Machine-Learning Applications to Gait Biomechanics using Inertial Sensor Signals

by

Braveena K. Santhiranayagam

Bachelor of Science in Engineering (Hons)

Submitted in fulfilment of the requirements for

Doctor of Philosophy

College of Sport and Exercise Science

Institute of Sport, Exercise Science and Active Living

Victoria University

2016

Abstract

Minimum toe clearance (MTC) above the walking surface is a critical representation of toe-trajectory control related to tripping risk. Reliable and precise MTC measurements are obtained in the laboratory using 3D motion capture technology. Real-world gait monitoring using body-mounted sensors presents considerable data processing challenges when estimating kinematic parameters, including MTC. This Thesis represents the first study employing machine-learning to estimate young and older adults' toe-height at MTC using inertial data captured from a foot-mounted sensor. Age-group specific Generalized Regression Neural Network (GRNN) models estimated MTC with root-mean-square-error (RMSE) of 6.6 mm with 9 optimum inertial-signal features for the young and 7.1 mm with 5 features for the older during treadmill walking. These RMSE values are approximately one third of the previously reported (Mariani et al., 2012; McGrath et al., 2011) and GRNN modeling also performed well as reflected in no significant difference between 3D measured reference and model estimated MTC_Height. The GRNN model specific to older adults showed good generalizability when applied to data from slower and dual task walking.

In adopting a machine-learning technique to estimate MTC it was essential to determine the proportion of gait cycles <u>not</u> showing a clearly defined MTC event, i.e." non-MTC" gait cycles. Young demonstrated only 2.9% non-MTC gait cycles but they were more frequent in older adults (18.7%). In constrained walking conditions up to 37.7% of non-MTC gait cycles were observed. Eliminating the biomechanically hazardous MTC event by adopting more non-MTC gait cycles could be an adaptive

locomotion strategy in reducing the likelihood of toe-ground contact when gait is destabilized. Some participants revealed more than 90% of non-MTC gait cycles and to utilize those strides in MTC modeling, toe-height at typical MTC timing was demonstrated to be an appropriate measure of "indicative" toe-height in non-MTC gait cycles.

Student Declaration

Doctor of Philosophy Declaration

"I, Braveena K. Santhiranayagam, declare that the PhD thesis entitled Machine-Learning Applications to Gait Biomechanics using Inertial Sensor Signals is no more than 100,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work".

[redacted] 08/01/2016

Signature Date

Dedication

This Thesis is dedicated to my parents, Aiya and Amma who have loved me unconditionally and trusted my abilities. I also dedicate this work to my grandma, Ammamma who has been a pillar of strength for me and my family. My greatest debt of gratitude is to my husband, Ketha who has been a constant source of support and encouragement during the challenges of graduate school and family life. I am truly blessed for having my son Aran in my life whose eyes filled with love and happiness has been the most powerful motivation to strive harder.

Acknowledgement

Throughout my University education, I have received insight, support, and encouragement from many people, to whom I always will be extremely grateful. I sincerely thank my primary Doctoral Supervisor Professor Rezaul Begg for his academic guidance and support and throughout my candidature. I am grateful for having Dr Daniel Lai as my associate Supervisor, who introduced me to the scientific research, played a major role in the technical developments associated with this study and has been a wonderful guiding influence. I also acknowledge the invaluable advice and assistance provided by Dr Tony Sparrow, who gave me many precious hours of patient reflection and encouragement throughout the writing up stage of my Thesis.

I would like to acknowledge Professor Marimuthu Palaniswami for being a mentor and providing financial assistance for conference attendance. I thank Alistair for co-authoring a journal paper and two conference papers during my candidature. I would like to express my gratitude to Rob, Rhett, Lucy, Hans, Simon and fellow students Bobo, Angela, Hojjat and Marco for being supportive colleagues and co-workers throughout my research study. I would like to thank my husband Ketha, who as a Technical Officer in the Biomechanics Laboratory helped with the experimental setup and pilot testing the apparatus and procedures. I also thank the administrative staff of ISEAL and CSES and the Graduate Research Centre, especially Grace and Elizabeth for their reliable and timely support and assistance. I acknowledge the Department of Education of Australian Government for providing me an International Postgraduate Research Scholarship to support my doctoral candidature.

Thanks to my sisters, especially Theepa, for proof reading, in-laws and friends for the encouraging long distance calls. I also thank my relatives and friends in Australia for making me feel home during this long tough journey.

Finally I would like to thank all the participants who volunteered to participate in the study and who ultimately made my goal attainable.

Table of Content

List of Tables

List of Figures

List of Abbreviations and Acronyms

Abbreviations and acronyms used in the Thesis are defined below.

MTC	Minimum Toe Clearance Toe’s (distal end of the shoe) minimum vertical displacement from the ground during swing phase of a gait cycle
IMU	Inertial measurement unit
SD	Standard deviation
IQR	Inter-quartile range, i.e. a measure of variability obtained by subtracting first quartile from third quartile.
TO	Toe-off, toe breaks the contact with the ground and enters in to swing phase
Mx1	First maximum vertical displacement of the foot (distal end of the shoe) after TO event within a swing cycle
Mx2	Second maximum vertical displacement or the maximum vertical displacement of the foot (distal end of the shoe) after TO event of within a swing cycle
corr	Correlation value between two series
ADL	Activities of daily living
AP	Anterior-posterior
ML	Medio-lateral
DT	Dual task
3D	Three dimensional
MEMs	Micro-electro mechanical systems

Acc	Acceleration
Vel	Velocity
Disp	Displacement
RMSE	Root-mean-square-error, $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}$ Where y_i the standard measurement is $\hat{y}_i$ is the corresponding estimated measurement and N is total number of measurements.
GRNN	Generalized Regression Neural Network
ANOVA	Analysis of variance
DOF	Degree of freedom
Young	Young with capital 'Y' denotes the young participants in the present study as a whole group
young	Young with simple 'y' denotes the young adults in general
Older	Older with capital 'O' denotes the older participants the present study as a whole group
older	Older with lowercase 'o' denotes the older adults in general
LOSO	Leave-one-subject-out
CV	Cross validation
PW	Preferred-speed walking
DW	Dual task walking – walking while holding a glass of water
SW	Slower walking, speed was matched at DW
Model_Y	The optimum GRNN model built specific to Young in the present project
Model_O	The optimum GRNN model built specific to Older in the present project

R^2	Coefficient of determination
r	Coefficient of Pearson's correlation
AccX	Acceleration in medio-lateral axis measured by accelerometer
AccY	Acceleration in anterior-posterior axis measured by accelerometer
AccZ	Acceleration in sagittal-vertical axis measured by accelerometer
GyroX or AngVelX	Angular velocity about medio-lateral axis measured by gyroscope
GyroY or AngVelY	Angular velocity about anterior-posterior axis measured by gyroscope
GyroZ or AngVelZ	Angular velocity about sagittal-vertical axis measured by gyroscope
Measured or reference MTC_Height	MTC_Height obtained from reference 3D position-time data
Estimated MTC_Height	MTC_Height estimated by the GRNN models using inertial sensor data

1 GENERAL INTRODUCTION

As people age, their risk of falling increases and the consequences of a fall are more serious. Worldwide the population aged more than 60 was estimated to be 688 million in 2006 but is projected to grow to almost two billion by 2050 (World Health Organization, 2007). Lord et al. (2006) reported that many older people fall even when walking on a level surface, and in 2007 over 18,000 older Australians died from unintentional fall injuries (Australian Bureau of Statistics, 2012). The medical cost associated with falls in older adults is already very high, for example, in the United States of America, the total cost of all fall-related injuries for older adults in 1994 was $27.3 billion and it is estimated that by 2020 the cost will be $43.8 billion (National Center for Injury Prevention and Control, 2012).

The causes of falls are multifactorial but they can be generally categorized as intrinsic and extrinsic. Extrinsic factors are typically environmental features that destabilize the individual, such as uneven or raised surfaces, ground-based obstacles and stairs. Intrinsic factors specific to ageing include sensorimotor deficits, cognitive declines and perceptual impairments. Recent falls monitoring of frail older adults in long-term residential care facilities showed that 49% of falls occurred while walking (Robinovitch et al., 2013). From a biomechanical perspective falls during locomotion result from different destabilizing events with 74% are due to tripping, slipping and loss of balance (Sherrington et al., 2004). Most important for the present study is that of these falls-related biomechanical events, tripping accounts for more than 50% of falls (Sherrington et al., 2004) and in community-dwelling older adults there is a high association between tripping frequency and falling (Pavol et al.).

Tripping results directly from unsuccessful toe-ground clearance, primarily during the swing phase of a gait cycle. Previous research with both young and older populations have, therefore, focused on how lower limb swing-phase trajectory control influences toe-ground clearance (Begg et al., 2007; Lai et al., 2008c; Mills et al., 2008). Figure 1-1 shows vertical displacement of toe with time for one complete gait cycle. Low clearance (~10-30mm) observed during the mid-swing phase of the gait cycle at Minimum Toe Clearance event (MTC_Height) in addition to high foot velocity (~4.60 m/s) and a single-foot base of support poses a significant hazard to locomotion (Begg et al., 2007; Lai et al., 2008c; Mills et al., 2008).

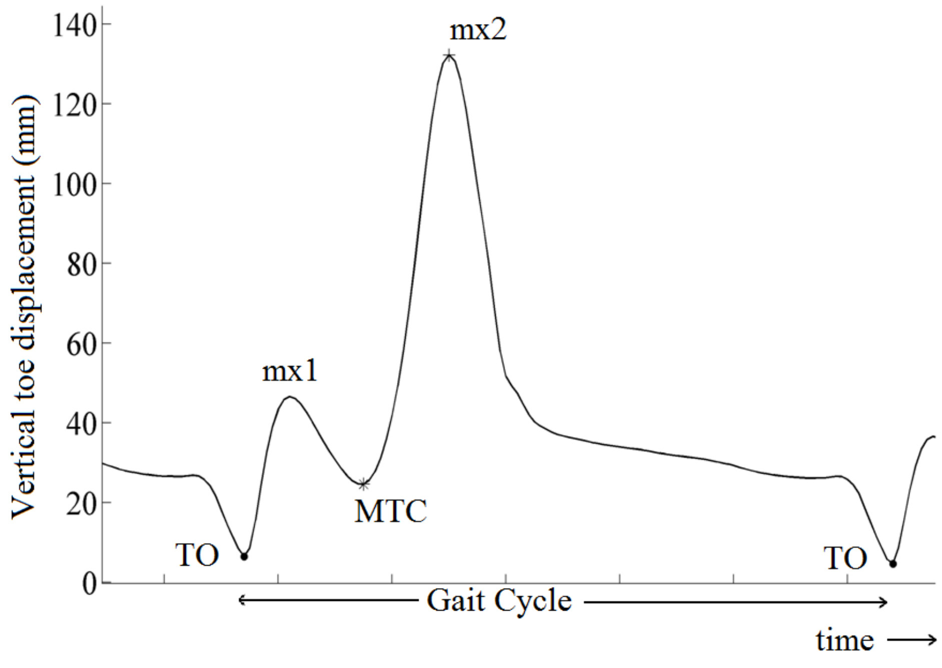


Figure 1-1 Vertical end point foot trajectory and MTC event is illustrated during the mid-swing phase

To maintain the clearance, older adults demonstrate similar MTC_Height central tendency, measured by mean or median, as young individuals (Begg et al., 2007; Mills et al., 2008). In contrast, the MTC_Height dispersion, characterized using either the standard deviation (SD) or inter quartile range (IQR), increases with ageing and this greater stride-to-stride variability in MTC_Height appears to increase tripping risk (Barrett et al., 2010; Begg et al., 2007; Mills et al., 2008). Failure to adequately compensate surface height variability by adjusting clearance at MTC increases tripping risk. The capacity to identify high risk toe trajectory control would allow the design of devices to alert pedestrians to modify their toe trajectory and reduce the risk of foot-ground contact (Tirosh et al., 2013). High risk gait could be identified by either calculating the tripping risk probability (Best & Begg, 2008) or by predicting lower MTC_Heights with high variability by monitoring lower limb trajectory parameters in real-time. The practicality of pre-emptive systems as an approach to falls prevention has however, been unrealized due to difficulties in obtaining MTC parameters using a portable measurement system during everyday locomotion.

MTC has previously only been measured under controlled conditions in the laboratory using 3D motion tracking systems (Guangyi et al., 2009; Zhou & Hu, 2008). Falls in older people occur, however, in the dynamic environments of unconstrained locomotion (Hamacher et al., 2011). Measuring MTC_Height in natural, everyday locomotion is, therefore, essential to understanding tripping-related falls (Lai et al., 2008b; Lau & Tong, 2008). Inertial Measurement Units (IMUs) comprising accelerometers and gyroscopes are increasingly used for motion analysis in unconstrained, non-laboratory environments (Dadashi et al., 2014; Ge & Shuwan, 2008; Lau et al., 2008; Mariani et al., 2012; Najafi et al., 2002; Zhou & Hu, 2008). IMUs directly measure linear accelerations and angular velocities (inertial sensor signals) but deriving positional data from inertial sensor signals is a major challenge due to noise and “drift” over time, the essential limitation to IMU technology (Findlow et al., 2008; Guangyi et al., 2009; Lai et al., 2008b). Techniques such as strap down integration and regression have improved inertial sensor data based measurement accuracy of stride length (Peruzzi et al., 2011; Sabatini, 2005; Sabatini et al., 2005), walking speed (Li et al., 2010; Mannini & Sabatini, 2014), and maximum toe-clearance (Mariani et al., 2010). Using IMUs to measure MTC_Height, a narrower-range biomechanical parameter, remains a challenge because small errors in integration and regression considerably affect accuracy.

Recently Mariani et al. (2012), used a de-drifted double-integration technique to estimate mean MTC_Height from 12 young healthy older adults’ IMU data and reported the mean (-12.7 mm) and standard deviation (9.0 mm) of the difference between estimated and reference mean MTC_Height as accuracy and precision respectively. From these results, a root-mean-square-error (RMSE) of 21.7 mm can be estimated by summing absolute accuracy and precision. Using a quadratic regression modeling technique, McGrath et al. (2011) showed that foot mounted inertial sensors could estimate mean MTC_Height with up to 17.3 mm RMSE. Given that MTC_Height is typically only 10-30 mm (Barrett et al., 2010; Begg et al., 2007; Nagano et al., 2011), the RMSE values reported above would be impractical for further implementation of real-time MTC monitoring of individual stride cycles.

Gait research has advanced technically due to the infusion of more sophisticated data analysis techniques such as machine-learning (Chan et al., 2011; Novak et al., 2013; Pogorelc et al., 2012). Machine-learning focuses on the development of models to reveal the underlying relationships between input training data and target parameters. These models can then adapt and 'grow' when exposed to new data sets. In contrast to traditional computing methods, machine-learning is well suited to noisy data and situations that have no clear algorithmic solutions. The approach to solving the problem of estimating MTC_Height adopted here was to employ machine-learning to model the relationship between MTC_Height and data from lightweight, low power, shoe-mounted IMUs. Lai et al. (2009b), for example, demonstrated the application of a machine-learning technique, Generalized Regression Neural Network (GRNN) to learn the underlying relationship between MTC_Height and *acceleration signals derived by double-differentiating motion captured position-time data*. They showed that individual stride MTC_Height with an RMSE of 6.1 mm could be achieved one gait cycle ahead. The application of machine-learning, specifically GRNN, to inertial sensor data to estimate MTC_Height has yet to be investigated. In this project, the input characteristics were the IMU-kinematics and the model output was MTC_Height. An important consideration in the modeling process was that the generalizing capability of a learned model is limited by its input training set. Given ageing effects on MTC_Height distributions a specific model was required for older adults. Furthermore, it was considered important to include additional experimental gait conditions to validate the model's generalizability to different gaits for both older and young participants.

To test the generalizability with respect to ageing the age-specific GRNN models were tested on the other age group in preferred-speed walking (condition I). The models were then validated in more destabilizing gait conditions, i.e., when walking slower than preferred (condition II) and while executing a secondary task, carrying a glass of water (condition III). Prior to validating the GRNN model in different gait conditions, it was considered important to ensure that the reference MTC_Height obtained from 3D motion capture for those testing conditions were different to preferred-speed data, which were used to train the model.

There are a few reports (Dell'oro, 2008; Schulz, 2011) that some gait cycles do not show a clearly defined MTC event (Figure 1-2). Direct comparison of every model-estimated MTC_Height with reference measurement is clearly not possible if the MTC event is absent, i.e., on "non-MTC" gait cycles. It was considered critical to know the proportion of such non-MTC gait cycles to understand the effect of not accounting for non-MTC gait cycles in the MTC_Height modeling process. Because non-MTC trials have usually been discarded (Dell'oro, 2008), little is known about toe trajectory control in non-MTC stride cycles. In such non-MTC gait cycles, toe-height extracted at typical MTC timing could be used to represent an indicative MTC_Height (Dell'oro, 2008). The concept of using toe-height at mean MTC_Time, however, has yet to be validated with larger samples, in older adults and across other walking conditions. Furthermore, while MTC_Height has been investigated extensively (Barrett et al., 2010) MTC_Time has been less frequently discussed (Mills et al., 2008). Given that toe-ground clearance amplitude may be related to timing within the stride cycle, it was considered important to characterise toe-trajectory control across different experimental conditions I-III above by measuring both MTC_Height and MTC_Time.

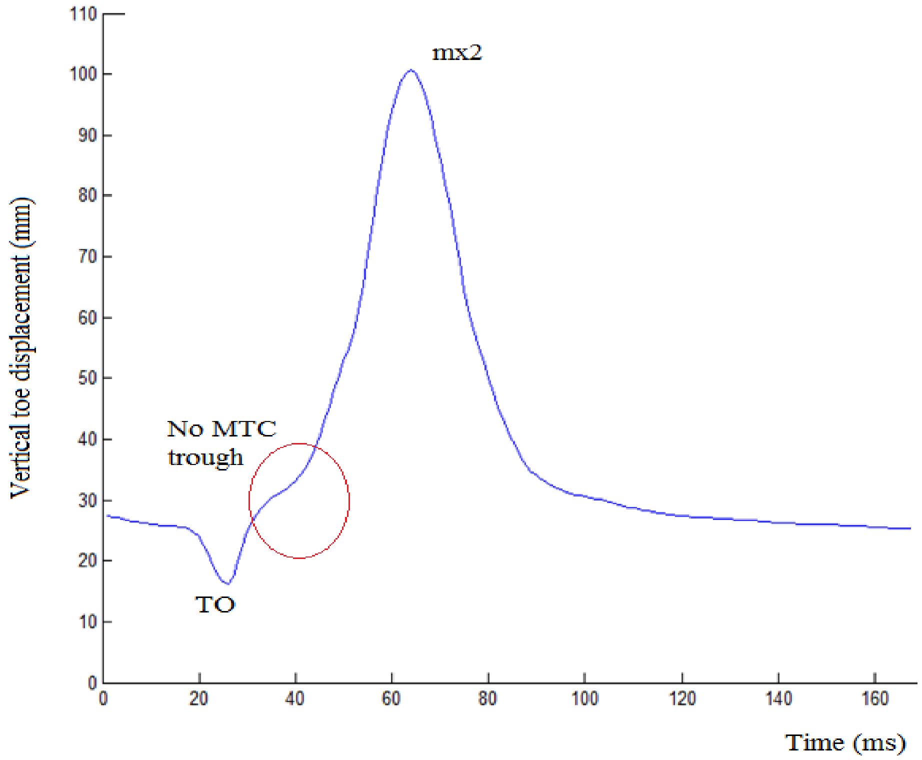


Figure 1-2 A gait cycle without a clearly defined MTC event

1.1.1 Research questions

As an approach to further understanding of lower limb control and falls prevention in older adults, the present Thesis was designed to address the following research questions:

Research Question 1: What are the effects of ageing and walking condition on MTC_Height, MTC_Time and non-MTC gait cycle frequency measures obtained from 3D motion-capture?

Research Question 2: Would machine-learning (GRNN) provide appropriate estimates of MTC_Height using inertial sensor signals?

The Aims and the hypotheses to address above Research Questions are presented in the final section of the Literature Review (page 49).

1.2 Thesis organization

The study has been presented as six chapters and brief outline of each chapter is presented below:

Chapter 2: Literature Review elucidates the significance of tripping falls in older adults, the rationale for studying minimum-toe-clearance (MTC) and the necessity of a wearable, inexpensive sensor system to measure MTC. The working principles of inertial measurement units (IMUs), their technical challenges and suitability as a foot-mounted sensor system and are surveyed in this chapter. The concept of machine-learning, especially Generalized Regression Neural Networks (GRNN) and steps in adopting the GRNN technique to gait biomechanics, i.e., MTC_Height estimation, are presented. As the conclusion to this chapter, the Aims and hypotheses to operationalise the Research Questions are presented.

Chapter 3: Technical Preparation presents the development of a wireless foot-mounted IMU consisting of a tri-axial accelerometer and a tri-axial gyroscope integrated with a microcontroller to transmit sensor data via Bluetooth to collect IMU kinematics of toe from the experimental conditions to address Research Question 2.

Chapter 4: Experimental Methods describes the experimental protocol used to collect toe trajectory gait data from 15 Young and 15 Older participants performing three walking conditions (I-III) using both a 3D motion tracking system and a foot-mounted IMU. Data processing techniques such as identifying gait cycle and extracting MTC event from the 3D displacement data are elaborated followed by inertial sensor signal processing and feature extraction to build age-specific GRNN models. Finally the statistical analysis procedures for MTC characteristics and non-MTC gait cycles are presented, followed by GRNN model validation.

Chapter 5: Experimental Results outlines the experimental results showing ageing and walking condition effects on toe-trajectory control for both young and older adults, followed by validation of toe-height at mean MTC_Time in non-MTC gait cycles as an indicative MTC_Height. Non-MTC gait cycle group frequency and individual frequency analysis are then presented. Finally GRNN model building outcomes for both young and older adults in preferred-speed walking are presented with model validation in slower and dual task walking conditions.

Chapter 6: General Discussion summarizes the study, discusses the findings and highlights the remaining challenges in using foot-mounted IMUs to measure MTC followed by recommendations for further research in sensor technology.

2 LITERATURE REVIEW

2.1 Epidemiology of ageing and falls

The World Health Organisation defines a fall as an event which results in a person coming to rest inadvertently on the ground or floor (World Health Organization, 2007). The human cost of falling includes distress, pain, injury, loss of confidence, loss of independence, and mortality. Injury following a fall is associated with a decreased quality of life and poor functional outcome, in severe injuries these effects continue for a prolonged period of time. The negative consequences of falls increase dramatically with age in both sexes and in all racial and ethnic groups. Falls account for 70 percent of accidental deaths in persons 75 years of age and older (Fuller, 2000; Wild et al., 1981). In 2013, for example, over 25 464 older Americans died from fall injuries (Centers for Disease Control and Prevention, 2013).

Direct costs associated with falls are the highest of all injury categories, for example, five times larger than the second ranked, road traffic accidents (Potter-Forbes & Aisbett, 2003). Hospital stays are reported to be twice as long in older patients who are hospitalized after a fall than for those admitted for other conditions (World Health Organization, 2007). Moller (2003) suggested that unless falls prevention strategies are implemented or treatment costs lowered, medical treatment due to falls will increase threefold to $1375 million per annum by 2051 (Figure 2-1). In America, the total cost of all fall-related injuries for older adults in 1994 was $27.3 billion and it is estimated that by 2020, the cost will be $43.8 billion (SAFE Aging Newsletter, 2005).

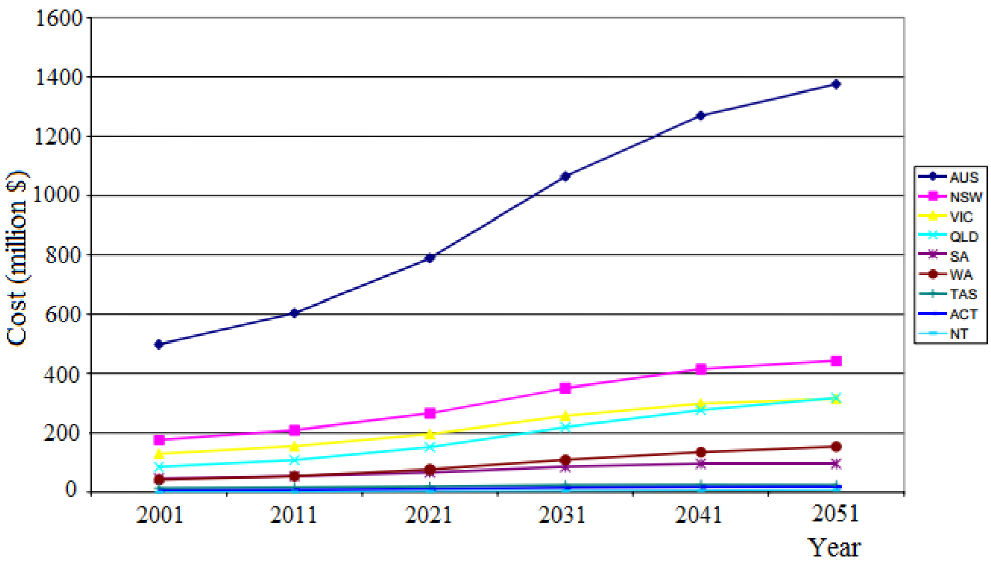


Figure 2-1 Total fall-related health cost trends in millions, adapted from Moller (2003).

Extrinsic falls-related factors are typically environmental features, such as ground surface properties or illumination, while intrinsic risk factors embrace perceptual-motor characteristics related to ageing, such as physical, cognitive and affective capacities that influence balance, visual acuity and proprioception (Figure 2-2). Research has been conducted to investigate a variety of approaches to reduce falls rates. Passive fall prevention techniques such as exercise programmes, safety equipment and medications have been shown to help in preventing falls indirectly. A recent Cochrane collaboration review of 111 randomized trials including 55,303 participants revealed that multi-component interventions consisting of two or more categories of exercise were effective in reducing the risk of falling (The Cochrane Collaboration, 2009). Yardley et al. (2008) have, however, found that nearly 60% of older adults would not voluntarily participate in group exercise sessions for the purpose of falls prevention, mainly due to lack of motivation. Furthermore, balance exercise interventions, such as Tai Chi, have to be executed with very high attention and care. Home safety interventions, for example, handrails and shower guards are effective only where they are installed. These findings clearly indicate that a new active intervention approach is necessary for reducing the rate and risk of falling. To develop active intervention approaches to reduce the falls occurrence, a biomechanical understanding of human locomotion and lower limb trajectory control is critical.

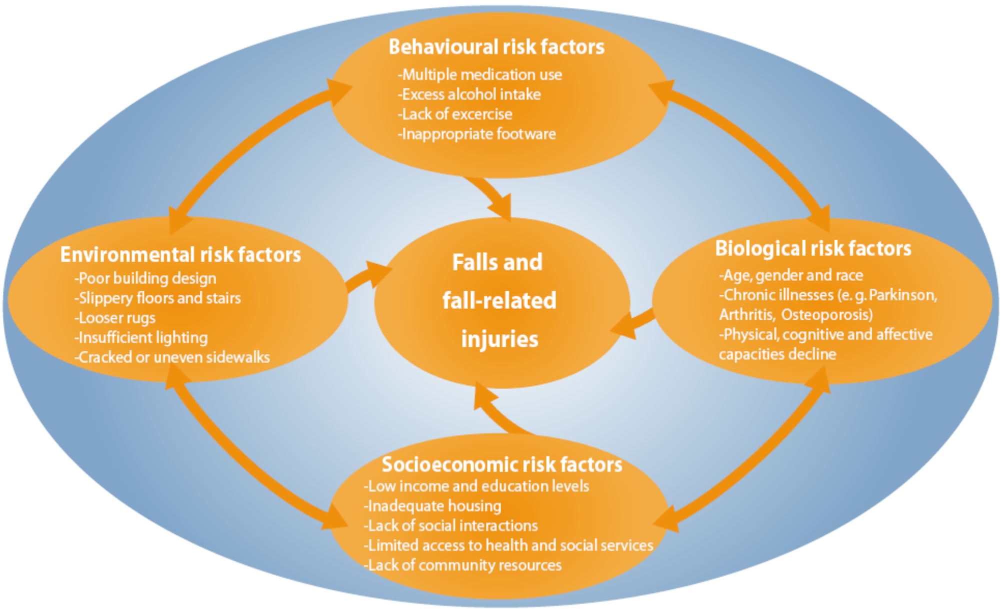


Figure 2-2 Risk factors for falls in older; environmental and socioeconomic risk factors are considered extrinsic causes while biological risk factors are intrinsic. Behavioural risk factors include both extrinsic and intrinsic causes, adapted from World Health Organization (2007)

Changes to gait biomechanics with ageing have been examined in an effort to identify risk factors for falls and predict individuals at high risk of falling (Barrett et al., 2010; Mills et al., 2008; Nagano et al., 2011; Sparrow et al., 2008; Sparrow et al., 2002; Taylor, 2012). Past studies have compared healthy young adults and carefully-screened healthy older adults to understand ageing effects on gait control, as far as possible, independent of ageing-related orthopedic, sensory or other "non-ageing" related lower limb trajectory control variables. Gait patterns of older individuals exhibit characteristic differences when compared with young adults.

From a biomechanical perspective, 74% of falls in people aged above 65 are due to tripping, slipping and balance loss during locomotion (Sherrington et al., 2004). Of these, tripping accounted for the highest percentage of falls (Figure 2-3).

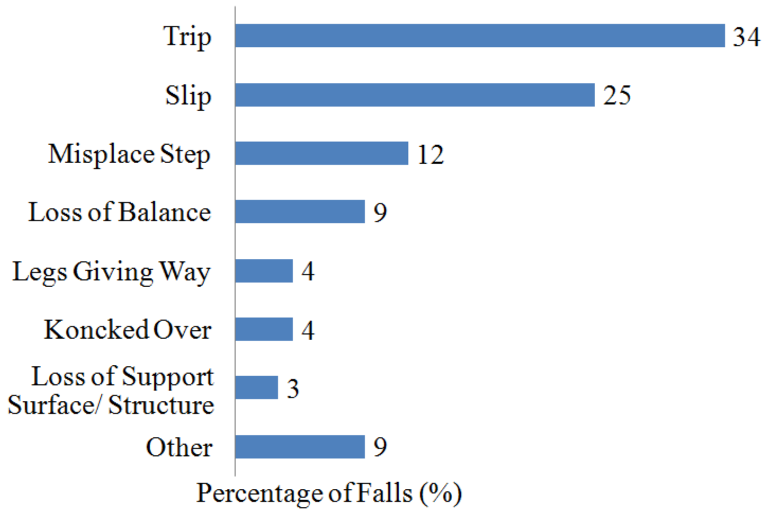


Figure 2-3 Destabilizing events causing falls; tripping accounted for the highest percentage of falls adapted from Sherrington et al. (2004)

Tripping is defined as an event in which the most distal feature of the swing limb, usually the lowest part of the shoe or foot, makes unanticipated contact with either the supporting surface or an obstacle with sufficient force to destabilise the pedestrian. Control of the sagittal plane toe trajectory is clearly an important consideration for safe walking since a lack of control could increase tripping risk. In a typical gait cycle, as shown in Figure 2-4, following events are observed in common: Toe-off (TO) - the toe breaks contact with the walking surface and enters the swing phase, first maximum (mx1) - the first maximum peak vertical displacement of the toe (25% into swing), second maximum (mx2) - the highest vertical displacement of the toe i.e., the second maximum peak, usually greater than mx1 observed at 90% of swing and minimum toe clearance (MTC) - the lowest toe-ground clearance between mx1 and mx2 (50% into swing). Among these gait events, MTC has been identified as a critical gait cycle event in determining the risk of tripping.

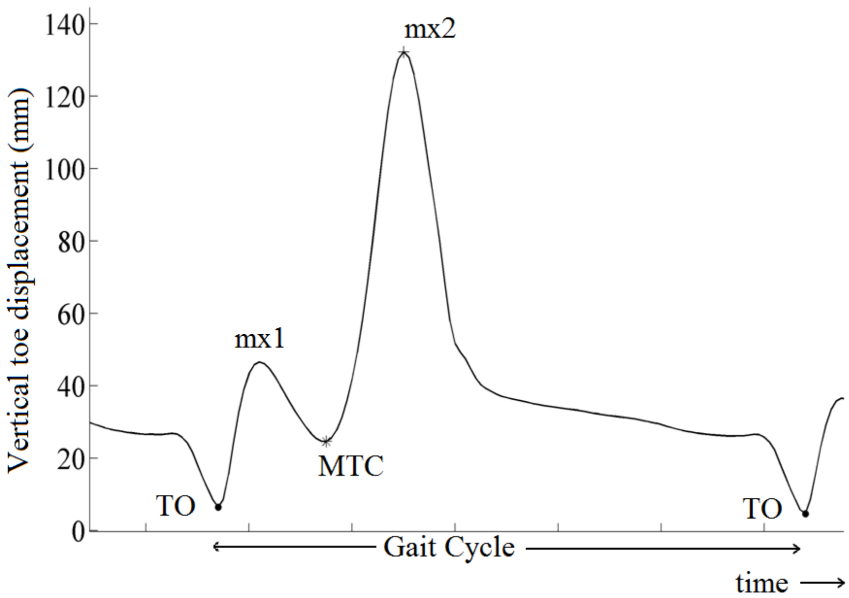


Figure 2-4 Sagittal plane toe vertical displacement within a time-normalized gait cycle; important cyclic events toe-off (TO), first maximum (mx1), MTC and second maximum (mx2) are marked.

2.2 Minimum Toe Clearance (MTC)

Toe clearance above the walking surface at MTC is only 10 mm to 30 mm (Figure 2-4) and instantaneous progression velocity is three times the walking velocity (Figure 2-5). These biomechanical tripping-related risk factors are further compounded by the consideration that at MTC the body is single-limb supported and the whole body centre of mass (COM) is outside the supporting base formed by the single stance foot. Balance recovery from tripping-related destabilization at MTC is, therefore, likely to be difficult.

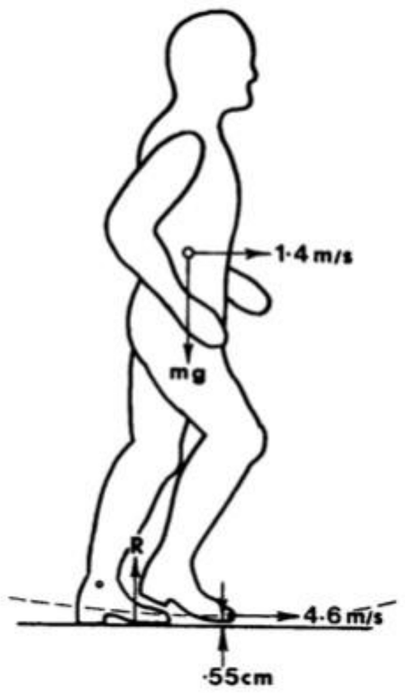


Figure 2-5 When the pedestrian walking at 1.4 m/s, the foot velocity at MTC event was 4.6 m/s, more than three times the walking speed, adapted from Winter et al.(1991).

2.2.1 Ageing effects on MTC

Murray (1969) obtained MTC_Height from participants aged between 20 and 87 years (Figure 2-6) in preferred and faster walking speed. While MTC_Height was found to be increasing with age (Figure 2-6) no statistical tests were reported by Murray (1969).

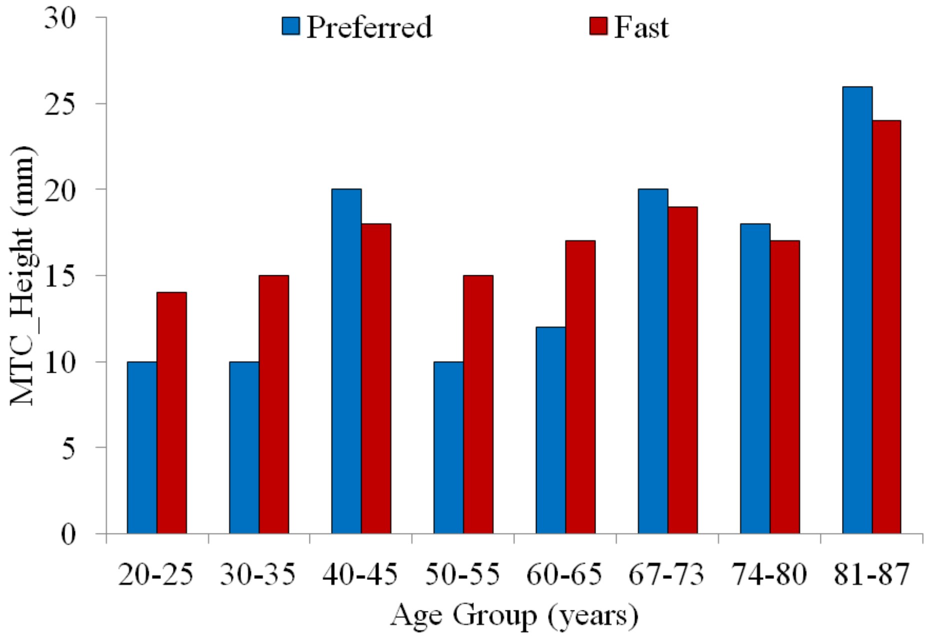


Figure 2-6 Longitudinal study results of ageing effects on MTC_Height in preferred and fast speed walking, adapted from Murray, et al. (1969). Overall with ageing MTC_Height increased.

Figure 2-7 from Begg et al.(2007) presents MTC_Height distributions for young and older adults in treadmill walking at preferred speed. To examine inter- and intra-individual toe –trajectory control, MTC_Height distributions were characterised using two measures of central tendency, either the mean or median, and two variability (dispersion) descriptors standard deviation (SD) or inter quartile range (IQR). These MTC_Height histograms show non-normal distributions for both young and older adults. Begg et al. (2007) suggested, therefore, that median and IQR would better represent MTC_Height central tendency and dispersion than the mean and SD.

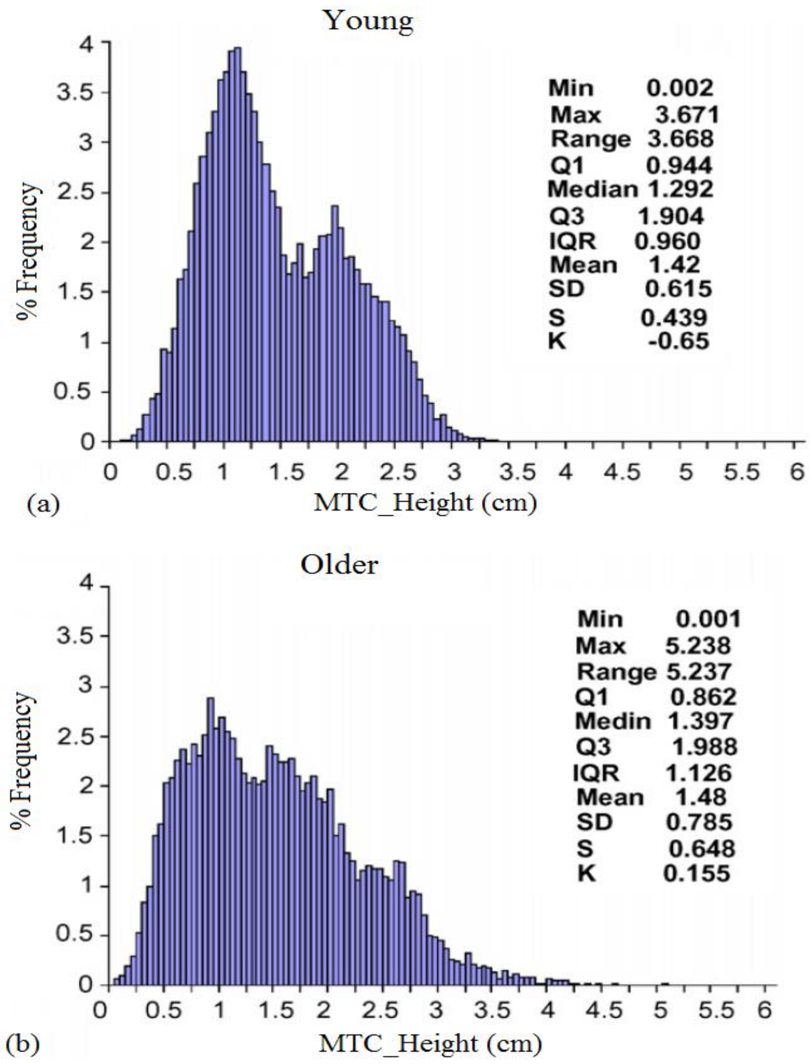


Figure 2-7 (a)Young vs. (b)Older MTC_Height histograms for preferred-speed walking, obtained from Begg et al. (2007).

MTC_Height mean or median was unaffected by age (Barrett et al., 2010; Begg et al., 2007; Mills et al., 2008). Critically, however, MTC_Height SD or IQR was significantly greater in the older than the young (Begg et al., 2007; Mills et al., 2008). Greater inter-stride MTC_Height variability (Figure 2-7) relative to their younger counterparts implies greater likelihood of toe-ground contact and is widely interpreted as an indication that older adults are at increased risk of tripping when walking on level surfaces. In a recent review Barrett et al. (2010) summarized the effect of age (young versus older adults) and falls history (older fallers versus older non-fallers) on characteristics of MTC_Height associated with increased risk of tripping. MTC_Height median or mean and IQR or SD from different studies were extracted and used to calculate standardized effect sizes (Cohen's d) and their corresponding 95% confidence intervals. Eleven out of 12 studies suggested increased MTC dispersion in healthy older adults compared to young groups. Two studies which compared older adults with and without a falls history confirmed that MTC variability is associated with a previous history of falls.

The unambiguous link between toe-ground clearance at MTC and tripping risk motivated a statistical modeling approach to calculate the probability of toe contact with an obstacle based on MTC_Height distribution characteristics (Best & Begg, 2008). Best & Begg (2008) proposed calculating tripping probability for varying unseen obstacle heights using MTC_Height median, IQR, skewness (S) and Kurtosis (K). The probability of a certain MTC_Height occurring during normal walking was calculated by numerically integrating an exponential power distribution incorporating median, SD, S and K. For example, tripping probability for an unseen obstacle height of 5 mm was calculated to be 1 in 95 strides. While MTC is a useful gait parameter for determining ageing effects on toe trajectory control, MTC modeling can also be used to calculate the risk of tripping.

As MTC_Height is a very narrow-range biomechanical gait parameter it is measured using a high accurate 3D motion capture systems in laboratories. In reporting the MTC_Height, there has been inconsistency between studies that can, in major part, be accounted for by differences in measurement. Begg et al. (2007), for example, reported group mean MTC_Heights for young and older of 14.2 mm (SD = 6.15 mm) and 14.8 mm (SD = 7.85 mm) respectively. In contrast, Dell'oro (2008) found greater group mean MTC_Heights for both groups (Young = 23.0 mm and Older = 20.4 mm). As shown in Figure 2-8, Begg et al. (2007) reference MTC_Height from the toe vertical displacement at toe-off but Dell'oro (2008) measured MTC_Height from the walking surface, i.e. the treadmill belt. In the present study MTC_Height was measured from the walking surface as reported by Dell'oro (2008), as the interest was to obtain the toe-clearance above the walking surface.

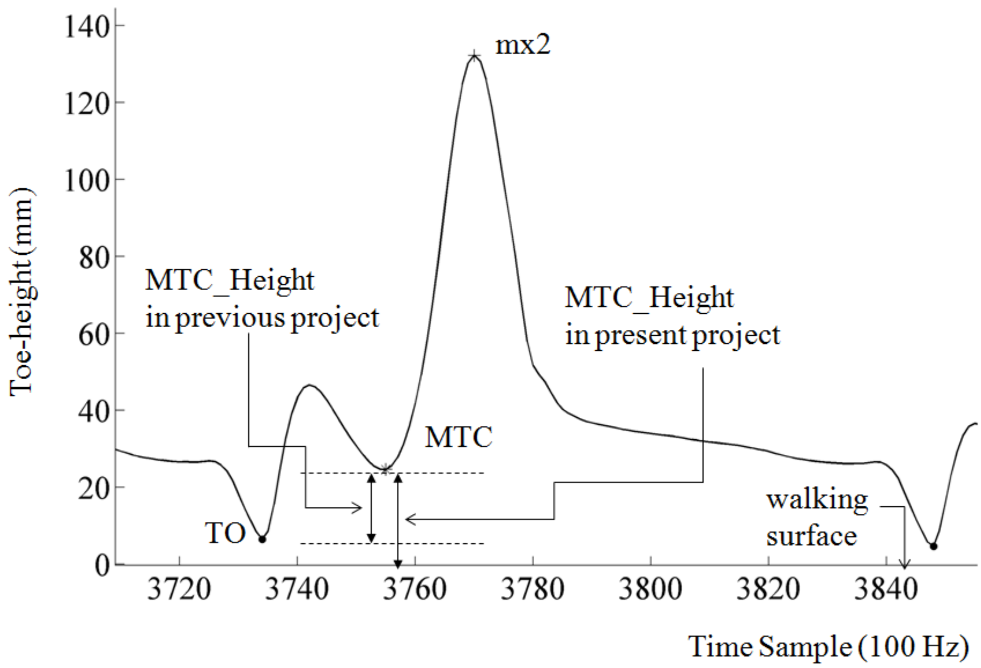


Figure 2-8 MTC_Height measurement using different lower reference

2.2.2 Task and speed effects on MTC

It was considered important to include additional experimental gait conditions to verify the generalizability of the machine-learned model for estimating MTC_Height. For this purpose, in the present study, a dual task walking experiment was devised in which participants undertook a concurrent task of carrying a glass of water. The dual task required attention to be shared, disturbing performance on one or both tasks if processing capacity was exceeded (Ka-Chun et al., 2008). Performing a concurrent task while walking is considered hazardous to older people (Canning, 2005; Ka-Chun et al., 2008; Laessoe et al., 2008). Sparrow et al. (2002) investigated ageing effects on dual task walking and found that the resource cost of walking was greater in older people. Furthermore, a more challenging foot-targeting task had higher attention demands than an unconstrained condition for both young and older groups. A common observation on dual task walking is that participants slow down in response to increased attention demands (Hollman et al., 2007; Speciali et al., 2012). An answer to the question of how performing a concurrent task while walking (dual task) changes lower limb gait characteristics, Nordin et al. (2012) reported that older individuals aged 75 years and above who demonstrated change in gait parameters such as mean step-width, mean step-time and step-length variability when walking while carrying a cup and saucer were less falls prone. Given Nordin et al.'s (2012) report on reduced post-study falls observations, it was expected that a similar dual task condition older adults would significantly modify toe-trajectory control for safer gait, reflected in MTC parameters.

In an attempt to understand the changes to MTC_Height while executing similar dual task walking, carrying a glass of water on a tray, Schulz et al. (2010)

reported *no difference* in mean MTC_Height in young healthy adults. While their experiment provided useful background to dual task effects on MTC, they neither reported MTC_Height variability nor included older adults in the experimental design. Further, any effects on MTC characteristics in a dual task condition could be due to dual tasking, reduced walking speed or the interaction of both independent variables. In preferred-speed treadmill walking MTC_Heights are typically 15.6 mm (Begg et al., 2007) and 14.9 mm (Mills et al., 2008). Miller et al. (2009) reported that MTC_Height reduced by 4.3 mm per 1 m/s of increase in speed. In contrast, Winter et al. (1991) reported no change in MTC_Height when walking speed was greater than preferred. To confirm dual task effects on toe trajectory control it was, therefore, important to run a speed-matched control condition without the dual task constraint. Schulz et al. (2011) normalized gait cycles to accommodate different waking speeds while dual tasking but no previous reports incorporated a speed-matched control trial when comparing dual tasking and preferred-speed walking. No reports of slower walking effects on MTC have been found.

To collect sufficient sequential gait cycles for gait research, for example to model tripping risk using MTC_Height (Begg et al., 2007) and to analyse lower limb joint angle related to toe-trajectory control (Mills et al., 2008) treadmill walking has been chosen (Riva et al., 2013; Sparrow et al., 2008; Tirosh et al., 2013). Treadmill walking, however, has demonstrated changes to natural walking mechanics and may not properly represent normal overground locomotion (Nagano et al., 2011). Nagano et al. (2011) reported significantly lower dominant foot MTC_Height during preferred-speed treadmill walking for both young and older (n=11 for each group) than preferred- speed overground walking. The choice of procedure is influenced by whether an extended data set is required, as in tripping risk calculation using MTC_Height, (Begg et al., 2007) or only a more limited sample is needed to statistically test between-group or between-condition effects (Schulz, 2011). The aims of the current Thesis required continuous IMU data for MTC_Height modeling that were only practicably obtainable using treadmill walking.

2.2.3 Non-MTC gait cycles

The earlier discussion of MTC as a characteristic of the swing phase trajectory may suggest that all gait cycles demonstrate a well-defined MTC event. In a doctoral research project, however, Dell'oro (2008) reported that considerable number of gait cycles did not show a well defined MTC event (Figure 2-9). Dell'oro (2008) documented that 8,814 gait cycles of 75,193 strides (11.7%) from both young and older (n=12 for each group) in preferred-speed treadmill walking and in attention division gait tasks did not demonstrate MTC. Dell'oro (2008) indicated that 50% of her participants demonstrated at least 10% non-MTC gait cycles and those individuals were excluded from the statistical analysis. In young adults MTC does appear to be reliably observed unless a significant change to lower limb trajectory is demanded, such as clearing obstacles or climbing stairs. Schulz (2011), for example, found that in young participants, 98% of gait cycles in unconstrained preferred-speed level walking demonstrated an MTC event but the frequency declined to 80% during obstacle crossing. Most previous studies, however, have not reported the frequency of non-MTC gait cycles, suggesting that either MTC was observed consistently both within or between participants or a proportion of non-MTC gait cycles were discarded.

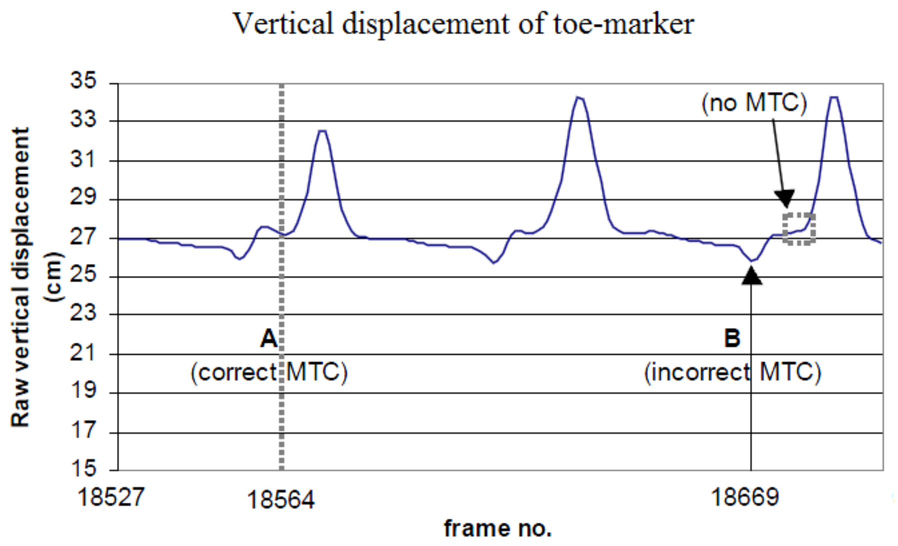


Figure 2-9 Illustration of non-MTC gait cycle adapted from Dell'oro (2008). Non-MTC gait cycle's toe-off was observed at frame number 18669.

In the present project the goal of the computational model was to estimate MTC_Height for every gait cycle using IMU-kinematics. It was, therefore, essential to determine whether individuals consistently show an MTC event and, if not determine the frequency of non-MTC cycles as a proportion of total gait cycles. MTC data for individual participants in each age group were examined to account for the frequency of non-MTC cycles within each age group. Examination of non-MTC gait cycles for age groups would also be important for determining further age-specific toe trajectory controls. This analysis was considered essential for any future application of the foot sensor technology in either MTC_Height estimation or in tripping-falls prevention because some individuals may show too few MTC cycles for a viable MTC-based hazard detection approach. In this respect, Non-MTC cycles "hidden" in group frequency could be due either to many participants having a relatively equal number of non-MTC cycles or caused by relatively few participants who do not display a characteristic MTC event at all. Individual non-MTC frequencies, therefore, were calculated for both young and older across walking conditions. Walking condition manipulations included in the present project, slower and carrying a glass of water enabled the analysis of non-MTC frequencies across age groups and conditions.

Further, it was also critical to identify an indicative toe-height for non-MTC gait cycles at usual MTC event time to compare the model-estimated MTC_Height with the 3D motion capture reference MTC_Height. MTC was considered to occur during mid-late swing phase. Mills et al. (2008) used MTC_Time to analyse the lower limb joint angles at the MTC event to further understand swing phase biomechanics. Dell'oro (2008) examined mean MTC_Time for *one* young adult and proposed that toe-height at mean MTC_Time could be incorporated in non-MTC gait cycles to conduct MTC characteristics analysis. This technique of an indicative MTC_Height, however, was yet to be validated in larger population including both young and older adults and different walking conditions. From a clinical biomechanical point of view, it was considered important to investigate the difference between young and older groups in terms of non-MTC gait cycles and MTC_Time, in addition to MTC_Height to further understand toe-trajectory control. Given the lack of previous research findings on MTC timing characteristics and non-MTC gait cycles, when formulating the testable hypotheses to address the Aims listed at the end of Literature Review (page 49), the age, condition effects on MTC_Time and non-MTC gait cycles were more speculative than for MTC_Height. From a biomechanical perspective, however, by attaining MTC earlier (shorter MTC_Time), it was expected that the pedestrian may transit more quickly from the hazardous low-clearance zone of the toe trajectory to the higher clearance phase. Further, exhibiting a greater proportion of non-MTC gait cycles mechanism was anticipated to minimise the possibility of toe-ground contact in a challenged gait.

2.3 Inertial Measurement Units (IMUs)

An IMU is a single electronics module which collects linear acceleration and angular velocity data respectively from accelerometers and gyroscopes (Castillo, 2005). IMUs are increasingly used in gait related applications, such as falls detection, activity classification, and gait parameter estimation. In automatic falls detection applications (Medical Alert Advice; Philips), accelerometers are used to measure a sharp decrease in whole body acceleration while falling, followed by a corresponding deceleration "spike" on landing (Lee & Carlisle, 2011; Lindemann et al., 2005). Accelerometers in smart phones enabled development of applications (iDown and Fall Alert) to detect falls and call a designated person in case of an emergency. Senior users, however, have reported that the device picks up only half of falls and frequently registers activities of daily living (ADL) as a fall (Lindemann et al., 2005). Identifying ADL using IMU technology is crucial for developing a continuous gait monitoring system (Meng et al., 2009.; Nyan et al., 2006; Santhiranayagam et al., 2013). For example, Meng et al. (2009) demonstrated IMUs comprising accelerometers and gyroscopes to differentiate walking in different terrains such as a flat surface, ascending and descending stairs, and ascending and descending walkways.

2.3.1 Working principle of inertial measurement units

The location and orientation of an object free to move in 3D space is determined by its position, described by three degrees of freedom (x, y, z) and attitude, characterised by three rotational degrees of freedom (ψ, θ, φ). Analogous to an IMU system, the human vestibular system detects these six independent variables simultaneously, (Zeng & Zhao, 2011). The semicircular canals sense rotational movements while the otoliths are sensitive to translation (Figure 2-10). The semicircular canal and the otolith sense the body acceleration and head rotation, which are subsequently transferred to the central and peripheral neural system for balance control and gaze stabilization.

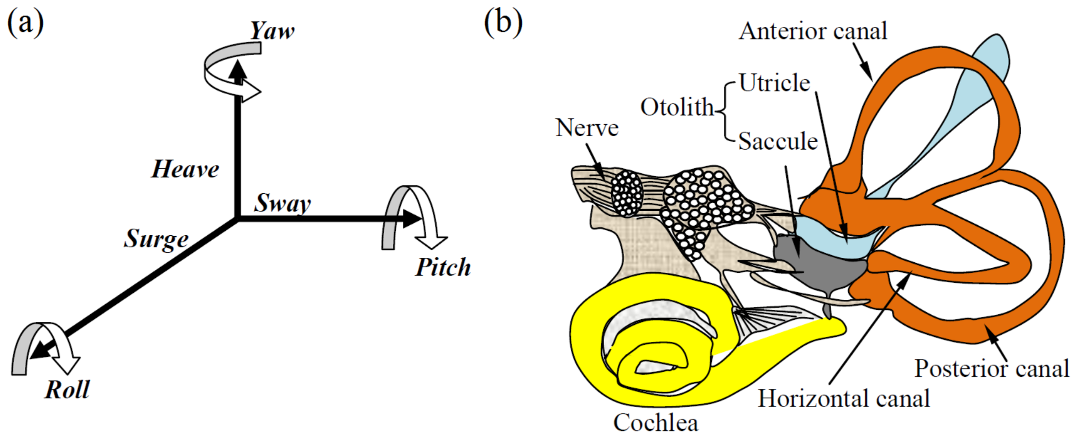


Figure 2-10 Inner ear mechanism to detect position and motion of the head (a) The six independent variables fully describing the motion characteristics of an object. (b) Schematic of the human vestibular system showing the three perpendicular semi-canals and the otolith (utricle and saccule) in the inner ear (Zeng & Zhao, 2011).

Recent developments of micro-electro-mechanical systems (MEMs) have provided the impetus for miniaturized, low cost accelerometers and gyroscopes that can be integrated into practical portable devices. MEMs accelerometers are based on

Newton's second law of motion, i.e. when acceleration is applied to a mass an inertial force develops that displaces the mass in the opposite direction (Castillo, 2005; Zeng & Zhao, 2011). As shown in Figure 2-11 when acceleration occurs, inertial forces displace the movable plates with respect to the fixed plates opposing the direction of motion. Change in the gaps between the moving plates and the fixed plates alter the electrical capacitance (C_l, C_r) of the system, which is measured as a voltage output. Produced voltage is proportional to the applied acceleration of the object.

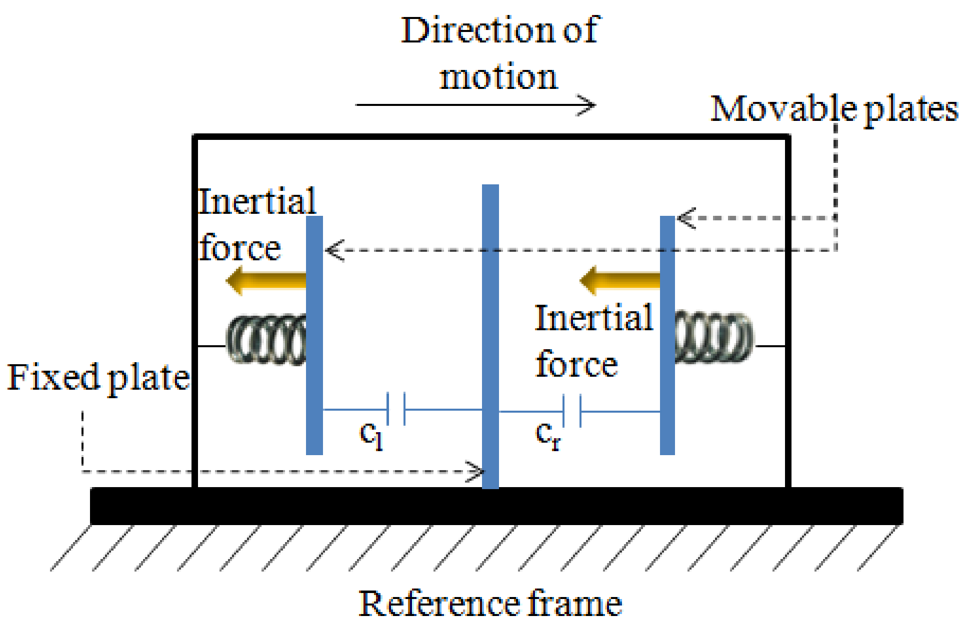


Figure 2-11 Working principle of MEMs accelerometer, adapted from (Santhiranayagam, 2015); When the sensor is displaced in the direction as shown in the figure, an inertial force is created in the opposite direction. Inertial force displaces the movable plates and creates unequal capacitances C_r and C_l between fixed plate and movable plate

The principle of MEMs gyroscopes is the Coriolis Effect on a vibrating structure. In MEMs gyroscopes, a pair of oppositely vibrating masses (capacitive sheets) is attached by a string, similar to a tuning fork (Figure 2-12). The goal is to measure the rotation applied about the axis perpendicular to the vibrating objects' direction of motion. When rotation is applied "Coriolis" forces are generated on the vibrating masses as shown in the figure below (Figure 2-12). These Coriolis forces displace the vibrating masses and change the overlapping areas of fixed plates and vibrating mass resulting in a difference in capacitance (C_l, C_r) between the plates. The difference in capacitance is amplified, demodulated, and filtered to produce a voltage that is proportional to the angular velocity. When the objects undergo only linear acceleration in any direction, the distance between individual masses and the fixed plate will be equal, thus the difference in capacitance remains zero.

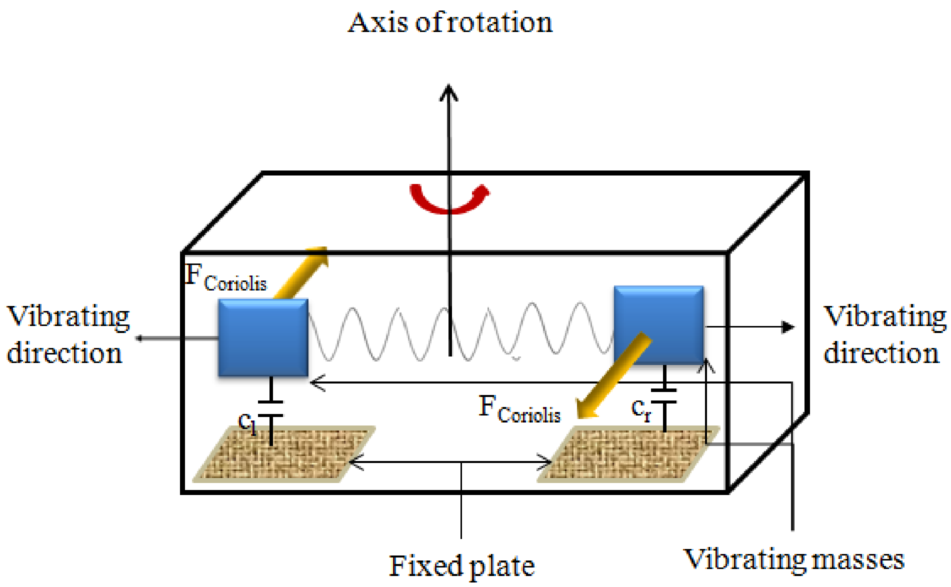


Figure 2-12 Working principle of MEMs gyroscope adapted from (Santhiranayagam, 2015); when the sensor is rotated about axis of rotation as shown by red arrow, $F_{Coriolis}$ forces in vibrating masses moves the masses and change the effective capacitance C_r and C_l between fixed plate and vibrating masses.

2.3.2 Inertial sensor signals based MTC_Height estimation

A foot-mounted sensor system consisting of a tri-axial accelerometer and a tri-axial gyroscope was developed as described in Chapter 3 to capture inertial sensor signals. As IMU measure acceleration and angular velocity, deriving positional measurement such as MTC_Height is not a straightforward process. The traditional technical approach to estimating MTC_Height from inertial sensor signals has limitations that required an entirely new method to be developed; a principal aim of the present investigation. As a background to the considerations in developing a modeling technique for application in this project three fundamental limitations of earlier approaches, and proposed solutions, are reviewed below.

Sensor Orientation

To obtain MTC_Height, a positional measurement from IMU-measured linear acceleration and angular velocities, signals must be first transformed from the local sensor axis (ß) to a global reference system (R) as shown in Figure 2-13. For this purpose sensor's initial orientation must be known. Using the accelerometer readings, sensor's initial inclination with respect to gravity is determined. An additional device, such as a magnetometer is required to obtain initial sensor transverse planar orientation of the sensor with respect to magnetic North. With the advent of MEMs magnetometer, it was possible to integrate orientation estimation to accelerometer and gyroscope system.

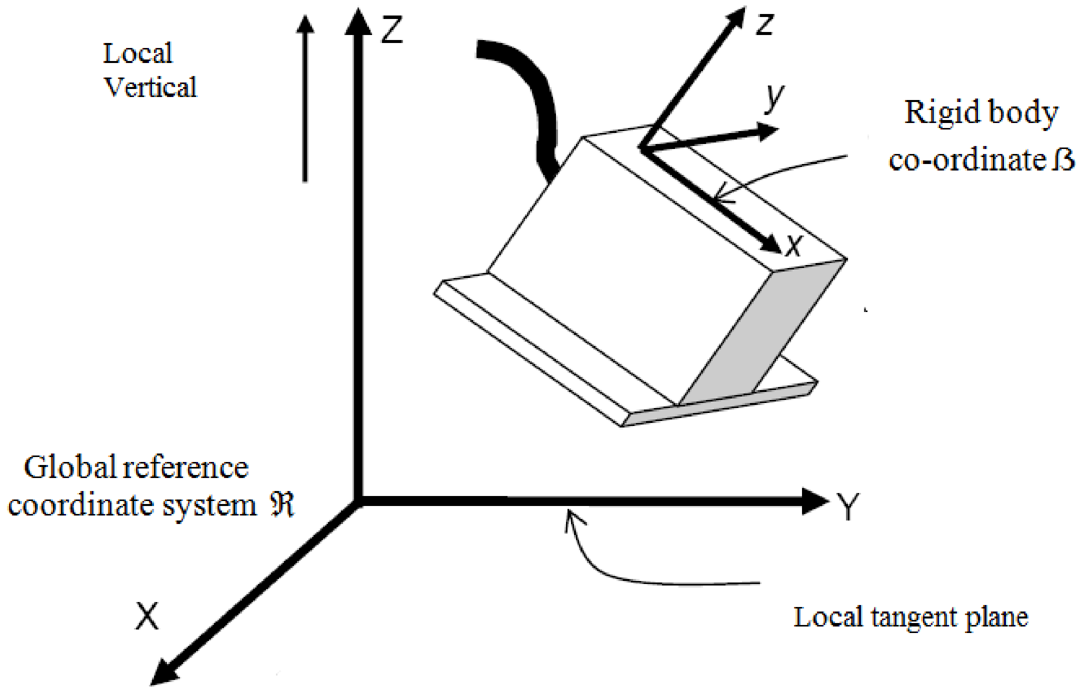


Figure 2-13 IMU co-ordinate system (ß) and global reference coordinate system (R)

Co-ordinate Transformation

To track the continuous change in the orientation of sensor axes (ß) with respect to the reference co-ordinate system three dimensional angular velocities are obtained from gyroscopes. The angular velocities are integrated over time to obtain the change in angle over them time from the initial orientation. This computationally complex problem is approached using quaternion vector representing the orientation of the sensor body co-ordinate system ß with respect to the reference co-ordinate system (R).

"Drift" over time

Following inertial sensor signal co-ordinate transformation to a global reference system, gravitational components of the accelerometer signals are isolated before double-integrating to obtain a displacement signal (Sabatini et al., 2005). In the integration process, thermal–mechanical and electronic noise in the accelerometers introduce a nonlinear error; the essential limitation to IMU technology (Djurić, 2000; Thong et al., 2004). Sabatini (2005) proposed a strap-down integration technique to improve the accuracy of positional measurements using an IMU by exploiting the cyclical properties of the walking gait. In the strap-down technique, integration is carried over each stride cycle to reset the drift in foot velocities to zero (Li et al., 2010; Yun et al., 2007).

Mariani et al. (2012) employed strap-down integration techniques to estimate MTC_Height from 12 healthy adults performing short walking trials at self-selected, slow, and fast speeds. The method computed foot orientation and trajectory from sensor signal data fusion, combined with gait event detection of toe-off and heel-strike. Three algorithms were devised for 2D and 3D foot models and the results were validated against optical motion capture for 2D and 3D data respectively. Their system obtained -12.7 mm accuracy and 9 mm precision (average and standard deviation of the difference between the reference MTC obtained from a motion capture system and the estimated MTC using an IMU), resulting in an overall root-mean-square-error (RMSE) of 21.7 mm. Given that MTC_Height is typically only 20-30 mm, the MTC_Height estimation accuracy using inertial sensor signals with integration techniques would not be sufficient.

2.4 Modeling approaches to MTC_Height estimation

The approach to modeling MTC_Height using IMU data in the present Thesis was also simultaneously pursued by McGrath et al. (2011) who proposed a quadratic regression model to link raw IMU kinematic data to MTC_Height mean and coefficient of variation. McGrath et al. (2011) conducted an experiment in which nine healthy young adults walked at different walking speed conditions (1.56m/s, 1.10m/s, 0.65m/s, and 0.48m/s) wearing a tri-axial accelerometer and a tri-axial gyroscope mounted on foot and shank with data collected using a 3D motion capture system. In a modeling approach, transforming raw data into *features* that better represent the underlying relationship between the target parameter and the raw data is critical. McGrath et al. (2011) used correlation (r) analysis between reference MTC_Height and features calculated over a synchronized portion of the vertical angular velocity and acceleration signals for each walking trials for each subject. Mean values of both absolute angular velocity and vertical linear acceleration showed maximum r values. In this proof of concept study, McGrath (2011) used those identified inertial-signal features to model MTC_Height and demonstrated that quadratic regression (RMSE = 17.34 mm) outperformed a linear regression (RMSE = 35.86 mm) by estimating MTC_Height by 50% more accurate. An improved RMSE for quadratic regression suggested a non-linear relationship between inertial kinematics and MTC_Height.

McGrath (2011) fitted a quadratic regression curve to MTC_Height and related IMU features but did not validate the model using an unknown sample set to test the model’s generalizability (Figure 2-14). In developing a modeling approach to estimate MTC_Height it is essential to validate the performance of the model with unknown dataset to the model, i.e., a blind data set. For future developments in real-time MTC monitoring, it is also important to estimate stride-specific MTC_Height rather than estimating the mean and coefficient of variation of a number of strides captured from a walking trial. The above limitations were addressed in the present project by building models for young and older adults to estimate MTC_Height for each stride and testing these models in different conditions, i.e., dual task walking and slower walking.

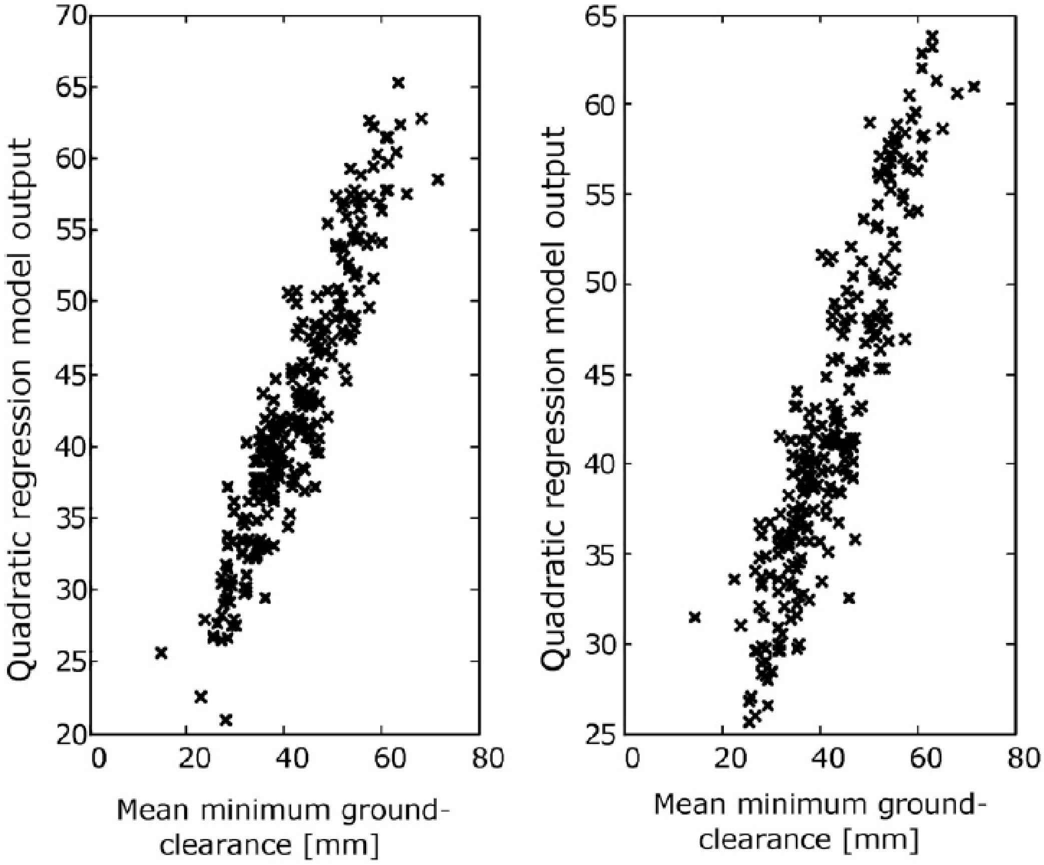


Figure 2-14 Mean MTC_Height (minimum ground clearance, MGC) and coefficient of variation MTC_Height outputs from quadratic regression for foot senor against mean MTC_Height and coefficient of variation (CV) of MTC_Height derived from optical motion capture system adapted from McGrath, et al. (2011).

The non-linear relationship between MTC_Height and other swing phase trajectory kinematic variables within the same stride is due to toe-trajectory modulations following toe-off. If there were no discrete changes to toe trajectory following toe-off, any two events would be predicted to be highly correlated (Santhiranayagam et al., 2010). Table 2-1 for example, shows correlations between mx1_Height and MTC_Height (refer Figure 2-4) for young and older adults in preferred-speed walking from the present study. It can be seen that young adults showed lower correlations than older adults and this ageing effect on the correlations between swing-phase variables would also be reflected in the related IMU kinematics. It was, therefore, anticipated that separate models built using inertial-signal features would be required for older and younger people.

Table 2-1 Correlations (corr, r) between mx1 and MTC for young (YP) and older (OP) individuals obtained from present study's preferred-speed walking data

Preferred-speed walking data			
	Young corr (r)		Older corr (r)
YP01	0.75	OP01	0.84
YP02	0.55	OP02	0.76
YP03	0.41	OP03	0.89
YP04	0.32	OP04	1.00
YP05	0.94	OP05	0.94
YP06	0.43	OP06	0.87
YP07	0.64	OP07	0.95
YP08	0.36	OP08	0.91
YP09	0.84	OP09	0.99
YP10	0.61	OP10	0.83
YP11	0.50	OP11	0.56
YP12	0.77	OP12	0.33
YP13	0.60	OP13	0.80
YP14	0.59	OP14	0.82

2.5 Machine-Learning in gait analysis

Machine-learning is being employed in different application areas such as aerospace, automobile, weather forecast, financial market analysis and real estate business in which a large volume of data needs to be processed fast enough and with high accuracy to address continuous demands. Machine-learning techniques are envisioned to result in more cost-effective, efficient, and easy-to-use systems, which would address global shortages in medical personnel and rising medical costs. Given the non-linear relationship between inertial kinematics and MTC_Height in the present project a machine-learning approach was considered more appropriate to modeling toe-height. Machine-learning offers the ability to investigate nonlinear data relationships, enhance data interpretation, design more efficient diagnostic methods and extrapolate model functionality (Lai et al., 2009a; Shilton et al., 2012). Machine-learning is a mathematical, algorithm-based technology that forms the basis of historical data mining and modern big-data science (Bell, 2014). It is a fusion of learning mechanisms and computation specifically suited for powerful decision systems capable of interpreting and processing large volumes of data such as extended walking trials providing multiple gait cycles.

An essential component of the machine-learning based wearable-sensor approach to gait measurement is that the computational model is required to learn the specific relationship between the input signals, represented by signal features and the estimated target gait parameter (Bell, 2014). Artificial learning was inspired by the human brain which learns from previous experience and continuously updates information to form new knowledge structures. The brain is an interconnected web of neurons transmitting elaborate patterns of electrical signals (Shiffman, 2012). As shown in Figure 2-15, dendrites in a neural cell receive multiple inputs from other inter-connected neurons and fire an output via axon. A perceptron is the simplest artificial neural network (ANN) with inputs, a processor and an output (Shiffman, 2012). Depicting the human brain in ANN, multiple interconnected layers are created with several nodes in each layer. These nodes receive inputs, weigh them and sum to generate an output (Figure 2-16).

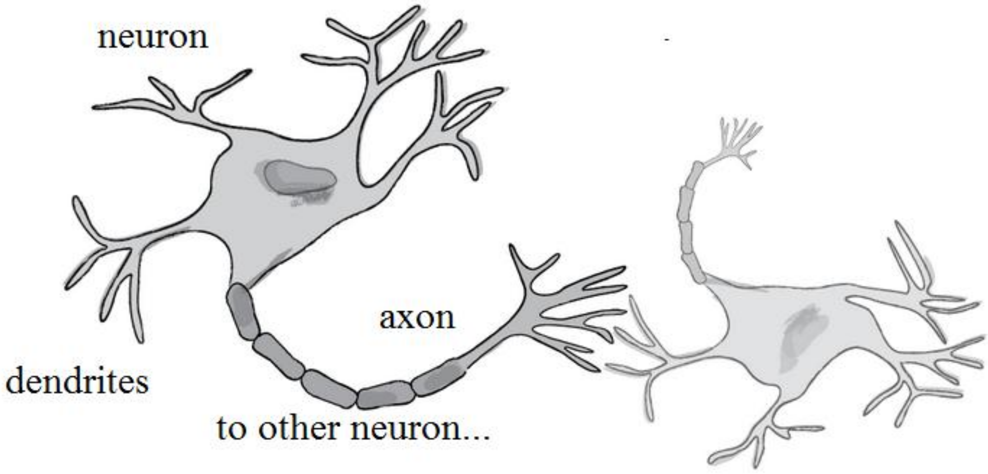


Figure 2-15 Dendrites in a neural cell receive input signals from inter-connected neurons and based on those inputs, fire an output signal via an axon (adapted from (Shiffman, 2012))

Machine-learning techniques such as supervised learning, unsupervised learning, symbolic learning and genetic learning, have been applied to pattern recognition and system modeling. In supervised learning an external supervisor provides a set of parameters and desired outputs to the machine and trains the machine to learn the relationship between input parameters (features) and the outputs (targets). Once the machine has learned the relationship, it could be used to estimate the targets of new features which the machine has not seen previously.

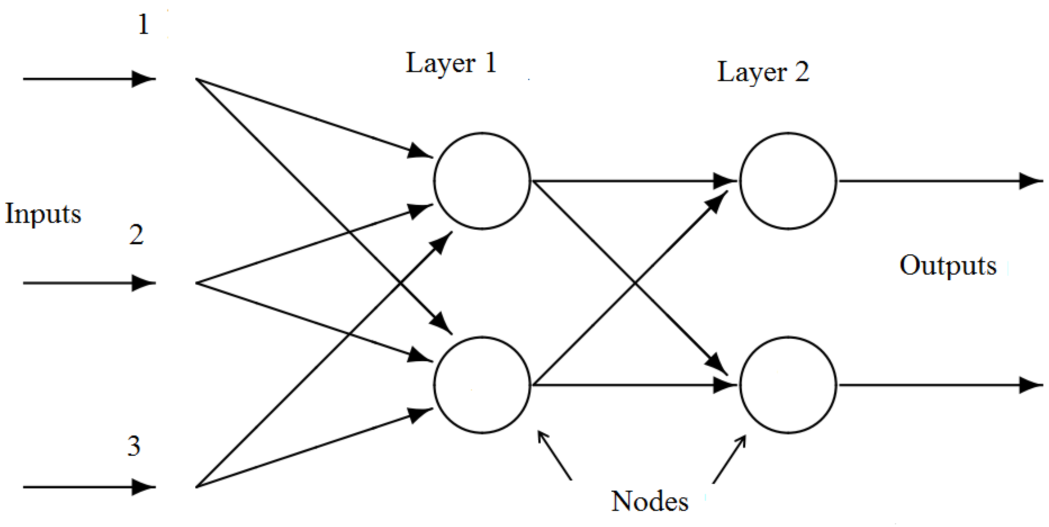


Figure 2-16 Two layer neural network with 3 inputs. Nodes in these layers receive the inputs, weigh them and sum to generate outputs.

Rescio et al. (2013), for example, used a supervised clustering technique (one-class support vector machine classifier) to detect falls event successfully out of IMU data collected from several practical every day activities such as walking, sitting down in a chair, lying down and kneeling down. In an activity recognition application, Terrier et al.(2001) employed a Neural Networks (NN) technique to detect level, downhill, and uphill walking from accelerometers located at the hip and pelvic bone. Begg et al. (2005), showed that the support vector machines could be a useful tool to differentiate different types of gaits for example young and old gait cycles could be classified with up to 90% accuracy.

Using a Generalized Regression Neural Network (GRNN), Lai et al. (2009b) demonstrated the potential of a machine-learning technique in lower-limb trajectory gait biomechanics. Lai et al. (2009b) recorded foot positional data from 10 healthy adults (25–32 years) and 11 older adults (65–82 years) with a history of falls using a 3D motion capture system. They obtained acceleration data by double differentiating the position-time signal and extracted 5 peak amplitudes and corresponding normalized time with respect to toe-off event as input features to GRNN model. Lai et al. (2009b) demonstrated that acceleration features from double differentiated motion-captured 3D displacement-time data could predict individual stride MTC_Height with an RMSE of 6.1 mm one gait cycle ahead. In Lai et al.'s study (2009b), the GRNN machine was able to learn the underlying relationship between toe trajectory control and acceleration derived double differentiating motion captured position-time data.

The GRNN is based on nonlinear regression theory for function estimation (Specht, 1991). The network architecture of GRNN is a one-pass learning algorithm which does not require an iterative training procedure as in the back-propagation method (Specht, 1991). Even with sparse data in a multi-dimensional measurement space, the algorithm provides smooth transitions from one observed value to another (Özgür, 2006). Unlike feedforward back-propagation method, GRNN simulations performance is less sensitive to randomly assigned initial weight value. Further, the local minima problem was not faced in GRNN simulations (Özgür, 2006). Despite these advantaged no previous studies have applied GRNN machine-learning to estimate MTC_Height from inertial sensor signals. In the present study, GRNN consisting of a radial basis layer and a special linear layer (Specht, 1991) was used to learn the underlying relationship between IMU data and the target, i.e. MTC_Height.

The estimated MTC_Height $\hat{y}_i$ is obtained using the following equation where σ is the width of the radial basis function:

$$G(Z)=\frac{1}{2\pi\left(\frac{k+1}{2}\right)}e^{-\frac{\|z\|^2}{2}}$$

$$\hat{y}_i=\frac{\sum_{i=1}^{n}y_i e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}}{\sum_{i=1}^{n}e^{\frac{-\|x-x_i\|^2}{2\sigma^2}}}$$

The distance between the training sample and point of prediction (x - x_i) measures how well each training sample represents the predicted position. If this distance is small, the exponential component becomes large such that a particular training sample best predicts the new value. The distance between the other training samples and the point of prediction is large, thus the exponential component becomes small and contributes less to the prediction. With a very small σ parameter, the model over-fits the training data and reduces the generalizability of the model; on the other hand, with larger σ, the estimation becomes smoother (generalization increases), but may be less accurate.

GRNN implementation to gait analysis is an iterative process of fine tuning the model parameters and selecting optimum features as input. The block diagram in Figure 2-17 shows the stages for adapting the GRNN technique to the present study for estimating MTC_Height using IMU features.

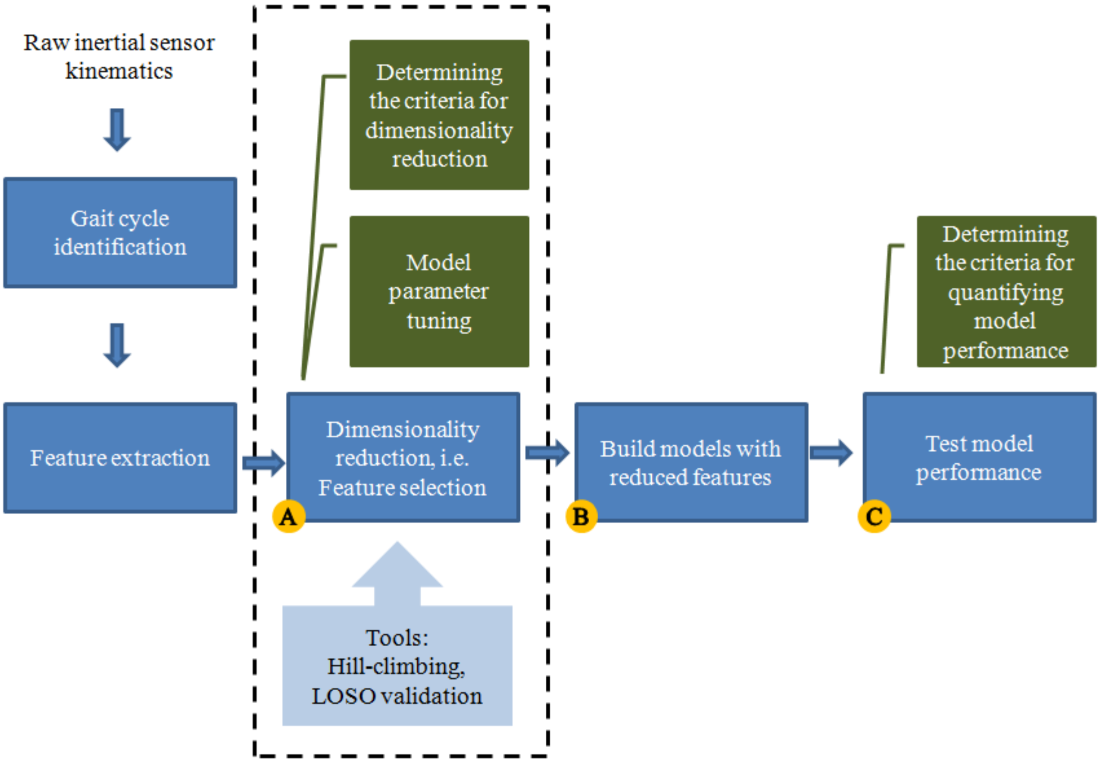


Figure 2-17 Customized machine-learning process in the present study for MTC_Height estimation using inertial sensor signals. In first stage gait cycle was identification in inertial sensor signals and features with possible association with MTC_Height were extraction. In Stage A, more relevant features were identified using iterative feature-selection algorithms with leave-one-subject-out (LOSO) cross validation. In stage B, age-specific GRNN models were built and in the final stage (C) the model performances were tested.

Gait cycle identification using inertial sensor data

In gait biomechanics a walking cycle is usually defined from a heel contact to consecutive heel contact of the same foot (Begg et al., 2007; Nagano et al., 2011). Alternatively in some studies toe-off (Winter et al., 1991) is used to define the initiation and termination of a gait cycle. In a present study, the gait cycle was defined as the interval between a toe-off and the consecutive toe-off of the same foot, as the IMU sensor was mounted on the distal end of the foot (toe). Detection of toe-off requires knowledge of inertial kinematics when the foot breaks contact with the ground. Sabatini et al. (2005) proposed minimum anti-clockwise medio-lateral toe angular velocity was detected as the toe-off event (Figure 2-18).

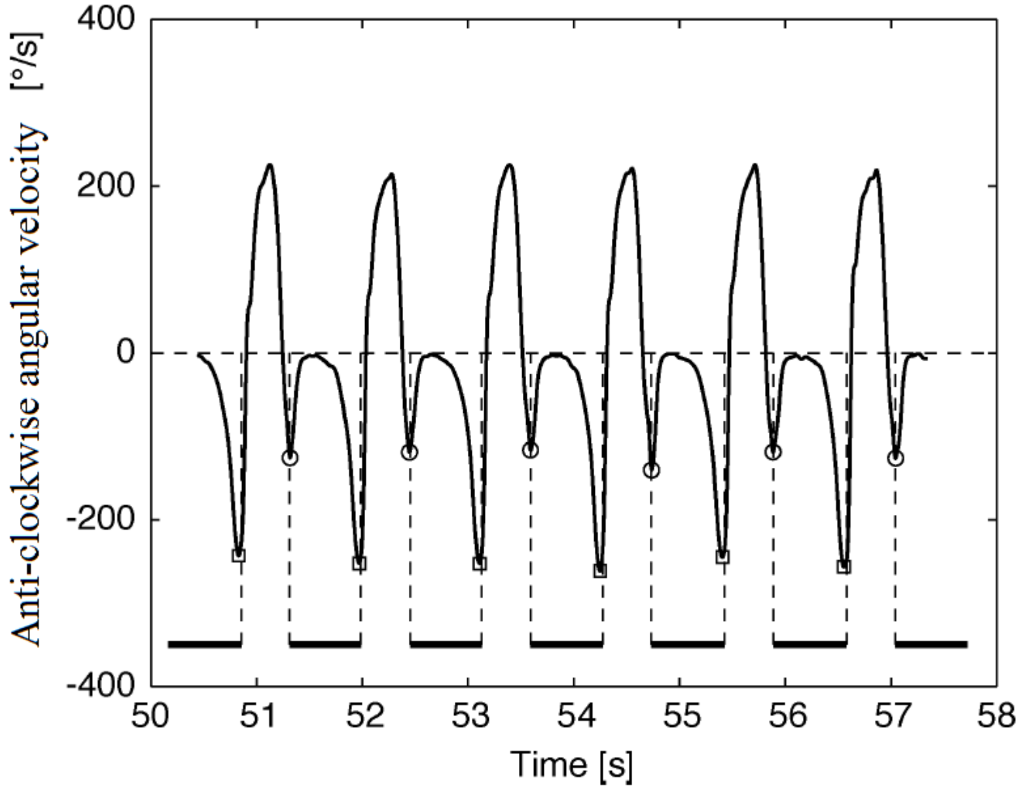


Figure 2-18 Toe-off [▫] and heel-strike (˚) marked in IMU medio-lateral angular velocity, adapted from Sabatini (2005).

Feature extraction

To perform machine-learning tasks, it was necessary to extract features from IMU kinematics associated with MTC_Height. Input features were extracted from three acceleration and angular velocity raw inertial signals. Inertial sensor signals were further exploited by extracting features from single- and double- integrated inertial signals to determine whether those features would improve estimation accuracy. These procedures are described further in the research methods section (page 76).

Stage A: Feature-Selection

When the dimension of a feature space is high, learning the relationship between input parameters and the target is difficult. In addition, irrelevant and/or redundant features in the learning data degrade generalization performance of the learned model. The feature-selection approach consists of detecting and discarding features that are demonstrated to minimally contribute to accurate prediction. In short, feature-selection is a process of finding the minimum number of features to maximize model performance. Figure 2-19 illustrates that in machine-learning the complete data set goes through feature evaluation and cross validation in order to determine an appropriate dimensionality reduction in training data.

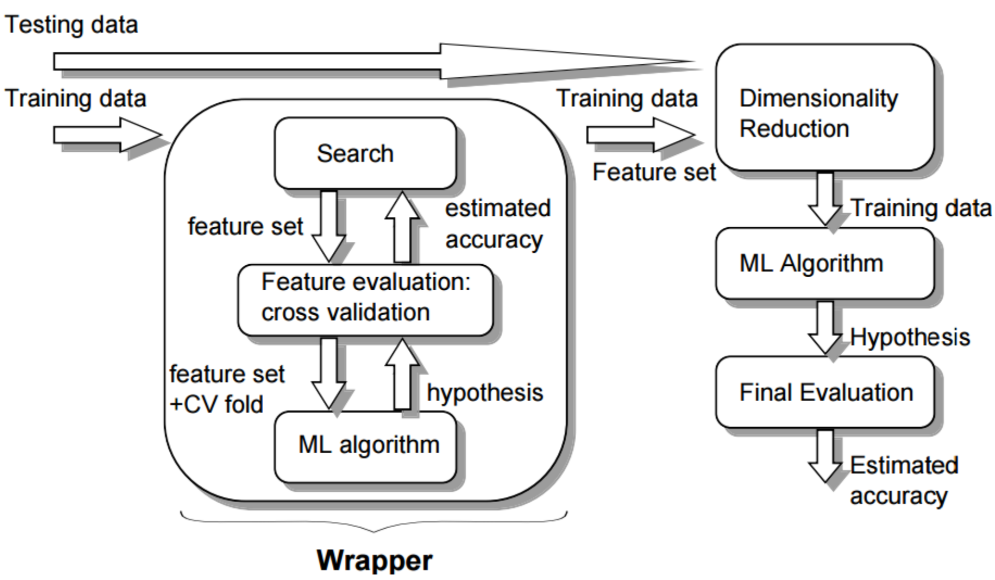


Figure 2-19 Wrapper feature-selection with iterative cross validation (CV) process used in machine-learning (ML), adapted from Hall (1999).

Begg et al. (2005) employed the hill-climbing sequential wrapper feature-selection technique to choose optimum MTC event features to classify young and older adults and the same approach was used in the present study. Hill-climbing is an iterative procedure that adds a feature at each step, while assessing the effects of these modifications according to pre-defined quantitative criteria. Minimum features would be useful when implementing the algorithm in embedded systems to perform online calculations rather than offline computations. The forward hill-climbing feature-selection was preferred as it starts from zero dimensions and obtains the minimum feature-set, whereas in backward feature-selection, step-wise elimination of features does not guarantee the minimum number of features (Aha & Bankert, 1996).

A leave-one-subject-out (LOSO) cross-validation is used to evaluate the performance of the features across testing subjects. Feature-selection and cross validation employed in the present study is explained as follows using a simplified example with three participants (say A, B and C) and 4 IMU features (say F1, F2, F3, and F4). Reference MTC_Height series from a particular trial for participant A is denoted as y_{a1}, y_{a2}, y_{a3}, …, y_{an} and the GRNN-model estimated MTC_Height time series corresponding to the reference MTC_Heights for A is given as y_{a1}', y_{a2}', y_{a3}', …, y_{an}', where n is total number of MTC gait cycles for participants A and m and p are the total number of MTC gait cycles for B and C respectively.

The first step in the LOSO cross validation is explained in Figure 2-20 using only one feature, F1. LOSO cross validation begins with leaving out the participant A from the training set. The reference MTC_Heights and the corresponding IMU feature F1 of B and C are used to build the A'GRNN model with a fixed model parameter *s*. The model parameter *s* determines the 'spread' of the kernel; small values of kernel produce overfitting whereas larger widths of kernel produce more smoothing of estimation. When testing data set A is fed into the A'GRNN model, the model generates a series of MTC_Height estimates. This LOSO based model building and MTC_Height estimation is then performed for participants B and C as shown in rows 2 and 3 in Figure 2-20. Once LOSO is completed for all three participants, as shown in Table 2-2 the root-mean-square-error (RMSE) (Lai et al., 2009b) corresponding to F1 is calculated using both reference MTC_Heights and GRNN-model estimated MTC_Heights for A, B and C. The entire process shown in Figure 2-20 is then repeated for all 4 features.

The feature producing lowest RMSE, in the present example, F2 (as shown in Figure 2-21, 2nd row), would then be combined with the remaining features (F1, F3, F4) in sequence and the LOSO validation executed for these feature pairs. The feature pair producing the lowest RMSE (F3, F2 = 11.4 mm) would be combined with the remaining features and the LOSO scheme repeated (as in Figure 2-21 3rd row). In this example, note that when 3 features were combined, the lowest RMSE (13.3 mm) was greater than when only 2 features were considered (11.4 mm). Thus, a feature combination comprising F3 and F2 is considered optimum for this particular fixed model parameter *s*. The complete process is repeated by changing *s* to obtain the optimum model parameter for the optimum feature-set.

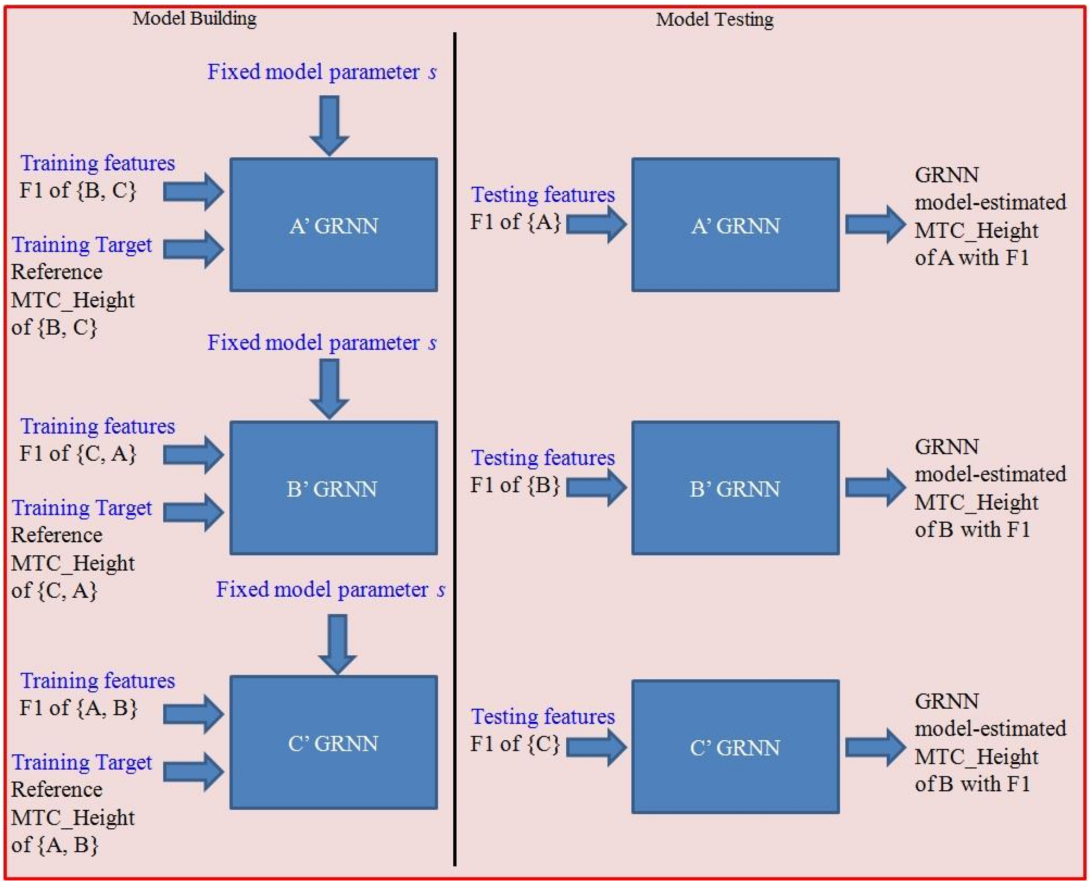


Figure 2-20 Leave-one-subject-out (LOSO) cross validation illustrated with 3 participants (A, B, and C) and only one inertial feature, F1 (see text for explanation).

Table 2-2 RMSE calculation for feature F1 using reference and model estimated MTC_Height for participants A, B and C.

Participant	Reference MTC_Height (mm)	GRNN-model estimated MTC_Height (mm)
A	ya1	ya1’
	ya2	ya2’
	ya3	ya3’
	.	.
	.	.
	.	.
	yan	yan’
B	yb1	yb1’
	yb2	yb2’
	yb3	yb3’
	.	.
	.	.
	.	.
	ybm	ybm’
C	yc1	yc1’
	yc2	yc2’
	yc3	yc3’
	.	.
	.	.
	.	.
	ycp	ycp’

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2},$$

where N = n +m+ p

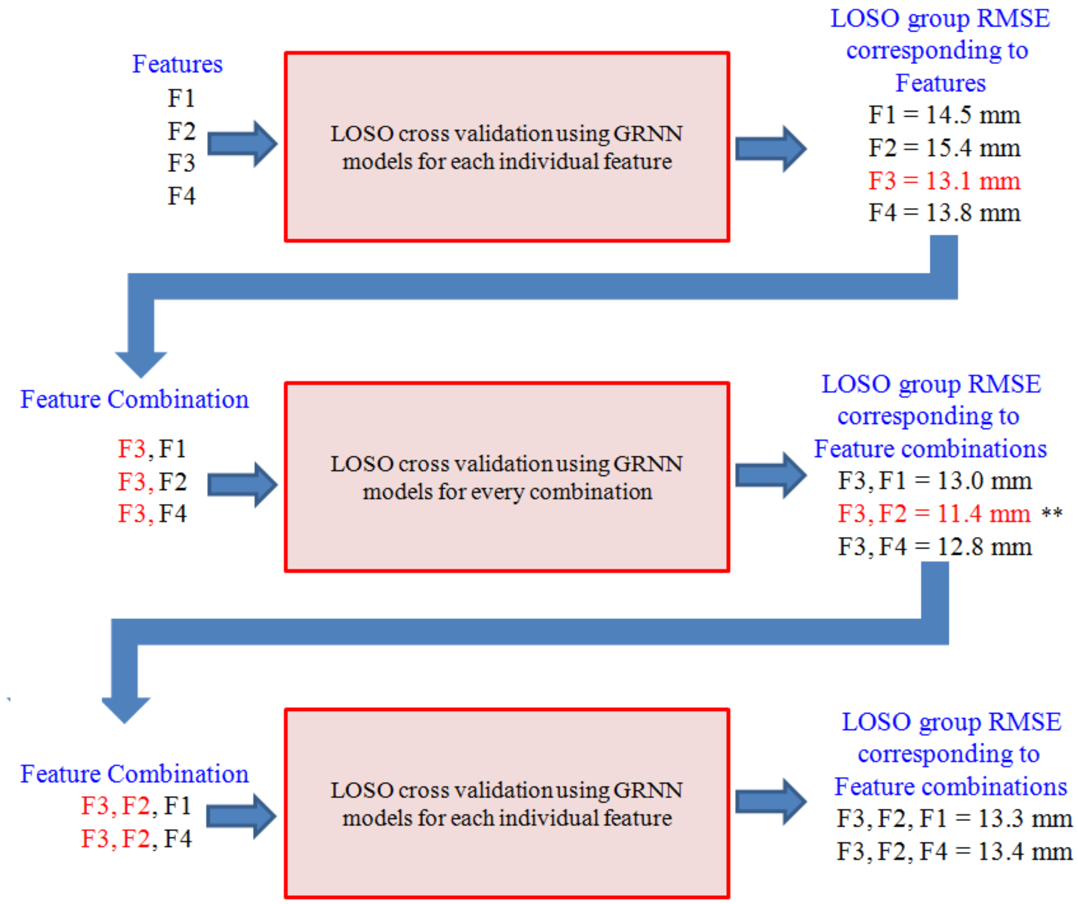


Figure 2-21 Hill-climbing feature-selection demonstrated with 3 participants (A, B, and C) and inertial features F1, F2, F3 and F4. The process within the red block is as illustrated in Figure 2-20. The optimum feature-set obtaining combining F3, F2 is denoted by **.

Stages B and C: Building and validating age-specific models

The optimum inertial-signal feature-set for each group identified in Stage A corresponding to reference MTC_Heights were used to build the age-specific GRNN models for young (Model_Y) and older adults (Model_O) separately. These age-specific GRNN models were tested for the same age group's dual task and slower walking data and for the other age group across three walking conditions.

2.6 Evaluating the GRNN model performance in estimating MTC_Height

The goal of the machine-learning in the present project was to minimize RMSE between reference MTC_Height and estimation MTC_Height and, in so doing, outperform previous studies demonstrating RMSE in the range 17.34 mm to 21.7 mm. A further criterion for evaluating the models' prediction accuracy was to consider the modeling successful if there was no statistical difference between the model-estimated MTC_Height and reference MTC_Height characterised by central tendency and dispersion. For this comparison, mean and SD of estimated and reference MTC_Height were considered in line with previous MTC_Height estimation studies (Mariani et al., 2012). This criterion was set as the previous biomechanical gait research to evaluate the age and condition effects on MTC_Height were performed based on the statistical tests (Barrett et al., 2010; Mills et al., 2008). Bland and Altman (2010) proposed a "graphical representation" for comparing two measurements systems for accuracy. They argued that in measuring a biological phenomenon, the criterion for replacing an established practice is a difference in measurement of ±1.96 SD (standard-deviation) between the new and the existing system. It was important to consider the "clinical significance" of the research findings, despite the applied requirements of MTC_Height estimation accuracy as yet to be determined.

2.7 Aims and hypothesis

The following aims were addressed in order to answer the Research Questions presented in the Introduction.

Research Question 1: "What are the effects of ageing and walking condition on MTC_Height, MTC_Time and non-MTC gait cycle frequency measures obtained from 3D motion-capture?"

To determine ageing, and condition effects on MTC variables and non-MTC frequency derived from 3D motion-capture, the following Aims were addressed:

I. To determine ageing (Young vs. Older) and walking condition (preferred vs. slow and preferred vs. dual task) effects on central tendency and dispersion of MTC_Height and MTC_Time distributions.

II. To determine ageing and walking condition effects on the frequency of non-MTC gait cycles.

III. To validate toe-height at mean MTC_Time as an indicative MTC_Height to used in the non-MTC gait cycles.

Research Question 2: "Would machine-learning (GRNN) using inertial sensor signals provide appropriate estimates of MTC_Height?"

To answer Research Question 2 the following Aims were formulated:

I. To create age-specific GRNN models to estimate MTC_Height using experimental inertial sensor signals and reference 3D position-time data from preferred-speed walking.

II. To evaluate the estimation accuracy between GRNN modelled MTC_Height and MTC_Height from 3D position-time data for both groups across walking conditions.

Following hypotheses were developed to address the Aims formulated to answer the Research Questions.

Hypotheses related to Research Question 1

Hypothesised ageing effects during preferred-speed walking:

a. MTC_Height and MTC_Time central tendency would show no difference between old and young.
b. MTC_Height variability, MTC_Time variability and the proportion of non-MTC gait cycles would be greater for older.

Hypothesised walking condition effects (slow vs. preferred and dual task vs. preferred) on MTC variables and the proportions of non-MTC gait cycles:

c. In slow walking both groups would maintain MTC_Height central tendency but reduce MTC_Time central tendency.
d. In slow walking both would increase variability of MTC_Height and MTC_Time and display greater proportions of non-MTC gait cycles
e. In dual task walking both groups would maintain MTC_Height central tendency but reduce MTC_Time central tendency.

f. In dual task walking both would reduce variability of MTC_Height and MTC_Time and display greater proportions of non-MTC gait cycles

Hypothesis regarding reference and indicative MTC_Height:

g. Toe-height extracted at mean MTC_Time (indicative MTC_Height) would be no different to reference MTC_Height in gait cycles which show well-defined MTC.

Hypothesis regarding the indicative MTC_Height in non-MTC gait cycles:

h. Indicative MTC_Height in non-MTC gait cycles would be greater than reference MTC_Height in gait cycles which show well-defined MTC.

Hypotheses related to Research Question 2

i. For both groups, in preferred-speed walking, RMSE between GRNN-model estimated MTC_Height and reference MTC_Height would be lower than previously reported.

3 TECHNICAL PREPARATION

In designing the sensor module to estimate MTC_Height, the IMU placement landmark and the choice of IMU with respect to range and number of axes were important. In the current work, the sensor was designed to be foot-mounted, because McGrath et al. (2011) showed that an IMU attached to the foot (RMSE = 17.34 mm) estimated MTC_Height with better accuracy than when shank-mounted (RMSE = 21.58 mm).

In the design stage, when using an accelerometer with 4g measurement range, the sagittal plane vertical acceleration saturated at 41 m/s^2. As shown in Figure 3-1, a 4g IMU was inadequate for measuring complete acceleration kinematics, because most of the signal information around the maximum peak was not captured. An ADXL 345 with a ±16g full range capacity accelerometer was used in constructing the foot-mounted sensor for this project. With respect to measurement axes (DOF) a tri-axial accelerometer and a tri-axial gyroscope were used.

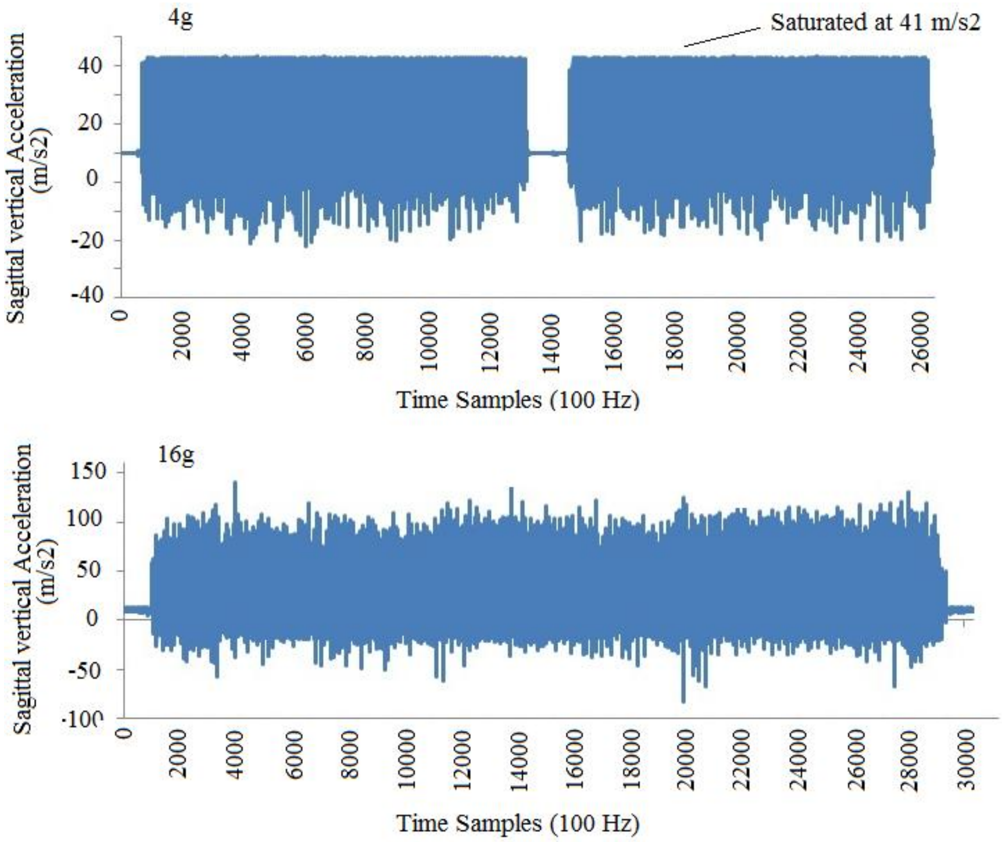


Figure 3-1 Vertical sagittal acceleration signal saturated when using a ±4g (top) and captured complete kinematics when using ±16g (bottom)

3.1 Sensor hardware development

A wireless foot-worn sensor module was built utilizing a *Sparkfun* IMU digital "Combo Board" with 6 degrees of freedom (DOF) consisting of an accelerometer - ADXL345 and a gyroscope- ITG3200 to measure the distal foot linear accelerations and angular velocities (Figure 3-2). The ultra low-powered tri-axis accelerometer had a ±16g (g represents gravitational acceleration, 1g = 9.8 m/s^2) capacity in full-scale and a maximum 3200 Hz bandwidth. The ITG3200 16 bit digital gyroscope had a sensitivity of 14.375 LSBs/sec and a full-scale range of ±2000 ˚/s. The sensing unit was powered by a Sony Ericsson BST-41 Li-Polymer rechargeable Battery with an energy capacity of 1500 mAh that could transmit 100 Hz data wirelessly for approximately 11 hours. The completely assembled sensor system weighed 78.7 g including a battery.

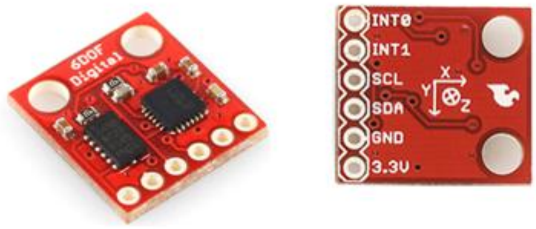


Figure 3-2 A 6 degrees of freedom Sparkfun IMU digital “combo board” consisting of an accelerometer - ADXL345 and a gyroscope- ITG3200

The embedded onboard system was implemented on a Freescale Semiconductor MCU (8-bit MC9S08SH8) and Bluetooth 2.0/EDR communications were used to (Sena ESD200/210) transfer the sensor data to a computer. The sensor module was built with a microcontroller, an IMU (accelerometer and gyroscope), radio transmission to control system (Bluetooth device), indicators and a battery unit (Figure 3-3). The accelerometers and gyroscopes in digital IMU sensor communicate over I2C (Inter-Integrated Circuit) and one INT output pin from each sensor. The SDA (Serial Data Line) port transmits data where as SCL (Serial Clock Line) port acts as a clock to synchronize both sensors. The SDA pin was connected to port A20 of the microcontroller and the SCL was connected to port A19. External crystal clock was connected to the processor. Front and rare view of the printed circuit board figures are shown in appendix A. The circuit board was milled in the Electronics Laboratory of Victoria University with the assistance of Rhett Stephens.

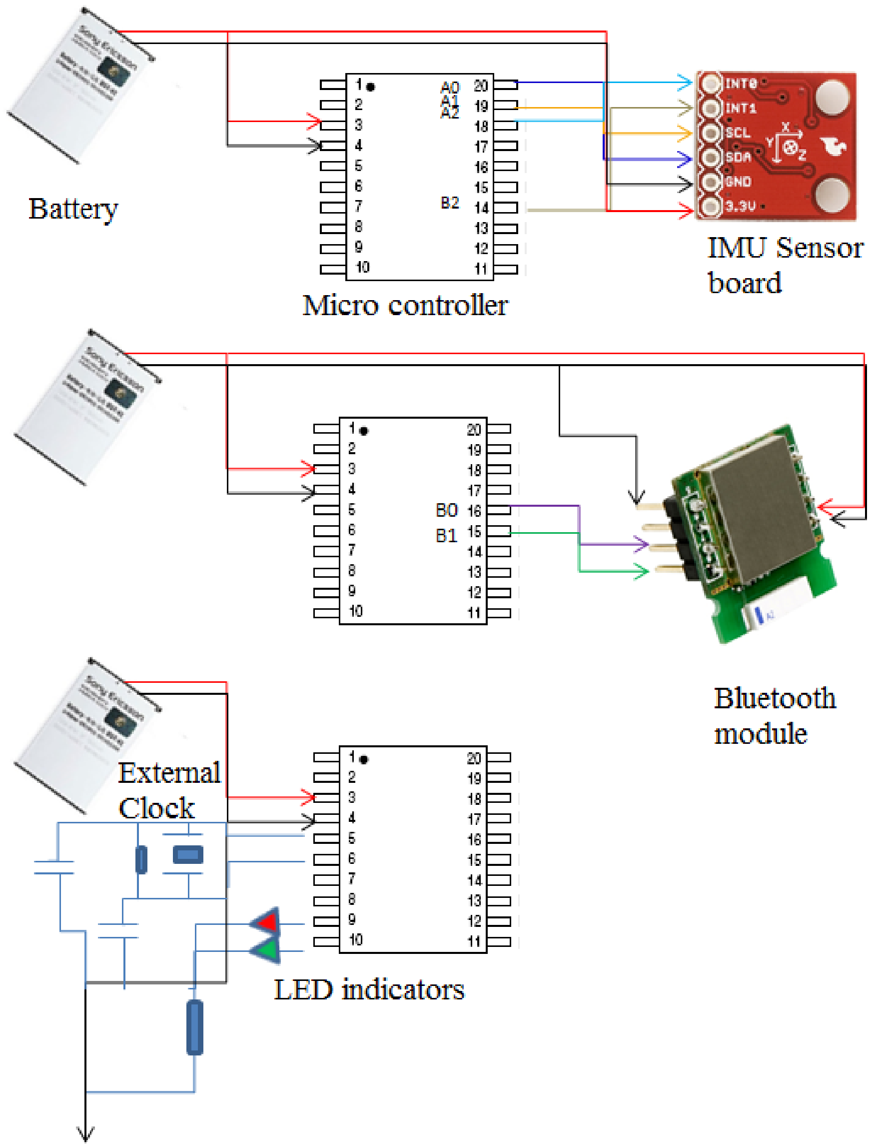


Figure 3-3 Integration of IMU, Bluetooth, external Oscillator and LED lights to microcontroller

A Bluetooth dongle was used to establish a connection between a receiving computer and the transmitting sensor module (Figure 3-4). Graphical user interface (GUI) was written by associate supervisor Daniel Lai in Matlab v7.0 (see Figure 3-5) to visualize the acceleration and angular velocity captured by the IMUs and to log them into a text file. The script first opens a serial port to receive Bluetooth transmitted IMU data. Once the port is open and connection established the script used a ‘fread’ command to read the data once available to the port. The label ‘D2C’ in received data is used as the delimiter to identify the packets transmitted. The computer displays tri-axial linear accelerations and tri-axial angular velocities in the two windows (Figure 3-5) created using MATLAB.

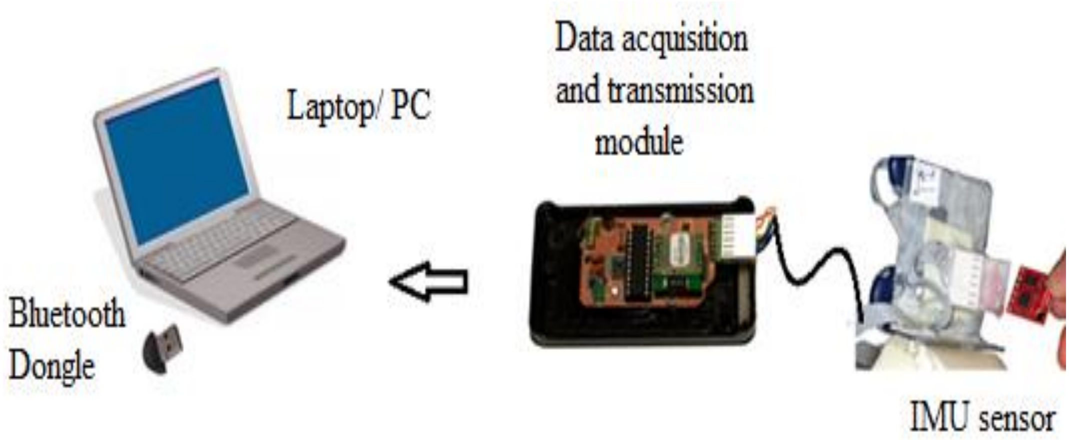


Figure 3-4 IMU data is acquired and transmitted to laptop via Bluetooth.

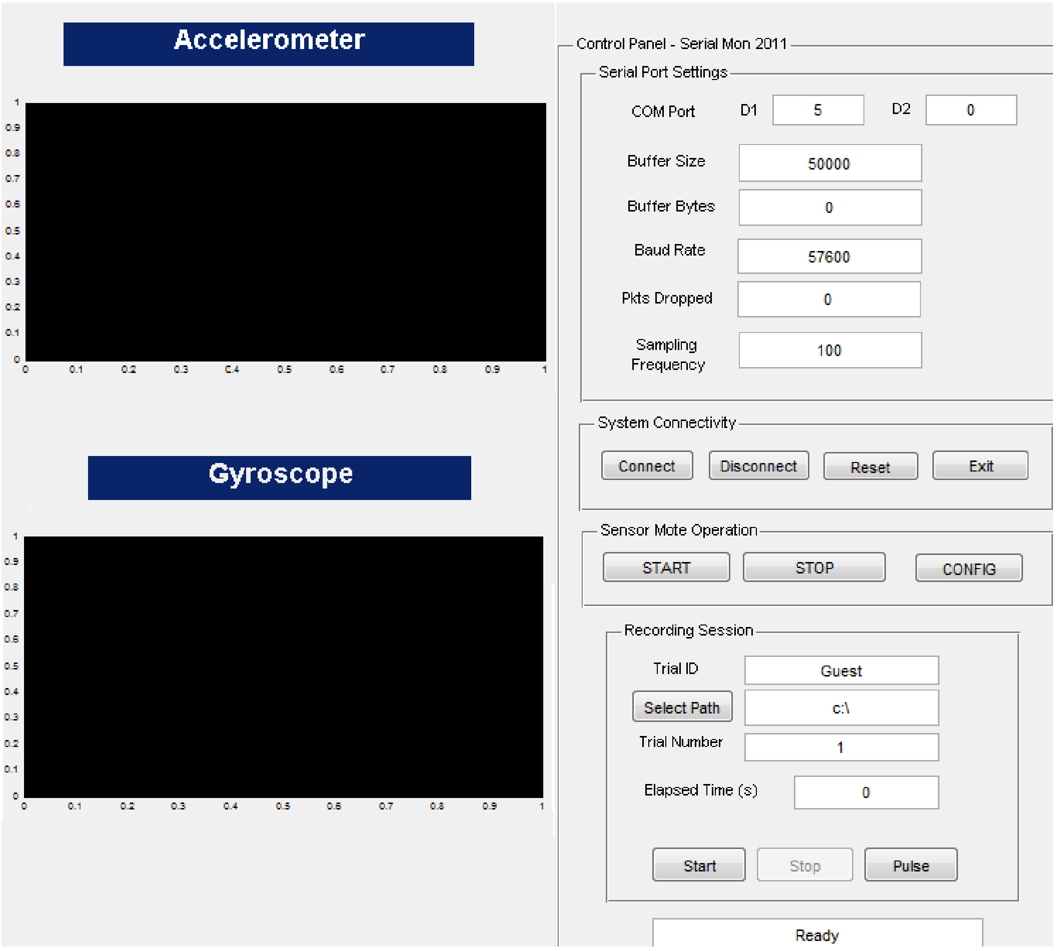


Figure 3-5 MATLAB GUI to view and log IMU sensor data

3.2 3-D Rigid body marker construction

The rigid body on which the infra-red emitting active markers (diodes) were attached was custom made using a rigid plastic shoe-shaper such that it could be attached to the distal end of the shoe with minimal motion artifacts (Figure 3-6). The active markers were attached to an 'L' shaped aluminum metal bracket which was screwed to the shoe-shaper to ensure a clear line-of-sight to the motion capture towers. To track the position of any point with respect to the rigid body in sampling 3D volume, minimum 3 infra-red active markers were required. Published recommendations for creating a rigid body are that markers should be placed at least

2.5 cm apart to avoid possible overlap in motion tracking (Taylor, 2012). The rigid body was then connected to the NDI (Northern Digital Inc) control box and the markers' 3D alignment with respect to each another was registered using NDI Architect software. This one-off process is called creating '.rig' files. This .rig file was used later in data collection to indicate to the tracking unit that the three markers belong to this particular .rig file to track the position of other points with respect to each other.

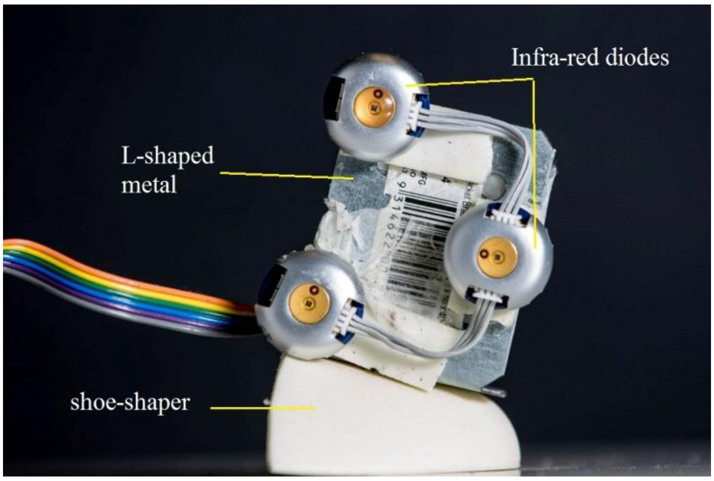


Figure 3-6 The rigid-body with infra-red diodes

4 EXPERIMENTAL RESEARCH METHODS

4.1 Participants

The experiment was conducted in the Victoria University Biomechanics Laboratory, Melbourne, Australia. Fifteen young healthy adults were randomly recruited through advertisements placed on University notice boards and through personal contacts. For the older group, adults aged 65+ were considered as approximately 28-35% of people aged of 65 and over fall each year increasing to 32-42% for those over 70 years of age (World Health Organization, 2007). Fifteen older adults were recruited through the paper advertisement appeared in a local newspaper (Appendix B) and through personal contacts. Interested volunteers made contact by phone or email and went through the initial screening based on a health questionnaire (Appendix C). Older individuals with the ability to perform everyday walking for 30 minutes without a walking aid and having no orthopaedic, respiratory and cardiac conditions were recruited. Selected participants were then sent out a copy of information to participant document (Appendix D) prior to their visit to the laboratory for testing. On the testing day, Older participants also underwent following screening tests: (i) timed up and go (< 13.5 secs (Iersel et al., 2008)), (ii) visual acuity (> 6/12) and (iii) contrast sensitivity (Melbourne edge test > 6/15 (Lord & Dayhew, 2001)).

Table 4-1 Physical characteristics, preferred walking speed and dual task walking speed of Young and Older. F = Female, M= Male, * = p < .05.

Variable	Young (n = 15) Mean (SD)	Old (n = 15) Mean (SD)	p value
Age (years)	26.1 (3.8)	73.1 (5.6)	< 0.05*
Body mass (kg)	72.4 (7.6)	71.5 (15.2)	0.848
Stature (m)	175.1 (7.9)	167.9 (9.2)	0.014*
Preferred walking speed (m/s)	1.06 (0.14)	0.94 (0.42)	0.067
Slower walking speed (m/s)	0.53 (0.09)	0.42 (0.08)	< 0.05*
Gender	4 F, 11 M	7 F, 8 M	-

4.2 Experimental protocol

All participants completed informed consent procedures approved by the Victoria University Research Ethics Committee (Appendix E). Participants' height, mass, age and gender were recorded at the beginning of the experiment. A safety harness was worn while walking on the motorized treadmill. A rigid body of infra-red emitting diodes and the inertial sensor were attached to the distal end of the right shoe (Figure 4-1). A rigid body comprising 3 infra-red emitting diodes was attached to the distal end of the right shoe to record three dimensional (3D) position-time coordinates using an Optotrak (NDI, Canada) motion tracking system. An imaginary marker was digitized at the lowest distal extremity of the shoe to represent the toe with respect to the rigid body. The inertial sensor was fixed to the extreme proximity of the right shoe with one sensitivity axis orientated approximately medio-lateral and the other axis approximately anterior-posterior. Both the 3D motion capture system and the inertial sensor sampled the toe trajectory at 100 Hz (Santhiranayagam et al., 2011b).

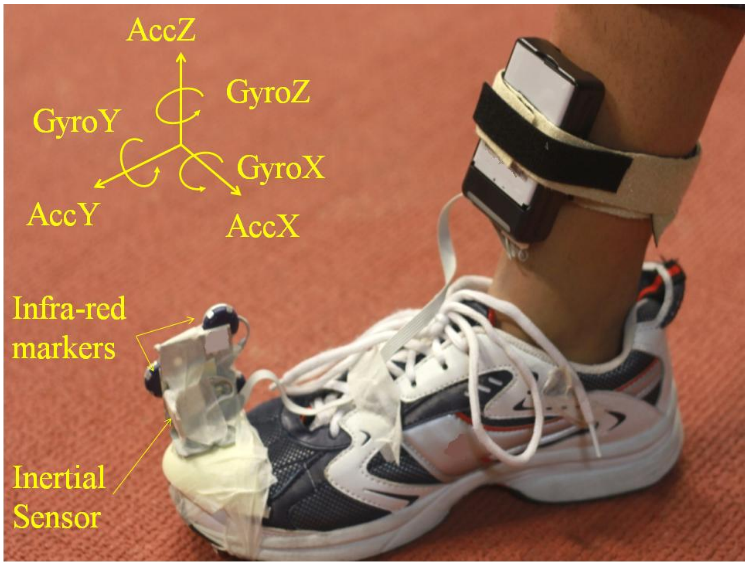


Figure 4-1 Rigid body marker set up and the IMU sensor attached to the distal end of a shoe. The axes of the IMU sensor unit are marked in yellow. The battery pack and the data transmission unit were attached to the shank.

The three-dimensional coordinates of the markers were tracked relative to a three dimensional LAB-based reference system, which will be referred as the "global reference" system here onwards. The horizontal plane of the global coordinate system was the treadmill deck surface, with the anterior-posterior axis directed in line with the treadmill belt motion (Figure 4-2). The tracking units have been reported to have a maximum RMS accuracy of 0.15 mm for 3D motion capture at 2.25 m distance from camera (Taylor, 2012). The camera towers and the marker set were connected to the NDI control box which was connected to a computer to collect data. The custom built foot-mounted sensor unit was also attached to the distal end of the right shoe and a laptop was used to collect wirelessly transferred IMU data.

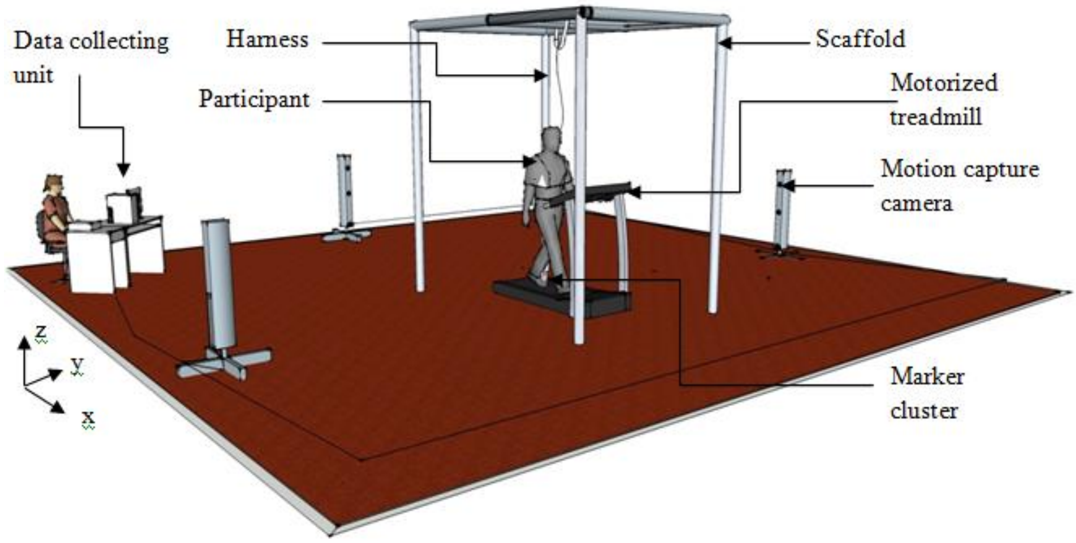


Figure 4-2 Laboratory setup for collecting data from 3D-motion capture while a participant walking on a treadmill wearing a safety harness.

4.2.1 Experiment conditions

Participant’s preferred walking speed (PWS) on a treadmill was determined by first increasing the treadmill speed until the participant reported the speed to be uncomfortably fast (fast limit). It was then decreased until reported to be uncomfortably slow (slow limit). The mean of three fast and three slow limits was taken as PWS (Nagano et al., 2011). When required, participants were given 10-15 minutes familiarization before determining PWS. Participants’ comfortable walking speed while carrying a glass of water was also determined as above. Then they performed the following walking conditions for 5 minutes each (i) preferred-speed walking (PW), (ii) walking while carrying a glass of water at a comfortable walking speed (dual task walking- DW), and (iii) speed-matched at DW speed without the glass of water (slower walking- SW) as outlined in Santhiranayagam et al. (2015b). In first and last 30 s of the trial, participants did not walk, and the standing duration was used to sync Optotrak and foot-mounted sensor data. Participants were instructed to walk without spilling water while performing the dual task walking. All participants undertook the preferred-speed walking first and presentation order of the other two conditions was partially counterbalanced, such that 8 participants performed control walking followed by dual task condition, with the order reversed for 7 participants in each age group.

4.3 3D-motion capture data processing

Position-time data from the Optotrak 3D motion capture system was exported to Visual3D (C-motion, Canada) analysis software and the raw data were first interpolated to compensate any occluded signals using a window of up to 10 frames, i.e. 0.1s (Taylor, 2012). A 4th order zero-lag Butterworth filter with a cut-off frequency of 12 Hz was then applied to toe displacement data. As the marker cluster for the 3D capture system was attached to the foot segment which goes through a rapid motion compared to the other segments of the body a higher cut-off frequency was considered to not over-smooth the toe trajectory signal (Nagano et al., 2011). Conditioned data were saved as text files for further processing using in-house developed MATLAB v7.2 scripts (The Mathworks, Natick, MA, USA).

4.3.1 MTC extraction

MTC is found in the characteristic vertical displacement “trough” between Toe-off (TO) and mx2 (refer Figure 1-1). To approximate toe-off, the sample frame at which anterior-posterior toe-displacement was minimum was initially detected (Figure 4-3). An eleven sample window (5 frames pre and 5 post) around this minimum frame was then established. Toe-off was defined as the minimum vertical toe-displacement within this window. The maximum vertical displacement between two successive Toe-off events was used to detect mx2. The algorithm was further devised to identify the “MTC trough” by detecting changes in the signs of the tangents of a 5-point data series comprising vertical displacement values at samples n-2, n-1, n, n+1 and n+2 (Santhiranayagam et al., 2015b).

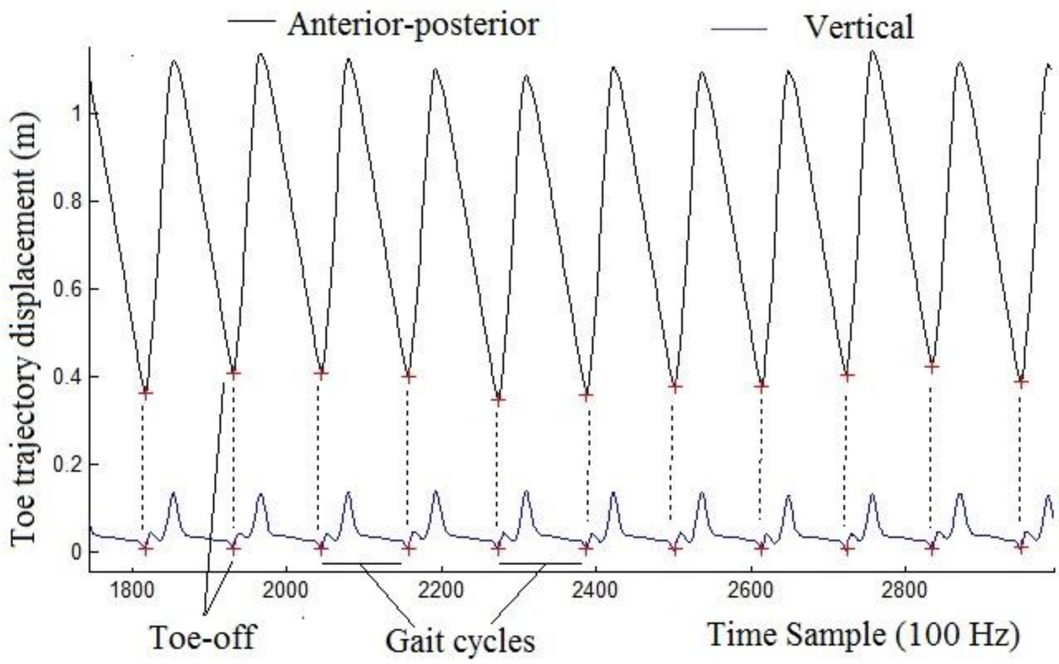


Figure 4-3 Time aligned anterior-posterior toe displacement and vertical toe displacement to show the Toe-off events.

Descriptive statistics of these MTC_Height data for each group across conditions were calculated. These statistical descriptors were measures of central tendency (mean, median), variability (SD, IQR), 1st quartile (Q1), 3rd quartile (Q3), range, symmetry (S) and peakedness (K), maximum, minimum. Further, for each individual participant, in each walking condition, mean, median, standard deviation

(SD) and inter-quartile range (IQR) for MTC_Height were calculated for inferential statistical analysis.

MTC_Time Calculation

MTC_Time was calculated as a percentage of total number of samples within a gait cycle using the formula:

$$MTC\_Time = \frac{n_{MTC}}{n_{gaitcycle}} x100\%$$

where n_{MTC} is the number of samples from TO event to MTC, and $n_{gait\ cycle}$ is the number of total samples within that gait cycle, defined from one toe-off to the consecutive toe-off event (Figure 4-4).

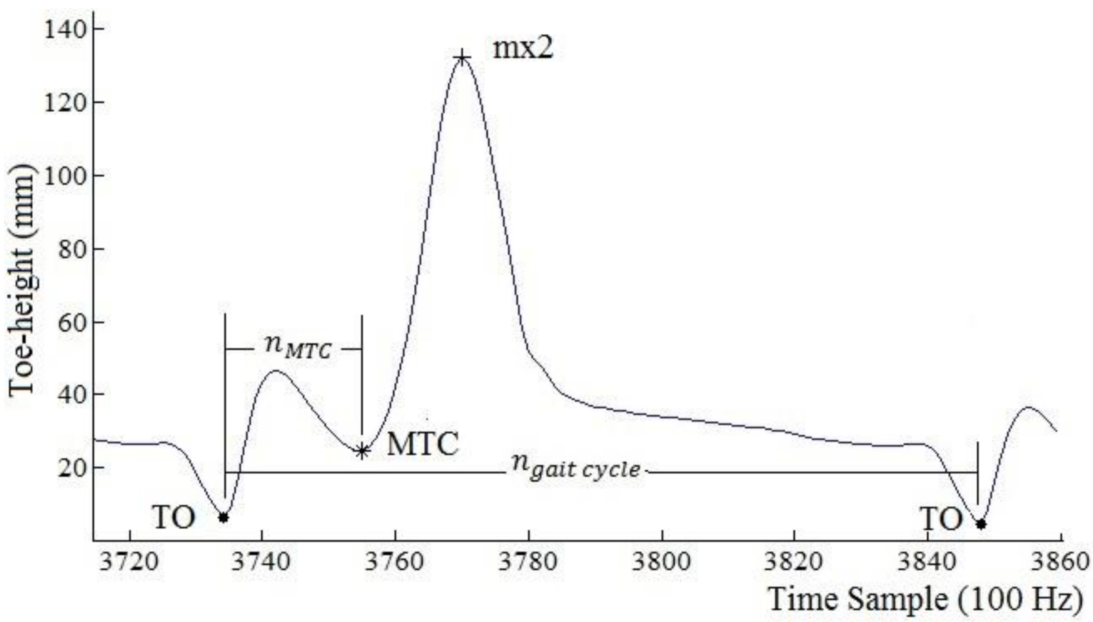


Figure 4-4 MTC_Time calculation, where n_{MTC} is number of samples from a toe-off (TO) event to MTC, and $n_{gait\ cycles}$ is number of total samples within the gait cycle, defined from one TO to the consecutive TO event.

Group descriptive statistics of the MTC_Time distribution for young in different conditions were calculated. Further, for each individual participant for each walking condition mean median, SD and IQR for MTC_Time were calculated.

To validate the concept of using toe-height at mean MTC_Time as an indicative MTC_Height in non-MTC gait cycles, toe-height at mean MTC_Time was extracted in gait cycles which showed well-defined MTC (Figure 4-5). These indicative MTC_Heights were extracted for each individual participant in each walking condition. The difference between reference MTC_Height and indicative MTC_Height was calculated as a root-mean-square-error (RMSE) for each subject under different walking conditions. Further, Pearson's correlation values between the measured and indicative MTC_Height were calculated for each subject under different walking conditions.

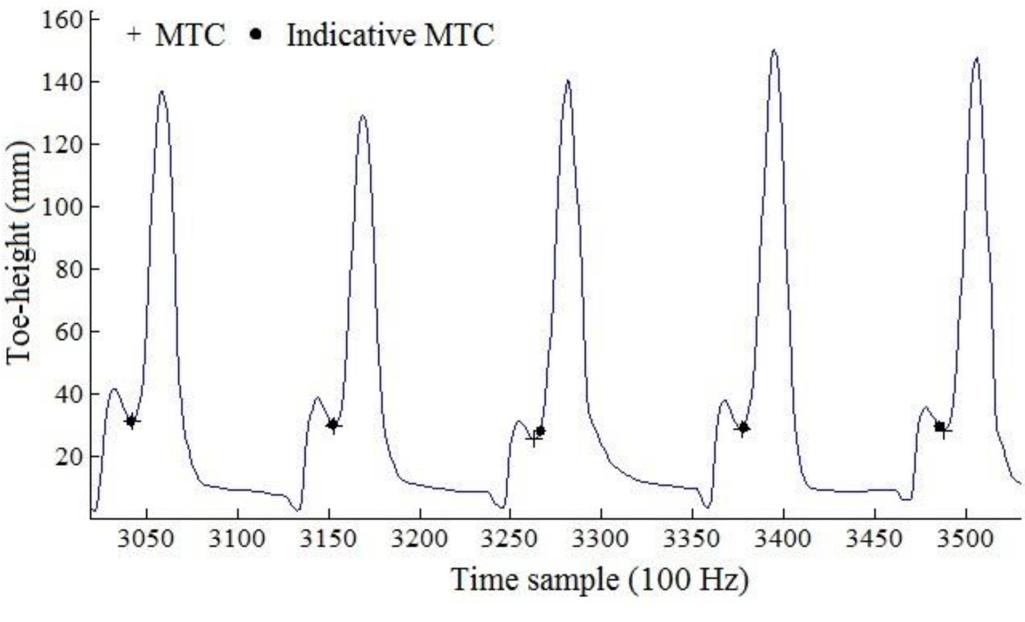


Figure 4-5 Toe-height at MTC (+) and indicative MTC (.) within gait cycles which demonstrated well defined MTC

4.3.2 Non-MTC gait cycles

Non-MTC gait cycles were defined as those in which a trough was not detected using the 5-point data series method (page 63). Raw position-time signals (not interpolated and not filtered) of such non-MTC gait cycles were randomly re-examined visually to ensure that non-MTC phenomenon was present in the original signal and not resulted because of any processing techniques (Figure 4-6). For both Young and Older, for each walking condition, total number of gait cycles, total number of MTC gait cycles and total number of non-MTC gait cycles were counted. Total number of non-MTC gait cycles within each age group across conditions were calculated and reported as a proportion of total number of gait cycles. For each condition, number of participants exhibited at-least 3 non-MTC gait cycles was counted. Further, for each participant, total gait cycles, non-MTC gait cycles and proportions of non-MTC gait cycles were calculated.

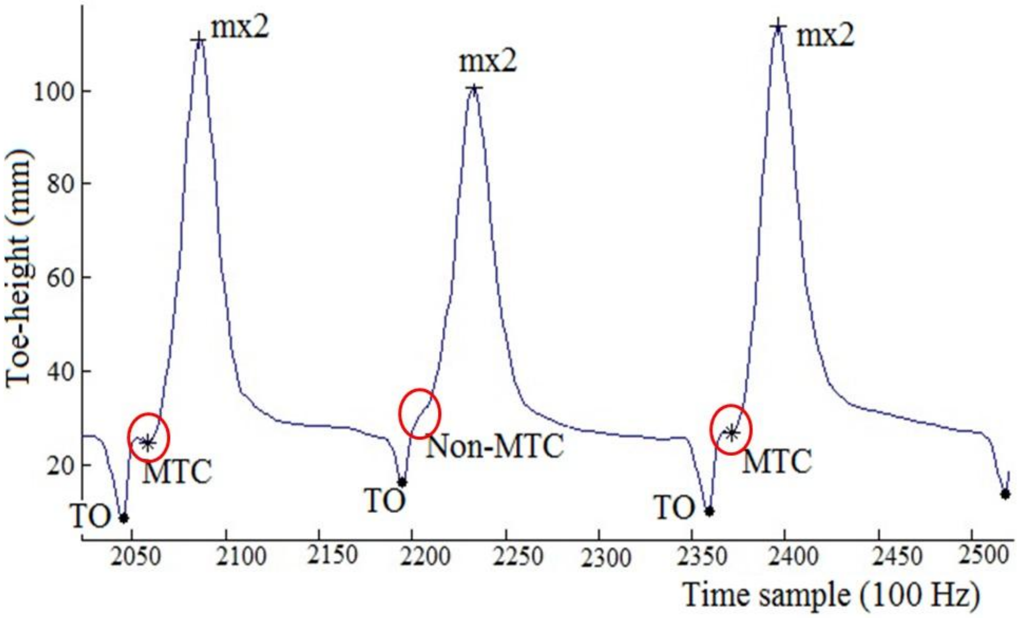


Figure 4-6 A series of gait cycles with a well defined MTC and without a MTC event, i.e. non-MTC gait cycles within a trial

Further, in a non-MTC gait cycle, indicative MTC_Height, i.e., toe height at mean MTC_Time (calculated from gait cycles showed defined MTC) was extracted and averaged across multiple non-MTC gait cycles for the walking condition (Figure 4-7).

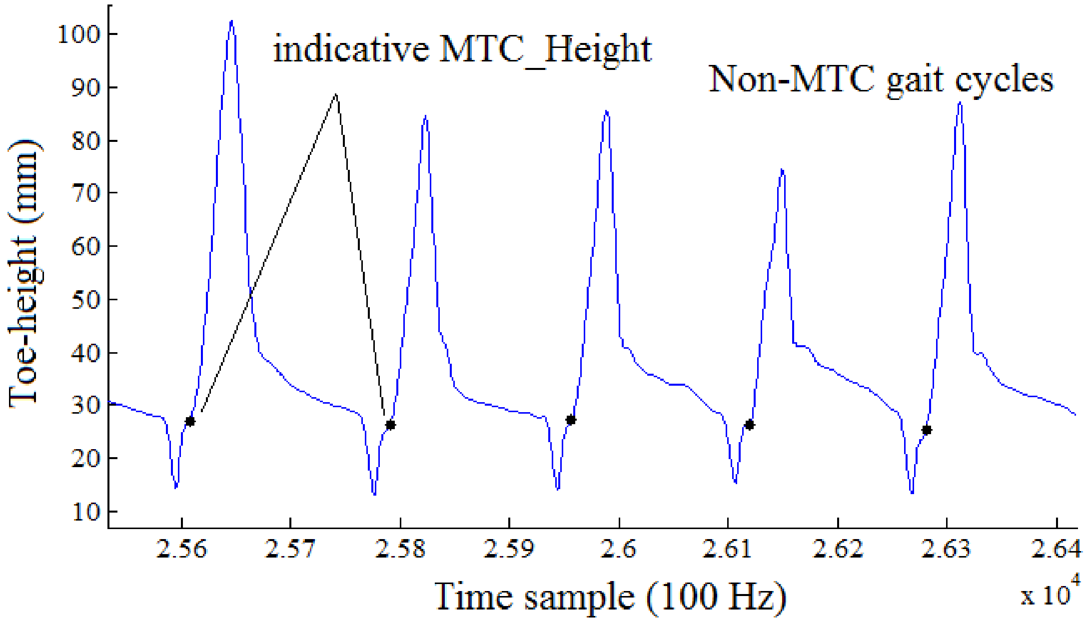


Figure 4-7 Indicative MTC_Height, i.e. toe-height at mean MTC_Time in non-MTC gait cycles

4.4 Statistical tests

4.4.1 Distributions of MTC characteristics

Prior to designing the statistical tests on the MTC_Height and MTC_Time, the group distributions were plotted across walking conditions for Young and Older. The histograms presented in Figure 4-8 show the MTC_Height histograms for Young across preferred-speed (PW), slower (SW) and dual task (DW) walking conditions. These MTC_Height distributions showed non-zero skewness in preferred walking (S

= 0.26) and in slow walking (S = 0.51). MTC_Height distributions were platykurtic in both slow walking (Kurtosis, K = -0.42) and dual task walking (K = -0.29). Furthermore, a bimodal distribution could be observed in dual task walking. The histogram of Older (Figure 4-9) in preferred-speed walking was more skewed (S=0.89) compared to Young and in dual task walking the distribution was further skewed (S=1.28). Bimodality could be observed in both slower and dual task walking but more distinctive in slower walking.

MTC_Time distributions for both Young (Figure 4-10) and Older (Figure 4-11) in both dual task and speed matched slow walking were shifted left reducing the central tendency compared to preferred-speed walking (median MTC_Time PW: Young = 18.02%; Older = 18.68%; SW: Young=14.72%; Older = 16.48% and DW: Young = 13.89%; Older = 14.28%;). The left shift of the MTC_Time distributions was reflected in mean, median, Q1 and Q3 reductions. For both Young and Older, MTC_Time distributions became more platykurtic in slow and dual task conditions. Bimodality was also observed in Young in slower walking and Older in the glass carrying task.

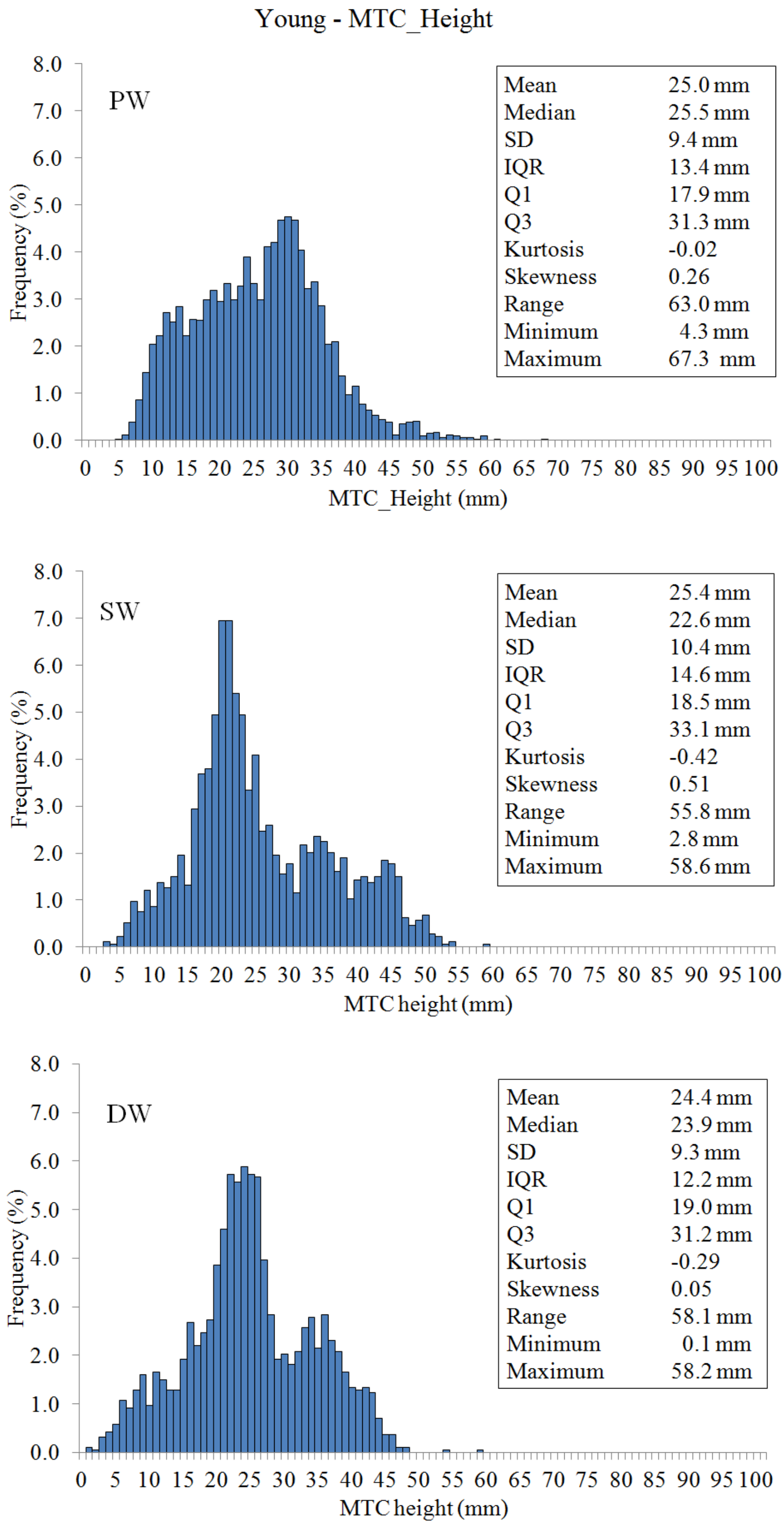


Figure 4-8 MTC_Height histograms for Young across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking

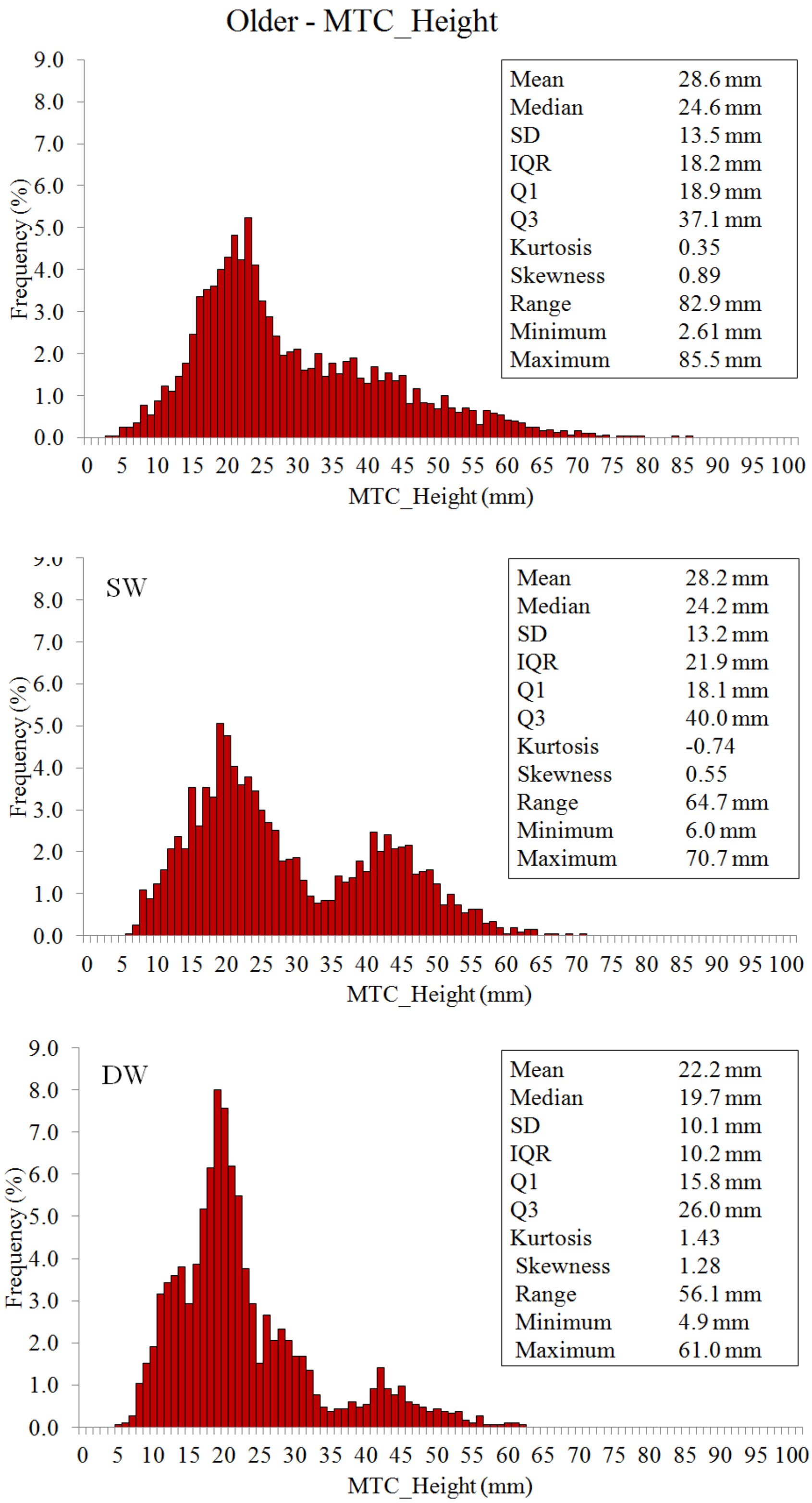


Figure 4-9 MTC_Height histograms for Older across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking

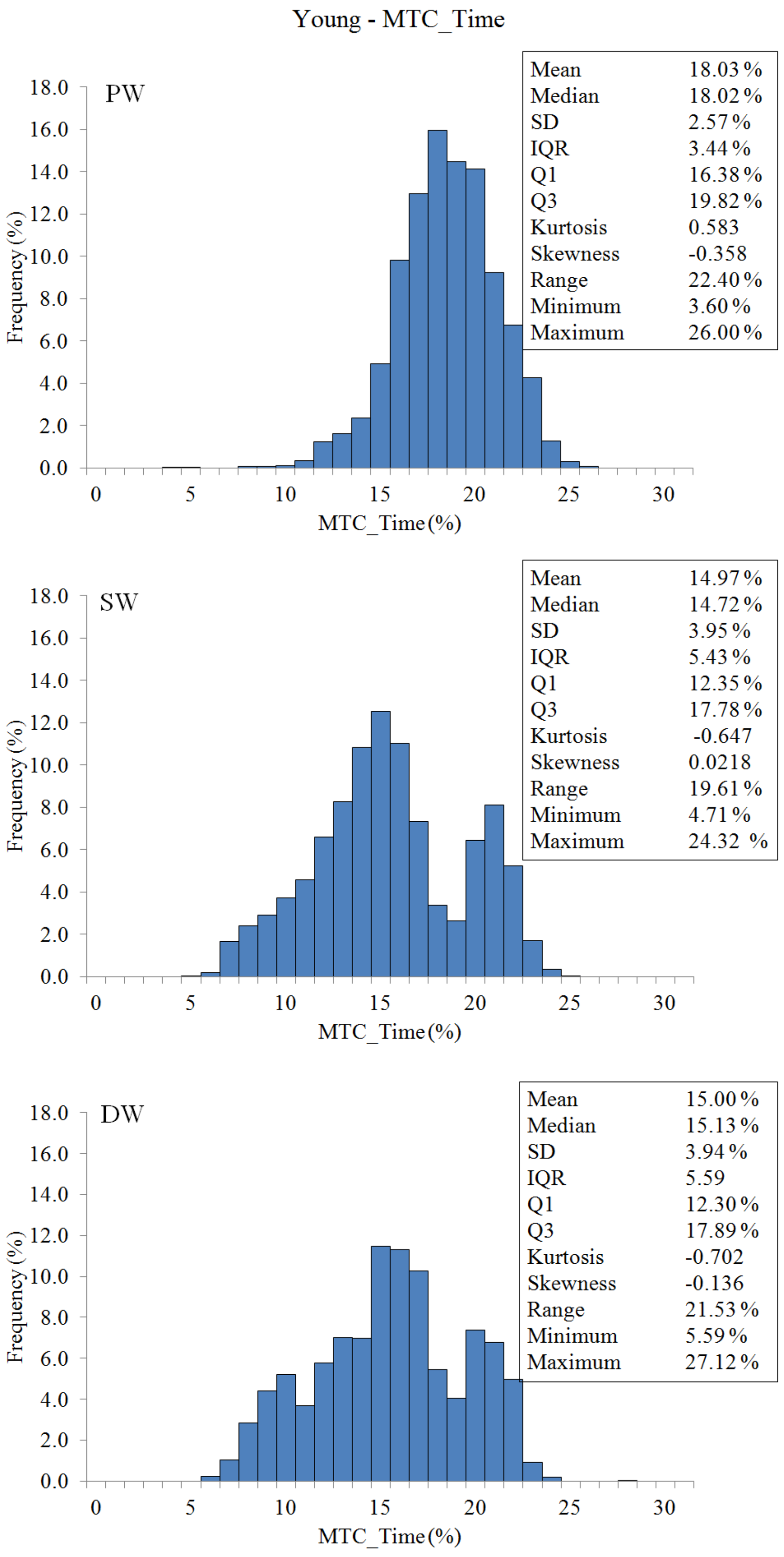


Figure 4-10 MTC_Time histograms for Young across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking.

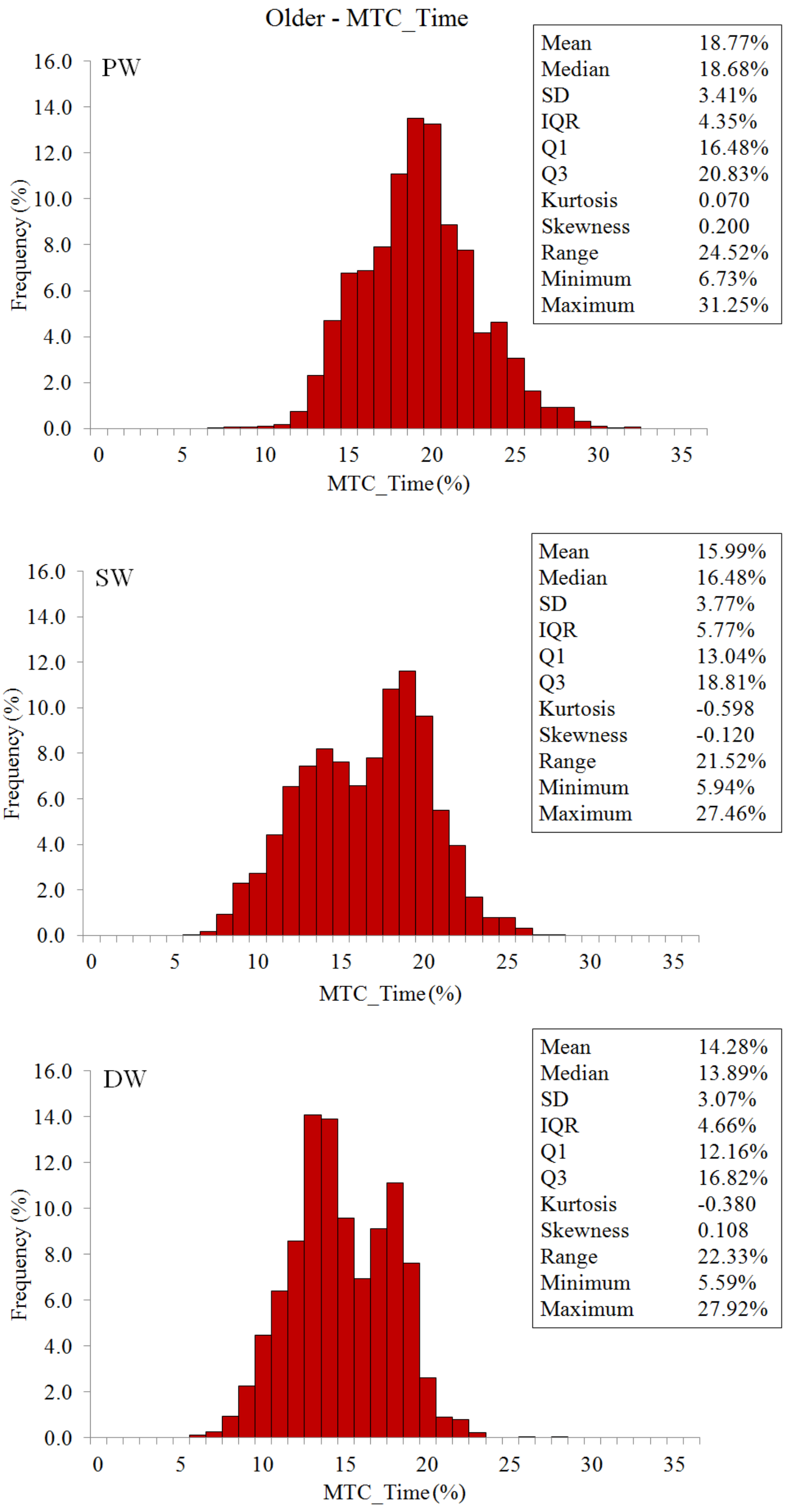


Figure 4-11 MTC_Time histograms for Older across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking

4.4.2 Statistical test design

Visual examination and statistical descriptors of MTC_Height group distributions for both Young and Older revealed that MTC_Heights were not normally distributed, consistent with previous reports (Begg et al., 2007; Dell'oro, 2008). Shapiro Wilks normality tests confirmed that the distributions were non-normal ($W = 0.9372$, $p < 2.2e\text{-}16$). In the present study MTC_Time distributions were also observed to be non-normally distributed for both age groups across conditions ($W = 0.7172$, $p < 2.2e\text{-}3$). Since the group data were determined to be non-normal, two non-parametric tests, Kruskal-Wallis and Friedman's were applied to evaluate the hypothesised (page 50) age, walking condition and measurement method effects on MTC variables. The Kruskal-Wallis test is the non-parametric equivalent of one-way ANOVA and the Friedman's test is the non-parametric equivalent of a one-way ANOVA with repeated measures. Significant effects from Friedman's procedure with more than two independent variables were followed-up with multiple pair-wise comparisons using multcompare() command in MATLAB. Pair-wise z-tests were performed to test the proportions of non-MTC gait cycles. In all the statistical analysis the significance level was α=.05, unless specified.

4.5 Inertial sensor signal processing and GRNN modeling

The three dimensional acceleration measurements obtained from the IMU were foot acceleration along the medio-lateral (AccX), anterior-posterior (AccY), and longitudinal (AccZ) axes (Figure 4-2). Foot rotation about the medio-lateral axis (GyroX), anterior-posterior axis (GyroY) and longitudinal axis (AccZ) were measured using the gyroscope. The accelerometers were calibrated by aligning their axes parallel and anti-parallel to gravity (Ferraris, 1995); angular velocities measured using the gyroscopes were calibrated by subtracting the mean of the gyroscope output while stationary prior to walking (Mannini & Sabatini, 2014). IMU data was also processed in MATLAB v7.2. One participant from each group was excluded in further IMU data processing, as IMU data were not properly logged. Both accelerometers and gyroscopes signals were high-pass filtered forward and reverse using a 2nd order Butterworth filter (cut-off frequency 1 Hz (Lai et al., 2008b)) to ensure zero phase shift and to remove any sensor drift. Voltage outputs (V) of the IMU sensor were converted to SI (Standard-International) units using sensitivity scaling factor:

- Accelerometer (acc): $9.812*V_{acc}*31.2/1000$
- Gyroscope (gyro): $V_{gyro}/14.375$

Figure 4-12 shows tri-axial accelerometer and tri-axial gyroscope signals obtained for three complete walking cycles. While walking, the foot orientation is continuously changing, such that not only the sagittal plane inertial sensor signals but also the transverse and frontal acceleration and angular signals contributed to the vertical component of the foot trajectory throughout the swing phase.

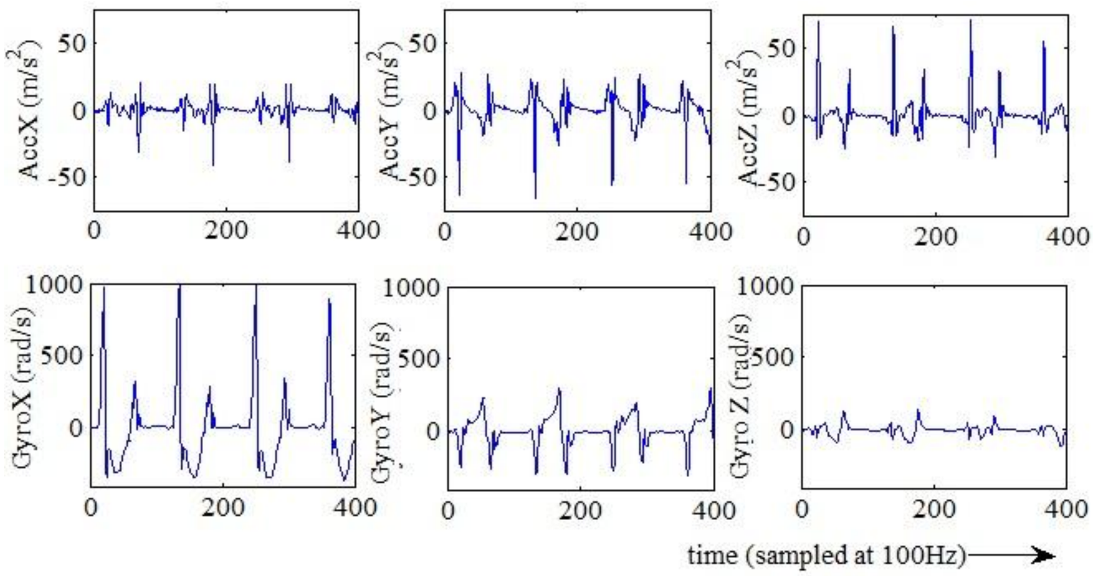


Figure 4-12 Tri-axial accelerometers and tri-axial gyroscopes obtained for 3 complete gait cycles. In addition to the greater range of sagittal planar kinematics (AccZ and GyroX), frontal and transverse planar kinematics also show non-negligible readings when IMU is attached to foot.

Automatic gait cycle identification in inertial sensor signals

A MATLAB script was developed to automatically find the maximum medio-lateral toe angular velocity GyroX as the beginning of a gait cycle, as shown in Figure 4-13. The inertial sensor signals at toe-off were time synchronised with the corresponding toe-off identified in the 3D position-time data. Positional and IMU data of non-MTC gait cycles were separated from the MTC gait cycles in further implementation of GRNN models. As explained on page 80, these non-MTC gait cycles were included in the final stage of the model validation.

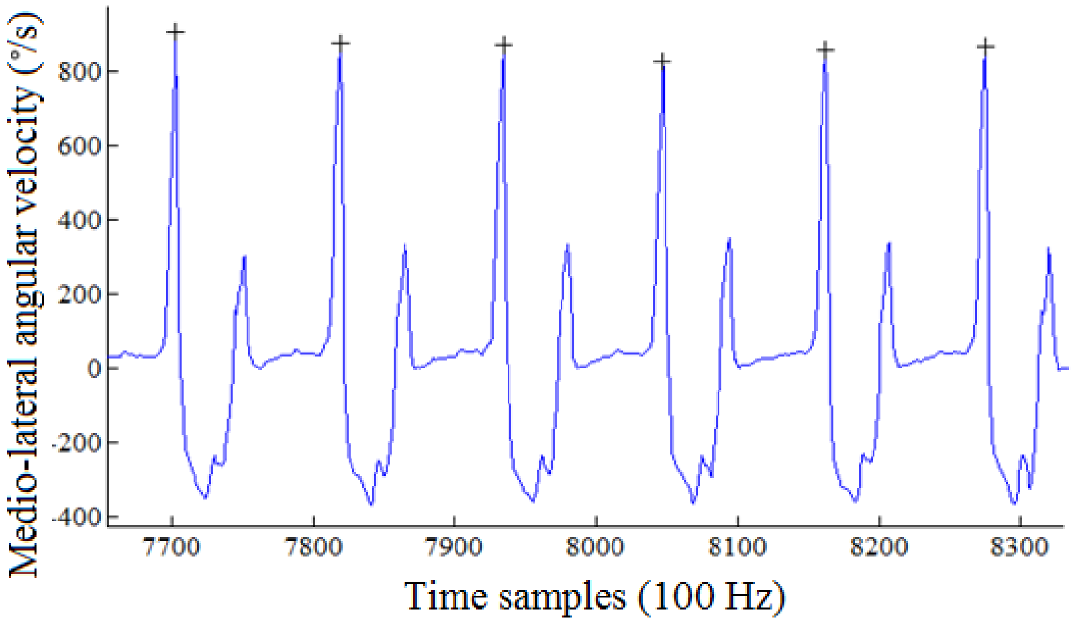


Figure 4-13 Gait cycles marked (+) in IMU medio-lateral angular velocity

Feature Extraction

Raw and integrated signals from both young and older individuals across conditions were visually examined to understand the nature of inertial-signals. When extracting features, inertial sensor signals which were consistent across individuals, age group and conditions were given more importance. In other words, since sagittal plane signals were more cyclic throughout, more features were extracted. First maximum and minimum were extracted from raw acceleration and gyroscope signals from every stride cycle. The raw acceleration and gyroscope signals were then integrated with respect to time. Drift and noise accumulation were minimized by integrating over every *individual* gait cycle (90-130 samples). Before integrating each gait cycle, all participants' inertial sensor data were plotted to determine whether the foot had entered the swing phase. It was determined that the minimum number of samples prior to maximum medio-lateral angular velocity to ensure zero initial velocity was10 samples (0.6 s). Each gait cycle was, therefore, integrated from 10 samples prior to toe-off. The integrated signals were high-pass filtered forward and reverse using a 2nd order Butterworth filter (cut-off frequency 1 Hz (Lai et al., 2008a)). Visual examination confirmed cyclical events in the sagittal signals - AccZ (VelZ) and GyroX (AngDispX). Maximum and minimum of VelZ and three clearly identifiable points (one maximum and two minimum) AngDispX were extracted. Representations of frontal and transverse movements were the maximum and minimum peaks of VelX, VelY, AngDispY, and AngDispZ signals.

Integration was again applied to velocity signals to obtain linear displacement signals. By integrating angular displacement over time a variable was created to represent “accumulated angles” (Accum.Ang). For a second time, integrated signals were high-pass filtered, forward and reverse, using a 2nd order Butterworth filter (cut-off frequency 1 Hz). Sagittal plane superior directional (DispZ) maximum, minimum and midpoint, i.e. between maximum and minimum ($DispZ_{mid}$) displacements were extracted, as these events were periodically consistent across gait cycles. Similarly, one maximum and (two) minima either side of the maximum sagittal plane AccumAngX were extracted. In addition, the maximum and minimum peaks of DispX, DispY, Accum.AngY and Accum.AngZ were obtained (Santhiranayagam et al., 2015a). A total of 40 inertial-signal features (Figure 4-14) were extracted and each feature’s correlation with reference MTC_Height was examined for both Young and Older in preferred-speed walking. Correlations between reference MTC_Height and statistical properties of inertial sensor signals (raw, SI and DI) have been presented in Appendix F.

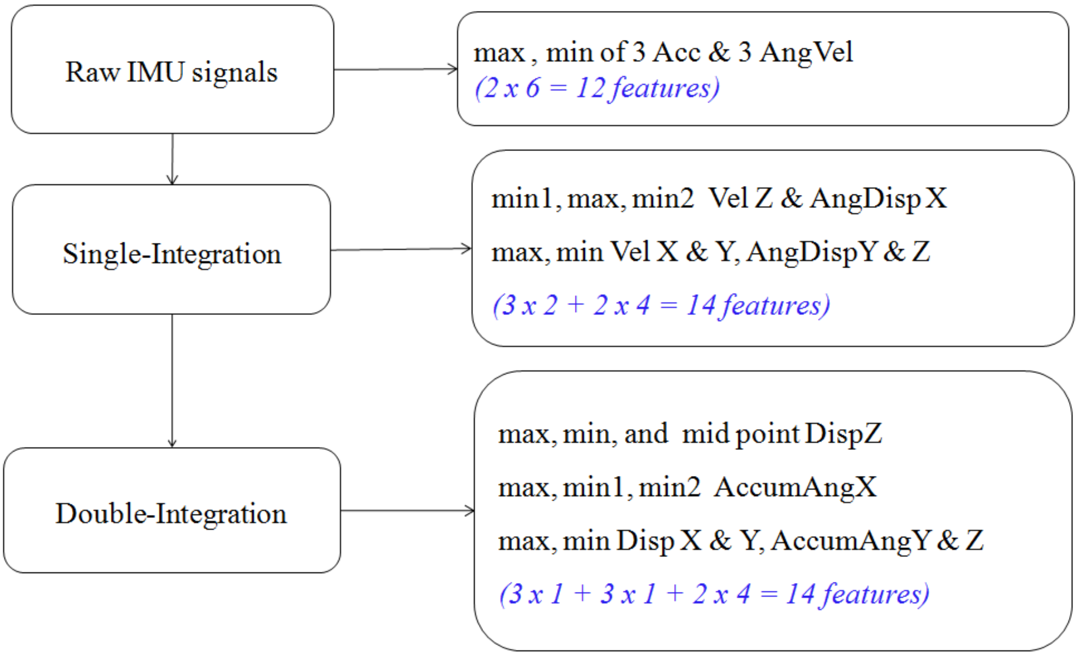


Figure 4-14 Complete feature-set obtained from raw and integrated versions of inertial signals. Twelve features from raw inertial sensor signals and fourteen each from single- and double-integrated inertial sensor signals were formed.

Stage A: Feature-Selection

Feature-selection was carried out for Young and Older separately using their preferred-speed walking data. To identify age-specific optimum feature-sets leave-one-subject-out (LOSO) cross validation was incorporated. For the LOSO validation, multiple GRNN models were created for different combinations of feature using hill-climbing feature-selection. The feature-set producing the overall lowest RMSE for the group was considered optimum. In the present project, the feature-selection process explained in Figure 2-20 and Figure 2-21 was initiated by computing the LOSO validation RMSE for an individual feature using following model parameters: 0.0001, 0.01, 0.1, 1, 10, 50, 100, 500, and 1000 (Santhiranayagam et al., 2011a). Age-specific hill-climbing feature-selection with LOSO cross validation was first applied to raw IMU signal features. Single-integrated IMU signal features were then combined with the raw features prior to feature-selection and LOSO cross validation to determine whether RMSE reduced by including single-integrated IMU signals. Finally, feature-selection with LOSO cross validation was undertaken with all three inputs, i.e., the features of both double-integrated and single-integrated IMU signals combined with the raw inertial features. In all cases, each inertial sensor feature was scaled by calculating its z-score (i.e.,$(x-\mu)/\sigma$, where μ is the mean and σ is the SD for the training gait feature) before applying them to the regressor.

Once the optimum feature-set was obtained, the model parameter was narrowed to a 0.5-1.5 window and tested in 0.1 increments for fine-tuning. The parameter which produced lowest LOSO mean RMSE across 14 subjects for both groups separately was considered in age-specific model development in Stage B (refer Figure 2-17). The RMSE obtained for LOSO cross validation with the optimized feature-set and model parameter were reported for same group preferred-speed walking data. Further, Bland and Altman plots were investigated to estimate the limit of agreement between the GRNN-model estimated and reference MTC_Height.

Stages B and C: Age-specific model building validation

Age-specific optimum GRNN model was built using the identified age-specific optimum inertial-signal features and the corresponding reference MTC_Height for Young and Older separately. The model parameter was fixed at the model parameter value which produced lowest RMSE in age-specific feature-selection Stage B. The age-specific optimum GRNN model for the Young would be referred as “Model_Y” and the optimum model for Older as “Model_O”. Age-specific GRNN models Model_Y and Model_O were tested on the same group in dual task and slower walking conditions and for the counter group across three walking conditions. The RMSE between reference MTC_Height and model-estimated MTC_Height across walking conditions were calculated for both age groups. Further, to complete the modeling validation, each age-specific model was tested incorporating non-MTC gait cycles for Young and Older separately with the three experimental walking conditions data.

GRNN model validation

To further evaluate the estimation accuracy, GRNN-model estimated MTC_Height was statistically compared with reference MTC_Height for individual subjects across the different experimental conditions using Wilcoxon signed-rank test which is a nonparametric test for repeated measurements from a single sample. This comparison was made for both of the age-specific GRNN models, i.e. Model_Y and Model_O. A finding of no statistical difference between reference and estimated MTC_Height was considered the criterion for successful MTC_Height estimation.

5 EXPERIMENTAL RESULTS

The Experimental Results chapter first presents individual subject characteristics including walking speed. Individual participant's MTC_Height and MTC_Time characteristics are then described using median, mean, IQR and SD. The statistical analysis to test the hypotheses (page 50) formulated to address the effects of ageing and walking condition on central tendency and dispersion of MTC_Height and MTC_Time are then presented in section 5.2. Evaluation results of toe-height at mean MTC_Time as indicative MTC_Height in non-MTC gait cycles are described in Section 5.3. Section 5.4 reports the analysis of non-MTC gait cycles for both groups across walking conditions. Comparisons between measured MTC_Height and indicative MTC_Height extracted at mean MTC_Time in non-MTC gait cycles are also outlined. The findings of the machine-learning approach to estimating MTC_Height using inertial sensor data, i.e. inertial signal pre-conditioning, hill-climbing feature-selection and leave-one-subject-out (LOSO) cross validation are documented in Section 5.6. This section also illustrates age-specific models ModelY and ModelO building and validation of these models for both groups in other walking conditions. Final section of this chapter summarizes the results of the present study.

5.1 Subject characteristics

Individual subject characteristics; gender, age, stature and mass, are presented in Table 5-1. Mean ages for young and elderly were 26.1 years (SD = 3.8 years) and 73.1 years (SD = 5.6 years) respectively. Young subjects were on average 7 cm taller than their older counterparts with mean stature for young and elderly of 1.75 m (SD

= 0.08m) and 1.68m (SD = 0.09m) respectively. No significant difference observed between Young and Older group mass.

Table 5-1 also presents individual participant's preferred walking speed and walking speed while dual task. Older walked slower than the Young in preferred-speed walking, however, the difference was not statistically significant (Young = 1.06 m/s, SD = 0.14 m/s; Older = 0.94 m/s, SD = 0.26 m/s). In the dual task walking condition both reduced their walking speed compared to preferred-speed walking ($p<0.05$) and Older walked significantly slower than the Young in the dual tasking ($p<0.05$).

Table 5-1 Individual Young and Older participant's physical characteristics, preferred walking speed (PW) and dual task walking (DW) and speed matched slower walking speed (SW). Group mean of age, height, mass and walking speeds are in blue.

Participant	Gender (F=female, M=male)	Age (years)	Stature (m)	Mass (kg)	Walking speed PW (m/s)	Walking speed DW & SW (m/s)
YP01	F	21	1.58	61.6	0.81	0.61
YP02	M	28	1.76	75.6	1.14	0.50
YP03	M	32	1.70	71.5	1.14	0.47
YP04	M	29	1.73	72.4	1.19	0.47
YP05	M	29	1.82	73.5	1.06	0.47
YP06	F	21	1.68	64.6	1.17	0.56
YP07	M	32	1.66	69.2	0.83	0.47
YP08	F	27	1.70	67.2	1.11	0.61
YP09	M	22	1.88	76.2	1.17	0.47
YP10	F	28	1.76	61.0	0.81	0.53
YP11	M	27	1.81	75.5	1.11	0.47
YP12	M	22	1.80	73.4	1.17	0.64
YP13	M	28	1.76	72.6	1.00	0.42
YP14	M	22	1.85	92.0	1.11	0.47
YP15	M	24	1.78	79.2	1.03	0.75
OP01	F	80	1.56	67.0	0.50	0.28
OP02	F	76	1.61	47.6	1.08	0.44
OP03	F	71	1.53	59.5	0.94	0.53
OP04	F	71	1.66	82.5	1.11	0.47
OP05	M	66	1.80	109.4	1.06	0.58
OP06	F	73	1.54	63.3	0.67	0.42
OP07	M	73	1.84	87.7	0.56	0.39
OP08	M	72	1.73	79.6	0.92	0.47
OP09	M	89	1.75	69.9	0.58	0.28
OP10	M	71	1.69	56.9	0.97	0.39
OP11	M	66	1.76	84.4	0.86	0.42
OP12	M	74	1.73	71.3	1.25	0.44
OP13	F	72	1.65	62.0	1.31	0.36
OP14	M	72	1.65	61.6	1.31	0.44
OP15	M	70	1.69	70.1	0.94	0.33

5.2 Ageing and walking condition effects

Figure 5-1 presents Kruskal Wallis tests to examine the hypothesised ageing effects on MTC_Height and MTC_Time median and IQR in preferred-speed walking (page 50).

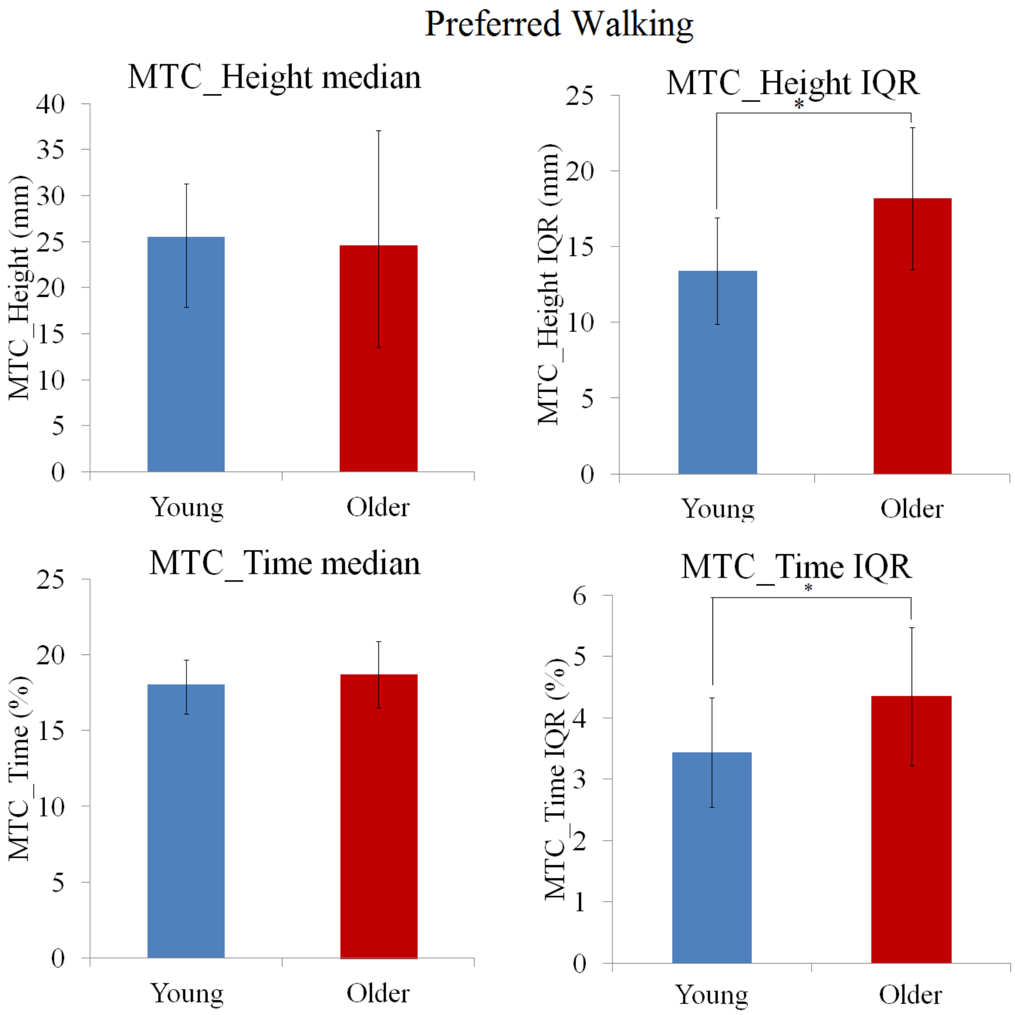


Figure 5-1 MTC characteristics between Young and Older at preferred walking for median MTC_Height, MTC_Height IQR median MTC_Time, and MTC_Time. * denotes significant ageing effects. Median error bars are denoted by Q1 (1st quartile) and Q3 (3rd quartile) and IQR error bars present standard error (IQR/√n, where n was sample size)

As hypothesised, there was no difference observed in MTC_Height central tendency, represented by median, between Young (25.5 mm) and Older (24.6 mm) in preferred walking. It was also confirmed that MTC_Height variability was significantly greater (H=6.72, 1 df, p=.0095) in Older (18.2 mm) than Young (13.4 mm). Non-parametric statistical test on median MTC_Time (Young = 18.02%; Older = 18.68%) confirmed no ageing effect. As anticipated, Older adults' MTC_Time variability (4.35 %; Young = 3.44%) was greater in preferred-speed walking (H=7.77, 1 df, p=.0053).

Walking condition effects on Young adults across three walking trials are shown in Figure 5-2. As expected, Young maintained median MTC_Height while walking slowly (SW = 22.6 mm; PW = 25.5 mm) but showed no significant differences in MTC_Height variability across walking conditions (PW = 13.4 mm; SW = 14.6 mm). Further, Young reduced (H=10.38, 2 df, p=.0056) median MTC_Time in slower walking (SW = 14.72%, PW = 18.02%) but did not show any speed effect on MTC_Time IQR (PW = 3.44%, 5.43%). In dual task walking, as anticipated, Young maintained the MTC_Height similar to preferred-walking (DW = 23.9 mm; PW = 25.5 mm). In contrary, Young also showed no difference in MTC_Height IQR in more attention demanding glass carrying task (12.2 mm; PW = 13. 4mm). Young also maintained MTC_Time central tendency (PW = 18.02%; DW = 15.13%) and dispersion (PW = 3.44%; DW = 4.59%) in dual task despite of the reduction in walking speed and task difficulty.

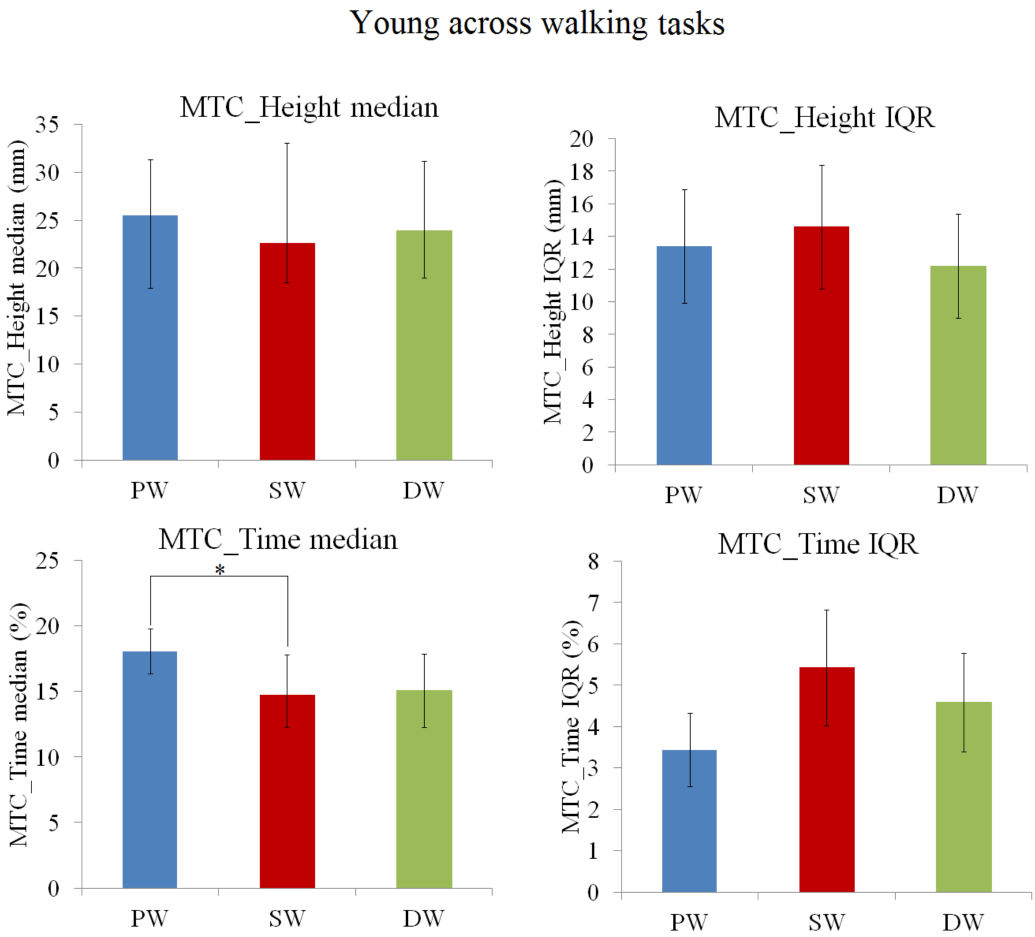


Figure 5-2 Young MTC characteristics across preferred (PW), slower (SW) and dual task (DW) walking conditions for median MTC_Height, MTC_Height IQR, median MTC_Time, and MTC_Time. * denotes significant walking condition effects. Median error bars are denoted by Q1 (1st quartile) and Q3 (3rd quartile) and IQR error bars present standard error (IQR/√n, where n was sample size)

Figure 5-3 depicts the walking condition effects on Older. Slower walking did not show any significant effect on all four MTC characteristics compared to preferred-waling in Older. In dual task walking, however, MTC_Height IQR (PW = 18.2 mm; DW = 10.2 mm) was significantly reduced (H= 14.27, 2 df, p=.0008). Median MTC_Time (PW = 18.68%; DW = 13.89%) was shortened in the glass carrying task (H= 20.37, 2 df, $p<10^{-5}$). MTC_Time IQR, however, showed no dual task effects in Older. Median MTC_Height (H= 9.8, 2 df, p=.0075) and median

MTC_Time (H= 20.37, 2 df, $p<10^{-5}$) were significantly reduced in DW compared to same speed normal walking (SW).

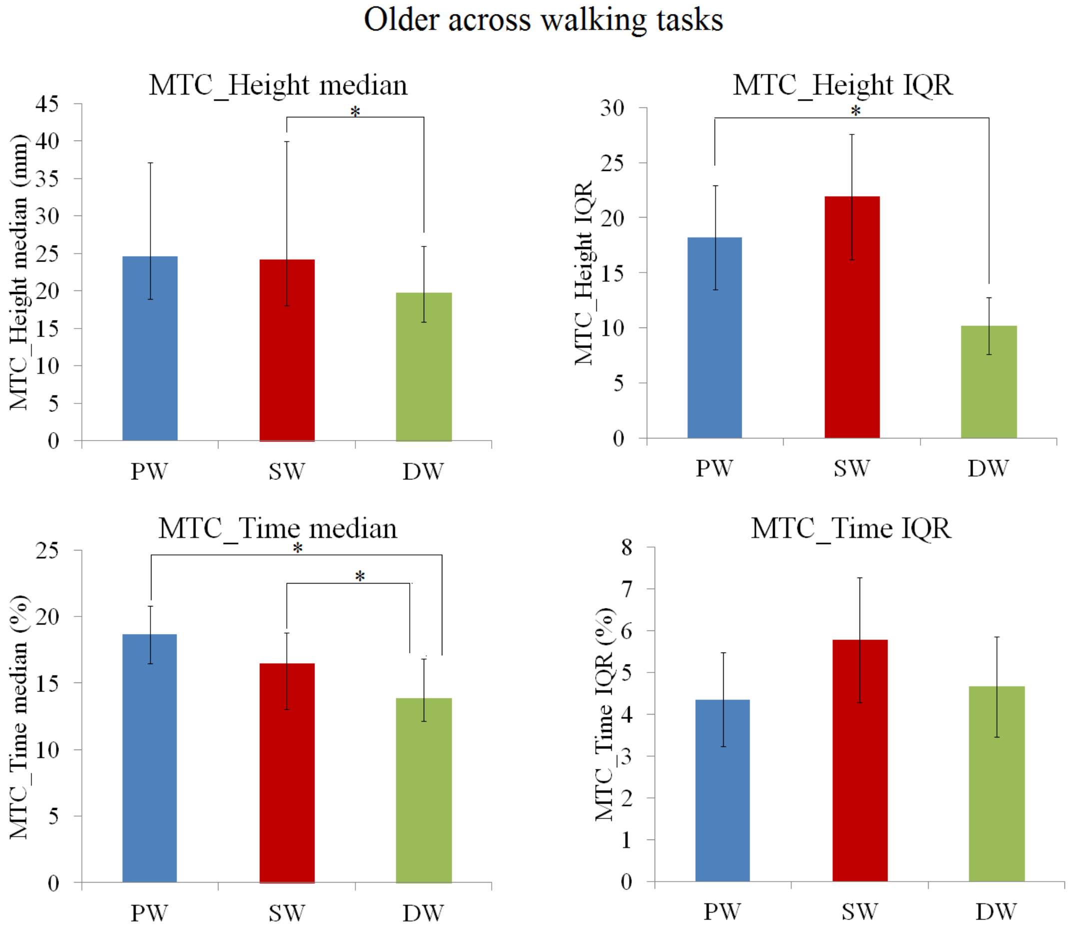


Figure 5-3 Older MTC characteristics across preferred (PW), slower (SW) and dual task (DW) walking trials for median MTC_Height, MTC_Height IQR, median MTC_Time, and MTC_Time. * denotes significant walking condition effects. Median error bars are denoted by Q1 (1st quartile) and Q3 (3rd quartile) and IQR error bars presented standard error (IQR/√n, where n was sample size)

Individual participant's MTC_Height median, mean, IQR and SD are presented in Table 5-2 and Table 5-3. In preferred-speed walking, YP07 (41.0 mm) and OP09 (58.4 mm) showed the greatest MTC_Height within their age groups. The MTC_Height IQR of YP07 (9.9 mm) was also the greatest (group IQR mean: Young = 4.6 mm). OP09 continued to maintain the elevated MTC_Height in slow and dual task walking, whereas YP07 reduced it in both slower (34.1 mm) and dual task (28.4 mm). OP01 exhibited the greatest MTC_Height IQR (12.2 mm) in preferred-speed walking but it was reduced in slower (5.9 mm) and dual task (4.5 mm) walking conditions. Similar trends could be also seen in individual participant's MTC_Height mean and SD given in Table 5-3.

In slow walking, 7 out of 15 Young participants reduced median MTC_Height and 8 increased MTC_Height (Table 5-2). Older individual median MTC_Height was similar to Young individuals in preferred-speed walking. Ten out of 15 young participants increased their MTC_Height while walking slowly compared to preferred-speed walking. Thirteen of 15 older participants reduced their MTC_Height while dual task walking compared to speed matched walking trial. One participant's (OP07) median MTC_Height did not change and just one participant increased his or her MTC_Height. When variability was analysed 11/15 participants reduced their IQR in dual task compared to slow walking.

Table 5-2 Individual participant's median and IQR of MTC_Height across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking, YP = young participant and OP = older participant.

Participant	PW		SW		DW	
	MTC_ Height median (mm)	MTC_ Height IQR (mm)	MTC_ Height median (mm)	MTC_ Height IQR (mm)	MTC_ Height median (mm)	MTC_ Height IQR (mm)
YP01	35.3	5.1	34.4	3.3	34.3	3.1
YP02	31.8	3.6	44.1	4.4	39.3	4.5
YP03	16.1	3.1	20.0	2.2	21.8	3.2
YP04	10.3	2.8	19.2	4.3	15.7	3.3
YP05	29.0	4.2	35.1	5.0	34.1	10.1
YP06	20.0	3.0	20.9	2.5	22.2	2.4
YP07	41.0	9.9	34.1	9.7	28.4	6.1
YP08	12.6	3.5	11.1	5.6	8.8	4.4
YP09	26.6	4.0	25.0	2.9	25.4	3.2
YP10	19.5	6.2	17.5	3.7	20.2	4.7
YP11	30.1	5.4	33.4	5.3	33.9	6.3
YP12	31.4	3.3	33.6	4.9	34.1	2.9
YP13	25.8	3.4	24.6	4.1	25.2	2.3
YP14	22.1	2.7	27.5	3.9	27.3	3.2
YP15	21.6	8.4	19.7	6.4	20.4	6.4
OP01	28.0	13.5	31.8	5.9	29.1	4.5
OP02	23.0	2.9	19.7	5.0	18.4	2.6
OP03	18.3	4.1	20.0	3.8	18.8	2.5
OP04	21.7	3.0	26.5	4.1	20.6	3.3
OP05	27.5	9.0	38.2	8.2	18.2	5.3
OP06	20.4	10.8	38.9	8.4	12.9	2.1
OP07	23.4	11.6	16.4	5.7	23.3	6.4
OP08	43.1	7.0	45.0	5.3	29	3.9
OP09	58.4	9.2	51.7	7.4	47.9	7.9
OP10	32.9	7.3	45.1	6.1	37.6	6.2
OP11	49.2	8.2	41.6	3.9	41.6	3.9
OP12	36.2	11.8	19.2	5.9	16.3	5.0
OP13	12.4	5.2	12.7	5.7	10.9	3.2
OP14	17.9	5.1	23.4	5.4	20.5	3.4
OP15	26.9	7.4	29.9	4.1	27.1	3.2

Table 5-3 Individual participant's mean and SD of MTC_Height across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking, YP = young participant and OP = older participant. Mean of MTC_Height mean and SD were shown in blue.

Participant	PW		SW		DW	
	MTC_ Height mean (mm)	MTC_ Height SD (mm)	MTC_ Height mean (mm)	MTC_ Height SD (mm)	MTC_ Height mean (mm)	MTC_ Height SD (mm)
YP01	35.3	3.8	34.4	2.8	34.1	2.8
YP02	31.8	2.7	44.3	3.7	39.6	3.4
YP03	16.4	3.1	20.2	1.8	21.8	2.3
YP04	10.4	2.2	19.1	3.2	15.9	2.6
YP05	29.9	4.4	34.3	5.1	34.1	7.7
YP06	20.3	2.4	20.9	2.0	22.2	1.9
YP07	42.0	6.8	34.4	6.5	28.7	4.3
YP08	12.6	3.0	11.7	4.8	8.9	3.8
YP09	26.8	3.1	25.1	2.6	25.7	3.1
YP10	20.1	4.7	18.1	3.6	20.3	3.3
YP11	30.8	4.8	33.0	5.5	34.1	5.7
YP12	31.6	2.6	33.9	2.9	34.1	2.0
YP13	25.8	2.7	25.0	2.8	25.3	1.8
YP14	22.0	2.8	26.5	3.1	27.0	2.8
YP15	22.6	6.9	20.8	5.5	20.9	4.9
OP01	29.4	6.7	31.1	4.8	28.7	3.3
OP02	23.2	2.3	20.0	3.2	18.2	1.9
OP03	18.8	3.3	20.2	2.6	18.7	2.0
OP04	21.8	2.3	26.6	3.2	21.0	2.3
OP05	27.4	6.4	38.7	7.0	19.1	5.1
OP06	25.5	12.2	38.7	5.9	12.9	2.0
OP07	23.9	6.6	16.9	4.2	23.9	4.6
OP08	43.9	5.5	45.1	4.3	29.4	3.3
OP09	59.5	7.4	52.1	6.2	48.2	5.6
OP10	33.2	5.7	44.8	5.1	38.0	6.4
OP11	49.3	6.5	42.1	3.4	42.1	3.4
OP12	36.6	8.6	19.5	4.4	16.6	3.7
OP13	12.2	3.7	13.4	4.0	11.0	2.4
OP14	18.5	4.5	23.5	4.0	20.5	2.8
OP15	27.5	5.7	30.2	3.0	27.8	3.0

Individual MTC_Time characteristics presented in Table 5-4 and Table 5-5 revealed that central tendency of MTC_Time of both young and older individuals varied within a wide range in preferred-speed walking (Young: 7.8% - 22.0%; Older: 8.9% - 23.7%). Older individuals exhibited greater variability compared to Young in preferred-speed walking. Twelve of 15 Young and Older reduced MTC_Time in slower walking. All older participants shortened their MTC_Time median in dual task walking. Findings presented here suggested that MTC timing calculated as a percentage of samples between toe-off to consecutive toe-off vary within participants and walking conditions. Thus while validating the concept of using toe-height at mean MTC_Time as an indicative MTC_Height, it was important to obtain condition specific mean MTC_Time for individual participants (page 93).

Table 5-4 Individual participant's MTC_Time characteristics across walking conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking, YP = young participant and OP = older participant. Mean of individual MTC_Time median and IQR were shown in blue.

Participant	PW		SW		DW	
	MTC_ Time median (%)	MTC_ Time IQR (%)	MTC_ Time median (%)	MTC_ Time IQR (%)	MTC_ Time median (%)	MTC_ Time IQR (%)
YP01	12.8	2.2	11.5	2.3	12.1	2.5
YP02	16.3	1.2	16.6	1.3	16.6	1.2
YP03	19.3	1.1	13.9	1.2	14.3	1.0
YP04	21.1	1.3	13.9	1.4	15.5	1.3
YP05	18.9	1.7	13.2	2.7	12.6	7.6
YP06	17.6	1.6	11.9	1.1	12.2	1.1
YP07	16.0	3.2	14.7	1.6	13.4	4.0
YP08	22.0	1.5	20.5	1.2	20.7	1.3
YP09	17.9	1.6	9.3	1.5	9.5	1.4
YP10	19.2	1.9	15.6	1.2	15.9	1.5
YP11	17.4	1.6	13.3	3.4	14	3.0
YP12	16.5	3.8	20.5	3.4	18.1	3.9
YP13	17.3	1.3	7.8	1.5	8.1	1.1
YP14	15.7	1.3	7.8	1.3	9.0	1.3
YP15	19.8	2.3	20.3	1.6	19.8	1.5
OP01	11.6	3.7	10.0	1.1	9.8	1.1
OP02	14.3	2.3	8.9	2.4	9.1	2.1
OP03	15.0	2.4	11.6	2.1	11.7	2.1
OP04	19.4	2.2	13.0	2.1	12.8	1.1
OP05	17.5	2.3	20.0	2.9	13.7	2.3
OP06	14.4	3.9	20.0	4.4	10.2	1.4
OP07	14.9	1.7	13.6	1.6	12.9	1.8
OP08	21.6	3.5	18.2	2.8	14.1	2.3
OP09	20.9	4.8	18.6	3.5	18.4	2.9
OP10	20.2	2.7	23.1	3.0	19.8	3.2
OP11	20.7	1.7	17.2	1.9	17.2	1.9
OP12	23.7	2.4	18.1	2.6	17.3	2.3
OP13	18.2	1.8	17.8	1.9	17.4	1.2
OP14	19.8	1.7	13.4	2.2	13.2	1.8
OP15	17.8	1.6	10.4	1.8	9.7	2.2

Table 5-5 Individual participant's MTC_Time characteristics across conditions PW = preferred-speed walking, SW= slow walking and DW = dual task walking, YP = young participant and OP = older participant. Mean of MTC_Time mean and SD were shown in blue across conditions for young and older individuals.

Participant	PW		SW		DW	
	MTC_ Time mean (%)	MTC_ Time SD (%)	MTC_ Time mean (%)	MTC_ Time SD (%)	MTC_ Time mean (%)	MTC_ Time SD (%)
YP01	13.0	1.5	11.6	1.4	12.0	1.6
YP02	16.4	0.9	16.9	1.8	16.5	1.1
YP03	19.4	0.8	13.9	0.9	14.2	0.8
YP04	21.0	0.9	13.7	1.2	15.6	0.9
YP05	18.8	1.5	13.3	3.4	13.5	4.3
YP06	17.7	0.8	11.9	0.8	12.2	0.7
YP07	16.4	2.1	14.7	1.5	12.7	2.2
YP08	21.8	1.1	20.5	1.0	20.6	1.1
YP09	17.9	1.1	9.3	1.3	9.4	1.3
YP10	19.2	1.3	15.7	1.0	15.8	1.0
YP11	17.4	1.8	13.3	2.4	14.1	1.9
YP12	17.2	2.6	20.5	1.7	17.4	2.8
YP13	17.2	1.1	7.9	1.3	8.1	1.0
YP14	15.3	1.5	7.9	1.1	8.9	1.0
YP15	19.9	1.7	20.3	1.2	19.8	1.3
OP01	11.1	2.2	10.0	1.0	9.7	0.8
OP02	14.1	1.5	9.0	1.5	9.0	1.5
OP03	15.1	1.8	11.5	1.7	11.5	1.5
OP04	20.0	2.5	13.0	1.4	12.8	0.9
OP05	17.5	1.9	20.0	2.1	13.6	1.8
OP06	15.0	3.1	20.1	2.6	10.1	0.9
OP07	14.9	1.1	13.5	1.3	13.0	2.1
OP08	21.8	2.7	18.3	2.0	14.2	1.5
OP09	21.0	3.1	18.9	2.5	18.5	2.3
OP10	20.0	2.0	22.7	2.5	19.5	2.5
OP11	20.8	2.0	17.3	1.6	17.3	1.6
OP12	23.6	1.8	18.1	1.9	17.2	1.6
OP13	18.1	1.5	17.8	1.4	17.5	1.3
OP14	19.8	1.2	18.1	3.4	13.0	1.6
OP15	17.9	1.2	10.2	1.3	9.9	1.4

5.3 Indicative MTC_Height validation

This section presents the evaluation of toe-height at mean MTC_Time as an indicative MTC_Height in gait cycles which showed a well defined MTC event. As illustrated for a typical young and an older participant in Figure 5-4, at preferred-speed walking indicative MTC_Height extracted at mean MTC_Time in gait cycles which showed MTC closely followed reference MTC_Height. Wilcoxon signed-rank test revealed no difference between indicative MTC_Height and reference MTC_Height for both groups, across walking conditions.

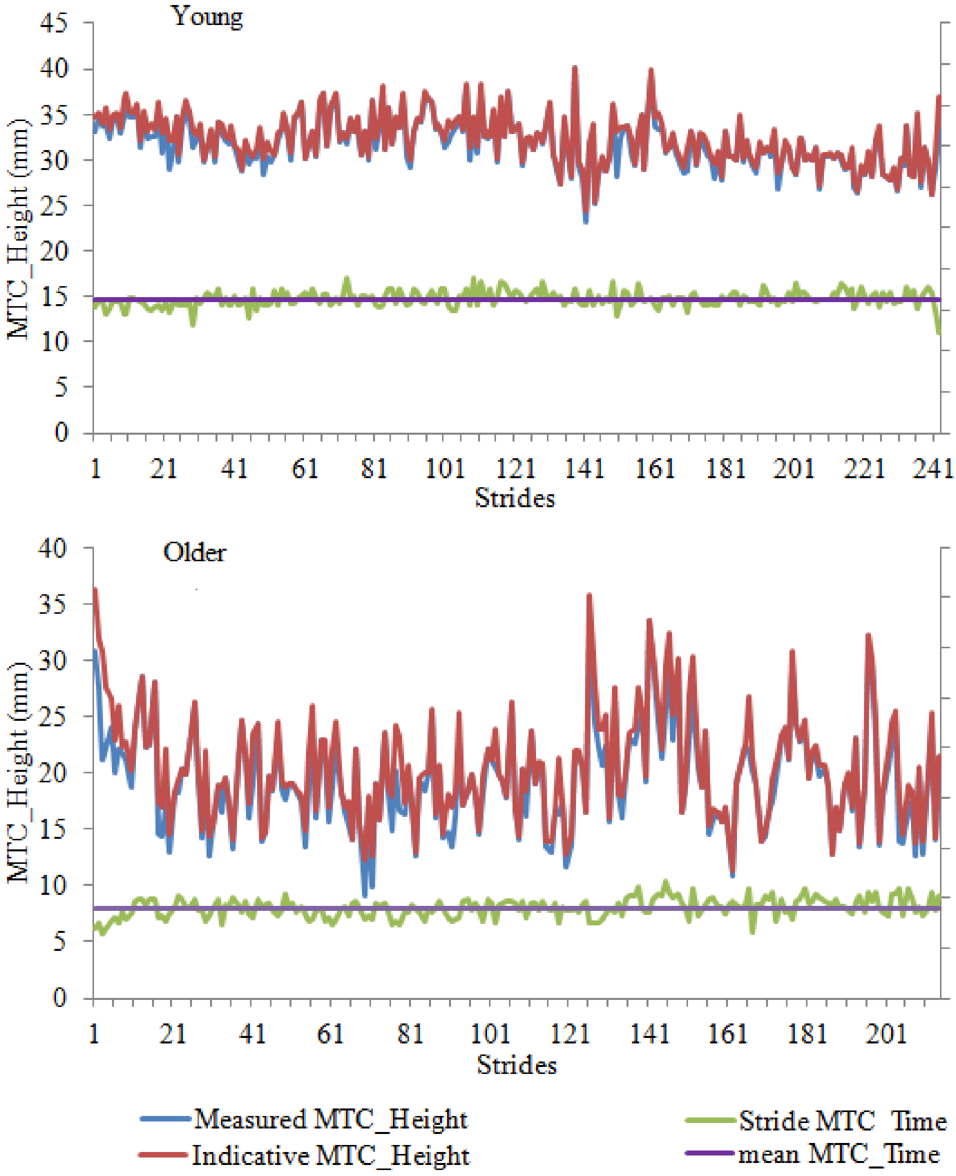


Figure 5-4 Typical series of reference MTC_Height and indicative MTC_Height were plotted in primary axis (left) and mean MTC_Time and stride specific MTC_Time were plotted in secondary axis (right) for a young adult (MTC_Time SD = 0.9%) and an older participant (MTC_Time SD 3.1%) in preferred-speed walking.

RMSE between reference MTC_Height and indicative MTC_Height across trials for individual participants were given in Table 5-6. For all participants except one (YP05 in SW and DW) the difference between indicative and reference MTC_Height was less than 2.8 mm in all three experimental conditions.

Table 5-6 RMSE between measured and indicative MTC_Height across trials PW = preferred-speed walking, SW = slow walking and DW = dual task walking for individuals, YP = young participant and OP = older participant.

Young RMSE (mm)				Older RMSE (mm)			
Participant	PW	SW	DW	Participant	PW	SW	DW
YP01	1.0	0.9	1.2	OP01	1.0	2.0	0.6
YP02	0.8	1.7	1.7	OP02	1.4	1.0	1.1
YP03	1.5	0.9	0.9	OP03	1.7	1.4	0.8
YP04	1.0	1.4	0.9	OP04	2.8	1.2	0.6
YP05	1.2	4.4	7.1	OP05	1.6	2.8	1.5
YP06	1.0	0.6	0.5	OP06	2.0	2.8	0.4
YP07	1.7	1.3	1.1	OP07	0.9	1.0	1.5
YP08	2.2	1.6	1.7	OP08	1.7	1.3	0.8
YP09	1.3	0.8	1.2	OP09	2.5	2.8	1.6
YP10	2.8	1.4	1.5	OP10	1.9	1.5	1.1
YP11	2.5	2.0	2.0	OP11	1.1	0.9	0.9
YP12	2.1	1.0	1.7	OP12	2.1	1.8	1.2
YP13	1.8	0.8	0.7	OP13	0.9	2.1	1.5
YP14	1.4	1.2	0.6	OP14	2.2	1.5	1.1
YP15	2.8	2.1	2.0	OP15	1.9	1.1	1.1

Table 5-7 shows the correlation (r) between reference and indicative MTC_Height for young and older individuals across walking conditions.

Table 5-7 Correlation (r) between measured and indicative MTC_Height across trials PW = preferred-speed walking, SW = slow walking and DW = dual task walking for individuals, YP = young participant and OP = Older participant.

Young RMSE (mm)				Older RMSE (mm)			
Participant	PW	SW	DW	Participant	PW	SW	DW
YP01	1.0	1.0	0.9	OP01	1.0	1.0	0.9
YP02	1.0	0.9	0.9	OP02	0.9	0.9	1.0
YP03	0.9	0.9	1.0	OP03	0.9	0.9	0.9
YP04	0.9	0.9	1.0	OP04	0.7	1.0	0.9
YP05	1.0	0.6	0.4	OP05	1.0	1.0	0.9
YP06	1.0	1.0	1.0	OP06	1.0	1.0	0.9
YP07	1.0	1.0	1.0	OP07	1.0	1.0	1.0
YP08	0.9	1.0	0.9	OP08	1.0	1.0	1.0
YP09	0.9	1.0	0.9	OP09	1.0	1.0	0.9
YP10	0.9	1.0	0.9	OP10	1.0	1.0	1.0
YP11	0.9	1.0	1.0	OP11	1.0	1.0	1.0
YP12	0.8	1.0	0.7	OP12	1.0	1.0	1.0
YP13	0.8	1.0	0.9	OP13	1.0	0.9	0.9
YP14	0.9	1.0	1.0	OP14	0.9	0.9	1.0
YP15	1.0	1.0	0.9	OP15	1.0	1.0	1.0

The r values of YP05 in slower (r=0.6) and dual task walking (r=0.4) were comparatively lower than the remaining participants' correlation values (r=~0.9). In dual task walking, YP05 (Table 5-9) had relatively lower number of MTC gait cycles (38) compared to total number of individual gait cycles (147) and as shown in individual MTC timing characteristics in Table 5-4, YP05's MTC_Time variability in dual task condition was relatively higher (7.6%) compared to average group MTC_Time IQR (2.2%). As shown in Figure 5-5, YP05 had only 38 gait cycles with MTC event and 12 of them showed greater difference between indicative and reference MTC_Height. Above presented results, in summary suggested that toe-height at mean MTC_Time (indicative MTC_Height) is an acceptable representation of reference MTC_Height.

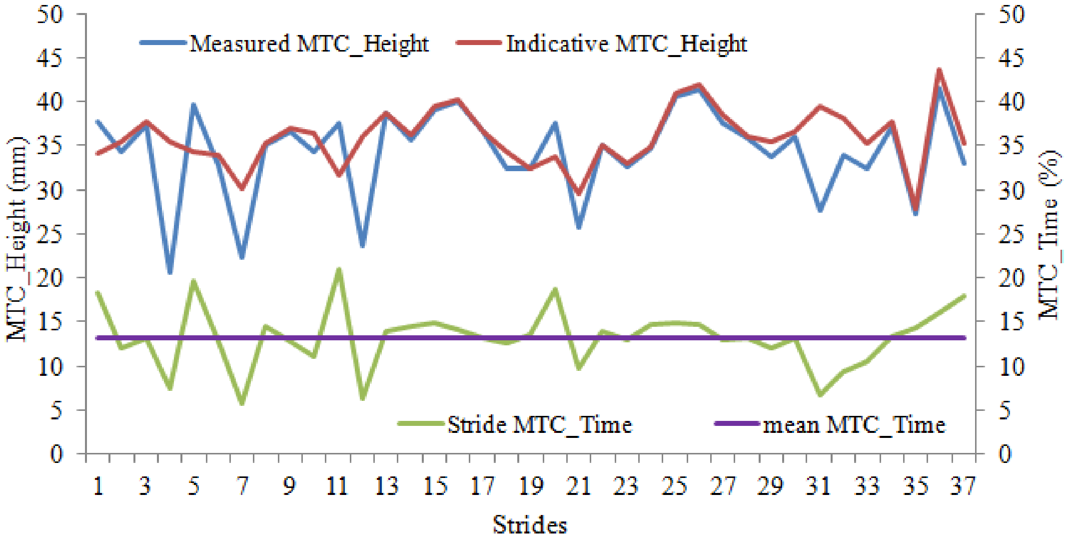


Figure 5-5 Typical series of reference MTC_Height and indicative MTC_Height were plotted in primary axis (left) and mean MTC_Time and stride specific MTC_Time were plotted in secondary axis (right) for a YP05 (MTC_Time SD 4.3%) in dual task walking

5.4 Non-MTC gait cycles

Table 5-8 summarizes the group data of total numbers of gait cycles, MTC gait cycles and non-MTC gait cycles for Young and Older across walking conditions. Older adults demonstrated higher number of non-MTC gait cycles in preferred-speed walking compared to Young in the same walking condition. Both groups, however, increased number of non-MTC gait cycles in slower and dual task walking conditions. As the total number of gait cycles for different walking conditions were not the same, the frequency of non-MTC gait cycles was examined as a percentage of total number of gait cycles.

Table 5-8 Total numbers of gait cycles, MTC gait cycles and non-MTC gait cycles across walking conditions PW = preferred-speed walking, SW = slow walking and DW = dual task walking for Young and Older.

	Young			Older		
	PW	SW	DW	PW	SW	DW
Total no. of gait cycles	3759	2713	2744	4178	3261	3056
Total no. of gait cycles with MTC event	3651	1989	2119	3395	2134	1903
Total no. of non-MTC gait cycles	108	724	625	783	1127	1153

In Figure 5-6 proportions of non-MTC gait cycles were expressed as a percentage of total number of gait cycles for a particular walking condition of a group. In preferred-speed walking, only 2.9% of total gait cycles were non-MTC gait cycles. These finding were consistent with Schulz et al. (2010) who found 2% of MTC unidentifiable gait cycles in overground walking in young adults. In the present study the non-MTC gait cycles proportion were, however, 6 folds in Older in preferred-speed walking. Statistical test performed on proportions of non-MTC gait cycles confirmed that in preferred waling Older had greater proportion of non-MTC gait cycles ($z = -22.36$, $p < 10^{-3}$). As expected both groups significantly increased the proportion of non-MTC gait cycles in both slow and dual task walking trials compared to preferred-walking (refer Appendix G for z-test results). Young showed the greatest proportion of non-MTC gait cycles in slower walking but Older in dual task walking. In both slower and dual tasking, however Older exhibited greater proportions of non-MTC gait cycles than the Young.

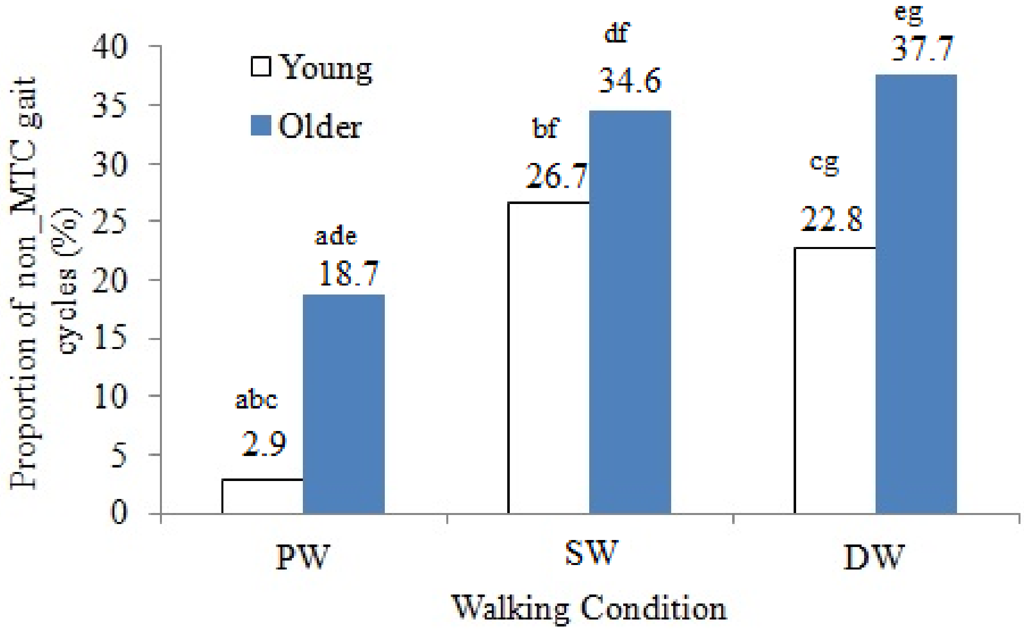


Figure 5-6 Proportions of non-MTC gait cycles for Young and Older across walking conditions PW = preferred-speed walking, SW = slow walking and DW = dual task walking (afg: $p< .05$ for group differences, bcde: $p< .05$ for condition differences).

Number of individual participants demonstrated at least 3 non-MTC gait cycles were considered. Only four of 15 Young participants demonstrated at least 3 non-MTC gait cycles in preferred-speed walking. In slower and dual task walking trials, 8 Young adults demonstrated non-MTC gait. Number of Older exhibited at least 3 non-MTC gait cycles in preferred-speed walking were 9 and across walking conditions more Older showed non-MTC phenomenon than Young. As shown in Figure 5-7, statistical test on number of participants showed non-MTC gait cycles, demonstrated that more participants from Older than Young in preferred-speed walking exhibited this non-MTC phenomenon ($p<0.05$). Compared to preferred-speed walking in slower and dual task conditions, more participants in Young group demonstrated non-MTC gait cycles ($p<0.05$). Although in preferred-speed walking more participants from the Older group demonstrated non-MTC gait cycles than Young, the increase in Older in slower and dual task walking were not significant.

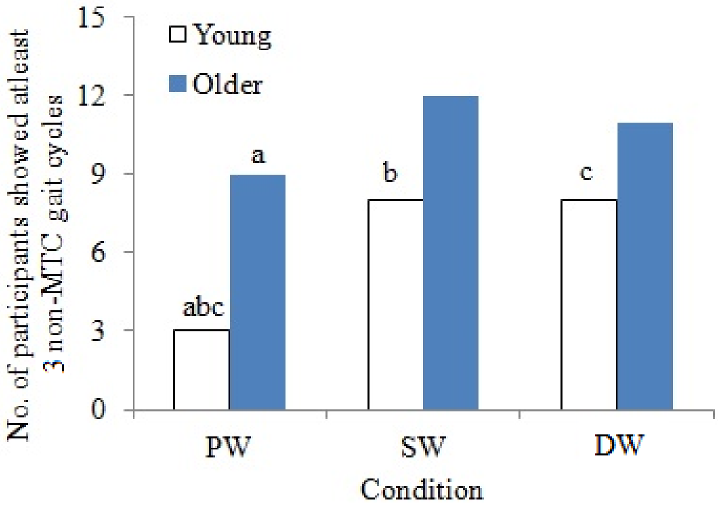


Figure 5-7 Number of participants demonstrated at least 3 non-MTC gait cycles for Young and Older across trials PW = preferred-speed walking, SW = slow walking, and DW = dual task walking (a: p<.05 for group differences, bc p<.05, for walking condition differences)

To illustrate how each participant contributed to the entire group Non-MTC frequency, the total number of gait cycles, non-MTC gait cycles and proportion of non-MTC gait cycles as a percentage of total gait cycles are presented in Table 5-9. In preferred-speed walking although non-MTC group frequency for Young was 2.9%, three young participants (YP01, YP12 and YP14) exhibited more than 10% of non-MTC gait cycles. In slower and dual task walking trials a greater proportion of non-MTC gait cycles were observed; YP01, for example, who had 18.2% of non-MTC gait cycles in preferred-speed walking, increased her frequency to 80.3% in dual task walking. The maximum non-MTC gait cycle proportion for Young across walking condition was as high as 96.5%.

From Table 5-9, it can also be seen that across walking conditions non-MTC gait cycles were more pronounced in older people, for example, OP01 and OP06 had more than 90% non-MTC gait cycles. Similar to young people, more older participants demonstrated greater frequency of non-MTC gait cycles in slower and dual task walking. The proportion of non-MTC gait cycles was as high as 97.8% (OP10) for an older individual in slower walking. Participants OP04, OP12 and OP13, however, did not have more than 2 non-MTC gait cycles in any of the walking condition. In summary, the data in Table 5-9, show that more of the older individuals showed a high proportion of non-MTC gait cycles and the more challenging walking condition also increased proportions of non-MTC gait cycles.

Table 5-9 Number gait cycles, number of non-MTC gait cycles and proportion of non-MTC gait cycles for individuals across trials PW = preferred-speed walking, SW = slow walking and DW = dual task walking. YP = young participant and OP = older participant. Mean values were shown in blue.

Participant	PW			SW			DW		
	Total gait cycle	Non-MTC gait cycle	% of Non-MTC	Total gait cycle	Non-MTC gait cycle	% of Non-MTC	Total gait cycle	Non-MTC gait cycle	% of Non-MTC
YP01	236	43	18.2	218	175	80.3	206	101	49.0
YP02	243	1	0.4	183	0	0.0	187	0	0.0
YP03	266	0	0.0	174	0	0.0	174	0	0.0
YP04	265	0	0.0	179	0	0.0	165	0	0.0
YP05	245	1	0.4	144	108	75.0	147	110	74.8
YP06	274	0	0.0	197	2	1.0	187	4	2.1
YP07	242	8	3.3	179	3	1.7	181	2	1.1
YP08	261	0	0.0	220	0	0.0	216	0	0.0
YP09	244	0	0.0	136	14	10.3	141	19	13.5
YP10	224	0	0.0	188	0	0.0	186	0	0.0
YP11	235	0	0.0	174	93	53.4	163	84	51.5
YP12	263	29	11.0	214	90	42.1	201	194	96.5
YP13	245	0	0.0	159	23	14.5	172	97	56.4
YP14	247	28	11.3	153	120	78.4	144	115	79.9
YP15	251	0	0.0	227	0	0.0	233	0	0.0
OP01	197	182	92.4	156	127	81.4	154	143	92.9
OP02	289	18	6.2	175	124	70.9	179	122	68.2
OP03	276	0	0.0	208	19	9.1	201	12	6.0
OP04	274	0	0.0	194	0	0.0	189	2	1.1
OP05	297	15	5.1	232	32	13.8	273	24	8.8
OP06	267	247	92.5	215	159	74.0	256	209	81.6
OP07	190	6	3.2	172	57	33.1	160	7	4.4
OP08	298	10	3.4	182	1	0.5	252	68	27.0
OP09	263	93	35.4	171	77	45.0	176	45	25.6
OP10	304	22	7.2	274	268	97.8	282	264	93.6
OP11	300	190	63.3	259	148	57.1	259	148	57.1
OP12	311	2	0.6	211	0	0.0	216	2	0.9
OP13	330	0	0.0	249	0	0.0	305	2	0.7
OP14	298	0	0.0	190	23	12.1	199	5	2.5
OP15	284	0	0.0	169	120	71.0	160	80	50.0

Figure 5-8 shows a typical time series of MTC_Height and extracted toe height at mean MTC_Time (indicative MTC_Height) for non-MTC gait cycles for a young and an older participant during preferred-speed walking. Indicative MTC_Height was characteristically greater than reference MTC_Height and Older more frequently demonstrated multiple consecutive non-MTC gait cycles (Santhiranayagam et al., 2015b).

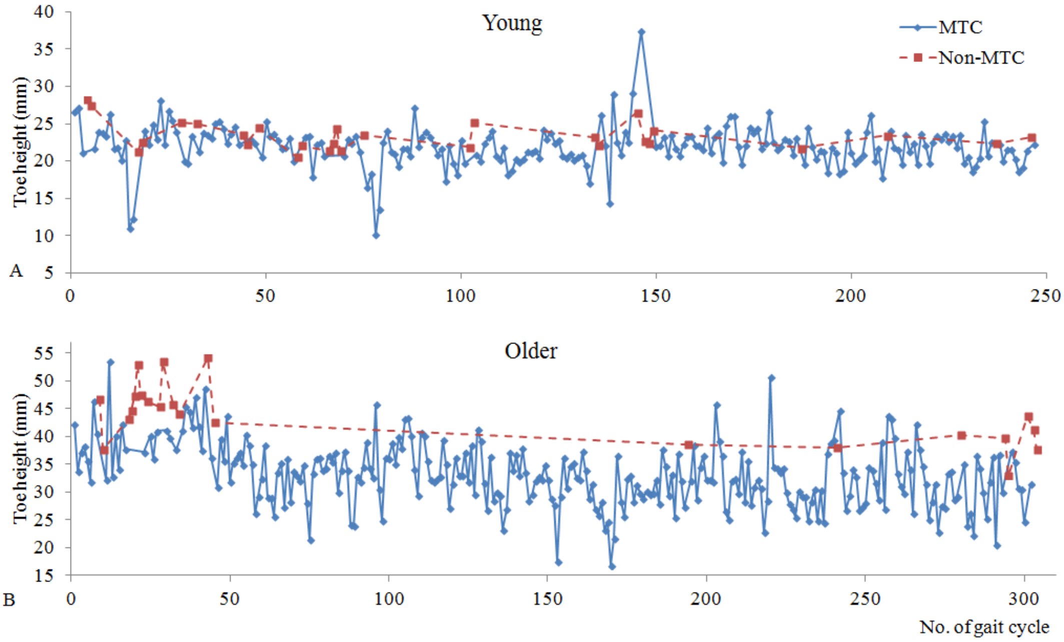


Figure 5-8 Toe heights at MTC for MTC gait cycles non-MTC gait cycles during preferred-speed walking for a young (A) and an older (B) participant. The number of gait cycles for the two participants differed due to self selected walking speed, cadence and stride length.

When all three walking conditions were combined for each group, median toe height extracted at mean MTC_Time was significantly greater than MTC_Height median (Wilcoxon signed-rank test - Young: $p<10^{-4}$; Older: $p<10^{-7}$). Figure 5-9 presents the median MTC_Height and median toe-height extracted at mean MTC_Time in the gait cycles which did not demonstrate an MTC event in different walking conditions for both young and older groups. For both young and older, median toe height extracted at mean MTC_Time was greater than median MTC_Height in all the conditions.

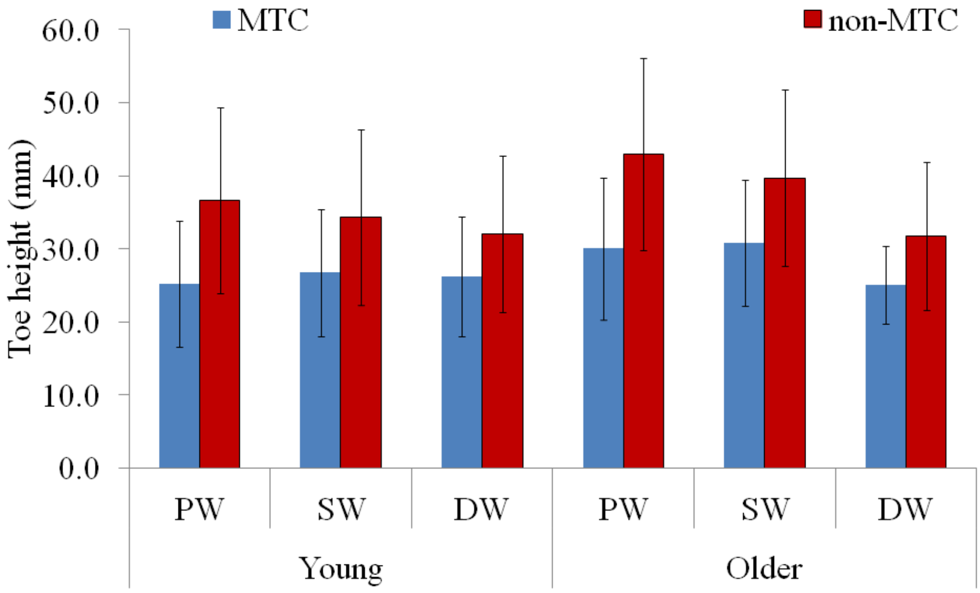


Figure 5-9 Median MTC_Height and median extracted toe height at the mean MTC_Time for non-MTC gait cycles for preferred-speed walking (PW), matched at DW speed without a glass for Young and Older (SW) and dual task walking: while holding a glass of water (DW).

In summary, MTC characteristics and non-MTC gait cycle results presented above answered the first Research Question and the hypotheses (page 49) concerning the ageing and walking condition effects on MTC. MTC_Height characteristics of Older and Young in preferred-speed walking were different, confirming the requirement for the later development of different models for young and older. The identified walking condition effects on MTC characteristics confirmed that the additional experimental conditions, slower and dual task walking, were suitable for testing the GRNN models' generalizability to different conditions. An important result of the non-MTC gait cycle analysis was that although younger people demonstrated only 2.9% non-MTC gait cycles in preferred-speed walking, when individual non-MTC characteristics were analyzed one younger person revealed 18% non-MTC gait cycles. Furthermore, non-MTC gait cycles increased with ageing and walking condition constraints. For some Young and Older participant's non-MTC gait cycles were as high as 90% making it necessary to develop a technique to utilize the non-MTC gait cycles when using modeling to estimate MTC_Height. Toe-height at mean MTC_Time in gait cycles which had an MTC event was shown to provide a valid "indicative" MTC_Height when clearly defined MTC event is not present.

5.5 Inertial sensor signals and GRNN machine-learning for MTC_Height estimation

This section of the Results chapter presents inertial sensor signal processing, GRNN machine-learning approach, feature-selection and GRNN model validation for Young and Older. Figure 5-10 shows IMU obtained kinematic signals of few typical gait cycles from a participant. Even when there was no motion in foot (stance phase), AccZ had an approximate reading of 9.8 m/s^2 as it was reading gravitational acceleration. Acceleration signal (top) readings were prominent in Y and Z direction as they correspond to progression and vertical accelerations in sagittal plane respectively. Similarly gyroscope angular velocity signal had greater reading about medio-lateral axis.

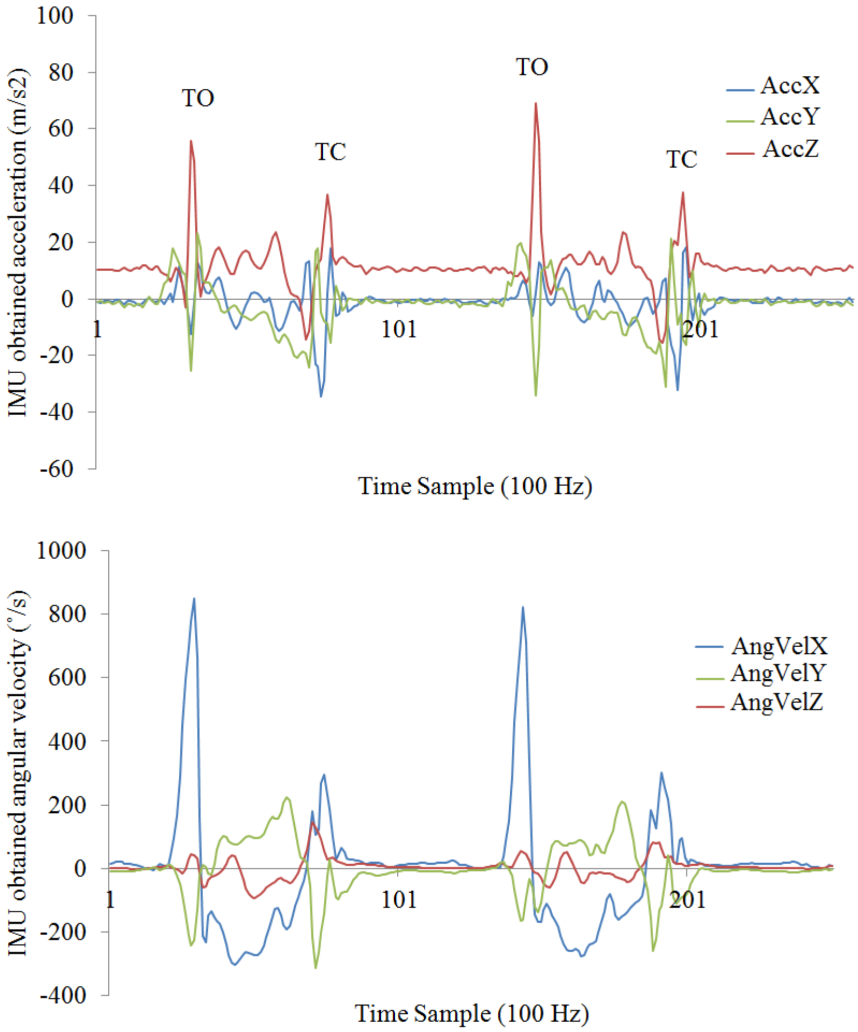


Figure 5-10 IMU obtained typical accelerometer (top) and gyroscope (bottom) signals of seven complete gait cycles. AccX, AccY, AccZ represent medio-lateral, anterior-posterior and sagittal vertical accelerations respectively. AngVelX, AngVelY, AngVelZ denotes angular velocities measured about medio-lateral, anterior-posterior and sagittal vertical axis respectively. TO: Toe-off, TCL Toe-contact.

As shown in Figure 5-11, toe-off event in inertial sensor signals, identified using maximum medio-lateral angular velocities were time synchronised with the corresponding toe-off event in 3D-measured positional data.

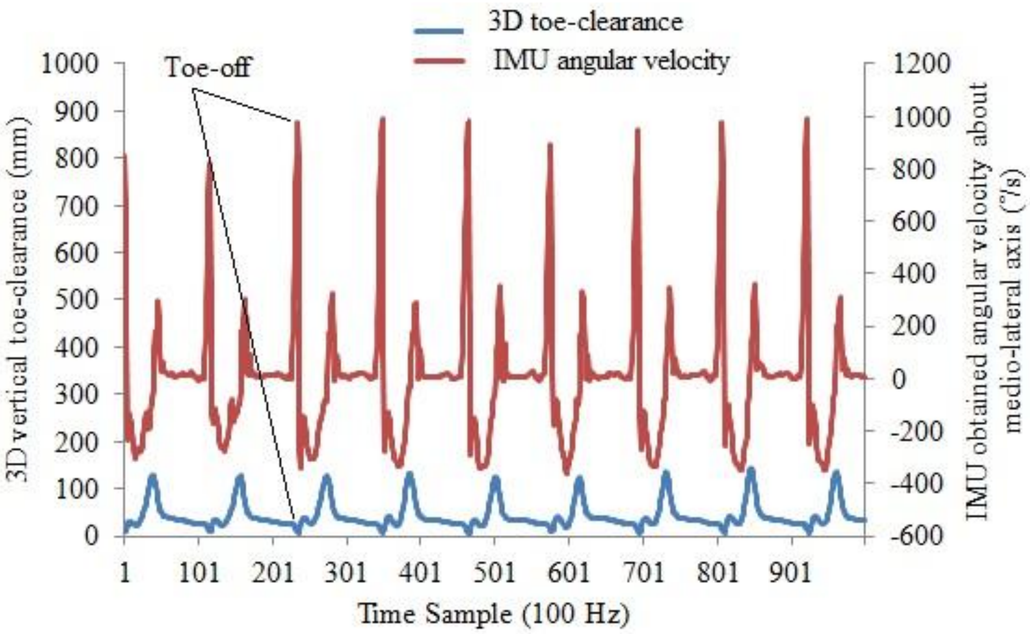


Figure 5-11 Time synchronized 3D-measured toe-trajectory (blue) and IMU obtained angular velocity about medio-lateral axis (red). Toe-off event detected in 3D-measured positional data and IMU obtained kinematics were synced using toe-off events.

Table 5-10 summarizes the correlations between reference MTC_Height and extracted IMU features for Young and Older in preferred-speed walking with absolute correlation (r) values greater than 0.3 in bold. For both groups sagittal plane IMU features usually showed greater correlations with MTC_Height than IMU features in the frontal and transverse planes, for example, maximum r values were observed for Older was the midway displacement between minimum and maximum vertical sagittal plane (r=0.79, p=0.001) and for Young was the minimum vertical velocity approximately at the end of the toe-contact (r=0.61, p=0.001). As anticipated inertial-signal features' association with MTC_Height were not the same for both groups. For example, the correlation between IMU measured minimum medio-lateral angular displacement (AngDispX) showed 0.61 correlation with group MTC_Height for Older, but it was only 0.38 for Young.

Table 5-10 Correlations (r) between IMU features and reference MTC_Height for Young and Older in preferred-speed walking. Absolute r values greater than 0.3 have been marked in blue. Acc = acceleration, Vel = velocity, Disp = displacement, AngVel = angular velocity, AngDisp = angular displacement and AngAccum = accumulation of angle over time. X, Y, Z represent medio-lateral, anterior-posterior and sagittal vertical directions.

	Accelerometer Features		Young (r)	Older (r)	Gyroscope Features		Young (r)	Older (r)
Raw	AccX	Max	0.08	0.05	AngVel X	Max	-0.39	-0.47
		Min	0.01	-0.05		Min	0.37	0.43
	AccY	Max	-0.37	-0.04	AngVel Y	Max	0.06	0.00
		Min	0.17	0.29		Min	-0.16	-0.11
	AccZ	Max	-0.40	-0.42	AngVelZ	Max	0.16	-0.16
		Min	0.39	-0.05		Min	-0.10	0.10
Single-Integration	VelX	Max	0.09	0.18	AngDisp X	Max	-0.20	-0.55
		Min	< 0.00	0.22		Min	0.38	0.61
	VelY	Max	-0.45	-0.28	AngDisp Y	Max	0.13	0.00
		Min	0.18	0.16		Min	-0.13	-0.18
	VelZ	Max	-0.04	-0.05				
		Min1	0.43	0.48	AngDisp Z	Max	0.13	-0.11
		Min2	0.61	0.29		Min	-0.02	0.21
Double-Integration	DispX	Max	0.05	-0.04	AngAccumX	Max	-0.31	-0.58
		Min	0.11	0.20		Min1	0.32	0.44
	DispY	Max	0.18	0.18		Min2	-0.07	0.59
		Min	-0.37	-0.38	AngAccumY	Max	0.16	0.04
		Min2	0.46	0.50		Min	-0.15	-0.08
	DispZ	Max	-0.60	-0.61	AngAccumZ	Max	0.18	-0.23
		Min	0.36	0.28		Min	-0.02	0.28
		Mid	0.40	0.79				

Stage A: Feature-Selection

LOSO cross validation average RMSE between GRNN-model estimated and reference MTC_Height across fourteen participants for each group was used to test the appropriateness of features, as they were combined in sequence using hill-climbing by generating multiple GRNN models. As shown in Figure 5-12, RMSE decreased as the selected features were combined in sequence using hill-climbing but as additional features were included RMSE began to increase. In Figure 5-12, those features up to the point of increase (marked by an arrow) were, therefore, considered optimum for age-specific model. When only raw signals were used to train the GRNN model using hill-climbing, the lowest average RMSE produced by LOSO GRNN models with optimum feature-set was 9.2 mm for Young and 12.8 mm for Older. As illustrated in Figure 5-13, when features from single- and double-integrated signals were combined with raw inertial signals, RMSE reduced by up to 45% . The outcome of the feature-selection process was 9 and 5 features of the 40 original features identified as optimum for Young and Older respectively.

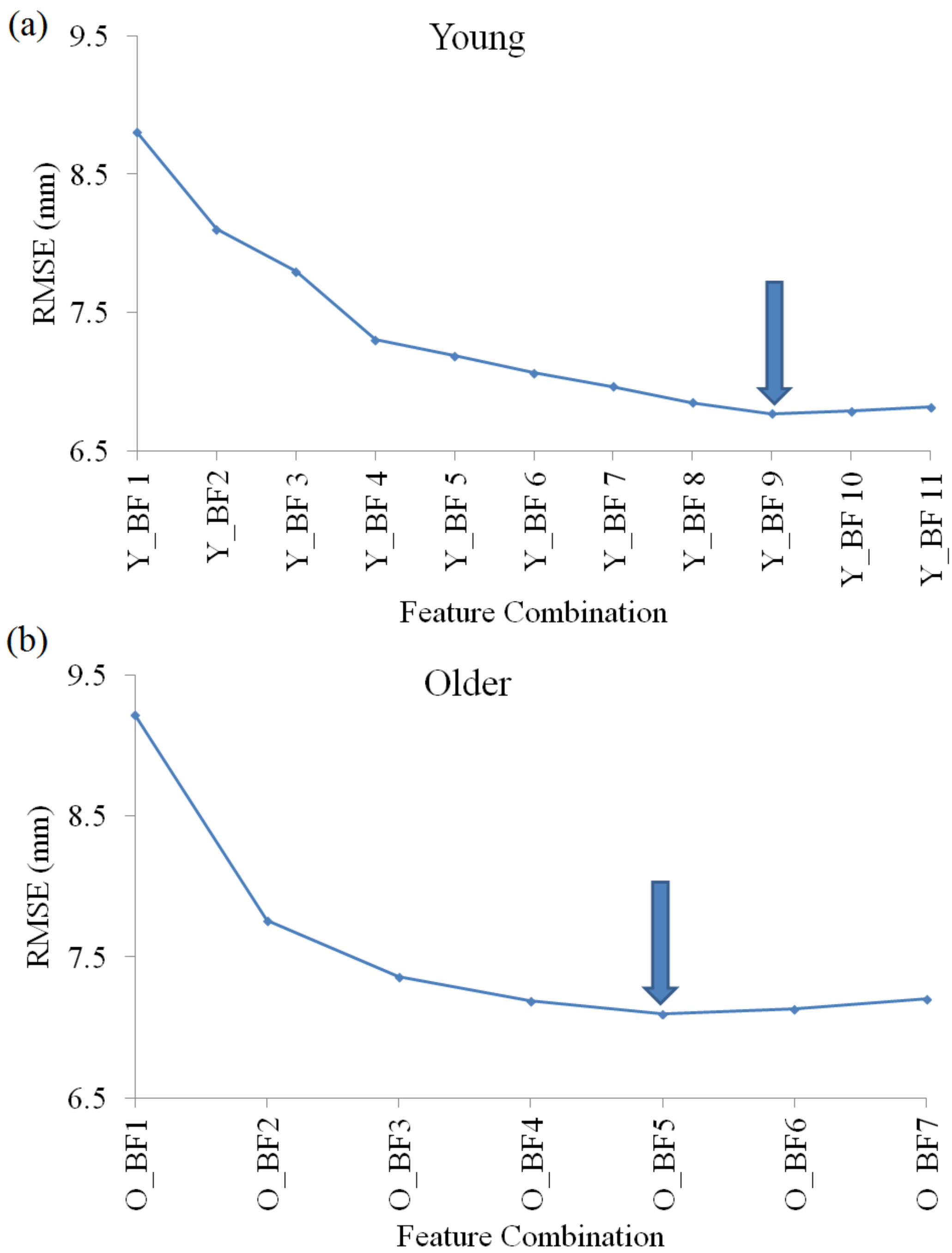


Figure 5-12 RMSE for MTC_Height estimation when the hill-climbing feature-selection was applied to the raw and integrated IMU features of (a) Young and (b) Older. Arrows denote the end of the optimum feature-set; Y_BF and O_BF represent features of Young and Older respectively.

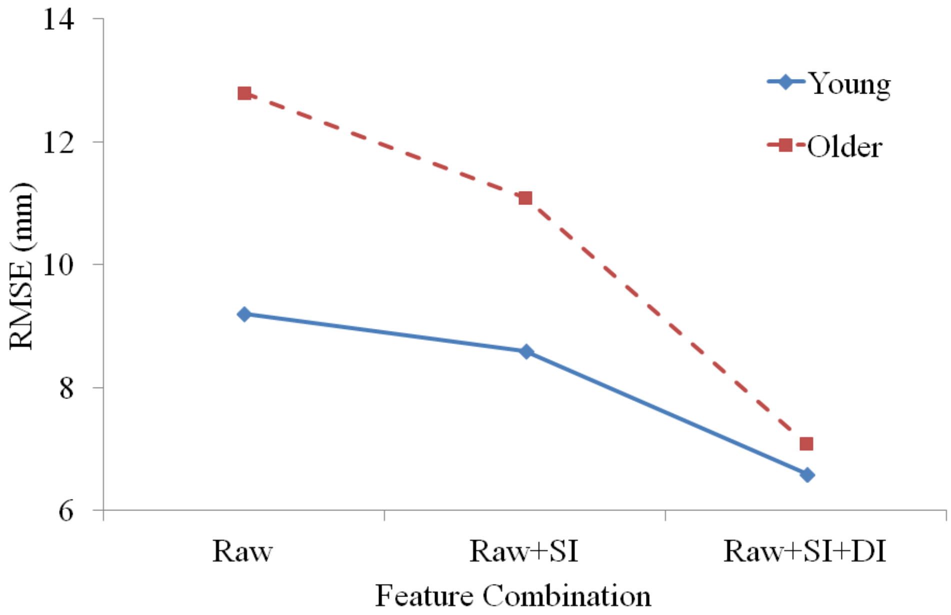


Figure 5-13 LOSO GRNN models produced average RMSE for different combinations of feature-set obtained by hill-climbing. Raw = raw IMU features, SI = single-integrated, DI = double-integrated (see text).

Table 5-11 describes the optimum GRNN model features and their correlation with MTC_Height. The first feature selected by the GRNN model showed the highest correlation with MTC_Height; i.e. minimum vertical velocity (AccZ) for Young (r=0.61) and $DispZ_{mid}$, (midway between minimum and maximum displacement) for Older (r=0.79). Optimum feature-set also consisted of IMU kinematics which did not show a good correlation (< 0.3), confirming the non-linear relationship between IMU kinematics and toe-trajectory control.

Table 5-11 Individual optimum features obtained using hill-climbing for (a) Young and (b) Older and their correlations (r) with reference MTC_Height.

Young			Older		
Feature ID	Feature Description	r	Feature ID	Feature Description	r
Y_BF1	Minimum VelZ	0.61	O_BF1	$DispZ_{mid}$	0.79
Y_BF2	2nd Minimum AccumAngX	-0.07	O_BF2	Maximum AngDispX	-0.55
Y_BF3	$DispZ_{mid}$	0.40	O_BF3	Maximum VelX	0.18
Y_BF4	Maximum GyroX	-0.61	O_BF4	Maximum VelY	-0.28
Y_BF5	Minimum VelX	0.00	O_BF5	2nd Minimum AngAccumX	0.59
Y_BF6	Minimum AccZ	0.40			
Y_BF7	Minimum GyroZ	-0.10			
Y_BF8	Minimum DispX	0.11			
Y_BF9	Maximum AccZ	-0.40			

Figure 5-14 shows inertial signals with the age groups clearly differentiated with respect to optimum feature-sets for a typical gait cycle. The optimum features for accelerometer data were predominantly vertical (z); and for the gyroscope medio-lateral (x), showing that sagittal plane motion contributed most to MTC_Height estimation. The features common to both groups, were sagittal plane motion as reflected in $DispZ_{mid}$, midway between minimum and maximum displacements and medio-lateral angular accumulation over time at the end of the swing phase.

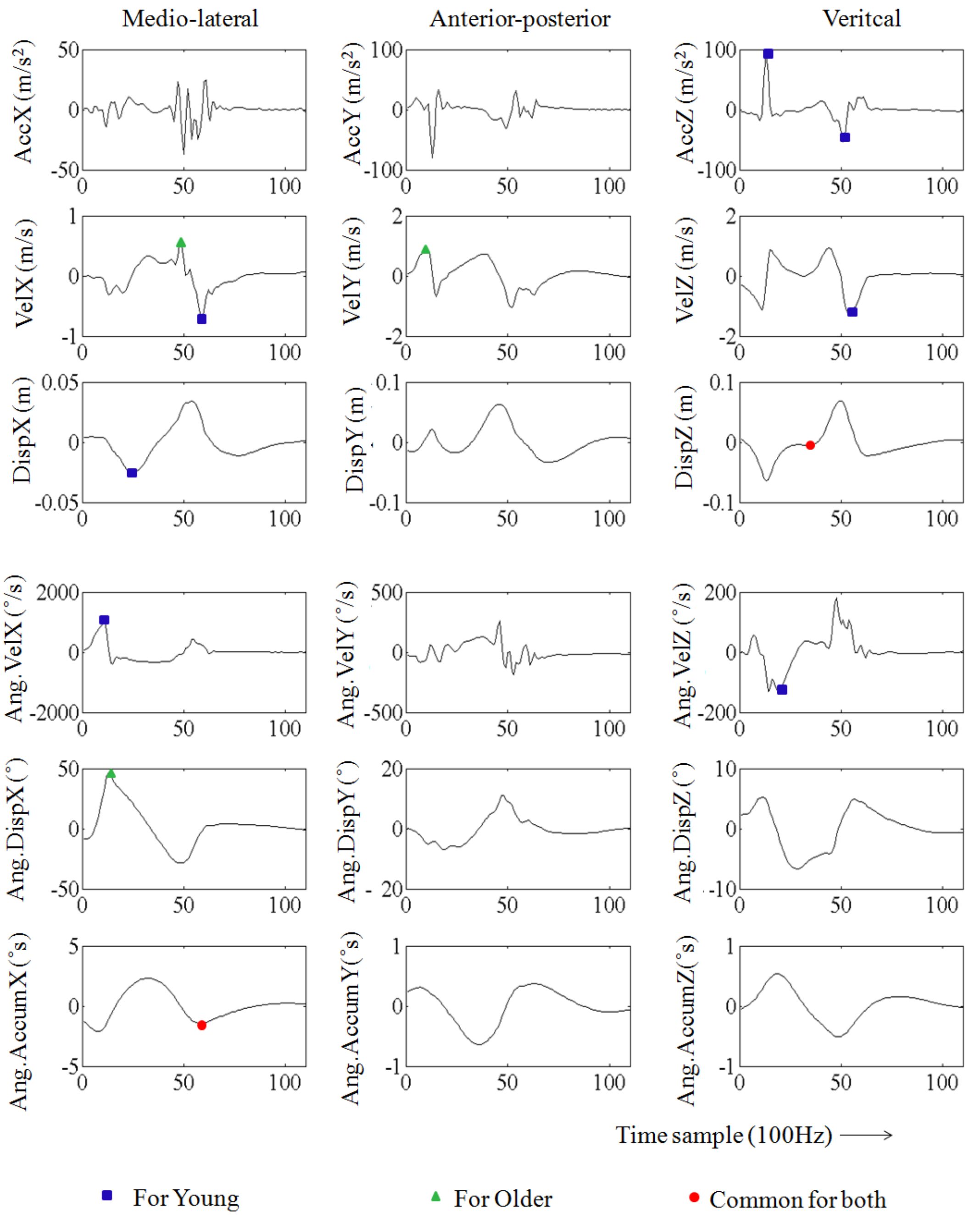


Figure 5-14 Optimum features for Young and Older within a typical gait cycle signal recorded via IMU. The top three rows are raw acceleration (acc), single-integrated velocity (vel) and double-integrated displacement (disp); medio-lateral (X), progression/ anterior-posterior (Y) and vertical (Z). Rows 4-6 are gyroscope signals and single- and double-integrated waveforms in each axis.

Leave-one-subject-out (LOSO) cross validated GRNN models with the optimum features (including raw, SI and DI) produced average RMSE of 6.6 mm for Young and 7.1 mm Older. Figure 5-15 shows scatter plots, linear regression lines of model-estimated and reference MTC_Heights. The LOSO GRNN model results for preferred-speed walking were considered to evaluate the modeling technique in preferred-speed walking for the same age group. For both age groups, lowest RMSE was obtained using the same s parameter (0.8). Both RMSE were within one standard deviation (Young: 9.4 mm; Older: 13.5 mm) of their mean MTC_Height (Young: 25.0 mm; Older: 28.6 mm). Further, estimated MTC_Height using the GRNN model and hill-climbing feature-selection was highly positively correlated with MTC_Height for both groups (Young: r=0.71; Older: r=0.85). Furthermore, for both groups no difference was found between GRNN-model estimated MTC_Height and motion captured reference MTC_Height in their respective median (Young: p=1.000; Older: p= .7609) and IQR (Young: p=.5016; Older: p=.1040). In Figure 5-15, it was interesting to observe a series of data points in both the Young and Older subjects' scatter plots parallel to the horizontal axis, reflecting the same estimated MTC_Height across a range of measured MTC_Height. The horizontal data points were primarily associated with a single subject in each group.

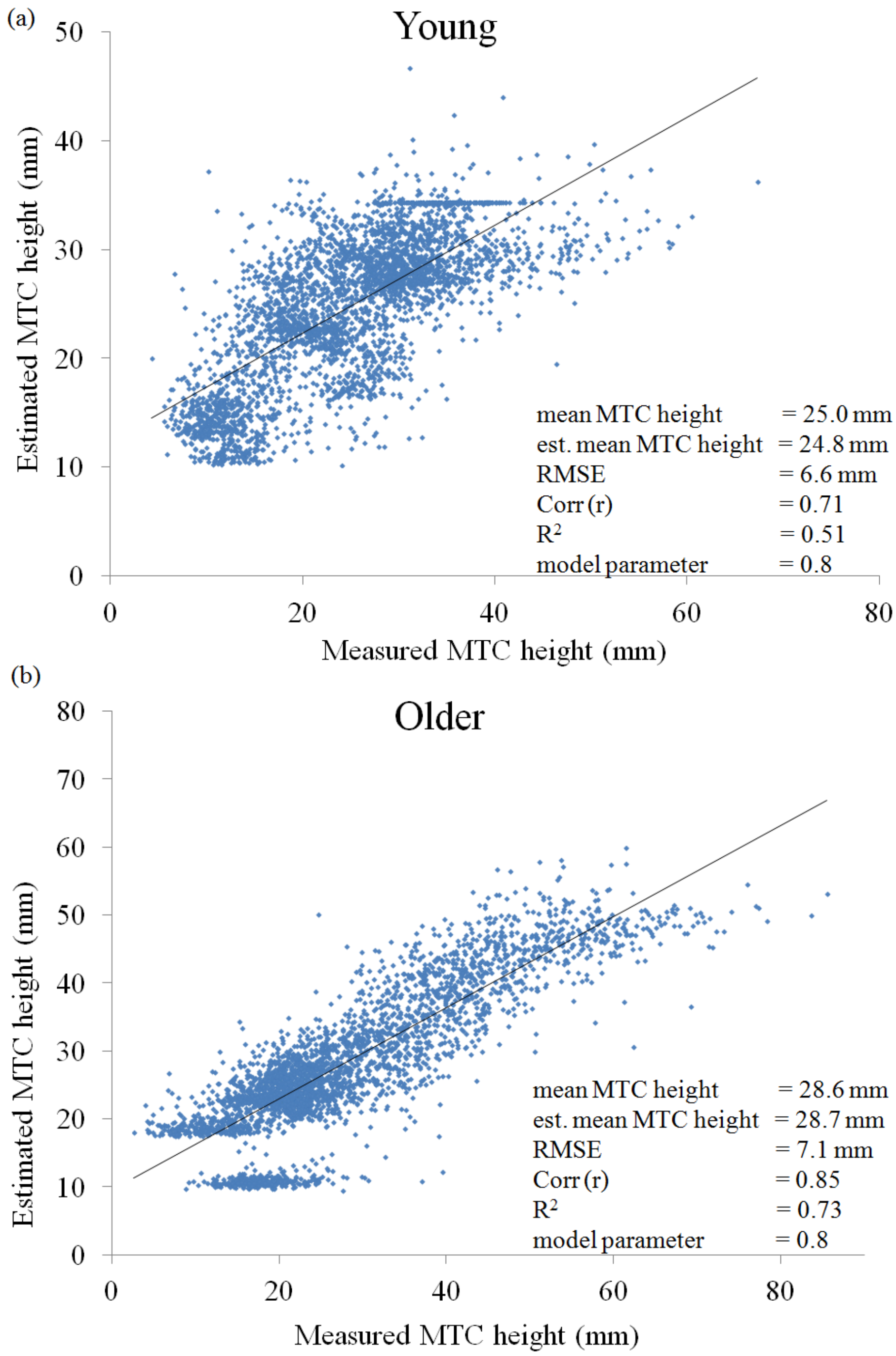


Figure 5-15 Scatter plot and linear regression line for model-estimated MTC_Height vs. reference MTC_Height for (a) Young and (b) Older with LOSO

Table 5-12 summarizes the measured and estimated MTC_Height mean and SD for individual participants. For both Young and Older estimated MTC_Heights closely approximate the measured values but prediction performance was notably reduced for three participants, YPS07, OP09 and OP13. These participants' measured MTC_Heights were in two cases (YP07, OP09) atypically high and in one participant (OP13) low.

Table 5-12 Measured and estimated MTC_Height mean and SD for young (YP) and older (OP) individuals

Participant	Mean MTC_Height (mm)		MTC_Height SD (mm)	
	Measured	Estimated	Measured	Estimated
YP01	35.3	34.1	3.8	3.1
YP02	31.8	31.3	2.7	2.0
YP03	16.3	19.8	3.1	3.6
YP04	10.4	15.5	2.2	2.4
YP05	29.9	29.3	4.4	5.3
YP06	20.3	23.8	2.4	1.9
YP07	42.0	29.4	6.8	2.7
YP08	12.6	13.4	3.0	2.8
YP09	26.8	25.3	3.1	5.4
YP10	20.1	21.1	4.7	2.8
YP11	30.9	27.4	4.6	1.5
YP12	31.6	27.6	2.6	1.7
YP13	25.8	21.4	2.7	4.3
YP14	22.0	25.7	2.8	4.7
OP01	29.2	28.7	6.9	3.9
OP02	23.2	21.3	2.3	2.3
OP03	18.8	21.6	3.3	3.9
OP04	21.8	23.6	2.3	2.0
OP05	27.4	30.0	6.4	4.3
OP06	24.8	24.9	12.0	5.7
OP07	23.9	30.1	6.6	3.1
OP08	43.9	46.5	5.5	5.4
OP09	59.5	43.6	7.4	3.3
OP10	33.2	31.9	5.7	6.3
OP11	49.2	47.8	6.4	5.2
OP12	36.6	31.2	8.6	12.3
OP13	12.2	20.1	3.7	1.6
OP14	18.4	16.1	4.4	4.6

Further, Figure 5-16 shows the Bland–Altman plot for mean MTC_Height obtained from GRNN model against the reference MTC_Height reference and the limit of the 95% confidence interval (±1.96 SD). GRNN model performances were within the confidence level for all the participants except YP07 and OP09. It is important to note that YP07 and OP09 had the highest individual MTC_Height within their respective age groups. It was important to note that Bland-Altman, however, failed to capture the considerable RMSE produced by OP13 (Table 5-12).

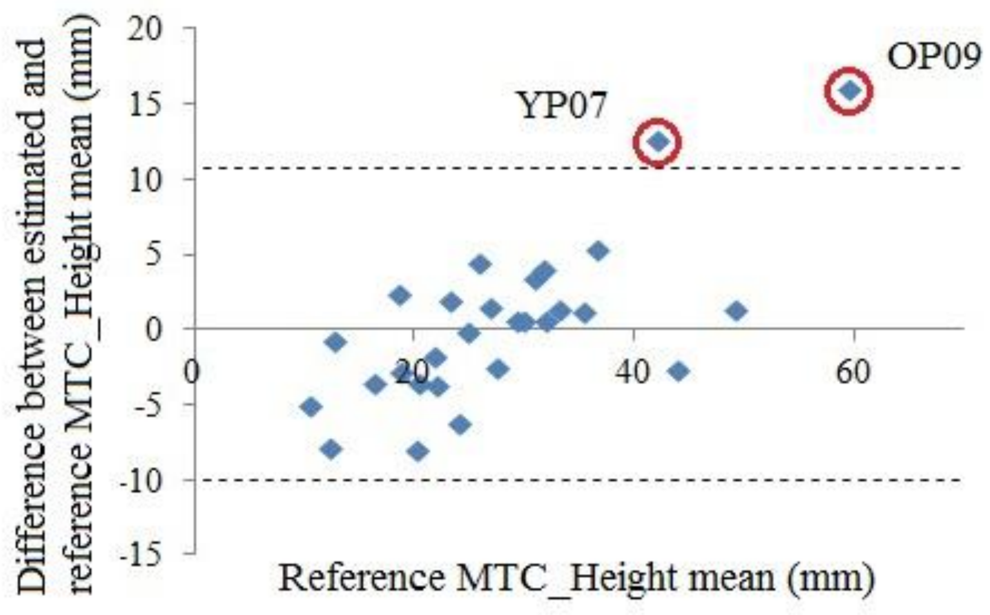


Figure 5-16 Bland and Altman plots of the mean (dotted line) ± 1.96 SD limit of agreement (dashed line) of the difference between the LOSO GRNN models and reference MTC_Height. Participants YP07 and OP09 were beyond the agreement limit (circled in red).

Stages B and C: Building and validating age-specific GRNN model

This section presents validation of age-specific GRNN models, Model_Y and Model_O, on the opposite age groups and walking conditions excluding and including non-MTC gait cycles.

Table 5-13 lists the RMSE obtained with Model_Y when tested on the same group in slower and dual task walking and Older group in all three walking conditions. RMSE obtained with Model_Y when tested on the same group in slower (13.0 mm) and dual task (13.8 mm) walking produced greater RMSE than the average RMSE produced by LOSO GRNN modeling in preferred-speed walking (6.6 mm). The statistical test revealed that Model_Y under estimated MTC_Height mean and SD compared to reference MTC_Height mean and SD. For Older in preferred-speed walking, however, Model_Y-estimated MTC_Height mean and SD were not significantly different, as indicated by 'TRUE' in Table 5-13 but in slower and dual task walking, Model_Y underperformed ('FALSE'). Overall results suggested that Model_Y did not demonstrate an acceptable generalizability in different walking conditions.

Table 5-13 RMSE produced by Model_Y across group and walking conditions. Non-significant differences between model-estimated MTC_Height and reference MTC_Height were highlighted in blue.

Group	Condition	RMSE (mm)	No significant difference in mean MTC_Height	No significant difference in MTC_Height SD
Young	SW	13.0	FALSE $p<10^{-4}$	FALSE $p<10^{-4}$
	DW	13.8	FALSE P= .0017	FALSE p=.0017
Older	PW	11.7	TRUE p=.8077	TRUE p=.3910
	SW	16.1	FALSE p=.0107	FALSE p=.0052
	DW	17.3	FALSE p=.0023	FALSE $p<10^{-4}$

Table 5-14 shows the RMSE produced by Older-specific GRNN model. Model_O estimated MTC_Height mean and SD were not different to reference MTC_Height for Older adults in other walking conditions. It was interesting to note that the GRNN built using Older adults' preferred-speed walking was able to produce lower RMSE for Young slower and dual task walking compared to the model built using only Young data. Model_O estimated MTC_Height mean for both Older and Young were not different to reference MTC_Height mean. Variability in Older adults in slower and dual task walking was also captured well by Model_O, represented by no significant difference between reference and estimated MTC_Height SD. For Young, however the Model_O-estimated MTC_Height SD values were significantly different to reference MTC_Height SD across conditions. Overall, Model_O demonstrated a good generalizability for Older across walking conditions.

Table 5-14 RMSE produced by Model_O across group and walking conditions. Non-significant differences between model-estimated MTC_Height and reference MTC_Height were highlighted in blue.

Group	Condition	RMSE (mm)	No significant difference in mean MTC_Height	No significant difference in MTC_Height SD
Young	PW	10.2	TRUE	FALSE
			p=.0676	$p<10^{-5}$
	SW	9.0	TRUE	FALSE
			p=.0906	p=.0166
	DW	10.0	TRUE	FALSE
			p=.0785	p=.0134
Older	SW	11.3	TRUE	TRUE
			p=.1353	p=.2958
	DW	11.6	TRUE	TRUE
			0.1419	0.3910

Table 5-15 shows the RMSE produced by Model_Y when the non-MTC gait cycles were included in the testing data set. Model_Y-estimated MTC_Height mean was not different to reference MTC_Height for Older adults in preferred-speed walking and slower walking. Model_Y, however, still failed to produce satisfactory RMSE in other tasks for both Young and Older.

Table 5-15 RMSE produced by Model_Y across group and walking conditions including non-MTC gait cycles. Non-significant differences between model-estimated MTC_Height and reference MTC_Height were highlighted in blue.

Group	Condition	RMSE (mm)	No significant difference in mean MTC_Height	No significant difference in MTC_Height SD
Young	SW	12.4	FALSE	FALSE
			p=.0245	p<10-4
	DW	12.3	FALSE	FALSE
			p=.0052	$p<10^{-4}$
Older	PW	12.8	TRUE	TRUE
			p=1.000	p= .5416
	SW	14.4	TRUE	FALSE
			p=.0676	p= .0017
	DW	15.3	FALSE	FALSE
			p=.0040	$p<10^{-4}$

Table 5-16 shows the RMSE produced by Model_O when testing data included non-MTC gait cycles. Model_O held the generalizability for Older across walking conditions with no difference in mean and SD of model-estimated and reference MTC_Height.

Table 5-16 RMSE produced by Model_O across group and walking conditions including non-MTC gait cycles. Non-significant differences between model-estimated MTC_Height and reference MTC_Height were highlighted in blue.

Group	Condition	RMSE (mm)	No significant difference in mean MTC_Height	No significant difference in MTC_Height SD
Young	PW	10.4	TRUE p=.0676	FALSE $p<10^{-4}$
	SW	12.6	TRUE p= .0619	FALSE p=.0085
	DW	10.5	TRUE p=.0676	FALSE p=.0134
Older	SW	10.7	TRUE p=.2676	TRUE p=.3258
	DW	10.6	TRUE p=.1040	TRUE p=.3575

In summary, for Older, the leave-one-subject-out (LOSO) cross validation based MTC_Height RMSE with the optimum feature and parameter was low (7.1 mm) compared with previous error estimates for young participants using quadratic regression (RMSE = 17.34 (McGrath et al., 2011)) and strap-down techniques (RMSE = 21.7 mm (Mariani et al., 2012)). The GRNN modeling approach reported here was also demonstrated to perform well as reflected in no significant difference between model-estimated MTC_Height and reference MTC_Height mean and SD in preferred-speed walking. Furthermore, in slower and dual task walking the Older-specific GRNN model, Model_O was capable of estimating MTC_Height for *both* Young and Older with no statistical difference from reference MTC_Height mean. In contrast, although the LOSO GRNN RMSE was as low as 6.6 mm for their preferred-speed data, Model_Y failed to estimate MTC_Height which is not statistically different to reference MTC_Height even for the same group in slower and dual task walking trials.

5.6 Results summary

The first aim related to Research Question 1 was to determine ageing (Young vs. Older), speed (preferred vs. slow) and task (preferred vs. dual task) effects on median and IQR of MTC_Height and MTC_Time distributions. Median and IQR of MTC_Height and median and IQR of MTC_Time were compared between young and older in preferred-speed and for Young and Older separately across walking conditions. Table 5-17 presents the summary of the statistical test on MTC_Height and MTC_Time. In preferred walking no ageing effects were found on median MTC_Height and median MTC_Time. Variability measured by IQR, however, was significantly greater in Older in preferred-speed walking. Neither young nor older adults revealed speed effects on median and IQR of MTC_Height and MTC_Time. In dual task walking, however, Older reduced MTC_Height variability significantly compared to preferred walking. It was interesting to note that Older MTC_Height IQR in the glass carrying task was even less than Young in dual task. Young adults' median MTC_Time was significantly shortened in slower walking compared to preferred-speed walking. In contrast, Older adults demonstrated significantly shorter MTC_Time in dual task compared to preferred walking. Neither group's MTC_Time IQR revealed any walking condition effects.

Table 5-17 Results summary on MTC_Height and MTC_Time statistical descriptive

Hypothesis	Findings	Support
No age effect on median MTC_Height in PW	(PW) Young = 25.5 mm; Older = 24.6 mm; no age effect	Yes
Greater MTC_Height IQR for older than young in PW	(PW) Young = 13.4 mm: Older = 18.2 mm; Greater MTC_Height IQR for older	Yes
No age effect on median MTC_Time in PW	(PW) Young = 18.02%; Older = 18.68%; no age effect	Yes
Greater MTC_Time IQR for older than young in PW	(PW) Young = 4.35%; Older = 3.44%; Greater MTC_Time IQR for older	Yes
No speed effect in median MTC_Height for both group	(SW) Young = 22.6 mm; Older = 25.5 mm; no speed effect	Yes
Greater MTC_Height variability in SW compared to PW for both groups	(SW) Young = 14.6 mm; Older = 21.9 mm; no speed effect	No
Shorter MTC_Time in SW compared to PW for both groups	(SW) Young = 14.72%; Older = 16.48%; Shorter MTC_Time in SW compared to PW only for the Young	Yes only for Young
Greater MTC_Time variability in SW compared to PW for both groups	(SW) Young = 5.43% Older = 5.77%; no speed effect	No
No difference in MTC_Height in DW compared to PW for both group	(DW) Young = 23.9 mm; Older = 19.7 mm; no age effect	Yes
Reduced MTC_Height IQR in DW compared to PW for both groups	(DW) Young = 12.2 mm; Older = 10.2 mm; Reduced MTC_Height IQR in DW compared to PW only for Older	Yes only for Older
Shorten MTC_Time in DW compared to PW for both groups	(DW) Young = 15.13%; Older = 13.89%; Shorten MTC_Time in DW compared to PW only for Older	Yes only for Older
Reduced MTC_Time IQR in DW compared to PW for both groups	(DW) Young = 4.59% Older = 4.66%; no task effect	No

The second aim related to Research Question was 1 to establish ageing (Young vs. Older), speed (preferred vs. slow) and dual task (preferred vs. dual task) effects on the frequency of non-MTC gait cycles. Non-MTC gait cycles were quantified as proportions of total gait cycles from a walking trial. In preferred-speed walking, the non-MTC gait cycles were infrequent for Young. Compared to Young, in preferred-speed walking, Older showed greater proportions of non-MTC gait cycles. In slower and dual task walking both Young and Older exhibited greater proportions of non-MTC gait cycles. Older showed the greatest proportion of non-MTC gait cycles in dual task walking but Young in slower walking.

The third aim of Research Question 1 was to validate toe-height at mean MTC_Time as an indicative MTC_Height to use in non-MTC gait cycles. In gait cycles which showed an MTC event, actual MTC_Height and toe-height at mean MTC_Time were compared across walking conditions for both young and older but no significant differences was detected. RMSE between actual MTC_Height and toe-height at mean MTC_Time was less than 2.8 mm for both young and older individuals across walking conditions except for YP05. High correlation between actual MTC_Height and toe-height at mean MTC_Time also suggested that toe-height at mean MTC_Time was an appropriate indicative MTC_Height in non-MTC gait cycles.

The first aim of Research Question 2 was to create age-specific GRNN models to estimate MTC_Height using experimental inertial sensor signals from preferred-speed walking. IMU data was collected from an in-house built foot-mounted sensor system comprising a tri-axial accelerometer and tri-axial gyroscope.

Gait cycles were identified in the inertial sensor data using maximum medio-lateral rotation of the toe. GRNN input features were extracted from raw, single- and double-integrated inertial signals. Using hill-climbing feature selections by employing a leave-one-subject-out (LOSO) cross validation, age-specific optimum features were identified for both young and older using the lowest group root-mean-square-error (RMSE). To evaluate the estimation accuracy between GRNN estimated MTC_Height and MTC_Height from 3D system position-time data the lowest RMSE of LOSO cross validation was considered, as the RMSE produced was with a blind data set. The RMSE was 6.6 mm with 9 optimum inertial sensor features for the young adults and 7.1 mm with 5 features for the older. GRNN modeling also performed well as reflected in no significant difference between model-estimated MTC_Height and 3D measured MTC_Height. Nine of forty features for young and five for older were found to be optimum to estimate MTC_Height. These optimum features of all 14 participants from each group were used to create optimum age-specific GRNN models, Young: Model_Y, Older: Model_O were built to estimate MTC_Height.

The Young-specific GRNN-model, Model_Y, was sensitive to walking conditions and its generalizability was limited to Older in preferred-speed walking. Model_O, however, showed good generalizability when applied to data from slower walking and dual task walking. Statistical tests revealed that the mean and SD of Model_O estimated MTC_Height were not different to the mean and SD of reference MTC_Height for Older in slower and dual task walking. When the non-MTC gait cycles were included, Model_O was still able to produce MTC_Height estimates which were not different to the reference MTC_Height.

6 GENERAL DISCUSSION

The first section of the General Discussion summarizes the effects of ageing and walking condition on MTC characteristics in light of previous research findings. In section 6.2 the effects of the independent variables on the frequency of non-MTC gait cycles is presented. Section 6.3 presents the findings from the GRNN modeling approach and model validation for generalizability. The final section 6.4 reviews the project's contribution to gait monitoring using body mounted IMUs and provides the project summary, including suggestions for future research and further developments in gait monitoring using sensor technology.

6.1 Ageing and walking condition effects on MTC characteristics

MTC_Height measurements obtained from 3D motion capture were positively skewed in line with the previous reports (Begg et al., 2007; Dell'oro, 2008). Inferential statistical analysis were, therefore, performed on median and IQR as the measures for central tendency and dispersion respectively. MTC_Heights medians in the present study for Young and Older were 25.5 mm (IQR = 13.4 mm) and 24.6 mm (IQR = 18.2 mm) respectively but these values were greater than MTC_Heights previously reported in similar treadmill walking experiments (Barrett et al., 2010; Begg et al., 2007). Begg et al. (2007), for example, reported group median MTC_Heights of 12.9 mm (IQR = 9.6 mm) for Young and 14.0 mm (IQR =11.3 mm) for Older. Begg et al. (2007) referenced MTC_Height from the toe vertical displacement at toe-off but in the present study MTC_Height was measured from the treadmill belt, a lower reference (Figure 2-8). Taking into account the higher reference such as stance phase and toe-off clearances used by other researchers (Begg et al., 2007)for MTC_Height calculations, MTC_Heights reported here were comparable to previous studies with similarly aged healthy young adults and older adults walking at preferred-speed (Dell'oro, 2008).

Consistent with previous studies, there was no difference in MTC_Height between Older and Young in preferred-speed walking (Barrett et al., 2010; Begg et al., 2007; Mills et al., 2008). The ability of the locomotor system to maintain adequate toe-clearance near to mid-swing was unaffected in the Older group examined here during their preferred-speed walking. As expected, MTC_Height variability was higher in Older participants in preferred-speed walking and this intra-individual variability for older individuals has been interpreted as indicating diminished gait control (Begg et al., 2007; Mills et al., 2008). Greater variability in MTC_Height suggests reduced precision in low-limb trajectory control. Older adults are therefore, at higher risk of tripping not due to reduced mean MTC_Height but as a consequence of greater stride-to-stride variability in toe-trajectory control. Begg et al. (2007) suggested that healthy older adults compensate the tripping risk due to greater stride-to-stride variability by reducing the spread of MTC_Height in the lower quartile range and increasing it in the upper quartile, in other words by exhibiting more positively skewed MTC_Height distribution. The MTC_Height distributions' skewness in the present study (Young = 0.26; Older = 0.89) support Begg at al. (2007) in suggesting that older adults increase the frequency of higher MTC_Heights to compensate the lack of precise control of toe-trajectory.

Inclusion of dual task and speed-matched slower (than preferred) walking facilitated further exploration of MTC variables' central tendency and variability. In dual task walking both young and older groups have been reported to reduce their walking speed (Sparrow et al., 2008). In the present experiment, as in previous studies, both groups reduced walking speed relative to preferred in the dual task trial, furthermore, in dual tasking Older (0.42 m/s) walked significantly ($p < 0.05$) slower than Young (0.53 m/s). Schulz et al. (2010) found that MTC_Height may depend on the nature of the secondary task, for example in their study young participants increased MTC_Height while carrying a laundry basket but lowered MTC_Height when answering questions while walking. In the present study although the individual participants' MTC_Height characteristics presented in Table 5-2 showed that 11 of 15 older adults reduced MTC_Height in the glass carrying task, the difference between glass carrying and slower walking was not statistically significant for either age group. This result of no walking condition effect on median MTC_Height is consistent with Schulz et al. (2010) for younger individuals but there are no previous reports of similar gait task effects on MTC for older adults. In response to the challenge posed by dual task walking, older pedestrians may have remained safe not by increasing MTC_Height, but, as with their younger counterparts, by preserving their habitual (preferred-speed) toe-ground clearance.

In the dual task manipulation, relative to preferred walking, both groups reduced MTC_Height variability but only significantly ($p = 0.095$) for older adults. In the speed-matched slower walking condition, however, MTC_Height IQR was not different from preferred-speed walking. This combination of results is interesting in revealing that reduced MTC_Height variability in the divided attention condition was not due to reduced walking speed. Furthermore, the Older MTC_Height IQR in dual task walking was lower than the Young's dual task MTC_Height IQR which was also the lowest of the three walking conditions. The histograms in Figure 4-9 showed that in dual task walking older group increased MTC_Height skewness (1.28) compared to their preferred-speed walking (0.89). Individual participants' MTC_Height characteristics presented in Table 5-2 showed that 11 of 15 Older reduced MTC_Height and 13 reduced MTC_Height IQR. This reduction in MTC_Height and variability suggested that observed increase in skewness in Older in dual task walking was not due to all participants increasing the frequency of MTC_Height in the higher region of the distribution; rather it was due to the majority increasing their frequency of lower clearance cycles. Nordin et al. (2012) reported that individuals aged 75 years and above who demonstrated change in step-width, step-time and step-length variability relative to preferred conditions while carrying a cup and saucer were *less* falls prone. It could, therefore, be suggested that in a more challenging gait task, such as dividing attention, older adults reduce MTC_Height variability to compensate the increased frequency of lower clearances. It would be interesting to examine older adults with a falls history and individuals with gait pathology in dual task walking to confirm whether MTC_Height control reduces in a more challenging task.

The experimental results also uncovered lower limb control characteristics reflected in MTC timing, i.e. MTC_Time. Research on MTC timing is scarce but it has been concluded that MTC_Time is approximately 50% of the swing phase (Begg et al., 2007; Levinger et al., 2012; Mills et al., 2008). The measurement procedures employed in this earlier work defined MTC_Time relative to heel-contact, such that the present findings cannot be directly compared with previous work. In preferred-speed walking the groups had essentially the same MTC timing (Young = 18.02%;

Older = 18.68%). Young mean MTC_Time was comparable with Dell'oro (2008) who also calculated MTC_Time from toe-off for *one* young participant (17.2%) while preferred-speed walking. When walking more slowly without glass carrying Young reduced MTC_Time, suggesting a speed effect of on MTC timing. In contrary, the Older did not show significantly ($p < 10^{-5}$) shorten MTC_Time in slower walking but their dual task MTC_Time was significantly shorter than both preferred-speed and slower walking conditions. Reduced MTC_Time could be due to either a shorter swing phase or attaining MTC more quickly with constant swing time. To resolve this question an additional work including heel contact time at the end of swing would be required.

A further finding was that older showed significantly ($p < 10^{-5}$) higher MTC_Time variability (IQR) across the walking conditions compared to young adults. Higher variability in MTC timing suggested ageing-related weaker MTC_Time control. In dual task walking however MTC_Time variability of Older (4.66%) was less than the Young (5.59%), suggesting that it was important for Older to precisely control MTC timing in a difficult gait.

6.2 Ageing and walking condition effects on non-MTC gait cycles

A limitation in discussing these findings is that previous published reports of toe-ground trajectory control during walking had neither documented nor discussed non-MTC gait cycles (Barrett et al., 2010; Begg et al., 2007; Best & Begg, 2008; Mills et al., 2008; Nagano et al., 2011). An important phenomenon, comprehensively documented here for the first time, was that non-MTC gait cycles were relatively *in*frequent in younger participants walking at preferred speed. In the present results

2.9 % of all gait cycles for young participants at preferred walking speed did not show a clearly defined MTC event. This result supports Schulz (2011) who reported that in overground unconstrained preferred-speed walking 98% of gait cycles demonstrated an MTC event for young participants, i.e. only 2% non-MTC gait cycles. The only other data on non-MTC gait cycles was in Dell'oro 's (2008) unpublished doctoral thesis. Dell'oro (2008) reported that of a total 75,193 strides collected from 24 (12 young and 12 older) subjects treadmill walking, 8,814 gait cycles did not demonstrate an MTC (11.7%) and those non-MTC gait cycles were deleted to exclude from the analysis. Dell'oro (2008) recorded that the proportions of gait cycles deleted because of not showing an MTC event ranged from 0% to 87%. In her study, the proportions of non-MTC gait cycles were not presented to reveal any age or walking condition related effects but 6 young and 6 older participants' (50% of the sample) were excluded from the analysis as they showed more than 10% non-MTC gait cycles. More of the older participants exhibited a significantly ($p < 10^{-3}$) greater proportion of non-MTC (18.8%) than Young (2.9%) in preferred-speed walking. Furthermore, in both Young and Older the proportions of non-MTC gait cycles increased significantly in slower and dual task walking. In all three walking conditions, however, Older had a greater proportion of non-MTC gait cycles.

Individual participant's non-MTC gait cycle characteristics presented in Table 5-9 provided more depth understanding the group mean non-MTC frequency data. Participants were categorized as exhibiting non-MTC characteristics if at least three non-MTC gait cycles were observed within a walking trial. More Older (9 of 15) exhibited non-MTC cycles compared to Young (4) in preferred-speed walking and the number of participants increased for both Young and Older in both slower and dual task walking trials.

An important finding from walking condition specific individual non-MTC frequency analysis in the current experiment was that even in Young there were participants who demonstrated more that 10% of non-MTC gait cycles in preferred-speed walking, suggesting that while non-MTC gait cycles are infrequent in young healthy adults, the MTC event is not manifest in the gait pattern of some individuals. With ageing and walking condition manipulation, the proportion of individual non-MTC gait cycles increased up to 90%. These findings suggest that non-MTC gait cycles should be considered in biomechanical studies of lower limb swing phase trajectory control.

Given the prevalence of non-MTC gait cycles, it was necessary to obtain an indicative toe-height at the expected MTC timing to compare the model-estimated MTC_Height with the reference MTC_Height. Dell'oro (2008), examined mean MTC_Time for *one* young adult and proposed that toe-height at mean MTC_Time could be used to reveal non-MTC gait cycle toe-trajectory control characteristics.In the present study, it was shown that group MTC_Time was non-normally distributed for both Young and Older across walking conditions. Hence, median MTC_Time was presumed to be a better representation of central tendency. A non-parametric repetitive measures test between mean MTC_Time and median MTC_Time for both Young and Older across walking conditions revealed no statistical difference. Toe-height at mean MTC_Time, therefore, was used as the "indicative" MTC_Height as suggested by Dell'oro (2008). While Dell'oro (2008) did not extend this indicative

MTC_Height technique, in the present thesis the indicative MTC_Height technique was validated by comparing toe-height at mean MTC_Time with reference MTC_Height from gait cycles which demonstrated MTC. Both Young and Older showed RMSE between actual and indicative MTC_Height in preferred-speed walking of less than 2.8 mm and high correlations ($r > 0.8$) between actual and indicative MTC_Height.

In slower and dual task walking experiments, it is important to note that MTC_Height was not different from preferred-speed walking data but MTC_Time was significantly reduced. This finding demonstrates that walking condition effect on individual-specific MTC_Time should be considered when analysing toe-height in non-MTC gait cycles. The above observation concerning walking condition specificity is further supported by the correlation results revealing that in both slower and dual task walking, toe-heights at an individual participant’s mean MTC_Time were highly correlated with actual MTC_Heights. For both age groups, median indicative MTC_Height exceeded the condition specific median MTC_Height, suggesting that in non-MTC strides, toe-ground clearance at mid-swing (the usual MTC_Time) is maintained higher. MTC is a critical representation of toe-trajectory control and requires skilled and fine motor control performance for optimum and safe gait. When fine motor control is not possible an adaptive locomotor control strategy to reduce the likelihood of toe-ground contact is to increase toe-height by eliminating the biomechanically challenging MTC event. In so doing the gait data will be characterised by increased frequency of non-MTC gait cycles. As might be expected the non-MTC response is, furthermore, prevalent when gait is destabilized, either by extrinsic environmental factors or intrinsic causes such as ageing. In non-

MTC gait cycles the ankle is possibly more dorsiflexed, elevating the toe and increasing ground clearance. Measures to increase ankle dorsiflexion in older people or gait-impaired populations may be successful in reducing tripping risk by eliminating MTC. Immediate future research should investigate the contribution of lower limb joint angles in generating non-MTC gait cycles.

In determining these “adaptive” characteristics of toe height control at MTC, it was important to consider that the gait data was obtained from treadmill walking. It has been previously reported that in treadmill both young and older adults reduced their preferred-speed and MTC_Height compared to overground walking (Nagano et al., 2011). The reported ageing and walking condition effects on the central tendency and variability of MTC_Height and MTC_Time should be, therefore, confirmed in overground walking and the frequency of non-MTC gait cycles may be different in overground walking. The reported ageing and condition effects on MTC were on median and inter-quartile-range, an interesting dimension to future studies would be the characterization of other MTC distribution parameters such as skewness, kurtosis, 1st quartile, 3rd quartile and range (Begg et al., 2007). Probability modelling (Begg et al., 2007) to specify precisely the “risk” of toe-ground contact across the walking conditions would be beneficial in confirming the suggested adaptation techniques and their implications towards tripping risk. MTC_Height distribution analysis, including skewness, central tendency and variability could be employed to determine whether the reported MTC control adaptations to dual task walking significantly reduce tripping risk.

6.3 GRNN machine-learning modeling

The GRNN-modeling employing leave-one-subject-out (LOSO) cross validation used inertial sensor signals to estimate MTC_Height with RMSE of approximately 7 mm (Young = 6.6 mm; Older = 7.1 mm) in preferred-speed walking. Lower RMSE observed for Young was consistent with Lai et al. (2009b) who also reported reduced RMSE for young controls than for older adults with a falls history. The above RMSE were up to 68% lower than in previous studies employing quadratic regression (McGrath et al., 2011) and strap-down integration (Mariani et al., 2012). Individual participants' measured and estimated MTC_Height medians presented in Table 5-12 showed that the age-specific GRNN models captured the inter-subject variability well. The data points observed parallel to the horizontal axis in Figure 5-15, reflecting the same estimated MTC_Height across a range of measured MTC_Heights, was due to the leave-one-subject-out (LOSO) cross-validation protocol. In selecting the optimum GRNN model parameter and features set to minimize RMS error for the group as whole, a proportion of these individuals' gait cycles were "over-smoothed" with reduced sensitivity to the cycle-to-cycle MTC_Height variability. Despite these observations, even the lowest performing participants, with the largest difference between measured and estimated MTC_Height, demonstrated considerably better MTC_Height estimation than any previously reported techniques.

The GRNN modeling approach developed here estimated MTC_Height for every stride whereas previous studies estimated a gait trial mean based on a number of strides. A further point of difference is that the LOSO validation results reported here were obtained with no prior knowledge of the tested participant's gait characteristics. The LOSO validation results, therefore, represented a more robust modeling technique for estimating MTC_Height across a range of self-selected preferred walking speeds.

The approach to MTC_Height estimation incorporated features of both raw and integrated inertial signals to train GRNN models using a hill-climbing feature-selection method. Based on previous research (Lai et al., 2008c) it was anticipated that relatively few of all (in this study forty) gait-related inertial-signal features would contribute constructively to MTC_Height estimation. The correlation results confirmed a different relationship for young and older participants between MTC_Height and IMU measured swing phase kinematics within the same stride. For Older IMU measured minimum medio-lateral angular displacement (AngDispX) and group MTC_Height, for example, were highly correlated (r=0.61) but less strongly correlated for Young (r=0.38). These findings illustrated that to accurately estimate MTC_Height it was critical to identify inertial-signal features that would be highly predictive for all participants. LOSO validation was used to choose the optimum predictive inertial signal kinematics incorporation with hill-climbing feature-selection. The inertial signals' feature-set which produced the lowest RMSE was considered optimal. Hill climbing is a "greedy" one-way feature-selection, in which the optimum determination depends on the features selected and tested sequentially. When raw and integrated signals were combined MTC_Height estimation error reduced by up to 44.5% relative to using only raw inertial signals.

For both groups that feature showing the highest linear correlation with MTC_Height was returned as the first optimum by the hill-climbing technique. Not all optimum features were, however, highly correlated with MTC_Height, suggesting the GRNN technique was successful in accommodating the underlying non-linear associations between inertial sensor signals and MTC_Height (McGrath et al., 2011). Most optimum features (6/ 9 for the Young and 3/5 for Older) were from the sagittal plane; not unexpected, given that gait is more sagittally constrained. Two optimum features were common to both age groups, (i) sagittal plane displacement midway between minimum and maximum vertical displacement ($DispZ_{mid}$) and (ii) minimum medio-lateral angular accumulation over time at the end of the swing phase. Biomechanically, $DispZ_{mid}$ was the sensor-signal derived displacement in the sensor coordinate system that best approximated MTC_Height, as revealed by high correlations with reference MTC_Heights (Young: r=0.40, Older: r=0.71). Estimation of MTC_Height based only on $DispZ_{mid}$, produced RMSE of 9.2 mm but when other features were included RMSE reduced to 7.1 mm in the Older, confirming that foot movement in all three sensor coordinates contribute to accurate estimation of MTC_Height. Future MTC_Height estimation research using other feature selection techniques such as a principal component analysis (Yoshiyuki et al., 2014) could confirm the present findings or possibly identify more optimal feature combinations using a non-sequential approach.

Lai et al. (2009b) performed a time series analysis of MTC and two other end-point foot control parameters mx1 and mx2 (Figure 2-4). They found high autocorrelations in a group of older adults with a history of falls indicating cyclic patterns in their walking strategies compared to almost random walking patterns in healthy young participants. In the present modeling, five optimum features for the Older compared to nine for the Young may also represent more long term structure in the gait parameter time series with ageing. Other authors have also proposed that with ageing gait control is associated with reduced biomechanical "complexity" (Manor and Lipsitz, 2013). The Young's first optimum feature, for example, was foot vertical velocity at the end of the swing phase, possibly representing ground contact velocity at the terminal swing. This feature was absent in Older possibly because foot-ground contact is less deliberate and, therefore, did not appear as a significant feature to discriminate MTC_Height.

In the present project inclusion of dual task and speed-matched slower (than preferred) walking enabled the examination of the machine-learned models generalizability. From the 3D system measured MTC_Height results it is clear that ageing and walking conditions influenced the distribution characteristics. The focus of our discussion now is the project's success in modeling a gait parameter that reveals considerable change in distribution characteristics as a function of age and walking condition. For each age group RMSE between measured and estimated MTC_Height increased when their age-specific GRNN models, Model_Y and Model_O, were tested across walking conditions. Model_Y estimated MTC_Height median and IQR showed a significant difference from the 3D-motion capture MTC_Height when applied to two other experimental gait conditions, slower and dual task walking. It was important to note that for Young there was no significant differences in 3D-motion capture MTC_Height across all three experimental conditions. For young people the inertial sensor features obtained using hill-climbing were, therefore, specific to preferred-speed walking resulting in a less generalizable GRNN model. In contrast, when Model_O, developed using preferred-speed walking data, was applied to the other experimental conditions, in both slower and dual task walking, Model_O still produced MTC_Height estimates that were *not* significantly different from the 3D motion captured MTC_Height. An acceptable performance of Model_O across walking conditions suggests that older adults' preferred-speed data training data contained sufficiently generalizable information and the feature-selection delivered appropriate features to represent the inertial sensor kinematics and reference MTC_Height. The generalizability of the older adult's GRNN model further supports the "complexity and ageing" hypothesis proposed earlier, because even though the older adults' 3D-motion capture MTC_Height in dual task walking was significantly different to preferred-speed ageing-related loss of complexity may have allowed the model to maintain good MTC_Height prediction.

RMSE also increased when Model_Y was tested across walking conditions with Older and vice versa. Model_Y built using young adults' preferred-speed walking data, accurately estimated older adults' preferred-speed MTC_Height but was unsuccessful in the other two experimental conditions. Model_O was successful in estimating MTC_Height central tendency of Young in all three walking conditions suggesting that older gait data used to train the model also had information which is common for Young.

6.4 Sensor technology developments and project summary

The need for ubiquitous health systems for real-time monitoring and patient feedback is increasing rapidly to meet the demand for improved patient care with reduced human resources. In this context inertial sensors are useful given their low cost, compact design, and low power consumption. Interpreting inertial sensor data, however, is a key challenge in employing them in health care applications such as gait monitoring. The adaptive learning models for sensor operation would contribute towards more efficient embedded data processing and minimizing the computational requirements of portable sensor networks. Model_O built using older adults' preferred-speed walking data in this project improved MTC_Height estimation accuracy such that it could now be trialed outside the laboratory.

One promising application is in using MTC feedback from remote sensors as intervention for increasing toe-ground clearance in real-time (Tirosh et al., 2013). In a laboratory setting using 3D motion capture data Begg et al. (2001) used a real-time display to present toe-trajectory and MTC_Height. With visual feedback both young and older adults significantly increased MTC_Height within a target band above a baseline no-feedback condition. These results clearly demonstrated that MTC increased with real-time foot clearance feedback. High risk gait could be identified by *predicting* either low MTC_Heights or greater variability in MTC_Height a number of gait cycles prior to the event. Another approach to high risk gait identification would be to calculate tripping risk probability by monitoring lower limb trajectory parameters in real-time. In implementing a portable device to monitor toe-trajectory in overground walking, it is important to note that the present study was conducted only in treadmill walking. The model's performance should now be validated in overground walking but given it was successful in slower and dual task walking, it is anticipated that it would perform well across a range of overground conditions.

The main criterion for assessing GRNN-based MTC estimation accuracy in this work was Root Mean Square Error (RMSE) which was compared with those reported in the literature using integration method which is extensively used in previous relevant work. It will be an interesting research question to directly compare the GRNN-based MTC estimation with the integration method on the same dataset as a future work. In adapting the inertial sensor based gait monitoring system, another important consideration is that the gait event detection algorithm presented in the present thesis was based on healthy gait. When applying similar technology in pathological gait a different threshold based algorithms (Jasiewicz et al., 2006; Lau & Tong, 2008) could be considered for successful gait event detection. Future data from over ground walking would also be important with respect to non-MTC gait cycles. It would be interesting to perform the statistical tests on the model estimated MTC_Height to determine the age and walking condition effects in future.

This project is the first to employ machine-learning to estimate young and older adults' MTC_Height using inertial data from a foot-mounted sensor. The research findings make an important contribution to falls prevention in demonstrating the possibilities of remote sensor monitoring. The inertial sensor signal processing, for example, may lead to proactive solutions to falls prevention by providing biomechanical information allowing pedestrians to modify foot trajectory parameters in real time using augmented MTC information. There will also be opportunities for applying sensor-based monitoring to other populations with gait pathology. A final significant outcome is the project's contribution to the broader scientific agenda of understanding how ageing influences biomechanical gait characteristics associated with tripping risk. In this regard, further analysis of higher clearance non-MTC gait cycles provides a new avenue for gait biomechanics with the potential to reveal important ageing effects on lower limb trajectory control.

References

Aha, D., & Bankert, R. (1996). A comparative evaluation of sequential feature selection algorithms. In D. Fisher & H.-J. Lenz (Eds.), *Learning from Data* (Vol. 112, pp. 199-206): Springer New York.

Australian Bureau of Statistics. (2012). Australian Commission on Safety and Quality in Health Care. Retrieved April 4, 2013, from http://www.safetyandquality.gov.au/wp-content/uploads/2013/10/Final-tagged-PDF-for-Web-Annual-Report-2012-13.pdf

Barrett, R. S., Mills, P. M., & Begg, R. K. (2010). A systematic review of the effect of ageing and falls history on minimum foot clearance characteristics during level walking. *Gait and Posture, 32*(4), 429-435.

Begg, R., Best, R., Dell'Oro, L., & Taylor, S. (2007). Minimum foot clearance during walking: Strategies for the minimisation of trip-related falls. *Gait and Posture, 25*(2), 191-198.

Begg, R. K., Palaniswami, M., & Owen, B. (2005). Support vector machines for automated gait classification. *IEEE Transactions on Biomedical Engineering, 52*(5), 828-838.

Bell, J. (2014). *Machine learning: Hands-on for developers and technical professionals*: John Wiley.

Best, R., & Begg, R. (2008). A method for calculating the probability of tripping while walking. *Journal of Biomechanics, 41*(5), 1147-1151.

Bland, J. M., & Altman, D. G. (2010). Statistical methods for assessing agreement between two methods of clinical measurement. *International Journal of Nursing Studies, 47*, 931-936.

Canning, C. G. (2005). The effect of directing attention during walking under dual-task conditions in Parkinson's disease. *Parkinsonism & Related Disorders, 11*(2), 95-99.

Castillo, P. (2005). Sensors, modems and microcontrollers for UAVs. *Modelling and Control of Mini-Flying Machines* (pp. 185-232): Springer London.

Centers for Disease Control and Prevention. (2013). Web-based Injury Statistics Query and Reporting System. Retrieved May 25, 2014, from http://www.cdc.gov//injury/wisqars/index.html

Chan, H., Mingjing, Y., Huiru, Z., Haiying, W., Sterritt, R., McClean, S., et al. (2011). *Machine learning and statistical approaches to assessing gait patterns of younger and older healthy adults climbing stairs*. Paper presented at the Seventh International Conference on Natural Computation.Shanghai, China

Dadashi, F., Mariani, B., Rochat, S., Büla, C. J., Santos-Eggimann, B., & Aminian, K. (2014). Gait and foot clearance parameters obtained using shoe-worn inertial sensors in a large-population sample of older adults. *Sensors (Switzerland), 14*(1), 443-457.

Dell'oro, L. A. (2008). *The contribution of divided attention to tripping while walking.* Unpublished PhD. thesis, Victoria University Melbourne.

Djurić, Z. (2000). Mechanisms of noise sources in microelectromechanical systems. *Microelectronics Reliability, 40*(6), 919-932.

Ferraris, F., Grimaldi, U., Parvis, M. (1995). Procedure for effortless in-filed calibration of three-axis rate gyros and accelerometers. *Sensors and Materials, 7*(5), 311-330.

Findlow, A., Goulermas, J. Y., Nester, C., Howard, D., & Kenney, L. P. J. (2008). Predicting lower limb joint kinematics using wearable motion sensors. *Gait and Posture, 28*(1), 120-126.

Fuller, G. F. (2000). Falls in the elderly. *American Family Physician, 61*(7), 2159.

Ge, W., & Shuwan, X. (2008). Portable preimpact fall detector with inertial sensors. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 16*(2), 178-183.

Guangyi, S., Yuexian, Z., Yufeng, J., Xiaole, C., & Li, W. J. (2009). *Towards HMM based human motion recognition using MEMS inertial sensors*. Paper presented at the IEEE International Conference on Robotics and Biomimetics.Bangkok, Thailand

Hall, M. A. (1999). *Correlation-based Feature Selection for Machine Learning.* The University of Waikato, Hamilton.

Hamacher, D., Singh, N. B., Van Dieën, J. H., Heller, M. O., & Taylor, W. R. (2011). Kinematic measures for assessing gait stability in elderly individuals: a systematic review. *Journal of The Royal Society Interface, 8*(65), 1682-1698.

Hollman, J. H., Kovash, F. M., Kubik, J. J., & Linbo, R. A. (2007). Age-related differences in spatiotemporal markers of gait stability during dual task walking. *Gait and Posture, 26*(1), 113-119.

Iersel, M. B. v., Kessels, R. P. C., Bloem, B. R., Verbeek, A. L. M., & Olde Rikkert, M. G. M. (2008). Executive functions are associated with gait and balance in community-living elderly people. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 63*(12), 1344-1349.

Jasiewicz, J. M., Allum, J. H. J., Middleton, J. W., Barriskill, A., Condie, P., Purcell, B., et al. (2006). Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals. *Gait and Posture, 24*(4), 502-509.

Ka-Chun, S., Catena, R. D., Li-Shan, C., van Donkelaar, P., & Woollacott, M. H. (2008). Effects of a secondary task on obstacle avoidance in healthy young adults. *Experimental Brain Research, 184*(1), 115-120.

Laessoe, U., Hoeck, H. C., Simonsen, O., & Voigt, M. (2008). Residual attentional capacity amongst young and elderly during dual and triple task walking. *Human Movement Science, 27*(3), 496-512.

Lai, D. T. H., Begg, R., Charry, E., & Palaniswami, M. (2008a). *Frequency analysis of inertial sensor data for measuring toe clearance*. Paper presented at the International Conference on Intelligent Sensors, Sensor Networks and Information Processing.Sydney, Australia.

Lai, D. T. H., Begg, R., Charry, E., Palaniswami, M., & Hill, K. (2008b). *Measuring toe clearance using a wireless inertial sensing device*. Paper presented at the International Conference on Intelligent Sensors, Sensor Networks and Information Processing.Sydney, Australia.

Lai, D. T. H., Begg, R. K., & Palaniswami, M. (2009a). Computational Intelligence in Gait Research: A Perspective on Current Applications and Future Challenges. *IEEE Transactions on Information Technology in Biomedicine, 13*(5), 687-702.

Lai, D. T. H., Begg, R. K., Taylor, S., & Palaniswami, M. (2008c). Detection of tripping gait patterns in the elderly using autoregressive features and support vector machines. *Journal of Biomechanics, 41*(8), 1762-1772.

Lai, D. T. H., Shilton, A., Charry, E., Begg, R., & Palaniswami, M. (2009b). *A machine learning approach to k-step look-ahead prediction of gait variables from acceleration data*. Paper presented at the The IEEE International Conference of Engineering in Medicine and Biology Society.Minneapolis, USA.

Lau, H.-Y., Tong, K.-Y., & Zhu, H. (2008). Support vector machine for classification of walking conditions using miniature kinematic sensors. *Medical and Biological Engineering and Computing, 46*(6), 563-573.

Lau, H., & Tong, K. (2008). The reliability of using accelerometer and gyroscope for gait event identification on persons with dropped foot. *Gait and Posture, 27*(2), 248-257.

Lee, R. Y. W., & Carlisle, A. J. (2011). Detection of falls using accelerometers and mobile phone technology. *Age and Ageing, 40*(6), 690-696.

Levinger, P., Lai, D. T. H., Menz, H. B., Morrow, A. D., Feller, J. A., Bartlett, J. R., et al. (2012). Swing limb mechanics and minimum toe clearance in people with knee osteoarthritis. *Gait and Posture, 35*(2), 277-281.

Li, Q., Young, M., Naing, V., & Donelan, J. M. (2010). Walking speed estimation using a shank-mounted inertial measurement unit. *Journal of Biomechanics, 43*(8), 1640-1643.

Lindemann, U., Hock, A., Stuber, M., Keck, W., & Becker, C. (2005). Evaluation of a fall detector based on accelerometers: A pilot study. *Medical and Biological Engineering and Computing, 43*(5), 548-551.

Lord, S. R., & Dayhew, J. (2001). Visual risk factors for falls in older people. *Journal of the American Geriatrics Society, 49*(5), 508-515.

Lord, S. R., Menz, H. B., & Sherrington, C. (2006). Home environment risk factors for falls in older people and the efficacy of home modifications. *Age and Ageing, 35*(suppl 2), ii55-ii59.

Mannini, A., & Sabatini, A. M. (2014). Walking speed estimation using foot-mounted inertial sensors: Comparing machine learning and strap-down integration methods. *Medical Engineering and Physics, 36*(10), 1312–1321.

Mariani, B., Hoskovec, C., Rochat, S., Büla, C., Penders, J., & Aminian, K. (2010). 3D gait assessment in young and elderly subjects using foot-worn inertial sensors. *Journal of Biomechanics, 43*(15), 2999-3006.

Mariani, B., Rochat, S., Bu, x, la, C. J., & Aminian, K. (2012). Heel and toe clearance estimation for gait analysis using wireless inertial sensors. *IEEE Transactions on Biomedical Engineering, 59*(11), 3162-3168.

McGrath, D., Greene, B. R., Walsh, C., & Caulfield, B. (2011). Estimation of minimum ground clearance (MGC) using body-worn inertial sensors. *Journal of Biomechanics, 44*(6), 1083-1088.

Medical Alert Advice. Automatic Fall Detection For Seniors. Retrieved December 12, 2010, from http://www.medicalalertadvice.com/fall-detection.php

Meng, C., Jingyu, Y., & Yangsheng, X. (2009.). *Gait pattern classification with integrated shoes*. Paper presented at the IEEE International Conference on Intelligent Robots and Systems.St. Louis, MO

Miller, C. A., Feiveson, A. H., & Bloomberg, J. J. (2009). Effects of Speed and Visual-Target Distance on Toe Trajectory During the Swing Phase of Treadmill Walking. *Journal of Applied Biomechanics, 25*(1), 32-42.

Mills, P. M., Barrett, R. S., & Morrison, S. (2008). Toe clearance variability during walking in young and elderly men. *Gait and Posture, 28*(1), 101-107.

Moller, J. (Writer). (2003). Projected costs of fall related injury to older persons due to demographic change in Australia. Australia: Commonwealth of Australia.

Murray, M. P., Kory, R. C., & Clarkson, B. H. (1969). Walking patterns in healthy old men. *Journals of Gerontology, 24*(2), 169-178.

Nagano, H., Begg, R. K., Sparrow, W. A., & Taylor, S. (2011). Ageing and limb dominance effects on foot-ground clearance during treadmill and overground walking. *Clinical Biomechanics, 26*(9), 962-968.

Najafi, B., Aminian, K., Loew, F., Blanc, Y., & Robert, P. A. (2002). Measurement of stand-sit and sit-stand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. *IEEE Transactions on Biomedical Engineering, 49*(8), 843-851.

National Center for Injury Prevention and Control. (2012). Ten Leading Causes of Death and Injury. Retrieved May 3, 2013, from http://www.cdc.gov/injury/wisqars/LeadingCauses.html

Nordin, E., Moe-Nilssen, R., Ramnemark, A., & Lundin-Olsson, L. (2012). Changes in step-width during dual-task walking predicts falls. *Gait and Posture, 32*(1), 92-97.

Novak, D., Reberšek, P., De Rossi, S. M. M., Donati, M., Podobnik, J., Beravs, T., et al. (2013). Automated detection of gait initiation and termination using wearable sensors. *Medical Engineering & Physics, 35*(12), 1713-1720.

Nyan, M. N., Tay, F. E. H., Seah, K. H. W., & Sitoh, Y. Y. (2006). Classification of gait patterns in the time frequency domain. *Journal of Biomechanics, 39*(14), 2647-2656.

Özgür, K. (2006). Generalized regression neural networks for evapotranspiration modelling. *Hydrological Sciences Journal, 51*(6), 1092-1105.

Pavol, M. J., Owings, T. M., Foley, K. T., & Grabiner, M. D. (1999). Gait characteristics as risk factors for falling from trips induced in older adults. *Journals of Gerontology - Series A Biological Sciences and Medical Sciences, 54*(11), M583-M590.

Peruzzi, A., Della Croce, U., & Cereatti, A. (2011). Estimation of stride length in level walking using an inertial measurement unit attached to the foot: A validation of the zero velocity assumption during stance. *Journal of Biomechanics, 44*(10), 1991-1994.

Philips. Most Economical: Lifeline Standard System. Retrieved June 22, 2012, from http://www.lifelinesys.com/content/lifeline-products

Pogorelc, B., Bosnić, Z., & Gams, M. (2012). Automatic recognition of gait-related health problems in the elderly using machine learning. *Multimedia Tools & Applications, 58*(2), 333.

Potter-Forbes, M., & Aisbett, C. (2003). *Injury costs! A valuation of the burden of injury in New South Wales 1998-1999*: New South Wales Injury Risk Management Research Centre.

Rescio, G., Leone, A., & Siciliano, P. (2013). Supervised Expert System for Wearable MEMS Accelerometer-Based Fall Detector. *Journal of Sensors, 2013*, 11.

Riva, F., Toebes, M. J. P., Pijnappels, M., Stagni, R., & van Dieën, J. H. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. *Gait and Posture, 38*(2), 170-174.

Robinovitch, S. N., Yang, Y., Schonnop, R., Sarraf, T., Feldman, F., Leung, P. M., et al. (2013). Video capture of the circumstances of falls in elderly people residing in long-term care: An observational study. *The Lancet, 381*(9860), 47-54.

Sabatini, A. M. (2005). Quaternion-based strap-down integration method for applications of inertial sensing to gait analysis. *Medical and Biological Engineering and Computing, 43*(1), 94-101.

Sabatini, A. M., Martelloni, C., Scapellato, S., & Cavallo, F. (2005). Assessment of walking features from foot inertial sensing. *IEEE Transactions on Biomedical Engineering, 52*(3), 486-494.

Santhiranayagam, B. K., Lai, D., Shilton, A., Begg, R., & Palaniswami, M. (2011a). *Regression models for estimating gait parameters using inertial sensors*. Paper presented at the 2011 Seventh International Conference on Intelligent Sensors, Sensor Networks and Information Processing (ISSNIP).Adelaide, Australia

Santhiranayagam, B. K., Lai, D. T., Sparrow, W., & Begg, R. K. (2015a). A Machine Learning Approach to Estimate Minimum Toe Clearance using Inertial Measurement Units. *Journal of Biomechanics*.

Santhiranayagam, B. K., Lai, D. T., Sparrow, W., & Begg, R. K. (2015b). Minimum toe clearance events in divided attention treadmill walking in older and young adults: a cross-sectional study. *Journal of NeuroEngineering and Rehabilitation, 12*(1), 58.

Santhiranayagam, B. K., Lai, D. T. H., Begg, R. K., & Palaniswami, M. (2010). *Correlations between end point foot trajectories and inertial sensor data*. Paper presented at the International Conference on Intelligent Sensors, Sensor Networks and Information Processing.Brisbane, Australia

Santhiranayagam, B. K., Lai, D. T. H., Begg, R. K., & Palaniswami, M. (2011b). *Estimation of end point foot clearance points from inertial sensor data*. Paper presented at the The IEEE International Conference of Engineering in Medicine and Biology Society.Boston, USA

Santhiranayagam, B. K., Lai, D. T. H., Shilton, A., Begg, R., & Palaniswami, M. (2013). *Autonomous detection of different walking tasks using end point foot trajectory vertical displacement data*. Paper presented at the IEEE International Conference on Intelligent Sensors, Sensor Networks and Information Processing.Melbourne, Australia

Santhiranayagam, B. K., XiaoChen, W., Lai, D.T.H., Begg, R.K. (2015). Inertial Measurement Units in Gait and Sport Motion Analysis. In K.-P. Mehdi (Ed.), *Encyclopedia of Information Science and Technology* (pp. 6892-6904). Hershey, PA, USA: IGI Global.

Schulz, B. W. (2011). Minimum toe clearance adaptations to floor surface irregularity and gait speed. *Journal of Biomechanics, 44*(7), 1277-1284.

Schulz, B. W., Lloyd, J. D., & Lee Iii, W. E. (2010). The effects of everyday concurrent tasks on overground minimum toe clearance and gait parameters. *Gait and Posture, 32*(1), 18-22.

Sherrington, C., Lord, S. R., & Finch, C. F. (2004). Physical activity interventions to prevent falls among older people: update of the evidence. *Journal of Science and Medicine in Sport, 7*(1 Supplement), 43-51.

Shiffman, D. (2012). Neural Networks. In Shannon Fry (Ed.), *The Nature Of Code*.

Shilton, A., Lai, D. T., Santhiranayagam, B. K., & Palaniswami, M. (2012). A note on octonionic support vector regression. *Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 42*(3), 950-955.

Sparrow, W. A., Begg, R. K., & Parker, S. (2008). Variability in the foot-ground clearance and step timing of young and older men during single-task and dual-task treadmill walking. *Gait and Posture, 28*(4), 563-567.

Sparrow, W. A., Bradshaw, E. J., Lamoureux, E., & Tirosh, O. (2002). Ageing effects on the attention demands of walking. *Human Movement Science, 21*(5/6), 961-972.

Specht, D. F. (1991). A general regression neural network. *IEEE Transactions on Neural Networks, 2*(6), 568-576.

Speciali, D. S., Oliveira, E. M. d., Santos, N. M. d., Pereira, F. V., Fracini, A. r. C., Fukuda, T. Y., et al. (2012). Use of the gait deviation index and spatiotemporal variables for the assessment of dual task interference paradigm. *Journal of Bodywork and Movement Therapies*(0).

Taylor, S. B. (2012). *The effect of ageing on the control of toe clearance during walking.* Unpublished PhD. thesis, Victoria University, Melbourne, Australia.

Terrier, P., Aminian, K., & Schutz, Y. (2001). Can accelerometry accurately predict the energy cost of uphill/downhill walking? *Ergonomics, 44*(1), 48-62.

The Cochrane Collaboration. (2009). Interventions for preventing falls in older people living in the community.

Thong, Y. K., Woolfson, M. S., Crowe, J. A., Hayes-Gill, B. R., & Jones, D. A. (2004). Numerical double integration of acceleration measurements in noise. *Measurement, 36*(1), 73-92.

Tirosh, O., Cambell, A., Begg, R., & Sparrow, W. A. (2013). Biofeedback training effects on minimum toe clearance variability during treadmill walking. *Annals of Biomedical Engineering, 41*(8), 1661-1669.

Wild, D., Nayak, U., & Isaacs, B. (1981). How dangerous are falls in old people at home? *British medical journal (Clinical research ed.), 282*(6260), 266.

Winter, D. A., McFadyen, B. J., & Dickey, J. P. (1991). *Adaptability of the CNS in human walking* (Vol. 78).

World Health Organization. (2007). *WHO global report on falls prevention in older age*.

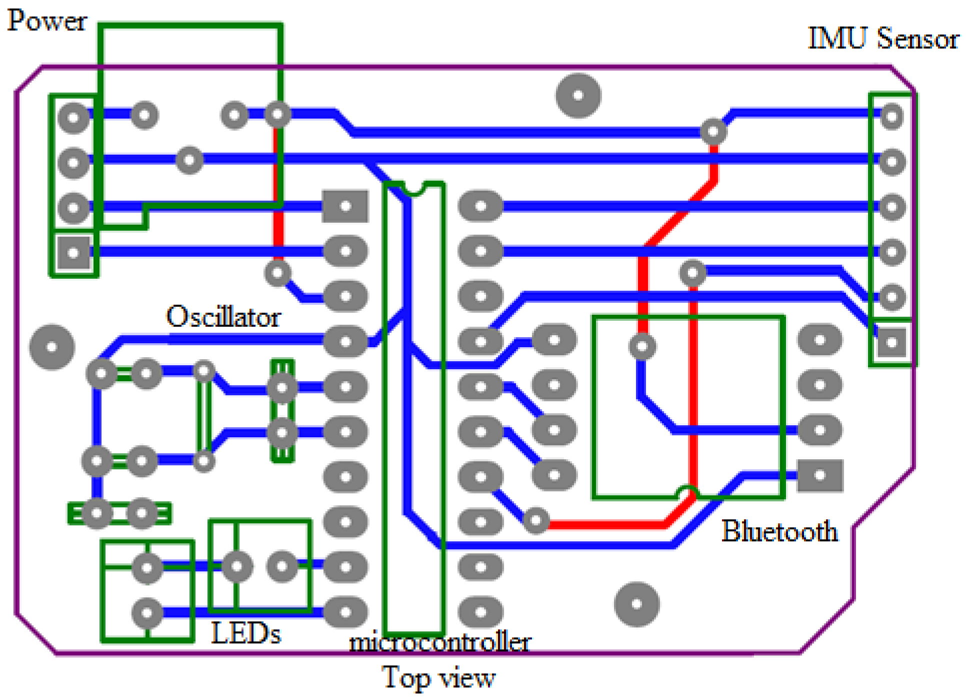
Yoshiyuki, K., Hiroaki, H., Shiho, M., & Masaaki, M. (2014). Key joint kinematic characteristics of the gait of fallers identified by principal component analysis. *Journal of Biomechanics, 47*(10), 2424-2429.

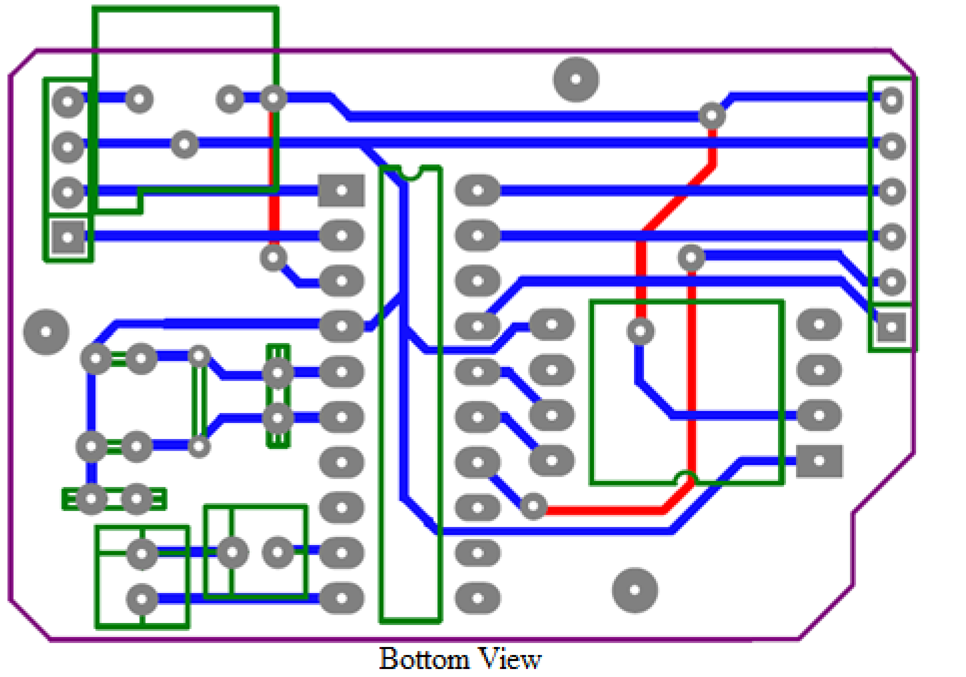
Yun, X., Bachmann, E. R., Moore, H., & Calusdian, J. (2007). *Self-contained position tracking of human movement using small inertial/magnetic sensor* *modules*. Paper presented at the IEEE International Conference on Robotics and Automation.Roma, Italy

Zeng, H., & Zhao, Y. (2011). Sensing movement: Microsensors for mody motion measurement. *Sensors, 11*(1), 638-660.

Zhou, H., & Hu, H. (2008). Human motion tracking for rehabilitation-A survey. *Biomedical Signal Processing and Control, 3*(1), 1-18.

Appendix A: Printed Circuit Board Layout





Foot-mounted sensor printed circuit board layout top and bottom view, designed using Protel (98)

Appendix B: Advertisement in 60plus newspaper

Appendix C: General Health Survey Questionnaire

General Health Survey Questionnaire

Please fill out as much as you can. When you are finished, please leave it with the investigator.

Statement of Confidentiality

All information that would permit identification of investigators or their participants will be regarded as strictly confidential, will be used only for the purpose of operating and evaluating the study, and will not be disclosed or released for any other purposes without prior consent, except as required by law.

Please circle the correct answer to the following questions. Please use the space provided to add any additional information you believe is required.

1. In general, would you say your health is?

a. Excellent
b. Very good
c. Good
d. Fair
e. Poor

2. Have you previously fallen, or tripped, in the past 24 months?

Yes No

(If no please skip to question 4)

If yes please provide date/s and description of fall/s and ____

____
____
____
____

3. Did the fall result in physical injury?

Yes No

If yes please describe injury and length of hospitalization and rehab if required?

4. Would you say you can walk comfortably without stopping for?

a. Less than 10 minutes
b. 10 to 30 minutes
c. 30 minutes to one hour
d. Greater than one hour

5. Do you live independently and require no aid for walking?

Yes No

6. Have you a history of orthopedic problems?

Yes No

If yes please explain

7. Do you suffer from any muscle or skeletal problems that you know of?

Yes No

If yes please explain

8. Have you ever suffered or do you currently suffer from any heart or respiratory problems that you know of?

Yes No

If yes please explain

9. Would you say your balance while both standing and walking is?

Good Poor

10. Do you currently take any psychotropic / antipsychotic medications?

Yes No

If yes, how long have you been using that drug for?

11. Do you suffer from any known allergic conditions caused by the adhesive gel used to attach the surface electrodes to the skin?

Yes No

Thank you for filling out this questionnaire.

Appendix D: Information to participants

Information to participants (age group: 65 years old and above) involved in research

Our Research

You are invited to participate in a research project entitled "Sensors and Actuators: A New Approach to Falls Prevention in Older Adults".

Project explanation

Falls are one of the major causes of injuries and the primary cause of accidents and deaths of older adults aged 65 years and above. The medical cost associated with the falls in older is already very high and is increasing at an extremely high rate. The overall vision of the project is to develop a shoe-mounted sensor system, which could continuously monitor the lower limb movement to predict the risk of a potential tripping hazard and fall.

The proposed study aims to explore the human locomotion system and how it is controlled. For this purpose the lower limb walking characteristics of 30 healthy older (aged 65 years and above) participants will be tested while walking on a treadmill under various speed conditions

Successful completion of this research will reduce the falls related injuries and significantly benefit older population of Australia and other countries. New mathematical models will find many applications in injury prevention, gait disorder diagnostics, sports performance enhancement and movement rehabilitation.

What will I be asked to do?

1 – All participants will be equipped with small markers attached on the important joint landmarks to record the motion of the body. They will be also attached with inertial sensors (accelerometers and gyroscopes) at the distal end of left/ right shoes/feet.

2 – Participants would be requested to wear safety harness to avoid any possible risk while walking on the treadmill. Participants will be first asked to walk naturally on a treadmill to estimate their preferred walking speed (PWS).

3 - Participants will be asked to complete walking on treadmill for 5 min with their PWS

4 - Participants will be asked to walk on a treadmill with a glass of water at preferred walking speed for 5 min

5 - Participants will be asked to walk on a treadmill without the glass at the same speed as above for 5 min

6 – Participants will be asked to complete overground walking for 10mins with a their PWS

During the experiment, all the participants will be provided with adequate rest between testing sessions and the participants will be allowed to withdraw from the experiment anytime.

What will I gain from participating?

- Making a contribution to gait research
- Understanding more about gait biomechanics and risks of falls

How will the information I give be used?

The information obtained through the experiment will be confidential and used only for the purpose of this study, which will include the research paper, thesis, posters, presentation, etc. The private information that can identify the individual (such as name, address, or contact information) will not be reported.

What are the potential risks of participating in this project?

There are no foreseen risks regarding to this experiment because the procedures involve only normal everyday healthy activities and there are no invasive physiological or medical research techniques. However to avoid any possible loss of balance/ miss-steps in treadmill, participants will be requested to wear harness. If a participant feels uncomfortable during the test, the test will be stopped immediately and the participant will be given the option to withdraw. Telephones are located within the facility if medical attention is needed, and the participants will be escorted to a convenient hospital.

How will this project be conducted?

Participants will be asked to walk on a flat, unobstructed, lighted, and non-slippery treadmill repeatedly. All the participants will have small markers placed on their right/left upper/lower limb segments for collecting data allowing gait to be characterized. They will be also attached with small sensors (accelerometers and gyroscopes) at the distal end of left/ right feet. Participants will be also asked to wear safety harness to avoid any possible risks. Walking patterns will be examined by measuring foot motion, and ground reaction forces. The participants can take rest any time and can also withdraw from the experiment any time.

Who is conducting the study?

School of Sports and Exercise Science, Biomechanics Laboratory, Footscray Park Campus

Principal Investigator
Prof Rezaul Begg
Phone: 0399191116
E-mail: rezaul.begg@vu.edu.au

Student Investigator
Ms Braveena Santhiranayagam
Phone: 0399199227
E-mail: braveena.santhiranayagam@live.vu.edu.au

Associate Investigator
Dr Daniel Lai
Phone: 0399194425
E-mail: daniel.lai@vu.edu.au

Any queries about your participation in this project may be directed to the Principal Researcher listed above. If you have any queries or complaints about the way you have been treated, you may contact the Secretary, Victoria University Human Research Ethics Committee, Victoria University, PO Box 14428, Melbourne, VIC, 8001 phone (03) 9919 4781.

Appendix E: Consent form for participants

Consent form for participants (age group: 65 years old and above) involved in research

We would like to invite you to be a part of a study involving gait examination, prediction of risk of falls and falls prevention. The overall aim of the project is to develop a sensor-based system, which could continuously monitor the foot motion to predict the risk of a potential fall. You are asked to participate in the testing procedures outlined below.

- This research has been approved by the Victoria University Human Research Ethics Committee.
- The physical risks associated with the procedures are minimal.
- The testing area will be kept private with access limited only to the researchers.
- All data will be kept confidential and only the researchers will have access to the data files.
- Please be advised that although you are volunteering for this research, you are free to withdraw at anytime.

CERTIFICATION BY PARTICIPANT

I, ____

of ____

certify that I am above 18 years old and that I am voluntarily giving my consent to participate in the research entitled: **Sensors and Actuators: A New Approach to Falls Prevention in Older Adults,** being conducted at Victoria University by: **Prof Rezaul Begg (supervisor), Dr. Daniel Lai (co-supervisor), and Ms Braveena Santhiranayagam (student researcher).**

PROCEDURES:

- The tester will take your body height and weight measurements
- The tester will attach small plastic shells to the upper and lower limbs and shoes using Velcro straps. These shells have small 'diode' markers that are tracked by a 3D camera system. The markers are connected to a small control box with wire cables. The control box will be attached to a waist belt. The markers are powered by low voltage batteries and will be fastened along the outside of the shoe using adhesive tape, safety pins and plastic clips.
- The tester will also attach 2 miniaturized inertial sensors (measures foot accelerations and rotations) to the distal end of the right and left shoes which are connected to the wireless transmitted attached to the same waist belt as in the previous procedure

- Preferred walking speed (PWS) of the participant would be estimated while the participant is getting familiarized with the treadmill machine.
- Participants would be requested to walk on treadmill and overground under following conditions. The maximum walking time would be 30 min for the older participants. Adequate rest would be provided between different conditions.

✓ Condition 1
  - Walk on treadmill with PWS for 5 min

✓ Condition 2
  - Walk on a treadmill with a glass of water at preferred walking speed for 5 min
  - Walk on a treadmill without the glass at the same speed as above for 5 min

✓ Condition 3
  - Overground walking with PWS to get 20 gait cycles

I certify that the objectives of the study, together with any risks and safeguards associated with the procedures listed hereunder to be carried out in the research, have been fully explained to me by Braveena Santhiranayagam. I certify that I have had the opportunity to have any questions answered and that I understand that I can withdraw from this research at any time and that this withdrawal will not jeopardise me in any way.

I have been informed that the information I provide will be kept confidential.

Signed:________________________

Date: ___________________

Any queries about your participation in this project may be directed to the researcher

Prof Rezaul Begg (ph 9919 1116) or Ms Braveena Santhiranayagam (ph 03 9919 9227). If you have any queries or complaints about the way you have been treated, you may contact the Secretary, Victoria University Human Research Ethics Committee, Victoria University, PO Box 14428, Melbourne, VIC, 8001 phone (03) 9919 4781.

Appendix F: Inertial-signal features correlations with MTC_Height

Correlations (r) between preferred-speed MTC_Height and statistical properties IMU obtained signals

Inertial sensor signal	Stat	Young (r)	Older (r)	Inertial sensor signal	Stat	Young (r)	Older (r)
AccX	max	0.08	0.05	AngVelX	max	-0.39	-0.47
	min	0.01	-0.05		min	0.37	0.43
	mean	0.04	-0.15		mean	-0.39	-0.54
	SD	0.05	-0.11		SD	-0.43	-0.51
	range	0.06	-0.09		range	-0.36	-0.49
	S	-0.08	0.05		S	-0.21	-0.07
	K	0.11	0.01		K	-0.14	-0.02
AccY	max	-0.37	-0.04	AngVelY	max	0.06	0.00
	min	0.17	0.29		min	-0.16	-0.11
	mean	-0.46	-0.35		mean	0.18	-0.01
	SD	-0.36	-0.34		SD	0.16	0.05
	range	-0.20	-0.32		range	0.13	0.08
	S	0.25	-0.35		S	0.06	0.03
	K	0.09	0.18		K	-0.10	0.18
AccZ	max	-0.31	-0.33	AngVelY	max	0.16	-0.16
	min	0.50	0.38		min	-0.10	0.10
	mean	-0.51	-0.43		mean	0.04	-0.29
	SD	-0.54	-0.40		SD	0.08	-0.22
	range	-0.47	-0.38		range	0.14	-0.14
	S	0.39	0.35		S	-0.18	-0.20
	K	0.24	0.40		K	0.18	0.28
VelX	max	0.09	0.18	AngDispX	max	-0.20	-0.55
	min	< 0.00	0.22		min	0.38	0.61
	mean	-0.12	-0.19		mean	-0.39	-0.53
	SD	-0.06	-0.13		SD	-0.38	-0.54
	range	0.05	-0.04		range	-0.29	-0.59
	S	-0.06	0.27		S	0.02	0.39
	K	0.20	0.42		K	0.17	-0.06
VelY	max	-0.45	-0.28	AngDispY	max	0.13	< 0.00
	min	0.18	0.16		min	-0.13	-0.18
	mean	-0.47	-0.43		mean	0.14	0.06
	SD	-0.41	-0.39		SD	0.15	0.06
	range	-0.05	-0.32		range	0.14	0.09
	S	-0.03	0.10		S	0.03	-0.40
	K	0.50	0.25		K	0.01	0.05

(continued)

Inertial sensor signal	Stat	Young (r)	Older (r)	Inertial sensor signal	Stat	Young (r)	Older (r)
VelZ	max	-0.04	-0.05	AngDispZ	max	0.13	-0.11
	min	0.43	0.48		min	-0.02	0.21
	mean	-0.50	-0.45		mean	0.09	-0.31
	std	-0.55	-0.42		std	0.08	-0.26
	range	-0.62	-0.32		range	0.07	-0.19
	std	0.35	0.54		std	0.04	0.12
	K	-0.08	0.30		K	0.04	0.31
DispX	max	0.05	-0.04	AngAccumX	max	-0.31	-0.58
	min	0.11	0.20		min	0.32	0.44
	mean	-0.12	-0.16		mean	-0.39	-0.54
	std	-0.09	-0.15		std	-0.37	-0.54
	range	-0.05	-0.12		range	-0.35	-0.52
	std	0.10	0.16		std	-0.15	-0.17
	K	0.11	0.15		K	0.09	0.31
DispY	max	0.18	0.18	AngAccumY	max	0.16	0.04
	min	-0.37	-0.38		min	-0.15	-0.08
	mean	-0.34	-0.43		mean	0.11	0.06
	std	-0.37	-0.42		std	0.12	0.07
	range	-0.40	-0.40		range	0.16	0.07
	std	-0.21	0.28		std	-0.04	-0.15
	K	-0.12	0.53		K	-0.06	-0.08
DispZ	max	-0.60	-0.61	AngAccumZ	max	0.18	-0.23
	min	0.36	0.28		min	-0.02	0.28
	mean	-0.51	-0.30		mean	0.10	-0.31
	std	-0.52	-0.36		std	0.11	-0.29
	range	-0.51	-0.45		range	0.12	-0.26
	std	-0.46	-0.44		std	0.32	0.16
	K	-0.13	-0.10		K	0.10	0.24

Appendix G: Statistical Test Results

Statistical summary tables for ageing effect on median MTC_Height at preferred-walking

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	45.63	1	45.6333	0.59	0.4429
Error	2201.87	28	78.6381		
Total	2247.5	29			

Statistical summary tables for ageing effect on MTC_Height IQR at preferred-walking, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	520.83	1	520.833	6.72	0.0095*
Error	1725.67	28	61.631		
Total	2246.5	29			

Statistical summary tables for ageing effect on median MTC_Time at preferred-walking

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	8.53	1	8.5333	0.11	0.74
Error	2238.47	28	79.9452		
Total	2247	29			

Statistical summary tables for ageing effect on MTC_Time IQR at preferred-walking, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	598.53	1	598.533	7.77	0.0053*
Error	1633.97	28	58.356		
Total	2232.5	29			

Statistical summary tables for task effect on median MTC_Height for Young

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	0.5333	2	0.26667	0.53	0.7659
Error	29.4667	28	1.05238		
Total	30	44			

Statistical summary tables for task effect on MTC_Height IQR for Young

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	0.1	2	0.05	0.13	0.9355
Error	22.4	28	0.8		
Total	22.5	44			

Statistical summary tables for task effect on median MTC_Time for Young, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	10.0333	2	5.01667	10.38	0.0056*
Error	18.9667	28	0.67738		
Total	29	44			

Statistical summary tables for task effect on MTC_Time IQR for Young, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	0.2333	2	0.11667	0.26	0.8763
Error	26.2667	28	0.9381		
Total	26.5	44			

Statistical summary tables for task effect on median MTC_Height for Older, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	9.6333	2	4.81667	9.8	0.0075*
Error	19.8667	28	0.70952		
Total	29.5	44			

Statistical summary tables for task effect on MTC_Height IQR for Older, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	14.0333	2	7.01667	14.27	0.0008*
Error	15.4667	28	0.55238		
Total	29.5	44			

Statistical summary tables for task effect on median MTC_Time for Older, * denotes $p < 0.05$

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	20.0333	2	10.0167	20.37	3.8E-05*
Error	9.4667	28	0.3381		
Total	29.5	44			

Statistical summary tables for task effect on MTC_Time IQR for Older

Source	SS	df	MS	Chi-sq	Prob>Chi-sq
Columns	3.0333	2	1.51667	3.25	0.1969
Error	24.9667	28	0.89167		
Total	28	44			

Young and Older Z-test results for proportions of non-MTC gait cycles across tasks,* = p < 0.05, NA = comparison not applicable, - = comparisons not performed. Direction of the significant comparisons can be determined from the proportions

		Young			Older		
		PW	SW	DW	PW	SW	DW
Young	PW (2.9%)	NA	-22.24*	-25.07*	-22.36*	-	-
	SW (26.7%)	-22.24*	NA	3.35*	-	-	-
	DW (22.8%	-25.07*	3.35*	NA	-	-	-
Older	PW (18.7%)	-22.36*	-	-	NA	-15.50*	-2.62*
	SW (34.6%)	-	-	-	-15.50*	NA	-2.62*
	DW (37.7%)	-	-	-	-2.62*	-2.62*	NA

Appendix H: Optimum feature-set from other combinations

Optimum feature-set obtained with hill-climbing features-selection for (i) raw features only and (ii) raw + SI features

(i) Raw features only	
Young	**Older**
Minimum longitudinal acceleration (AccZ) Maximum medio-lateral angular velocity (GyroX) Maximum longitudinal angular velocity (GyroZ) Minimum longitudinal angular velocity (GyroZ) Minimum anterior-posterior acceleration (AccY)	Maximum medio-lateral angular velocity (GyroX) Minimum medio-lateral acceleration (AccX) Minimum longitudinal acceleration (AccZ)

(ii) Raw + SI features	
Young	**Older**
2nd minimum longitudinal velocity (VelZ) Minimum longitudinal angular velocity (GyroZ) Minimum medio-lateral acceleration (AccX)	Minimum medio-lateral angular displacement Minimum longitudinal angular velocity (GyroZ) Maximum anterior-posterior angular displacement (DispY) Maximum longitudinal angular velocity (GyroZ) Maximum medio-lateral angular displacement Maximum medio-lateral acceleration (AccX)