Self-Paced Regulation of Treadmill Speed Using Model Predictive Control

by

Ali Akbar Estarami

Master of Science in Electrical Engineering, KNTU, 2015

A Thesis Submitted in Partial Fulfillment of
the Requirements for the Degree of

Master of Science in Engineering

in the Graduate Academic Unit of Electrical and Computer Engineering

Supervisor: Jonathon Sensinger, Ph.D., Electrical and Computer Engineering

Examining Board: Chris Diduch, PhD, Electrical and Computer Engineering
Erik Scheme, PhD, Electrical and Computer Engineering
Jeremy Nobel, PhD, Kinesiology

This thesis is accepted by the
Dean of Graduate Studies

THE UNIVERSITY OF NEW BRUNSWICK

June 2025

© Ali Akbar Estarami, 2025

Abstract

A self-paced treadmill is a powerful tool enabling users, especially those with gait abnormalities, to perform clinical gait analysis at their own comfortable speed, unlike a fixed-speed treadmill. It comprises two components: position estimation and controller design. Position estimation determines the participant's real-time location, while the controller adjusts the speed based on location data. This study utilized a model predictive controller to forecast the user's walking state and employed two position estimation methods: marker-based (requiring the participant to wear markers) and markerless (embedded in CAREN system belts). To evaluate the designed self-paced treadmill, healthy adult participants walked on it in a simulated New York City environment, completing three trials and filling out a questionnaire afterward. Results indicated that participants felt more comfortable with the marker-based method, although the markerless method scored closely.

Acknowledgment

I would like to express my deepest gratitude to all those who supported me throughout the journey of completing this thesis.

First and foremost, I would like to thank my advisor, Dr. Jon Sensinger, whose guidance, support, and patience were invaluable. Your insightful feedback and encouragement pushed me to sharpen my thinking and brought my work to a higher level.

I would like to extend my heartfelt thanks to our physiotherapist, Luke Dillman, whose exceptional support was instrumental in the completion of this thesis. Your assistance in coding in Lua, implementing the designed tests in the lab environment, and helping during the data collection sessions was invaluable. Your dedication and expertise significantly contributed to the success of this research, and for that, I am deeply grateful.

I am also grateful to the members of my thesis committee, Chris Diduch, Erik Scheme, and Jeremy Nobel, for their time, effort, and valuable suggestions, which greatly improved my work.

A special thanks goes to my parents and my wife, whose unwavering support and belief in me kept me motivated.

I would also like to extend my gratitude to my friends and colleagues, particularly Zahed Dastan, our PhD student at IBME, for his constant support, insightful discussions, and the moments of relief they provided during stressful times.

Additionally, I would like to acknowledge the financial support from NSERC, which made this research possible.

Finally, I would like to thank all the participants who spent their precious time in the lab for data collection sessions and collaborators involved in this research. Your contributions and cooperation were essential for the completion of this thesis.

Thank you all for your unwavering support and encouragement. Sincerely,

Ali

Table of Contents

Abstract ii

Acknowledgment iii

Table of Contents v

List of Tables x

List of Figures xi

List of Appendices xiii

Symbols xiv

Abbreviations xvi

1 Introduction 1

1.1 Background and Motivation 1

1.2 Purpose of the Thesis and Specific Aims 3

1.3 Significance of Study 4

1.4 Overview of the Thesis Structure 5

2 Literature Review 7

2.1 Benefits of Advanced Treadmill Technologies 7

2.1.1 Integration of Treadmill with Virtual Environments 7

2.1.2 Treadmill Speed Regulation Benefits 8

2.2 Methods Used to Regulate Treadmill Speed 10

2.3 Overview of Markerless and Marker-Based Motion Tracking Systems 14

2.3.1 Marker-based Approaches 16

2.3.2 Model-based Markerless Approaches 17

2.3.3 Modeless Markerless Approaches 19

2.3.4 Outcomes of Self-Regulating Treadmill Approaches 20

3 Aim 1: MPC Controller Design 22

3.1.1 Intuitive Discussion 22

3.1.2 Mathematic Discussion 23

3.2 Real-time Treadmill Speed Regulation Controller Using MPC 24

4 Aim 2: Development of an Accurate Markerless Position Estimation Method..28

5 Aim 3: Methodology 30

5.1 Experimental Design 30

5.2 Participants 30

5.2.1 Sample Size 30

5.2.2 Apparatus and Environment 31

5.3 Ensuring Gait Changes 33

5.4 Trials 35

5.4.2 Inclusion and Exclusion Criteria.....37

5.4.3 Examination of Speed Variability Within Trials 38

5.5 MPC Parameters 39

5.6 Data Analysis 41

5.6.1 Primary Outcome Measure 41

5.6.2 Secondary Outcome Measure 41

5.6.3 Exploratory Outcome Measure 42

6 Aim 3: Comparative Analysis of The Markerless and Marker-based Position Estimation Results 43

6.1 Visual Analog Score Results 43

6.2 Speed Variability in Different Trials 51

6.3 Exploratory Outcome Measure 54

6.3.1 Subjective Feedback 58

7 Discussion 60

7.1 Interpretation of Results 60

7.2 Implications of Findings 61

7.3 Limitations of the Study 62

7.4 Suggestions for Future Research 63

8 Conclusion 65

8.1 Summary of Key Findings 65

8.2 Contribution to the Field 66

9 References.....68

10 Appendix.....85

10.1 Appendix A: Visual Analog Scale (VAS)Questionnaire 85

10.2 Appendix B: Demographic Form 87

10.3 Appendix C: Prescreening Document.....89

Curriculum Vitae

List of Tables

Table 1. Demographic details of the participants..... 38

Table 2. R^2 values comparing markerless and marker-based CoM estimates for all participants..... 55

List of Figures

Figure 1. Free body diagram of a person with gravity and ground reaction forces shown25

Figure 2. Control block diagram of the self-paced markerless treadmill 29

Figure 3. An example participant seen walking on the CAREN system in front of the simulated New York walking scene 33

Figure 4. Schematic representation of the traffic light and countdown timer used in each trial.....35

Figure 5. Randomized order of trials completion 37

Figure 6. Quantified participant responses to question 1 (0 = No Control, 10 = Complete Control).....44

Figure 7. Quantified participant responses to question 1 (0 = No Control, 10 = Complete Control).....45

Figure 8. Quantified participant responses to question 3 (0 = No Control, 10 = Complete Control).....46

Figure 9. Quantified participants responses to question 4 (0 = No Control, 10 = Complete Control).....47

Figure 10. Quantified participant responses to question 5 (0 = Not at all, 10 = Felt the same).....48

Figure 11. Quantified participant responses to question 6 (0 = Not at all, 10 = Felt the same).....49

Figure 12. Median speed during normal pace across participants 52

Figure 13. Speed difference variability between fast and slow pace 53

Figure 14. The scatter plot for a participant with $R2 = 0.93$ 56

Figure 15. Marker-based and markerless CoM over time 57

List of Appendices

Appendix A. Visual Analog Scale (VAS) Questionnaire.....85

Appendix B. Demographic Form.....87

Appendix C. Prescreening Document.....89

Symbols

Symbol	Description
J	Cost Function
N_x	State Prediction Horizon
N_u	Control Prediction Horizon
u	Control Input
Δu	Control Input Change
x	Position
a	Acceleration
h	Center of Mass Height
F	Force Applied to Both Belts in the Anterior-Posterior Direction
P	Gravity Force
N	Force Generated by the Person
t	Time
A	State Matrix
B	Input Matrix
Q	State Weighting Matrix

R	Input Weighting Matrix
x_{ref}	Reference Point of x
T_f	Final Time
m	Mass
l	Height
I	Moment of Inertia About the Center of Mass
θ	Angle Deviation from Vertical Axis,
g	Gravity
x_W	World Reference Frame
x_T	Treadmill Belt Position
x_R	Person's Position Relative to Treadmill
V	Velocity
$\mathbb{R}^+$	Positive Real Number

Abbreviations

Abbreviation	Meaning
CoM	Center of Mass
CoP	Center of Pressure
ANOVA	Analysis of Variance
VAS	Visual Analog Scale
MPC	Model Predictive Control
CAREN	Computer Assisted Rehabilitation Environment
MoCap	Motion Capture

1 Introduction

1.1 Background and Motivation

In clinical gait analysis, understanding human locomotion is crucial for diagnosing and treating various medical conditions [1], [2], [3]. Traditional overground gait analysis, while effective, often requires extensive space and limits the ability to capture repetitive strides [4], [5]. Instrumented treadmills have emerged as a popular alternative, offering the ability to capture data from repetitive strides in a controlled environment, enhancing the reliability and consistency of gait measurements [6], [7], [8]. However, treadmill walking can influence gait, often resulting in decreased preferred walking speed and stride length, slightly reduced joint range of motion, and subtle changes in EMG activation patterns [9]. These differences may stem from the absence of visual flow [10], the limited length of the treadmill belt [11], or the imposition of a fixed walking speed [12]. A fixed walking speed is a significant limitation in rehabilitation because it prevents patients from walking at their natural pace, which makes an adaptive, self-paced treadmill more suitable [13], [14].

Self-paced treadmill technology is an emerging technique that attempts to address this limitation by dynamically adjusting to the user's speed, ensuring a more natural gait during analysis [15], [16]. One common approach is a self-paced treadmill, which typically consists of two main components: a controller that adjusts the speed, and a position estimator that tracks the user's position on the treadmill [17], [18]. Unlike standard treadmills with fixed settings, self-paced treadmills provide individuals with the freedom to dictate the step-by-step pace of their workout, making them highly

adaptable to different levels of gait analysis—from basic observation to advanced biomechanical modeling—and to diverse goals, whether focused on clinical rehabilitation (e.g., improving gait symmetry) or research and performance assessment (e.g., quantifying joint angles or walking efficiency).[19], [20]. This user-centric approach encourages a more personalized exercise experience, as individuals can tailor their routines to match their gait aspirations and gradually increase intensity over time [21]. A significant limitation in existing self-paced algorithms is the difficulty of accurately predicting a user's intended gait patterns in real time, which is essential for adjusting the treadmill's behavior to support natural movement, effective rehabilitation, and personalized treatment plans.

To address this challenge, this thesis employs a Model Predictive Controller (MPC). MPC allows for the prediction and adjustment of gait dynamics in real-time by optimizing control actions based on a model of the human locomotion system. This predictive capability allows interventions to be dynamically tailored to the individual's needs, leading to effective outcomes such as a smoother, more natural, and comfortable self-paced treadmill experience—an essential factor in accurate and meaningful gait analysis. Smooth speed adjustments will minimize abrupt changes, reducing the risk of discomfort, instability, or potential injury, which is critical for patients recovering from conditions such as stroke, orthopedic surgeries, or neurological disorders [22]. By allowing the treadmill to seamlessly adapt to the user's pace, it can better mimic natural walking or running conditions, promoting more effective motor learning and retraining of gait patterns. This can lead to improved rehabilitation outcomes, as patients are able to practice walking in a way that closely resembles their natural movement, helping

them regain confidence and mobility faster [23]. The smooth speed transitions also reduce the cognitive and physical effort required to maintain balance, allowing patients to focus more on the quality of their movements, ultimately enhancing the effectiveness of the rehabilitation process [24]. Overall, the implementation of a smooth self-paced treadmill in rehabilitation settings can significantly enhance patient outcomes by providing a safer, more comfortable, and more effective environment for gait analysis.

1.2 Purpose of the Thesis and Specific Aims

The purpose of this thesis is to design a self-paced treadmill algorithm capable of smoothly and accurately responding to changes in a person's self-determined walking speed. The implementation of a self-determined walking speed treadmill requires a controller that adjusts the treadmill's belt speed according to the user's movements. While various controllers can achieve this, the focus of this thesis is on ensuring the smoothness of the treadmill's belt movements. Model Predictive Control (MPC) is well suited for this purpose due to its ability to predict future states and adjust treadmill speed in real time based on the user's position data—a key advantage in managing the dynamic and anticipatory nature of self-paced walking. As detailed in Chapter 3, MPC's predictive framework provides flexibility and responsiveness, making it a strong candidate compared to other control strategies. This predictive capability makes MPC ideal for maintaining smooth and responsive belt movements in real-time. To enable a treadmill to function as a self-paced device, real-time position data must be continuously fed to the controller, allowing it to make immediate adjustments to the treadmill speed based on the user's movements. This thesis considers two methods for

obtaining position data: marker-based and markerless. This thesis uses the term markerless to align with the convention used in the self-paced treadmill literature, in which it is defined as estimating the user's position using data from the treadmill's equipped force plates, rather than relying on attached devices or traditional marker-based motion capture. It is important to note that in other fields (particularly vision-based machine-learning), the term markerless refers to camera or infrared sensor-based position estimation. The marker-based method requires reflective markers to be attached to the user's body.

This thesis was achieved through the following Specific Aims:

Specific Aim 1: Develop a real-time treadmill speed regulation controller using MPC.

Specific Aim 2: Incorporate marker-based and markerless position estimation methods into the controller for enhanced treadmill performance.

Specific Aim 3: Conduct a comparative analysis of the markerless position estimation method against marker-based methods using MPC, through a pilot study with data collected from six subjects.

1.3 Significance of Study

The significance of this thesis lies in its use of an MPC controller to regulate the speed of a self-paced treadmill. This is the first study to apply an MPC controller in the context of gait analysis. The MPC controller has been designed for a self-paced treadmill to balance competing objectives—including ensuring that speed adjustments are smooth, that the user walks at their desired speed, and that the user does not walk

off the end of the treadmill— by predicting the user's next steps and dynamically adjusting the treadmill speed accordingly. This ensures a smoother and more tailored exercise experience, accommodating individual variations in gait and pace. Additionally, the MPC controller simplifies the tuning process for clinicians—such as physical therapists and rehabilitation specialists—by requiring fewer control parameters to adjust. These parameters are meaningful because they directly relate to how the treadmill responds to the user's gait. Overall, the use of an MPC controller enhances the usability, adaptability, and effectiveness of self-paced treadmills compared to traditional control methods, making them more suitable for rehabilitation, fitness training, and research studies.

An additional aspect of significance for this study is that most self-paced treadmills rely on markers attached to the user's lower back. However, these markers pose significant issues, such as being covered by clothing, falling off the user's body, and being expensive. While markers offer precision, they prove to be a cumbersome tool. Estimating the user's position using a markerless approach helps overcome these problems, providing a safe and efficient self-paced treadmill experience.

1.4 Overview of the Thesis Structure

The remainder of this thesis is structured as follows:

Chapter 2 provides a literature review on speed regulation controllers for self-paced treadmills, and marker-based and markerless position tracking systems.

Chapter 3 details the creation of a real-time MPC controller for self-paced treadmill

speed regulation.

Chapter 4 describes the development of an accurate markerless position estimation method.

Chapter 5 describes the experimental methodology, including setup and data collection procedures.

Chapter 6 presents experimental results evaluating position estimation methods.

Chapter 7 discusses the implications of these results and addresses limitations.

Chapter 8 provides a conclusive summary of the findings and their broader implications.

2 Literature Review

2.1 Benefits of Advanced Treadmill Technologies

There are two main ways in which advanced treadmills improve over conventional treadmills, and many systems include both of them. They include integration with virtual environments and treadmill speed regulations. Both advances are reviewed below.

2.1.1 Integration of Treadmill with Virtual Environments

A limitation of conventional locomotor training is that walking on a treadmill eliminates optic flow. Optic flow is the visual motion sensed by the eyes as the body moves through the environment, which is important for controlling gait speed [25], [26] and stride length [26], [27]. Incorporating a virtual environment into treadmill training restores the optic flow of forward motion and may increase immersion and motivation [28], making visual information regarding movement relevant and important for improving walking patterns [25]. For individuals recovering from stroke, treadmill training with an integrated virtual environment system encourages increased gait speed [29], endurance, and community participation [30]. However, it is critical for optic flow to match proprioceptive feedback from the limbs [31]. Any incongruence between leg velocity and optic-flow velocity causes the user to alter their gait characteristics in order to reduce the mismatch between competing visual and proprioceptive feedback. [31]. It is well known that movement patterns can be modified using visual or proprioceptive inputs (e.g., with prism glasses, virtual

environments, posturography platforms, split-belt treadmills). By aligning visual and proprioceptive feedback, incorporating a virtual environment in treadmill training can significantly enhance gait analysis accuracy and improve overall walking patterns for individuals.

2.1.2 Treadmill Speed Regulation Benefits

Regulating treadmill speed is critical for enabling natural gait patterns and enhancing user experience [32]. Self-paced treadmill training offers several advantages over overground gait training. It can be conducted in a compact space, allows for a higher volume of steps, and enables precise control of walking speed [33]. Moreover, since the subject remains stationary and often elevated, the therapist's positioning is better for providing assistance [34]. Additionally, overhead body weight-support systems can be used to relieve the subject of a portion of their weight, making it safer and enabling earlier training during the recovery period [6], [35]. In normal treadmill training the speed remains constant; however, self-paced treadmills permit accelerations and decelerations that can be performed [36]. Incorporating these dynamic adjustments enhances the naturalness and effectiveness of gait training on self-paced treadmills.

Various methods have been explored to achieve an overground walking experience by regulating treadmill speed, including feedback-controlled self-paced treadmills and integration of treadmills with virtual environments. Additionally, numerous studies have demonstrated that self-paced walking on treadmills more accurately simulates over-ground walking compared to traditional treadmill systems [9], [36], [37], [38], [39], [40]. Self- paced treadmills offer more natural and adaptive walking experiences

[8], [9], [12], making them valuable tools for gait analysis [38], rehabilitation [40], and virtual reality applications [37], [39]. Despite their advantages, challenges such as system complexity, cost, and the need for precise calibration and maintenance remain [38], [41], [42].

It is important to recognize that self-paced treadmills can also effectively address the limitations imposed by fixed walking speeds in these contexts. Traditional treadmills constrain users to a predetermined pace, which can negatively impact their natural gait patterns and overall performance. In contrast, self-paced treadmills' adaptability is particularly beneficial in environments where visual stimuli are varied, as it enables users to focus on their movement without the distraction of an unchanging treadmill speed [43], [44]. The ultimate goal for all for most users, particularly in rehabilitation settings, is to transition from treadmill walking to overground walking; therefore, the control strategy used in on the treadmill and overground walking modality must be similar to ensure that improvements made during treadmill walking transfer effectively to overground walking. Theoretically, if a person's walking speed on a treadmill matches their natural overground gait speed, and the treadmill belt moves at a constant speed, there should be minimal biomechanical differences between treadmill and overground walking. Self-paced treadmills, by allowing for dynamic speed adjustments, help in achieving this alignment, making the transition to overground walking more seamless [45]. The following sections review key studies that have contributed to this field highlighting their methodologies, findings, advantages, and disadvantages.

2.2 Methods Used to Regulate Treadmill Speed

Many studies have utilized traditional controllers such as proportional (P) feedback [37], to regulate treadmill speed. The P feedback includes a pelvic position controller designed to ensure users maintain a central position on the treadmill while they change their walking speed. This controller uses a simple proportional feedback mechanism, which can be less responsive and susceptible to disturbances than proportional-derivative (PD) or proportional-integral-derivative (PID) controllers. This proportional feedback control aims to maintain the user's position by adjusting the treadmill speed based on the user's location, but it may face challenges in quickly adapting to sudden movements or external influences [37]. The findings of [37], which utilized P feedback, align with the property of the P controller that makes the closed-loop system improve transient response. Therefore, while P feedback is useful, its limitations highlight the need for more advanced control methods to ensure optimal performance in varying conditions.

Some studies add extra features to their P controllers, including dead zones and gain-scheduling. The "gain as a function of position" [46] control scheme utilizes P feedback and implements two distinct algorithms to regulate treadmill speed. The first algorithm operates by dividing the treadmill surface into zones and adjusting the belt speed based on the user's position relative to a central "dead zone." When the user moves outside this zone, the treadmill increases speed incrementally across successive zones to help stabilize them, particularly at the beginning of their walk. As the user moves farther from the center, the last three zones trigger larger speed increases to quickly

prevent the user from reaching the treadmill's edges. This method focuses on counteracting inertia and friction forces to maintain balance during initial movements. In contrast, the second algorithm divides the entire walking surface into 95 equal regions, allowing for a smoother, more linear adjustment of the treadmill's speed [46]. As the user moves across these regions, the belt speed gradually increases in a uniform manner, ensuring consistent speed adjustments across the walking area. This approach provides a steadier and more stable walking experience by avoiding abrupt speed changes.

Proportional-Derivative (PD) feedback is the other class of common controllers which has been used to regulate the speed of a treadmill in many articles, e.g. [9], [38]. A PD feedback for a self-paced treadmill does speed correction proportional to the difference in position between the subject and the middle of the belt, and to the speed of the subject, with its Derivative- gain also a function of the position [38]. Proportional-derivative (PD) feedback is used to regulate treadmill speed by not only considering the subject's position error but also the rate at which this error is changing [47]. The P term measures the current error by comparing the subject's actual position with the desired central position on the treadmill. If the subject deviates from this central zone, the system detects the error and adjusts the treadmill's speed accordingly. The derivative term (D), on the other hand, predicts future error by assessing the rate of change of the current error [38]. This helps in smoothing out the adjustments and prevents overcorrection by dampening the response to rapid movements, ensuring more stable and responsive control compared to using proportional feedback alone. In other words, the proportional part of the algorithm reacts to the position error - how far the

subject is from the desired position - while the derivative part considers the rate of change of the position, which is how quickly the subject is moving away from or towards the desired position.

An extension to PD control is provided in [38], [39], where they augment PD control with a feed-forward term. This approach ensures that the treadmill can better predict and react to the subject's movements. By adding a feed-forward term, the system can predict the required speed adjustments based on expected changes in the subject's gait, resulting in a more responsive and smoother control. This combined method improves the treadmill's ability to maintain a central position and adapt to sudden movements, offering a more stable and efficient walking experience for the user. The study in [39] models the interaction between the walker and the platform as a second-order system by considering the position and velocity of the walker. The control law implementation involves two key quantities: the velocity and acceleration of the user, which are not directly measurable. To address this issue, the researchers developed two separate estimators to estimate the velocity and acceleration. After a short transient period, both estimates converge to their true values when the user is moving at a constant acceleration and velocity. This control scheme stabilizes the controlled treadmill and helps to update the visualization of the virtual scene correctly.

To date, a variety of self-paced modes have been developed based on standard PD-controllers, in which the belt speed is controlled by the feedback of the subject’s position on the belt along with their walking speed. Several variations are reported including a central zone [38], a feed-forward term in the control mechanism [47], or

differential gain as a function of position [46]. The extent to which PD feedback self-paced walking will resemble the natural behaviour of the subject is expected to depend on a specific feedback algorithm and its parameters. An optimum is likely to exist, with the unwanted effects of the accelerations and decelerations minimized, while physiological variability is facilitated [9]. The achievements of the papers that used PD feedback align with the expected properties, resulting in faster and more damped system responses.

The most common controller to regulate the treadmill speed up to date is proportional-integral-derivative (PID) [36], [39]. The PID feedback scheme employs three coefficients to regulate the treadmill's speed in response to varying conditions. This approach makes the controller design process more flexible, offering more free parameters to tune and meet performance criteria like smoothness and eliminating overshoot by considering the system stability as a controller designer [39]. The PID feedback mechanism operates by measuring the pelvis tracker's distance from the treadmill center. The feedback software then calculates the treadmill's desired speed to minimize this distance, incorporating the current distance, the rate of change since the last frame, and the cumulative distance. As the distance increases, the treadmill speed gradually rises to re-center the user. While greater proportional and derivative coefficients can quickly return users to the center, this often results in sharp, sudden movements that may be uncomfortable for inexperienced users. Thus, careful tuning of these coefficients is essential for a balance between responsiveness and comfort [36]. While PID controllers are prevalent in industry due to their versatility, they have notable disadvantages. Specifically, PID controllers react to instantaneous data and do

not account for the effects of the control law on the future behavior of the closed- loop system.

No self-paced algorithms have used MPC, but it is a commonly used controller in many industrial applications. It is particularly well suited to this application due to its predictive capabilities. While both MPC and PID controllers are popular in industry, MPC is distinguished by several key differences. The most important difference is that MPC uses a mathematical model of the system to predict future behavior over a specific time horizon and optimizes the control signal by solving an optimization problem at each step. This approach allows MPC to predict the system's future output and adjust the control signal to minimize future errors. Additionally, MPC can explicitly handle input and output constraints during the optimization process, making it highly effective in complex control scenarios [48].

2.3 Overview of Markerless and Marker-Based Motion Tracking Systems

To regulate the speed of a self-paced treadmill smoothly, the controller needs to know the center of mass (CoM) of the participant. The CoM is the point at which the mass of the object appears to be concentrated, and it represents the point at which the total effect of gravity acts on the object [49]. In the context of rehabilitation, accurately estimating the CoM is vital for analyzing and improving human movement, balance, and posture [50], [51]. Rehabilitation professionals use CoM estimation to design effective therapeutic interventions (e.g., balance training, fall prevention programs, and gait rehabilitation exercises) [52], [53], to create customized prosthetics [54], [55], and to

develop exercise programs tailored to individual needs [56], [57]. By understanding the CoM relative to the base of support, therapists can more accurately assess a patient's gait and balance. This allows them to identify areas of weakness or instability when the CoM moves too far outside the base of support, which can lead to loss of balance. With this information, therapists can implement targeted strategies to enhance functional mobility, improve balance control, and prevent falls by ensuring that the CoM remains within a stable range relative to the base of support during movement [58], [59]. This application is particularly important for patients recovering from injuries, surgeries, or those with conditions affecting their musculoskeletal or neurological systems, ultimately contributing to a more efficient and successful rehabilitation process [60], [61]. Overall, the accurate estimation of CoM is a cornerstone of effective rehabilitation, enabling tailored interventions that significantly enhance patient outcomes.

Using an accurate method to estimate or access the CoM is vital for the controller to determine the appropriate speed adjustments for seamless treadmill operation. The most common approaches for estimating the CoM in self-paced algorithms include:

- Marker-based approaches, which attach reflective markers to the user's body to estimate the CoM.
- Model-based markerless approaches, which use an instrumented force plate to gather force and pressure data, which can then be converted into position information.
- Modeless markerless approaches. These approaches use sensors such as ultrasound

or inertial measurement units to estimate position.

Many recent papers have explored video-based markerless motion-capture using deep-learning approaches to estimate skeleton structure [62], [63] but these approaches have yet to be used for real-time control of self-paced treadmills; likely because temporary glitches in current approaches could lead to dangerous control actions.

2.3.1 Marker-based Approaches

Most self-paced treadmills rely on reflective markers to track the user's position in real time. Motion Capture (MoCap) cameras are sophisticated tools used to estimate the position and movement of objects or individuals in three-dimensional space. MoCap systems typically involve multiple cameras arranged around the area where the motion will be captured. These cameras can be infrared or optical. The cameras are calibrated to ensure they have a common reference frame, allowing accurate three-dimensional position estimation. Reflective markers are placed on key anatomical points of the subject's body. These markers reflect infrared light emitted by the cameras, which is then captured by the cameras. The cameras capture the reflected light from the markers, recording their positions in each frame. The system then triangulates the position of each marker using data from multiple cameras, calculating the three-dimensional coordinates of each marker in space. The captured data is processed using specialized software that reconstructs the motion of the markers in three dimensions. The software connects the markers to create a digital representation of the subject's movements, often overlaid on a skeletal model.

There are several limitations to marker-based approaches. These include potential

discomfort of markers placement, the potential for markers occlusion leading to inaccuracies, the limited flexibility in terms of user compatibility, the complexity and time required for setup, the dependence on controlled environmental conditions, and the potential for the markers to fall off [64] [65]. These limitations highlight the field's continued reliance on marker-based systems underscores the need for more user-friendly and versatile solutions.

2.3.2 Model-based Markerless Approaches

Recent advancements have introduced model-based markerless self-paced treadmills, which use estimation models to monitor and interpret users' movements without the need for external sensors or markers [66], [67]. Force plates measure the ground reaction forces and moments exerted by a person standing, walking, or performing other activities. In biomechanics, the Center of Pressure (CoP) is defined as the point of application of the resultant ground reaction force vector on the surface of contact, typically a force plate. It represents the location on the ground where the total sum of all pressure fields (forces) act, leading to a single point of application. The CoP is a critical parameter for analyzing balance, posture, and gait, as it reflects the body's response to maintain stability by adjusting the forces exerted by the feet on the ground [68]. The CoP is calculated using the moments (M_x, M_y) and the vertical force (F_z) as follows,

$$CoP_x = -\frac{M_y}{F_z}, \tag{1}$$

$$CoP_y = -\frac{M_x}{F_z}. \tag{2}$$

The CoP is the location of the resultant reaction force relative to the base of support. In quiet standing, the center of gravity sways around near the center of the base of support, while the CoP moves even faster to push the weight force back to the center of the base of support. The total movement and velocities of these two variables are potent measures of a person's balance.

The total movement and velocities of these two variables are potent measures of a person's balance [69]. During quiet standing or slow movements, the CoM and CoP are closely related, but they are not the same. The CoM represents the weighted average position of body mass, while the CoP is the point where the resultant force acts. For dynamic activities like walking or jumping, the CoM moves relative to the CoP [68]. The relationship between CoM and CoP can be modeled using the inverted pendulum model, where the body is considered, a pendulum pivoting around the CoP. Force plate-based methods benefit from providing accurate measurement of ground reaction forces and moments, but it suffers from requiring expensive equipment and dedicated laboratory space and is limited to the measurement area of the force plates [38], [70].

Model-based markerless approaches for estimating the CoM utilize mathematical or computational models to predict the CoM based on the body's physical characteristics [71]. These methods involve creating a detailed model of the human body, often segmented into multiple parts like the torso, arms, and legs, each with assigned properties such as mass and length [72]. By incorporating static data (e.g., segment dimensions) and dynamic data (e.g., joint angles and external forces), these models

compute the CoM through various equations. For instance, in a segmental model, the CoM is calculated as a weighted average of the CoMs of individual segments, with weights corresponding to their masses. This approach allows for accurate estimation of the CoM in both static and dynamic conditions, making it valuable in fields such as biomechanics, sports science, and rehabilitation, where precise understanding of body mechanics and movement is crucial [73]. A general overview of model-based methods used to estimate the CoM is presented.

2.3.3 Modeless Markerless Approaches

There are a variety of modeless markerless approaches. They include:

- **Inertial Sensor-Based Methods**. Inertial Sensors offer benefits such as portability and ease of use. However, they suffer from two main issues: susceptibility to sensor drift over time and sensitivity to sensor placement and orientation, which can affect accuracy [74].

- **Computer vision approaches**. This approach uses regular or depth cameras to estimate user position without physical markers, form a significant category of markerless tracking systems. These methods offer advantages in flexibility and user comfort compared to marker-based systems or sensors embedded in equipment, though they face challenges such as occlusion, varying lighting conditions, and computational demands.

- **Ultrasound range finders.** This approach works by emitting sound waves

from a transducer, which then bounce off a passive reflector attached to the user's body. The time it takes for the sound waves to return to the transducer is used to calculate the distance between the sensor and the reflector, allowing for the determination of the user's position in space. This method typically involves placing the ultrasound device in a fixed position while the user moves, allowing the system to track the movement of the reflector on the user's body, typically aligned with the chest to approximate the CoM [38].

Ultrasound-based CoM estimation is advantageous because it is non-invasive, relatively cost-effective, and can be employed in real-time, making it suitable for dynamic environments like rehabilitation or gait analysis. Although ultrasound sensors can be sensitive to environmental factors in general, in controlled environments like rehabilitation labs where sensor location and angle remain fixed and temperature and humidity changes are slow, these effects are expected to be minimal. The ultrasound range finders may also face challenges in maintaining accuracy over longer distances or with non-ideal surface textures on the body, potentially leading to errors in position estimation. Moreover, while ultrasound can track movement well in two dimensions, it may struggle to provide reliable data for CoM estimation in three-dimensional space without additional sensors or calibration techniques.

2.3.4 Outcomes of Self-Regulating Treadmill Approaches

Recent studies have focused on enhancing the functionality and effectiveness of self-paced treadmill systems and motion capture technologies in gait analysis and

rehabilitation. Yoon et al. developed an algorithm that accurately estimates walking speed based on body movement and applies this to control the treadmill's speed dynamically [75]. Canete et al. designed an algorithm that dynamically adjusts the treadmill speed based on the user's walking behavior, aiming to replicate natural walking conditions more accurately. Wiens et al. [76] compared the markerless system with a traditional marker-based system in terms of joint kinematics. Wang et al. focused on improving treadmill speed adaptation and reducing acceleration ripples to enhance the user's walking experience. The novel aspect of this study is the introduction of a virtual force and a virtual force moment balance kinetic model to design the treadmill's acceleration [77]. Song et al. evaluated a novel markerless motion capture system for its precision and stability in clinical environments. Key novel contributions include markerless technology: the system eliminates the need for physical markers, making it more practical and less intrusive for clinical use, real-time analysis: the system provides real-time data processing, enhancing its utility for immediate clinical feedback and decision-making. The findings indicate that the markerless system offers comparable accuracy to traditional methods, with added benefits of ease of use and reduced preparation time, making it a viable option for clinical motion analysis [78].

3 Aim 1: MPC Controller Design

To control the treadmill speed and enable it to be self-paced, a controller is required to modulate the treadmill speed dynamically [48]. Model Predictive Control (MPC) is commonly used in industrial applications due to its ability to handle multi-variable control problems, optimize performance over a horizon, and incorporate constraints, but has not yet been applied to self-paced walking. MPC has been employed for this purpose due to its ability to predict future states and make decisions accordingly, and operates based on four main components [79], [80], [81]:

1- **Cost Function (Terminal Cost):** Quantifies system performance based on specific criteria, penalizing deviations from desired states to ensure the system reaches its desired final values.

2- **Prediction horizon:** The time interval over which the future behavior of the system is predicted, determining how far into the future the controller looks to make decisions.

3- **Control horizon:** The duration within the overall prediction horizon during which the controller actively adjusts control inputs.

4- **Update mechanism:** MPC operates in a receding horizon fashion, solving the optimization problem at each time step and applying the first element of the optimal control sequence to the system.

3.1.1 Intuitive Discussion

Consider driving a vehicle on a straight road with normal visibility (let's say 100 meters). The driver plans their course for the next 100 meters, better route planning, balancing values of gas consumption, early obstacle detection, and ride smoothness. They implement the first step of this plan while continually adjusting based on new information. Of course, if a deer jumps out unexpectedly, they have not committed to their entire sequence of actions, and they can revise their plan. MPC is a control strategy that acts in similar way, enables planning several steps ahead but only commits to the first step, unlike controllers that only consider the current state without predicting the consequences of actions across a horizon.

3.1.2 Mathematic Discussion

As implied by its name, MPC requires a model, so consider a continuous-time linear system described by the dynamics (3),

$$\dot{x}(t) = Ax(t) + Bu(t), \tag{3}$$

where $x(t) \in \mathbb{R}^n$ is the state vector at time t, $u(t) \in \mathbb{R}^m$ is the control input, $A \in \mathbb{R}^{n\times n}$ is the state matrix, and $B \in \mathbb{R}^{n\times m}$ is the input matrix.

The scalar quadratic cost function for MPC over a finite time horizon T_f, which refers to the future prediction period over which the control algorithm optimizes its decisions, is given by (4),

$$J = \int_0^{T_f} \left[\left(x(t) - x_{ref}(t)\right)^T Q \left(x(t) - x_{ref}(t)\right) + u(t)^T R u(t) \right] dt. \tag{4}$$

Here, $Q \in \mathbb{R}^{n\times n}$ and $R \in \mathbb{R}^{m\times m}$ are positive definite weighting matrices, and $x_{ref}(t)$ is

the reference trajectory for the state. The Q matrix influences the importance of minimizing deviations in the state trajectory from the reference, thus affecting the system's response to state variations. On the other hand, the R matrix dictates the significance of minimizing deviations in the control input, influencing the controller's effort to adjust and optimize control actions. The careful tuning of Q and R matrices is essential for achieving desired performance and stability in MPC applications.

Subject to (3) and potential state and input constraints, the MPC optimization problem aims to minimize J,

$$\min_{u(t)} J,$$

$$\text{Subject to } \dot{x}(t) = Ax(t) + Bu(t), \tag{5}$$

and additional constraints on states and inputs.

The solution to this optimization problem provides a sequence of control inputs that optimize the performance criteria over a finite time horizon. Unlike classical control strategies such as proportional-integral-derivative (PID) control, MPC can accommodate an unlimited range of optimization functions and evaluate trade-offs across a horizon. The fact that it only executes the first action before recalculating the optimal trajectory ensures that it is robust to uncertainty caused by the user's interactions. MPC accordingly provides a theoretically robust control strategy that interfaces well with the types of values clinicians would like to optimize in a self-paced controller.

3.2 Real-time Treadmill Speed Regulation Controller Using MPC

To design an MPC controller, we first need a model of a person's position while walking on the treadmill. To have the person's position on the treadmill, we need a model of the person walking on the treadmill. In this context, we will assume that the person can be effectively modeled as an inverted pendulum [82]. Additionally, it is assumed that the treadmill can be represented as a massless, frictionless cart. That is a reasonable assumption because the treadmill we will use is regulated by a high-gain feedback loop that enables it to achieve the targeted speed with a time constant of 0.06 ms. Consider the free-body diagram that has been illustrated in Figure 1.

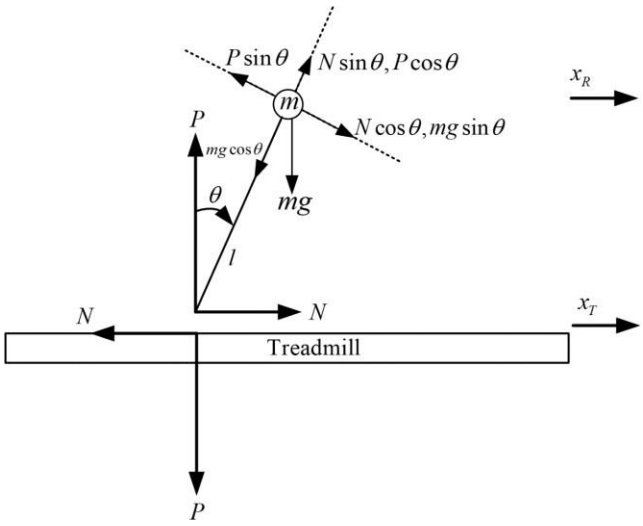


Figure 1. Free body diagram of a person with gravity and ground reaction forces shown

There are three coordinates reference frames and associated horizontal coordinate x: the treadmill, the person relative to the treadmill, and the world reference frame, denoted by x_T, x_R, and $x_w = x_R + x_T$, respectively. In Figure 1, N represents the input force generated by the person. The output involves the kinematics of the treadmill, wherein each of x_T, $\dot{x}_T$ or $\ddot{x}_T$ can be chosen, and the others are determined by integration or differentiation. l is the height of the person's CoM on the treadmill. θ is the angle of

the person with respect to the vertical axis, and m is the mass of the person. Applying the first dynamical equation to the free body diagram in the horizontal direction, we obtain (6)

$$N = m\ddot{x}_T\left(1 - \frac{l}{l + \frac{I}{ml}}\right). \tag{6}$$

It is important to note that to derive (6), certain safe assumptions such as considering the person remains reasonably upright $\theta \cong 0$ and x_R is small relative to the base support, were made, given that their impact was deemed negligible [70].

In this study, the cost function and prediction horizon are defined as follows,

$$J = \alpha_1(V^2 + 1)x^4 + \alpha_2\Delta u^2, \tag{7}$$

$$N_x = \alpha_3, \tag{8}$$

$$N_u = \alpha_4, \tag{9}$$

where $\alpha_1 \in \mathbb{R}^+$ and $\alpha_2 \in \mathbb{R}^+$ are prioritization coefficients, V is the velocity, x is the position, u is the control variable, N_x is the prediction horizon, N_u is the control horizon, and $\alpha_3 \in \mathbb{R}^+$ and $\alpha_4 \in \mathbb{R}^+$are constants. The larger values $\alpha_i, i = 1,2$ the greater the impact on the value of the cost function. The first term of the treadmill will be used to ensure that if the person's position is far away from our set point and their speed is fast, a high-speed control signal is inputted to maintain them in their desired position. The second term of the cost function J ensures that the person's position on the treadmill will be penalized if they are far away from our set point, regardless of their speed. The second coefficient, α_2, acts like a low-pass filter. Therefore, it will

provide a much smoother next speed if a greater value of α_2 has been selected. It is worth mentioning that a very large value of α_2 will result in a slow reaction to the person's movement on the treadmill and might feel uncomfortable. For larger absolute values of the error, position plays a more influential role in the cost function. Additionally, a larger $\alpha_3 \in \mathbb{R}^+$ allows the controller to better capture the system's future behavior, and a larger $\alpha_4 \in \mathbb{R}^+$ provides more freedom for the controller to optimize future control moves.

4 Aim 2: Development of an Accurate Markerless Position Estimation Method

Although certain studies have explored markerless solutions, they encounter challenges associated with the noisy estimation of people's positions [36], [73], [83]. In this context, an algebraic equation will be employed to directly relate CoP to CoM without numerical drift [70], [84], [85], [86],

$$CoM = CoP + a\frac{h}{g}. \tag{10}$$

This technique establishes the relationship between the CoM in the anterior-posterior direction, to the CoP using (10), where g is the acceleration due to gravity, a is the acceleration, and h is the height of the person's CoM. Linear acceleration is calculated from the total force applied to both belts in the anterior-posterior direction, F, and the user's mass, m, such that,

$$a = \frac{F}{m}. \tag{11}$$

CoM height, h, is computed as a fraction of the user's height, l, in [87] such that,

$$h = 0.551 \times l. \tag{12}$$

By integrating the human model as an inverted pendulum, the MPC controller, a realistic model of a person walking on the treadmill, and the position estimator, the closed-loop block diagram of the system is depicted in Figure 2.

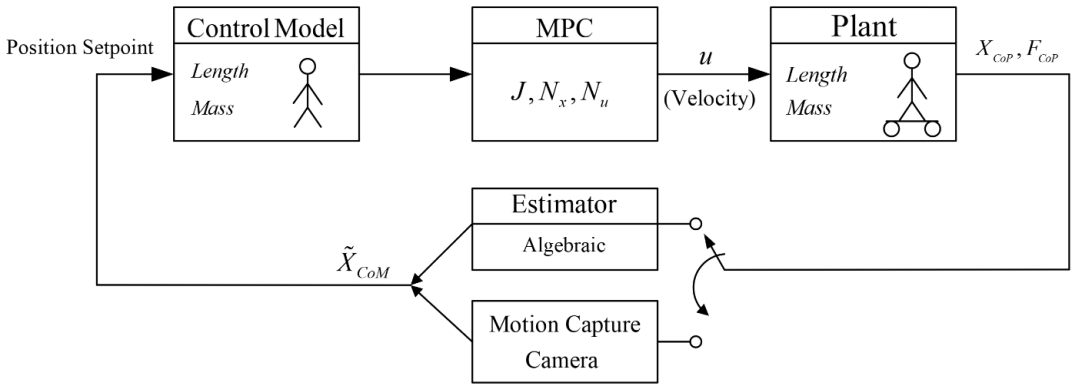


Figure 2. Control block diagram of the self-paced markerless treadmill

Figure 2 demonstrates the details of how the self-paced treadmill operates. In our control model block, we use an inverted pendulum to represent a person, which defines the nominal system for our controller. The MPC controller optimizes the cost function based on this model, considering both the control horizon and prediction horizon, and outputs the velocity as the control input. In real life, the plant, which describes a person walking on the treadmill, will have the sequence of u applied to them, allowing them to walk at their preferred pace. The treadmill's force plates will send X_{CoP} and F_{CoP}. We have two choices for estimating the position $\tilde{X}_{CoM}$: using a motion capture camera or an algebraic estimator. This procedure continues until the user decides to stop, at which point the treadmill smoothly brings them to the position setpoint and stops the treadmill's belts.

5 Aim 3: Methodology

5.1 Experimental Design

This study investigates the development and evaluation of a real-time treadmill speed regulation controller using MPC. The primary goal is to test the feasibility of integrating MPC to adapt treadmill speed responsively to user movements, aiming to create a safer and more comfortable treadmill experience. The experimental protocol was reviewed and approved by the Research Ethics Board (REB) under approval number REB 2024-044. All participants provided informed consent prior to participation, ensuring they were fully aware of the study's procedures, risks, and benefits. The experiments were conducted using the CAREN system, a motion platform that integrates treadmill and motion capture technologies. The dynamics of the CAREN system—such as platform responsiveness and latency—were carefully considered in the design and tuning of the MPC models to ensure accurate speed adjustments and effective synchronization between the controller and treadmill environment.

5.2 Participants

In this section the number of participants, their age, gender, height, and weight in this study will be discussed.

5.2.1 Sample Size

We recruited six participants for this exploratory study. No power analysis was

performed, given that it was an exploratory study.

5.2.2 Apparatus and Environment

The investigational device used in this study was a Computer Assisted Rehabilitation Environment (CAREN) System Treadmill [88]. The CAREN system is a sophisticated multi-sensory platform designed for rehabilitation, research, and training purposes [89]. It integrates various technologies, including motion capture, virtual reality, force plates, and treadmill systems, to create a highly immersive and controlled environment for assessing and improving human movement and function [90], [91]. The CAREN system enables clinicians, researchers, and therapists to conduct comprehensive assessments, develop personalized rehabilitation programs, and provide real-time feedback to patients or subjects. The CAREN treadmill works the same as a normal gym treadmill, except the belt speed can be adjusted based on the user's walking speed. To ensure the safety of the participants, they were connected to the treadmill by a safety bridge, and a harness was attached to them while they were on the treadmill.

In this study, a trial refers to one complete walking attempt under a specific test condition. Each participant, an individual who volunteered for the study and will be called a subject, completed 3 trials, including standard, algebraic, overground. In each trial, subjects walked at their own pace for 5 minutes while interacting with a large wrap-around screen that presented a New York City landscape demonstrated in Figure 3. Also, the cameras of the Motion Capture system can be seen at the bottom and sides of the screen, and the reflections from the markers can be seen on the hips in Figure 3. During each trial, participants were instructed to respond to the countdown timer as

they would in a real-world scenario to determine whether to continue walking across the street, accelerate to make it on time, or stop and wait for the next walk signal.

The treadmill speed and the visual cues automatically updated in real time using the MPC algorithm, which adjusts the speed based on the user's current position and movement to provide smooth and responsive control. The walking sessions simulation included features such as traffic lights, pedestrian walking, and barriers. Subjects were given a two-minute break between trials. Also, in all 3 trials the markers plate was placed on the participant's lower back. During each trial the following data was collected:

- Force data [N]: measured using the embedded force plates in the CAREN treadmill, which capture ground reaction forces during walking.
- CoP data from the force plates: derived from the force plate data and represents the point of application of the resultant ground reaction force.
- CoM from markers: estimated using motion capture markers placed on the participant's body, tracked by the CAREN system's integrated optical tracking setup.
- Controller speed data [m/s]: captured from the treadmill control module, representing the real-time belt speed as regulated by the self-paced control algorithm.



Figure 3. An example participant seen walking on the CAREN system in front of the simulated New York walking scene

5.3 Ensuring Gait Changes

The test featured crosswalk timers at each intersection in the New York simulation that were designed to mimic real-world crosswalk timers. A green timer represented a ‘walk light’, signaling for the participant to continue walking across the intersection. A red timer indicated that the participant should stop and wait for the timer to turn green before continuing to walk across the intersection. Finally, a white timer with a countdown indicated how much time the participant had to cross the intersection before

the timer would change to red. The green state was presented at 15% of intersections. For the remaining 85% of the time, two distinct schemes for the countdown timer were implemented, utilizing the following formula to prompt participants to take appropriate actions:

$$t = \frac{\Delta x}{v}\alpha, \tag{13}$$

where t represents the amount of time available for a user to cross, Δx denotes the distance from the participant to the beginning of the crosswalk, v indicates the user's current velocity, and α is a weighting coefficient. All variables were accurately measured and calculated while ensuring that the countdown timer remained within the participant's visible range. Specifically, a weighting coefficient of $\alpha = 0.9$ was employed for 35% of the time to encourage users to accelerate while crossing the cross walking, whereas a coefficient of $\alpha = 0.6$ was utilized for the remaining 50% to prompt them to come to a stop. The purpose of the 50% and 35% probabilities for red and yellow lights was to simulate real-world conditions, requiring participants to stop or speed up at several crosswalks, mimicking the need to adjust speed when approaching an intersection. Participants' responses depended on their decisions: they could choose to speed up to pass the crosswalk or slow down and stop. Figure 4 shows how the traffic light and count down timer works in each trial.

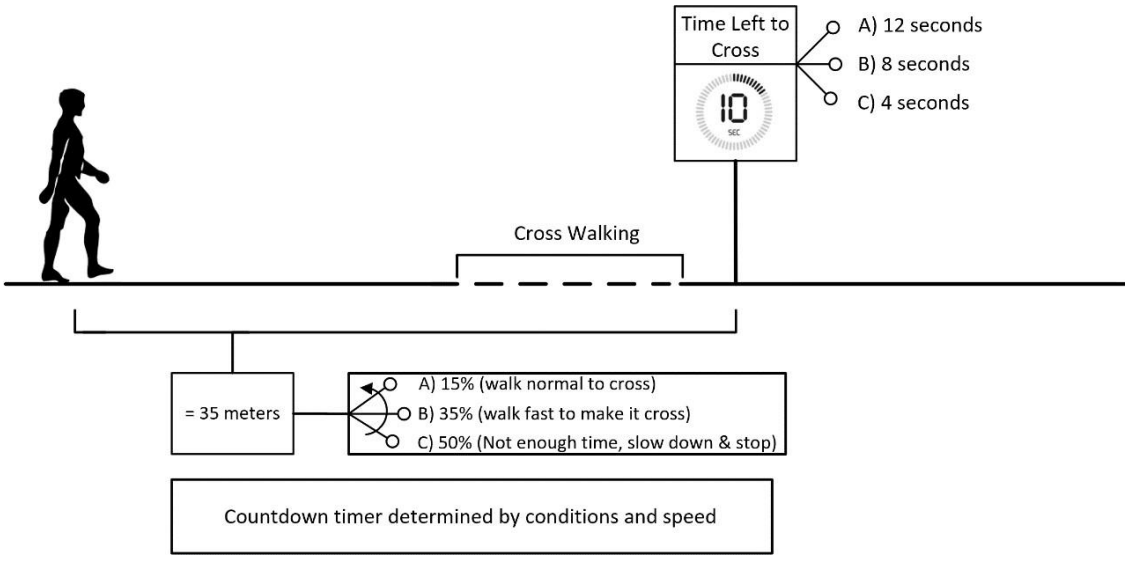


Figure 4. Schematic representation of the traffic light and countdown timer used in each trial.

Figure 4 illustrates that when a participant is 35 meters away from the next traffic light, the countdown timer begins if the traffic light is not green. The countdown timer is initialized based on one of the three conditions shown in Figure 4 and the participant's speed. The time allocated to the participant results in them walking at a normal pace to cross 15% of the time, walking quickly to make it across 35% of the time, and slowing down to stop 50% of the time.

5.4 Trials

The study consisted of three trials in randomized order:

- **Normal Treadmill Trial.** In this trial, the participants were instructed to disregard traffic signs. The beginning of the 2-minute familiarization period for this trial was used to find each participant’s comfortable walking

speed. To do this, the treadmill speed was increased from 0 by 0.05 m/s increments until the participant reached a self-determined comfortable walking speed, which was recorded. Subsequently, the operator further increased the treadmill speed until the participant indicated they felt they were walking at a brisk pace. The speed was then gradually decreased to establish a second comfortable walking speed for the participant. This speed was also recorded. The treadmill speed was then set to the average of these two comfortable recorded speeds for the remaining 5-minute portion of the trial.

- **Marker-based Treadmill Trial.** In this trial, the participant was notified to follow the traffic signs and the countdown timers. To get used to this, they had two minutes of familiarization. After the two-minute familiarization, their data was collected for five minutes. They were informed that the treadmill would react to their movements: if they walked slowly, the treadmill belts would move slowly; if they walked fast, the belts would move fast; and if they stopped or did not move, the belts would not start moving. The participants' position in this trial was estimated by markers attached to their lower back.

- **Markerless Treadmill Trial.** This trial was conducted in the same manner as the Marker-based treadmill trial, except that the participants' position was estimated using a markerless approach based on an algebraic method applied to force plate data, rather than using motion capture markers.

The trials were conducted in a randomized order for each participant to minimize order effects. This randomized order was made to avoid bias when participants responded to the Visual Analog Scale (VAS) after completing each trial, and VAS form has been added to Appendix A. Figure 5 illustrates the procedure for completing the trials for each participant.

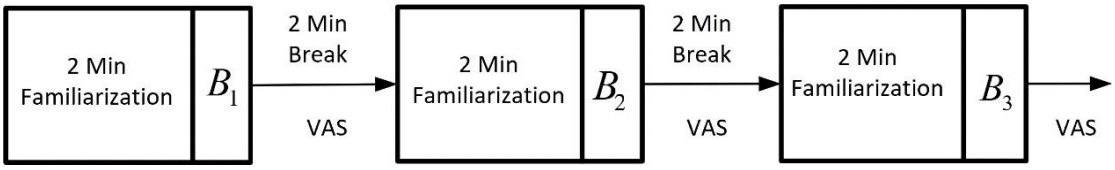


Figure 5. Randomized order of trials completion

In each block, $B_1, B_2,$ and B_3 represent one of the following trials: normal treadmill, markerless self-paced treadmill, and marker-based self-paced treadmill. Each participant underwent a 2-minute familiarization period for each trial to acclimate to the specific trial condition. Following this familiarization, participants walked on the treadmill for 5 minutes while data was collected. After each trial, participants had a 2-minute break during which they were asked to complete the VAS questionnaire. This procedure was repeated three times for each participant.

5.4.2 Inclusion and Exclusion Criteria

he participants' demographic details are presented in the following table, and the demographic form is provided in Appendix B. 83% of the participants were female, and 17% were male. The prescreening document is provided in Appendix C.

Table 1. Demographic details of the participants

	Age	Height (cm)	Weight (kg)
Interval	[19,25]	[153,188]	[42,79]
Average	21.5	169.2	58.7
Standard deviation	2.1	11.8	13.3

5.4.3 Examination of Speed Variability Within Trials

For the Marker-Based and Markerless trials, four distinct conditions were defined based on real-time interactions with countdown timers and traffic signals within a 6-second window, and their speed medians have been reported:

- **Speed During Slow (MSDS):** Recorded when the countdown timer signals the need for the participant to slow down and stop at a red traffic light. The data was collected during a 6-second window immediately before the participant came to a complete stop.
- **Speed During Fast (MSDF):** Recorded when the countdown timer prompts the participant to increase speed, often resulting in speeding up to cross the intersection before the light turns red. The data was collected over a 6-second window, starting exactly 6 seconds before the participant passed

the countdown timer.

- **Speed During Normal (MSDN):** Recorded when approaching a traffic light with a countdown timer with enough time remaining to ensure safe crossing at the current speed without the need for speed adjustments. The data was collected over a 6-second window, starting 3 seconds before and ending 3 seconds after the traffic light passed.
- **Speed During None (MSD none):** Recorded when no countdown timer is present, indicating a standard speed condition. The data was collected over a 6-second window, starting exactly 3 seconds after the participant passed the traffic light.

These conditions were investigated to analyze participant responses and adjustments in speed relative to environmental cues provided by countdown timers and traffic signals.

5.5 MPC Parameters

Users are most sensitive to changes in platform speed when they are standing still [32]. Consequently, the most difficult situation for unobtrusive platform control is when the user abruptly stops walking. In this case, the treadmill must decelerate sufficiently fast to keep the user within the boundaries of the platform and then bring the user back to its center. However, it should not stop too quickly because this would destabilize the user. To understand this, consider the analogy of a person walking forward in a moving train. As long as the train is moving at a constant speed, accelerations and decelerations during walking are unproblematic. However, if the train stops at the same moment as

the person stops walking, the person's momentum would catapult them forward. Abrupt changes in treadmill velocity would have the same effect and, besides endangering the user (by the risk of falling), would disrupt the immersiveness of the virtual environments. Therefore, changes in treadmill speed should be kept as small as possible. Depending on how fast the user is walking before stopping and what their position on the platform is, these two constraints of keeping the person within the walking area and reducing changes in treadmill speed may be incompatible. Therefore, choosing appropriate coefficients for MPC controller is vital since the cost function (7), prediction horizon (8), control horizon (9), and sampling time parameters significantly affect the system response. These parameters were heuristically tuned based on preliminary user feedback provided by the co- investigators. The smoothness of the speed is directly related to these parameters, but the system remains stable as long as (14) and (15) is greater than zero. The following parameters were used for the controller,

$$\alpha_1 = 12, \tag{14}$$

$$\alpha_2 = 0.4, \tag{15}$$

$$N_x = 0.92sec, \tag{16}$$

$$N_u = 0.9sec. \tag{17}$$

A sampling time of $h = 0.04$ seconds was chosen. The prediction horizon of 0.92 seconds indicates that the participant's position on the treadmill is estimated 0.92 seconds into the future, based on the methodology proposed in Section 3.2. The control horizon of 0.9 seconds implies that we are generating our control input sequence for

the subsequent 0.9 seconds, though only the first entry of this sequence is applied at each sampling instance.

5.6 Data Analysis

5.6.1 Primary Outcome Measure

The primary outcome measure was a series of visual analog scales asking participants after each trial how various aspects of the experience were compared with normal walking. Each of these questions was compared between trials (e.g., normal treadmill, marker, and markerless) using robust factorial repeated measures ANOVA [92] and, where differences were noted, a post-hoc Bonferroni [93] test was done to assess which conditions yielded significant differences ($p < 0.05$).

5.6.2 Secondary Outcome Measure

The secondary outcome measure was an analysis of the variation in walking speed between the various controllers. Due to the dynamic environment in which participants had to speed up to cross street intersections before a red light, or slow down to wait for the next green light, the ability to naturally vary speed was important. For each of the three algorithms, data was labeled according to four categories: steady-state walking (the pedestrian light is green, and there is plenty of time to cross the intersection), slowing down (average speed in the window 6 seconds before a red-light where subjects were given 60% of the time necessary to cross the street at their typical speed), speeding up (average speed in the window 6 seconds before a red-light where subjects were given 90% of the time necessary to cross the street at their typical speed), and

none (there are no traffic lights ahead, and the participants' speed is not influenced by traffic light conditions). This condition has been averaged over a 6-second window, starting 5 seconds after the participant passed the green light, with no traffic lights visible during the subsequent 6 seconds.

5.6.3 Exploratory Outcome Measure

The markerless estimate of the CoM was compared with the gold-standard marker-based CoM using the coefficient of determination (R^2), which is a statistical measure that represents the proportion of the variance in a dependent variable that is predictable from one or more independent variables.

6 Aim 3: Comparative Analysis of The Markerless and Marker-based Position Estimation Results

The purpose of this study was to design a self-paced treadmill that smoothly adjusts to the person's speed. There were two methods for achieving a self-paced treadmill: marker-based and markerless. We also examined the conventional treadmill, where individuals can set their desired speed and begin their workout. We aimed to determine the level of control participants felt over their speed when they were forced to stop or speed up during each trial. To evaluate this, we collected their force plate data, CoM, CoP, treadmill speed, their distance to the traffic light, and the state of the light across three conditions. Additionally, after each trial, VAS scores were collected from participants during their 2-minute break.

6.1 Visual Analog Score Results

The VAS questionnaire, which has 6 questions, is provided in Appendix A. Every participant filled in the VAS after the end of each trial, and their feedback was quantized from the analog scale into digitally quantized values that include fractional (non-integer) steps, within a range of zero to ten. In the first four questions, zero denotes an answer of "No Control" and ten reflects "Complete Control". For questions five and six, zero reflects "Not at all" and ten reflects "Felt the same". In the following, Figures 6 to 11 demonstrate the results.

Question 1: please mark how this trial felt whenever you were standing still during the trial. VAS scores are shown in Figure 6.

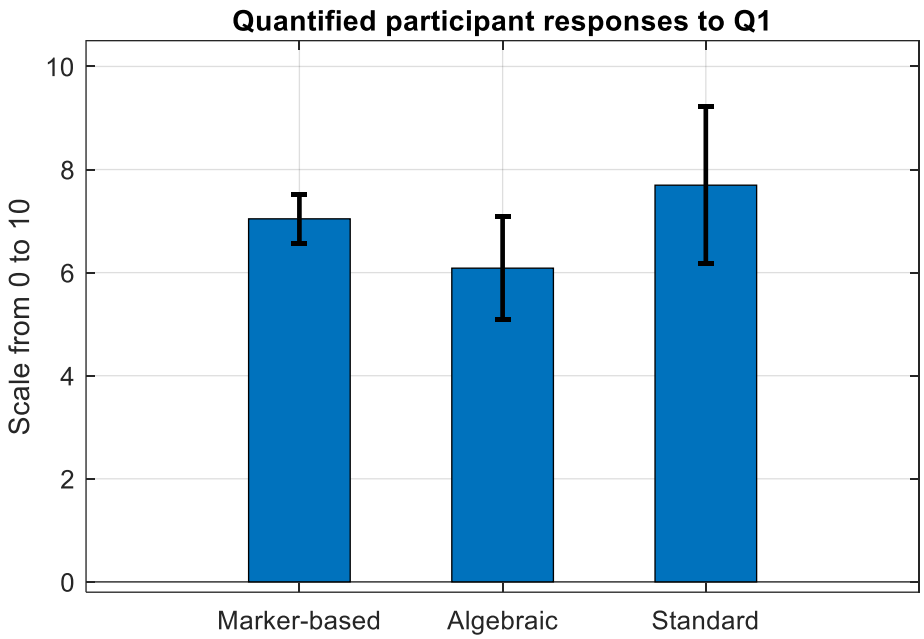


Figure 6. Quantified participant responses to question 1 (0 = No Control, 10 = Complete Control)

Marker-Based Trial: Participants generally felt comfortable standing still, with a high mean score of 7.05 and a low standard deviation of 1.15, indicating consistent responses.

Algebraic Trial: The mean score was 6.09 with a higher standard deviation of 2.43, suggesting more variability in participants' comfort levels.

Standard Treadmill: The mean score was 7.69, with a high standard deviation of 3.71, indicating mixed feelings among participants.

Robust factorial repeated measures ANOVA was applied, and the p-value for three

different conditions is 0.583, meaning that we cannot reject the null hypothesis for this pilot data that one of the methods was statistically different than the others.

Question 2: please mark how this walking trial felt whenever you started and stopped walking. VAS scores are shown in Figure 7.

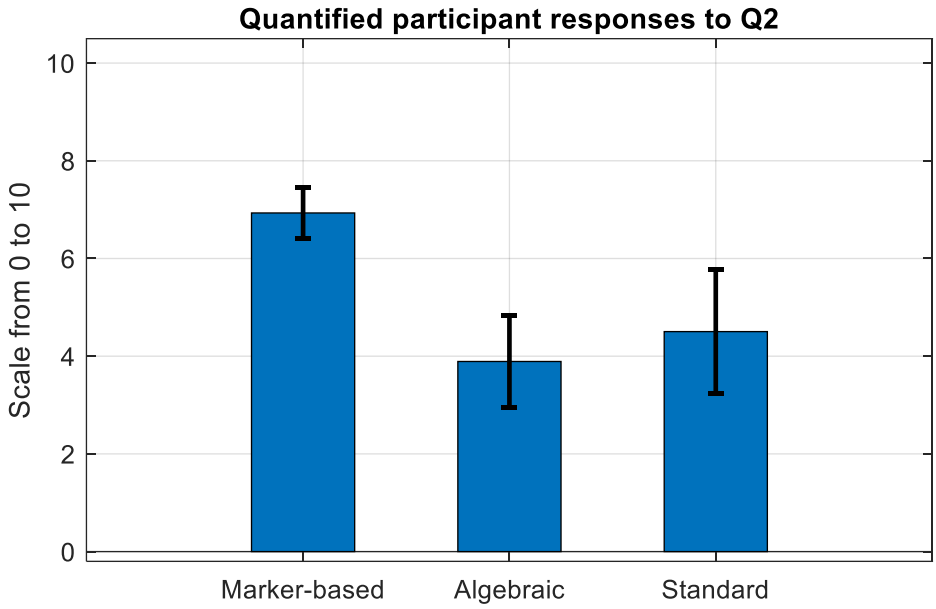


Figure 7. Quantified participant responses to question 1 (0 = No Control, 10 = Complete Control)

Marker-Based Trial: Participants found starting and stopping walking relatively easy, with a high mean score of 6.94 and a low standard deviation of 1.25.

Algebraic Trial: The mean score was 3.9 with a standard deviation of 2.29, indicating more difficulty and variability in responses.

Standard Treadmill: The mean score was 4.5, with a standard deviation of 3.09, showing mixed experiences.

The robust factorial repeated measures ANOVA was applied and the p-value for three different conditions is 0.0898, meaning that we cannot reject the null hypothesis that one of the methods was statistically different than the others.

Question 3: please mark how this walking trial felt whenever you were speeding up to make it across an intersection or slowing down to wait for the next green light. VAS scores are shown in Figure 8.

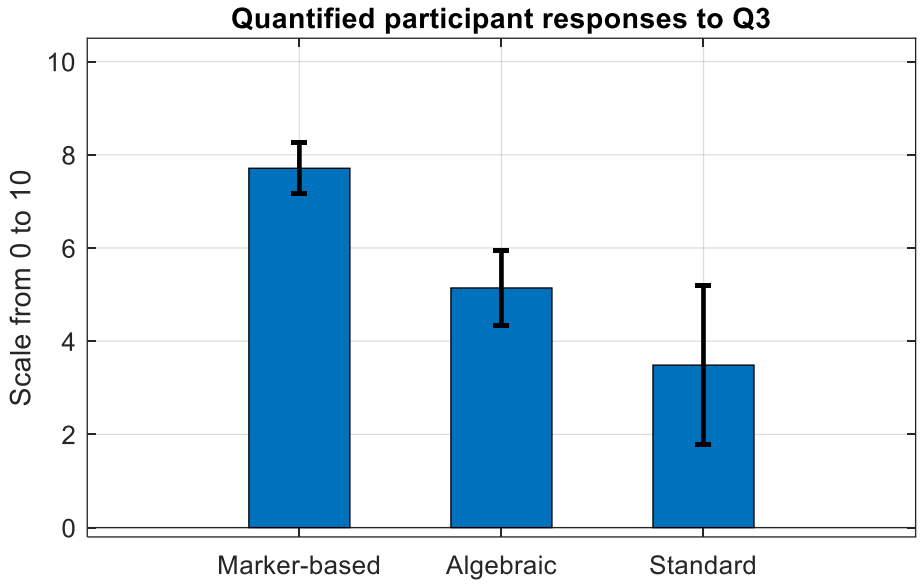


Figure 8. Quantified participant responses to question 3 (0 = No Control, 10 = Complete Control)

Marker-Based Trial: Participants were comfortable with changing speeds, as shown by the high mean score of 7.71 and a low standard deviation of 1.34.

Algebraic Trial: The mean score was 5.14 with a standard deviation of 1.95, indicating moderate difficulty and some variability.

Standard Treadmill: The mean score was 3.48, with a high standard deviation of 4.17,

suggesting mixed experiences and greater difficulty.

Robust factorial repeated measures ANOVA was applied, and the p-value for three different conditions is 0.0553, meaning that we cannot reject the null hypothesis for this pilot data that one of the methods was statistically different than the others.

Question 4: please mark how this walking session felt while you were walking at a steady speed. VAS scores are shown in Figure 9.

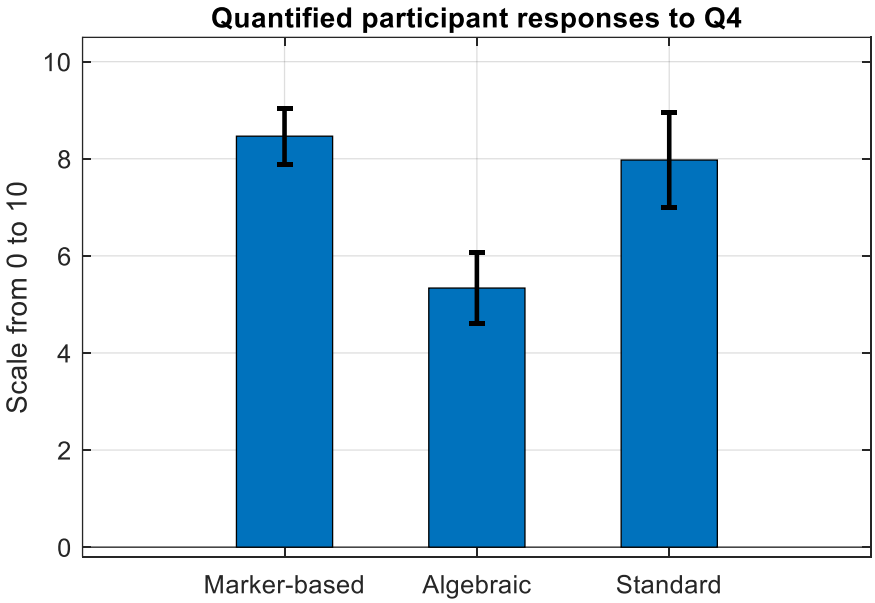


Figure 9. Quantified participants responses to question 4 (0 = No Control, 10 = Complete Control)

Marker-Based Trial: The high mean score of 8.47 and low standard deviation of 1.41 suggest that participants perceived their walking experience as being similar to overground walking.

Algebraic Trial: The mean score was 5.33 with a standard deviation of 1.76, indicating moderate comfort and some variability.

Standard Treadmill: The mean score was 7.97, with a standard deviation of 2.4, showing relatively high comfort levels.

Robust factorial repeated measures ANOVA was applied, and the p-value for three different conditions is 0.0264 for the average answer to question 4. Significant differences were found between the marker-based and algebraic conditions. Since the average for the marker-based condition (8.47) is higher than that for the algebraic condition (5.43), it can be concluded that the marker-based condition is better.

Question 5: please mark how this walking trial felt like walking overground. VAS scores are shown in Figure 10.

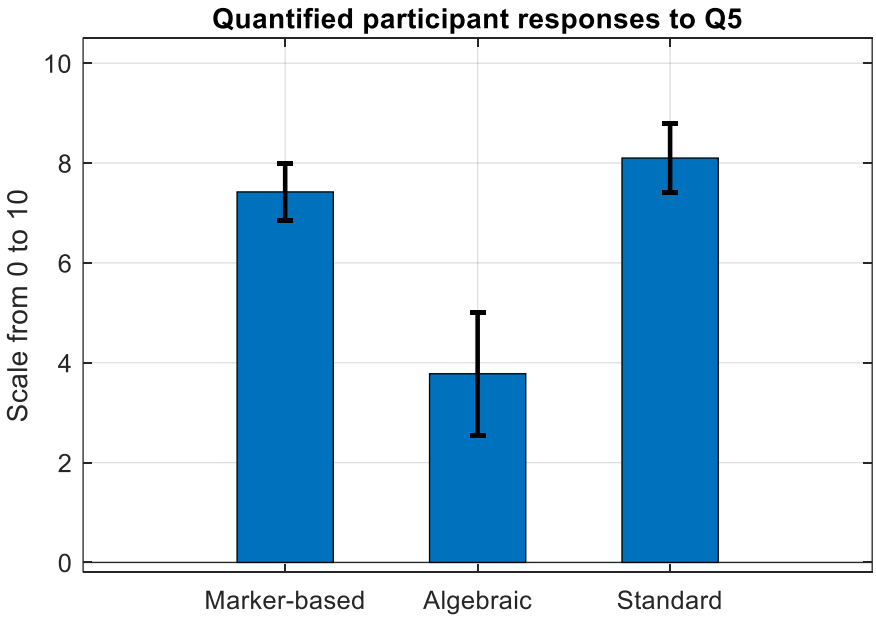


Figure 10. Quantified participant responses to question 5 (0 = Not at all, 10 = Felt the same)

Marker-Based Trial: Participants felt a high level of comfort walking overground, with a mean score of 7.42 and a standard deviation of 1.41.

Algebraic Trial: The mean score was 3.78 with a higher standard deviation of 3.02, indicating varied experiences.

Standard Treadmill: The mean score was 8.1, with a standard deviation of 1.68, suggesting consistent comfort levels.

Robust factorial repeated measures ANOVA was applied, and the p-value for three different conditions is 0.0073 for the average answer to question 5. Significant differences were found between the marker-based and algebraic conditions. Since the average for the marker-based condition (7.42) is higher than that for the algebraic condition (3.78), it can be concluded that the marker-based condition is better.

Question 6: please mark how much this walking trial felt like walking on a normal treadmill. VAS scores are shown in Figure 11.

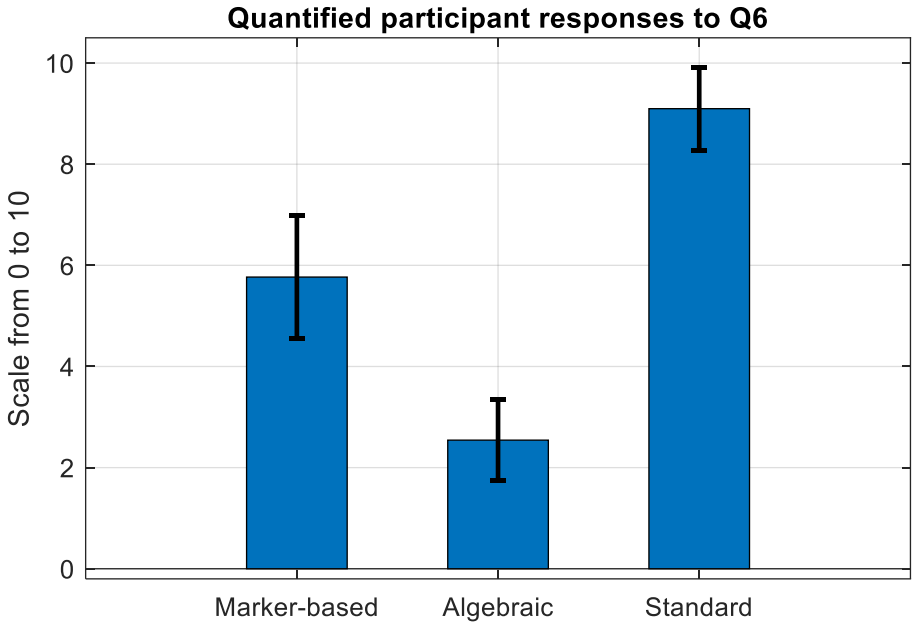


Figure 11. Quantified participant responses to question 6 (0 = Not at all, 10 = Felt the

same)

Marker-Based Trial: The mean score was 5.76 with a standard deviation of 2.97, indicating moderate comfort with some variability.

Algebraic Trial: The mean score was 2.54 with a standard deviation of 1.97, indicating lower comfort levels and variability.

Standard Treadmill: The mean score was 9.09, with a standard deviation of 2.01, showing high and consistent comfort levels.

Robust factorial repeated measures ANOVA was applied, and the p-value for three different conditions is 0.0009 for the average answer to question 6. Significant differences were found between the algebraic and standard conditions. Since the average for the algebraic condition (2.54) is higher than that for the standard condition (9.09), it can be concluded that the standard condition is better.

The VAS questionnaire showed a significant difference in three experiences: walking at a steady speed, comparing the trial with overground walking, and comparing with walking on a normal treadmill. The Bonferroni test revealed that participants found a significant difference between the marker-based and algebraic self-paced treadmills in their experience of finding a steady speed. Their scores demonstrate that it was easier to walk at a steady speed with the marker-based trial compared to the markerless trial.

A significant difference was observed when participants compared walking on a self-paced treadmill to overground walking, with the marker-based trial rated as most similar to overground walking. Another significant difference appeared when

comparing all trials to walking on a standard gym treadmill; as expected, the standard trial received higher similarity scores, highlighting a clear distinction between the algebraic and standard conditions. To investigate significant differences between the same algebraic conditions, marker-based, and standard trials, p-values were calculated for comparable conditions. For example, the average comfortable speed on the standard trial was compared to the speeds during the "none" and "normal" conditions of the markerless trial, but no significant differences were found.

6.2 Speed Variability in Different Trials

Speed variability is a critical factor in biomechanical analysis, as fluctuations in treadmill speed between trials can introduce inconsistencies in movement patterns and kinematic measurements. When comparing different trials for the same participant, uncontrolled speed variations may affect the reliability of CoM estimates, making it difficult to determine whether observed differences are due to actual biomechanical changes or external inconsistencies. Assessing speed variability ensures that any deviations in markerless and marker-based CoM estimations are not simply artifacts of inconsistent treadmill speeds, strengthening the validity of the comparisons.

To compare speed variability between marker-based and markerless trials, all participants considered. Two schemes were devised to illustrate the speed variability of the trials:

1. Considering the participant's normal speed while walking on both algebraic and marker-based self-paced treadmills.

2. Measuring the difference between the maximum and minimum speed of each walking trial and comparing them.

The first scheme helps interpret how much the position estimation technique might potentially alter the participant's average speed. The second scheme helps assess the variation between the maximum and minimum speeds while the participant walks on both marker-based and algebraic self-paced treadmills.

Speed variability at normal speed and the maximum and minimum speed differences across all participants are illustrated in figure 12 and figure 13.

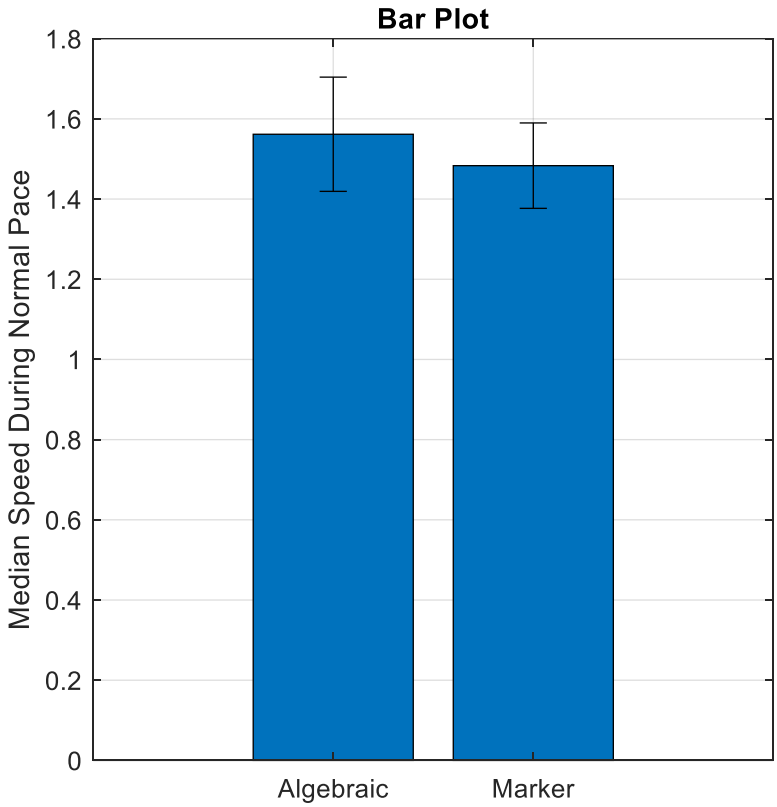


Figure 12. Median speed during normal pace across participants

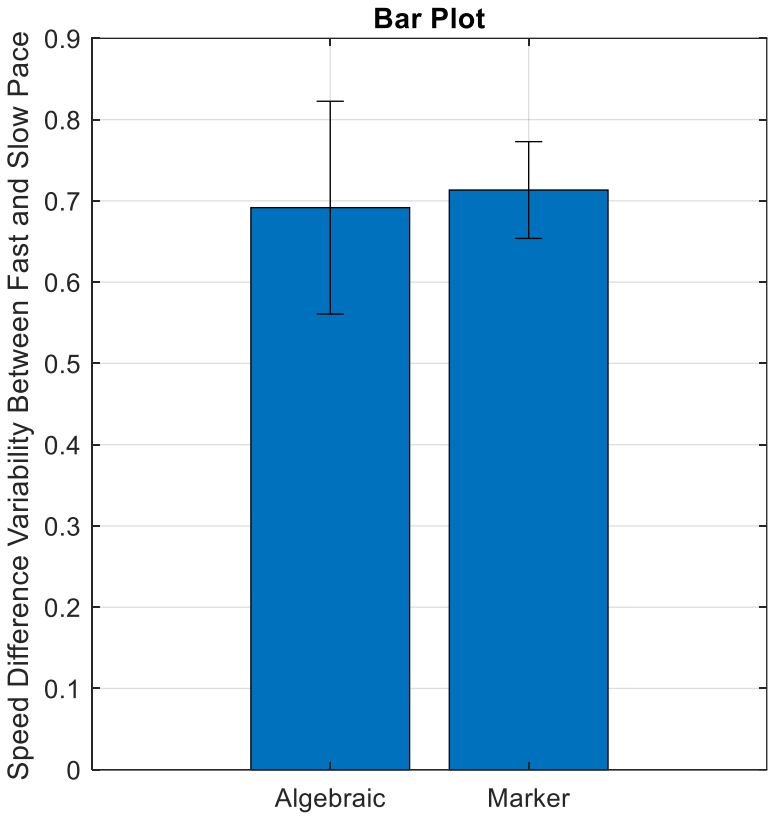


Figure 13. Speed difference variability between fast and slow pace

The median walking speed at a normal pace for the algebraic and marker-based methods is 1.56 m/s and 1.48 m/s, respectively, with standard deviations of 0.14 and 0.1. The Wilcoxon matched-pairs test value is 0.29, so the null hypothesis that the nominal speeds are the same between conditions cannot be rejected. The speed difference variability between fast and slow walking speeds for the algebraic and marker-based methods is 0.69 m/s and 0.71 m/s, respectively, with standard deviations of 0.13 and 0.06. The Wilcoxon matched-pairs test value is 0.625, so the null hypothesis that the speed variability between conditions is the same cannot be rejected.

6.3 Exploratory Outcome Measure

R^2 statistical analysis was implemented to assess the accuracy of the markerless CoM estimates compared to the gold-standard marker-based CoM data. For each of the three trials conducted with each participant, markerless and marker-based position data were aligned to ensure precise comparisons. Then R^2 was calculated by fitting a linear regression model, where the marker-based CoM data served as the dependent variable and the markerless CoM data as the independent variable. The R^2 value indicates the proportion of variance in the marker-based CoM that is predictable from the markerless CoM, effectively measuring the strength and accuracy of the markerless estimates.

The results demonstrated that the markerless CoM estimates were remarkably close to the marker-based CoM, with most R^2values consistently falling from 0.89 to 0.94. The R^2 value of all six participants is presented in Table 2.

This high R^2 range suggests a strong correlation between the two methods, indicating that the markerless system was highly effective in estimating the CoM. Additionally, a scatter plot for a randomly selected participant is illustrated in Figure 14, where the x-axis represents the marker-based position data, and the y-axis represents algebraic estimation data. Most of the data points lie close to the fitted regression line, indicating that the algebraic estimation closely follows the marker-based values. This demonstrates a very strong linear relationship between the marker-based and algebraic position estimation methods.

Table 2. R^2 values comparing markerless and marker-based CoM estimates for all participants

Participant number	R^2 value	Slope	Intercept
Participant 1	0.89	0.92 [0.8,1.1]	0.11 [0.04,0.22]
Participant 2	0.93	0.94 [0.8,1.2]	0.16 [0.08,0.3]
Participant 3	0.9	1.1 [0.9,1.25]	0.12 [0.06,0.19]
Participant 4	0.89	0.91 [0.8,1.2]	-0.15 [-0.25,-0.1]
Participant 5	0.94	0.97 [0.8,1.2]	-0.09 [-0.2,-0.04]
Participant 6	0.93	1.04 [0.8,1.2]	0.15 [0.05,0.27]

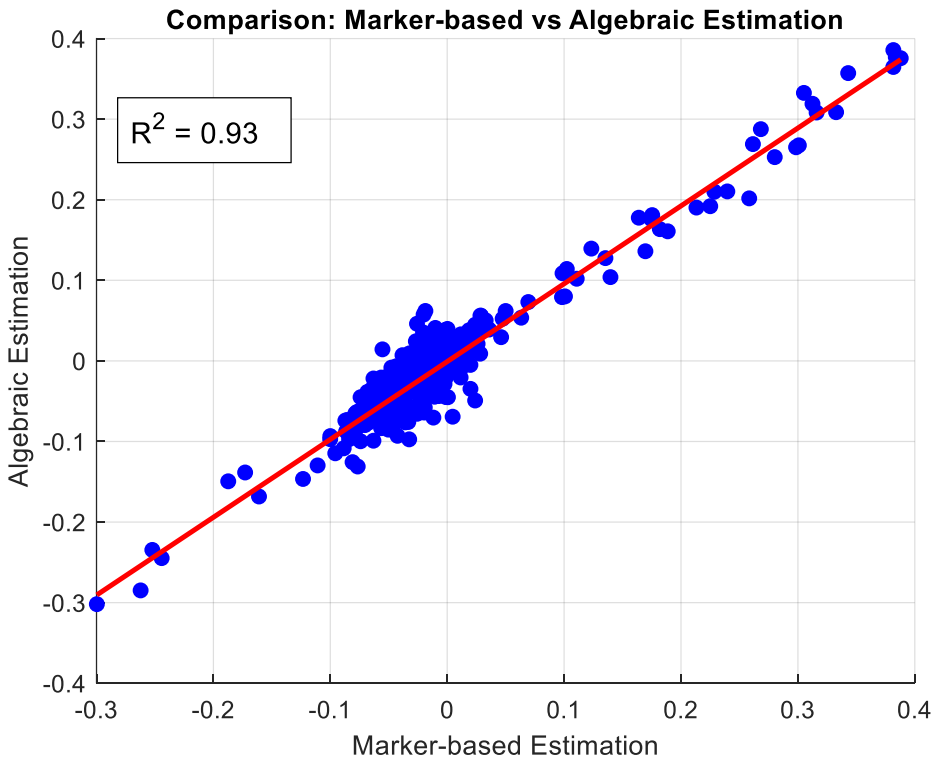


Figure 14. The scatter plot for a participant with $R^2 = 0.93$

To compare the marker-based CoM and algebraic CoM, a random participant was selected, and the position data for one of the trials is illustrated over time in Figure 15.

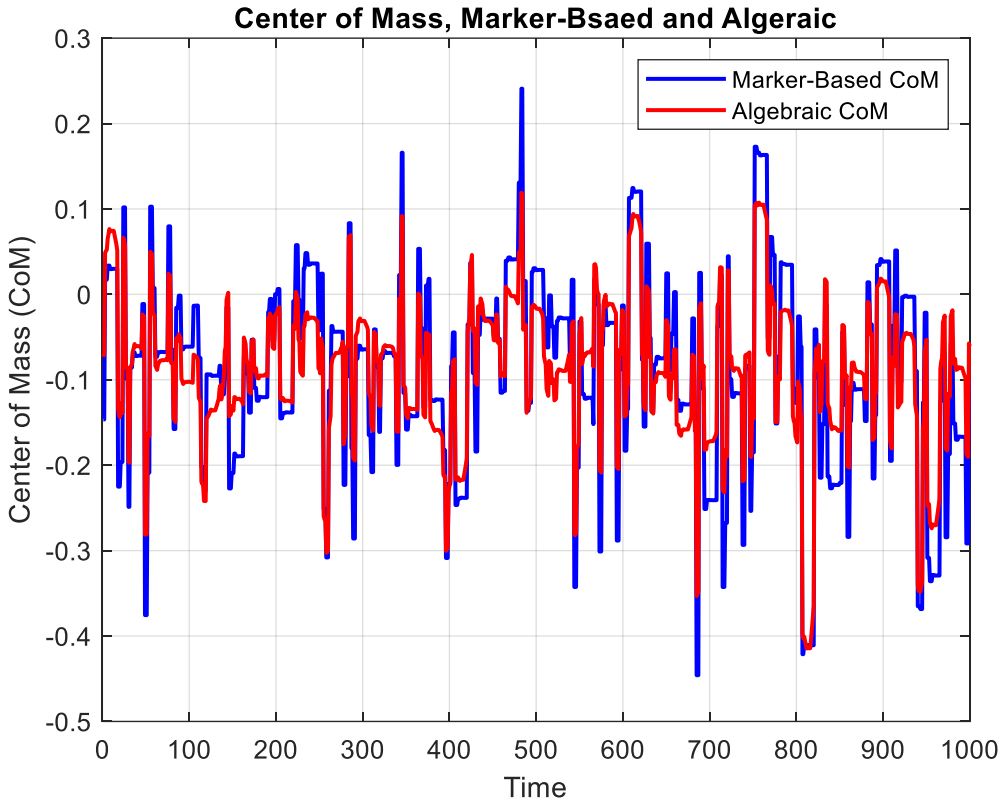


Figure 15. Marker-based and markerless CoM over time

The consistency of these results across different trials and participants supports the reliability and validity of the markerless approach, showing that it can serve as a practical alternative to the more cumbersome marker-based systems in various applications, such as gait analysis and rehabilitation. Although the algebraic self-paced treadmill achieved a similar score to the marker-based system from the participants, it performed worse in terms of feedback provided by the participants. Shift and Noise may be main reasons that describe the difference between the marker-based position data, considered the gold standard, and the algebraic position estimation technique, as shown in Figure 15. Additionally, a shift in the position data estimation can result in off-target predictions, which can affect decision-making in control actions. The

algebraic method overestimated the CoM position for four participants and underestimated it for two participants. This suggests that a systematic shift may not exist, as a consistent bias in one direction would require all intercepts to be either positive or negative. However, due to the small sample size, definitive conclusions cannot be drawn, and further studies with a larger participant pool are needed to confirm this finding. Noise is indeed another critical factor to consider. Noise—stemming from environmental conditions or participant-specific variability—can introduce random fluctuations in the data and likely contributed more to the observed discrepancies than any consistent methodological bias. Given the small sample size of only six participants, the impact of noise is particularly pronounced, making it a source of the differences observed between the two methods.

6.3.1 Subjective Feedback

Subjective comments were recorded verbatim but were not analyzed with a formal qualitative method; they are therefore reported as anecdotal observations only.

Marker-Based Trial Feedback

1 - **Immersion**: Participants reported a high level of immersion during the trial.

2 - **Fluidity and Enjoyment**: The trial was described as fluid for starting, stopping, and changing speed. Overall, participants enjoyed walking during this trial and felt it was the most natural experience.

3 - **Control**: Participants noted that they had good control throughout the trial.

4 - **Adaptation Period**: The system felt touchy at first, but participants adapted within a few minutes.

Markerless Trial Feedback

1 - **Adaptation Period**: Participants required more time to get used to this trial compared to others, and it did not feel as fluid.

2 - **Jerky Experience**: The trial was described as a bit jerky. Participants found it challenging to maintain a consistent speed and to adjust speed in small increments, managing only large increments.

3 - **Stride Length**: Participants exhibited shorter stride lengths during the algebraic trial, which, combined with the increasing treadmill speed, seemed to reduce the difficulty experienced in this condition.

Standard Trial Feedback

The participants did not provide any feedback for the normal treadmill trial.

7 Discussion

7.1 Interpretation of Results

The motivation for this study was rooted in addressing the limitations of existing self-paced treadmill algorithms, particularly their inability to accurately predict and control gait analysis, which are essential for effective rehabilitation and personalized treatment. Self- paced treadmills, which dynamically adjust to the user's speed, provided a more natural gait analysis environment and allowed users to dictate their workout pace. However, these systems often face challenges with abrupt speed changes, leading to discomfort, instability, or potential injury, especially for patients recovering from strokes or orthopedic surgeries. To overcome these issues, a Model Predictive Controller (MPC) was employed in this study. This approach enabled real-time speed adjustments that responded to user movement, aiming to reduce abrupt transitions and support a safe and comfortable environment for gait analysis. By addressing these challenges, the study provides a foundation for future work toward enhancing rehabilitation outcomes and improving user confidence and mobility.

The results presented in Figure 6 to 11 indicate that some participants' answers varied significantly, reflected in the high standard deviations for certain questions. Despite being instructed to clarify any questions about the VAS questionnaire, some participants may have misunderstood specific items. For example, Question 3 asked about their experience with speeding up and slowing down. It is known that there was no control over speed in either direction during the standard treadmill trial. However, the VAS results show responses of 9.58, 7.58, and two 0 out of 10, resulting in a high

standard deviation. This variation suggests that some participants may have misinterpreted the question, leading to inconsistent scores. Additionally, the average answer for question 6 reveals that the algebraic trial, which scored 2.59 out of 10, indicating it did not feel comparable to walking overground. In contrast, the standard trials received a high score of 9.09, suggesting they closely matched the overground walking experience. This disparity is further corroborated by the subjects' feedback, as detailed in the subsequent section.

7.2 Implications of Findings

This study demonstrates that the marker-based self-paced treadmill outperforms the algebraic self-paced treadmill in terms of user experience and steady speed maintenance. However, despite its relative superiority, participants still did not feel entirely comfortable using the marker-based self-paced treadmill, as indicated by only satisfactory scores.

Four main implications can be drawn from these findings and are listed below

1. Design Improvements:

The marker-based system, while better, still has room for improvement. The satisfactory scores suggest that users may experience subtle issues with comfort or usability that need addressing. Future designs should focus on refining the marker-based system to enhance user comfort by minimizing latency, improving marker placement to reduce occlusion and enhance tracking accuracy during dynamic movements, and enhancing robustness to marker loss or noise through advanced

filtering techniques.

2. Algorithm Development:

The results indicate that algorithmic adjustments could further improve the user experience. Researchers should explore modifications to the markerless algorithms to reduce any remaining discomfort.

3. MPC Cost Function and Tuning Parameters:

The behavior of the treadmill's response is directly influenced by MPC parameters, such as the prediction horizon, control horizon, and prioritization coefficients. Like many other controllers with free coefficients, these MPC parameters are not straightforwardly adjustable. Adjusting these coefficients could lead to an improved performance score, as measured by the same VAS. Furthermore, altering the cost function within the MPC framework can significantly impact response behavior, potentially leading to a more comfortable experience for users on a self-paced treadmill.

4. Participant Feedback and Adaptation:

The study highlights the importance of participant feedback in the iterative design process. Understanding specific areas of discomfort or dissatisfaction can guide targeted improvements. This user-centered approach ensures that the developed systems meet the practical needs and preferences of the users.

7.3 Limitations of the Study

There were three primary limitations in this study. Firstly, the number of participants

was limited to six healthy adults, which is insufficient for robust statistical testing, though it did demonstrate the effects and differences of the trials. Secondly, the age range of participants was narrow, all young adults aged 18 to 25, which limits the generalizability of the results to this age group. Lastly, all participants were healthy, but the designed treadmill aims to help individuals suffering from disability or diseases such as Parkinson's disease, multiple sclerosis, and stroke. The goal was to design a controller and test its efficacy under controlled conditions, ultimately benefiting those with gait abnormalities caused by these conditions.

The prediction horizon and control horizon could theoretically be greater than 0.92 and 0.9 seconds, respectively. However, this was not feasible in practice due to the computational limitations of the available hardware.

7.4 Suggestions for Future Research

A future study should involve designing an adaptive PID controller and comparing its performance with the MPC controller on a self-paced treadmill using force plate data. Additionally, since the MPC control sequence is generated by optimizing the cost function, modifying this cost function could lead to significant improvements. Therefore, it would be valuable to design another MPC controller with a new cost function. The study could

also include a running trial based on participant feedback to investigate responsiveness and user experience, specifically addressing concerns about the jerkiness of the algebraic self-paced treadmill at slow walking speeds and the perceived improvements when transitioning to faster speeds. Ultimately, research should consider including tests

with individuals who have gait abnormalities to better understand the controller's efficacy in real-world scenarios. Additionally, incorporating an overground trial to obtain overground walking speed will provide valuable data to compare with controlled conditions. This approach will help to validate the system's effectiveness and ensure its applicability to a broader population, including those with disabilities or diseases.

8 Conclusion

8.1 Summary of Key Findings

The purpose of this study was to design a self-paced treadmill that smoothly adjusts to a person’s speed, using two methods: marker-based and markerless techniques. Additionally, a conventional treadmill, where individuals set their desired speed, was examined as a baseline. This research aimed to determine the level of control participants felt over their speed when they were required to stop or speed up during each trial. Data collected included force plate data, CoM, Center of CoP, treadmill speed, distance to the traffic light, and the state of the light across three conditions.

The MPC system showed significant promise in maintaining a steady speed and adapting to users' gait patterns compared to traditional control methods. By optimizing the control sequence through a cost function, the MPC system provided a more responsive and smoother walking experience. However, the study also identified limitations in the computational capacity of available hardware, which restricted the prediction and control horizons. This study's implications extend to the design of more responsive and user- friendly self-paced treadmills. The integration of user feedback is crucial in developing systems that meet practical needs and enhance comfort.

The VAS results provided valuable insights into user experiences. Participants rated the marker-based self-paced treadmill higher than the algebraic version, indicating a preference for the marker-based approach in maintaining a steady speed. Despite this preference, the overall scores suggested that participants still found the marker-based

system only satisfactory, highlighting areas for further improvement.

The integration of MPC controllers in self-paced treadmills shows significant promise in improving user experience and walking dynamics. However, further advancements in controller design, computational capacity, and user-centric refinements are essential to fully realize the potential of this technology. The insights gained from the VAS questionnaire underscore the importance of ongoing user feedback in the development process, ensuring that future iterations meet the practical needs and comfort expectations of diverse users.

8.2 Contribution to the Field

This thesis makes a significant contribution to the field of rehabilitation and biomechanics by introducing and implementing MPC on a self-paced treadmill system. The application of MPC in this context addresses several critical challenges in current treadmill technology, particularly in accommodating individual gait variations and dynamically adjusting treadmill speed in real-time.

By developing a real-time treadmill speed regulation controller using MPC (Specific Aim 1), this demonstrates that MPC can be effectively applied to anticipate and respond to user movement, enabling real-time speed adjustment. The integration of MPC not only enhances the precision of speed adjustments but also simplifies the tuning process, making it more adaptable for clinicians and researchers.

Moreover, the thesis explores the feasibility and accuracy of markerless position estimation methods (Specific Aim 2), providing an alternative to marker-based systems

that are prone to practical limitations such as marker displacement and cost. This innovation not only improves accessibility but also enhances the safety and reliability of self-paced treadmill. However, participant feedback indicated dissatisfaction with markerless position estimation due to perceived jerkiness during trials.

Based on the detailed analysis and participant feedback from this study (Specific Aim 3), the findings significantly contribute to advancing the field of self-paced treadmill technology and biomechanics. The comparison between marker-based and algebraic techniques, alongside a conventional treadmill, highlights nuanced differences in user experience and control over speed adjustments during various walking conditions. Notably, participants consistently rated the marker-based method higher in providing a more natural and controllable walking experience, particularly in scenarios involving starting, stopping, and adapting speed based on environmental cues such as traffic lights. These insights underscore the effectiveness of using MPC algorithms to enhance real-time adjustment capabilities, thereby improving user comfort and engagement in rehabilitation and fitness settings.

In summary, this thesis establishes MPC as a pivotal technology in advancing self-paced treadmill systems, offering new avenues for enhancing mobility assessment, therapeutic interventions, and biomechanical research. The insights gained contribute to the ongoing evolution of rehabilitation technologies, empowering clinicians and researchers with innovative tools to improve patient outcomes and enhance understanding of human locomotion dynamics.

9 References

[1] S. R. Simon, “Quantification of human motion: Gait analysis - Benefits and limitations to its application to clinical problems,” *J Biomech*, vol. 37, no. 12, pp. 1869–1880, Dec. 2004, doi: 10.1016/j.jbiomech.2004.02.047.

[2] M. Bonanno, A. M. De Nunzio, A. Quartarone, A. Militi, F. Petralito, and R. S. Calabrò, “Gait Analysis in Neurorehabilitation: From Research to Clinical Practice,” Jul. 01, 2023, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/bioengineering10070785.

[3] M. McGrath, J. Wood, J. Walsh, and P. Window, “The impact of Three-Dimensional Gait Analysis in adults with pathological gait on management recommendations,” *Gait Posture*, vol. 105, pp. 75–80, Sep. 2023, doi: 10.1016/j.gaitpost.2023.06.014.

[4] I. Klöpfer-Krämer, A. Brand, H. Wackerle, J. Müßig, I. Kröger, and P. Augat, “Gait analysis – Available platforms for outcome assessment,” *Injury*, vol. 51, pp. S90– S96, May 2020, doi: 10.1016/j.injury.2019.11.011.

[5] K. John *et al.*, “Accuracy of Video-Based Gait Analysis Using Pose Estimation During Treadmill Walking Versus Overground Walking in Persons After Stroke,” *Phys Ther*, vol. 104, no. 2, Feb. 2024, doi: 10.1093/ptj/pzad121.

[6] S. J. Lee and J. Hidler, “Biomechanics of overground vs. treadmill walking in healthy individuals,” *J Appl Physiol*, vol. 104, pp. 747–755, 2008, doi:

10.1152/japplphysiol.01380.2006.-The.

[7] A. G. Robinson, A. M. Dennett, and D. A. Snowdon, “Treadmill training may be an effective form of task-specific training for improving mobility in people with Parkinson’s disease and multiple sclerosis: a systematic review and meta-analysis,” Jun. 01, 2019, *Elsevier Ltd*. doi: 10.1016/j.physio.2018.11.007.

[8] K. Y. Nam, H. J. Kim, B. S. Kwon, J. W. Park, H. J. Lee, and A. Yoo, “Robot-assisted gait training (Lokomat) improves walking function and activity in people with spinal cord injury: a systematic review,” *J Neuroeng Rehabil*, vol. 14, no. 1, Mar. 2017, doi: 10.1186/s12984-017-0232-3.

[9] L. H. Sloot, M. M. van der Krogt, and J. Harlaar, “Self-paced versus fixed speed treadmill walking,” *Gait Posture*, vol. 39, no. 1, pp. 478–484, Jan. 2014, doi: 10.1016/j.gaitpost.2013.08.022.

[10] K. Theunissen, B. Van Hooren, G. Plasqui, and K. Meijer, “Self-paced and fixed speed treadmill walking yield similar energetics and biomechanics across different speeds,” *Gait Posture*, vol. 92, pp. 2–7, Feb. 2022, doi: 10.1016/j.gaitpost.2021.11.005.

[11] A. Van Bladel, R. De Ridder, T. Palmans, R. Van der Looven, and D. Cambier, “Comparing spatiotemporal gait parameters between overground walking and self- paced treadmill walking in persons after stroke,” *Disabil Rehabil*, vol. 45, no. 6, pp. 1016–1021, 2023, doi: 10.1080/09638288.2022.2046875.

[12] L. H. Sloot, M. M. van der Krogt, and J. Harlaar, “Self-paced versus fixed speed treadmill walking,” *Gait Posture*, vol. 39, no. 1, pp. 478–484, Jan. 2014, doi: 10.1016/j.gaitpost.2013.08.022.

[13] W. R. Hiatt, E. E. Wolfel, R. H. Meier, and J. G. Regensteiner, “Superiority of Treadmill Walking Exercise Versus Strength Training for Patients With Peripheral Arterial Disease Implications for the Mechanism of the Training Response.”

[14] R. F. Macko, G. V. Smith, C. L. Dobrovolny, J. D. Sorkin, A. P. Goldberg, and K. H. Silver, “Treadmill training improves fitness reserve in chronic stroke patients,” *Arch Phys Med Rehabil*, vol. 82, no. 7, pp. 879–884, 2001, doi: 10.1053/apmr.2001.23853.

[15] S. A. Morrison, D. Lorenz, C. P. Eskay, G. F. Forrest, and D. M. Basso, “Longitudinal Recovery and Reduced Costs After 120 Sessions of Locomotor Training for Motor Incomplete Spinal Cord Injury,” *Arch Phys Med Rehabil*, vol. 99, no. 3, pp. 555–562, Mar. 2018, doi: 10.1016/j.apmr.2017.10.003.

[16] M. J. Highsmith *et al.*, “ Gait Training Interventions for Lower Extremity Amputees: A Systematic Literature Review ,” *Technol Innov*, vol. 18, no. 2, pp. 99–113, Sep. 2016, doi: 10.21300/18.2-3.2016.99.

[17] J. C. Polese, L. Ada, C. M. Dean, L. R. Nascimento, and L. F. Teixeira-Salmela, “Treadmill training is effective for ambulatory adults with stroke: A systematic review,” *J Physiother*, vol. 59, no. 2, pp. 73–80, Jun. 2013,

doi: 10.1016/S1836- 9553(13)70159-0.

[18] E. Swinnen, D. Beckwée, D. Pinte, R. Meeusen, J.-P. Baeyens, and E. Kerckhofs, “Treadmill Training in Multiple Sclerosis: Can Body Weight Support or Robot Assistance Provide Added Value? A Systematic Review,” *Mult Scler Int*, vol. 2012, pp. 1–15, 2012, doi: 10.1155/2012/240274.

[19] N. A. Bayona, J. Bitensky, K. Salter, and R. Teasell, “The Role of Task-Specific Training in Rehabilitation Therapies,” 2005. [Online]. Available: www.thomasland.com

[20] R. Teasell, J. Bitensky, K. Salter, and N. A. Bayona, “The Role of Timing and Intensity of Rehabilitation Therapies,” 2005. [Online]. Available: www.thomasland.com

[21] R. J. Nudo, “Adaptive plasticity in motor cortex: Implications for rehabilitation after brain injury,” in *Journal of Rehabilitation Medicine, Supplement*, 2003, pp. 7–10. doi: 10.1080/16501960310010070.

[22] J. Lee, K. Lee, and C. Song, “Speed-Interactive Treadmill Training Using Smartphone-Based Motion Tracking Technology Improves Gait in Stroke Patients,” *J Mot Behav*, vol. 49, no. 6, pp. 675–685, Nov. 2017, doi: 10.1080/00222895.2016.1271300.

[23] M. M. G. Lewis *et al.*, “Gait patterns during overground and virtual omnidirectional treadmill walking,” *J Neuroeng Rehabil*, vol. 21, no. 1, Dec. 2024, doi: 10.1186/s12984-023-01286-6.

[24] G. N. Chaparro, J. J. Sosnoff, and M. E. Hernandez, “Effects of aerobic fitness on cognitive motor interference during self-paced treadmill walking in older adults,” *Aging Clin Exp Res*, vol. 32, no. 12, pp. 2539–2547, Dec. 2020, doi: 10.1007/s40520-020-01479-2.

[25] A. Lamontagne, J. Fung, B. J. McFadyen, and J. Faubert, “Modulation of walking speed by changing optic flow in persons with stroke,” *J Neuroeng Rehabil*, vol. 4, 2007, doi: 10.1186/1743-0003-4-22.

[26] “CAREN Level 0 Operator Training Agenda (Session 1)_2023-09-11”.

[27] M. A. Sheik-Nainar and D. B. Kaber, “The utility of a virtual reality locomotion interface for studying gait behavior,” *Hum Factors*, vol. 49, no. 4, pp. 696–709, Aug. 2007, doi: 10.1518/001872007X215773.

[28] J. Fung, C. L. Richards, F. Malouin, B. J. Mcfadyen, and A. Lamontagne, “A Treadmill and Motion Coupled Virtual Reality System for Gait Training Post-

Stroke,” 2006. [Online]. Available: www.liebertpub.com

[29] D. L. Jaffe, D. A. Brown, C. D. Pierson-Carey, E. L. Buckley, and H. L. Lew, “Stepping over obstacles to improve walking in individuals with poststroke hemiplegia,” *J Rehabil Res Dev*, vol. 41, no. 3 A, pp. 283–292, 2004, doi: 10.1682/JRRD.2004.03.0283.

[30] A. Mirelman, P. Bonato, and J. E. Deutsch, “Effects of training with a robot-virtual reality system compared with a robot alone on the gait of individuals

after stroke," *American Heart Association J*, vol. 40, no. 1, pp. 169–174, Jan. 2009, doi: 10.1161/STROKEAHA.108.516328.

[31] T. Prokop, M. Schubert, and W. Berger, "Visual influence on human locomotion Modulation to changes in optic flow," *Experimental Brain Research*, vol. 114, no. 1, pp. 63–70, Mar. 1997, doi: https://doi.org/10.1007/pl00005624.

[32] J. L. Souman, P. R. Giordano, I. Frissen, A. De Luca, and M. O. Ernst, "Making virtual walking real," *ACM Trans Appl Percept*, vol. 7, no. 2, pp. 1–14, Feb. 2010, doi: 10.1145/1670671.1670675.

[33] K. Pariser, "Optimal adaptive treadmill control to maximize propulsion during gait",

University of Delaware, 2023.

[34] X. Ai, V. Santamaria, I. Omofuma, and S. K. Agrawal, "Effects of Boundary-Based Assist-as-Needed Force Field on Lower Limb Muscle Synergies During Standing Posture Training," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 2306–2314, 2023, doi: 10.1109/TNSRE.2023.3273990.

[35] "Spinal Cord Control of Movement: Implications for Locomotor Rehabilitation Following Spinal Cord Injury." [Online]. Available: https://academic.oup.com/ptj/article/80/5/477/2842511

[36] J. Von Zitzewitz, M. Bernhardt, and R. Riener, "A novel method for

automatic treadmill speed adaptation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 3, pp. 401–409, Sep. 2007, doi: 10.1109/TNSRE.2007.903926.

[37] J. Kim, H. S. Park, and D. L. Damiano, "An interactive treadmill under a novel control scheme for simulating overground walking by reducing anomalous force," *IEEE/ASME Transactions on Mechatronics*, vol. 20, no. 3, pp. 1491–1496, Jun. 2015, doi: 10.1109/TMECH.2014.2341039.

[38] A. E. Minetti, L. Boldrini, L. Brusamolin, P. Zamparo, T. Mckee, and L. Bru- Samolin, "A feedback-controlled treadmill (treadmill-on-demand) and the spontaneous speed of walking and running in humans," *J Appl Physiol*, vol. 95, pp. 838–843, 2003, doi: 10.1152/japplphysiol.00128.2003.-A.

[39] R. L. Woods, E. Peli, L. Lichtenstein, and J. Barabas, "A Feedback-Controlled Interface for Treadmill Locomotion in Virtual Environments," *ACM Trans Appl Percept*, vol. 4, no. 1, p. 7, 2007, doi: 10.1145/1227134.1227141.

[40] Z. Ripic, M. Nienhuis, J. F. Signorile, T. M. Best, K. A. Jacobs, and M. Eltoukhy, "A comparison of three-dimensional kinematics between markerless and marker- based motion capture in overground gait," *J Biomech*, vol. 159, Oct. 2023, doi: 10.1016/j.jbiomech.2023.111793.

[41] H. Wang and K. J. Hunt, "Self-paced heart rate control for treadmill exercise," *Frontiers in Control Engineering*, vol. 4, Mar. 2023, doi: 10.3389/fcteg.2023.1158164.

[42] T. P. Luu, Y. He, S. Brown, S. Nakagame, and J. L. Contreras-Vidal, “Gait adaptation to visual kinematic perturbations using a real-time closed-loop brain-computer interface to a virtual reality avatar,” *J Neural Eng*, vol. 13, no. 3, Apr. 2016, doi: 10.1088/1741-2560/13/3/036006.

[43] K. S. Pechtl, J. R. Jennings, and M. S. Redfern, “Optic flow and attention alter locomotion differently in the young and old,” *Gait Posture*, vol. 76, pp. 1–6, Feb. 2020, doi: 10.1016/j.gaitpost.2019.10.022.

[44] L. H. Sloot, J. Harlaar, and M. M. van der Krogt, “Self-paced versus fixed speed walking and the effect of virtual reality in children with cerebral palsy,” *Gait Posture*, vol. 42, no. 4, pp. 498–504, Oct. 2015, doi: 10.1016/j.gaitpost.2015.08.003.

[45] P. O. Riley, G. Paolini, U. Della Croce, K. W. Paylo, and D. C. Kerrigan, “A kinematic and kinetic comparison of overground and treadmill walking in healthy subjects,” *Gait Posture*, vol. 26, no. 1, pp. 17–24, Jun. 2007, doi: 10.1016/j.gaitpost.2006.07.003.

[46] D. L. T. D. Stavar A, “Design, test and experimental validation of a VR treadmill walking compensation device. In: SOCOLNET Doctoral Conference on Computing, Electrical and Industrial Systems, DoCEIS 2011. Technological Innovation for Sustainability – Second International Federation for Information Processing 349,” 2011, pp. 402–411.

[47] J. L. Souman, P. R. Giordano, I. Frissen, A. De Luca, and M. O. Ernst, “Making virtual walking real,” *ACM Trans Appl Percept*, vol. 7, no. 2, pp.

1–14, Feb. 2010, doi: 10.1145/1670671.1670675.

[48] E. F. Camacho, C. Bordons “Advanced textbooks in control and signal processing - Model Predictive Control”, *Springer*, 1999.

[49] J. Hamill, K. Knutzen, T. Derrick, “Biomechanical Basis of Human Movement”, Wolter Kluwer, 2021.

[50] R. Baker, “Gait analysis methods in rehabilitation,” *J Neuroeng Rehabil*, vol. 3, Mar. 2006, doi: 10.1186/1743-0003-3-4.

[51] H. Zhou and H. Hu, “Human motion tracking for rehabilitation-A survey,” 2008, *Elsevier BV*. doi: 10.1016/j.bspc.2007.09.001.

[52] F. Horak *et al.*, “Role of Body-Worn Movement Monitor Technology for Balance and Gait Rehabilitation Innovative Technologies Special Series Post a Rapid Response to,” 2015. [Online]. Available: https://academic.oup.com/ptj/article/95/3/461/2686562

[53] N. F. Mulligan, B. A. Tschoepe, and M. B. Smith, “Balance retraining in community- dwelling older adults: Highlights of interventions strategies that hold promise in physical therapy practice,” 2014, *Lippincott Williams and Wilkins*. doi: 10.1097/TGR.0000000000000015.

[54] M. J. Major and N. P. Fey, “Considering passive mechanical properties and patient user motor performance in lower limb prosthesis design optimization to enhance rehabilitation outcomes,” *Physical Therapy Reviews*, vol. 22, no. 3–4, pp. 202–216, Jul. 2017, doi:

10.1080/10833196.2017.1346033.

[55] L. Resnik *et al.*, “Advanced upper limb prosthetic devices: Implications for upper limb prosthetic rehabilitation,” 2012, *W.B. Saunders*. doi: 10.1016/j.apmr.2011.11.010.

[56] T. Mikolajczyk *et al.*, “Advanced technology for gait rehabilitation: An overview,” *Advances in Mechanical Engineering*, vol. 10, no. 7, Jul. 2018, doi: 10.1177/1687814018783627.

[57] D. González-Ortega, F. J. Díaz-Pernas, M. Martínez-Zarzuela, and M. Antón- Rodríguez, “A Kinect-based system for cognitive rehabilitation exercises monitoring,” *Comput Methods Programs Biomed*, vol. 113, no. 2, pp. 620–631, Feb. 2014, doi: 10.1016/j.cmpb.2013.10.014.

[58] W. Wei, C. McElroy, and S. Dey, “Using Sensors and Deep Learning to Enable On- Demand Balance Evaluation for Effective Physical Therapy,” *IEEE Access*, vol. 8, pp. 99889–99899, 2020, doi: 10.1109/ACCESS.2020.2997341.

[59] G. F. Devetak, R. C. D. Bohrer, A. L. F. Rodacki, and E. F. Manffra, “Center of mass in analysis of dynamic stability during gait following stroke: A systematic review,” Jul. 01, 2019, *Elsevier B.V.* doi: 10.1016/j.gaitpost.2019.06.006.

[60] C. Pizzolato *et al.*, “Non-invasive approaches to functional recovery after spinal cord injury: Therapeutic targets and multimodal device

interventions," May 01, 2021, *Academic Press Inc.* doi: 10.1016/j.expneurol.2021.113612.

[61] S. L. Chaparro-Cárdenas, A. A. Lozano-Guzmán, J. A. Ramirez-Bautista, and A. Hernández-Zavala, "A review in gait rehabilitation devices and applied control techniques," 2018, *Taylor and Francis Ltd*. doi: 10.1080/17483107.2018.1447611.

[62] R. M. Kanko *et al.*, "Assessment of spatiotemporal gait parameters using a deep learning algorithm-based markerless motion capture system," *J Biomech*, vol. 122, Jun. 2021, doi: 10.1016/j.jbiomech.2021.110414.

[63] K. Bae, S. Lee, S. Y. Bak, H. S. Kim, Y. Ha, and J. H. You, "Concurrent validity and test reliability of the deep learning markerless motion capture system during the overhead squat," *Sci Rep*, vol. 14, no. 1, Dec. 2024, doi: 10.1038/s41598-024- 79707-2.

[64] A. Van Bladel, R. De Ridder, T. Palmans, R. Van der Looven, and D. Cambier, "Comparing spatiotemporal gait parameters between overground walking and self-paced treadmill walking in persons after stroke," *Disabil Rehabil*, vol. 45, no. 6, pp. 1016–1021, 2023, doi: 10.1080/09638288.2022.2046875.

[65] G. Ploof, B. Alqahtani, F. Alghamdi, G. Flynn, and C. X. Yang, "Center of Mass Estimation Using Motion Capture System," in 2017 IEEE 15th Intl Conf on Dependable, Autonomic and Secure Computing, 15th Intl Conf on Pervasive Intelligence and Computing, 3rd Intl Conf on Big Data

Intelligence and Computing and Cyber Science and Technology Congress(DASC/PiCom/DataCom/CyberSciTech), IEEE, Nov. 2017, pp. 287–292, Orlando, FL, USA. doi: 10.1109/DASC-PICom-DataCom-CyberSciTec.2017.61.

[66] M. Kasaei, A. Ahmadi, N. Lau, and A. Pereira, "A Robust Model-Based Biped Locomotion Framework Based on Three-Mass Model: From Planning to Control," in *2020 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC)*, Apr. 2020, pp. 257–262, Ponta Delgada, Portugal. doi: https://doi.org/10.1109/icarsc49921.2020.9096150.

[67] M. Boldo, R. Di Marco, E. Martini, M. Nardon, M. Bertucco, and N. Bombieri, "On the reliability of single-camera markerless systems for overground gait monitoring," *Comput Biol Med*, vol. 171, Mar. 2024, doi: 10.1016/j.compbiomed.2024.108101.

[68] Huston, R. "Principles of Biomechanics (1st ed.)", *CRC Press*, 2008. https://doi.org/10.1201/9781420018400

[69] D. Knudson "Fundamentals of Biomechanics.", *Springer Cham*. 2007. https://doi.org/10.1007/978-3-030-51838-7

[70] A. Banks, R. He, L. Dillman, C. McGibbon, and J. Sensinger, "A Comparison of Force-Plate Based Center of Mass Estimation Algorithms," in *IEEE International Conference on Rehabilitation Robotics*, IEEE Computer Society, 2022. doi: 10.1109/ICORR55369.2022.9896525.

[71] A. Crétual, “Which biomechanical models are currently used in standing posture analysis?,” 2015, *Elsevier Masson SAS*. doi: 10.1016/j.neucli.2015.07.004.

[72] G. Pavei, E. Seminati, D. Cazzola, and A. E. Minetti, “On the estimation accuracy of the 3D body center of mass trajectory during human locomotion: Inverse vs. forward dynamics,” *Front Physiol*, vol. 8, no. MAR, Mar. 2017, doi: 10.3389/fphys.2017.00129.

[73] R. Gupta, I. S. Dhindsa, and R. Agarwal, “Continuous angular position estimation of human ankle during unconstrained locomotion,” *Biomed Signal Process Control*, vol. 60, Jul. 2020, doi: 10.1016/j.bspc.2020.101968.

[74] C. Nüesch, E. Roos, G. Pagenstert, and A. Mündermann, “Measuring joint kinematics of treadmill walking and running: Comparison between an inertial sensor based system and a camera-based system,” *J Biomech*, vol. 57, pp. 32–38, May 2017, doi: 10.1016/j.jbiomech.2017.03.015.

[75] J. Yoon, H. S. Park, and D. L. Damiano, “A novel walking speed estimation scheme and its application to treadmill control for gait rehabilitation,” *J Neuroeng Rehabil*, vol. 9, no. 1, 2012, doi: 10.1186/1743-0003-9-62.

[76] S. Canete and D. A. Jacobs, “Novel velocity estimation for symmetric and asymmetric self-paced treadmill training,” *J Neuroeng Rehabil*, vol. 18, no. 1, Dec. 2021, doi: 10.1186/s12984-021-00825-3.

[77] W. Wang, K. Yang, Y. Zhu, and H. Mu, “Speed adaptation and acceleration

ripple suppression of treadmill user system using a virtual force moment balance model," *Transactions of the Institute of Measurement and Control*, vol. 42, no. 2, pp. 322– 329, Jan. 2020, doi: 10.1177/0142331219868924.

[78] S. Song, H. Choi, and S. H. Collins, "Using force data to self-pace an instrumented treadmill and measure self-selected walking speed," *J Neuroeng Rehabil*, vol. 17, no. 1, Jun. 2020, doi: 10.1186/s12984-020-00683-5.

[79] S. Vazquez *et al.*, "Model predictive control: A review of its applications in power electronics," 2014, *Institute of Electrical and Electronics Engineers Inc.* doi: 10.1109/MIE.2013.2290138.

[80] M. Schwenzer, M. Ay, T. Bergs, and D. Abel, "Review on model predictive control: an engineering perspective," Nov. 01, 2021, *Springer Science and Business Media Deutschland GmbH*. doi: 10.1007/s00170-021-07682-3.

[81] J. H. Lee, "Model predictive control: Review of the three decades of development," Jun. 2011. doi: 10.1007/s12555-011-0300-6.

[82] M. McGrath, D. Howard, and R. Baker, "The strengths and weaknesses of inverted pendulum models of human walking," *Gait Posture*, vol. 41, no. 2, pp. 389–394, 2015, doi: 10.1016/j.gaitpost.2014.10.023.

[83] J. Kim, A. Gravunder, and H. S. Park, "Commercial Motion Sensor Based Low-Cost and Convenient Interactive Treadmill," *Sensors (Basel)*, vol. 15, no. 9, pp. 23667– 23683, Sep. 2015, doi: 10.3390/s150923667.

[84] S. Kajita, F. Kanehiro, K. Kaneko, I. Fujiwara, K. Yokoi, and H. Hirukawa, “A Realtiine Pattern Generator for Biped Walking,” 2002.

[85] V. M. Zatsiorsky and D. L. King, “An algorithm for determining gravity line location from posturographic recordings,” 1998.

[86] F. Yang and Y. C. Pai, “Can sacral marker approximate center of mass during gait and slip-fall recovery among community-dwelling older adults?,” *J Biomech*, vol. 47, no. 16, pp. 3807–3812, Dec. 2014, doi: 10.1016/j.jbiomech.2014.10.027.

[87] J. Reher and A. D. Ames, “Dynamic Walking: Toward Agile and Efficient Bipedal Robots,” 2021, doi: 10.1146/annurev-control-071020.

[88] MOTEK, “The World’s Most Advanced Biomechanics Lab.” Accessed: Jul. 22, 2024. [Online]. Available: https://www.motekmedical.com/solution/caren/

[89] CAREN, “Computer Assisted Rehabilitation Environment.” Accessed: Jul. 22, 2024. [Online]. Available: https://nydnrehab.com/treatment-methods/caren-nyc/

[90] J. S. Hebert, E. Parent, M. Rehani, L. J. Hébert, R. Stiegelmar, and M. Besemann, “Use of the CAREN system as a treatment adjunct for Canadian Armed Forces members with chronic non-specific low back pain: a pilot study,” *J Mil Veteran Fam Health*, vol. 1, no. 1, pp. 47–58, Feb. 2015, doi: 10.3138/jmvfh.2014-05.

[91] C. Formica *et al.*, “The effect of Computer Assisted Rehabilitation Environment (CAREN) in cognitive impairment and coping strategies in Parkinson’s disease: a preliminary study,” *Sci Rep*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023- 29299-0.

[92] S. W. Huck and R. A. Melean, “Using a Repeated Measures ANOVA to Analyze the Data from a Pretest-Posttest Design: A Potentially Confusing Task,”1975.

[93] T. J. Cleophas and A. H. Zwinderman, “Statistical Analysis of Clinical Data on a Pocket Calculator.”, Springer Dordrecht, 2011. https://doi.org/10.1007/978-94-007- 1211-9

10 Appendix

10.1 Appendix A: Visual Analog Scale (VAS) Questionnaire

Subject ID: _____

Trial number: _____

For questions 1-4, please consider how much control you felt you had over the speed of the treadmill.

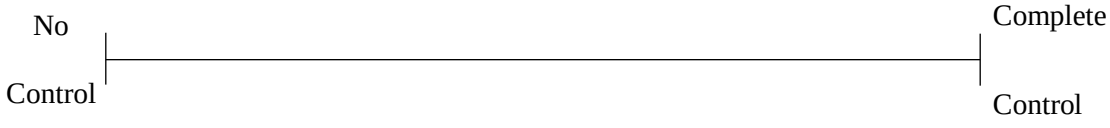
1. Please mark how this walking trial felt whenever you were standing still during the trial:



2. Please mark how this walking trial felt whenever you started and stopped walking:



3. Please mark how this walking trial felt whenever you were speeding up to make it across an intersection or slowing down to wait for the next green light:



4. Please mark how this walking session felt while you were walking at a steady speed:



5. Please mark how much this walking trial felt like walking overground:



6. Please mark how much this walking trial felt like waking on a normal treadmill:



Please list any additional comments that describe this trial or how you felt about it:

10.2 Appendix B: Demographic Form

Date (YYYY/MM/DD):____/_____/_____ Subject ID: ___

Age: __ Height: _____

Weight: _____

Gender identity (select all that apply):

_____Woman,

_____Man,

_____Transgender,

_____Non-binary/non-conforming,

_____Prefer not to respond.

Sex at birth:

_____Female,

_____Male,

_____Intersex,

_____Prefer not to respond.

Race/ethnicity (optional):

__Aboriginal (First Nations, Inuk/Inuit, Métis, North American Indian),

__Black (e.g., African, Haitian, Jamaican, Somali),

__East/Southeast Asian (Chinese, Korean, Japanese, Taiwanese, Filipino, Vietnamese, Cambodian, Thai, Indonesian, other Southeast Asian descent),

__Latino (Latin American, Hispanic descent),

__Middle Eastern (Arab, Persian, Afghan, Egyptian, Iranian, Lebanese, Turkish, Kurdish),

__South Asian (East Indian, Pakistani, Bangladeshi, Sri Lankan, Indo-Caribbean),

__White (Caucasian, European descent),

__Other_____,

__Do not know,

__Prefer not to respond.

10.3 Appendix C: Prescreening Document

IBME Self-Paced Treadmill Prescreening Document

If you answer yes to any of these questions you will be ineligible to be enrolled into the Evaluation of Markerless Regulation of Treadmill Speed study.

1. Have you recently undergone any surgeries or medical procedures?
2. Do you have a history of seizures or conditions affecting balance and coordination?
3. Do you have a severe respiratory condition that may be aggravated by exercise, such as uncontrolled asthma?
4. Do you have severe balance issues or difficulty walking without assistance?
5. Are you taking medication that affects your ability to exercise safely or increases the risk of dizziness or fainting?
6. Are you experiencing cardiovascular conditions such as uncontrolled hypertension, recent heart attack, or severe heart disease?

Curriculum Vitae

Ali Akbar Estarami

Education

M. Sc. in Electrical Engineering-Biomedical Engineering **Ongoing**

University of New Brunswick, Electrical Engineering | NB, Canada

Self-paced Regulation of Treadmill Speed using Model Predictive Control

Ph.D. in Electrical engineering: Control systems **Jan 2021(quit)**

KNT University of Technology, Electrical Engineering | Tehran, Iran

Analytical stability investigation of a transcendental triple-delay fractional-order system

M. Sc., in Electrical Engineering-Control Systems **Sep 2015**

Model order reduction from integer-order to fractional-order system

KNT University of Technology, Electrical Engineering | Tehran, Iran

B. Sc., in Electrical Engineering-Control Systems **Sep 2013**

Sahand University of Technology, Electrical Engineering | East Azerbaijan, Iran

Publications

[1] M. Ghorbani, M. Tavakoli-Kakhki, and A. A. Estarami, "Robust FOPID stabilization of retarded type fractional order plants with interval uncertainties and interval time delay," *Journal of the Franklin Institute*, vol. 356, no. 16, pp. 9302–9329, Nov. 2019, doi: https://doi.org/10.1016/j.jfranklin.2019.08.035.

[2] Linear Control Systems, Nasir Publication, 2nd Edition, 2 Volumes, https://nasir.ir/StoreView.aspx?.id=Ia2gWyHadrE=

[3] Technical English for Electrical Engineer, Nasir Publication, https://nasir.ir/StoreView.aspx?.id=lcFkxp88w24=