leg. However, considering the size of iPhone, the best location to mount the iPhone is on the user's shank which is suitable for detecting the movement of the heel and estimating the MaxFC. Therefore, we focused on estimating the MaxFC rather than the MinFC.

2.4.1. Estimation of Foot Clearance by IMUs

In recent studies, an IMU has been placed on the foot segment and used to estimate changes in gait parameters such as FC during the swing phase of walking in an outdoor environment or at home [8], [9], [12]–[14]. This type of wearable sensor system may be able to contribute to long-term monitoring of everyday walking, allowing investigation of how gait parameters such as variability of FC are possibly linked to the risk of falls in elderly individuals during actual daily activities.

Kitagawa et al. [13] developed a system to monitor human gait in an outdoor environment using an IMU consisting of a tri-axial accelerometer and gyroscope attached to the dorsum of the foot. Results show that the proposed system successfully estimated the FC and stride length during human walking with reasonable accuracy.

Benoussaad et al. [8] introduced a method for the robust estimation of FC during walking, using a single IMU placed on the subject's foot ankle joint. This system is insensitive to misalignment of IMU axes with respect to foot axes, which was claimed to be a source of error in another study [18]. The findings demonstrate a proper method for estimating FC in daily activity among healthy adults.

Trojaniello et al. [14] proposed a method for assessing MaxFC during over-ground walking and obstacle passing using magnetic and inertial measurement units (MIMUs) placed above the ankle in both healthy subjects and a patient with Parkinson 's disease. The outcome was satisfactory and shows precise estimation of MaxFC.

Bailey et al. [12] investigated the suitability of using foot mounted inertial sensors to assess foot kinematics such as FC and stride velocity in steady state running. The results show that foot-worn sensors could be a way to aid in injury rehabilitation.

Mariani et al. [9] described the validation of a new wearable system for assessment of 3D spatial parameters of gait such as FC, stride length, stride velocity and turning angles. Measurements were performed in both young and elderly volunteers who were asked to perform U-shaped and 8-shaped walking trials and then a 6-minute walking test (6MWT). The accurate findings of this study suggest that this system is suitable for clinical application requiring objective evaluation of gait outside of the lab environment.

The advantages of our system address some existing drawbacks of the above systems. It does not require the user to wear any physical sensors on the body, it is inexpensive because it requires only a smartphone and it analyzes the walking data in real time to generate feedback to the user.

2.5. The Need for a Mobile Health application

Although FC variability plays an important role in fall prevention, surprisingly, no application currently has the ability to estimate FC's parameters. In particular, since seniors' safety is highly dependent on their ability to perform their routine tasks and avoid the hazards presented by obstacles, the analysis of MaxFC in real time can be especially useful for self-assessment of risk of falling. Therefore, it is beneficial to design mobile health applications as self-monitoring tool, independent of clinical practices and expensive laboratory equipment. There are important advantages to develop a smartphone-based solution to estimate MaxFC in comparison to commercial IMU devices available in the market. First, using a smartphone to track MaxFC has no additional cost for the user, as many people own a smartphone. Second, users do not need a clinician's help for analyzing data because the app processes, generates and saves the mean MaxFC and variation for each test. Any decrease in MaxFC's mean, especially combined with an increase in variation, compared with the previous test's results, informs the user that they could potentially be at risk of tripping during walking. Moreover, tracking MaxFC in long term can be also useful for rehabilitation purposes, such as for people who have had knee or hip surgery. They could benefit from measuring and monitoring their improvement in FC during rehabilitation, which would motivate physiotherapy over the period of rehabilitation. In addition, this can be very useful for people, especially seniors, to recognize any significant variation in their MaxFC as it happens, thus enabling appropriate intervention in time to avoid possible falls. Finally, independent of any installation or server connection, users can examine their MaxFC everywhere as smartphones are widely portable.

In summary, the most important aspect of our system is the real time processing of walking data to generate fast feedback to the user that is convenient for those who are interested to self-monitor their own walking pattern either for assessing the risk of fall or for rehabilitation.

2.6. iPhone Platform

Smart mobile phones have become widely available commercially over the past decade. These devices provide a rich technology platform for users and developers to explore mobile computing possibilities that present a promising capability for improving prevention, treatment and follow-up of health issues [5]. This increased the demand for new mobile health (m-Health) that effectively takes advantage of this technology to communicate with patients and clinicians as well as self-monitoring various health conditions [31]. In particular, many m-health application developers have chosen Apple's iOS mobile devices such as iPad, iPhone, or iPod as the target device to provide more convenient and richer user experience, as evidenced by the rapidly increasing number of m-health apps in Apple's App Store [32]. Therefore, in this study, the iOS platform was selected to represent mobile software platforms, and the latest iPhone smartphone called iPhone 7Plus was used for experiments to represent the mobile device.

2.6.1. Technical Specification

The iPhone 7Plus, seen in Figure 2.1 [33], comes with a 5.50-inch touchscreen display with a resolution of 1080 pixels by 1920 pixels at a PPI of 401 pixels per inch. The Apple iPhone 7Plus is powered by quad-core Apple A10 Fusion processor 64-bit and it comes with 3GB of RAM and 32GB of internal storage [34]. Apple states that A10 Fusion processor has 40% greater CPU performance and 50% greater graphics performance compared to its predecessor [35]. As far as the cameras are concerned, the iPhone 7Plus packs a 12-megapixel primary camera on the rear and a 7-megapixel front shooter. The iPhone 7Plus runs iOS 10 and is powered by a 2900mAh non-removable battery. It measures 158.20 x 77.90 x 7.30 (height x width x thickness) and weighs 188.00 grams [36].

Image removed due to copyright.

Figure 2.1. A picture of iPhone 7Plus

2.6.2. iPhone Sensors

Contained in most phones there are different sensors including: Compass Magnetometer, Proximity sensor, Accelerometer, Ambient light sensor, and Gyroscope. In recent years, smartphone manufactured have adopted micro technologies such as micro electromechanical systems (MEMS) accelerometers and gyroscopes to determine device orientation. For the current study, the focus is just on the efficient use of accelerometer and gyroscope, as a result, the review is concentrated on the usage of these two sensors.

According to the Apple Developer Documentation [37], the accelerometer is actually made up of three accelerometers, one for each axis-x, y, and z as illustrated by the left image in Figure 2.2. Each one measures changes in velocity over time along a linear path. Combining all three accelerometers, device movement in any direction and device's current orientation can be detected. The gyroscope measures the rate of rotation around the three axes, right image in Figure 2.2 [37].

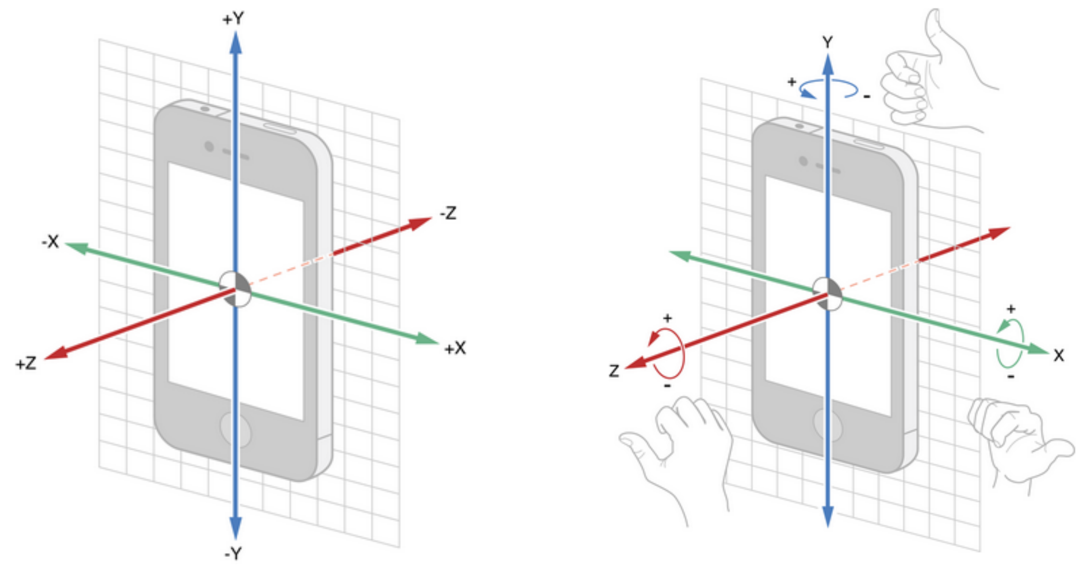


Figure 2.2. Left Image: The accelerometer measures changes along the x, y, and z-axes. Right Image: The gyroscope measures rotation rate around the x, y, and z-axes

To manage accelerometer and gyroscope sensor data, motion data manager is needed. The motion manager includes accelerometer and gyroscope readings and the data rate can be set individually from 10 Hz up to 100 Hz [37]. If the data is not received at exactly the same time, interpolation may be necessary. Potentially, the MEMS accelerometers in these iPhones can provide meaningful data of user's movement and may be useful for gait analysis, assessment and monitoring [5].

Nishiguchi et al. [21] evaluated the reliability and validity of a smartphone accelerometer. Results obtained by the smartphone showed statistically significant and considerable correlations with the same parameter results obtained by the tri-axial accelerometer. Similarly, Chan et al. [5] studied the capabilities of the accelerometer within a smart mobile device for identification of gait events from walking along a flat surface. The results prove that it is possible to extract features from the accelerometer of an iPhone such as step detection, stride time and cadence. Galán-Mercant et al. [38] further evaluate the reliability and validity of the accelerations with a smartphone in an Extended Timed Get Up and Go test. The results reveal that the inertial sensor mounted in the iPhone is sufficiently reliable and accurate to evaluate and identify the kinematic patterns.

These studies show that smartphones are reliable for gait analysis and their built-in sensors can be as good as IMUs. Building on the computational capabilities and reliability of built-in sensors, we explored the use of smartphones to analyze the walking data in real time for MaxFC estimation in gait analysis.

Chapter 3.

Methodology

3.1. Foot Clearance Algorithm on a Smartphone

The algorithm presented in this study uses the iPhone 7Plus's built-in 3D-accelerometer and 3D-gyroscope to estimate the MaxFC. This algorithm is based on filtering the signals, detection of temporal cycles and foot flat phase, and computation of foot orientation from accelerometer and gyroscope sensor's signal data fusion at each timestamp. Then the gravity-compensated translational acceleration is double-integrated over time during the swing phase in each stride. The Ankle joint clearance is first estimated and then one bias is added in terms of the distance between the ankle joint and the heel [8]. An overview of the algorithm is shown in Figure 3.1.

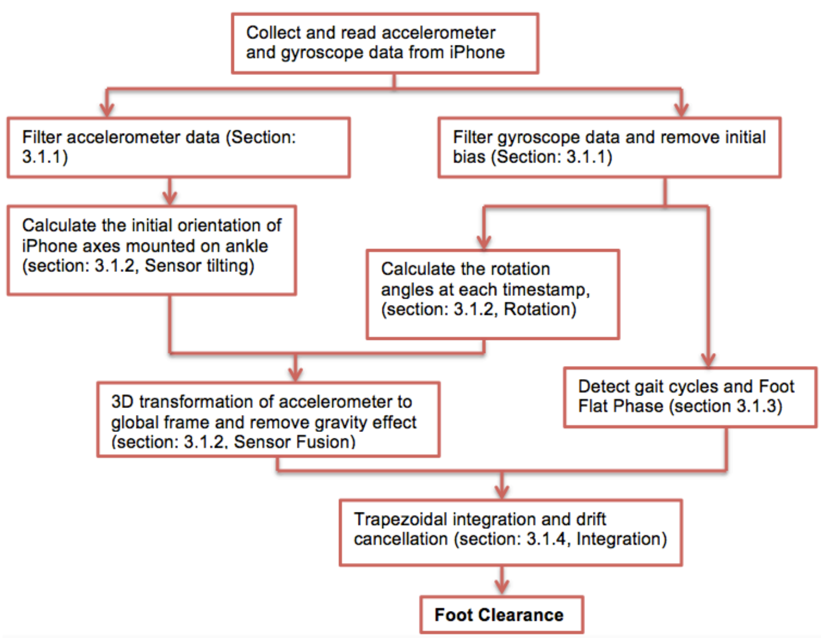


Figure 3.1. Overview of Foot Clearance Algorithm

3.1.1. Filtering

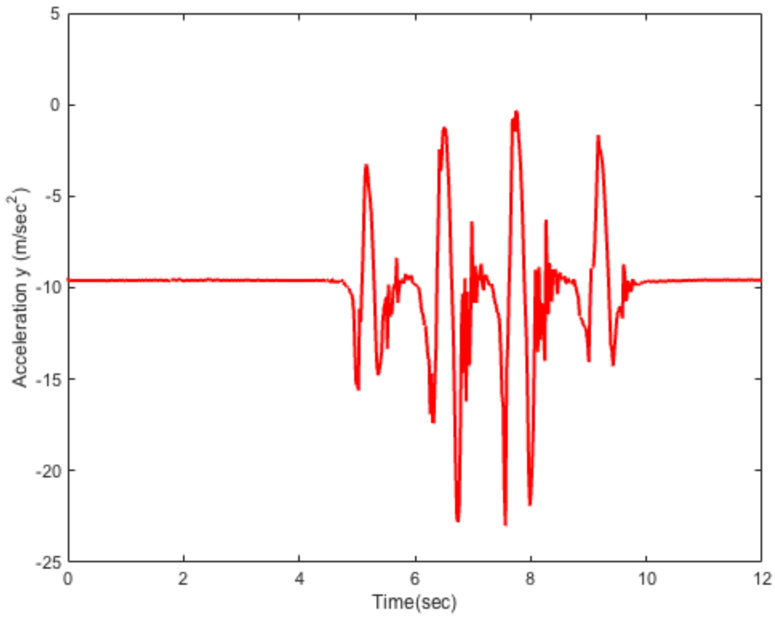
According to the Apple documentation [34], the common update intervals for accelerometer and gyroscope can be varied between 10HZ to 100HZ. The Table 3.1 shows the suggested frequency rate for iPhone sensors regarding application requirements [37].

Table 3.1. Common update intervals for acceleration events from the Apple Guidelines

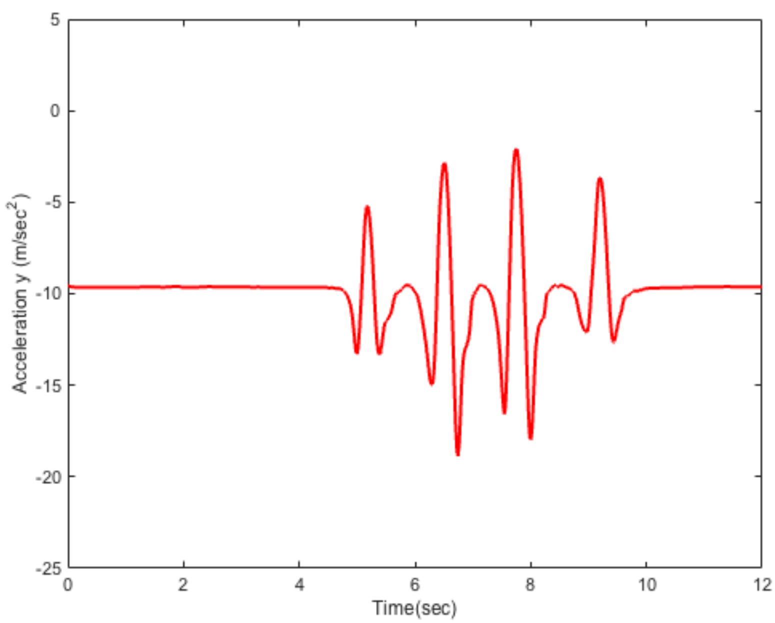
Event Frequency (HZ)	Usage
10-20	Suitable for determining a device's current orientation vector.
30-60	Suitable for games and other apps that use the accelerometer for real-time user input.
70-100	Suitable for apps that need to detect high-frequency motion. For example, you might use this interval to detect the user hitting the device or shaking it very quickly.

The common update intervals for accelerometer and gyroscope can be varied between 10HZ to 100HZ; however, it is suggested that the frequency rate between 30HZ-60HZ is appropriate for applications that use sensors for real time user input [37]. For our application requirements, data acquisition frequency of 51HZ was chosen to avoid data missing and make sure the application keeps up with the updates. To remove noise from the sensor's signals, filtering has to be applied to both accelerometer and gyroscope data. The filtering's cut-off frequency was chosen according to the Fast Fourier Transform (FFT) of the acceleration signal on the Y-axis for the acceleration, and angular velocity signal on the Z-axes for rotation rate. For three-axis acceleration data, a low-pass filter with 8-Hz cut-off frequency was applied to remove high-frequency noise. Figure 3.2 shows the signal of accelerometer from one subject before and after applying filtering.

Three-axis gyroscope data were band-pass filtered between 0.08 Hz and 6 Hz to remove constant and high frequency components. Figure 3.3 shows the signal of gyroscope from one subject before and after applying filtering. It is also essential to use Zero-Phase filtering to keep zero–phase distortion between accelerometer and gyroscope values [16]. In other word, the zero phase distortion filtering is used to avoid any shift in signal after filtering the data compare to the raw data signal.

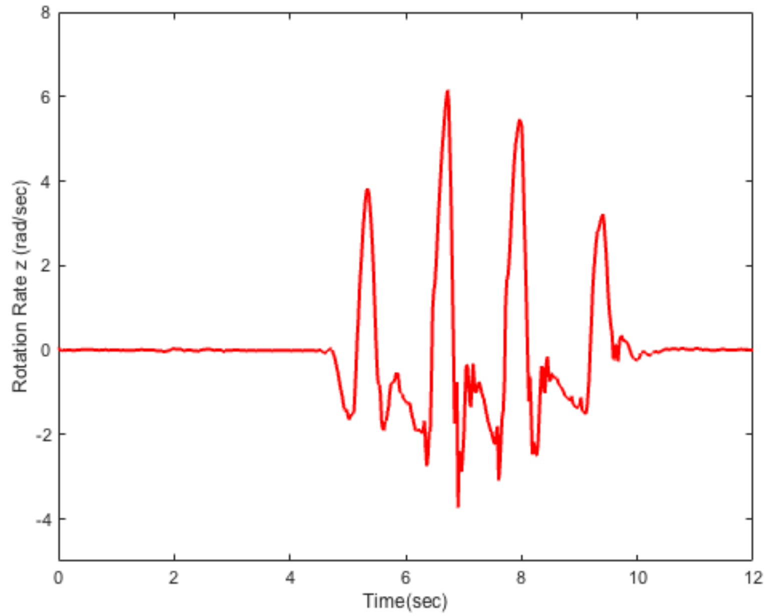


(a)

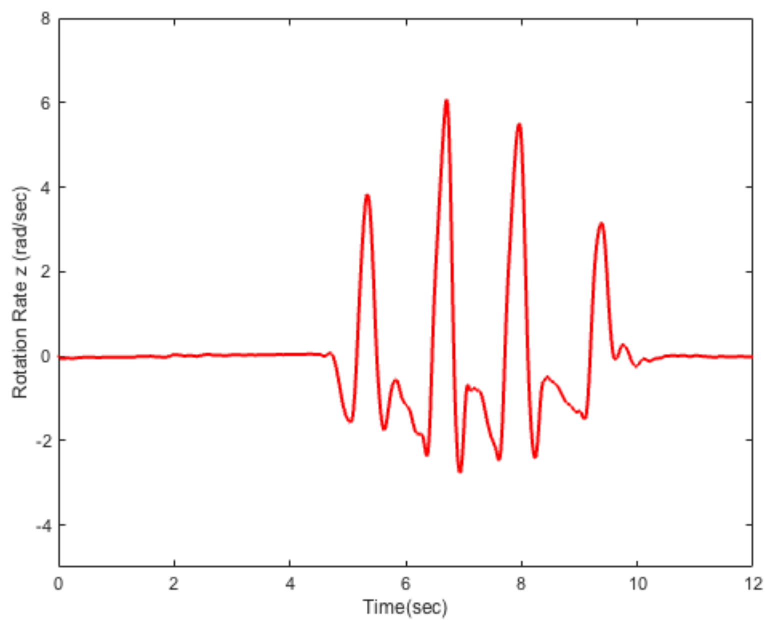


(b)

Figure 3.2. Acceleration signal on y-axis. (a) Signal before filtering and (b) Signal after filtering



(a)



(b)

Figure 3.3. Rotation Rate on z-axis. (a) Signal before filtering and (b) Signal after filtering

3.1.2. Translational Accelerometer (Linear Acceleration)

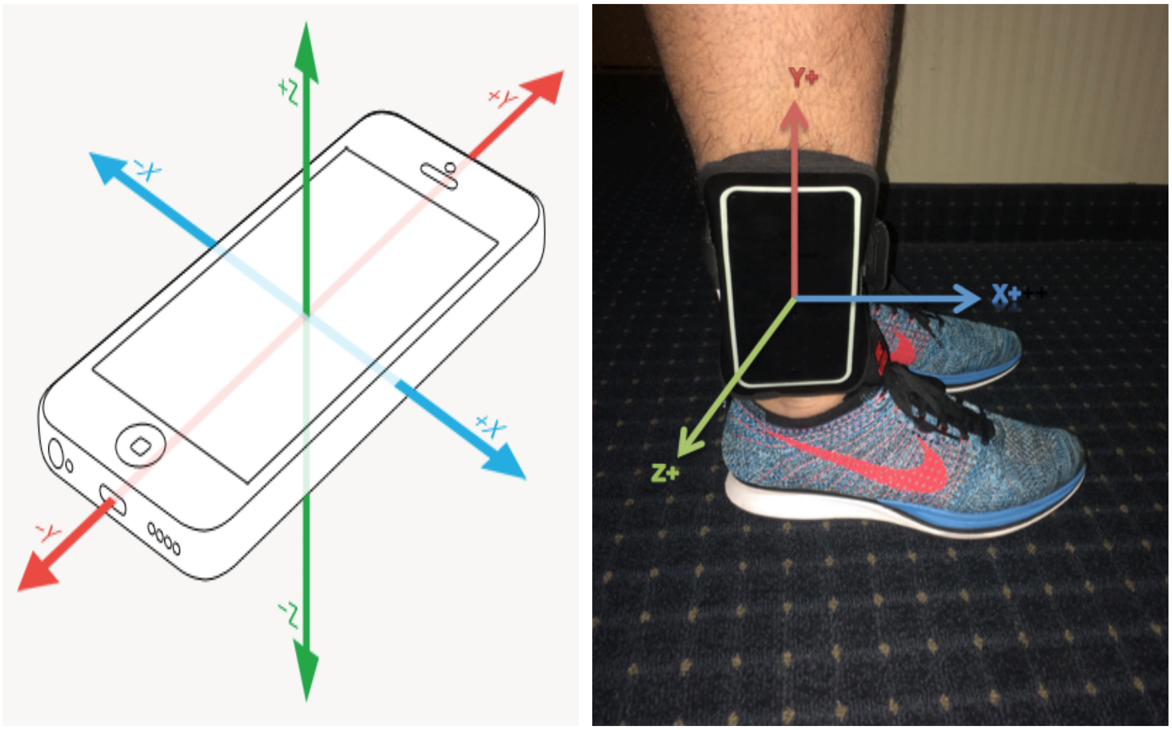
Processing of gyroscope data is crucial for calculating gravity-free acceleration that is just based on a subject's movement, since the measured acceleration also includes the gravity effect. Therefore, proper initialization of angles (tilt angles), integration of gyroscopic data to determine rotation around three axes and transformation of the measured acceleration to global frame are required to provide proper vertical displacement estimation.

Sensor Tilting

Benoussaad et al. [8] propose a method to estimate FC that is insensitive to misalignment of IMU axes with respect to foot axes. However, many other studies made the initial assumptions that the sensors are initially set in the sagittal plane and do not move during the experiment [12], [17], [39]. In our study, we also calculate and take into consideration the initial angle of the smartphone to the foot axes while the phone is mounted to the shank. For this purpose, as suggested by [8], [40] the misalignment angles can be estimated by projection of the gravity vector on three axes measured by accelerometers during the stationary period, prior to the start of movement.

According to the Apple documentation [37] the device reference frame, when the phone is flat on a table, is that the z-axis is always vertical, and the x- and y-axes are always orthogonal to gravity, as shown in Figure 3.4(a). In our Experiment, when the phone is attached to shank of a subject, the gravity vector will be [0, -1, 0], which shows the y-axis is in the opposite direction of gravity as shown in Figure 3.4(b). The projection of gravity vector (S_G) on the three axes is described as (Equation (1)), [37], [40], [41] where R is the rotation matrix:

$$\begin{bmatrix} S_{G_x} \\ S_{G_y} \\ S_{G_z} \end{bmatrix} = R * \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix} \tag{1}$$



(a) (b)

Figure 3.4 (a) iPhone Orientation (b) gravity vector of the test

The orientation of the smartphone can be defined by its pitch, roll and yaw rotations from an initial position. According to Figure 2.2, pitch is rotation around the X-axis, increasing as the device tilts toward you, decreasing as it tilts away; roll is rotation around the Y-axis, decreasing as the device rotates to the left, increasing to the right; and yaw is rotation around the (vertical) Z-axis, decreasing clockwise, increasing counter-clockwise.

The pitch, roll and yaw rotation matrices, which transform a vector (such as the earth's gravitational field vector g) under a rotation of the coordinate system by angles θ in pitch, φ in roll, and ψ in yaw about the x, y and z axes respectively, are [42]:

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta & -\sin\theta \\ 0 & \sin\theta & \cos\theta \end{bmatrix} \tag{2}$$

$$R_y(\varphi) = \begin{bmatrix} \cos\varphi & 0 & \sin\varphi \\ 0 & 1 & 0 \\ -\sin\varphi & 0 & \cos\varphi \end{bmatrix} \quad (3)$$

$$R_z(\psi) = \begin{bmatrix} \cos\psi & -\sin\psi & 0 \\ \sin\psi & \cos\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (4)$$

To project the gravity vector on three axes, we first need to define the ordering of rotation matrixes. The orientation angles are depended on the orders in which the rotations are applied and the most common order is the aerospace sequence of yaw then pitch and finally a roll rotation [40].

Accelerometer sensors are insensitive to rotation about the earth's gravitational field vector and cannot be used to determine such a rotation [40]. Therefore, considering the iPhone accelerometer direction, Figure 2.2, the lack of dependency on the roll rotation angle φ is easy to understand. We assume the order of rotation as $R_z(\psi) * R_x(\theta)$, therefore we have:

$$\begin{bmatrix} S_{G_x} \\ S_{G_y} \\ S_{G_z} \end{bmatrix} = R_z(\psi) * \ R_x(\theta) * \begin{bmatrix} 0 \\ -1 \\ 0 \end{bmatrix} \quad (5)$$

Considering the order of rotation defined above (Equation (5)), these initial angles (tilt angles) were calculated using the following equations:

$$\begin{bmatrix} S_{G_x} \\ S_{G_y} \\ S_{G_z} \end{bmatrix} = \begin{bmatrix} \cos\theta_0 * \sin\psi_0 \\ -\cos\theta_0 * \cos\psi_0 \\ -\sin\theta_0 \end{bmatrix} \quad (6)$$

$$\tan(\psi_0) = \frac{-S_{G_x}}{S_{G_y}} \ \Rightarrow \psi_0 = \arctan\left(\frac{-S_{G_x}}{S_{G_y}}\right) \quad (7)$$

$$\tan(\theta_0) = \frac{-S_{G_z}}{\sqrt{{S_{G_x}}^2 + {S_{G_y}}^2}} \ \Rightarrow \theta_0 = \arctan\left(\frac{-S_{G_z}}{\sqrt{{S_{G_x}}^2 + {S_{G_y}}^2}}\right) \quad (8)$$

Rotation

The measured raw acceleration corresponds to the acceleration in the device sensor frame, whereas the useful acceleration should be the acceleration with respect to the global reference frame. For this purpose, we need to estimate the transformational matrix $(R_z(\psi) * R_x(\theta))$ at each time stamp and apply it to the raw acceleration at the device reference frame. The initial orientation was calculated based on Equation (7) and Equation (8). During the movement, the orientation angles must be calculated by integrating the relative angular velocity (w) at the current and previous time stamp. The initial estimated angles should then be added to the estimated orientation angles during movement [16]–[18], [39], [42], [43].

$$\theta(t_i) = \int_{t_{i-1}}^{t_i} w(t)dt + \theta_0 \tag{9}$$

$$\psi(t_i) = \int_{t_{i-1}}^{t_i} w(t)dt + \psi_0 \tag{10}$$

Sensor Fusion

Using the orientation matrix and rotation angles at each time stamp, the device sensor frame acceleration (acc) can be transformed to the reference frame (F_{acc}).

$$Gr_t = \begin{bmatrix} \cos\psi_t & -\sin\psi_t & 0 \\ \sin\psi_t & \cos\psi_t & 0 \\ 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\theta_t & -\sin\theta_t \\ 0 & \sin\theta_t & \cos\theta_t \end{bmatrix} \tag{11}$$

$$F_{acc}(t) = Gr_t * acc(t) \tag{12}$$

Gravitational acceleration can then be removed to obtain the gravity-free acceleration in the global frame Ga:

$$Ga = F_{acc} - \begin{bmatrix} 0 \\ 9.81 \\ 0 \end{bmatrix} \tag{13}$$

3.1.3. Stride Phase detection

The continuous walking motion must be segmented into a series of stride cycles to compute the vertical movement in each stride and perform drift cancellation. The gyroscope signal is used to determine the shank vertical event and thereby bounds each cycle [16]–[18], [39], [43] as shown in Figure 3.5. According to the Laudanski et al. [39] and Li et al. [17], when the IMU is attached to the shank, the start point of each gait cycle is from mid-stance where the shank is parallel to the direction of gravity; thus, this point is considered as the start point of any new stride cycle. The procedure of segmentation divides the gait cycle into four phases adopted by Sabatini et al. [43] and Salarian et al. [44]: mid-stance (MS), heel-off (HO), swing (SW) and heel-strike (HS).

Stance phase is the event, which uses the angular rate about the Z-axis (w_z) to automatically detect when the foot is flat on the ground. It is also called Foot Flat Phase (FFP); such events are detected based on the detection of the minimum angular velocity at each stride cycle [8]. The mid-stance time corresponds to the period of time between heel-strike and heel-off in which the angular rate about the Z-axis (w_z) is close to zero, as the foot is almost motionless.

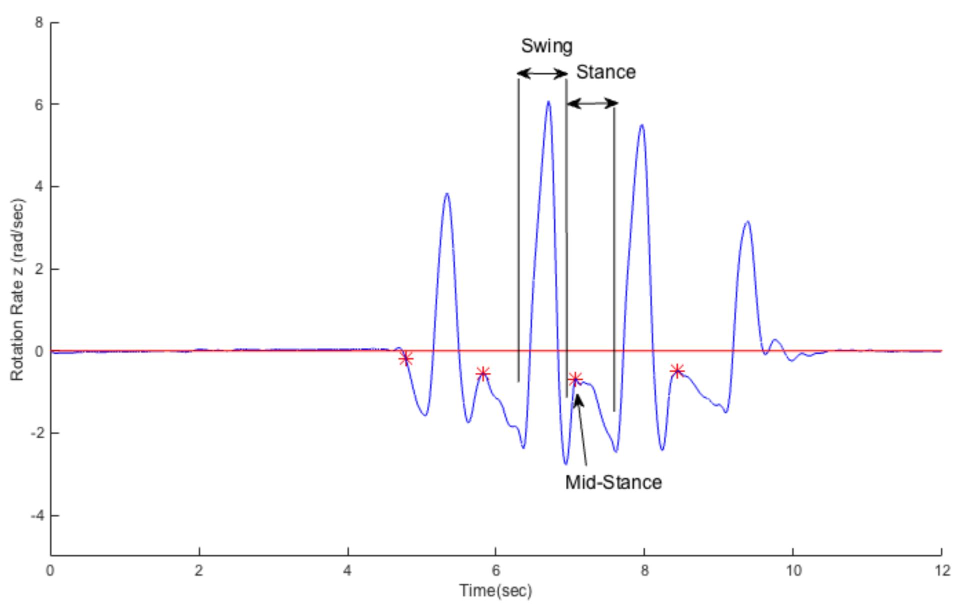


Figure 3.5. Angular velocity (rad/s) of the shank during four strides.

The initial state is that the subject is standing still in the upright posture and the foot is motionless. While in the state, the algorithm waits for the transition to the HO phase; that is the first negative maximum in the first half of the gyroscope signal of a single stride [43]. The next transition is from HO to SW. This starts when the foot w_z reaches the maximum value in the clockwise direction, and foot take off occurs. During the swing phase, the gyroscope signal has totally positive values, whose peak occurs at mid-swing during the gait cycle. During late swing, the angular velocity decreases as foot is rotating clockwise. Next event is HS, which occurs when the foot contacts the ground and angular velocity reaches the maximum value (a negative value) for the second time in the gait cycle.

3.1.4. Trapezoidal Integration over time

The sensor bias directly affects the estimating velocities when duration of integration is long. To reduce the influence of this error, the gait segmentation algorithm was developed in section 3.1.3 such that integration is performed over short time duration. This gait segmentation avoids the accumulation of drift error between different strides. To calculate the maximum vertical displacement (known as MaxFC), the transformed gravity-free acceleration around the y-axis should be double-integrated in each gait cycle. The first integration of the vertical acceleration (Equation (14)) provides the instantaneous velocity in vertical direction:

$$v_y(t) = \int_{t_0}^{t_{end}} Ga_y(t)dt + v_y(0) \tag{14}$$

Where $v_y(0)$ is the initial vertical velocity computed from shank angular velocity based on assumption that the shank is approximately rotating about the ankle joint in the stance phase [18].

$$v(0) = w(0) \times L^{\rightarrow} \tag{15}$$

Where $v(0)$ is the local shank velocity on the tangential direction of the shank at the beginning of the cycle. L is the distance vector between the iPhone location on the shank and ankle joint; thus, the initial vertical velocity at the beginning of the cycle is computed by following Equations:

$$\mathrm{v_t(0)} = \begin{bmatrix} \cos\psi_0 \\ -\sin\psi_0 \\ 0 \end{bmatrix} * \mathrm{norm(v(0))} \tag{16}$$

$$\mathrm{v_y(0)} = -\sin\psi_0 * \sqrt{\mathrm{v_x(0)^2 + v_y(0)^2 + v_z(0)^2}} \tag{17}$$

The same method was used to obtain the end shank velocities:

$$\mathrm{v(T) = w(T)} \times L^{\rightarrow} \tag{18}$$

$$\mathrm{v_{t\_y}(T)} = \begin{bmatrix} \cos\psi_T \\ -\sin\psi_T \\ 0 \end{bmatrix} * \mathrm{norm(v(T))} \tag{19}$$

$$\mathrm{v_{t\_y}(T)} = -\sin\psi_T * \sqrt{\mathrm{v_x(T)^2 + v_y(T)^2 + v_z(T)^2}} \tag{20}$$

At the end of each stride, a local drift appears as an error between integrated (Equation (14)) and theoretical data (Equation (20)), corresponding to the foot-flat phase [8]. Using the initial and end shank velocities, the shank velocity drifts bias were compensated as Equation (21) [8], [16]–[18], [39]:

$$\mathrm{v_{y-corrected}(t)} = \mathrm{v_y(t)} + \frac{Vt\_y - \mathrm{v_y(T)}}{\mathrm{T - t_0}} * \mathrm{(t - t_0)} \tag{21}$$

To estimate the vertical foot displacement (MaxFC), we first integrated the corrected vertical velocity ($\mathrm{v_{y-corrected}(t)}$) and then applied the same drift cancellation on this vertical foot displacement, assuming zero displacement at the end of the stride (foot-flat phase) [8].

$$\mathrm{x_y(t)} = \int_{\mathrm{t_0}}^{\mathrm{t_{end}}} \mathrm{v_{y-corrected}(t)dt} + \mathrm{x_y(0)} \tag{22}$$

Where $\mathrm{x_y(0)}$ are the initial shank vertical displacements, respectively, which are reset to zero at the beginning of each shank velocity cycle [18], because when the foot is in mid-stance condition, it is almost motionless and has no displacement. This second correction used the following model:

$$x_{y-corrected}(t) = x_y(t) - \frac{x_y(T)}{T - t_0} * (t - t_0) \quad (23)$$

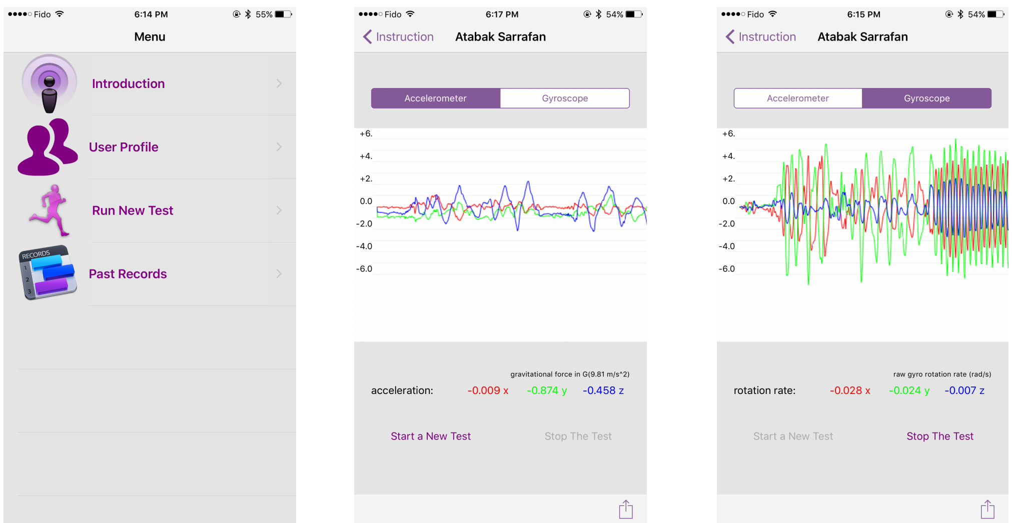
Where $x_y(t)$ is the vertical foot displacement obtained by trapezoidal integration of the corrected velocity (Equation (22)), $x_y(T)$ is the calculated displacement at the end of the stride phase and $x_{y-corrected}(t)$ is the vertical foot displacement after correction during the stride phase. The maximum of the $x_{y-corrected}(t)$ in each stride plus the distance between the ankle joint and the heel is our considerable MaxFC.

3.2. Design and Implementation of Application

3.2.1. Design of the smartphone app

In this study, we present *FootClearance*, an iPhone mobile application that detects Maximum Foot Clearance (MaxFC) and serves as a fall risk assessment tool with long-term monitoring by the user. *FootClearance* can collect data from the iPhone's built-in accelerometer and gyroscope during walking, and can analyze the MaxFC in real time. Figure 3.6(a) illustrates the screen shot of the app's main screen. The user mounts the iPhone by an armband to their shank and choses the "Run New Test" icon from the main menu. To start the test, as shown in Figure 3.6(b), the user can press the "Start a New Test" button to activate the iPhone's built-in sensors. As the user begins to walk, the sensors start to collect the gait data. When the user stops walking and presses the stop button, Figure 3.6(c), the application does real time processing to provide feedback and informs the user of the mean of MaxFC from all strides taken and the standard deviation (SD) of the MaxFC of all the strides, as shown in Figure 3.7(a). Also, the app can save the raw data for offline processing that can be useful whenever the user realizes that his pattern of walking is risky and wants a clinician to analyze his or her gait more accurately.

We evaluated the design of the first prototype of the application by 5 seniors between the ages of 55-65. Their general perspective toward the application was very positive, especially those who had experienced falls in their family or relatives.

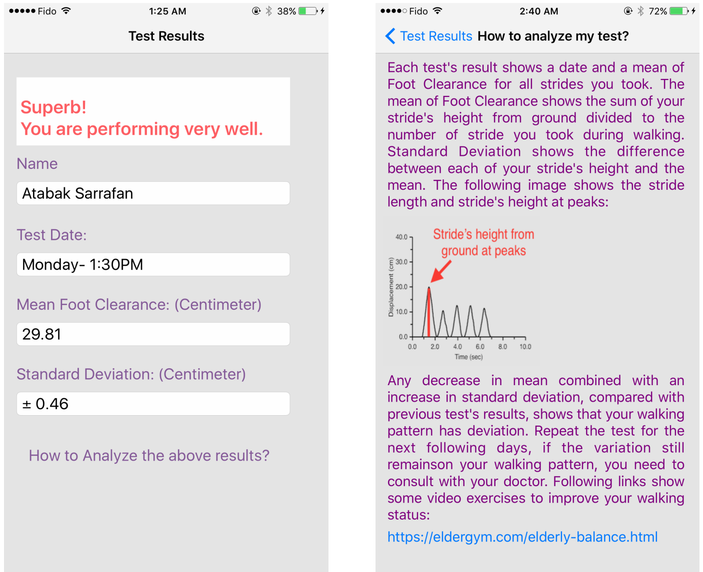


(a) (b) (c)

Figure 3.6. (a). Screen shot of the App menu (b). Screen Shot Start a Test (c). Screen Shot from Stop a Test

Note1: By choosing the Accelerometer or Gyroscope button at the top of the page, the plot signals change according to the acceleration or rotation rate.

Note2: The email button provides the option to email the raw data as a CSV file to any recipients for any required offline processing.



(a) (b)

Figure 3.7. (a). Results (b). Sample of Analysis

3.2.2. Implementation

There are two types of applications for the iPhone: native applications and web applications. Web apps are created using web technologies such as HTML, CSS and Javascript and are run inside the web browser on the phone. Native iPhone applications on the other hand are written in Objective-C and Swift languages and are compiled and executed by the iPhone operating system. The current application is mainly written in the Objective-C programming language.

iPhone development is done in recent version of Xcode 8.1, Apple's Integrated Development Environment (IDE), using the iPhone Software Development Kit (SDK) [45]. Xcode contains an iPhone simulator that lets developers test their software without deploying it on the device, or the iPhone can be easily connected to the computer so that the application launches into the device for any test. The IDE also contains various tools for debugging and measuring memory and CPU consumption. Applications can also be written in C, C++ and newly developed language called Swift. The main two frameworks used to implement this iPhone Application were CoreData and Core Motion frameworks.

Core Data was used to save the personal information of the users as well as users' past records from previous tests. It was very important to keep and save the users' information and their previous tests' results for further analysis. According to the apple developer documents [46] much of Core Data's functionality depends on the schema that developers create to describe the application's entities, their properties, and the relationships between them. The Core Data stack is a collection of framework objects that handles all of the interactions with the external data stores so that your application can focus on its business logic as shown in Figure 3.8. The stack consists of three primary objects: the managed object context, the persistent store coordinator (NSPersistentStoreCoordinator), and the managed object model (NSManagedObjectModel). When data is stored in the Core Data persistent store, an NSFetchRequest should be called to access that existing data.

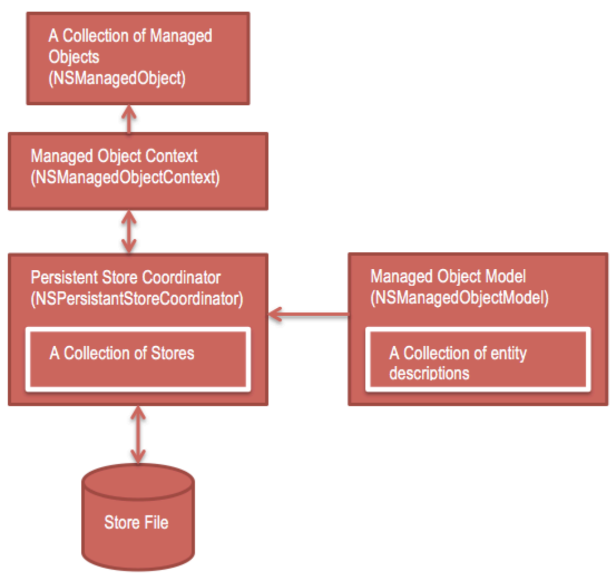


Figure 3.8. CoreData Framework Flowchart

According to [47], the Core Motion framework allows the application to receive motion data from device hardware and process that data. The framework supports accessing both raw and processed accelerometer and gyroscope data as well as processed data reflecting the attitude and rotation rates of the device through CMMotionManager object as shown in Figure 3.9. A CMMotionManager object is the gateway to the motion services provided by iOS. This object provides the access to CMAccelerometerData, CMGyroData, CMDeviceManager. An instance of the CMAccelerometerData class represents an accelerometer event. It is a measurement of raw acceleration along the three spatial axes at a moment of time, the total acceleration is equal to gravity plus the acceleration the user imparts to the device. In addition, an instance of the CMGyroData class contains a single measurement of the device's raw rotation rate around all three axes at each timestamp. On the other hand, an instance of CMDeviceMotion encapsulates measurements of the attitude, rotation rate (the biased from raw gyroscope data is removed), and acceleration of a device (the user acceleration without any effects of gravity).

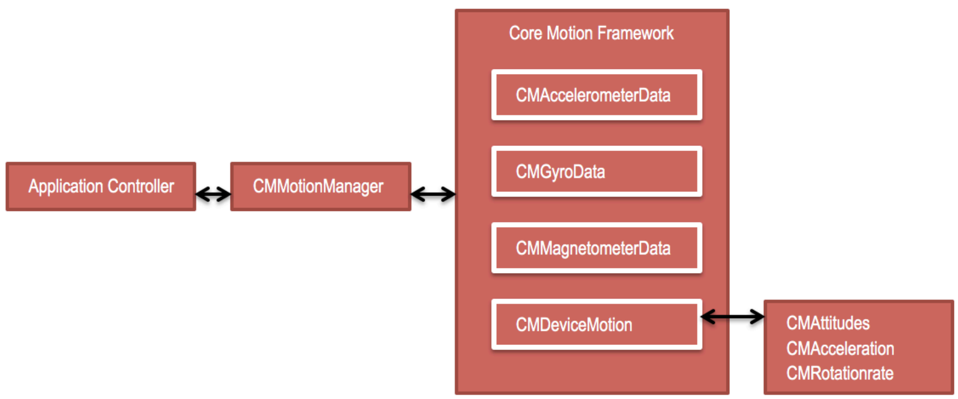


Figure 3.9. CoreMotion Framework Flowchart

Chapter 4.

Experiments

4.1. Experimental Protocol to Measure Accuracy and Performance

For validation of our foot clearance estimation method, an experimental procedure was performed on healthy participants in a Kinesiology laboratory located at our institution. During the lab experiment, we were trying to estimate the MaxFC of each participant and compare our system's results with a gold standard measurement to estimate our system's accuracy. Eight participants were recruited by email and provided their written informed consent. Their characteristics are summarized in Table 4.1.

Table 4.1. Characteristics of the Participants

Subject (ID)	Gender (F/M)	Height (cm)	No. Strides
1	M	182	28
2	M	187	28
3	M	170	29
4	M	171	29
5	F	171	23
6	F	160	30
7	F	167	21
8	F	158	29

Each subject was asked to stand upright, remain still for two seconds and then walk a distance of approximately 4 m (this short walk was due to space limitation in the laboratory). As shown in Figure 3.4(b), the iPhone was mounted to the shank above the ankle joint by sport armbands. Each subject covered this distance five times with the iPhone first attached on the right foot and then on the left foot. Simultaneously, the participants were observed by a Qualisys motions capture system, using reflective markers located on the heel, ankle joint and smartphone. This system was considered highly accurate and would serve as a gold standard for calculation of the FC. We set up 8 cameras to capture the 4m walkway (based on start and end markers). Subsequently, the walkway volume was calibrated using a static L-frame and calibration wand. This calibration was accurate up to 0.98 mm. The cameras were equipped with Infra-red (IR) LEDs placed around the lens of the camera. During measurement, the LEDs were flashing at 640 Hz. The IR-light hit the spherical markers and the light was reflected back to the cameras, projecting bright, circular shapes on the camera's image sensor.

4.2. Data Collection for Validation

Data for each subject were collected from iPhone's accelerometer and gyroscope using the Apple CoreMotion framework. We analyzed the data using the iPhone *FootClearance* application that we developed (Figure 3.6 and Figure 3.7). The MaxFC was estimated by our algorithm inside the mobile phone. The collected data were automatically segmented into stride cycles, and the peak of each cycle was compared one by one to the MaxFC provided by the motion capture system's heel reflective marker. The distance between the iPhone on the shank and the ankle joint (L) was set to 15cm for all participants. After each experiment, the app analyzes the raw data in real time and generates feedback to the user about their estimated MaxFCafter the test is finished. In addition, the collected data can be saved as CSV files in the app to be analyzed offline. This file can easily be transferred via email from the app to any clinician for deep gait analysis purposes, if there is any concern with the user's walking pattern. The results of each test can be saved in the application using Apple CoreData framework to provide the opportunity for the user to track any significant changes in MaxFC, as illustrated in Figure 3.7(a).

4.3. Validation Analysis

To analyze the MaxFC during the steady walking, we eliminated all the first and last strides from our analysis. Two trials from two of the participating subjects were excluded because the motion capture system's camera missed finding the marker on the heel. In total 217 strides from subjects were computed and compared one by one to the ground truth system. The RMS value of MaxFC errors (RMSE) was quantified for the evaluation of MaxFC estimation performance as well as normalized RMSE (NRMSE) percentage value, using the following criterion:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum(\mathrm{X_m} - \mathrm{X_a})^2} \tag{11}$$

$$\mathrm{NRMSE} = \frac{\mathrm{RMSE}}{\mathrm{X_m}} * 100 \tag{12}$$

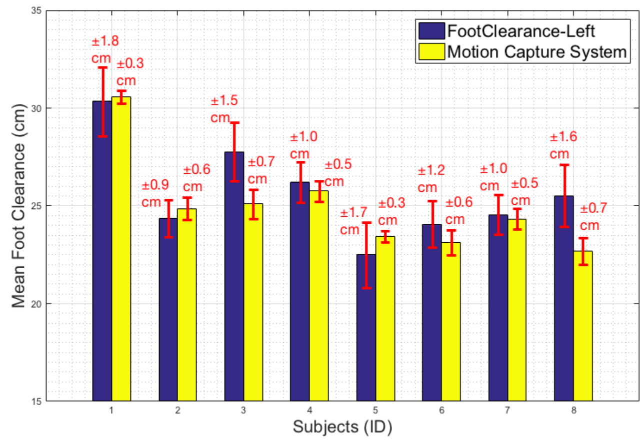
Where X_m and X_a are respectively the measured MaxFC for each stride by motion capture system's marker on the heel of participants and the estimated MaxFC for each stride by our iPhone application. Table 4.2 shows experimental results for MaxFC estimation and the RMSE obtained from both motion capture system and our application for all eight participants on their feet. The results show good MaxFC estimation using the proposed method during normal walking for various subjects with different heights.

Table 4.2. Experimental Results

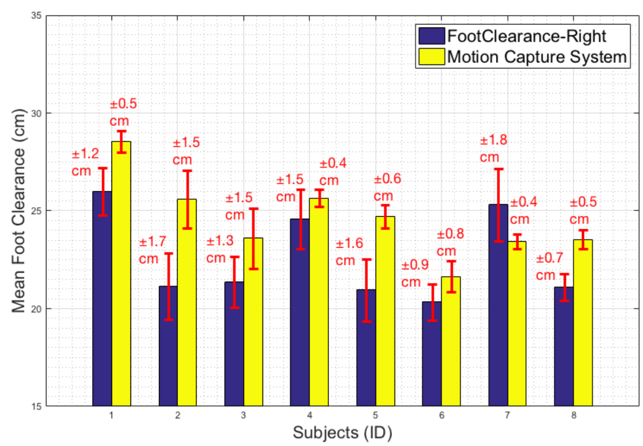
Subject (ID)	Motion Capture System	Mean Error Estimation Using iPhone on the Left Shank			Motion Capture System	Mean Error Estimation Using iPhone on the Right Shank		
	Mean MaxFC±sd (cm)	Mean MaxFC±sd (cm)	RMSE (cm)	NRMSE (%)	Mean MaxFC±sd (cm)	Mean MaxFC±sd (cm)	RMSE (cm)	NRMSE (%)
1	30.6±0.3	30.3 ±1.8	1.3±1.0	4.2%	28.5±0.5	25.6±1.2	2.5±1.2	8.8%
2	24.9±0.6	24.3 ±0.9	1.0±0.6	4.0%	25.6±1.5	21.1±1.7	4.4±1.8	17.2%
3	25.1±0.7	27.7±1.5	2.6±1.3	10.3%	23.6±1.5	21.3±1.3	2.8±1.3	11.9%
4	25.8±0.5	26.2±1.0	1.0±0.9	3.9%	25.6±0.4	24.5±1.5	1.7±1.1	6.6%
5	23.4±0.3	22.5±1.7	1.1±1.3	4.7%	24.7±0.6	20.9±1.6	3.7±1.8	15.0%
6	23.1±0.6	24.1 ±1.2	1.2±0.7	5.2%	21.6±0.8	20.3± 0.9	1.3±0.8	6.0%
7	24.3±0.5	24.5±1.0	0.6±0.4	2.5%	23.4±0.4	25.3±1.8	2.2±0.9	9.4%
8	22.7±0.7	25.5±1.6	2.8±1.4	12.3%	23.5±0.5	21.1±0.7	2.4±0.6	10.2%
Avg	**25.0±0.5**	**25.7±1.3**	**1.4±0.9**	**5.8%**	**24.6±0.8**	**22.5±1.3**	**2.6±1.2**	**10.6%**

Figure 4.1 shows MaxFC estimation obtained from both motion capture system and our application for all 8 participants. These bar charts correspond to the MaxFC results obtained during normal walking in Kinesiology lab. The height of each bar corresponds

to the mean MaxFC of each participant for both systems and the standard deviation of the MaxFC for each subject, over all their strides, is marked red.



(a)



(b)

Figure 4.1. Bars represent the average MaxFC estimated by application and by the motion capture system for each subject. The standard deviation is marked as red. (a) Foot Clearance on the left foot (b) Foot Clearance on the right foot

4.4. User Feedback and Interface Design

In addition to measuring the accuracy and performance of *FootClearance*, we followed a user-centered iterative approach process to design the user interface of the *FootClearance* application. We carried out a user study to understand how our target users (seniors) perceive the application, what their expectations are, and how we can improve the initial design. We recruited five older adults between the ages of 55-66 (one female and four male) and gave them different scenarios to explore our first prototype application. We solicited their feedback through questionnaires and brief interviews. Overall, the participants noted benefits of using such an application within the comfort of their home to alert themselves if their walking status is declining. They explained that this self-monitoring application can bring physiological privileges for those who had fall history and are now afraid of walking. It can increase their confidence by showing improvement in their walking pattern and motivating them to have more exercises. Two of the participants had experienced falls in the family and they found the concept of the application very useful. However, one of them argued that they are unlikely to use the app for self-monitoring unless they experience the fall and become concerned about their health issues. Two of the participants who were familiar with iPhone applications and use iPhone in their daily basis found the app moderate to understand; however, for others it was difficult to analyze the app. While numerical values and plots are necessary for diagnosis from a clinician's perspective, we found that seniors would not be able to interpret these values on their own. They preferred having verbal feedback as well as numbers to inform the user if they their gait analysis results were poor, moderate, good or excellent. Our participants also suggested having just one big button to both start and stop the app so that do not care about pressing correct button. Moreover, what they were looking for after taking the test was any feedback about how to perform better (e.g., any exercise example or medical link to guide them to improve their condition). Based on this user feedback, we carried out another design iteration and simplified the presentation of the MaxFC estimation and improved our UI design (as shown in Figure 3.6 and Figure 3.7). In Figure 3.7(a), the users can see both the numbers and verbal feedback of their test. If it is hard to understand, they can simply press "How to analyze the test" to read a brief explanation about the concepts used in the test results and how they can interpret that for themselves, Figure 3.7(b).

Chapter 5.

Discussion and Conclusion

In this study, we introduced a new approach to estimate the MaxFC by using iPhone sensors. An iPhone mobile application, *FootClearance*, was designed to implement the computational tasks and generate feedback to the user. We validated the proposed MaxFC calculation algorithm using a motion capture system and found satisfying correspondence between MaxFC values estimated with our method and those measured with the ground truth system as a reference. In 75% of all experiment cases on the left foot, the RMS errors remained less than 1.3 cm with an average of RMS errors around 1 cm. The estimation results were not so accurate on the right foot, since the average of RMS errors increased to 2.6 cm, with a maximum value of 4.4 cm (right foot, Subject 2). Two of the tests on the right foot of the subject 2 and 5 have the greatest error. We analyzed the related raw data offline with Matlab software, and we realized that the large error was mostly due to the unexpected minor movements of the cellphone when it was not fastened tightly enough to the shank. Excluding those two tests from our analysis, the average of all NRMSE on the right foot would decrease to 7.1% (1.7cm) while the average of NRMSE over all experiments would drop to 6.4% corresponding to 1.6cm. Furthermore, 87% of all experimental cases have NRMSE less than 10.3% corresponding to 2.5cm error when the MaxFC is approximately 24.8cm.

Although our approach has performance limitations as we could only collect data at frequency 51HZ and were not able to place the smartphone directly on the ankle (unlike Benoussaad et al. [8] who mounted an IMU exactly on the ankle joint and collected the data at frequency of 200HZ), we are the first to show the feasibility of accurately estimating MaxFC values using a smartphone alone (requiring no other special equipment) with capability of processing the walking data in real time and generating feedback to the user immediately after each test is finished.

In designing our algorithm, the signal filtering turned out to be very critical. Low pass filtering of the gyroscope signals at less than 6HZ made the signal very smooth and had a negative effect on the mid-stance detection. Moreover, low pass filtering of the accelerometer signal at less than 8HZ caused important events to be missing in the signal. In addition, the initial placement of the iPhone on the shank according to the X, Y, Z axis was very important to achieve accurate results.

Our main contribution is in building a real time analysis system using a smartphone that is convenient for users who are interested in self-monitoring their own walking pattern either for assessing the risk of fall or for rehabilitation. While *FootClearance* cannot replace the clinical measurements for MaxFC, the app can be used as an effective screener to determine whether further exact clinician analysis is necessary. The availability of smartphones makes *FootClearance* a convenient tool for at-home monitoring of walking patterns with real time analysis of data to generate the feedback, which can play a key role in helping prevent falls, especially among seniors.

5.1. Limitations and Future work

Despite the overall positive results, our study has limitations which could be addressed in future work. For example, we observed performance degradation in some of the trials mainly due to how tightly the iPhone was fastened to the shank and any minor and unnecessary movement had an impact on mid-stance detection in the gait cycle algorithm. The lack of an available armband which fits to any shank size caused unnecessary movements in trials in which the subject's shank was very thin. This limitation could have affected our foot clearance calculation. Furthermore, some errors arose in the calculation of distances between ankle joint, the iPhone mounted to the shank, and the heel. We had to consider a fixed distance between ankle joint and the heel as well as a fixed distance between the ankle joint and the iPhone located on the shank for all participants. One possible future challenge is to identify the dynamics of the shank's movement according to the ankle joint's movement to overcome one of the main sources of error when placing the iPhone on the shank, this can significantly improve the system.

A major hurdle to make the system deployable is to ensure the data quality. The interface designed in our work is capable of processing the raw data from the subject's walking pattern in real time and interprets to generate fast feedback to the user. The accuracy of the generated results relies on the user to follow the instructions to fasten the device tight enough and at the perfect location. To help the user to locate the smartphone accurately, an automated signal quality detector could be very helpful by detecting whether the collected signal is stable enough for analysis, and could alert the user to adjust the device position and perform the data collection again

The small walking area in the kinesiology lab limited the number of strides we could gather from our participants, so we had to eliminate the first and last stride from each trial to analyze the steady walking.

While we have promising results for accuracy and performance based on our sample of healthy adults, in the future we would like to include seniors and people with disabilities in our experiment (we currently did not have enough facilities to invite a broader set of users to our lab). We were still able to solicit initial feedback from seniors about our first prototype design and used it improve the design of our user interface. We believe that a close partnership in the design process with seniors can be invaluable in designing such self-assessment health monitoring applications as the UI design can influence whether or not the end user will engage and benefit from the application [48].

As discussed earlier, other gait parameters such as speed of walking, stride length, number of strides and stride time can impact an individuals' MaxFC. There are many opportunities in future work to further explore the estimation and reporting of the analyses based on these additional parameters. In particular, these should be investigated not only with seniors or people with disabilities, but also with healthy people who have developed bad habits of walking by striking their foot completely flat on the ground instead of having correct heel strike. These groups of people may have difficulty to walk as they get older and this can be detected while monitoring the FC. In this case, detecting the FC alone is not enough –the individuals' bad walking habits have to be detected and the users to be alerted. It is also worth testing the application on uneven ground such as going up and down hills or stairs and in different walking conditions such as running or walking with obstacles.

While the iPhone presents a significant advantage over IMUs or other devices, there is still potential for future work to explore running a similar algorithm on other devices such as a smart watch or iPod nano to further ease the self-monitoring process. The iPod is smaller, cheaper and lighter than the iPhone. On the other hand, smart watches will make starting and stopping the test more convenient by connecting to the smartphone that is attached to the shank. Another suggestion for simplifying the communication between the user and the application for starting and stopping the test is defining a body gesture such as double tapping of the foot or toe to the ground as a notification to activate or deactivate the sensors to collect the data and do the real time processing. Furthermore, future work can also explore addition of alert and notification systems to simplify the communication between the app and the user. It can be very helpful to guide the user how to use the app and how to analyze the generated results as well as alerting the user about any risky gaits.

In summary, we presented *FootClearance*, a smartphone-based application for real time analysis of the MaxFC using the iPhone's built-in sensors. Estimating MaxFC by smartphones is an inexpensive tool that can be very helpful for seniors to recognize any significant variation in their walking pattern as it happens and to prevent falls in their natural environment. Our system was validated on both feet of 8 healthy young subjects with different height and gait against the ground truth using the Qualisys motion capture system. The results indicate that in the best estimation of our system, the average of all normalized errors (NRMSE) is less than 10.3% corresponding to 2.5cm. This study is a first attempt in estimating MaxFC by a smartphone platform, introducing a self-monitoring tool for those who need home monitoring of their gait.

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