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Investigating the Effectiveness of a Haptic Feedback System to Improve the Gait Speed of Older Adults in Overground Walking

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INVESTIGATING THE EFFECTIVENESS OF A HAPTIC FEEDBACK SYSTEM TO IMPROVE THE GAIT SPEED OF OLDER ADULTS IN OVERGROUND WALKING.

By

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An Abstract of the Thesis Presented
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While the use of tactile feedback for modifying gait has recently shown promising results in a number of research studies, there has been little attention given to its ability to effect change in the gait of older adults nor has the effect of the frequency of this feedback been examined. Given the important associations of walking speed with the health of older adults, the goal of this study was to determine if a recently developed haptic feedback system could increase the walking speed of older adults and whether the frequency at which this feedback was provided would have an impact on the results. In order to achieve a faster walking speed, peak thigh extension was selected as a biomechanical surrogate for stride length with vibrotactile haptic feedback being provided to the thighs to increase that parameter and, consequently, increase speed. Further, the influence of the frequency of the feedback on several other gait parameters was also investigated. Ten healthy older adults (68.4 ± 4.1 years) were recruited for this study, in which their peak thigh extension, cadence, normalized stride length, and normalized stride velocity, as well as their coefficients of variation (COV), were compared among six different experimental conditions.

The study's findings demonstrated that when compared to their pretest values, older people using the haptic feedback device had considerably longer peak thigh extensions

during both post-tests and feedback walking conditions. The longer stride length made possible by this more extended thigh angle allowed for a corresponding rise in walking velocity. Surprisingly, none of the gait metrics examined were substantially impacted by the feedback's frequency. In other words, regardless of how frequently the input was given, the haptic feedback device was successful in improving elderly people's walking abilities. These results indicate the haptic feedback device has the potential to enhance gait speed, stride length, and stride velocity, which are essential elements involved with keeping independence and mobility in older people.

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CHAPTER 1

INTRODUCTION

1.1 Important Definitions Related to Gait

A few important definitions related to gait and haptic feedback are provided here.

- Gait: It is a rhythmic cyclical locomotive motion of the lower body to move the whole body forward. It requires sophisticated coordination of the neuromuscular system of the upper and lower body [1].

- Stride Length: It is the distance between two consecutive events of the same foot. For example, in Fig. 1.1 the left red-dashed line indicates the Right Heel Strike(RHS), and the right red-dashed line indicates the second RHS. Stride length would be the distance between these two events of the same foot [1].

- Step length: It is the distance between the same events of one leg and another. For example, in Fig. 1.1 the left red-dashed line indicates the Right Heel Strike(RHS), and the green-dashed line indicates the heel strike of the left foot. The step would be the distance between these two events of the different feet [1].

- Cadence: It refers to the number of steps taken within a one-minute duration of time [1].

1.2 The Significance of Gait: Exploring Its Impact on Health and Well-being

Walking is one of the essential activities of daily living that requires the precise coordination of the muscles, nerves, and brain system [2]. Precise coordination of arms, hips, and legs is necessary to have a smooth gait pattern [3]. Overall health and the presence of various diseases can be detected by an examination of gait parameters [3, 4]. Gait analysis is also used as an index of the effect of rehabilitation programs in general and, specifically, in fall prevention interventions [5]. Among the various gait characteristics,

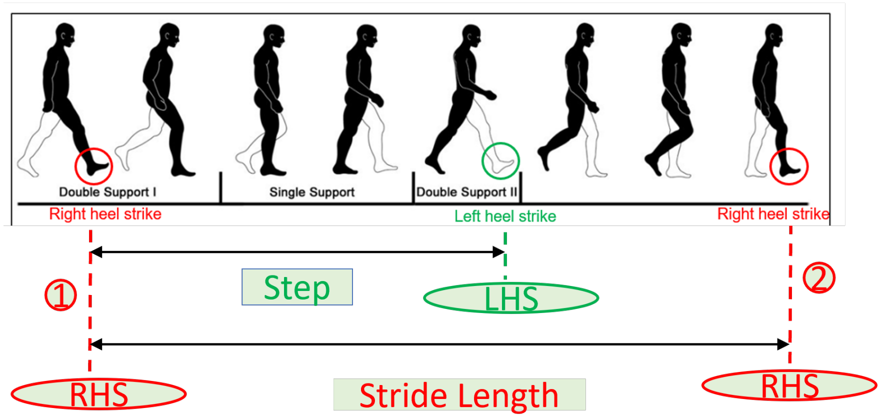


Figure 1.1. A few basic definitions related to gait.

gait speed is one of the most commonly utilized parameters to evaluate health [6]. Mielke et al. [7] demonstrated that a slower gait is associated with a reduction in cognitive ability. Slower gait speed is also linked to the severity of heart disorders, mortality, disability, frailty, and respiratory problems [8–11] indicating that the maintenance of a normal walking speed is necessary to ensure good health [11]. For independent life, the capacity to walk effectively is essential. Even though many elderly people in the community are able to move on their own, they frequently exhibit mild to severe abnormal gait patterns [12], which can increase their risk of falling, and cause them to lose mobility [13, 14].

In older people who have no functional restrictions, gait speed is a crucial component of survival [13]. A greater mortality risk is highly correlated with a decreased gait speed. According to research involving 34,485 community-dwelling older adults aged 65 or more, those who walked more slowly had substantially lower life expectancies than those who walked more quickly [13]. A substantial decrease in the chance of death is predicted by increasing gait speed by more than 0.1 m/s in a year [15]. Because it incorporates both known and unknowable constraints in numerous organ systems that have an impact on longevity, gait speed is frequently regarded as an indicator of vitality [16]. Therefore, walking speed offers a simple yet powerful method for overlooking the condition of the intricate neuromotor system.

Compared to younger adults, older adults walk with a reduced gait speed [17], shorter stride length [18], higher variability [19], and a decreased range of motion [20]. In particular, gait speed has been found to decline with age [21], which contributes to an increase in the risk of falling [22]. Hardy et al. [15] showed that enhancing gait speed within a year increased a person's chances of living for the next eight years and lowered their death rate. Additionally, maintaining a normal walking speed is essential for preventing the risk of falls [23], enhancing physical functioning [24], and maintaining range of motion [25]. The existing literature provides robust evidence that exercise intervention aimed at improving gait speed is crucial for older adults [23]. According to a study by Huijben et al. [26], enhancing walking speed in older adults can lead to improvements in gait parameters that are associated with a lower risk of falls, such as symmetry, stability, regularity, and stride frequency. All of these factors can have a detrimental effect on how older individuals move.

1.3 Motor Learning and Different Modes of Feedback

Although aging can lead to various challenges, such as a decline in muscle power generation, pain, and a deterioration in both the cardiopulmonary system and joint structure, it has been reported that many older adults with age-related walking difficulties demonstrate sufficient force production [27] and joint range of motion for walking [28]. As a result, impaired motor control may be the primary cause of early changes in gait observed during aging [27]. Motor control issues are very susceptible to deterioration, especially those involving gait speed [29], stride length [30], and step and stride length/time variations [31]. Interventions that focus on the musculoskeletal and cardiopulmonary systems are unable to treat these deficiencies [28]. Instead, the focus of suitable treatments should be on strengthening the perceptuomotor system's ability to generate more steady and efficient movement coordination for walking [32]. This form of motor learning can only be accomplished through consistent practice and useful feedback [33]. In order to accomplish substantial and long-lasting gains in complicated motor coordination tasks like gait, recent research in motor behavior emphasizes the significance of constant task-specific training. Such training must be used over an extended length of time and seamlessly incorporated into users' everyday walking exercises to be effective [34]. Despite the fact that older people must undergo repetitive task-specific training to increase gait speed, little is known about the composition of this training.

Different modes of feedback, such as auditory, visual, and tactile feedback, have been utilized in previous gait training to improve motor learning [35–37]. Tactile feedback for gait training has advantages over auditory and visual feedback since it does not interfere with important sources of information that a user may receive from the environment while walking. All sources of feedback have the potential to compete for attentional resources if provided during walking; however, tactile feedback has been established to be less attention-demanding than visual or auditory feedback and, thus, is less likely to produce deleterious effects on gait while in use [38]. Providing tactile feedback to the user's body may improve sensory reactions and foster motor development. In order to increase walking speed, haptic feedback may be delivered to various body parts, such as the lower and upper limbs. This promotes a more coordinated gait pattern and promotes a better gait.

1.4 The Role of Haptic Feedback in Gait Training: A Review

In the past decade, there has been a growing interest in using haptic feedback to facilitate gait training. Fig. 1.2 shows a few haptic feedback training systems used in different studies recently. Xia et al. [39] used a customized shoe that can modify foot progression angle (FPA) as shown in Fig. 1.2a. The shoe has an in-built microcontroller, vibromotors, and other motion sensors to measure and provide feedback based on FPA value. This shoe has the potential to reduce knee osteoarthritis (KOA). He et al. [40] developed a portable system to reduce the knee adduction moment (KAM) to stop the progression of KOA (Fig. 1.2b). They created two units like gait training unit with motion sensors and a measurement unit with pressure sensors.

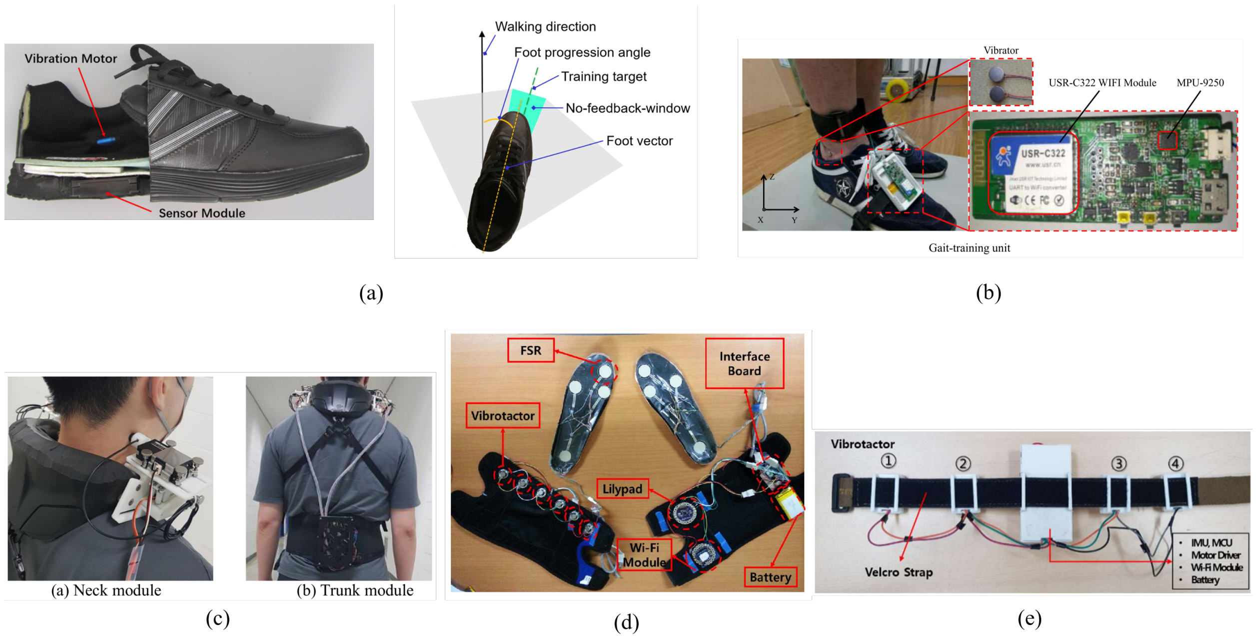


Figure 1.2. Examples of haptic feedback system used for gait training. (a) Xia et al. [39], (b) He et al. [40], (c) Lee et al. [41], (d) Afzal et al. [42], (e) Lee et al. [43].

Another study by Lee et al. [41] provided two-dimensional haptic feedback on the neck in mediolateral(ML) and anterior-posterior (AP) directions for balance training (Fig. 1.2c). They showed with the subject study that under different circumstances balance could be improved using their system without affecting their gait speed meaning that it does not have any negative effect on gait speed. Afzal et al. [42] developed a customized insole for post-stroke gait training that consists of four sensitive resistors (FSRs) and other vibromotors which provided haptic feedback based on gait irregularities (Fig. 1.2d). Lee et al. [43] developed a haptic bracelet (Fig. 1.2e) to train arm swing for stroke patients to improve gait symmetry.

Based on the paretic foot pressure in lab settings, Saichi et al. [44] provided feedback on the back of the torso of six-stroke patients (73.7 ± 17.7 years) with a goal of adjusting stride length, foot pressure, and walking velocity. Participants were able to increase their stride length but not their gait velocity, while their foot pressure improved marginally using this biofeedback device as shown in Fig. 1.3a. Xu et al. [37] measured the foot progression angle (FPA) and provided haptic feedback to the shank if the angle was out of the desired range. The researchers recruited older adults (72.5 ± 6.0 years) who walked on the treadmill with the goal of lowering KAM (Fig. 1.3b). Chen et al. [45] conducted a further investigation on decreasing KAM that focused on multiple gait characteristics such as FPA and step width. Using their haptic ankle bracelet (Fig. 1.3c), they successfully demonstrated that multiple gait characteristics could be trained with great effectiveness. Schenck et al. [46] introduced a system that provided haptic biofeedback (Fig. 1.3d) on the shank to regulate the peak ankle moment, which is linked to energy consumption during walking. Twenty healthy subjects (26 ± 5 years) walked on an instrumented split-belt treadmill and were able to alter their peak ankle moment in response to the biofeedback.

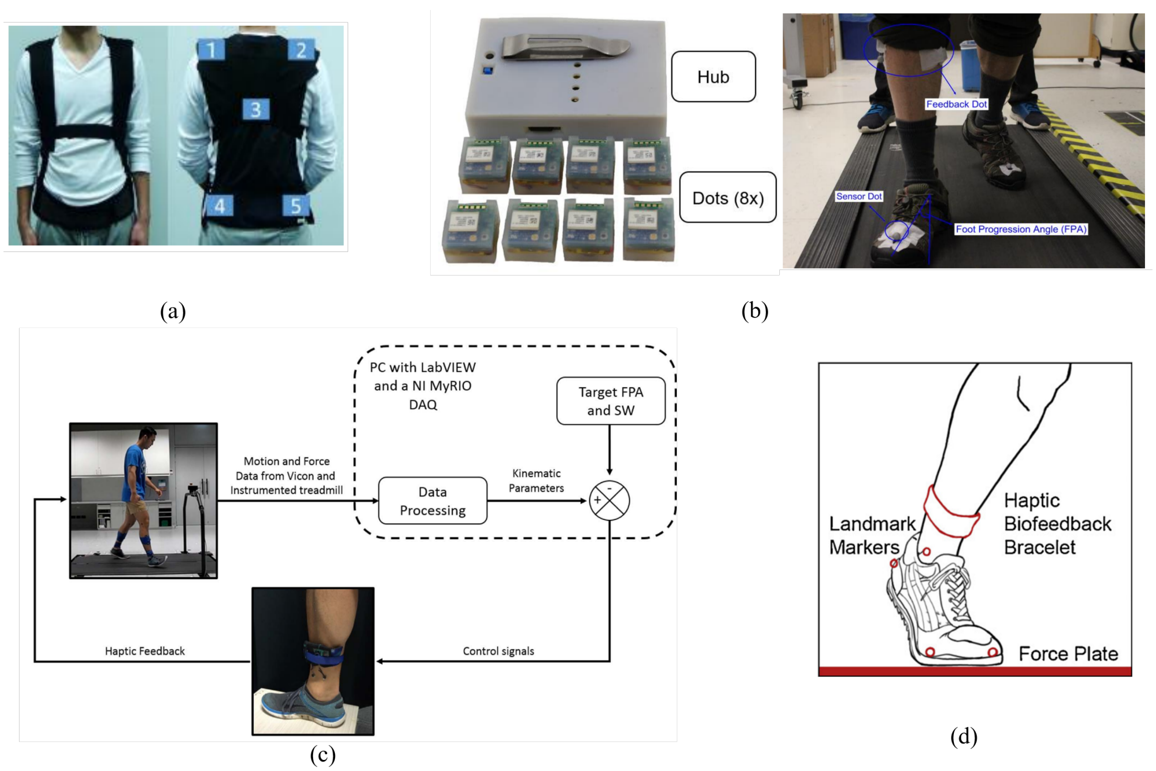


Figure 1.3. Diverse examples of haptic feedback systems used for gait training. (a) Saichi et al. [44], (b) Xu et al. [37], (c) Chen et al. [45], (d) Schenck et al. [46].

Dowling et al. [47] provided feedback on the right shoe to reduce KAM based on foot pressure and they were successful to reduce the KAM (Fig. 1.4a). Shull et al. [48] provided tactile feedback on knee, foot, and back to reduce the KAM. The researchers were able to reduce the KAM by 30% or more as shown in Fig. 1.4b. Lee et al. [43] provided haptic forces based on a device equipped with force and LIDAR sensors to improve the gait speed and step length and the study was done by recruiting six healthy subjects and one stroke patient (Fig. 1.4c). Kodama et al. [49] examined the effect of vibrotactile biofeedback training on the temporal structure of the center of pressure during quiet stance in patients with chronic stroke (Fig. 1.4d). Demircan et al. [50] applied feedback to the back, knees, and ankles of healthy volunteers (ages 20 to 39) in order to lower the knee flexion moments (KFM) during running. Trunk sway, cadence, and foot strike were used as surrogate parameters. All the subjects altered gait surrogates and reduced KFM to 30-85% of their

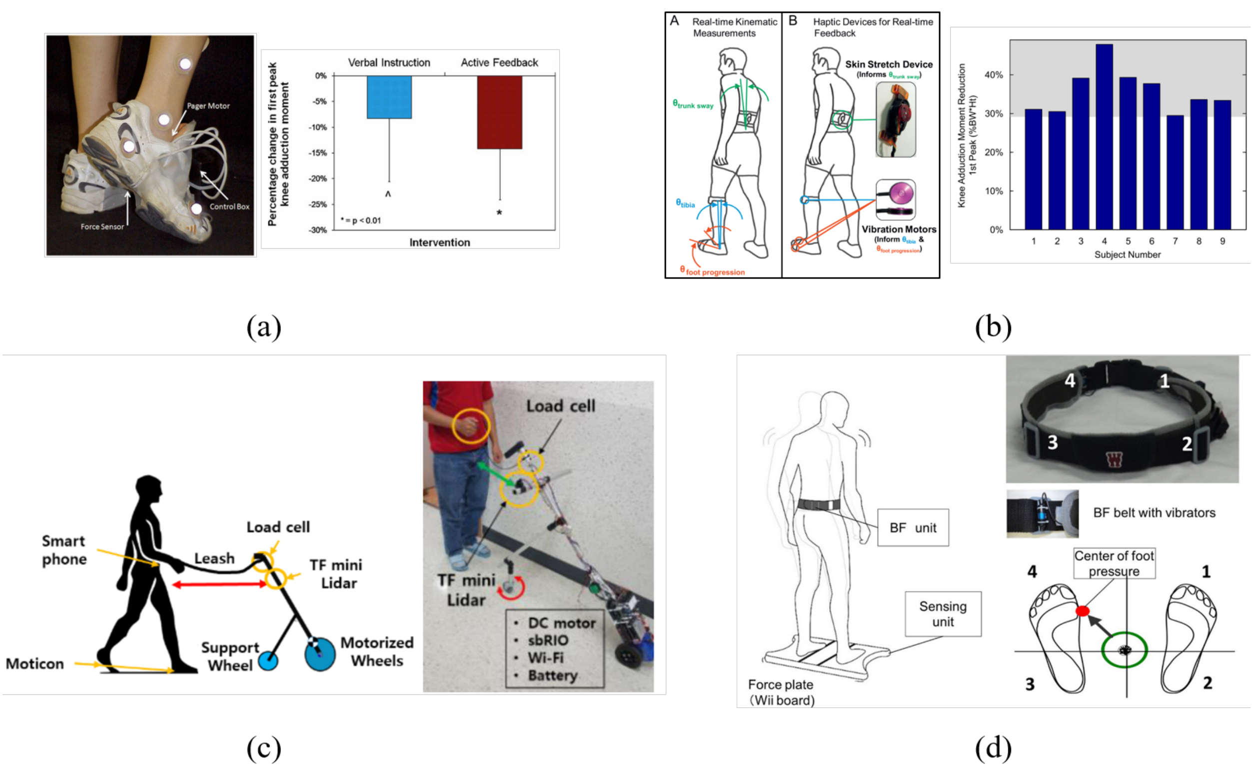


Figure 1.4. Further examples of popular haptic feedback systems used for gait training. (a) Dowling et al. [47], (b) Shull et al. [48], (c) Lee et al. [43], (d) Kodama et al. [49].

baseline values. Noghani et al. [51] delivered feedback to younger adults' thighs and shanks during overground walking to modify two surrogates of stride length, peak thigh and shank extension angles, in an attempt to increase stride length and speed. The researchers found that by using such feedback stride length and gait speed improved substantially compared to subjects' normal walking with no feedback. Another work by Noghani et al. [52] provided haptic feedback to observe the effect of arm motion on gait in younger adults and they showed how the changes in the arm cycle time can affect the gait.

These were a few of the key studies in the area of haptic feedback for gait training. It is obvious that recently this field has attracted a lot of attention and has kept its promise to improve gait through training.

1.5 Objectives of Thesis

The majority of studies using biofeedback for KAM, FPA, and peak ankle moment as gait training to modify specific impairments using lab-based systems. However, home-based gait training of older adults to improve key outcomes such as speed remains largely unexplored. This is mainly due to the lack of (1) a wearable and user-friendly system for training and (2) a biomechanics-driven model to specifically target the underlying mechanism affecting the speed during training. A first-of-its-kind wearable haptic system has been recently developed (i.e., lightweight, low profile, and portable) and controlled by a smartphone that promoted home-based gait training [51]. While this study's results do provide proof of concept for the new haptic feedback system's functionality, more work is needed to show that it is helpful for older adults in particular.

Furthermore, although there have been some studies of older adults, most research has examined younger adults and has used treadmill walking. Thus, any extrapolation of such work to older adults walking overground can not be directly applicable. Finally, there has been little investigation of the effect of the frequency at which feedback is provided on the performance of the users. There is a large body of literature in the motor learning field that has generally shown that varying the frequency of feedback during practice can have significant effects on the amount of learning engendered [53]. Clearly, there is a noticeable gap in terms of implementing a biofeedback system for healthy older adults, particularly in overground walking. To address that gap, the two main goals of this study were to investigate the potential of tactile feedback to improve walking speed in older adults during overground walking and to understand the effect of the frequency of that feedback during walking.

This thesis describes a study that used haptic feedback to help elderly persons walk better. This study aims to enhance peak thigh extension angle, which corresponds with stride length, by giving haptic feedback to the lower limb, especially to the thigh.

In this study, a haptic feedback device was used that provides vibration feedback on elderly person's thighs while they walk. The system was designed to provide real-time feedback on thighs that influence gait patterns. The expectation was that haptic feedback would enhance lower-level biomechanical surrogates, which, in turn, would improve higher-level biomechanical surrogates, such as the stride length and stride velocity of older individuals, by boosting their sensory feedback and fostering motor learning. This project is extensively discussed in the following chapters.

Overall, this study demonstrates the potential of haptic feedback as a non-invasive and effective approach for improving the walking speed of older adults. The results of these studies have important implications for promoting mobility and independence in the older adult population. Motor learning can be promoted, leading to improved walking speed and quality of life in older adults, by providing targeted haptic feedback to specific body parts.

CHAPTER 2

METHODOLOGY

In this chapter, the participants, the biomechanical surrogate, the haptic feedback system, and its development process will be discussed. Additionally, the software for the experiment, experimental design, and the data analysis process will also be covered.

2.1 Participants

All prospective participants went through an online screening procedure prior to the experiments to make sure only qualified people were chosen. A Google form was sent to each participant with a few questionnaires. Volunteers needed to be able to walk continuously and independently for at least twenty minutes in order to participate. Peripheral neuropathy, neuromuscular diseases including Parkinson's disease or multiple sclerosis, and clearly present cognitive impairment were among the exclusion criteria. Ten healthy older persons (6 males and 4 females, mean age 68.4 ± 4.1 years, body mass 78.6 ± 12.8 kg, height 171.3 ± 8.5 cm) were chosen for the study after the Institutional Review Board of the University of Maine approved all methods. All subjects gave their written consent before the experiment started.

2.2 The Biomechanical Surrogate

Two very important types of feedback techniques are Knowledge of Performance(KP) and Knowledge of results (KR). In KP, feedback is provided on some underlying specific movements (lower level parameter) that will improve the outcome (higher level movement) whereas, in KR, feedback is given based on the outcome or result of the movement [54]. A descriptive example is given in Fig. 2.1 to understand the concepts of KP and KR. To improve the throw, a coach might, for instance, comment on the shot's arc, arm position, and foot placement. Here, the KP approach is applied since those three fundamental

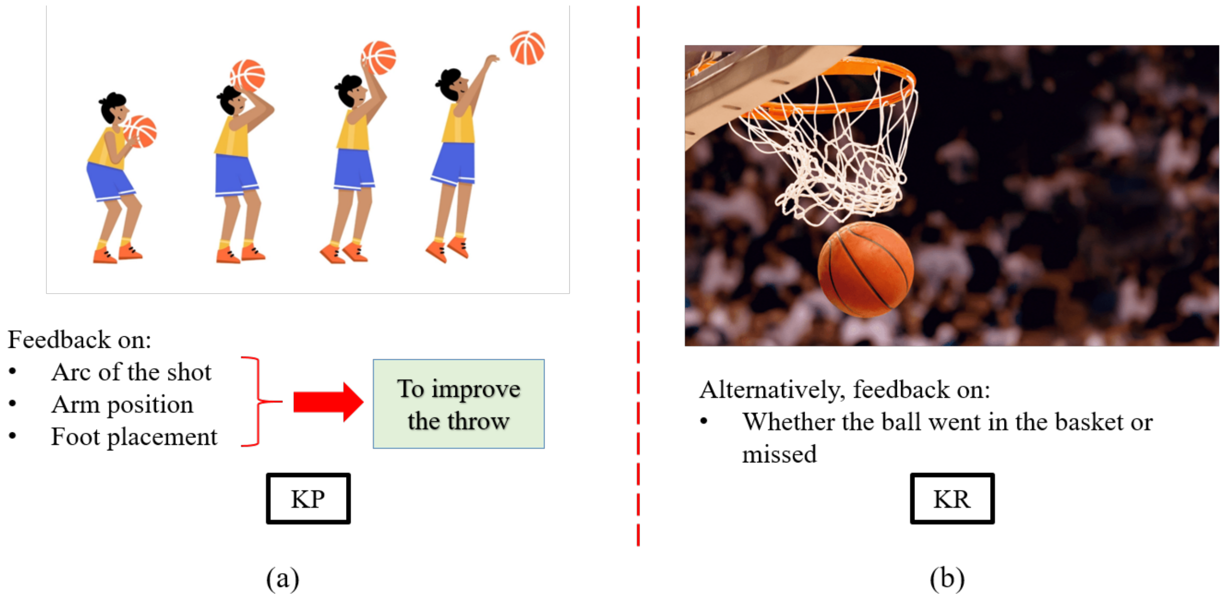


Figure 2.1. Concepts of KP and KR.

factors improved the outcome (subplot 2.1a) whereas another coach could only provide feedback on whether the ball went into the basket or not (subplot 2.1b). In this thesis, the concept of KP is used.

An individual's gait speed can be improved by giving feedback (sometimes referred to as the knowledge of performance or KP) on a critical parameter of the movement pattern. This crucial metric can serve as a biomechanical surrogate for the target activity. It is difficult to convey to users to increase their speed because it is unclear to users how to do that. Instead, according to the knowledge of performance (KP) strategy [55], it is necessary to guide users to modify specific parameters (i.e., the surrogates for speed) that can lead to improving their speed. Previous research that used biofeedback for gait training had previously used the idea of a biomechanical surrogate. [50], for example, employed foot strike, cadence, and trunk sway as substitutes for KFM, attempting to lessen KFM by changing the substitutes via tactile feedback. Peak thigh extension T_{PEx}, a significant predictor with a large effect size for stride length (L), was found as a biomechanical surrogate for height-normalized stride length ($\overline{L}$) in an earlier study by [51] as shown in

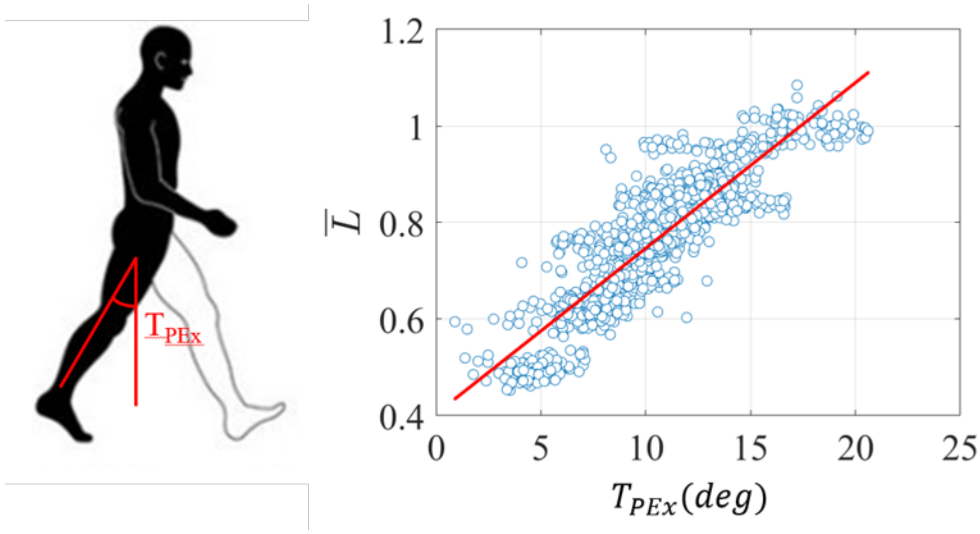


Figure 2.2. Relationship between the T_{PEx} and height-normalized stride length ($\overline{L}$). Noghani et al. [51]

Fig. 2.2, which examined data from young people walking without feedback. Stride length and, thus, gait velocity were raised via haptic feedback on this parameter. The concept of height-normalized stride length and gait velocity was used before in various research papers [56, 57].

The goal of the present study is to alter T_{PEx} to see if individuals who are older adults will see comparable gains. To give feedback and raise T_{PEx}, the haptic cell was positioned in the center of the posterior side of the thigh, matching the direction of thigh extension (as illustrated in Fig. 2.3a). Two haptic feedback modules were attached to the side of the thighs to control the vibration of the haptic cells. Two IMUs were also attached to the foot and thighs, as shown in Fig. 2.3a.

2.3 Haptic Feedback System

Fig. 2.3a shows a user wearing a feedback system, whereas Fig. 2.3b shows a participant utilizing a feedback system during an experiment. Four inertial measurement units (IMUs) were attached to the feet and thighs and connected to a phone through Bluetooth at a frequency of 60 Hz to stream orientation in quaternion form and free acceleration in an earth-fixed frame. The thigh feedback module, seen in Fig. 2.3a, had an 850 mAH battery, a custom-designed circuit board for operating vibromotors, and a 3D-printed casing for the ESP 8266 Thing microcontroller. Fig. 2.4 shows a detailed component of the system on how the feedback components work and communicate each other. For the motors to operate at their rated current, a supply of up to 500 mA at battery voltage was made possible by the custom Printed Circuit Board (PCB). In contrast, the Input/Output pins could only supply up to 12 mA, which would not be sufficient for a motor to operate. The haptic cell, which has three eccentric-mass motors with a 12 mm diameter, was activated for 0.5 seconds in response to a feedback request. Each thigh received an additional mass of around 61g. The ESP8266 microcontrollers were programmed as HTTP servers connected to the phone's WiFi network, and an Android application was created to serve as the system's primary controller, comparing the peak thigh extension for each cycle to the target and sending requests for vibrations to the ESP8266 microcontrollers. According

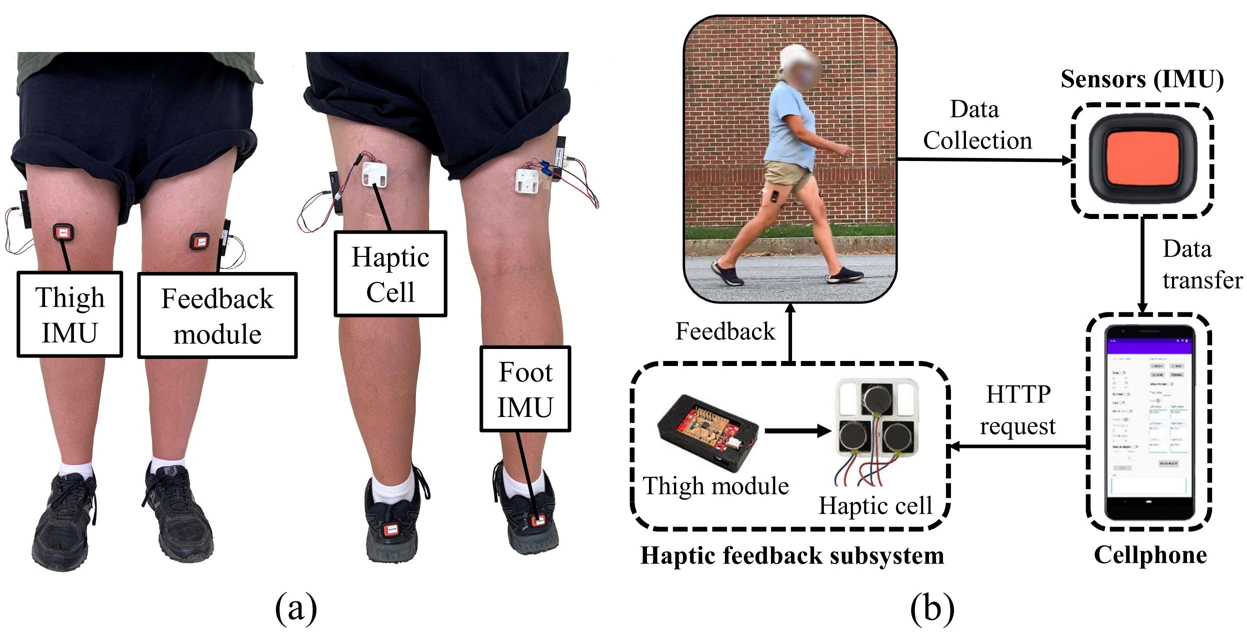


Figure 2.3. (a) A subject wearing the haptic feedback system and (b) a schematic diagram of the experimental setup.

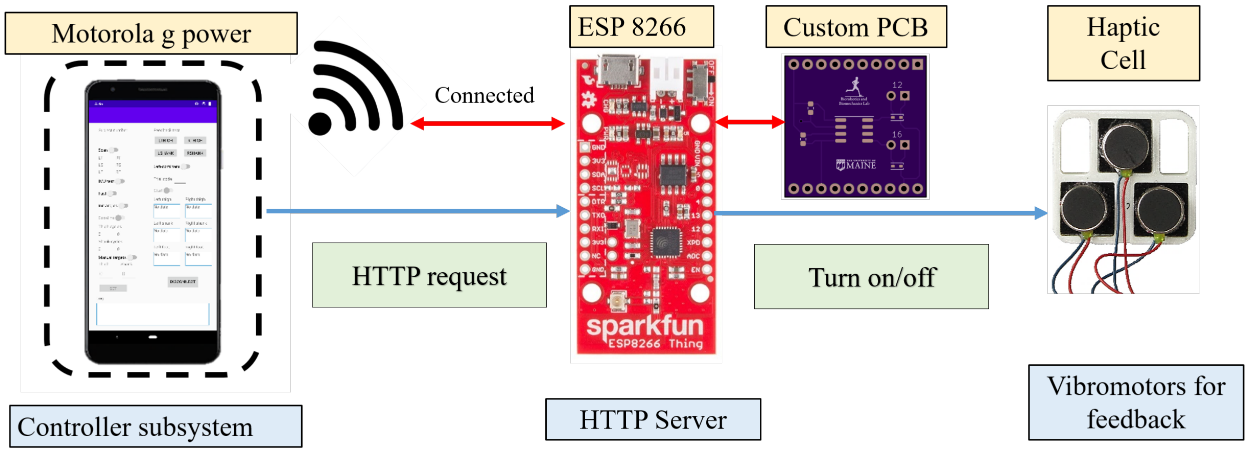


Figure 2.4. Components of the haptic feedback system.

to spectral analysis, the haptic cells' vibration frequency was close to 240 Hz [51], which is in line with the human skin's maximal mechanoreceptor sensitivity (245 Hz) [51, 52].

2.4 Software

The Android app was developed using Android Studio, a software development environment (IDE) for Android app development. The integration of the Xsens DOT Software Development Kit (Android Version v2020.2) into the Android Studio development environment made it possible to use Xsens DOT motion sensors in the Android application. The Xsens DOT Software Development Kit (SDK) is a collection of software resources designed to help developers construct applications for Xsens DOT motion sensors. This SDK allowed the project to utilize the Xsens DOT motion sensors within the Android application. The Basic flow of building the application using SDK is described below.

- Integration of the Xsens Dot SDK in Android Studio: The Xsens Dot SDK was initially downloaded from the website and then its zip file was extracted on the computer. It was then added to the project's folder and the build settings were adjusted to include the SDK in the program. It was then ready to use the Xsens Dot SDK.

- Creating the User Interface in Android Studio: The "Design" tab in Android Studio was used to design and build the user interface. UI elements like buttons, text boxes, and labels are essentially dragged and dropped onto the layout canvas. In the "Code" view, the XML code can be edited, or it can be produced automatically by dragging and dropping UI elements. Fig. 2.5 shows the application interface that was created for our experiment.

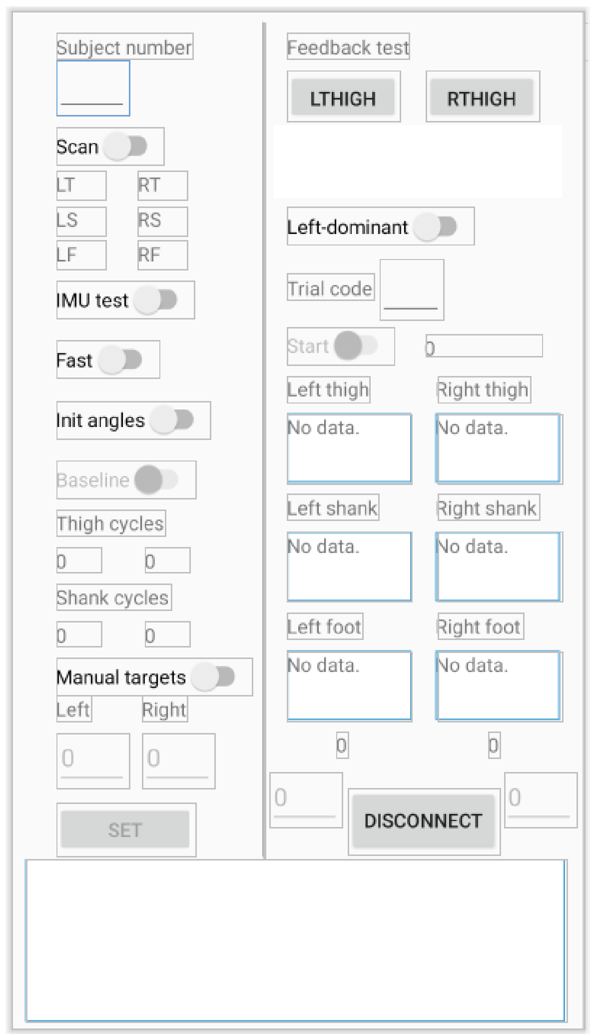


Figure 2.5. User Interface for the Android Application.

- Configuring and Connecting to the Xsens Dot Sensors: In essence, this stage involves configuring the app to communicate with the app and setting up the sensors. A set of standard classes and functions are used from Xsens Dot SDK, and their corresponding names are mentioned in the following description. A detailed description of the classes and functions can be found in Xsens Dot SDK documentation. The "XsensDotSdk" class instance was initialized, the sensor rate was set, and the sensor ID was set before the sensor was turned on. When the Scan switch (Fig, 2.5) is enabled, scanning for the DOT sensors is initiated by the phone. Upon scanning a sensor, the callback function "onXsensDotScanned" is used. In this function, a check is performed to verify if the sensor is relevant to the experiment. Once confirmed, a connection is attempted. The sensors are initialized before initiating a measurement, and the ready flag is set thereafter. An object of "XsensDotDevice" was declared as "xsDevice," which represents one of the sensors connected to the application. Upon successful sensor connection, data can be measured. Upon function execution completion, the sensors transmit data to the phone.

- Handling Data Received From a Sensor: Each time a packet of data was received, it was handled by "onXsensDotDataChanged" function. In that function, a sensor was checked from which the data has come (the "address" field).

  There are a few state switches, as shown in Fig. 2.5 like IMU test, Fast, Init angles, Baseline, etc. In each scenario (state), the data received has to be handled differently. The variables above are defined to specify the exact state of the sensor. The state variables are mutually exclusive, meaning that when one of them is set to true, the others are set to false. The classes are created in the onCreate method, which is called when the main activity is launched (when the app is opened). Inside the callback function for each switch, at some point, measurement is started with startMeasuring() function call.

- Handling Data Packets Received From The Sensors and Data Analysis within the App: This step includes extracting relevant motion data from the raw sensor data,

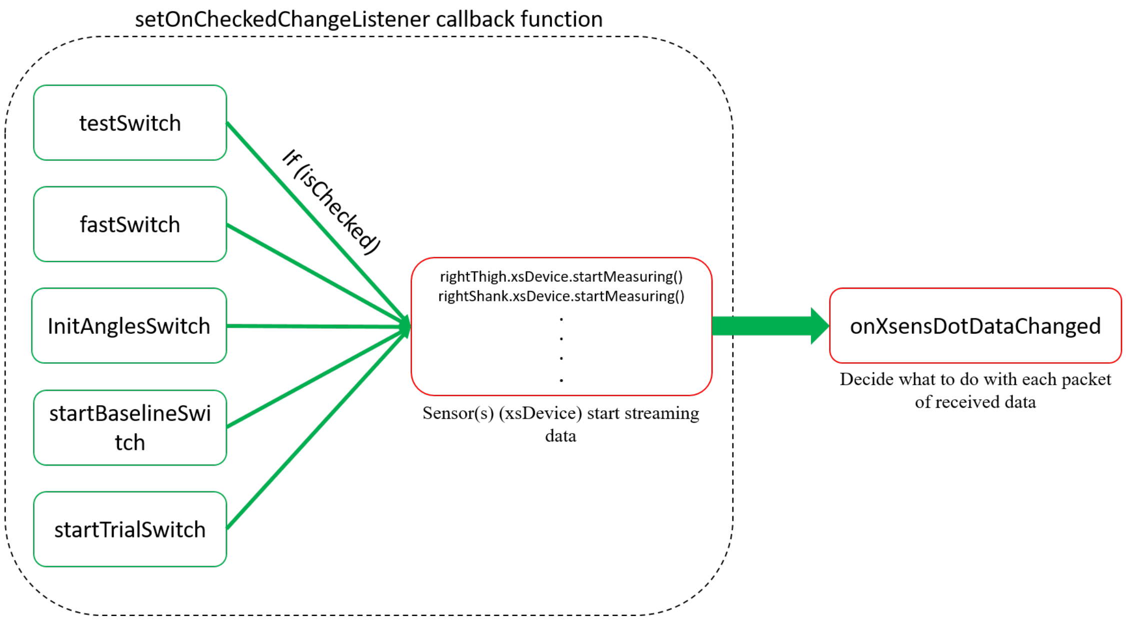


Figure 2.6. Basic Flow of the Application.

such as orientation and acceleration. Orientation is collected in quaternion form and from which angle was extracted. When data is received from a sensor, the callback function onXsensDotDataChanged is called. We first check which sensor the data has come from by checking its Media Access Control(MAC) address. Then we check what state (test, fast, etc.) that segment is currently in. Fig. 2.7 provides an overview of the operations in each state.

- Sending HTTP requests: For sending HTTP requests, "okhttp3" package is used. Asynchronous HTTP GET request for each segment is constructed in the "sendRequest" function in URL form. The ESP8266 microcontroller in the feedback module parses the requests and acts accordingly. It then sends back a response, which is displayed and stored in the log file.

- Displaying The Processed Data and The Status in The User Interface of The App: The log file at the base of the user interface contains processed data. The log file's time stamp and the average for Peak Thigh Extension T_{PEx} in various trials were displayed. The log file also displayed which sensors were connected.

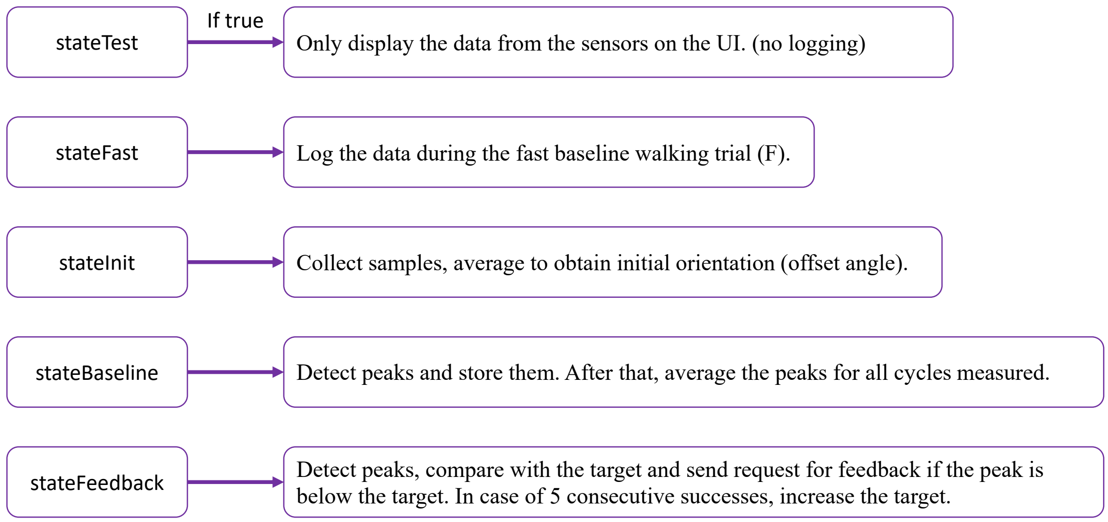


Figure 2.7. Notable Operations in Each State.

- Debugging and Publishing the App: Finally, debugging was done to find errors and the app was tested in many different situations so that it worked perfectly. After that, an Android phone (Motorola moto g power 2020) was connected to the PC via a USB cable, and the application was uploaded to the phone.

2.5 Experimental Design

The studies were conducted with a dual purpose in mind. To begin, the purpose of this experiment was to determine whether or not the presence of tactile feedback during walking could influence the maximum extension of the thigh, which, in turn, could have an effect on stride length and walking speed when compared to the condition in which the participants walked without the presence of feedback. Secondly, the purpose of the experiments was to ascertain whether or not the frequency of feedback would have an effect on the walking performance of the participants. Not to be confused with the vibrocell's natural frequency, the term "feedback frequency" in this context refers to the proportion of trials in which feedback was provided (240 Hz). The investigations consisted of seven separate trials, each of which was carried out on a U-shaped walkway that measured 54 m x 3 m (as shown in Fig. 2.8). The experimental order is outlined in Fig. 2.9. Each participant was given some

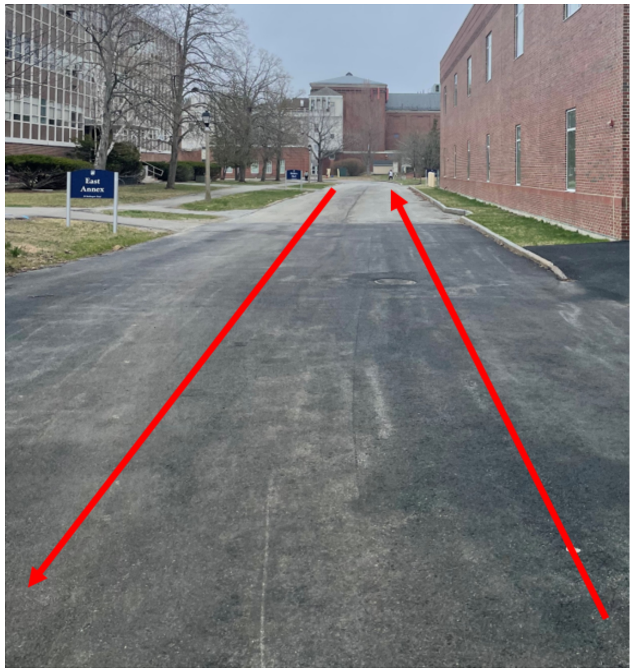


Figure 2.8. Walkway for the study.

background information about the experiment and given the opportunity to try out the haptic feedback device. Under the circumstances that included feedback, the participants only got feedback if their maximum thigh extension was lower than the target value, which was known as an "error." The context of "error" (on the left) and "no error" (on the right) is depicted by two-layered subplots in Fig. 2.13a. The "error" condition, shown in the figure on the left, occurs when the subject's peak thigh extension is below the target, causing vibration feedback. The "no error" situation, is shown in the picture on the right when the subject's peak thigh extension is equal to or greater than the target and there is no feedback. Feedback was provided on each leg individually based on their performance and participants responded to individual legs separately. The volunteers were not given the instruction to walk at a faster speed; rather, they were asked to respond to the haptic input that was being applied to their thighs, which promoted a larger thigh extension angle. To guarantee that the participants had reached a steady state of walking, the first 10 cycles of each of the seven conditions were omitted from the analysis. Moreover, a

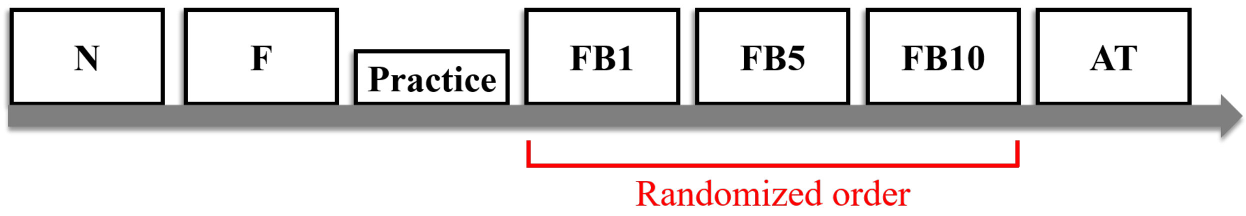


Figure 2.9. The order of baseline self-selected normal (N) and fast (F) walking, practice, and after-training (AT) trials were always consistent. The order of feedback trials (FB1, FB5, and FB10), on the other hand, was chosen at random.

one-minute break was provided between each condition to prevent any potential carry-over effects from occurring. The experimental conditions are described below.

- Normal baseline walking (N): The first trial in the experiment, which was known as Normal baseline walking, did not involve any participants receiving any kind of haptic feedback. They were instructed to walk at a regular normal walking speed that was determined by themselves. The average value of the peak thigh extension ($\overline{T}_{PEx,N}$) was determined by the Android application by taking the data gathered from cycle 11 all the way through cycle 40 and averaging them (30 strides).

- Fast baseline walking (F): The participants were not given any feedback, and they were given the instruction to walk as fast as they were able to do so without risking falling over. The Android application determined the average peak thigh extension ($\overline{T}_{PEx,F}$) for a total of 30 cycles, beginning on the 11$^{\text{th}}$ cycle and ending on the 40$^{\text{th}}$ cycle.

- Practice: Participants completed a preliminary trial consisting of one lap to become familiar with the feedback system and learn how to adjust their gait in response to haptic feedback.

- Feedback condition 1 (FB1): Fig. 2.10 shows the schematic for FB1. During feedback condition 1 (FB1), participants were given the opportunity to get feedback for each cycle in which they made an error. After allowing the individuals to reach a steady-state walking pattern during the first 10 cycles of the experiment, which were carried out without feedback, feedback was then enabled for the remaining 30 cycles (11^{th} to 40^{th} cycle) of the experiment. Under this circumstance, participants would get feedback in every cycle when a lower value from the target peak thigh angle was detected, resulting in a frequency of feedback delivery that was equal to one hundred percent (100%) of the time. This 100% of the time is the most amount of feedback that they are able to get; nevertheless, if their peak thigh extension meets the target or goes beyond the target, they will not receive any feedback at all.

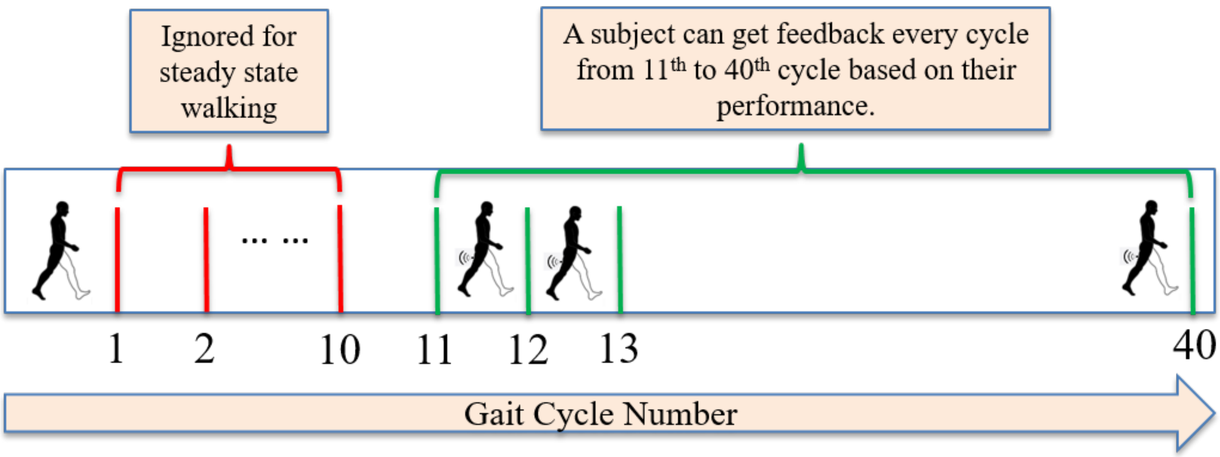


Figure 2.10. Schematic diagram for FB1.

- Feedback condition 2 (FB5): A feedback frequency of 20% was achieved by providing the participant with feedback every 5^{th} gait cycle when it was needed, meaning the peak thigh extension is less than the target value. This trial was five times as long as the previous one, totaling 150 strides (11^{th} to 160^{th} cycle). This was done so that the number of gait cycles that included feedback would be comparable between the FB1 and FB5 conditions. This condition is shown in Fig. 2.11, where it is explained schematically.

- Feedback condition 3 (FB10): If there was an error in FB10, the participants were informed every 10^{th} cycle; hence, the feedback frequency was 10%. There were a total

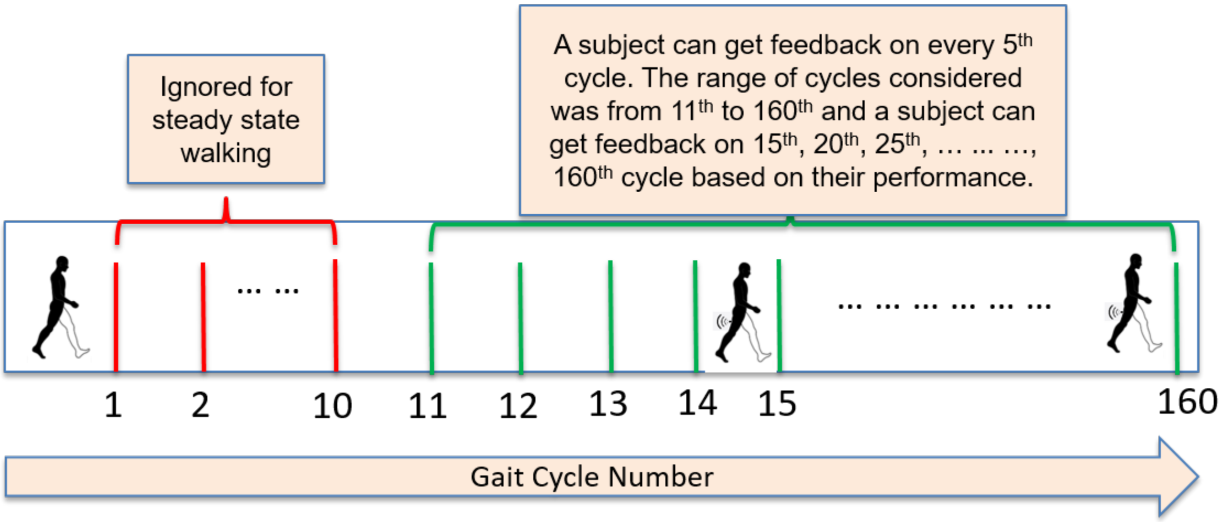


Figure 2.11. Schematic diagram for FB5.

of 300 strides (11$^{\text{th}}$ to 310$^{\text{th}}$ cycle), however, feedback was only allowed once per ten cycles since error ensured that a similar exposure to feedback was achieved when compared to FB1 and FB5. For the course of the experiment, these three feedback conditions were subject to randomization. This condition is shown in Fig. 2.12.

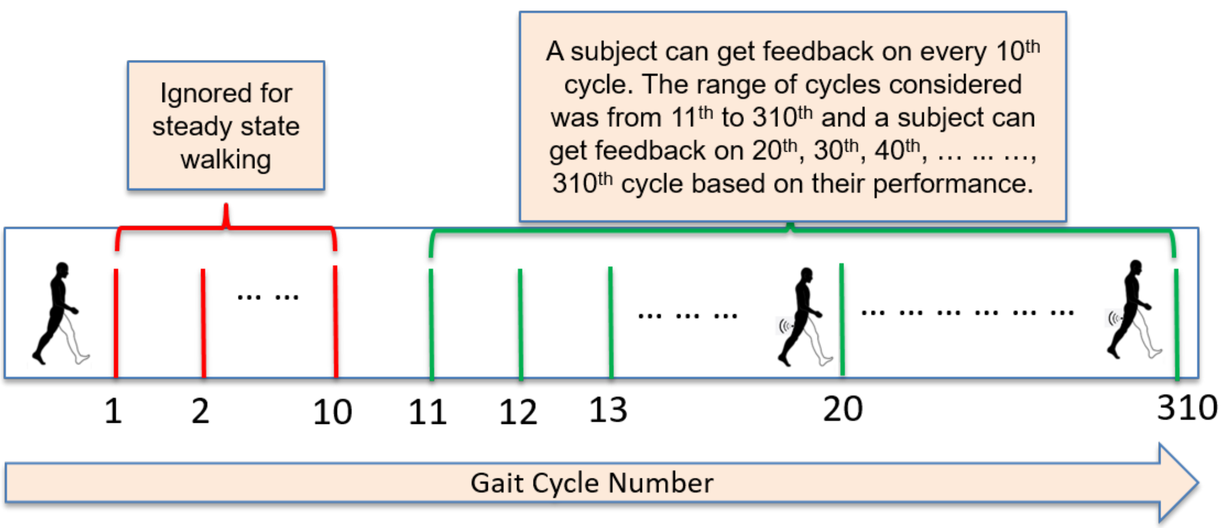
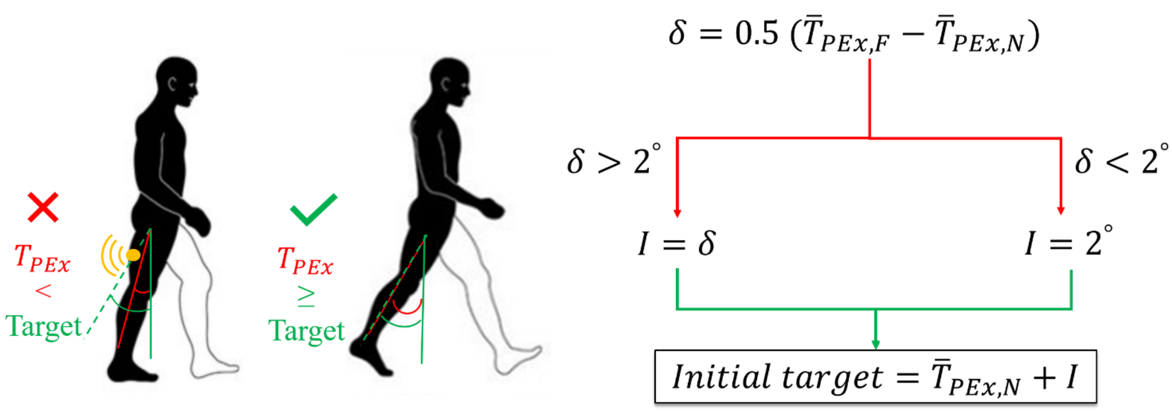


Figure 2.12. Schematic diagram for FB10.

- After training (AT): The participants were told to walk in the same manner as when feedback was available, but in this study, they received no such feedback. The purpose of this experiment was to find out if people could retain how to walk with their increased thigh extension without any assistance. This phase of the trial was always the last one.

In Fig. 2.13b a schematic representation of the algorithm is used to establish the starting target for the peak thigh extension. The average values of T_{PEx} in baseline trials for both F and N were calculated, and from there a parameter δ was defined as the half of the difference between the average values of T_{PEx} in trials F ($\overline{T}_{PEx,F}$) and N ($\overline{T}_{PEx,N}$). After that, we decided on an increment (I) based on whether δ was less than 2° or not. It was decided that 2° would be used because it is twice the IMUs' dynamic inaccuracy of 1°. I was added to $\overline{T}_{PEx,N}$ to achieve the starting target for peak thigh extension. During a trial, the Android app tracked the subject's T_{PEx} in real-time and compared it to their own custom target number (named "target"). In the event that T_{PEx} is less than the set goal, the participant will get feedback in accordance with the condition specified (i.e., FB1, FB5, FB10). This was helpful to personalize the target value for each participant.



(a) (b)

Figure 2.13. (a) Concepts of "error" and "no error", (b) The algorithm for determining the initial target value for increasing the peak thigh extension by feedback.

When a participant was able to successfully complete five consecutive cycles in any of the three feedback conditions, which meant that their peak thigh extension angle (T_{PEx}) was more than the target angle, the Android program increased the target angle for the second time by adding a parameter I to direct the participant towards higher values of T_{PEx}. This was done to encourage the participant to achieve higher levels of T_{PEx}. At the conclusion of the fast walking condition, the Android program determined the value of I on its own. Upon successful completion of each of the three feedback conditions, the angle of the target was returned to its starting target value.

The preceding method enabled individualized training by providing participants with feedback depending on the speeds they set for themselves. Thigh angle trajectories, θ_T, and their peak extension, T_{PEx}, are shown in Fig. 2.14 for the N, F, and feedback FB1 conditions, demonstrating that T_{PEx} increased with feedback, analogous to walking at a fast self-selected speed without any feedback. The figure shows representative examples of the thigh angle during N, F, and FB1 trials at different points in a gait cycle.

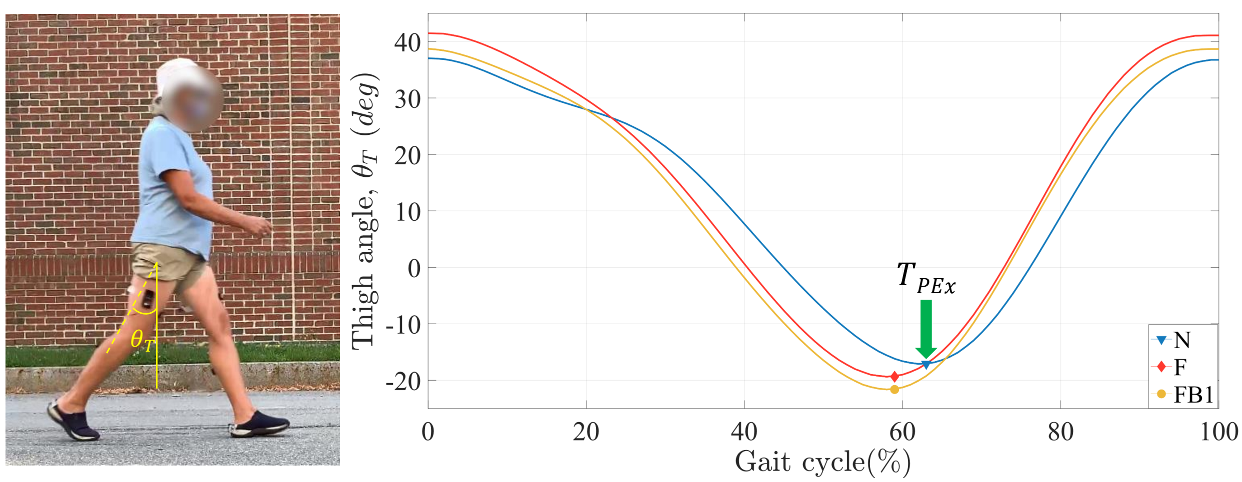


Figure 2.14. Representative examples of the thigh angle in N, F, FB1 trials within a gait cycle.

2.6 Data Analysis

Data obtained from the IMUs included the orientation and acceleration and then used in MATLAB (R2020b, MathWorks, Natick, MA, USA) to compute spatiotemporal parameters. The sensor orientation data from IMUs were sent to the Android application with respect to the local-earth fixed frame in the form of a unit quaternion ${}^{S}\boldsymbol{q}_E$. Quaternions are a better form of angle measurement than Euler angle because of no gimbal lock, smooth interpolation, efficient computation, and no redundancy. So, data were collected in the form of the equation presented below.

$$ {}^{S}\boldsymbol{q}_E = (q_0, q_1, q_2, q_3) \tag{2.1} $$

The elements of the rotation matrix ${}^{S}\boldsymbol{R}_E$ can be expressed by using the dot products of the unit vectors of the axes of the two frames, based on the definition of ${}^{S}\boldsymbol{R}_E$ [58].

$$ {}^{S}\boldsymbol{R}_E = \begin{bmatrix} \hat{\boldsymbol{x}}_E \cdot \hat{\boldsymbol{x}}_S & \hat{\boldsymbol{x}}_E \cdot \hat{\boldsymbol{y}}_S & \hat{\boldsymbol{x}}_E \cdot \hat{\boldsymbol{z}}_S \\ \hat{\boldsymbol{y}}_E \cdot \hat{\boldsymbol{x}}_S & \hat{\boldsymbol{y}}_E \cdot \hat{\boldsymbol{y}}_S & \hat{\boldsymbol{y}}_E \cdot \hat{\boldsymbol{z}}_S \\ \hat{\boldsymbol{z}}_E \cdot \hat{\boldsymbol{x}}_S & \hat{\boldsymbol{z}}_E \cdot \hat{\boldsymbol{y}}_S & \hat{\boldsymbol{z}}_E \cdot \hat{\boldsymbol{z}}_S \end{bmatrix} \tag{2.2} $$

The angle can be found using the (3, 3) element of the above matrix.

$$ \begin{aligned} \hat{\boldsymbol{z}}_E \cdot \hat{\boldsymbol{z}}_S &= |\hat{\boldsymbol{z}}_E||\hat{\boldsymbol{z}}_E| \cos\theta \\ &= 1 \cdot 1 \cdot \cos\theta \\ &= \cos\theta \end{aligned} \tag{2.3} $$

The rotation matrix can also be expressed in terms of quaternion form as follows [59],

$$ R_{33} = q_0^2 - q_1^2 - q_2^2 + q_3^2 \tag{2.4} $$

Rewriting the above equation utilizing the characteristic of unit quaternions such as $q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1$,

$$ R_{33} = 1 - 2q_1^2 - 2q_2^2 \tag{2.5} $$

Combining the equation 2.3 and 2.4, we can write as follows,

$$\cos\theta = 1 - 2q_1^2 - 2q_2^2 \tag{2.6}$$

From equation 2.6 we can compute the values of θ,

$$\theta = arccos(1 - 2q_1^2 - 2q_2^2) \tag{2.7}$$

This was the approach taken to measure the angle in the sagittal plane. The angle was expressed in degrees. The thigh angle and foot angle were measured following the above procedure.

At this point, the procedure for stride length calculation is presented here. The approach involves combining the acceleration data with a zero-velocity update, which was required to precisely compute the stride length [60]. In Fig. 2.15, a simplified explanation of how the acceleration data was used to calculate velocity and stride length is shown. To estimate the sensor's velocity, the acceleration of the sensor was first integrated into the earth-fixed frame Fig. 2.15a. To reduce errors brought on by drift following the integration procedure, the zero-velocity locations corresponding to the foot-flat occurrences were found Fig. 2.15b. The data were integrated again after correcting for drift error in order to calculate the sensor's position in relation to the earth-fixed frame. The sensor's location was determined by integrating the de-drifted velocity that resulted in Fig. 2.15c, and the stride length was calculated as the distance between two heel strike (HS) events. In summary, the following two equations were followed to estimate the stride length.

$$Velocity = \int_{t=HS_i}^{t=HS_{i+1}} a\,dt \quad \text{where } i = 1, 2, 3, \ldots \tag{2.8}$$

$$StrideLength = \int_{t=HS_i}^{t=HS_{i+1}} v\,dt \quad \text{where } i = 1, 2, 3, \ldots \tag{2.9}$$

The subject's anterior-posterior direction was represented by the earth's X-axis, its medial-lateral direction by the Y-axis, and its vertical position by the Z-axis. As the Z axis

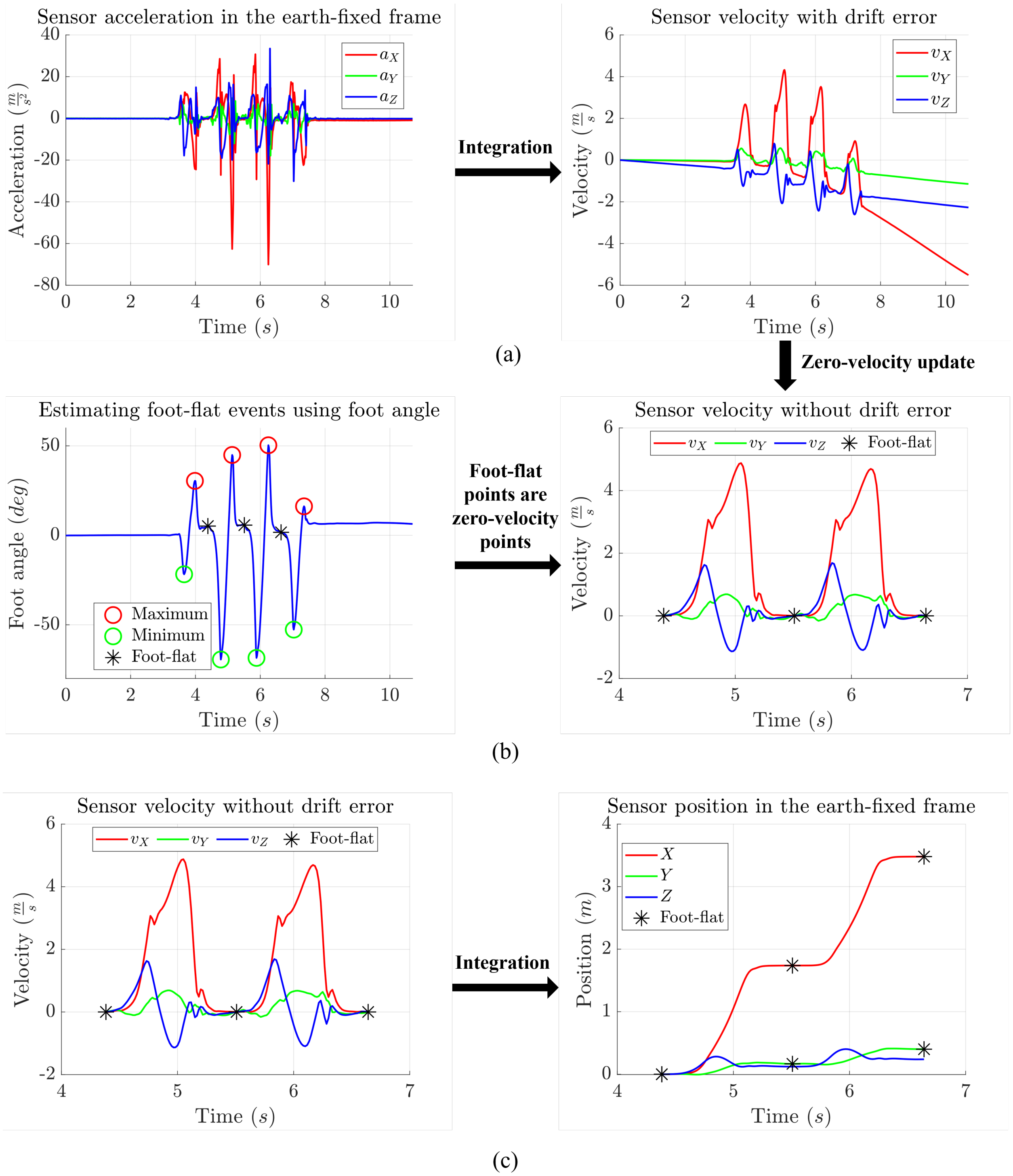


Figure 2.15. (a) Integration of acceleration data to get velocity with drift error, (b) zero-velocity update using foot-flat points to calculate velocity without drift error, and (c) integration of velocity.

is along the body. Therefore, it will not have any effect on measuring stride length from this component. Therefore, X and Y components will contribute to measuring the stride length following the below equation.

$$StrideLength = \sqrt{x^2 + y^2} \tag{2.10}$$

The output of this whole procedure is shown below in Fig. 2.16. This is a top-down visual example of a subject taking the right strides. The alternate black and red colors are given for clarity and to understand the two consecutive right strides with ease. As an illustration, the first black color denotes the first right stride, and the following red color denotes the second right stride. Only the right stride is shown in this figure, but the left side also underwent a similar process. An average was then calculated for both sides.

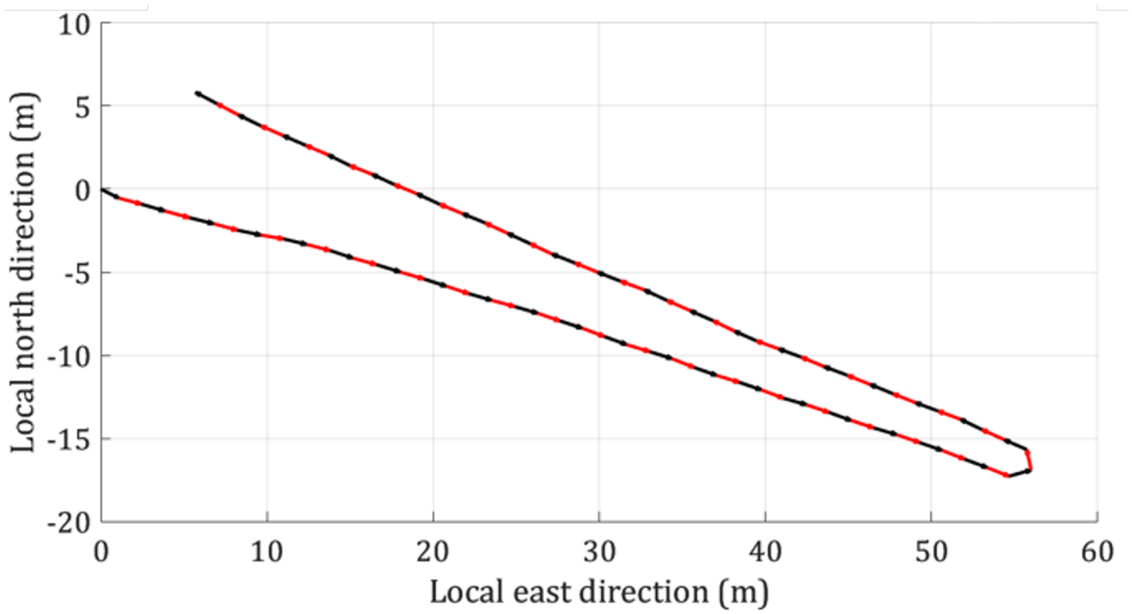


Figure 2.16. Top-down view of right strides.

Next, the procedure for gait cycle time is explained here. First, the foot angle is measured following eq. 2.7 and plotted with time. Then heel strikes (maximum point) and toe-off (minimum point) are detected. Gait cycle time is the time difference between two heel-strike points. A Fig. 2.17 is shown below to show the gait cycle time. Lastly, the gait speed was calculated by dividing the stride length by the corresponding gait cycle time,

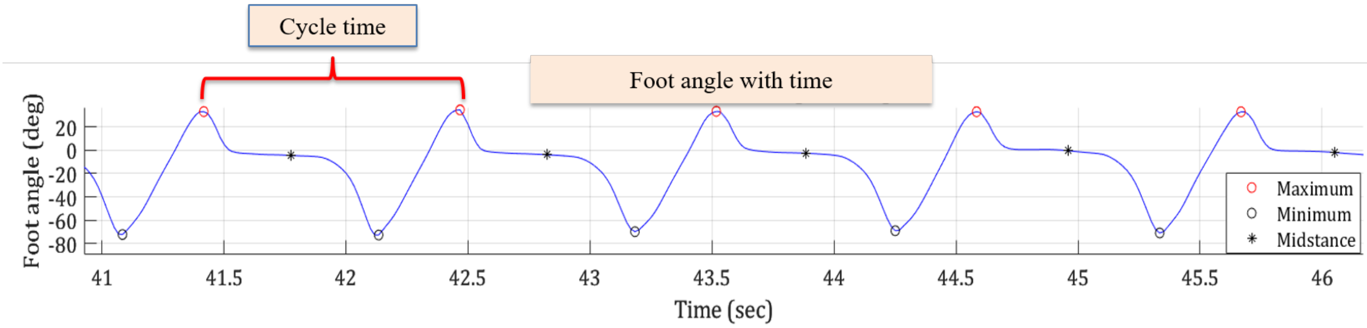


Figure 2.17. Foot angle with time.

and the cadence was calculated using the gait cycle time [61]. Height-normalized gait characteristics were obtained by dividing the participants' stride length and velocity by their own height [56, 57]. The formulas for height-normalized stride length ($\overline{L}$) and height-normalized gait velocity ($\overline{V}$) are given below.

$$\overline{L} = \frac{\text{Stride Length}}{\text{Subject's Height}} \tag{2.11}$$

$$\overline{V} = \frac{\text{Gait Velocity}}{\text{Subject's Height}} \tag{2.12}$$

The statistical studies were carried out using SPSS software (SPSS Inc., Chicago, IL, USA). A repeated measures analysis of variance (ANOVA) was carried out with a significance threshold of $\alpha = 0.05$ in order to assess whether or not there were any significant differences between the various conditions [62]. Mauchly's test was used in order to check the sphericity assumption, and in the event that the assumption was not met, the Greenhouse-Geisser adjustment was utilized [62]. The assumption of sphericity is critical since failure to meet it can result in inflated Type I error rates and incorrect conclusions. A post-hoc analysis using the Bonferroni correction was used in order to determine whether conditions and their respective pairings had a statistically significant difference [62]. Gait cycles that occurred in the U-shaped pathway while turning were not included in the study because we wanted to be sure that turning did not affect the findings. On the other hand, it is important to point out that there were only a few turns along the walkway since the portion of the path that was curved was a lot shorter than the one that was straight. After they had finished the experimental trials, the participants were given a questionnaire to fill out that asked them to rate their experience with the feedback system based on the following criteria.

- Comfort level during the experiment
- The haptic feedback is noticeable.
- How intuitive the haptic feedback is
- Simplicity of modifying gait

When rating the questions, a scale ranging from 1 to 10 was used, with a higher score indicating better performance with regard to the criteria.

CHAPTER 3

RESULTS

In this chapter, the results of peak thigh extension, spatiotemporal parameters, and the Coefficient of variations for different gait parameters will be presented. The results are summarized in bar pots and tables to provide a comprehensive understanding of the gait parameters.

3.1 Peak Thigh Extension (T_{PEx})

The bar plots of thigh peak extension are shown in Fig. 3.1a for each of the six different conditions. An ANOVA with repeated measurements revealed a condition-specific difference that was statistically significant (F (5, 45) = 15.0, p < 0.001) and had a large effect size ($\eta_p^2 = 0.625$) within the context of the conditions. In the post-hoc analysis, significant differences were found between normal walking and the other conditions. There were no statistically significant differences found between any of the three feedback conditions that used different frequencies of feedback. Peak thigh extension, T_{PEx} was shown to be 18.5% higher in F, 33.8% higher in FB1, 33.6% higher in FB5, 29.8% higher in FB10, and 26.1% higher in AT as compared to normal walking N. Although there was no statistically significant difference between the AT and feedback conditions, the peak thigh extension in the AT trial was considerably higher than the baseline normal walking. This was the case despite the fact that there was no feedback presented in AT condition. The initial target was determined by adding an average increment I of 3.01°to the participants' individualized baseline T_{PEx}. All of the participants not only achieved the initial target, but they also increased the target value by successfully completing five cycles in a row without making any errors and keeping the correct thigh extension.

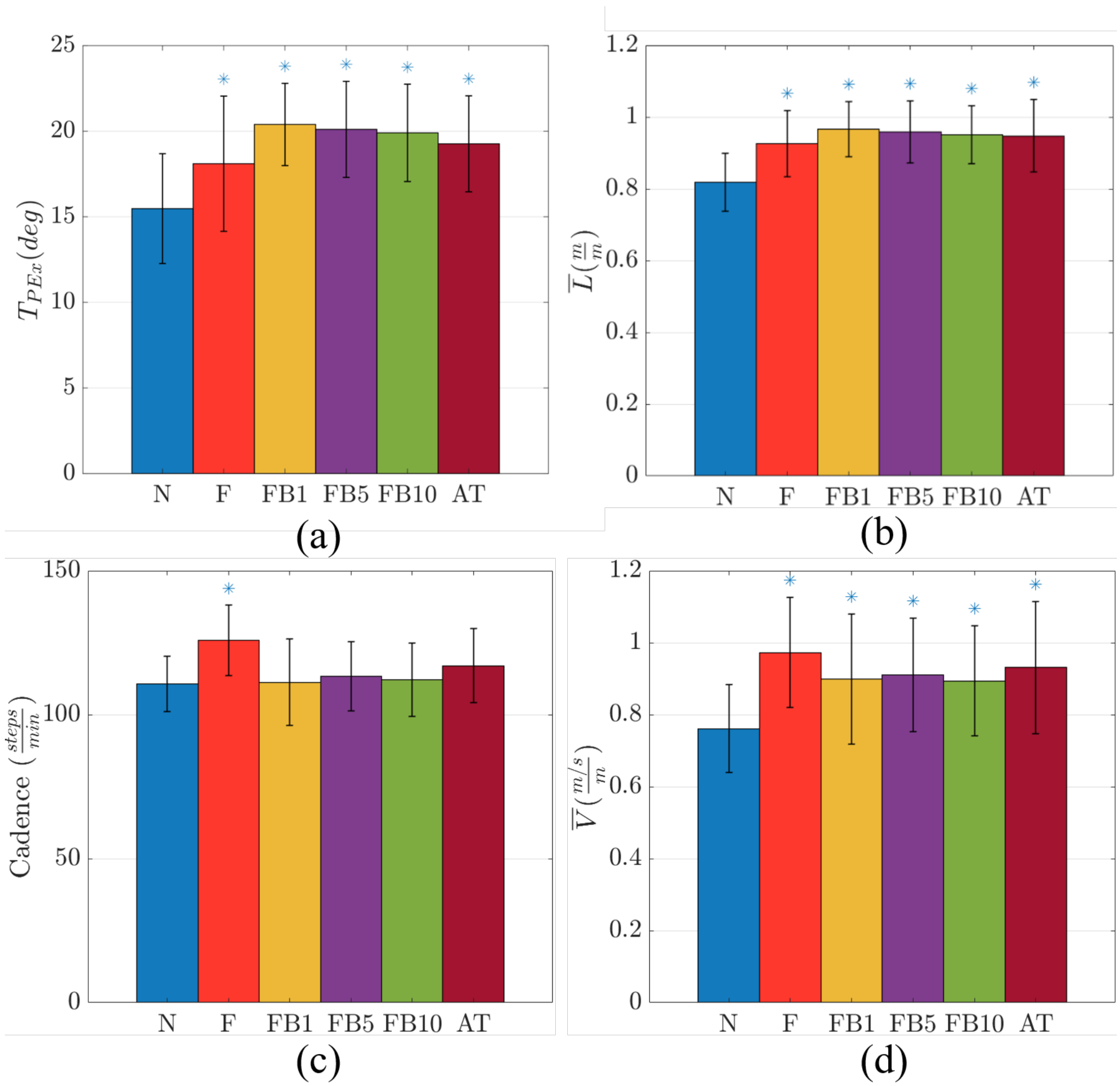


Figure 3.1. (a) Thigh angle, (b) normalized stride length, (c) cadence, and (d) normalized gait velocity for different experimental conditions. The error bars represent the condition's standard deviation.

3.2 Spatiotemporal parameters

With a substantial effect size (F (5, 45) = 37.2, p < 0.001, $\eta_p^2 = 0.805$), the results shown in Fig. 3.1b demonstrate that there were significant increases in height-normalized stride length, $\overline{L}$, across all experimental conditions. According to the post-hoc analysis, there was a significant increment in $\overline{L}$ in all of the feedback conditions compare to normal baseline walking, but there were no significant changes across the three feedback conditions. Similar to the T_{PEx} findings, the data also indicated that $\overline{L}$ in the AT condition significantly increased when compared to the N condition. In particular, for $\overline{L}$, there was an increase of 13.0% in F, 17.2% in FB1, 16.5% in FB5, 15.6% in FB10, and 15.0% in AT when compared to N. In Fig. 3.1c, the cadence for the six conditions showed statistically significant differences with a substantial effect size (F (1.78, 16.0) = 4.78, p < 0.05, η_p^2= 0.347). Only the difference between normal walking (N) and fast walking (F) was found to be statistically significant after post-hoc analysis; there were no other significant differences found between the other conditions. While compared to any other conditions, the cadence was highest while the subject was walking fast. When compared to the normal walking condition (N), the fast walking (F) showed a 13.9% increase in cadence, whereas the feedback conditions showed just a modest increase of less than 1%, and the AT walking condition showed a 4.2% increase. Fig. 3.1d illustrates the height-normalized stride velocity, denoted by the notation $\overline{V}$, for each of the experimental conditions. The results of an analysis of variance with repeated measurements showed that there was a significant effect of condition (F (5, 45) = 10.9, p < 0.001, η_p^2 = 0.548). According to the findings of the post-hoc analysis, every condition exhibited statistically significant increases in $\overline{V}$ compared to the N condition. When compared to N, there was an increase of 28.6% in F, 18.0% in FB1, 17.8% in FB5, 16.0% in AT, and there was a total of 20.3% in AT. There was no discernible difference between the three feedback conditions with regard to stride velocity similar to stride length or peak thigh extension. The findings of the statistical studies are outlined in Table 3.1, which provides a breakdown of the mean values and standard deviations of the gait characteristics.

3.3 Coefficient of Variation (COV)

Gait metrics such as peak thigh extension, normalized stride length, cadence, and normalized stride velocity had their coefficients of variation computed and compared across all conditions. For each participant in each condition, we divided the standard deviation of the relevant gait parameter by its mean value to get its coefficient of variation (COV) [63]. The first 30 strides from each condition were used to calculate the coefficient of variation for each participant per trial. The consistency between trials was maintained, and the amount of feedback's impact on gait parameters was monitored by taking only 30 strides, demonstrating that either less or more feedback can affect the gait parameters. Then, all the COVs from the participants within each condition were used to calculate the mean and standard deviation of that condition. The mean and standard deviation of each condition

Table 3.1. Statistics of the spatiotemporal parameters, presented as mean (std. deviation).

Gait parameters	N	F	FB1	FB5	FB10	AT
$T_{PEX}(deg)$	15.478 (3.209)	18.102* (3.951)	20.397* (2.403)	20.107* (2.807)	19.905* (2.843)	19.264* (2.804)
$\overline{L}(\frac{m}{m})$	0.819 (0.081)	0.926* (0.093)	0.966* (0.077)	0.959* (0.087)	0.951* (0.080)	0.948* (0.101)
Cadence $(\frac{steps}{min})$	110.683 (9.596)	125.868* (12.304)	111.212 (15.029)	113.389 (12.030)	112.243 (12.754)	117.035 (12.879)
$\overline{V}(\frac{m/s}{m})$	0.761 (0.122)	0.973* (0.152)	0.899* (0.182)	0.911* (0.157)	0.894* (0.153)	0.931* (0.183)

* Indicates significant difference with respect to N ($p < 0.05$)

Table 3.2. Means and standard deviations of gait parameters' COVs during the experimental conditions

Gait parameters	N	F	FB1	FB5	FB10	AT
T_{PEX}	0.099 (0.067)	0.151 (0.129)	0.111 (0.071)	0.097 (0.051)	0.097 (0.044)	0.124 (0.078)
$\overline{L}$	0.019 (0.006)	0.031 (0.022)	0.029 (0.011)	0.034 (0.020)	0.022 (0.006)	0.023 (0.014)
Cadence	0.018 (0.005)	0.016 (0.004)	0.024 (0.010)	0.022 (0.012)	0.019 (0.009)	0.029 (0.039)
$\overline{V}$	0.029 (0.011)	0.039 (0.021)	0.031 (0.011)	0.035 (0.010)	0.028 (0.008)	0.029 (0.013)

were then determined using all the COVs from the subjects within that condition. The values of COVs for each gait parameter across conditions are listed in Table 3.2 as a whole. None of the factors, including peak thigh extension angle (F (1.50, 13.5) = 1.22, p = 0.312), $\overline{L}$ (F (5, 45) = 1.45, p = 0.23), cadence (F (1.26, 11.3) = 0.77, p = 0.43), and $\overline{V}$ (F (2.41, 21.6) = 1.20, p = 0.33, showed statistically significant variations in COV.

3.4 Number of Cycles with Feedback

The average number of feedbacks per condition is shown below in Table 3.3. This is the average number taken per condition for both legs. There were no significant differences among any of these conditions. According to statistical analysis, none of the conditions showed any significant differences (as $p > 0.05$)

Table 3.3. Average number of vibrations in each of the feedback conditions.

Condition	Mean	Std. deviation
FB1	11.85	9.201
FB5	13.75	9.941
FB10	15.50	9.389

3.5 Ratings by participants

The mean values and standard deviations of the participants' evaluations are presented below: (a) comfort level in adapting the walking style (7.7 ± 1.62), (b) noticeability of the tactile response (9.20 ± 1.54), (c) intuitiveness of haptic feedback during the experiment (9.33 ± 1.05), and (d) ease of adjusting gait (7.7 ± 1.62). The subjective assessments gathered will provide insight into the system's potential for future home-based walking exercises.

CHAPTER 4
DISCUSSION

The primary purpose of this study was to determine whether or not applying haptic feedback to the thigh of a participant while they were walking may result in a higher peak thigh extension, which would lead to an increase in both the participant's stride length and walking speed. The study also examined whether any change in gait parameters would be influenced by the frequency at which that feedback was provided. The feedback that was provided was based on the peak thigh extension angle that was observed in the different feedback conditions and the participant's target was determined based on their normal walking condition as well as their fast walking condition. An earlier study showed that older persons have shorter strides than younger adults and that there are little to no changes in cadence with age [64]. Therefore, the goal was to increase stride length using a haptic feedback system on a lower-level biomechanical surrogate, which would then increase stride velocity.

The results of the experiment presented in Fig. 3.1 demonstrate the effectiveness of haptic feedback in enhancing peak thigh extension. Participants showed a substantial increase in peak thigh extension, which translated into a longer stride length and enhanced gait velocity. According to the findings of the research, the increase in gait velocity was caused by the influence of feedback on stride length alone, rather than a combination of longer strides and a higher cadence. The fact that the cadence analysis could not detect any significant differences across feedback conditions shows that the participants' stride length was mainly affected by the feedback. On the other hand, the F condition brought about an increase in gait speed as a consequence of a combination of a higher cadence and a longer stride length. It was not expected to observe any modifications to the cadence parameter because no feedback was supplied on cadence. The research suggested that haptic feedback is a useful tool for increasing peak thigh extension and stride length, which can eventually lead to increased gait velocity. This is supported by the fact that improvement can be achieved. Additional study is required to investigate the long-term effects of haptic feedback on gait in various groups, as well as the ideal feedback settings for accomplishing the goals.

The analysis of all gait parameters under different frequencies of feedback presentation yielded interesting results. Surprisingly, the frequency of feedback had little to no effect on any of the parameters studied. This contrasts with much of the existing research on motor skill learning, which suggests that high frequencies of feedback generally lead to better performance during practice. However, when retention is tested later, high frequencies of feedback often result in poorer skill learning compared to lower frequencies of feedback during practice [53]. These findings suggest that the impact of feedback frequency may depend on the specific task or skill being learned and further research is necessary to fully understand the effects of feedback frequency on gait and other types of movement. It is important to note that at the end of the feedback training, participants were instructed to walk in the manner indicated by the feedback. The results showed that participants were able to recall and implement the different walking patterns as instructed by the feedback. These findings suggest that haptic feedback can help individuals learn a new gait coordinative pattern, as demonstrated by the participant's ability to remember and reproduce the walking pattern indicated by the feedback. These results provide initial evidence for the potential of haptic feedback in improving gait coordination and promoting motor learning. Further research is needed to explore the effectiveness of haptic feedback in different populations and settings.

This study looked at the COV of the recorded gait parameters in order to understand how various feedback frequencies impact the consistency of gait coordination. According to a previous study, learners may strive to continually change their motor effort in response to the frequent change in the feedback they get; as a result, providing them with frequent changes in feedback may cause performance variability to increase across different experimental conditions [53]. Because no statistically significant variations in the COV of any of the gait characteristics were found to exist across the various feedback frequencies, this assertion was not found to be supported by the findings of the current research investigation. When the variability of gait characteristics under feedback settings was compared to the variability in baseline conditions, it was found that people were able to swiftly internalize the information that was presented.

At the end of each experiment, the participants were asked to give their subjective assessments so that we could gain some insight into the acceptability of the haptic feedback system for possible walking exercises that could be done at home. The goal of this evaluation was to determine how the user felt about the effectiveness of the system in terms of improving gait characteristics. During the course of the experiment, the findings of the subjective assessments revealed that the haptic feedback system was not only convenient but also noticeable and straightforward. The greater intuitiveness rating means that the participants knew how to alter their stride when the vibration was active. The noticeability rating indicates that the vibrations created by the system were significant enough to be felt while walking. In addition, participants noted that making adjustments to their gait was easy, and that following the training, walking felt completely natural. These good findings are particularly intriguing given that the participants only had a brief period of familiarization and practice. This indicates that the observed improvements in gait metrics might have significant and long-lasting benefits with additional training of a longer duration. Future studies should aim to examine the long-term effects of haptic feedback systems on gait parameters to determine their potential for use as part of clinical rehabilitation programs.

This work presents an early inquiry into the impacts of a unique haptic feedback device for home-based gait training. The findings of this study indicate that the system has the ability to improve participants' gait. However, further research is needed to assess the long-term impacts of training using the system, as well as the influence of feedback frequency on gait improvement retention. Future studies should focus on whether participants retain the benefits of the feedback system over time, as well as the ideal frequency of feedback for improving long-term retention of gait improvements. These findings will be useful in developing successful home-based gait training programs that use haptic feedback technology.

CHAPTER 5
CONCLUSION

In summary, this study examined the effectiveness of a haptic feedback system on improving a lower-level biomechanical surrogate, peak thigh extension, which is highly correlated to stride length. The results indicate that participants were able to increase their stride length by extending their peak thigh extension angle, leading to a higher gait speed. This finding suggests that the haptic feedback system has the potential to be an effective tool for improving gait parameters in individuals with gait impairments. Moreover, the study investigated the effect of the frequency of feedback on gait parameters. The results suggest that the frequency of feedback does not significantly affect gait parameters. This finding is important as it indicates that the benefits of the haptic feedback system are not limited by the frequency of feedback. This study also introduces a first-of-a-kind home-based gait training device that is modular, portable, and lightweight, making it easy to use in a home environment. This feature is particularly important as it enables individuals to continue their gait training outside of clinical settings, leading to improved long-term outcomes. However, further research is required to investigate its long-term retention. In conclusion, this study provides valuable insights into the potential benefits of haptic feedback systems in improving gait parameters, highlighting the importance of exploring novel approaches for home-based rehabilitation. The findings suggest that the haptic feedback system has the potential to be an effective tool for improving gait parameters in individuals with gait impairments, and its modular, portable, and lightweight design makes it a convenient option for home-based gait training for older adults.

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