

UNIVERSITY OF CALGARY

Changes in Running Gait Biomechanics Following Exercise Intervention Program in Older
Runners

by

Reginaldo Kisho Fukuchi

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE
DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF KINESIOLOGY

CALGARY, ALBERTA

JULY, 2013

© Reginaldo Kisho Fukuchi 2013

Abstract

The pursuit of healthy ageing has seen a dramatic increase in the number of older adults engaging in physical activity programs such as running. However, the incidence of running-related injuries among these runners has also increased representing a significant problem considering the inactivity associated with injury. The aim of the present thesis was to address two major problems for clinical researchers: (1) understanding the effects of biological ageing on musculoskeletal function and running biomechanics; (2) understanding the effects of exercise recommended to counteract the effects of ageing. Two studies were conducted to investigate the age-related adaptations in running biomechanics and their association with musculoskeletal function using traditional and an emergent data analysis technique. The first study involved a cross-sectional investigation using traditional statistics and we found an overall reduction in muscle strength and flexibility along with atypical running biomechanics for older runners compared to their younger counterparts. The second study involved a machine learning technique that demonstrated a promising ability to predict age-group membership based only on gait kinematic variables. When a more comprehensive and representative number of gait variables were tested using the same machine learning approach, the results were similar. The final experiment was a randomized controlled trial (RCT) to determine the effects of exercise on musculoskeletal function and running biomechanics in older runners. An innovative scoring approach was developed that demonstrated running biomechanical patterns were not changed following an 8-week stretching or strengthening protocol.

Preface

The following three chapters are based on scientific manuscripts:

- Chapter 3 Fukuchi, R.K., Stefanyshyn, D.J., Stirling, L., Duarte, M., Ferber, R. Flexibility, muscle strength and gait biomechanical adaptations in older runners. (submitted) *Clinical Biomechanics*.
- Chapter 4 Fukuchi, R.K., Eskofier, B.M., Duarte, M., Ferber, R. (2011) Support vector machines for detecting age-related changes in running kinematics. 44(3):540-542. *Journal of Biomechanics*.
- Chapter 5 Fukuchi, R.K., Stirling, L., Stefanyshyn, D.J., Ferber, R. (in preparation) Effects of exercise on muscle strength, flexibility and gait biomechanics in older runners quantified by a machine learning approach: a randomized controlled trial.

This dissertation is based on a collection of stand-alone manuscripts, and there may be some redundancy mainly in the introduction and methods sections of chapters 3 to 5. The author of this thesis was the main contributor for the conception, design, data acquisition, data analysis, interpretation, and writing under the supervision of RF. DJS and LS contributed to the conception, design and interpretation. MD and BME contributed to the conception, design and interpretation of chapter 3 and chapter 4, respectively. Whenever custom made software programs are mentioned in this thesis, they were implemented by the author.

Acknowledgements

Moving to Calgary for my PhD was truly a tremendous experience that I will never forget. I would like to express my gratitude to the following people that have significantly helped me since I decided to study abroad.

Mom and Dad you were the most important source of motivation that made me wake up every day as it was my birthday. Muito obrigado!

My supervisor, Dr. Reed Ferber for his trust, guidance, patience and to help me to be more confident in my research skills. You definitely have made me a better clinical researcher.

Dr. Darren Stefanyshyn for his guidance in the biomechanical aspects of my work and for always intriguing me with challenging questions that made me a better thinker.

Dr. Lisa Stirling for reading so many drafts I wrote over these years and to guide me through the high dimensional space; and for teaching the best course I took during my PhD along with Dr. Perter Federolf and Dr. Bjoern Eskofier.

Dr. Marcos Duarte to always encourage me to have a solid biomechanics and programming background and to introduce the Herman's law for graduate students which I did my best to follow.

Dr. Moises Cohen for being my clinical mentor since the beginning of my career and for the countless letters of recommendations to support my applications in Calgary and elsewhere.

CAPES agency under the Ministry of Education of Brazil for financial support. I will work hard to translate knowledge that I gained over these years.

Dr. Steve Boyd for serving in my candidacy and defence examination committee. Dr. John Matyas and Dr. Michael Hahn for acting as the external examiners in my candidacy and defence

examinations, respectively. Dr. Blayne Hettinga for his help during the preparation for the exams.

All the volunteers, particularly the 105 runners in the RCT study. Thank you so much for your help. Your energy, enthusiasm and dedication made me feel as the older runner. Special thanks to Martin Parnell to support my cause and help advertise the study.

Current and former members of the Running Injury Clinic that made my life in Calgary easier and more fun inside and outside the Lab. SK, Mike, Melissa Rabbito, Chandra, Danielle, Kimber, Karen, Kelsey, Wendy, Sean, Shari, Talia, Kathryn, Dylan, Jen and Kent Bates. Special thanks to Jill Baxter and Melissa Benson for helping me with all the logistics of my study. Joseph, Mandy and Cristina for helping with some data collections. Ryan Leigh for his friendship and for keeping me updated about the physiotherapy world.

My sister Cintia, Edmir and their little Gabi for reminding me that it is time to go home. It has been hard to be away from you.

Rosalie Kolstad for helping me during my application process and for answering random questions throughout these years.

Dale Butterwick and Breda Lau for their guidance during the KNES 371 Labs.

Sean, Sarah and Dr. Carolyn Emery for the opportunity to work in the OA systematic review team.

Masanori Sakaguchi for hosting me at Waseda University and in Tokyo, Japan.

Finally, I have been very fortunate to have the most outstanding woman beside me. Claudiane, thank you for being not only my wife but also a supporter, a friend and a confident over these years.

*To Claudiane,
for her continuing support and love*

Table of Contents

Abstract.....	ii
Preface.....	iii
Acknowledgements	iv
Table of Contents	vii
List of Tables	x
List of Figures and Illustrations	xii
List of Symbols, Abbreviations, Nomenclatures	xvii
Chapter 1: Introduction	1
Chapter 2: Literature Review.....	4
2.1 Age-related changes in the musculoskeletal system	4
2.1.1 Sarcopenia	4
2.1.2 Connective Tissue.....	10
2.2 Age-related functional changes and exercise intervention	11
2.2.1 Loss of muscle strength.....	11
2.2.2 Interventions to minimize muscle strength loss	13
2.2.3 Loss in flexibility	16
2.2.4 Interventions to minimize flexibility loss	17
2.3 Age-related running gait biomechanical adaptations.....	20
2.3.1 Temporal-spatial gait parameters	21
2.3.2 Joint kinematics	24
2.3.3 Joint kinetics	29
2.3.4 Ground reaction forces	32
2.3.5 Interventions to minimize changes in gait biomechanics	35
2.3.5.1 Flexibility exercises	35
2.3.5.2 Strengthening exercises	37
2.4 Machine Learning Approach.....	41
2.5 Summary.....	42
Chapter 3: Flexibility, muscle strength and running biomechanical adaptations in older runners.....	45
3.1 Introduction.....	45
3.2 Methods.....	47
3.2.1 Participants.....	47
3.2.2 Muscle Strength and Flexibility Measurements	48
3.2.3 Biomechanical Measures	54

3.2.4 Data Analysis	56
3.3 Results	56
3.4 Discussion	68
3.5 Conclusion	71
3.6 Summary	72
Chapter 4: Support Vector Machines for Detecting Age-Related Changes in Running Kinematics	74
4.1 Introduction	74
4.2 Methods	77
4.2.1 Subjects	77
4.2.2 Data Collection	78
4.2.2.1 Kinematics Measurements	78
4.2.3 Support Vector Machines	81
4.2.4 Pre-processing	91
4.2.5 Feature Extraction	92
4.2.6 Cross validation	93
4.2.7 Dimensionality Reduction	94
4.3 Results	95
4.4 Discussion	97
4.5 Conclusion	99
4.6 Summary	99
Chapter 5: Effects of exercise on muscle strength, flexibility and gait biomechanics in older runners quantified by a machine learning approach: a randomized controlled trial.....	101
5.1 Introduction	101
5.2 Methods	103
5.2.1 Study Design and Setting	103
5.2.2 Eligibility criteria and recruitment	103
5.2.3 Power analysis	104
5.2.4 Participant screening	104
5.2.5 Randomization	105
5.2.6 Blinding	105
5.2.7 Exercise Intervention	106
5.2.8 Dependent and Independent Variables	108
5.2.8.1 Study 1	108
5.2.8.2 Study 2	110
5.2.9 Primary and Secondary Outcomes	110

5.2.10 <i>Baseline Data Collection</i>	110
5.2.10.1 <i>Muscle Strength and Flexibility Measurements</i>	110
5.2.10.2 <i>Biomechanical Measures</i>	116
5.2.11 <i>Machine Learning Approach</i>	118
5.2.12 <i>Statistical Analysis</i>	120
5.3 Results	120
5.3.1 <i>Study 1</i>	120
5.3.2 <i>Study 2</i>	127
5.3.2.1 <i>Baseline Data</i>	129
5.3.2.2 <i>Primary Analysis</i>	131
5.3.2.3 <i>Participants Adherence and Exercise Load</i>	150
5.4 Discussion	152
5.4.1 <i>Study 1</i>	152
5.4.2 <i>Study 2</i>	154
5.5 Conclusion	156
Chapter 6: Summary and Future Directions	158
6.1 Describe the clinical (strength and flexibility) and biomechanical adaptations in older runners and examine the association between them.	158
6.2 Determine the ability of a machine learning algorithm (SVM) to discriminate age groups (young and elderly) based on gait kinematics parameters and a reduced set of discriminant variables.	159
6.3 Determine what subset of variables (clinical, biomechanical or both) yields an optimal combined discrimination between age-groups with a more comprehensive set of variables and larger sample size.	160
6.4 Determine what type of exercise intervention (strengthening and stretching) most effectively influences the identified features.	160
6.5 Limitations and future directions	161
References	164
APPENDIX A : Reference frame convention, joint kinematics and joint kinetics calculations	174
APPENDIX B :Instrumented treadmill calibration	187
APPENDIX C : Support Vector Machine algorithm workflow	192
APPENDIX D : Exercise intervention programs	195

List of Tables

Table 2-1. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated running temporal-spatial variables in young and older adult runners.	23
Table 2-2. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated stance phase running gait kinematic variables in young and older adult runners.....	26
Table 2-3. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated stance phase running gait joint kinetic variables in young and older adult runners.....	31
Table 2-4. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated running gait GRF variables in young and older adult runners.....	33
Table 3-1. Mean (SD) subject demographics information of the young and older groups.	57
Table 3-2. Mean (SD) ROM and MVIC variables of interest for young and older runners, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.	61
Table 3-3. Mean (SD) joint kinematic variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.	62
Table 3-4. Mean (SD) joint impulse variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.	63
Table 3-5. Mean (SD) joint work and GRF variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.	64
Table 4-1. Demographics information of the participants.	78
Table 4-2. Some of the commonly used kernels.	91
Table 4-3. List of discrete kinematic variables that were input into the SVM algorithm.....	92
Table 5-1. Demographics information at the baseline data collection.....	130
Table 5-2. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint kinematic variables in Study 2.	133
Table 5-3. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint moment impulse variables in Study 2.	134
Table 5-4. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint work variables in Study.....	135
Table 5-5. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the GRF variables in Study.	136
Table 5-6. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the MVIC measures.....	143

Table 5-7. Mean values pre and post intervention, mean change, 95% CI of the change (Low-Up) for the flexibility measures.	147
Table B-1. Mean ($\pm 1SD$) COP location error of six trials across calibration days for the right and left force platforms.....	189
Table B-2. Reconstruction error of the motion capture system.	191
Table C-1. Description of the steps taken to obtain the classification of young and older runners and to quantify the effects of exercise intervention.	194

List of Figures and Illustrations

Figure 2-1. Schematic summarizing the aetiologic factors involved in sarcopenia. Adapted from Narici and Maffulli (2010).....	6
Figure 2-2. Number of motor neurons as a function of age according to Tomlinson and Irving (1977).....	6
Figure 2-3. Relationship between total number of fibres and age (a) and number of motor units and age (b) according to Faulkner et al. (2007)	8
Figure 2-4. Percentage reduction of muscle fibre size across different fibre types in older compared to young adults according to Hunter et al. (1999).....	9
Figure 2-5. Pennation angle of an older male (OM) aged 75 years and a matched young adult male (YM) aged 20 years according to Narici et al. (2008).	9
Figure 2-6. Average force-time curves of isometric bilateral leg extension action in men of three different age groups according to Hakkinen, et al. (1995).	12
Figure 2-7. The patellar tendon force-elongation curves for the intervention group and control group before and after 14 weeks of resistive training according to Reeves, et al. (2003).	14
Figure 2-8. Knee extensor angle-torque relation normalized relative to the maximum torque after resistive exercise training according to Reeves et al.(2004b).....	16
Figure 2-9. Maximal hip flexion and extension angles as a function of age according to Nonaka, et al. (2002).	17
Figure 2-10. Passive stretching curves showing that the calf muscles increased their maximal length, length extensibility, maximal passive resistive force and mean passive resistive force Gajdosik et al. (2005a).....	18
Figure 2-11. Meta-analyses of the studies that investigated the effect of stretching on ankle dorsiflexion ROM. The order of the columns are as follows: study author and stretching duration, sample size (N) of stretching group (FXG), mean and standard deviation (SD) of ankle dorsiflexion ROM of the FXG, sample size of the control group (CTG), mean and SD of ankle dorsiflexion ROM of the CTG and forest plots with the 95% confidence interval (CI) of the point estimate according to Radford, et al. (2006).....	19
Figure 2-12. Schematic diagram of the hypothesis that neuromuscular adaptations are a response to impairment and play a key role in causing changes in gait of the elderly. The diagram links the impairments to the functional limitation and the neuromuscular adaptation, and its compensatory function. The dashed line arrows with "?" indicate potentially feasible scenarios not completely supported by the available data in the literature. Adapted from McGibbon (2003).	20
Figure 2-13. Forest plots of 8 studies using strength training to affect habitual gait speed according to Lopopolo et al. (2006).....	37
Figure 2-14. Mean \pm SD Z-scores (A–D panels) and individual Z-scores (E–H panels) (arbitrary units) for gait speed, stride length, cadence, and toe clearance in pre- and post-training period for experimental group according to Persch, et al. (2009). *Significantly different from pre-training ($P < .001$).	38

Figure 2-15. Group ensemble averages of time-series joint kinematics and kinetics during the stance phase of running for the three testing sessions (initial, mid and final). Foot inversion/eversion angle (top left), hip abd/add angle (top right), ankle inversion/eversion moment (bottom left) and knee add/abd moment (bottom right) according to Snyder, et al. (2009).	39
Figure 2-16. Ensemble average of frontal plane knee moment, before and after rehabilitation program. Thick dotted/solid lines represent the means, and thin lines represent the respective standard deviations according to Earl and Hoch (2011).	41
Figure 3-1. Participant's position for isometric strength test: (a) hip abductors, (b) hip extensors, (c) knee extensors, (d) ankle plantar flexors, (e) hip external rotators.	52
Figure 3-2. Participant's position for ROM testing: (a) hip adduction, (b) hip extension, (c) hip external rotation, (d) hip internal rotation, (e) ankle gastrocnemius, (f) ankle soleus, (g) hip flexion.	53
Figure 3-3. Marker set protocol used in this study depicting anatomical (black) and technical (white) markers used in the study.	54
Figure 3-4. Three-dimensional hip, knee, ankle and trunk/pelvis joint kinematics for young (solid blue line is mean, shaded area is $\pm 1SD$) and older (dashed red and dashed black are mean and $\pm 1SD$, respectively) runners during the stance phase of running at 2.7 m/s on a treadmill.	59
Figure 3-5. Three-dimensional hip, knee and ankle joint moments; and sagittal power for young (solid blue line is mean, shaded area is $\pm 1SD$) and older (dashed red and dashed black are mean and $\pm 1SD$, respectively) runners during the stance phase of running at 2.7 m/s on a treadmill...	60
Figure 3-6. Distribution of the flexibility measures for young (blue circles) and older runners (red triangles). Note: "*" indicates significant differences between groups.	65
Figure 3-7. Distribution of the strength measures for young (blue circles) and older runners (red triangles). Note: "*" indicates significant differences between groups.	66
Figure 3-8. Scatterplot depicting the relationship between clinical and running biomechanical measures in young and older runners.	67
Figure 4-1. Marker protocol used and joint angles convention adopted according to Fukuchi and Duarte (2008).	79
Figure 4-2. Digital cameras and treadmill set up for the data collection.	80
Figure 4-3. The aim of the classification process is to estimate a model by learning a relationship between inputs and outputs according to Lai et al. (2009a).	82
Figure 4-4. Classical pattern recognition approach. Adapted from Eskofier et al. (2012).	83
Figure 4-5. Possible decision boundaries (a). Optimal decision boundary which maximizes the margin of separation between groups (b).	84
Figure 4-6. Example of a discrete kinematic variable matrix arrangement to classify young (A) and elderly (B) runners.	85
Figure 4-7. Example of linearly non-separable data set (left) that become separable when transformed in higher dimensional space (right) according to Van Looy et al. (2007).	88

Figure 4-8. Optimal separating hyperplane and the margins dividing two datasets (circles and crosses); the vectors that lie closest to the margins are the support vectors according to Mountrakis et al. (2011).....	90
Figure 4-9. Graph of the overall accuracy rate of the linear, polynomial and RBF SVM when using different values for the penalty parameter C. In this experiment, five different values of parameter C (0.1, 1, 10, 100, 1000) were used to train the algorithm with all 31 kinematic input features.....	95
Figure 4-10. Performance of the SVM classifier using linear kernel on the number of features. The best performance was achieved with 6 features: KFLXRoM, ICKABD, PEAKAnkDF, KABDPEAK, TibRotRoM and ICToeOut.	96
Figure 4-11. Scatter plot graph showing the distribution of the best two discriminating features (KFLXRoM (horizontal axis) and ICKABD (vertical axis)) and the separating line (hyperplane) with linear and polynomial ($d=3$) kernel SVM.	97
Figure 5-1. Flow diagram of the SVM classification process of young and older runners.	109
Figure 5-2. Participant's position for isometric strength test: (a) hip abductors, (b) hip extensors, (c) knee extensors, (d) ankle plantar flexors, (e) hip external rotators.	114
Figure 5-3. (a) hip adduction, (b) hip extension, (c) hip external rotation, (d) hip internal rotation, (e) ankle gastrocnemius, (f) ankle soleus, (g) hip flexion.....	115
Figure 5-4. Marker set protocol used in this study depicting anatomical (black) and technical (white) markers used in the study.	117
Figure 5-5. 3D scatter plot of the three best flexibility variables (AGASROM, ASOLROM and HERROM) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of flexibility features.....	122
Figure 5-6. 3D scatter plot of three best muscle strength variables (APFS, HABDS and HIRS) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of strength features.....	123
Figure 5-7. Performance of the SVM classifier on the number of gait biomechanical features. The best performance (89%) was achieved with 9 features.	124
Figure 5-8. 3D scatter plot of best three biomechanical variables (Tho/Pel IR-ER, Hip ADD-ABD excursion and Max GRF loading rate) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of biomechanical features.....	125
Figure 5-9. Performance of the SVM classifier using linear kernel on the number of features. The best performance (94%) was achieved with 6 features selected from the subset of 4 flexibility, 4 strength and 9 biomechanical variables.	126
Figure 5-10. 3D scatter plot of APFS, HIP ADD-ABD and HERROM depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of these features.....	127
Figure 5-11. Flow diagram of the participants through the phases of the randomized controlled trials of three groups.	128

Figure 5-12. Average distance from the hyperplane before and after 8 weeks of exercise intervention for biomechanical measures. The distance was measured in nine dimensional space.	132
Figure 5-13. Mean and SD of the joint excursion angles for young and intervention groups before and after 8 weeks.	137
Figure 5-14. Mean and SD of the joint angular impulse variables for young and intervention groups before and after 8 weeks.	138
Figure 5-15. Mean and SD joint work for young and intervention groups before and after 8 weeks.	139
Figure 5-16. Mean and SD of the GRF variables for young and intervention groups before and after 8 weeks.	140
Figure 5-17. Average distance from hyperplane before and after exercise intervention for 6 MVIC variables. The distance was measured in six dimensional space.	142
Figure 5-18. Mean and SD of strength measures for young and intervention groups before and after 8 weeks.	144
Figure 5-19. Average distance from hyperplane before and after exercise intervention for 7 flexibility measures. The distance was measured in seven dimensional space.	146
Figure 5-20. Mean and SD of flexibility measures for young and intervention groups before and after 8 weeks.	148
Figure 5-21. Average distance from hyperplane before and after exercise intervention for the combined set of variables (clinical and biomechanical) measures. The distance was measured in six dimensional space.	150
Figure A-1. Anatomical landmarks and reference frame convention of the foot segment.	175
Figure A-2. Anatomical landmarks and reference frame convention of the shank segment (Van Sint Jan, 2007).	176
Figure A-3. Anatomical landmarks and reference frame convention of the thigh segment (Van Sint Jan, 2007).	177
Figure A-4. Anatomical landmarks and reference frame convention of the pelvic segment (Van Sint Jan, 2007).	178
Figure A-5. Anatomical landmarks and reference frame convention of the trunk segment (Leardini et al., 2011).	179
Figure A-6. Segment coordinate systems of the thigh and shank and the resulting knee JCS (Grood and Suntay, 1983; Van Sint Jan, 2007).	181
Figure A-7. Diagram showing the inverse dynamics workflow approach. Adapted from Zatsiorsky (2002).	182
Figure A-8. FBD of one foot segment demonstrating the forces and moments acting in the segment during propulsion phase of running. Adapted from Robertson (2004).	184
Figure A-9. Time-series curves of knee abduction moment patterns. The shaded area represents the joint moment impulse experienced by young (grey) and older (black) runners.	185

Figure A-10. Time series curves depicting positive and negative ankle joint work in young and older runners.	186
Figure B-1. MTD-2 calibration rod and an illustration of the calibration procedure.	188
Figure B-2. Average position of the markers outfitted on the MTD-2 calibration rod and the average location of the tip of the rod (COP_{std}) and the corrected COP location (COP_{transf}) for one data collection day.	190
Figure B-3. Selected distances between markers outfitted in the MTD-2 calibration rod to calculate the motion capture (MoCAP) system reconstruction error.....	191
Figure C-1. SVM model workflow utilized to classify young and older runners and to quantify the effects of exercise intervention (RCT study).	193

List of Symbols, Abbreviations, Nomenclatures

<i>Symbol</i>	<i>Definition</i>
3D	Three dimensional
ABD	Abduction
ADD	Adduction
ANN	Artificial neural networks
AT	Athletic therapist
BMI	Body mass index
BW	Body weight
C	SVM penalty parameter
CAR	Classification accuracy rate
CAST	Calibrated anatomical system technique
CI	Confidence interval
COM	Centre of mass
CONTRA	Trunk bending to the left
COP	Centre of pressure
CTG	Control group
DF	Dorsiflexion
DLT	Direct linear transformation
ER	External rotation
ES	Effect size
EV	Eversion
EXT	Extension
FLX	Flexion
FXG	Flexibility exercise group
GRF	Ground reaction force
HS	Heel strike
HSD	Honestly significant difference
ICC	Intra-class correlation
INV	Inversion

Symbol

IPSI

IR

ITB

LR

MTU

MVIC

NS

O

OA

PCSA

PF

PFPS

PT

RBF

RCT

ROM

SD

STG

SVM

TNF- α

Y

Definition

Trunk bending to the right

Internal rotation

Iliotibial band

Logistic regression

Muscle-tendon unit

Maximal voluntary isometric contraction

Number of subjects

Older

Osteoarthritis

Physiological cross-sectional area

Plantarflexion

Patellofemoral pain syndrome

Physiotherapist

Radial basis function

Randomized controlled trial

Range of motion

Standard deviation

Strengthening exercise group

Support vector machine

Tumor necrosis factor alpha

Young

Chapter 1: Introduction

In Canada, the number of older adults (65 years and over) increased 14.1% compared to 5.7% of younger individuals (age 15-64) between 2006 and 2011 representing an increase of nearly 5 million people (Canada, 2012). In particular, recent census data showed for the first time that there were more people in the age group 55 to 64, typically when people leave the labour force, than people entering (15 to 24 years) (Canada, 2012). Unfortunately, older adults are frequently affected by chronic diseases and functional disabilities, which result in tremendous social and medical costs (Newman et al., 2003; Willcox et al., 2006). Muscle weakness and loss of joint mobility have been observed in older individuals as a consequence of the structural changes in the musculoskeletal system that occur with biological ageing (e.g. sarcopenia) (Faulkner et al., 2007). Regular physical activity, including long distance running have been recommended to counteract the negative effects of the ageing process (Chodzko-Zajko et al., 2009). In fact, the participation of both men and women of 50 years of age and older in the New York City Marathon, has increased more than twice as much compared to younger age groups between the years of 1983 to 1999 (Jokl et al., 2004). Unfortunately, a concomitant increase in the incidence of musculoskeletal injuries has also been observed in older runners compared to their younger counterparts (Fields, 2011; McKean et al., 2006; Taunton et al., 2002; Taunton et al., 2003). The cause of the increased injury rate among older runners is yet to be determined.

The higher incidence of running-related injuries has been associated with the altered gait biomechanical movement patterns exhibited by older individuals (Bus, 2003; Fukuchi and Duarte, 2008; Fukuchi et al., 2011; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). It is known that recreational long distance running alone does not reverse the negative age-related effects associated with alterations in lower extremity walking gait patterns (Savelberg et al.,

2007). Muscle stretching and muscle strengthening exercises have been widely recommended to counterbalance the effects of ageing on the musculoskeletal system as well as serve to prevent running-related injuries (Chodzko-Zajko et al., 2009; Jenkins and Beazell, 2010; Johnston et al., 2003). It is still unknown what impact such exercises would have on biomechanical patterns in older runners as no previous studies have investigated whether stretching and/or strengthening programs result in concomitant changes in biomechanical running gait patterns for older adults. The complexity of human locomotion demands sophisticated analysis methods to better understand the underlying changes in gait mechanics following exercise intervention.

Traditionally, three-dimensional (3D) biomechanical gait data are analyzed using discrete variables and a univariate statistical approach. Given the multivariate and complex pathoetiology of running-related musculoskeletal injuries often demands a more robust analysis. The support vector machine (SVM) method has recently been applied to analyze biomechanical data due to its ability to identify complex associations (high-dimensionality) amongst many discrete gait variables (Begg and Kamruzzaman, 2005). However, to date, there is limited understanding of how this relatively new way to interpret data would enhance our understanding about the age-related adaptations of the gait movement patterns. Additionally, SVM has the potential to yield a reduced subset of variables that contain the best combined age-related discriminatory ability, thus reducing the dimension of the original data set while retaining relevant information (see chapters 4 and 5). The SVM also allows the progression of any exercise intervention program to be monitored by deriving a representative score (perpendicular distance to the SVM-hyperplane) of gait biomechanical function before and after an exercise intervention program (see chapter 5).

The objective of this dissertation was to address the following purposes:

1. Describe the clinical (strength and flexibility) and biomechanical adaptations in older runners and examine the association between them.
2. Determine the ability of a machine learning algorithm (SVM) to discriminate age groups (young and elderly) based on gait kinematics parameters. Determine the ability of the SVM to detect a subset of gait kinematic parameters, thus achieving an enhanced classification performance with a reduced number of input variables.
3. Determine what subset of variables (clinical, biomechanical or both) yields an optimal combined discrimination between age-groups considering a representative sample of well-matched young and older runners.
4. Determine what type of exercise intervention (strengthening and stretching) most effectively influences the identified features.

Three individual experiments and analyses were conducted to fulfill the purposes described above:

1. A cross-sectional observational study comparing running gait biomechanics, muscle strength and flexibility in young and older runners (chapter 3).
2. A cross-sectional observational study assessing the classification performance of a machine learning emerging technique (SVM) to detect young and elderly running kinematic patterns (chapter 4).
3. Further examination of the SVM approach trained with a larger sample based on more comprehensive set of variables (Chapter 5). In addition, a randomized controlled trial (RCT) study was conducted to determine the efficacy of exercise intervention on gait biomechanics (chapter 5).

Chapter 2: Literature Review

2.1 Age-related changes in the musculoskeletal system

2.1.1 Sarcopenia

Sarcopenia is defined as the loss of muscle mass associated with biological ageing (Rosenberg, 1997). Epidemiological studies have indicated that between the second and eighth decades of life, lean body mass declines approximately 18% in men and 27% in women with the difference across genders remaining fairly constant during this period of time (Janssen et al., 2002). In both genders, the loss in muscle mass appears to have a greater effect on the lower limb muscles (approximately 15%) compared to the upper limb muscles (approximately 10%) (Janssen et al., 2002), but the reason for this difference remains unknown. In terms of muscle physiological cross-sectional area (PCSA), the mass of the muscles required for locomotion (e.g. quadriceps muscles) can decline by up to 25% between the second and the seventh decade of life in both genders (Janssen et al., 2002). Previous studies have also shown an accompanied infiltration of fat and connective tissue (Taaffe et al., 2009). As a result of this infiltration, the non-contractile mass may represent approximately 15% of the total PCSA, or an increase of about 2.5 times in the proportion of non-contractile mass compared to that of young individuals. The reduction of muscle mass and the concomitant increased proportion of non-contractile tissue may explain the most pronounced musculoskeletal changes with ageing: reduced ***muscle strength*** and decreased ***flexibility***. The suggested underlying mechanism associated with the observed decreased strength and flexibility will be discussed in detail within this chapter.

The aetiology of sarcopenia is rather complex since it involves central and peripheral nervous system changes, as well as hormonal, nutritional, immunological and physical activity alterations as demonstrated in Figure 2-1. Nervous system changes are probably the most

important contributor to sarcopenia since a decrease in the number of motor neurons (Figure 2-2), and thus the number of motor units, results in fewer innervated muscle fibers (Brown, 1972). The cause by which we lose motor neurons as we age is not yet fully understood, but studies involving animal models have provided clues regarding the potential mechanisms (Guillet et al., 1999). For example, motor neuron degeneration is related to a decline in the protein ciliary neurotrophic factor that promotes differentiation and survival of motor neurons (Guillet et al., 1999). Due to this neuronal loss, a denervation of muscle fibres takes place, particularly type II, and some of these muscle fibres are reinnervated through axonal sprouting from type I nerve fibres (Frey et al., 2000). As a result of this adaptation, a larger motor unit action potential is induced in the remaining muscle fibres. Although this phenomenon yields a compensation for the loss of force generation by the myofibers, it also results in a greater innervation ratio, thus impairing the fine force control during muscle force production (Narici and Maffulli, 2010).

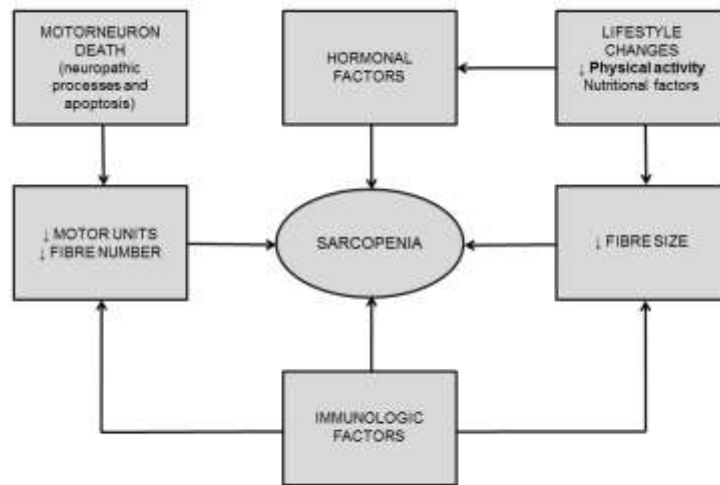


Figure 2-1. Schematic summarizing the aetiologic factors involved in sarcopenia. Adapted from Narici and Maffulli (2010).

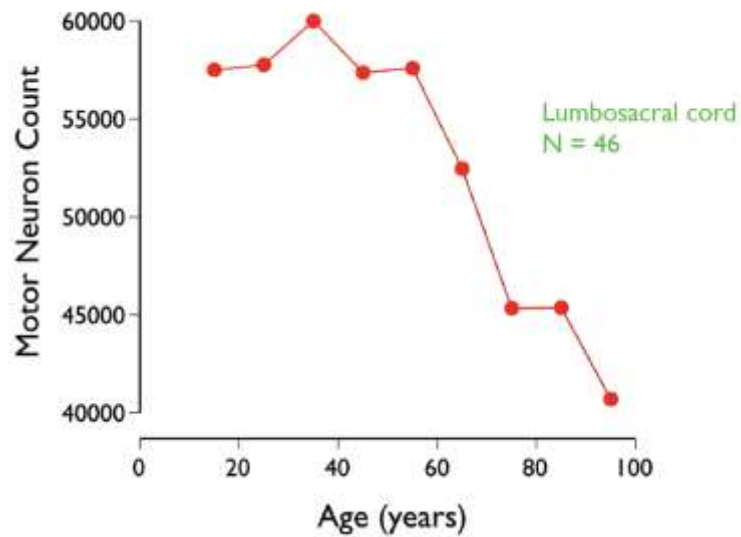


Figure 2-2. Number of motor neurons as a function of age according to Tomlinson and Irving (1977).

In addition to the aforementioned neurodegenerative changes, the muscle cell may also be directly affected during biological ageing in a process described as apoptosis of the myocytes (Dirks and Leeuwenburgh, 2005). Previous research has suggested that mitochondrial dysfunction and sarcoplasmic reticulum stress play a major role in inducing muscle cell apoptosis with ageing (Short et al., 2005). Muscle cell apoptosis seems to be caused by the activation of specific signalling pathways, initiated by a ligand binding of tumor necrosis factor alpha (TNF- α) to a cell membrane receptor. This triggers a cascade of caspases responsible for the proteolytic events resulting in cell breakdown and death (Dirks and Leeuwenburgh, 2005). Additionally, the release of calcium into the cytosol followed by the stress of the endoplasmic reticulum may result in apoptosis through the activation of cell breakdown and death (Narici and Maffulli, 2010).

As a result of both the neurodegenerative process and muscle cell apoptosis, a loss of motor neurons occurs as we age, leading to a reduction in the number of muscle fibres (Lexell et al., 1988). The total decrease in muscle mass is due to both a reduced fibre size and decreased fibre numbers (Narici and Maffulli, 2010). Before 50 years of age, the loss in muscle mass can be attributed to a loss of PCSA of individual muscle fibres (e.g. atrophy). The fibre size decrease is likely due to both an age-related decrease in hormone growth factor (e.g. IGF) and the decline in physical activity by the older population (Barton-Davis et al., 1999). In addition to the fibre size loss, the number of muscle fibres also decreases by approximately 50% between 50 and 80 years of age (Figure 2-3). The regularity and intensity of physical activity seems to drive, to a substantial degree, the intensity in which the muscle mass will be impacted by the fibre loss. Previous research reported that even physically active seniors are less active than younger individuals in their twenties, thus affecting even more the number and size of fibres (Morse et

al., 2004). However, master athletes that were involved in high level exercise for a life-long period seem to mitigate the age-related effects as a greater muscle fibre size of all types has been reported in this population compared to inactive older adults (Korhonen et al., 2006). Hence, high intensity-level exercise, over a prolonged period of time may mitigate, but does not necessarily prevent, the decline in muscle health as a result of biological ageing.

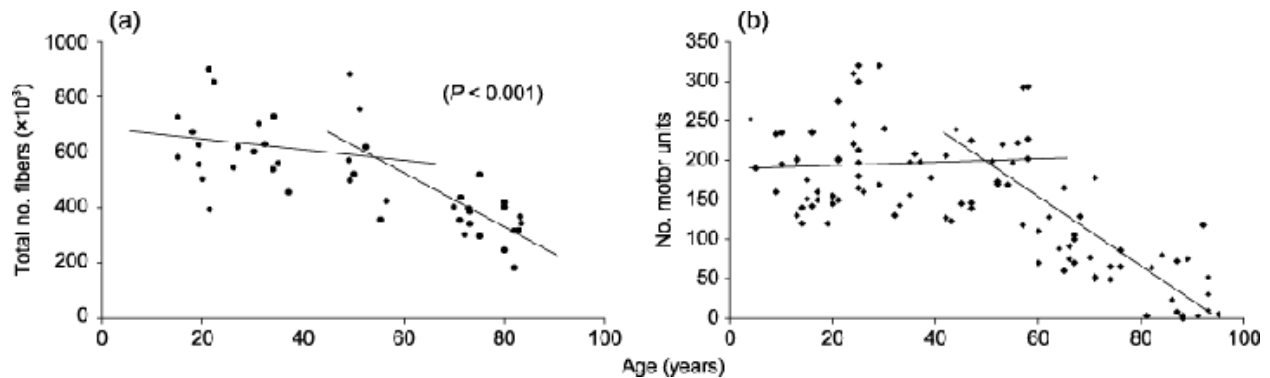


Figure 2-3. Relationship between total number of fibres and age (a) and number of motor units and age (b) according to Faulkner et al. (2007)

Previous studies have reported a decline in performance of 40% in endurance athletes and 60% in weight lifters between the age of 20 to 80 years (Faulkner et al., 2007). Moreover, there is an apparent reduction of the size and shift from faster fibres (type II) toward slower (type I) which may explain the reduction of force generation through the aged muscles (Korhonen et al., 2006) (Figure 2-4). Although, engaging in a physical activity program can slow down or even reverse the muscle fibre atrophy (by means of hypertrophy of the remaining fibres) it is unlikely that it can reverse the fibre number loss due to the neurodegenerative adaptation (Narici and Maffulli, 2010).

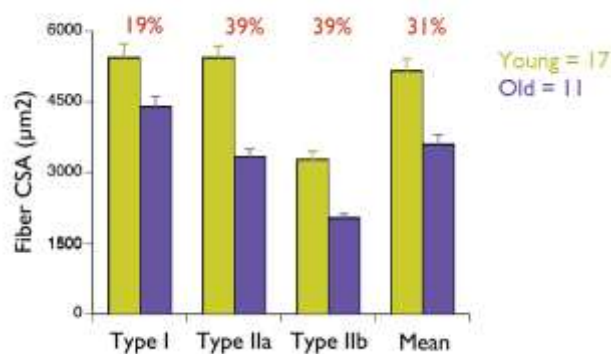


Figure 2-4. Percentage reduction of muscle fibre size across different fibre types in older compared to young adults according to Hunter et al. (1999).

Biological ageing also involves a remodelling of skeletal muscle architecture leading to a reduced pennation angle (Figure 2-5) and decreased fascicle length (Narici et al., 2003). These changes are likely caused by the consequences of muscle atrophy where the volume of contractile tissue is lost, thus reducing the concentration of tissue along the aponeurosis of the tendons. As a result of reduced protein synthesis, also associated with biological ageing and disuse, a removal of parallel and in-series sarcomeres takes place (de Boer et al., 2007). The functional outcome of these aforementioned changes is the loss of muscle power production: the product of force generation and velocity (Narici and Maffulli, 2010).

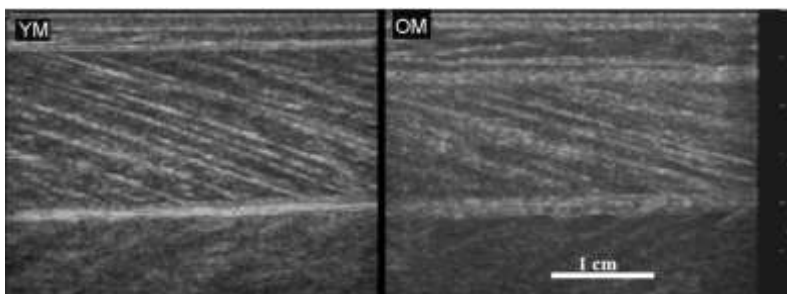


Figure 2-5. Pennation angle of an older male (OM) aged 75 years and a matched young adult male (YM) aged 20 years according to Narici et al. (2008).

2.1.2 Connective Tissue

Biological ageing not only affects the contractile tissues but also all collagenous structures (Viidik, 1982). The main cause of reduced joint mobility with ageing can be attributed to the increased collagen stiffness in the tissues surrounding the joints (capsule, ligaments, tendon and muscles). Although each of these tissues contributes individually to increased joint stiffness, it is challenging to experimentally determine their relative contribution. An increase in collagen cross-links has been associated with biological ageing, particularly in tissues that contain proteins with low turnover, such as collagen, in the articular capsule, ligaments and muscle-tendon units (MTU) (Abate et al., 2010; Kovanen and Suominen, 1988). In addition to the increased collagen cross-linking, there appears to be an increased amount of collagen of the perimysium and endomysium in the muscles (Alnaqeeb et al., 1984), and an increased amount of total collagen located within the muscles as we age (Kovanen, 1989). These structural changes have been followed by mechanical changes such as a decrease in elasticity and tensile strength, and an increased stiffness. In fact, increased muscle passive stiffness has been observed in a number of studies in older adults (Lexell et al., 1988; Vandervoort et al., 1992a). The muscle passive stiffness is driven by both connective tissues in parallel (e.g. extracellular epymisium, perimysium and endomysium) and in series (e.g. tendon) (Edman et al., 1988). Therefore, the accumulation of connective tissues would increase the passive stiffness which have been confirmed by animal models (Wilson et al., 1988). Several studies have also shown that the amount of connective tissue and non-contractile tissue increases with ageing (Barton-Davis et al., 1999). In terms of tendon properties with ageing, recent findings reported that older tendons were approximately 15% more compliant than younger tendons and this difference is likely a result of the changes in the material of the tendon as evidenced by the similarity in the tendon

dimensions between the two age groups (Narici et al., 2008). However, Magnusson et al. (2003) reported an increased tendon thickness in older individuals. In vitro studies have also shown that older tendons are associated with an increased collagen cross-linking, elastin content and type V collagen, and a reduction in collagen crimp angle, water and mucopolysaccharide content (Kjaer, 2004; Tuite et al., 1997). Most of the aforementioned factors would contribute to a reduction in stiffness of the tendon, but the tensile response of a tendon is a reflection of the combined net effect of these factors. Therefore, there is conflicting evidence on whether the tendons differ structurally and mechanically in older individuals. Several studies have also reported reduced muscle fascicle length in older individuals, particularly involving calf muscles (Gajdosik et al., 1999; Newsholme et al., 1988; Vandervoort et al., 1992b). Since an increased passive stiffness has been observed, it is reasonable to assume that the increased stiffness of the connective tissues outweigh the more compliant tendon, if it does exist, in older individuals.

2.2 Age-related functional changes and exercise intervention

2.2.1 Loss of muscle strength

Near the sixth decade of life, a rapid decline in muscle strength begins regardless of gender (Hakkinen et al., 1996). The maximal strength from age 30 to age 80 can decline as much as 30-40% (Komi, 2003) and, as previously discussed, is different across muscle groups with the lower extremity being the most affected (Frontera et al., 1991). In addition to the decline in maximal muscle strength, biological ageing results in an even greater reduction in explosive force production as demonstrated in Figure 2-6 (Hakkinen et al., 1995). This finding also supports the concept previously discussed that the atrophy involving fibre type II may be greater than that involving fibre type I. While sarcopenic-related alterations, would explain this impaired function, a greater reduction in muscle strength compared to muscle mass has also been observed

in older adults (Frontera et al., 2000). This suggests that structural changes in muscle fibres and motor neurons are accompanied by neuromuscular adaptations. In fact, an impaired motor neuron rate coding has also been displayed by older adults, where the average motor neurons discharge rates during maximal voluntary isometric contraction (MVIC) is reduced (Rubinstein and Kamen, 2005). The voluntary activation of the muscle fibre would therefore be impaired by this fact. Furthermore, the presence of co-contraction of antagonist muscles has been documented in older adults but this co-activation is suggested to be more pronounced in submaximal contractions (Patten and Kamen, 2000). Hence, the combination of both muscular changes and neuromuscular adaptations likely contributes to the remarkable decline in muscle function with biological ageing.

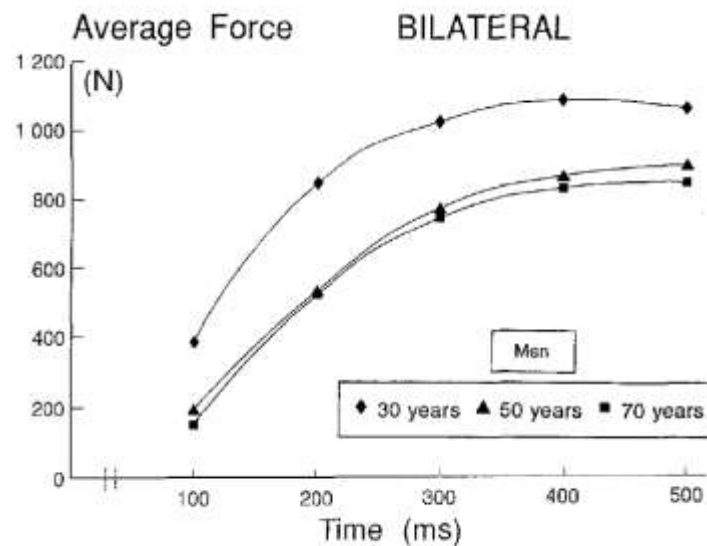


Figure 2-6. Average force-time curves of isometric bilateral leg extension action in men of three different age groups according to Hakkinen, et al. (1995).

2.2.2 Interventions to minimize muscle strength loss

As discussed previously, biological ageing affects not only the muscle fibre itself but also involves neuromuscular and tendinous adaptations. Strengthening exercises have been proposed as an effective method to counteract or even reverse, to some extent, the detrimental effects of sarcopenia associated with biological ageing (Macaluso and De Vito, 2004). In fact, muscle hypertrophy of 5-17% has been documented in older subjects following a resistance training regime of approximately 12 weeks in duration (Ferri et al., 2003). In addition, an increased length of muscle fascicles and an increased pennation angle following 14 weeks of a strengthening program has been observed in elderly individuals (Reeves et al., 2004a; Reeves et al., 2004b). A higher number of sarcomeres in parallel are likely to cause an increased maximal force production whereas an increased number of sarcomeres in series would likely result in an altered muscle force-length relationship. Furthermore, resistance training not only affects the contractile tissue but also the connective tissue in older adults (Narici et al., 2008). It has been shown that the patellar tendon increases its stiffness and Young's modulus following 14 weeks of a resistance training program by 65% and 69%, respectively (Figure 2-7) (Reeves et al., 2003). Changes in the structural and mechanical properties of the tendons following intervention would alter the effectiveness of the force produced by the muscles. An important role of the tendon is to transmit forces from the muscles to the bones (Nordin and Frankel, 2012) with a stiffer tendon providing a higher rate of contractile force transmission (Reeves et al., 2003). The functional implication of optimal tendon stiffness is the rapid generation of joint torque which is paramount, for instance, to respond to a momentary loss of balance; which is a repetitive process that occurs while running. However, the net MTU function is dependent on the interaction between muscle and tendon adaptations following intervention. Hence, the increased number of

sarcomeres in series observed following a period of resistive loading might occur to optimize the operating range of the muscle fibres (shortening) according to the tendon stiffness. Nevertheless, this proposed scenario needs to be confirmed experimentally.

All these positive adaptations in MTU with training would be ineffective if the neuromuscular control was impaired. However, it has been reported that older adults present an enhanced activation of the primary muscles along with an improved activation of the synergist muscles and a reduction in the activation of the antagonist muscles, thus resulting in an enhanced net force production (Enoka, 1988; Hakkinen and Pakarinen, 1994). Hence, strength training not only results in increased activation of the agonist muscle group but also reduces the co-activation of the antagonist muscles, likely by training learning effects.

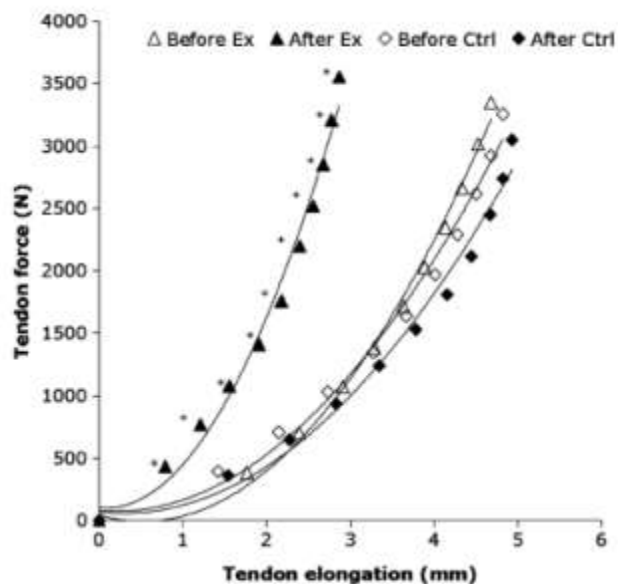


Figure 2-7. The patellar tendon force-elongation curves for the intervention group and control group before and after 14 weeks of resistive training according to Reeves, et al. (2003).

The aforementioned MTU and neural adaptations are suggestive of improvement in muscle function. In fact, increased muscle strength has been documented in older adults following resistance exercise in both single muscle fibre and whole muscle levels (Reeves et al., 2004a; Trappe et al., 2001; Trappe et al., 2000). Particularly, at the level of the whole muscle, strength training has been shown to increase specific force (maximum fascicle force divided by muscle PCSA) following a 14-week program (Reeves et al., 2004a). An increase in the force-producing capability of elderly muscle per unit area is, therefore, one factor contributing to the observed strength gains following resistive training programs (Narici et al., 2005). Other studies have consistently reported muscle strength gains in older adults following resistance exercise (Fiatarone et al., 1994; Hakkinen et al., 2000). However, as highlighted earlier the muscle force-length relationship may be affected by the combined adaptations in the MTU with strengthening exercises. In fact, Reeves, et al. (2004b) has observed that the knee extensor torque production following training was not constant over a joint range of motion (ROM) in older individuals, indicating that a shift in the optimal angle occurred, with longer lengths of muscle fascicles being able to generate the same force compared to prior training (Figure 2-8). Whether or not older runners modify their pattern to optimize the use of the muscles remains unanswered.

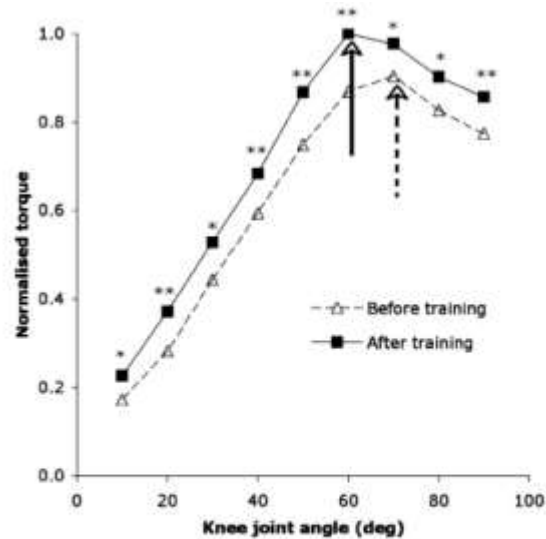


Figure 2-8. Knee extensor angle-torque relation normalized relative to the maximum torque after resistive exercise training according to Reeves et al.(2004b).

2.2.3 Loss in flexibility

The loss of both active and passive lower extremity joint ROM has been reported in older individuals (Grimston et al., 1993; James and Parker, 1989; Scott et al., 2007). The reduction in the length of the muscles, as a result of the reduced number of sarcomeres, and the increased stiffness of the connective tissues surrounding the joints have been suggested as the major cause of the reduced overall ROM documented in the older population (Wachtel et al., 1995), although the tendons become more compliant as we age (Narici et al., 2008). It has also been reported that muscles which remain in shortened positions for a prolonged time tend to exhibit a reduction in the total number of sarcomeres (Kuno et al., 1998) whereas muscles immobilized in a stretched position present an increased number of sarcomeres (Tabary et al., 1972). Therefore, a reduction in the daily physical activity with ageing presumably reduces the opportunity to stretch the muscles, thus leading to a concomitant reduction in the number of sarcomeres.

A decline in joint mobility of as much as 20-30% for the hips and spine and nearly 30-40% for ankle dorsiflexion by the age of 70 years, particularly in women has been reported (Chodzko-Zajko et al., 2009). In fact, reduced calf muscle flexibility has systematically been observed in older adults (James and Parker, 1989; Vandervoort et al., 1992b). Another study involving more than one thousand subjects reported a decline of more than 20% in hip extension ROM in older people compared to young (Roach and Miles, 1991). Nonaka et al. (2002) analyzed the passive ROM of the hip and knee joints using a geometrical approach that allowed the evaluation of the ROM under the effects of both monoarticular and biarticular muscles. These authors reported a progressive reduction in the passive ROM of the hip joint with advancing age (Figure 2-9) whereas knee joint flexibility remained unaltered. There is a dearth of research investigating whether active older individuals present improved flexibility compared to sedentary older people and more similar to young subjects.

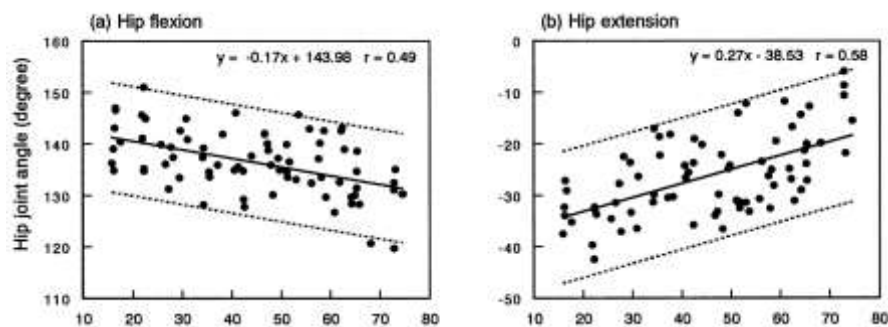


Figure 2-9. Maximal hip flexion and extension angles as a function of age according to Nonaka, et al. (2002).

2.2.4 Interventions to minimize flexibility loss

Flexibility exercises have been generally recommended for the older population to counteract the negative effects of biological ageing, although no specific recommendations have

been proposed for older runners (Chodzko-Zajko et al., 2009). Previous studies have indicated that the loss in joint ROM with ageing can be modified through intervention exercises. For example, Richard L. Gajdosik (2005b) reported a significant improvement in maximal dorsiflexion ROM, maximal passive resistive force (Figure 2-10) and the absorbed and retained passive elastic energy after an 8-week calf muscle static stretching program compared to baseline measurements in older women.

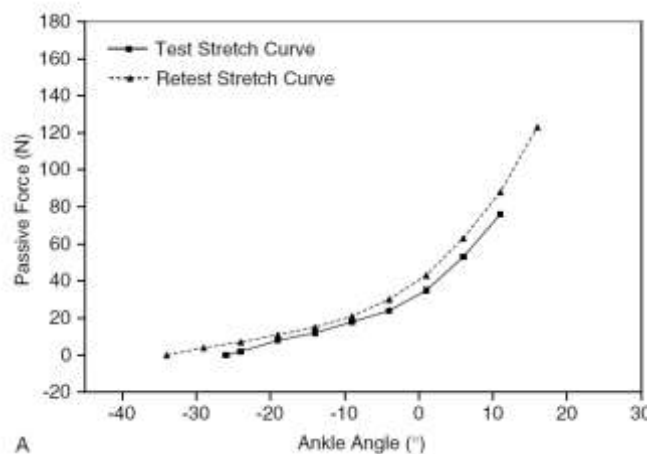


Figure 2-10. Passive stretching curves showing that the calf muscles increased their maximal length, length extensibility, maximal passive resistive force and mean passive resistive force Gajdosik et al. (2005a).

Similar findings have been reported for hip ROM. For instance, Kerrigan et al. (2003) reported significant increases in hip extension ROM following a 10-week home-based hip flexor stretching program. Likewise, Christiansen (2008) reported improved hip extension and ankle dorsiflexion ROM in older individuals following a similar home-based stretching program. A systematic review and meta-analysis investigated the effect of static ankle dorsiflexion on ankle flexibility and reported small but significant increases in ankle dorsiflexion flexibility following a static stretching program (see Figure 2-11) (Radford et al., 2006).

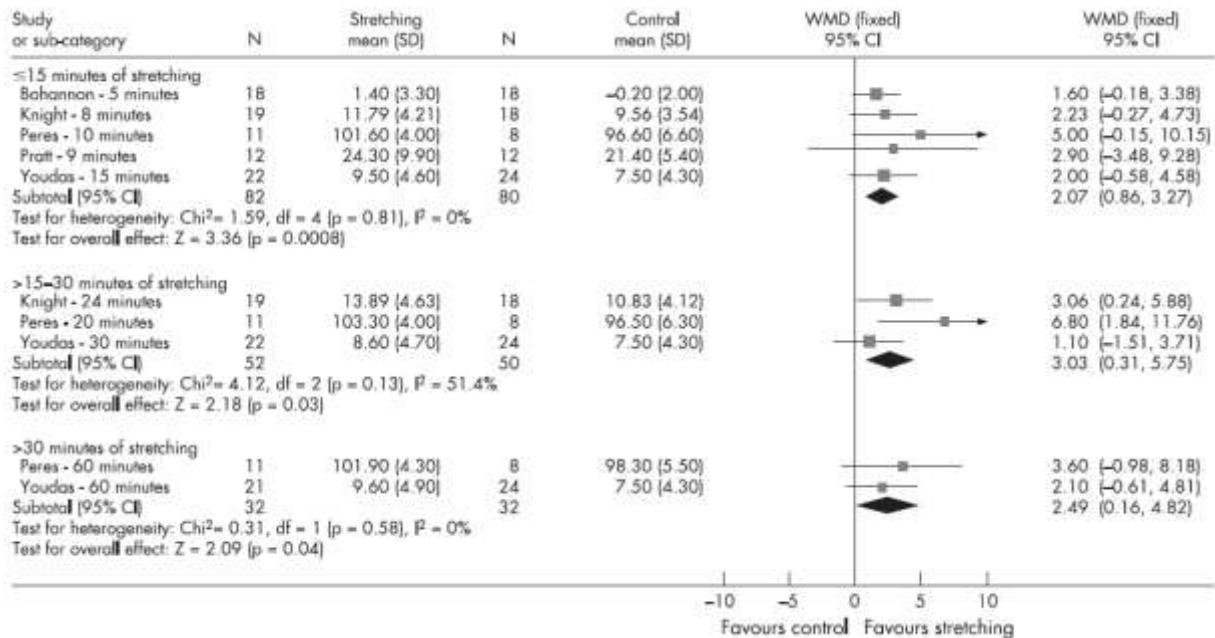


Figure 2-11. Meta-analyses of the studies that investigated the effect of stretching on ankle dorsiflexion ROM. The order of the columns are as follows: study author and stretching duration, sample size (N) of stretching group (FXG), mean and standard deviation (SD) of ankle dorsiflexion ROM of the FXG, sample size of the control group (CTG), mean and SD of ankle dorsiflexion ROM of the CTG and forest plots with the 95% confidence interval (CI) of the point estimate according to Radford, et al. (2006).

While these studies strongly suggest that stretching exercises can improve joint ROM irrespective of the duration of the exercise, it is still unclear whether these exercises would provide clinical benefits and positively alter gait impairments (Radford et al., 2006; Stathokostas et al., 2012).

2.3 Age-related running gait biomechanical adaptations

Previous studies strongly suggest that neuromuscular gait adaptations are a response to structural (e.g. sarcopenia) and functional impairments (e.g. muscle weakness and joint stiffness) (McGibbon, 2003). **Error! Reference source not found.** illustrates the proposed hypothesis of how lack of *muscle strength* and *joint mobility* potentially lead to changes in gait patterns (McGibbon, 2003). However, there is a dearth of literature that has simultaneously examined clinical (i.e. flexibility and strength) and biomechanical factors, particularly in older adult runners. Hence, a cause and effect relationship between these factors has not been established yet.

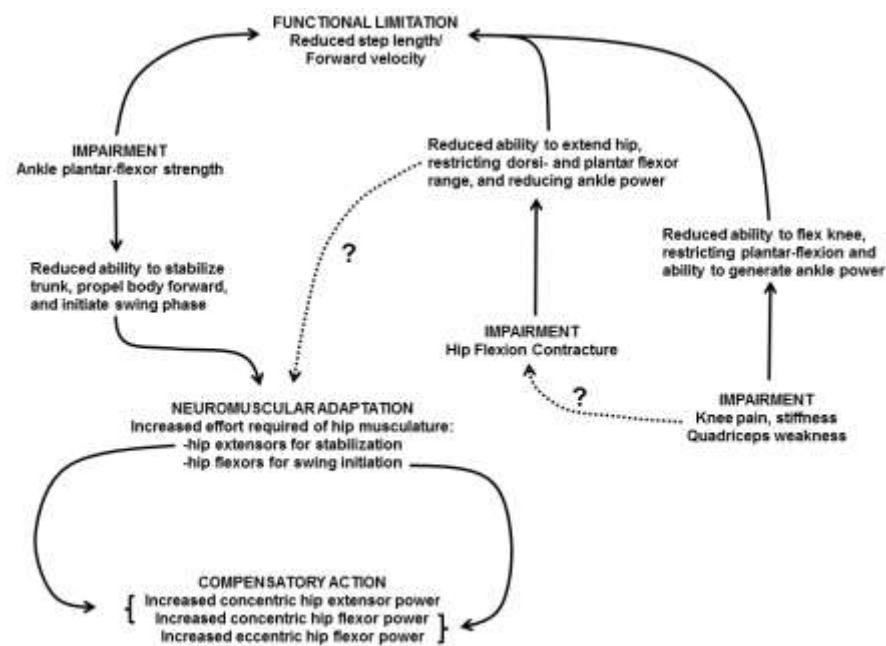


Figure 2-12. Schematic diagram of the hypothesis that neuromuscular adaptations are a response to impairment and play a key role in causing changes in gait of the elderly. The diagram links the impairments to the functional limitation and the neuromuscular adaptation, and its compensatory function. The dashed line arrows with "?" indicate potentially feasible scenarios not completely

supported by the available data in the literature. Adapted from McGibbon (2003).

Although age-related gait adaptations in walking have widely been explored (McGibbon, 2003), there are only few studies that have documented gait biomechanical patterns in older adults during running (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). In Tables 3.1 through 3.4 a comprehensive summary of the results from previous studies that examine running biomechanical patterns in older adults is provided. Effect sizes (ES) are presented to better enhance the understanding about the age-related differences in biomechanical variables (Equation 2.1). In the following sub-sections the known age-related gait biomechanical adaptations will be discussed in detail.

$$ES = \frac{\bar{X}_o - \bar{X}_y}{SD_{pooled}} \quad \text{Equation 2.1}$$

Where \bar{X}_o is the average of the older group, \bar{X}_y is the average of the young group and SD_{pooled} is the pooled standard deviation across groups of runners.

2.3.1 Temporal-spatial gait parameters

A summary and comparison of temporal-spatial parameters documented in the literature is provided in Table 2-1. Older runners choose to run slower when they are allowed to self-select their pace (Bus, 2003). In addition, older runners demonstrate reduced stride length (ES: 0.37 to 0.82) and increased stride frequency (ES: 0.38 to 0.59) at both controlled (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005) and self-selected speeds (Bus, 2003). Previous research also suggests that the decreased stride length and increased stride frequency may be related to reduced muscle force output as a result of biological ageing (Cavagna et al.,

2008). In fact, it has been observed that older runners spend less time in the flight phase ($ES=0.56$) (Karamanidis and Arampatzis, 2005) and exhibit an increased duty factor (ratio between contact time and total stride cycle time) compared to young adults ($ES=0.49$) (Karamanidis and Arampatzis, 2005). The higher duty factor has been suggested as a protective mechanism adopted by older runners through increasing the centre of mass (COM) transport and time of foot-ground contact while running (Karamanidis and Arampatzis, 2005). Unfortunately, the lack of documentation regarding clinical factors (muscle strength and flexibility) in older runners prevents further insight into whether the observed differences in running gait patterns are related to degenerative musculoskeletal adaptations.

Table 2-1. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated running temporal-spatial variables in young and older adult runners.

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Bus (2003)	Stride Length (m)	2.91	0.17	2.41	0.22	13	16	0.82	self-selected
Bus (2003)	Stride Length (m)	2.61	0.14	2.43	0.11	13	16	0.37	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Step Length (cm)	99.5	3.0	93.9	7.6	9	20	0.53	controlled @ 2.7 m/s
Fukuchi and Duarte (2008)	Stride Length (m)	2.23	0.12	1.97	0.25	17	17	0.51	controlled @ 3.1 m/s
Bus (2003)	Stride Frequency (Hz)	1.3	0.06	1.38	0.06	13	16	0.38	self-selected
Bus (2003)	Stride Frequency (Hz)	1.28	0.07	1.38	0.06	13	16	0.41	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Stride Frequency (Hz)	1.31	0.08	1.41	0.1	9	20	0.42	controlled @ 2.7 m/s
Fukuchi and Duarte (2008)	Stride Frequency (Hz)	1.37	0.07	1.58	0.32	17	17	0.59	controlled @ 3.1 m/s
Karamanidis et al. (2005)	Duty factor (%)	35.5	2.3	38.9	3.1	9	20	0.49	controlled @ 2.7 m/s
Karamanidis et al. (2005)	Flight time (ms)	112	19	80	25	9	20	0.56	controlled @ 2.7 m/s

*Abbreviations: NS=number of subjects; ES=effect size; Y=young; O=older

2.3.2 Joint kinematics

Changes in running gait joint kinematics have been previously reported in older runners (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). Table 2-2 summarizes joint kinematic variables that have been investigated along with the corresponding effect sizes. Older runners exhibit increased knee flexion upon landing (ES: 0.21 to 0.44) and a reduced knee excursion in the sagittal plane (ES: 0.35 to 0.66) compared to younger runners (Bus, 2003; Fukuchi and Duarte, 2008). Older runners also exhibit increased peak knee internal rotation (ES: 0.81) (Lilley et al., 2011), although Fukuchi and Duarte (2008) failed to show the same trend and reported that older runners exhibited slightly reduced knee internal rotation peak (ES: 0.11) as compared to their younger counterparts. These contrasting results may be partially explained by the increased variability in measuring the secondary planes of motion (frontal and transverse) of the knee (Ramsey and Wretenberg, 1999). Moreover, older runners display reduced ankle plantar flexion ROM (Bus, 2003; Karamanidis and Arampatzis, 2005) with a wide range of differences reported in the literature (ES: 0.06 to 0.40). This observation may be related to the fact that the calf MTU is most affected by ageing which commonly results in lack of flexibility (see section 2.2.3).

Rearfoot kinematics has been considered an important variable to investigate in running biomechanics due its association to running-related injuries. There has been contrasting evidence concerning ankle movement in the frontal plane with some research presenting lack of differences across age groups (Bus, 2003) while others report earlier peak rearfoot eversion (Fukuchi and Duarte, 2008), and others report greater peak rearfoot eversion (Lilley et al., 2011). These conflicting results may be explained by gender differences between mature female runners (Lilley et al., 2011) and older males (Bus, 2003; Fukuchi and Duarte, 2008). Nevertheless, if

older runners exhibit increased rearfoot eversion at a higher rate, this result could correspond to increased strain rate in the soft tissues surrounding the ankle joint, thus potentially resulting in higher injury rates compared to younger runners. Fukuchi and Duarte (2008) also reported an increased toe-out angle at touchdown in elderly runners and these authors suggested that the elderly subjects adopted this pattern as a protective mechanism to reduce the joint loadings in the medial compartment of the knee. Although, this proposed mechanism could not be examined in their study, it has, in fact, also been observed in a previous walking study (Chang et al., 2007).

Table 2-2. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated stance phase running gait kinematic variables in young and older adult runners.

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Bus (2003)	Knee FLX @ HS (°)	4.4	3	9.1	4.3	13	16	0.43	self-selected
Bus (2003)	Knee FLX @ HS (°)	4.2	3.6	9.8	4.3	13	16	0.44	controlled @ 3.34 m/s
Fukuchi and Duarte (2008)	Knee FLX @ HS (°)	5	6	10	6	17	17	0.21	controlled @ 3.1 m/s
Bus (2003)	Knee FLX ROM (°)	38.9	4.4	29.4	3.5	13	16	0.61	self-selected
Bus (2003)	Knee FLX ROM (°)	39.6	4	30.2	3.9	13	16	0.66	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Knee FLX ROM (°)	26.8	2.8	23.8	3.6	9	20	0.36	controlled @ 2.7 m/s
Bus (2003)	Knee EXT ROM (°)	29	4.5	22.3	2.9	13	16	0.43	self-selected
Bus (2003)	Knee EXT ROM (°)	29.8	4.3	22.2	3.5	13	16	0.50	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Knee EXT ROM (°)	24.7	3.1	18.1	5.9	9	20	0.66	controlled @ 2.7 m/s
Fukuchi and Duarte (2008)	Knee EXT ROM (°)	33	5	26	3	17	17	0.35	controlled @ 3.1 m/s
Bus (2003)	Ankle DF ROM (°)	17.8	2.4	15.9	1.8	13	16	0.23	self-selected

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Bus (2003)	Ankle DF ROM (°)	17.8	2.4	15.9	1.8	13	16	0.23	self-selected
Bus (2003)	Ankle DF ROM (°)	18.4	2	16	1.9	13	16	0.34	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Ankle DF ROM (°)	25.8	5.5	22.7	6.4	9	20	0.19	controlled @ 2.7 m/s
Bus (2003)	Ankle PF ROM (°)	46.8	4.5	41.3	5.6	13	16	0.34	self-selected
Bus (2003)	Ankle PF ROM (°)	46.9	4.7	41.3	6.3	13	16	0.33	controlled @ 3.34 m/s
Karamanidis et al. (2005)	Ankle PF ROM (°)	43.1	4.8	37.3	6.8	9	20	0.40	controlled @ 2.7 m/s
Fukuchi and Duarte (2008)	Ankle DF-PF ROM (°)	23	4	22	2	17	17	0.06	controlled @ 3.1 m/s
Bus (2003)	Ankle EV peak (°)	-12.8	4	-12	3.2	13	16	0.06	self-selected
Bus (2003)	Ankle EV peak (°)	-13.1	4.2	-11.8	3.2	13	16	0.09	controlled @ 3.34 m/s
Fukuchi and Duarte (2008)	Ankle EV peak (°)	-10	6	-12	6	17	17	0.08	controlled @ 3.1 m/s
Lilley et al. (2011)	Ankle EV peak (°)	6.7	1.6	12.3	2.1	15	15	0.91	controlled @ 3.5 m/s
Bus (2003)	Ankle EV ROM (°)	19	5.4	16.9	4.9	13	16	0.11	self-selected
Bus (2003)	Ankle EV ROM (°)	19.5	6	16.5	4.5	13	16	0.14	controlled @ 3.34 m/s
Fukuchi and Duarte (2008)	Ankle EV ROM (°)	12	4	11	3	17	17	0.06	controlled @ 3.1 m/s

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Lilley et al. (2011)	Knee IR peak (°)	2.3	1.6	7.4	2.8	15	15	0.81	controlled @ 3.5 m/s
Fukuchi and Duarte (2008)	Knee IR peak (°)	7	7	4	3	17	17	0.11	controlled @ 3.1 m/s
Fukuchi and Duarte (2008)	Tibial IR ROM (°)	12	2	9	2	17	17	0.37	controlled @ 3.1 m/s
Bus (2003)	Max. Vertical Speed Tibia (m/s)	0.62	0.13	0.66	0.13	13	16	0.09	self-selected
Bus (2003)	Max. Vertical Speed Tibia (m/s)	0.52	0.12	0.67	0.1	13	16	0.36	controlled @ 3.34 m/s

*Abbreviations: HS=heel strike; FLX=flexion; EXT=extension; DF=dorsiflexion; PF=plantarflexion; IR=internal rotation; EV=eversion; NS=number of subjects; ES=effect size; Y=young; O=older

2.3.3 Joint kinetics

Due to the degenerative changes in muscle strength and power with ageing, some atypical joint loading distribution is expected in older adults. A summary and comparison of joint kinetic parameters in older runners documented in the literature is provided in Figure 2-3.

The most remarkable gait adaptation as a result of the ageing process is the distal-to-proximal shift in the joint moments and powers across the lower extremity joints to generate the same overall support moment compared to young adults (DeVita and Hortobagyi, 2000; Savelberg et al., 2007). It has been suggested that the distal joints (e.g. ankle joint) are the most affected by biological ageing. Considering the higher demand running places on the skeletal muscles compared to walking, a greater shift in joint moment redistribution would be expected. However, there is limited understanding about the distribution of lower extremity joint loading in older runners as previous studies have only investigated individual planes of motion of single joints (Karamanidis and Arampatzis, 2005; Lilley et al., 2011). In particular, Karamanidis and Arampatzis (2005) observed reduced peak ankle moment and power in older runners in the sagittal plane, however, no significant differences were found in the knee joint loading. The lack of information about hip joint loadings limited our understanding on whether older adults also present the distal-to-proximal shift during running.

Since a higher running-related injury incidence has been claimed in older runners (Fields, 2011) and it has been linked to altered gait biomechanics (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011), it is therefore, imperative to examine whether atypical joint biomechanical risk factors are present in older runners. Lilley, et al. (2011) recently reported an increased peak knee abduction moment in female mature runners which has been suggested as a risk factor for developing conditions such as knee osteoarthritis (Miyazaki et

al., 2002) and patellofemoral pain syndrome (PFPS) (Stefanyshyn et al., 2006). Unfortunately, a dearth of literature on joint kinetic related factors for injuries has been identified which hampers any definitive conclusion on potential mechanism for running-related injuries.

Table 2-3. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated stance phase running gait joint kinetic variables in young and older adult runners.

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Karamanidis et al. (2005)	Peak Knee EXT Moment (Nm/kg)	1.81	0.37	1.66	0.45	9	20	0.14	controlled @ 2.7 m/s
Karamanidis et al. (2005)	Peak Ankle EXT Moment (Nm/kg)	3.15	0.57	2.63	0.43	9	20	0.32	controlled @ 2.7 m/s
Lilley et al. (2011)	Peak Knee ABD Moment (Nm/kg)	0.96	0.53	2.5	0.53	15	15	0.76	controlled @ 3.5 m/s
Karamanidis et al. (2005)	Max. Knee Sagittal Power (W/kg)	4.44	0.76	4.1	1.19	9	20	0.14	controlled @ 2.7 m/s
Karamanidis et al. (2005)	Min. Knee Sagittal Power (W/kg)	-5.26	1.37	-4.63	1.72	9	20	0.15	controlled @ 2.7 m/s
Karamanidis et al. (2005)	Max. Ankle Sagittal Power (W/kg)	10.55	1.93	8.33	2.48	9	20	0.38	controlled @ 2.7 m/s
Karamanidis et al. (2005)	Min. Ankle Sagittal Power (W/kg)	-12.11	4	-8.78	2.9	9	20	0.29	controlled @ 2.7 m/s

*Abbreviations: EXT=extension; ABD=abduction; NS=number of subjects; ES=effect size; Y=young; O=older

2.3.4 Ground reaction forces

During running, impact with the ground causes forces to transmit to the body at a higher rate compared to walking. Previous studies have reported that older runners demonstrate an increased ground reaction force (GRF) vertical impact loading rate (Bus, 2003; Lilley et al., 2011) and vertical impact peak (Bus, 2003) but a reduced active vertical GRF peak (Bus, 2003; Karamanidis and Arampatzis, 2005). A summary of the results from the literature is provided in Table 2-4. These results could be explained by the different running speeds adopted, however, Bus (2003) examined younger and older runners during controlled and self-selected running speeds and obtained similar results. To further investigate this finding, these authors quantified the vertical speed of the shank segment shortly before heel strike and observed that older runners did not present a significant correlation between vertical shank speed and impact force. In fact, it has been postulated that loss of elasticity and atrophy of the heel pad with ageing would compromise the shock absorption ability in older individuals (Hsu et al., 1998). In addition, older runners exhibited a reduced vertical GRF impulse and a reduced GRF horizontal impulse in both absorption and propulsion phases of running (Bus, 2003; Karamanidis and Arampatzis, 2005). The reduced muscle capacity (strength and contraction velocity) with ageing could act to impair our ability to propel our body towards toe-off during running.

Table 2-4. Mean, 1SD, Cohen's d effect size, number of subject per group and the gait speed adopted in previous studies that investigated running gait GRF variables in young and older adult runners.

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Bus (2003)	Max Loading Rate (BW/s)	85.5	19.4	107.5	22.3	13	16	0.32	controlled @ 3.34mps
Bus (2003)	Max Loading Rate (BW/s)	102.3	23.4	106.9	26.7	13	16	0.06	self-selected
Lilley et al. (2011)	Max Loading Rate (BW/s)	36.5	7.6	54.9	8.63	15	15	0.63	controlled @ 3.5 mps
Bus (2003)	Peak impact Force (BW)	1.89	0.22	1.89	0.26	13	16	0.00	self-selected
Bus (2003)	Peak impact Force (BW)	1.7	0.22	1.91	0.17	13	16	0.27	controlled @ 3.34mps
Lilley et al. (2011)	Peak impact Force (BW)	1.9	0.5	2	0.6	15	15	0.05	controlled @ 3.5 mps
Bus (2003)	Active Peak Vertical GRF (BW)	2.78	0.2	2.5	0.16	13	16	0.40	self-selected
Bus (2003)	Active Peak Vertical GRF (BW)	2.64	0.22	2.49	0.14	13	16	0.20	controlled @ 3.34mps
Karamanidis et al. (2005)	Active Peak Vertical GRF (N/kg)	23.68	2.45	21.62	1.97	9	20	0.29	controlled @ 2.7mps
Bus (2003)	Vertical Force Impulse (BW.s)	0.38	0.02	0.36	0.02	13	16	0.28	self-selected
Bus (2003)	Vertical Force Impulse (BW.s)	0.39	0.02	0.36	0.02	13	16	0.42	controlled @ 3.34mps

Reference	Variable	Young		Older		NS		ES	Speed
		Mean	SD	Mean	SD	Y	O		
Karamanidis et al. (2005)	Vertical Force Impulse (Ns/kg)	3.64	0.14	3.37	0.2	9	20	0.63	controlled @ 2.7mps
Bus (2003)	Braking Impulse (BW _s)	0.24	0.05	0.19	0.02	13	16	0.29	self-selected
Bus (2003)	Braking Impulse (BW _s)	0.22	0.03	0.19	0.02	13	16	0.29	controlled @ 3.34mps
Karamanidis et al. (2005)	Braking Impulse (Ns/kg)	-0.2	0.02	-0.17	0.03	9	20	0.49	controlled @ 2.7mps
Bus (2003)	Propulsive Impulse (BW _s)	-0.22	0.03	-0.18	0.03	13	16	0.38	self-selected
Bus (2003)	Propulsive Impulse (BW _s)	-0.21	0.02	-0.18	0.03	13	16	0.41	controlled @ 3.34mps
Karamanidis et al. (2005)	Propulsive Impulse (Ns/kg)	0.19	0.02	0.17	0.03	9	20	0.32	controlled @ 2.7mps

*Abbreviations: Max=maximal; BW=body weight; NS=number of subjects; ES=effect size; Y=young; O=older

2.3.5 Interventions to minimize changes in gait biomechanics

Increased risk for injury and falls has been a common motive for recommending flexibility and resistance training programs for older adults (Chodzko-Zajko et al., 2009). In fact, a position statement elaborated by scientific panels notes that these exercises may enhance postural stability, balance and gait patterns (Garber et al., 2011). In light of the presence of atypical running patterns described earlier in this section associated with musculoskeletal dysfunctions and the higher incidence of injuries, these exercise programs may therefore benefit older runners towards restoring typical gait. However, to the best of our knowledge no consistent link has been shown between such exercises and changes in gait patterns in older individuals, particularly in running.

2.3.5.1 Flexibility exercises

Flexibility are generally recommended for runners as a positive means to prevent injuries (Jenkins and Beazell, 2010), however the evidence supporting such recommendations is sparse. It has been postulated that flexibility training would benefit older individuals to a greater extent compared to young adults since their loss of joint ROM is more pronounced (Stathokostas et al., 2012). Kerrigan, et al. (2003) examined the gait kinematics and kinetics at comfortable and fast walking speeds before and after an 8-week home-based hip extensor stretching exercise program in older individuals. The authors reported no post-program improvements in dynamic hip extension during walking, although ankle plantar flexion motion and static hip extension ROM were significantly improved after the intervention. In a similar study, Christiansen (2008) also reported no significant changes in stride length and kinematic gait parameters following a home-based stretching program; although the subjects walked faster at a freely chosen speed. Rodacki

et al. (2009) examined the transient effects of a single hip flexor stretching exercise session on gait kinematics. The authors reported improvements in dynamic hip extension angle and increased gait speed after intervention. An increased pelvic tilt, pelvic rotation, step length and swing duration; along with a decreased stance and double-support duration were also observed following intervention (Rodacki et al., 2009). Unfortunately, the lack of a younger group weakens the external validity of these studies. Moreover, while walking speed is positively affected by flexibility training, the differences in walking speed across studies make comparisons difficult as highlighted in the review by Stathokostas, et al. (2012).

Despite the fact that stretching exercises have been recommended as a preventive measure for running-related injuries (Jenkins and Beazell, 2010), the studies described above have focused on the effects of stretching programs on **walking** gait. There have been no studies that have investigated either the transient or the long-term effect of a flexibility program on **running** biomechanical patterns in older runners, and only a handful of investigations involved younger runners. For example, Davis Hammonds et al. (2012) found no difference in lower extremity running kinematics immediately following passive hamstring stretching of young runners compared to control subjects, despite increases in passive hip ROM. Due to the nature of running where higher speeds, an airborne phase, and higher impact forces are experienced, increases in joint ROM are required compared to walking (Novacheck, 1998). Hence, it is reasonable to speculate that running forces the joints to function kinematically closer to the available ROM. Considering that biological ageing reduces the available joint ROM, an increased flexibility, as a result of stretching exercises, would, in turn, benefit older runners by buffering the joint ROM. Nonetheless, future research addressing this topic is warranted and highly desirable.

2.3.5.2 Strengthening exercises

Similar to flexibility studies, few studies have investigated the effects of a strengthening program on gait parameters and of those, they were primarily examining walking patterns, particularly focusing on fall-related variables (Lopopolo et al., 2006; Persch et al., 2009). As discussed previously, resistance training has shown positive effects dependent upon the training task. However, an important question is whether training effects can be transferred from the strength training task to other tasks such as walking and running. A systematic review conducted by Lopopolo et al. (2006) showed a significant effect of strength training on gait speed even though the authors did not consider the results to be clinically meaningful (see forest plots of the reviewed studies) in Figure 2-13.

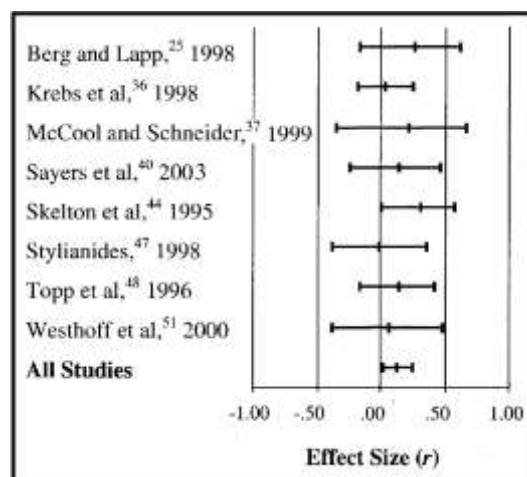


Figure 2-13. Forest plots of 8 studies using strength training to affect habitual gait speed according to Lopopolo et al. (2006).

In another study, Persch et al. (2009) conducted a randomized controlled trial (RCT) to examine the effects of a 12-week lower limb strength training program on walking kinematic parameters in elderly women. The Z-score analysis revealed that strength training was effective

in reversing gait impairments since the gait speed, stride length, cadence and toe clearance became more similar to normative values of young healthy women (Figure 2-14). Similarly, Pijnappels et al. (2008) reported an increased rate of moment generation, particularly at the ankle, following 16-weeks of resistance training in a small sample of elderly people, suggesting that they adopted a more effective recovery pattern after tripping compared to controls.

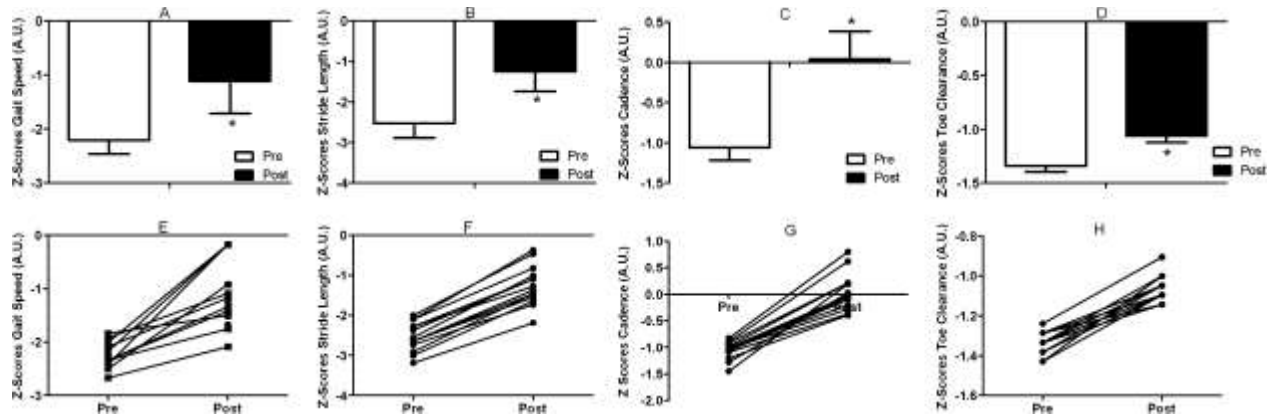


Figure 2-14. Mean \pm SD Z-scores (A–D panels) and individual Z-scores (E–H panels) (arbitrary units) for gait speed, stride length, cadence, and toe clearance in pre- and post-training period for experimental group according to Persch, et al. (2009). *Significantly different from pre-training ($P < .001$).

Surprisingly, there were no studies on running biomechanical patterns despite the increased participation of older individuals in running races (Jokl et al., 2004) and the consequent increased rate of injury (Fields, 2011; McKean et al., 2007; Taunton et al., 2003). Nonetheless, few studies have investigated the effects of resistance training on running biomechanics in younger individuals in both healthy (Snyder et al., 2009; Willy and Davis, 2011) and pathological conditions (Earl and Hoch, 2011; Ferber et al., 2011). Snyder et al. (2009) examined the effects of a six-week hip closed-kinetic chain strengthening program for hip

rotators, on hip strength and running gait biomechanical pattern in healthy women. The authors found a combination of changes, as a result of increased muscle strength, that may reduce injury risk in runners such as reduced ankle eversion ROM, ankle inversion moment and knee abduction moment and an increased hip adduction ROM (Figure 2-15), although hip adduction has also been linked to running injuries in other study (Noehren et al., 2012).

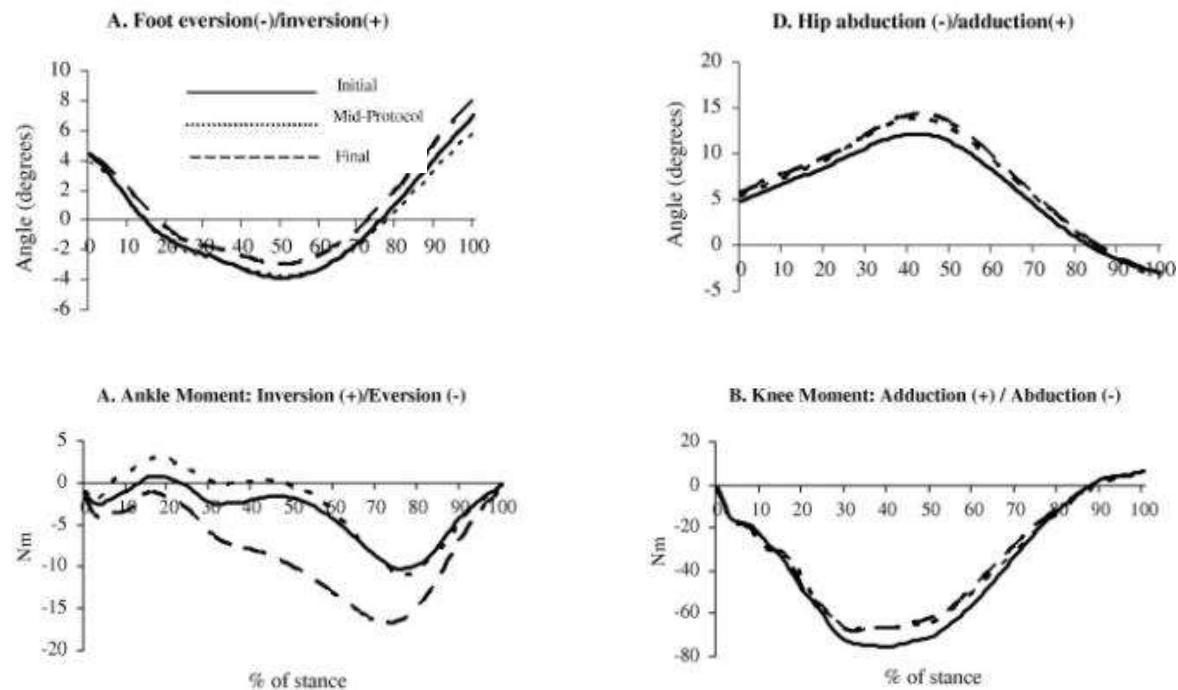


Figure 2-15. Group ensemble averages of time-series joint kinematics and kinetics during the stance phase of running for the three testing sessions (initial, mid and final). Foot inversion/eversion angle (top left), hip abd/add angle (top right), ankle inversion/eversion moment (bottom left) and knee add/abd moment (bottom right) according to Snyder, et al. (2009).

In contrast, Willy and Davis (2011) recently conducted a block-randomized controlled trial study in healthy female runners and found no differences in running gait kinematics after a hip-based strengthening intervention, although significant improvements in muscle force output

and squatting kinematics were shown. Considering that a squat training program was incorporated into the intervention group along with hip strengthening, the specificity between the mode of training and testing might have influenced the results as acknowledged by the authors (Willy and Davis, 2011). Ferber et al. (2011) examined the effects of a 3-week hip abduction strengthening protocol on the knee joint kinematics of runners with PFPS compared to baseline healthy runners. It was found that PFPS runners displayed reduced stride to stride knee variability after the strengthening program (Ferber et al., 2011). In the same line, Earl and Hoch (2011) found a reduction of the knee abduction moment during running (Figure 2-16) along with an increase in hip strength, following an 8-week hip strengthening program in runners presenting with PFPS. Hence, despite the existing evidence supporting the effectiveness of strength training to positively alter gait biomechanical factors related to injuries in young runners, there is no study investigating the same effect on older runners. Therefore, future research on this topic is warranted to determine whether resistance exercises would positively alter running biomechanical parameters related to injuries in the older population.

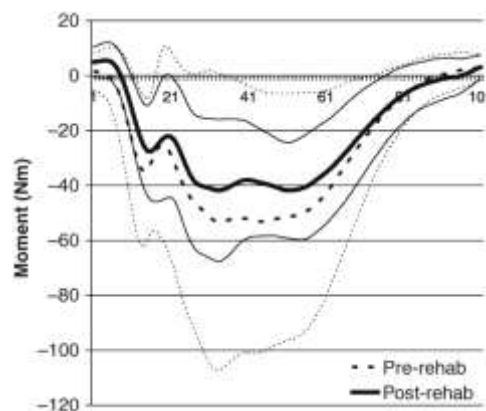


Figure 2-16. Ensemble average of frontal plane knee moment, before and after rehabilitation program. Thick dotted/solid lines represent the means, and thin lines represent the respective standard deviations according to Earl and Hoch (2011).

2.4 Machine Learning Approach

Gait analysis has become popular among clinicians and researchers. However, as the use of gait biomechanical analysis increases its popularity and the access to equipment is becoming more feasible, an increased volume of data and multiple dependent variables are usually present in gait analysis. In an attempt to address these challenges with gait data, researchers have used innovative methods based on data-driven models instead of the traditional hypothesis-driven models. As mentioned earlier in this chapter, the traditional statistical methods have been confronted by the complexities of the biomechanical gait data. To provide a basis of the pattern classification method used in this thesis, a review of the most important studies is presented.

Support Vector Machine has become one of the most popular machine learning methods used for biomechanical group classification (Begg and Kamruzzaman, 2005; Lai et al., 2009b; Levinger et al., 2009). The aim of the SVM method is to find a maximal separation between groups while minimizing a misclassification error during the training process. A user specified penalty parameter (C) determines the tradeoff between maximal margin a minimal training error. The SVM method has distinct advantages compared to other machine learning algorithms such as the global unique solution and lower computational costs (Noble, 2006). A detailed description of the SVM approach is offered in chapter 4 (see section 4.2.3).

There has been a lack of studies that used SVM approaches to discriminate age groups based on biomechanical data; however the few published studies have demonstrated promising

results for the application of these methods in the clinical context (Begg and Kamruzzaman, 2005; Wu and Wang, 2008). Begg and Kamruzzaman (2005) use the SVM method to automatically detect young and older gait patterns based on discrete gait biomechanical data. The authors reported a surprisingly result that a 91.7% overall classification accuracy rate (CAR) in distinguishing young and older gait, and the CAR achieved 100% when only three gait features were optimally combined. Similarly, Wu and Wang (2008) obtained 90% CAR in recognizing walking gait of young and elderly individuals but based only on GRF data. Nevertheless, to our knowledge, there have been no studies that used either SVM approaches or other machine learning techniques to discriminate young and older runners based on biomechanical variables despite the fact that ageing is related to both changes in movement patterns and injuries in runners.

2.5 Summary

Older adults are frequently affected by chronic diseases and functional disabilities, which has resulted in tremendous social and medical costs (Newman et al., 2003; Willcox et al., 2006). Regular physical activity, including running, may help to improve the health among older adults (Newman et al., 2006; Paffenbarger et al., 1993). In fact, one study found that over a 16-year period of time, participation rates for both men and women aged 50 years and older in the New York City Marathon, has increased more than twice as much compared to younger age groups (Jokl et al., 2004). The increased participation of older individuals in long distance running has likely resulted in positive health benefits, particularly for the cardiovascular system, but it may have concomitantly exposed these individuals to a higher risk of musculoskeletal injury (Marti et al., 1988; McKean et al., 2006). Previous research has suggested that the increased incidence of injuries in older runners is partly due to the degeneration of the musculoskeletal system (Narici

and Maffulli, 2010), and partly due to differences in running gait patterns between older and young adult runners (Bus, 2003; Fukuchi and Duarte, 2008; Fukuchi et al., 2011; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). Although, the cause and effect relationship of these factors (musculoskeletal changes vs. gait changes) has not been fully established, there has been strong evidence to support the notion that the altered gait patterns in older adult are a result of both structural and functional changes in the musculoskeletal system (McGibbon, 2003). However, there are no running biomechanical studies that have simultaneously examined both functional (joint flexibility and muscle strength) and gait changes in older runners to determine if there is any relationship between these factors. Furthermore, there is an obvious lack of studies investigating whether these reported changes in older runners are modifiable through flexibility and strengthening exercises, despite the fact that these exercises have been widely recommended to counteract the effects of biological ageing (Chodzko-Zajko et al., 2009). Previous studies have suggested that running biomechanical gait factors related to injuries are modifiable through exercises in young runners, however this remains unanswered in older individuals. To fully describe the age-related musculoskeletal and gait changes, biomechanical studies have to deal with a large amount of data which challenges the use of traditional statistical approaches due to the high dimensionality and the multivariate complex relationship of the data. Hence, this problem often demands more robust data analysis approach such as pattern recognition techniques. However, the application of this robust analysis is relatively new in biomechanical studies and requires further investigation. This review highlights several limitations in the current literature that need to be addressed in order to enhance our knowledge about the underlying mechanisms behind running gait adaptation. The identification of modifiable factors

related to gait adaptations and their change following intervention exercises will help in the design of optimal injury prevention exercise programs for older runners.

Therefore, the aims of this study are:

1) to describe clinical and gait biomechanical adaptations in older runners; and determine if there is an association between these factors.

2) to assess the ability of a machine learning emerging technique in discriminating age-groups of runners based on gait biomechanical data.

3) to identify a reduced set of clinical and biomechanical features that yield an optimal combined discrimination between age-groups.

4) to determine what type of exercise intervention is most effective in modifying the identified features towards the young group.

We hypothesized that:

1) the older runners would exhibit overall decreased muscle strength and flexibility along with changes in gait mechanics; and an association between clinical and biomechanical factors would exist.

2) the machine learning algorithm (SVM) would be able to accurately discriminate age-groups solely based on gait kinematics data.

3) the SVM combined with a feature selection algorithm would be able to detect a subset of, from a more comprehensive set of clinical and biomechanical, features that provided a optimal combined discriminatory information.

4) strengthening exercises would be more effective in modifying the SVM features in older runners.

Chapter 3: Flexibility, muscle strength and running biomechanical adaptations in older runners

3.1 Introduction

Over the last decade, a substantial increase in the number of older adults participating in physical activity programs has been observed, particularly in long distance running (Jokl et al., 2004). However, an increased number of running-related injuries among older runners has also been reported in the literature (Fields, 2011; McKean et al., 2006). The increased injury rate may be partly explained by the changes in musculoskeletal function such as loss in muscle strength (Faulkner et al., 2007) and joint mobility (Nonaka et al., 2002) and also partly explained by the changes in running gait patterns associated with biological ageing (Bus, 2003; Fukuchi and Duarte, 2008). Although cause and effect relationships between these factors have not yet been established, previous studies suggest that age-related gait changes are caused by musculoskeletal function degeneration (McGibbon, 2003).

One of the most remarkable changes in the gait pattern of older adults is the joint moment redistribution across lower extremity joints. Specifically, a higher hip joint moment has been reported to possibly compensate for the reduced moments generated by distal joints to produce the same overall support moment (DeVita and Hortobagyi, 2000; Savelberg et al., 2007). However, this distal-to-proximal shift in the moment distribution across the lower extremity joints has only been documented in walking. It is unknown whether this adaptation is also present in older adult runners or whether it would be amplified during running to help explain the disparate injury occurrence in older runners compared to their younger counterparts. Previous studies have limited their research to include only gait kinematics of the knee and ankle joints (Fukuchi and Duarte, 2008) or only the sagittal plane joint kinetics of the knee and ankle

(Karamanidis and Arampatzis, 2005). It has been shown that trunk movement patterns are influenced by lower extremity joint moments during gait (Nott et al., 2010). Therefore, one can postulate that trunk kinematics would also be affected if a change in the distribution of joint moments occurs during running in older adults. To our knowledge, no study has measured trunk kinematics in older runners.

Loss in ROM with biological ageing (Scott et al., 2007) has been associated with sagittal plane gait changes such as reduced knee and ankle joint angle excursion in older runners (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005). However this association has not been consistently observed in the secondary plane of motion. For example, Lilley et al. (2011) reported increased peak knee internal rotation and ankle eversion whereas Fukuchi and Duarte (2008) and Bus (2003) did not observe the same findings. The conflicting literature may be partly explained by a high level of variability in secondary plane kinematic data, possibly due to the small sample sizes used in these studies. In addition, these previous studies assumed that flexibility is reduced in older runners but did not measure these variables of interest (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005). Hence, a comprehensive description of the lower extremity joint kinematics, along with measures of flexibility in older runners is necessary.

Age-related gait biomechanical alterations have been strongly suggested as a consequence of reduced muscle strength observed in older individuals (McGibbon, 2003). However, the association between reduced MVIC and changes in gait kinetics in older runners has not been well investigated and has, to-date, been limited to the sagittal plane of the ankle and knee joints (Karamanidis and Arampatzis, 2005). One could hypothesize, for example, that reduced muscle force output would result in reduced joint work during running.

In summary, considering that muscle weakness and reduced muscle flexibility have been commonly associated with atypical walking biomechanics in older adults, it is possible that the connection between these factors may also be found in running. Despite the evidence suggesting that older runners are more prone to injuries, there is limited understanding on the association between clinical (flexibility and strength) and running biomechanical factors in this population. Therefore, the aim of this study was to investigate differences in muscle strength, flexibility and running gait biomechanical patterns, in a representative sample of young and older runners. We hypothesized that older individuals would exhibit (1) a distal-to-proximal shift in the lower extremity joint moments similarly to walking studies, as measured via angular impulse, to maintain (2) the same overall support moment. In addition, older runners would demonstrate a (3) reduced joint angle excursion concomitant with an (4) overall reduced joint flexibility and a (5) reduced muscle force output compared to their younger counterparts.

3.2 Methods

3.2.1 Participants

Thirty-five younger runners (21 males and 14 females) and 35 older adult runners (22 males and 13 females) were examined in this study. The age ranges for the young and older were 20-35 years and 55-75 years, respectively. This age range was determined based on the sarcopenic-related changes with biological ageing (Faulkner et al., 2007). Participants were recruited from local races and posted flyers. Prior to their participation, each subject signed an informed consent form. The demographic information of both groups of subjects can be found in Table 3-1. Each participant had to meet the following inclusion criteria: injury free for at least 3 months prior to the data collection; running mileage between 10-20 km per week; be familiar and

comfortable with treadmill running, and in good general health upon entry into the study. In addition, the potential participants were excluded if they presented one or more of the following: lower extremity injury within the last 3 months; surgery to the lower extremity within the last 8 months; head injury or vestibular disorder within the last 6 months, and inability to speak or read English. The sample size was determined based on an a priori statistical power analysis on the ankle abduction angle at the initial contact with the ground (Fukuchi and Duarte, 2008). Considering a within-group SD of 3° and expected difference between groups of 2°, a minimum of 34 subjects in each group were required to adequately power the study ($\alpha=0.05$, $\beta=0.8$).

3.2.2 Muscle Strength and Flexibility Measurements

The right leg was used as the test extremity for muscle strength and flexibility measures. Maximal voluntary isometric contraction (MVIC) muscle strength testing was performed on the following muscle groups: hip abductors strength (HABDS), hip extensors strength (HEXTS), knee extensors strength (KEXTS), ankle plantar-flexors strength (APFS) and hip external rotators strength (HERS). MVIC was measured using a hand-held dynamometer (HHD) (Nicholas MMT, Lafayette Instruments, Lafayette, USA) and non-elastic adjustable straps (Figure 3-1). The straps were anchored to the testing bed and the subjects performed each test by pushing into the dynamometer and against the strap. Hence, it was expected that this procedure removed any potential for tester strength or experience to influence the assessment. In all strength measures, the participants were asked to maximally push against the dynamometer by moving the joint toward the instructed direction for 5 seconds. One practice trial and three experimental trials were performed, with 15 seconds of rest in between. The mean force (N) of the three MVICs trials was then normalized as a percentage of body weight.

The HABDS and HERS were tested similarly to Snyder et al. (2009). The HABDS was tested with the participant in a side-lying position with the test leg facing upward. The HHD was placed 5 cm proximally to the knee joint line and it was secured to the leg using a strap that surrounded the leg and table (Figure 3-1a). The HEXTS test was performed with the subject lying in prone with the right knee in 90° of flexion (Figure 3-1b). The HHD was placed 5 cm proximal to the popliteal fold and it was secured to the leg using a strap that surrounded the leg and table. The KEXTS was tested similarly to Reese (2012) with the participants in a seated position with their hips and knees in 90° of flexion (Figure 3-1c). The tested lower leg was then positioned at 60° relative to the horizontal and the HHD was placed 5 cm above the midpoint between lateral and medial malleoli. An inclinometer was used to ensure that the tested lower leg was always at the same starting position angle. The APFS was measured with the participants in a prone position with their foot positioned beyond the edge of the testing bed and the ankle in a neutral position. The tester stabilized the subject's shank so that any movement of the participant's leg relative to the testing bed was minimized (Figure 3-1d). The HERS was tested with the participants seated with their hips and knees in 90° of flexion. The HHD was placed 5 cm above the medial malleolus and secured by a strap around the ankle that was anchored to a table leg (Figure 3-1e).

Joint ROM measures were taken by using either a universal goniometer or a digital inclinometer (Pro 360 digital protractor; SmartTool Technology, Inc, Oklahoma City, OK, USA). The hip adduction ROM (HADDROM) was tested with the subjects in side-lying, pelvis and shoulder aligned along the vertical plane, and the knee extended (Figure 3-2a). The examiner stabilized the pelvis with one hand while the other hand moves the thigh of the tested limb (the top limb) into hip flexion, abduction, and extension and then lowers the limb into adduction until

it stops via soft-tissue stretch or from posterior rotation of the pelvis, or both (Figure 3-2a). Hip extension (HEXTROM) was measured with the participants lying in supine with the hip joint positioned over the edge of the exam table. The subject was then asked to bring and hold their contralateral limb to their chest as such that the hip and knee remained in a flexed position (Figure 3-2b). To quantify the joint ROM, the inclinometer was then placed at the mid-point between the anterior superior iliac spine and patella, along the longitudinal axis of the lateral and anterior aspect of the thigh to measure HADDROM and HEXTROM, respectively (Ferber et al., 2010). Hip external rotation (HERROM) (Figure 3-2c) and hip internal rotation (HIRROM) (Figure 3-2d) were assessed while the subjects were seated with their hips and knees at 90° while the tester passively moved the lower leg towards the desired direction (Norkin and White, 2003). The axis of the goniometer was placed at the knee joint with the fixed arm in a vertical direction, which was determined visually, towards the ground and the movable arm along the participant's test leg (Norkin and White, 2003). Ankle dorsiflexion ROM was tested using a goniometer with the participants lying prone on the test bed and the tester passively moved the ankle into dorsiflexion. The axis of the goniometer was positioned at the lateral malleolus, the fixed arm was aligned to the fibula and the movable arm aligned to the fifth metatarsal. Ankle dorsiflexion ROM was assessed similarly to Johanson et al. (2008) with the knee both extended and flexed at 90° to better isolate gastrocnemius (AGASROM) and soleus (ASOLROM) muscle flexibility, Figure 3-2e and Figure 3-2f, respectively. The hip flexion (HFLXROM) was measured through a straight leg raise test. The participant's hip was passively moved into flexion while keeping the knee in full extension (Figure 3-2g). An inclinometer was then placed in the anterior aspect of the thigh to quantify the available ROM. Intra-class correlation coefficient (ICC 2,1) ranged from 0.60 to 0.87 and from 0.71 to 0.96 for the flexibility and strength measures, respectively;

thus indicating good to excellent reliability in the clinical measurements (Shrout and Fleiss, 1979).



Figure 3-1. Participant's position for isometric strength test: (a) hip abductors, (b) hip extensors, (c) knee extensors, (d) ankle plantar flexors, (e) hip external rotators.



Figure 3-2. Participant's position for ROM testing: (a) hip adduction, (b) hip extension, (c) hip external rotation, (d) hip internal rotation, (e) ankle gastrocnemius, (f) ankle soleus, (g) hip flexion.

3.2.3 Biomechanical Measures

For the biomechanical analysis, the participants were requested to run at a speed of 2.7 m/s on an instrumented treadmill (Bertec, Columbus, OH, USA). The participants first had an accommodation period on the treadmill for about three minutes. All participants wore standard, neutral shoes (Nike Air Pegasus, Nike, Portland, OR, USA) provided by our laboratory.

Biomechanical data were collected using an eight camera Vicon MX3 (Vicon Motion Systems, Oxford, UK) motion analysis system. A combination of anatomical and tracking markers was used to determine the position and orientation of the segments in three-dimensional space (Figure 3-3). This kinematic gait model has displayed good reliability (Pohl et al., 2010; Pohl et al., 2012) and a detailed description of the model can be found in APPENDIX A.

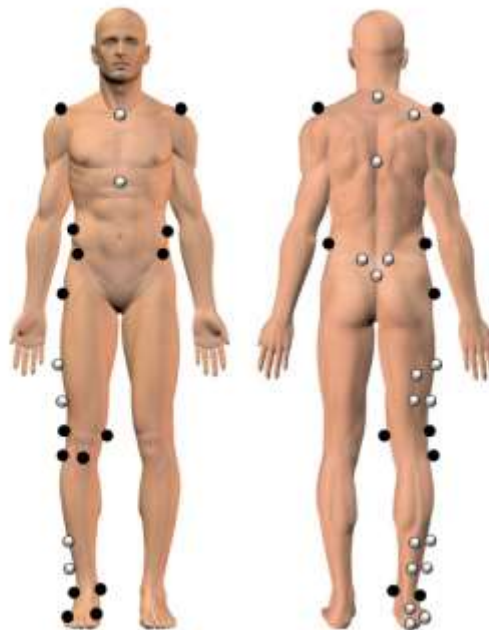


Figure 3-3. Marker set protocol used in this study depicting anatomical (black) and technical (white) markers used in the study.

Following a standing calibration trial, the anatomical markers were removed and the subjects ran on the treadmill. The kinematic data for ten footfalls were collected at a sample rate of 200 Hz and the GRF data were collected at 1000 Hz. The heel strike and toe off were determined when the vertical GRF crossed a 40 N threshold level. After residual analysis, raw marker trajectory data and GRF data were filtered using a fourth order low-pass Butterworth filter with cut-off frequencies of 10 Hz and 50 Hz, respectively (Winter, 2005). Three-dimensional hip, knee, and ankle joint angles were calculated using cardan angles with the distal segment expressed relative to the proximal segment. The net internal joint moments and joint powers were calculated using a standard inverse dynamics approach and they were resolved in a joint coordinate system. Joint power was calculated as the product of the torque and angular velocity at each joint. Joint impulse and joint work were computed as the area under the moment-time and power-time curves, respectively. The joint kinetic and the GRF variables were normalized by subject's body mass. A detailed description of the steps taken to calculate the biomechanical variables is offered in APPENDIX A. In addition, the centre of pressure (COP) of the force platforms was calibrated through the procedures detailed in APPENDIX B.

Visual 3D software (C-motion Inc, Germantown, MD, USA) was used to filter the marker and GRF data and to calculate joint kinematics and kinetics. Joint angles, joint moments and powers were normalized to the stance phase over 101 data points. The discrete variables were extracted from each stance phase and they were averaged to represent the subject's average pattern. This process was repeated across subjects to obtain the group pattern. The discrete variables calculations were performed using in-house algorithms developed in Matlab 7.12 (Mathworks Inc, Natick, MA, USA). The average time-distance parameters and average plots of kinematic and kinetic parameters were obtained from the 10 footfalls. For a better

characterization of the older runners' gait pattern, we selected variables commonly reported previously (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). Excursion angles (difference between maximal and minimal values) were obtained for all joints in all three planes of motion. The maximal loading rate, the magnitude of the impact peak and the active peak of the vertical GRF, and the magnitude of the braking and propulsion peaks of the horizontal GRF were also quantified.

3.2.4 Data Analysis

Descriptive statistics (means and standard deviations) were calculated for all biomechanical, strength and flexibility variables for both young and older runners. The normality of the data was verified by the Lilliefors's test. When the normality assumption was not met non-parametric statistics were used. Independent samples t-tests or Wilcoxon signed rank sum tests were carried out to detect differences, if any, between-groups and statistical analysis was performed in Matlab 7.12 (Mathworks Inc, Natick, MA). The mean ensemble time-series joint angle, joint moment, joint power and GRF curves across participants in each group were calculated to illustrate the overall group pattern. Pearson or Kendall's tau correlation analysis was employed on selected variables to assess the relation between some clinical and biomechanical factors. The Cohen's d effect size of each variable was also quantified (see Equation 2.1) with the significance level for statistical analyses set at $\alpha = 0.05$.

3.3 Results

The young and older runners were all matched in terms of body height, body mass, BMI and weekly running training hours (Table 3-1).

Table 3-1. Mean (SD) subject demographics information of the young and older groups.

	Young	Older	<i>P-value</i>
Demographics			
Age (years)	28.9 (4.7)	60.2 (4.2)	< 0.001
Mass (kg)	67.9 (11.5)	68.4 (11.0)	0.873
Height (cm)	171.7 (8.8)	171.1 (9.6)	0.772
BMI (kg/cm²)	22.9 (2.4)	23.2 (1.8)	0.536
Weekly running training (hours)	3.5 (1.9)	3.2 (0.8)	0.490

Detailed results of the strength and flexibility measures are provided in Table 3-2. The distribution of flexibility and strength data are shown in Figure 3-6 and Figure 3-7. In summary, the older runners were generally less flexible and weaker than the young group. Specifically, older runner exhibited significantly reduced HADDROM, AGASROM, ASOLROM, HIRROM and HERROM whereas HEXTROM and HFLXROM were similar between groups. In addition, the older runners demonstrated significantly reduced HABDS, HEXTS and APFS whereas no differences were found for HERS and KEXTS when compared to the younger runners (Table 3-3).

Ensembles mean (± 1 SD) group joint kinematics (Figure 3-4) and joint kinetics (Figure 3-5) are presented. Most of the lower extremity joint kinematic variables were similar between groups (Table 3-3), except that older runners exhibited significantly reduced ankle sagittal and hip frontal plane excursions. Older runners also demonstrated significantly reduced trunk excursion in the sagittal and transverse planes as demonstrated in Table 3-3 and Figure 3-4.

Detailed results of the joint kinetics and GRF variables are presented in Table 3-4 and Table 3-5. Joint moment impulses in the sagittal plane were similar between groups, indicating that the younger and older runners exhibited the same joint moment distribution across lower extremity joints, resulting in similar support moment impulse between groups. However, increased knee abduction, knee external rotation, and ankle abduction impulses; and increased maximal loading rate were observed in older runners (Table 3-5). Conversely, older runners presented decreased ankle inversion impulse (Table 3-4), knee and ankle positive work; and reduced GRF propulsion and GRF vertical active (Table 3-5).

Effect sizes were generally larger for the clinical variables (flexibility and strength) (Table 3-2) compared to the biomechanical measures (Table 3-3, Table 3-4, Table 3-5).

In regard to the correlation analysis, there were significant correlations across participants for APFS and ankle positive work ($r=0.23$, $P<0.01$); APFS and GRF propulsion peak ($r=0.18$, $P=0.03$); and APFS and GRF vertical active peak ($r=0.25$, $P<0.01$). In contrast, there was no significant correlation across participants for AGASROM and ankle DF-PF ($r=-0.04$, $P=0.72$); ASOLROM and ankle DF-PF ($r=0.02$, $P=0.80$); HADDROM and hip ADD-ABD ($r=-0.02$, $P=0.84$) and HADDROM and knee ABD impulse ($r=-0.10$, $P=0.22$). Scatter plots with the analysed correlations are shown in Figure 3-8.

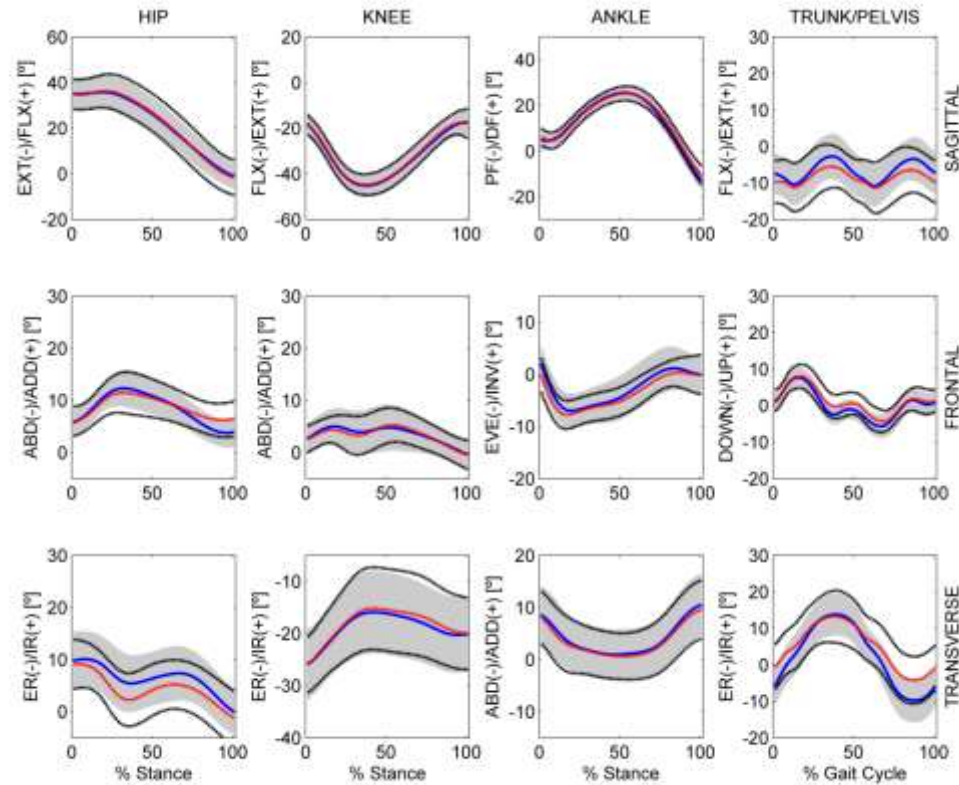


Figure 3-4. Three-dimensional hip, knee, ankle and trunk/pelvis joint kinematics for young (solid blue line is mean, shaded area is $\pm 1SD$) and older (dashed red and dashed black are mean and $\pm 1SD$, respectively) runners during the stance phase of running at 2.7 m/s on a treadmill.

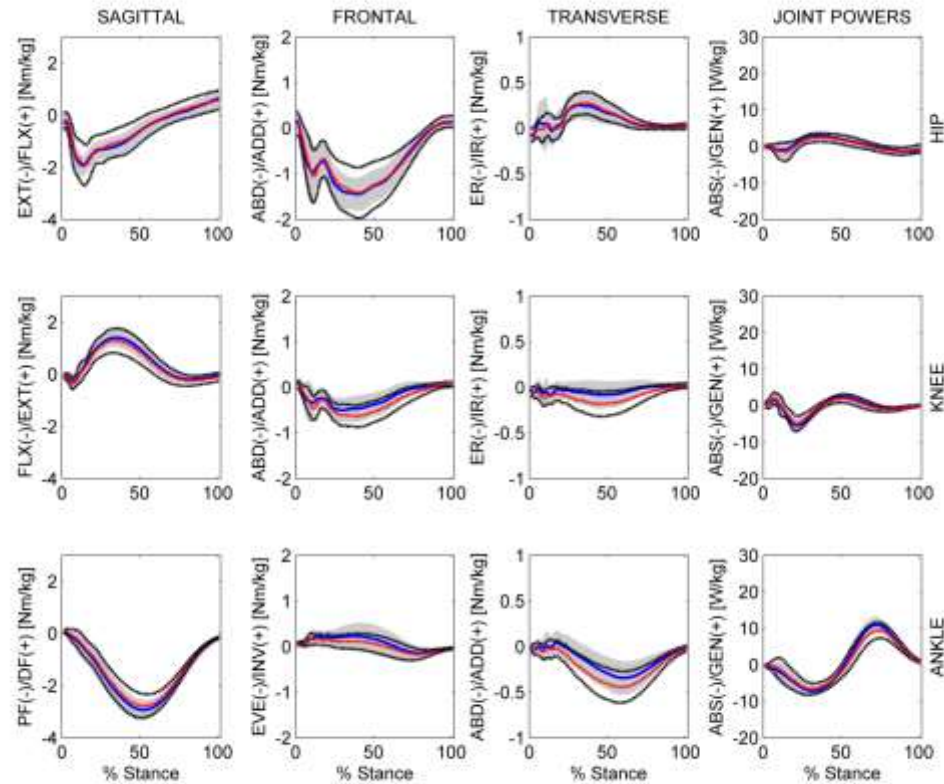


Figure 3-5. Three-dimensional hip, knee and ankle joint moments; and sagittal power for young (solid blue line is mean, shaded area is $\pm 1SD$) and older (dashed red and dashed black are mean and $\pm 1SD$, respectively) runners during the stance phase of running at 2.7 m/s on a treadmill.

Table 3-2. Mean (SD) ROM and MVIC variables of interest for young and older runners, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.

Variables	Young	Older	<i>P-value</i>	<i>Effect size</i>
<i>Flexibility</i>				
HEXTROM (°)	-16.4 (7.5)	-16.8 (9.6)	0.84	0.05
HADDROM (°)	-32.9 (5.7)	-27.0 (3.0)	<0.01*	1.28
HFLXROM (°)	81.2 (9.5)	77.6 (12.6)	0.18	0.33
AGASROM (°)	94.2 (5.8)	88.3 (4.6)	<0.01*	1.15
ASOLROM (°)	105.0 (6.8)	96.0 (3.9)	<0.01*	1.64
HERROM (°)	42.5 (7.3)	35.3 (5.6)	<0.01*	1.12
HIRROM (°)	45.0 (7.3)	37.6 (8.0)	<0.01*	0.98
<i>Strength</i>				
HABDS (%BW)	0.4 (0.1)	0.3 (0.1)	<0.01*	0.65
HEXTS (%BW)	0.3 (0.1)	0.2 (0.1)	<0.01*	0.78
APFS (%BW)	0.6 (0.1)	0.4 (0.1)	<0.01*	1.90
HIRS (%BW)	0.2 (0.0)	0.2 (0.1)	0.21	0.31
HERS (%BW)	0.2 (0.0)	0.2 (0.0)	0.09	0.41
KEXTS (%BW)	0.5 (0.1)	0.4 (0.1)	0.48	0.17

Table 3-3. Mean (SD) joint kinematic variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.

Variables	Young	Older	<i>P-value</i>	<i>Effect size</i>
Hip FLX-EXT (°)	38.0 (4.9)	38.9 (3.7)	0.35	0.23
Hip ADD-ABD (°)	10.7 (3.2)	8.4 (3.3)	<0.01*	0.72
Hip IR-ER (°)	3.6 (1.1)	3.7 (1.3)	0.71	0.09
Knee EXT-FLX (°)	31.5 (4.8)	29.4 (4.6)	0.06	0.46
Knee ADD-ABD (°)	7.0 (2.7)	7.0 (2.3)	0.95	0.02
Knee IR-ER (°)	11.7 (2.9)	12.6 (3.5)	0.27	0.27
Ankle DF-PF (°)	38.8 (3.7)	35.9 (4.4)	<0.01*	0.73
Ankle INV-EV (°)	11.0 (2.0)	10.2 (3.0)	0.20	0.31
Ankle ADD-ABD (°)	11.1 (2.8)	10.9 (2.8)	0.73	0.08
Tho/Pel EXT-FLX (°)	10.7 (2.9)	9.1 (2.8)	0.02*	0.57
Tho/Pel IPSI-CONTRA (°)	14.2 (2.8)	13.5 (3.6)	0.36	0.23
Tho/Pel IR-ER (°)	25.0 (6.6)	19.6 (5.5)	<0.01*	0.90

#Abbreviations: EXT=extension, FLX=flexion, ADD=adduction, ABD=abduction, IR=internal rotation, ER=external rotation, DF=dorsiflexion, PF=plantarflexion, INV=inversion, EV=eversion. Tho/Pel= joint angle between thorax and pelvic segments. For the Tho/Pel joint: trunk bending towards posterior (EXT) and anterior (FLX) side of the body, trunk bending to the right (IPSI) and left (CONTRA) side, trunk axial rotation to the right (ER) side and left (IR).

Table 3-4. Mean (SD) joint impulse variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes. Note: “*” indicates significant differences between groups.

Variables	Young	Older	<i>P-value</i>	<i>Effect size</i>
Hip EXT (Nms/kg)	-0.70 (0.20)	-0.72 (0.34)	0.61	0.13
Hip ABD (Nms/kg)	-0.78 (0.23)	-0.77 (0.29)	0.78	0.07
Hip ER (Nms/kg)	0.11 (0.06)	0.11 (0.06)	0.87	0.04
Knee EXT (Nms/kg)	0.51 (0.16)	0.46 (0.20)	0.26	0.28
Knee ABD (Nms/kg)	-0.25 (0.14)	-0.33 (0.15)	0.03*	0.54
Knee ER (Nms/kg)	-0.06 (0.05)	-0.10 (0.07)	<0.01*	0.65
Ankle PF (Nms/kg)	-1.56 (0.28)	-1.46 (0.26)	0.15	0.35
Ankle INV (Nms/kg)	0.14 (0.11)	0.08 (0.06)	<0.01*	0.65
Ankle EV (Nms/kg)	-0.06 (0.08)	-0.07 (0.06)	0.83	0.05
Ankle ABD (Nms/kg)	-0.17 (0.10)	-0.23 (0.09)	0.02*	0.58
Sagittal Support Moment (Nms/kg)	2.59 (0.40)	2.38 (0.47)	0.06	0.48

#Abbreviations: EXT=extension, FLX=flexion, ADD=adduction, ABD=abduction, IR=internal rotation, ER=external rotation, DF=dorsiflexion, PF=plantarflexion, INV=inversion, EV=eversion. Tho/Pel= joint angle between thorax and pelvic segments. For the Tho/Pel joint: trunk bending towards posterior (EXT) and anterior (FLX) side of the body, trunk bending to the right (IPSI) and left (CONTRA) side, trunk axial rotation to the right (ER) side and left (IR).

Table 3-5. Mean (SD) joint work and GRF variables of interest for young and older runners during the stance phase of running at 2.7 m/s on a treadmill, along with P-values and effect sizes.

Note: “*” indicates significant differences between groups.

Variables	Young	Older	<i>P-value</i>	<i>Effect size</i>
Joint Work				
Hip Positive Work (J/kg)	1.08 (0.57)	0.98 (0.69)	0.54	0.15
Hip Negative Work (J/kg)	-0.61 (0.33)	-0.70 (0.45)	0.32	0.24
Knee Positive Work (J/kg)	0.77 (0.27)	0.63 (0.28)	0.04*	0.52
Knee Negative Work (J/kg)	-1.15 (0.39)	-0.96 (0.43)	0.07	0.45
Ankle Positive Work (J/kg)	3.13 (0.72)	2.70 (0.58)	<0.01*	0.66
Ankle Negative Work (J/kg)	-2.16 (0.64)	-1.93 (0.58)	0.12	0.39
GRF				
Braking peak (N/kg)	-0.27 (0.05)	-0.26 (0.04)	0.25	0.28
Propulsion peak (N/kg)	0.21 (0.03)	0.19 (0.03)	0.03*	0.53
Impact peak (N/kg)	1.54 (0.22)	1.62 (0.21)	0.22	0.35
Vertical active peak (N/kg)	2.35 (0.21)	2.22 (0.26)	0.03*	0.55
Max. Loading Rate (BW/s)	36.11 (11.52)	42.67 (9.57)	0.03*	0.63

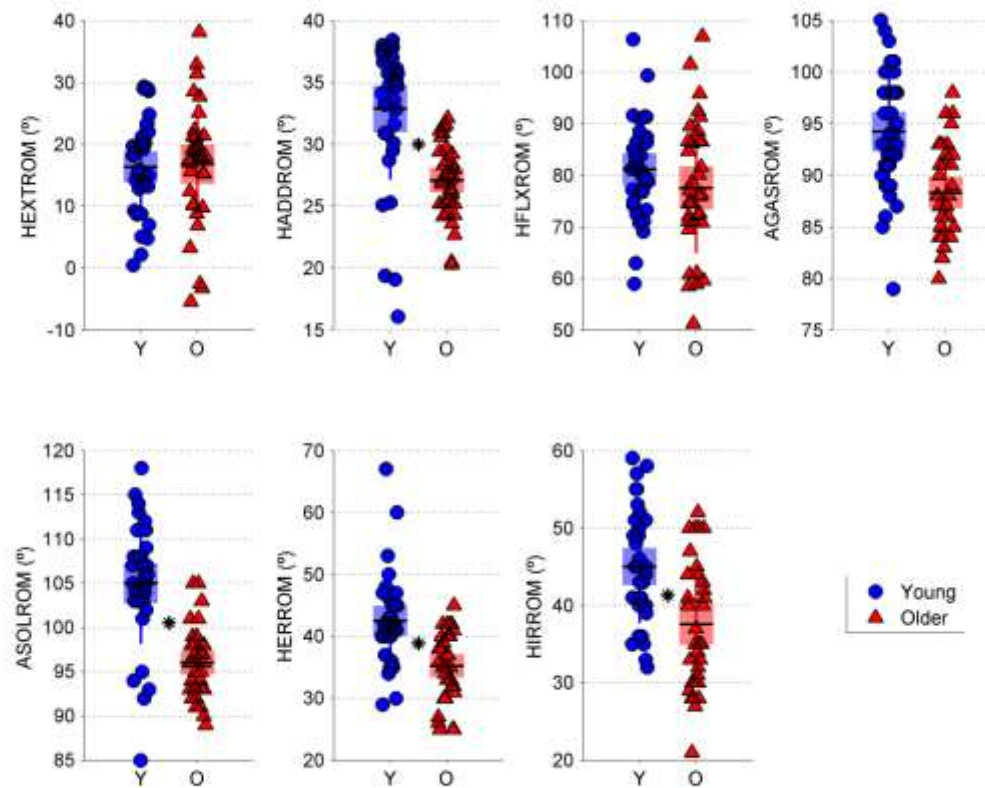


Figure 3-6. Distribution of the flexibility measures for young (blue circles) and older runners (red triangles). Note: “*” indicates significant differences between groups.

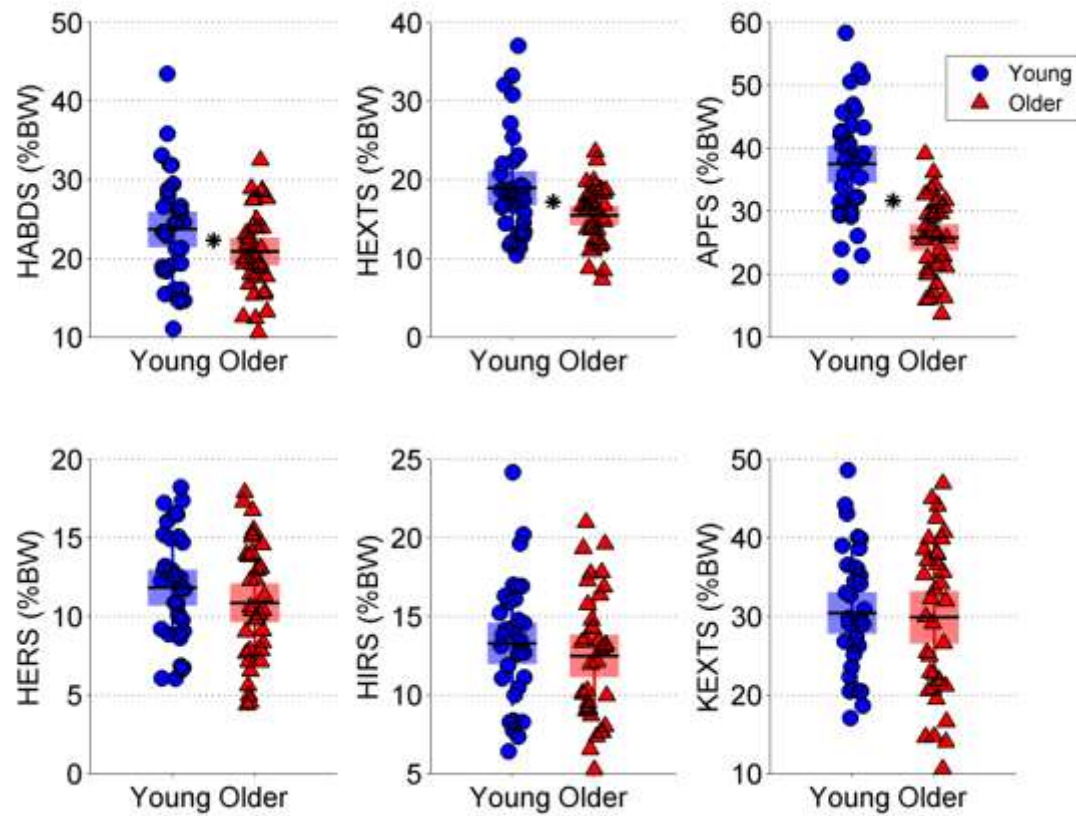


Figure 3-7. Distribution of the strength measures for young (blue circles) and older runners (red triangles). Note: “*” indicates significant differences between groups.

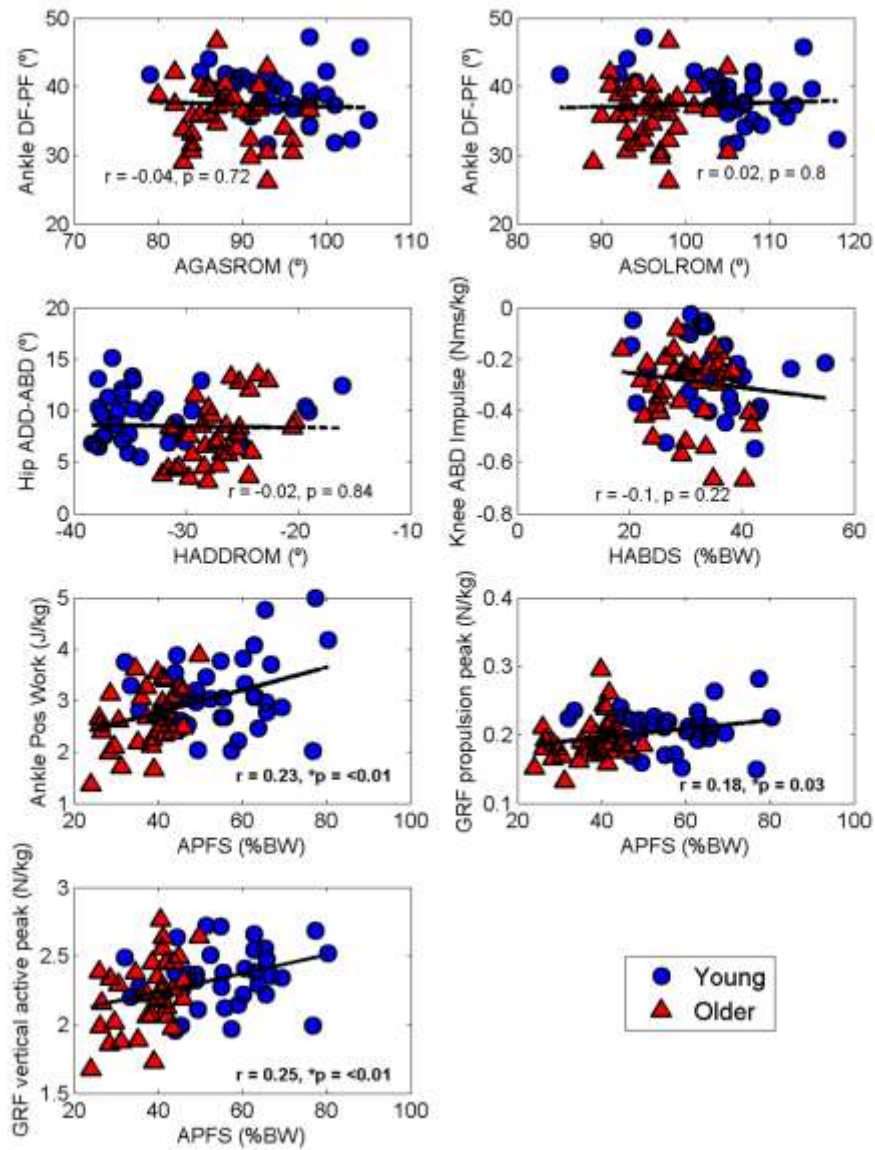


Figure 3-8. Scatterplot depicting the relationship between clinical and running biomechanical measures in young and older runners.

3.4 Discussion

The aim of this study was to examine the differences in flexibility, muscle strength and running biomechanics between younger and older runners. This is an important area of investigation considering the limited research related to understanding the inter-relationship between sarcopenia and the greater incidence in injury for older adults practicing long distance running.

A distal-to-proximal shift in joint moments has been previously documented in walking studies (DeVita and Hortobagyi, 2000; Savelberg et al., 2007). We hypothesized that such a shift should also occur during running and considering the higher demand running places on the skeletal muscles, we expected a similar or greater shift than during walking. Our results do not support this hypothesis as the older adults displayed similar joint moment impulse patterns as compared to the younger group. In fact, the joint moment impulse distribution across hip, knee and ankle joints were similar between groups, highlighting that the same strategy was adopted which was confirmed by the similar support moments impulse during running. The lack of joint moment redistribution in older runners might be due simply by the fact that walking is different than running and such comparison with previous literature is therefore not appropriate. Alternatively, the participants in the present study were well matched in terms of demographics and training levels; and the older individuals were generally more active as opposed to previous studies (DeVita and Hortobagyi, 2000; Savelberg et al., 2007). This fact may explain the absence of differences in joint moment distribution. The lack of studies investigating the joint moment distribution across lower extremity joints during running in older runners prevented any further comparison.

Although, the older runners exhibited reduced isometric force output as compared to younger runners, these differences were not consistently reflected in the joint work during running. In fact, there was a significant correlation between muscle force output and the corresponding joint work for the ankle but not for the hip and knee joints. The lack of correspondence between isometric force output and joint kinetics has previously been observed in older runners (Karamanidis and Arampatzis, 2005). An explanation could be that biological ageing affects the contraction velocity to a greater extent as compared to the maximal force generation that was measured in the present study. An alternative explanation may be related to the specific way the muscle strength measures were taken. While the position of the participants allowed good reliability in comparison with previous studies, the specific limb position may not represent the functional demands placed on the muscles during running. Nevertheless, the results of this study suggest that the weakness in distal muscles (e.g. calf muscles) compared to the proximal ones affected, in a greater extent, the running pattern in older runners.

In support of our hypotheses, older runners exhibited significantly reduced ankle flexibility and reduced ankle sagittal plane excursion during running compared to their young counterparts. However, no correlation was found between these variables. In fact, there is conflicting evidence on whether ankle sagittal plane excursion is affected by ageing during running with some studies reporting reduction (Bus, 2003; Karamanidis and Arampatzis, 2005) whereas other showing similar patterns (Fukuchi and Duarte, 2008). In addition, the older runners in the current study exhibited increased tightness in the iliotibial band (ITB) and reduced frontal plane hip excursion, but no correlation was found between them. Irrespective of their cause, reduced sagittal ankle ROM and hip frontal ROM, both static and dynamic, have been previously associated with injuries such as ITB syndrome, patellar tendinitis and plantar fasciitis

in young runners (Grau et al., 2011; Hudson and Darthuy, 2009; Malliaras et al., 2006; Wearing et al., 2006). Hence, it is reasonable to conclude that older runners may be at higher risk to sustain an injury.

The older runners in the present study exhibited a higher knee frontal plane impulse along with reduced hip abductor muscle force output as compared to the younger runners, although no correlation was found between these variables. Earl and Hoch (2011) also found reduced knee abduction moment and increased hip abductors strength following an exercise program in runners with PFPS. However, no correlation analysis was performed to assess the relationship between these variables. An increased frontal plane moment has also been documented in female mature runners (Lilley et al., 2011) and it has been considered a predictor of both PFPS syndrome (Stefanyshyn et al., 2006) and knee osteoarthritis (OA) progression (Miyazaki et al., 2002). In addition, hip abductor weakness has been identified in PFPS runners when compared to controls (Dierks et al., 2008). Hence, although previous studies suggest that knee frontal plane loading may be modified through hip abductor strengthening exercises, the underlying mechanism needs to be further explored.

In the present study, an increased knee ER impulse and greater ankle ABD impulse were found in older runners. The increased transverse plane knee moment has also been documented in individuals presenting moderate knee OA (Astefhen et al., 2008). Regardless their cause, the changes in secondary plane mechanics at the knee can trigger degenerative changes by placing new loads on regions of the articular cartilage that were previously conditioned for different load levels.

The older runners exhibited reduced vertical GRF active peak and horizontal GRF propulsion peak compared to the young runners and these results are similar to previous studies

(Bus, 2003; Karamanidis and Arampatzis, 2005). The reduced muscle force output, particularly in the calf musculature, may have contributed to these findings. In fact, there was a significant correlation between APFS and both GRF horizontal propulsion and GRF vertical active peak. An increased maximal loading rate of the vertical GRF was displayed by older runners, thus suggesting that they have poor shock absorption capability. Indeed, this finding has been consistently documented in previous studies that examined older runners' gait patterns (Bus, 2003; Lilley et al., 2011). Although not fully understood, high loading rates have been associated with stress fractures in younger runners (Zadpoor and Nikooyan, 2011) who presumably have an enhanced tissue shock absorption capabilities compared to their older counterparts. Hence, higher tissue strain rates as a result of the increased loading rates combined with reduced shock attenuation capabilities, reported previously in older adults (Hsu et al., 1998), may increase the injury risk of older runners.

An overall reduction in the trunk excursion was observed in older runners, particularly in the sagittal and transverse planes of motion (Fig. 5). Previous studies have observed reduced ROM, particularly in the lumbar spine with age (McGill et al., 1999). However, the lack of studies examining the trunk movements in older runners prevents any comparison with the literature. We speculate that the increased stiffness in the trunk and spine structures, although not directly measured, may have also negatively influenced trunk mobility during running and may contribute to musculoskeletal disorders such as low back pain (Mellin, 1990).

3.5 Conclusion

This is the first study to comprehensively investigate running gait biomechanics and measures of muscle strength and flexibility in older and younger runners. Overall, the results of

the present study provide further evidence that biological ageing results in reduced muscle force output, reduced joint range of motion, and alterations in running gait biomechanics. Future research is necessary to determine whether therapeutic exercise can alter or minimize these changes and reduce injury risk.

3.6 Summary

This cross-sectional study was the first to investigate both clinical and gait biomechanical adaptations in a representative sample of matched young and older runners. Our results indicate that older adults present clinical and biomechanical alterations that may explain their higher susceptibility to sustain a running-related injury. However, we found poor correlation between clinical and biomechanical variables, despite the fact that previous studies claimed the existence of such an association without providing quantification (Earl and Hoch, 2011; Snyder et al., 2009). It is possible that there is, in fact, no association between clinical and biomechanical variables, but our negative finding may also be a result of the method used to measure, particularly muscle strength. While maximal isometric force output may indicate the level of strength of an individual, it is a static measure whereas, the gait biomechanical variables represent the patterns during running. In addition, the older runners may have sufficient strength and ROM for running, despite their reduced levels when compared to young runners. Therefore, age-related weakness and lack of mobility might not be the source of the altered gait mechanics. This study compared seven flexibility measures, six muscle strength measures, and thirty-four gait biomechanical measures. The presence of multiple dependent variables may have impaired the ability of the statistical method used, due to the increased risk of incurring experiment-wise Type I error. A suggested solution for this problem would be the use of procedures to control the

inflation of this error or use a multivariate statistical approach (Knudson, 2009a). However, these techniques usually over fit the model to the example data, thus compromising the prediction ability. Since multiple dependent variables are often present in biomechanical studies, more robust data analysis techniques need to be identified and applied.

Chapter 4: Support Vector Machines for Detecting Age-Related Changes in Running

Kinematics

4.1 Introduction

The use of gait analysis has been crucial to improve clinical care since it provides substantial information to elaborate intervention strategies. For instance, a standard gait laboratory consists of a three-dimensional (3D) motion capture system along with force platforms (Allard, 1997). These sources would individually generate large amount of data, let alone the additional data that can be derived from the use of inverse dynamics such as joint moments and powers. This high volume of data and the multivariate and complex pathoetiology of a running-related musculoskeletal injury often demands robust data reduction techniques which need to be efficient in identifying clinically meaningful features. 3D biomechanical gait data have traditionally been analyzed using discrete variables and a univariate statistical approach (Bus, 2003; Fukuchi and Duarte, 2008; Lilley et al., 2011). These methods become unsuitable for large datasets due to the so called curse of dimensionality problem which is the problem that arises as the dimension of the data increases and the number of possible solutions also increases, but exponentially. Multiple comparison statistics using inappropriate methods have inadvertently been used in biomechanical research and could have resulted in wrong interpretations by increasing the chance of Type I error (Knudson, 2009a). In addition to the high dimensionality problem, gait analysis commonly presents high variability. Different sources contribute to this variability such as intra-subject, inter-subject, within-trial and between trial variability, not to mention the variability due to marker placement and instrumentation. Hence, these data are usually corrupted by noise or error to some extent. Furthermore, most traditional statistical techniques are based on the assumption of linearity among features. Despite the fact

that gait variables generally interact in a complex non-linear fashion. A classic example that illustrates this problem is the relationship between electromyographic signal characteristics and muscle force (Enoka, 2008). Relationships between gait variables are often difficult to describe analytically and often only subjective descriptions are available. There are a variety of multivariate analysis techniques that would partially address some of these challenges (e.g. MANOVA). The usefulness of these techniques is limited by the fact that they cannot be directly applied to a combination of features to detect or classify a subject belonging to one group or another. These classical statistical approaches also tend to optimally fit the model to a particular data set. If the model fits the data too tightly it compromises its ability to make good predictions for a different set of previously unseen data. For instance, logistic regression (LR) has often been used to solve binary classification problems. LR tries to fit a model as well as possible on subjects of the training set, even if some of them do not follow the underlying distribution (e.g. outliers). This results in a substantial number of misclassifications when applied in a new independent data set. Furthermore, LR is not able to identify possible nonlinear structures in a particular data set, limiting its ability to perform the more complex classification problems that are common in biomechanics research. The use of artificial neural networks (ANN) have become popular in biomechanics to overcome these challenges and solve classification problems (Chau, 2001b; Lai et al., 2009a). However, the presence of local minima and the curse of dimensionality challenge the use of the ANN. In contrast, the SVM method always find an unique optimal solution and it is computationally efficient (Noble, 2006).

The SVM method has recently arisen as an innovative approach to analyze biomechanical data and solve classification problems in the biomedical research field due to its ability to identify complex associations (high-dimensionality) amongst many discrete variables (Begg and

Kamruzzaman, 2005; Chan et al., 2010). In fact, previous studies have used SVM successfully to discriminate walking biomechanical patterns between age groups (Begg and Kamruzzaman, 2005; Wu and Wang, 2008). However, to date, there is a limited understanding on how this relatively new way to interpret data would enhance our understanding about the age-related adaptations on gait movement patterns. We are unaware of any study that has used this approach for running movement patterns in older adults.

SVM has the potential to yield a reduced subset of variables that contain the best combined age-related discriminatory ability, thus reducing the dimension of the original data set while retaining relevant information. SVM may overcome some of the aforementioned challenges. For instance, SVM optimizes the generalization of the classifier instead of minimizing the training error. SVM can also learn non-linear relationships by transforming the original variables into a higher dimensional space and finding an optimal separation between groups. Furthermore, SVM performs well in high dimensional data sets without suffering the curse of dimensionality since the algorithm relies only on the data points that are closest to the decision boundary (support vectors). A detailed description of the SVM algorithm is offered later in this chapter.

The greater incidence of injuries among older runners may be due to age-related changes in musculoskeletal properties, such as muscle weakness, joint stiffness, and/or changes in running movement patterns (Bus, 2003; Fukuchi and Duarte, 2008). Therefore, identification of changes in movement patterns in elderly people would be helpful for injury prevention. In chapter 3, we described the use of classical statistics to quantify differences in the running biomechanical patterns between young and older runners. However, as mentioned above, these statistical techniques are limited in their ability to discriminate between age groups based on the

high number of variables presented contrasted with the small number of between-group differences. In the present work, we hypothesized that SVM will be able to discriminate running patterns across age groups.

4.2 Methods

4.2.1 Subjects

Seventeen elderly male adults and 17 young male adults volunteered to participate in this study. The same data were used in a previous published study (Fukuchi and Duarte, 2008). The demographic information of the participants is shown in Table 4-1. All participants were regular runners, were injury-free and participated in amateur long-distance races. The inclusion criteria required all participants not to use any kind of orthosis, to run at least three times per week with a total weekly distance of more than 20 km, to be rearfoot strikers during running, and achieve a reported time of less than one hour for a recent 10 km running event. The exclusion criteria were any complaints of injury in the three months prior to the experiment and important biomechanical conditions in the legs (such as flat foot or knee valgus, among others). This study was approved by the ethics committee of the University of Sao Paulo, Brazil.

Table 4-1. Demographics information of the participants.

	Young	Elderly	p-value
Age (years)	31±6	69±2	<0.001
Height (m)	173±7	168±5	0.02
Mass (kg)	73±9	65±9	0.02
Weekly training (hours)	5±1	5±2	0.63

4.2.2 Data Collection

The participants were filmed while running on a motor-driven treadmill (Inbrasport, Porto Alegre, Brazil) at 3.1 m/s and no inclination. After about 5 min of familiarization period, at least five consecutive steps of the right leg were recorded for analysis. The speed was controlled and remained consistent for both groups, and was comfortable for all participants. The participants were required to wear their own running shoes used for training. Despite this condition, 29 of the 34 participants wore neutral running shoes (i.e., no anti-pronation or anti-supination elements in the outsole). There were not any noticeable differences among the running shoes concerning heel height, weight, and sole hardness. The mean values across five trials for the right knee and rearfoot angles were used for feature calculation.

4.2.2.1 Kinematics Measurements

In order to register the three-dimensional kinematics of the lower extremity we used the “Calibrated Anatomical System Technique” (CAST) experimental protocol according to Cappozzo et al. (1995). In the CAST protocol, rigid clusters with retro reflective markers are used to measure the motion of each segment of interest. Prior to this, a calibration trial was

performed when the participant stood in a neutral posture with both cluster and bony anatomical landmark markers on the right leg of the participant, as shown in Figure 4-1. Following the calibration trial, the running trials were performed only with the rigid clusters. All markers on the shoe were positioned by estimating their correspondent position on the foot by palpation.

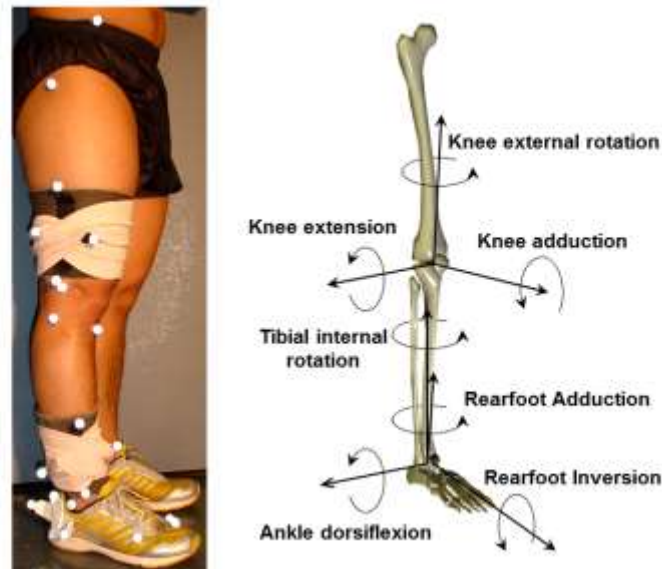


Figure 4-1. Marker protocol used and joint angles convention adopted according to Fukuchi and Duarte (2008).

The axes and planes of the anatomical coordinate systems were determined according to Grood and Suntay (1983). For the definition of the joint axes it was necessary to determine the hip, knee, and ankle joint centres. The hip joint centre was determined as suggested by Bell, Pedersen and Brand (1990). The knee and ankle joint centres were determined as the mean point between the femur epicondyles and the lateral and medial malleolus, respectively. The rotations about the knee and rearfoot in all anatomical planes (frontal, sagittal and transverse) were

calculated. In particular, we used the tibial rotation (the movement between tibia and foot) instead of abduction/adduction to report the foot movements in the transverse plane, because the tibial rotation better represents the coupling between foot and shank during the stance phase of running (Nigg et al., 1993). All angles were referenced to the angle values during standing, with the exception of inversion/eversion of the rearfoot. A zero reference for inversion/eversion was defined when the vertical axes of the calcaneus and tibia were parallel, a procedure similarly employed in other studies (McClay and Manal, 1997; McClay and Manal, 1998b). In addition to the joint angles, we investigated the absolute segmental angle of rotation of the femur, tibia, and foot. These angles were measured between the anterior axes of each segment reference system and the laboratory (global) reference system referenced by the standing anatomical calibration position.

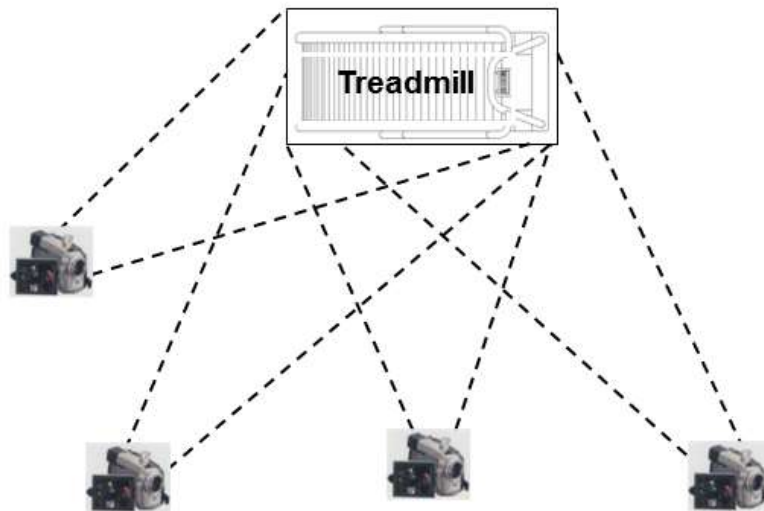


Figure 4-2. Digital cameras and treadmill set up for the data collection.

Kinematic data were recorded and digitized at a 120 Hz frequency with four digital cameras (GRDVL9800U, JVC Inc., Wayne, NJ, USA). The Figure 4-2 depicts the position of the cameras during the experiments. The four cameras were synchronised using a simultaneous sound event in their sound channel. We analyzed five support periods of the right foot for each runner. The digitisation of the marker positions was performed with the APAS software (Ariel Dynamics, Inc., Trabuco Canyon, CA, USA). A three-dimensional reconstruction of the marker positions was made via the Direct Linear Transformation (DLT) procedure and all data processing and analyses were performed in Matlab 6.5 (Mathworks Inc., Natick, MA, USA). The data were smoothed with a 20 Hz low-pass Butterworth filter of fourth order and zero lag. The average root-mean-square error of the three-dimensional reconstruction was 3.3 mm which is within the expected errors reported in the literature (Richards, 1999).

4.2.3 Support Vector Machines

Support Vector Machines is an algorithm that recognizes patterns through learning by example data (Noble, 2006). SVM originated from the statistical learning theory and was invented by Vladimir Vapnik. Its current standards including the soft margin consideration for binary classification was proposed by Cortes and Vapnik (1995). The use of the SVM in the movement science area is relatively new compared to other artificial intelligence techniques (e.g. ANN). However, the SVM method has previously been applied in other areas successfully such as to recognize fraudulent credit card behavior and handwritten digits by examining examples of both groups (for example, fraudulent and nonfraudulent behavior). Due to advancements in computer technology and the improvement of motion analysis equipment in the last decades, it is now possible to generate an increased amount of data. With the increased popularity of gait

analysis in clinical setting, clinicians have extensively relying on the results of the analysis to make decisions about either the diagnostics or treatment. However, they have been challenged by the complexities that come with this large amount of data such as high dimensionality and volume, nonlinear structures, complex correlations, variability and temporal dependencies among measured gait patterns (Chau, 2001a). It is therefore necessary to identify and implement more robust data analysis methods to deal with increasing amounts of data in biomechanical studies (Chau, 2001a). The SVM method has been considered to be a promising method to address these problems.

SVM is a supervised learning algorithm, meaning that the feature vectors are first labeled by a supervisor (clinician). For instance, if we want to train the SVM to be able to recognize age groups, we need to label the subjects accordingly. Then, the aim of the learning process (training) is to estimate a function that best represents the relationship between these feature vectors and their respective labels over the data set as demonstrated in Figure 4-3.

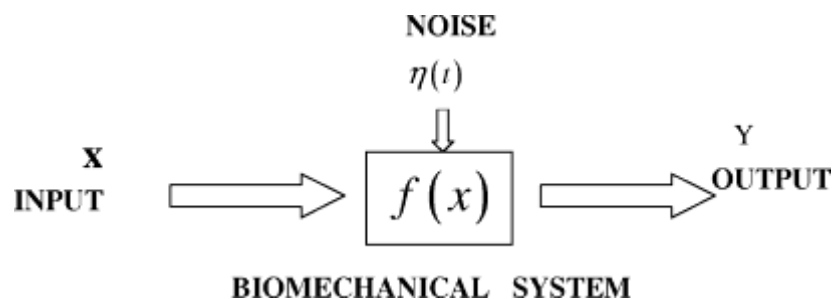


Figure 4-3. The aim of the classification process is to estimate a model by learning a relationship between inputs and outputs according to Lai et al. (2009a).

The estimation of the biomechanical model commonly follows the approach presented in Figure 4-4. Usually a cross-validation procedure is adopted where the input data are partitioned into smaller subsets to train and to test the model. By doing this process repeatedly, the model can be assessed in terms of goodness of fit and later its performance to generalize to prospective data can be tested.

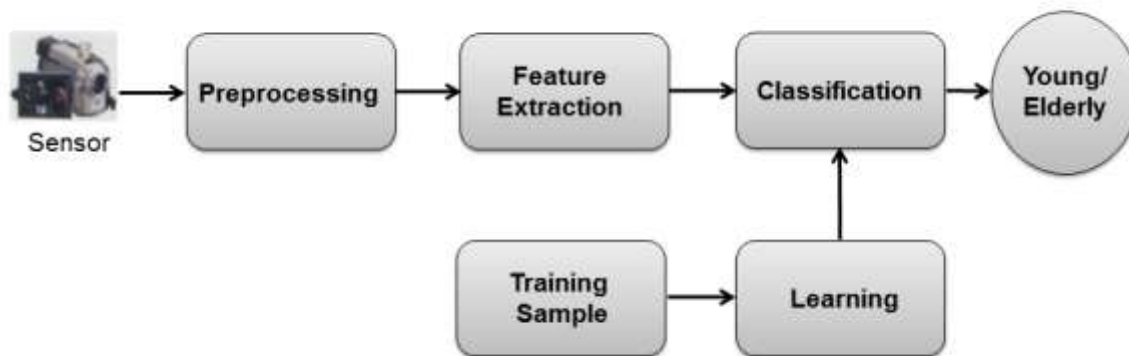


Figure 4-4. Classical pattern recognition approach. Adapted from Eskofier et al. (2012).

One of the most interesting assets of the SVM is the generalization of the training to classify new data. This would be most interesting if data contain noise or error, since the SVM will basically consider the underlying pattern rather than fitting the model to every single point in the training set.

The SVM classifies data by finding a decision boundary that separates the data points of one class from those of the other class. There may be several boundaries that work for the same data set as illustrated in Figure 4-5a. However, the aim of the SVM is to find the optimal decision function, which maximizes the margin of separation between groups (Figure 4-5b). For example, due to local minima problem ANN may stop once all training data are classified

without maximizing the margin of separation. Another unique asset of the SVM is that it relies on the position of the support vectors to determine the best separation plane. The support vectors are those data points that are closest to the separating hyperplane. In Figure 4-5b, the support vectors are those lying in the boundary of the slab.

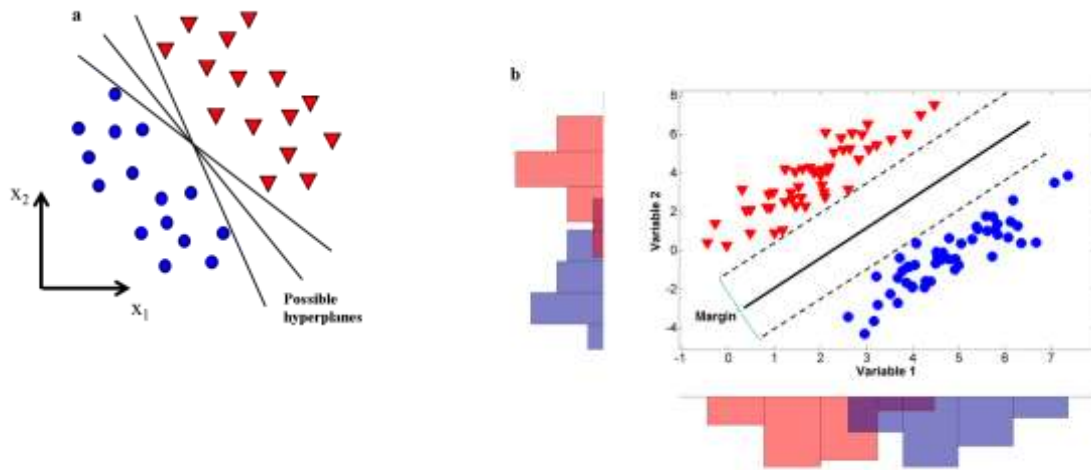


Figure 4-5. Possible decision boundaries (a). Optimal decision boundary which maximizes the margin of separation between groups (b).

To train the SVM, a data set containing the data point vectors x_i , along with their respective labels y_i need to be arranged as demonstrated in Figure 4-6.

Groups	Observations (y_i)	Variables					
		x_1	x_2	x_3	x_4	...	x_n
A	1						
	...						
	1						
B	-1						
	...						
	-1						

Figure 4-6. Example of a discrete kinematic variable matrix arrangement to classify young (A) and elderly (B) runners.

Therefore, for some dimension d , $x_i, \in \mathbb{R}^d$ and $y_i = [+1;-1]$, the equation of the hyperplane is:

$$\langle w, x_i \rangle + b = 0 \quad \text{Equation 4.1}$$

Where \mathbf{w} is the normal vector to the hyperplane and \mathbf{b} is the bias term (the distance of this hyperplane to the origin). Also, \mathbf{w} has the same dimension and resides in the same vector space spanned by average patterns ($\mathbf{w} \in \mathbb{R}^d$). The term $\langle w, x_i \rangle$ denotes the inner (dot) product between \mathbf{w} and x_i . Therefore, to find the best hyperplane that optimally separates the groups, one needs to find a combination of \mathbf{w} and \mathbf{b} that minimize $\|\mathbf{w}\|$ such that for all data points (x_i, y_i) :

$$y_i(\langle w, x_i \rangle + b) \geq 1 \quad \text{Equation 4.2}$$

The support vectors are the data points on the boundary, therefore they can be defined as:

$$y_i(\langle \mathbf{w}, \mathbf{x}_i \rangle + b) = 1 \quad \text{Equation 4.3}$$

Hence, the optimal solution \mathbf{w}, \mathbf{b} yield the classification of a vector \mathbf{z} as follows:

$$\text{class}(\mathbf{z}_i) = \text{sign}(\langle \mathbf{w}, \mathbf{z}_i \rangle + b) \quad \text{Equation 4.4}$$

For mathematical convenience, the problem is usually given as the equivalent of minimizing $\langle \mathbf{w}, \mathbf{w} \rangle / 2$ (or maximize $2 / \|\mathbf{w}\|$) which is a quadratic programming problem. The quadratic programming problem is computationally simpler to solve by constructing a Lagrangian and transforming into a dual problem. To obtain the dual, non-negative Lagrange multipliers (LM) α_i are multiplied by each constraint, and then subtracted from the objective function as follows:

$$L_p = \frac{1}{2} \langle \mathbf{w}, \mathbf{w} \rangle - \sum_i \alpha_i (y_i (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) - 1) \quad \text{Equation 4.5}$$

Then you look for a stationary point of L_p over \mathbf{w} and \mathbf{b} . If the gradient of L_p is set to 0, one obtains:

$$\begin{aligned} \mathbf{w} &= \sum_i \alpha_i y_i \mathbf{x}_i \\ 0 &= \sum_i \alpha_i y_i \end{aligned} \quad \text{Equation 4.6}$$

Hence, by substituting in $\mathbf{L_P}$, one obtains the dual $\mathbf{L_D}$ by:

$$L_D = \sum_i \alpha_i - \frac{1}{2} \sum_i \sum_j \alpha_i \alpha_j y_i y_j \langle \mathbf{x}_i, \mathbf{x}_j \rangle \quad \text{Equation 4.7}$$

$\mathbf{L_D}$ now can be maximized over $\alpha_i \geq 0$. In general many α_i are zero at the maximum. However, the non-zero α_i in the solution of the dual problem define the decision boundary, as demonstrated in Equation 4.6, which gives \mathbf{w} as the sum of $\alpha_i \mathbf{y}_i \mathbf{x}_i$. The data points \mathbf{x}_i corresponding to $\alpha_i > 0$ lie along the margins of decision boundary and are, therefore, support vectors. The derivative of $\mathbf{L_D}$ with respect to a nonzero α_i is zero at an optimum. Therefore, this results in:

$$y_i (\langle \mathbf{w}, \mathbf{x}_i \rangle + b) - 1 = 0 \quad \text{Equation 4.8}$$

If we take any $(\mathbf{x}_i, \mathbf{y}_i)$ with nonzero α_i , we can now find \mathbf{b} through the Equation 4.8. Therefore, to classify any test vector, the output is given by Equation 4.4, or:

$$\text{class}(z_i) = \text{sign} \left(\sum_i \alpha_i y_i \langle \mathbf{x}_i, \mathbf{x}_j \rangle + b \right) \quad \text{Equation 4.9}$$

Unfortunately, in reality many real data sets cannot be linearly separated (Figure 4-7). The leftmost example below shows a two dimensional input space (two input variables) and two groups of subjects (green squares and red circles) that could not be separated using a straight

line. In this case, the data can be transformed to a higher dimensional space using kernel methods before using the SVM to compute the class discrimination seen in the rightmost part of Figure 4-7. Since a new dimension was created by the transformation process, an optimal separation hyperplane might be able to distinguish between class groups.

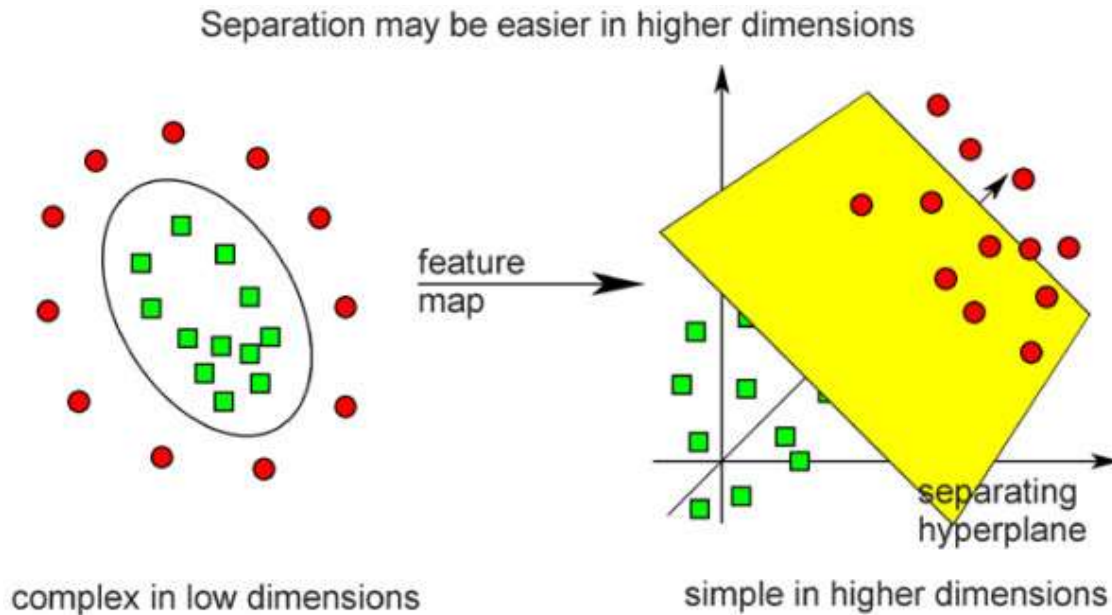


Figure 4-7. Example of linearly non-separable data set (left) that become separable when transformed in higher dimensional space (right) according to Van Looy et al. (2007).

If the data is not linearly separable, the minimization problem is modified to allow classification error by introducing some non-negative variables (S_i), often referred to as slack variables (Figure 4-8). Slack variables allow some data point to be a small distance on the wrong side of the hyperplane without violating the constraint, such that

$$y_i(\langle w, x_i \rangle + b) \geq 1 - S_i \quad \text{Equation 4.10}$$

In addition, the introduction of a penalty parameter C yields a soft margin that, essentially, allows some data points to push their way through the margin of the decision boundary without affecting the final result. Therefore, the new minimization problem accounting for both slack variables and penalty parameter is:

$$\min_{w, b, S} \frac{1}{2} \langle w, w \rangle + C \sum_i S_i \quad \text{Equation 4.11}$$

Subject to the constraint in Equation 4.10 and to $S_i \geq 0$

As can be seen in Equation 4.11, the penalty parameter C determines the trade-off between margin width and misclassification rate. In other words, when C increases, more importance is given to the slack variables S_i . Hence, the margin will become harder, and the optimization algorithm will not allow for misclassifications. In contrast, when C is small the misclassifications become less important and the margin will become softer. Therefore the penalty parameter C is a user-specified parameter that controls how many and how far the training data are allowed to violate and to cross the hyperplane.

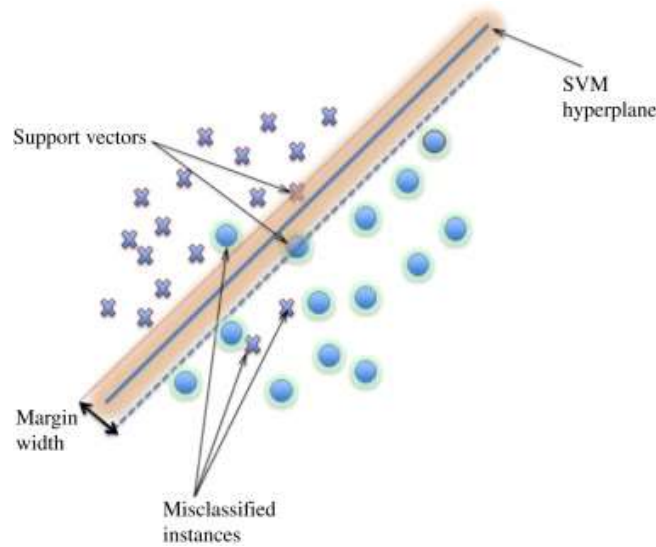


Figure 4-8. Optimal separating hyperplane and the margins dividing two datasets (circles and crosses); the vectors that lie closest to the margins are the support vectors according to Mountrakis et al. (2011).

Considering the data set presented in Figure 4-7 where the data are not linearly separable, transforming the original data into a higher dimensional space could be the solution to find a separation. This can be achieved by using the kernel trick which basically is a mathematical trick that allows the SVM to solve classification problems, when this problem cannot be solved in the original dimensional space. Even if that mapping adds new dimension to the data, kernel function is convenient because it retains all the simplicity of an SVM separating hyperplane. The Equation 4.12 shows the relation between the kernel function $\mathbf{K}(\mathbf{x}, \mathbf{y})$ and the non-linear feature mapping function $\varphi(\mathbf{x})$.

$$\mathbf{K}(\mathbf{x}, \mathbf{y}) = \langle \varphi(\mathbf{x}), \varphi(\mathbf{y}) \rangle$$

Equation 4.12

Therefore, there is a linear space \mathbf{H} and a function ϕ mapping \mathbf{x} to \mathbf{T} and the dot product occurs in the space \mathbf{T} . Hence, all the calculations for hyperplane classification use nothing more than dot products. The resulting classifier is in some space \mathbf{H} , but it does not need to be explicitly identified. Some of the kernels commonly used and available in the *svmtrain* function of MATLAB bioinformatics toolbox are shown in Table 4-2.

Table 4-2. Some of the commonly used kernels.

Kernel function	Mathematical formulation	
Linear	$K(\mathbf{x}, \mathbf{y}) = \langle \mathbf{x}, \mathbf{y} \rangle$	Equation 4.13
Polynomial	$K(\mathbf{x}, \mathbf{y}) = (1 + \langle \mathbf{x}, \mathbf{y} \rangle)^d$	Equation 4.14
Radial basis function (RBF)	$K(\mathbf{x}, \mathbf{y}) = \exp(-\langle (\mathbf{x} - \mathbf{y}), (\mathbf{x} - \mathbf{y}) \rangle / 2\sigma^2)$	Equation 4.15

* d : order of the polynomial kernel

The user must choose the appropriate kernel to enhance classification. To date, there is no analytical or empirical study that has conclusively established the superiority of one kernel over another.

4.2.4 Pre-processing

Prior to inputting the data into the classification algorithm, some preparation steps had to be taken to ensure that the data were properly arranged for use by the algorithm as exemplified in Figure 4-6. In the present study, all the support period of the trials were normalized to the stance phase over 101 data points.

4.2.5 Feature Extraction

Discrete gait kinematic variables were extracted from time series curves and they were averaged across five stance phases to represent the subject's gait pattern. Then the average and SD across subjects were obtained for each group to represent the young and the elderly runners' pattern. These variables were chosen based on previous studies (Bus, 2003; McClay and Manal, 1998a). Thirty-one running kinematic features were extracted from the recorded data, resulting in a feature matrix consisting of 34 subject rows (17 young and 17 elderly) and 31 feature (F) columns. The list of variables, their definitions and corresponding acronyms are presented in Table 4-3.

Table 4-3. List of discrete kinematic variables that were input into the SVM algorithm.

Number	Measured Variable	Abbreviation
F1	Rearfoot sagittal plane angle at initial contact (°)	ICAnkDF
F2	Peak rearfoot sagittal plane angle (°)	PEAKAnkDF
F3	Excursion rearfoot sagittal plane angle (°)	AnkDFRoM
F4	Rearfoot frontal plane angle at initial contact (°)	ICAnkEV
F5	Peak rearfoot frontal plane angle (°)	AnkEVPEAK
F6	Excursion rearfoot frontal plane angle (°)	AnkEVRoM
F7	Rearfoot transverse plane angle at initial contact (°)	ICAnkABD
F8	Peak rearfoot transverse plane angle (°)	AnkABDPEAK
F9	Excursion rearfoot transverse plane angle (°)	AnkABDRoM
F10	Tibial internal rotation (TIR) angle at heel strike (°)	ICTibRot
F11	Peak TIR angle (°)	TibRotPEAK

F12	Excursion TIR angle (°)	TibRotRoM
F13	Knee sagittal plane angle at initial contact (°)	ICKFLX
Number	Measured Variable	Abbreviation
F14	Peak knee sagittal plane angle (°)	KFLXPEAK
F15	Excursion knee sagittal plane angle (°)	KFLXRoM
F16	Knee frontal plane angle at initial contact (°)	ICKABD
F17	Peak knee frontal plane angle (°)	KABDPEAK
F18	Excursion knee frontal plane angle (°)	KABDRoM
F19	Knee transverse plane angle at initial contact (°)	ICKROT
F20	Peak knee transverse plane angle (°)	KROTPEAK
F21	Excursion knee transverse plane angle (°)	KROTROm
F22	Toe-out angle at initial contact (°)	ICToeOut
F23	Shank transverse plane angle at initial contact (°)	ICSHANKRot
F24	Thigh transverse plane angle at initial contact (°)	ICTHIGHRot
F25	Ratio of eversion and TIR excursion angles	EVTIR
F26	Time to peak rearfoot eversion angle (% stance)	IPeakEV
F27	Time to peak TIR angle (% stance)	IPeakTIR
F28	Time to peak knee flexion angle (% stance)	IPeakKFLX
F29	Time to peak knee internal rotation angle (% stance)	IPeakKROT
F30	Stride length (m)	SLength
F31	Stride frequency (Hz)	SFreq

4.2.6 Cross validation

Linear, Polynomial ($d=3$) and Gaussian radial basis function (RBF) kernels (Schölkopf and Smola, 2002) were adopted in the present study since the performance of the SVM may vary according to the chosen kernel. The only kernel independent parameter of the SVM was the C-parameter that defined the trade-off between margin width and misclassification rate. Different values for $C = [0.1, 1, 10, 100, 1000]$ were used in the evaluation to test the dependence of the approach on the C-parameter.

A 10-fold cross-validation (Duda et al., 2001) was performed and the dataset was divided into ten equal subsets with nine subsets used together to train the classifier, and one subset used to test. The generalization performance of the classifier in labeling unknown data was determined using this testing procedure. Overall classification accuracy rate was computed by examining the percentage of data points in the testing set that were correctly assigned to their group using all input features. Using this method, the general ability of the algorithm in successfully discriminating the young-elderly groups could be assessed.

4.2.7 Dimensionality Reduction

A forward feature selection approach was adopted in the present study to reduce the dimensions of the data set. This method works by creating a subset of features and then subsequently adding one new feature at a time, choosing the subset that most increased the classification accuracy (Kohavi and John, 1997).

All the computations including the classification process were performed in an algorithm implemented in Matlab 7.7 (Mathworks, MA, USA), where a cross-validation and a feature selection procedure were incorporated (APPENDIX C). Moreover, we utilized the *classperf* function of Matlab to calculate error rates.

4.3 Results

The linear kernel ($C=1$) exhibited the best performance reaching an overall classification accuracy rate (CAR), when all 31 features were used, of 91% compared to polynomial ($d=3; C=100$) and RBF ($\sigma=1; C=100$) kernels with 85% and 50%, respectively. The chosen C -parameters influenced the CAR and the best performance was achieved by the linear kernel when $C=1$ opposed to $C=100$ for the polynomial and RBF kernels (Figure 4-9).

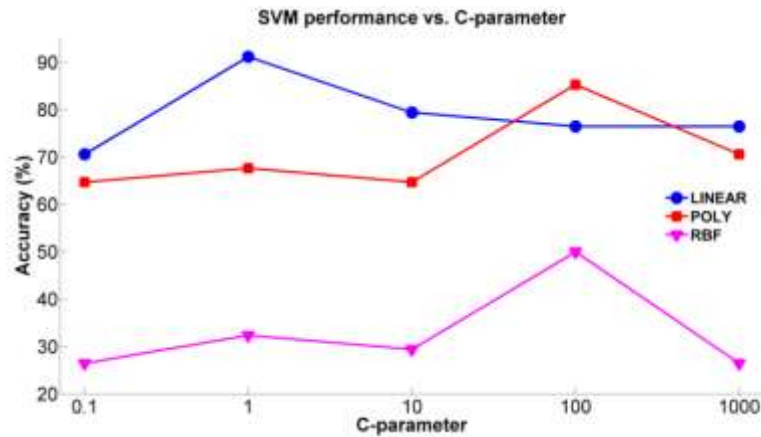


Figure 4-9. Graph of the overall accuracy rate of the linear, polynomial and RBF SVM when using different values for the penalty parameter C . In this experiment, five different values of parameter C (0.1, 1, 10, 100, 1000) were used to train the algorithm with all 31 kinematic input features.

The behavior of the SVM classifier, using the linear kernel ($C=1$), was assessed using the forward feature selection approach (Figure 4-10). This approach demonstrated that with only six selected features, the classifier achieved 100% performance in distinguishing young and elderly runners. The features containing the most discriminative information were the KFLXRoM, ICKABD, PEAKAnkDF, KABDPEAK, TibRotRoM and ICToeOut. Moreover, it can be

observed (Figure 4-10) that adding more than 18 features decreased the performance of the classifier.

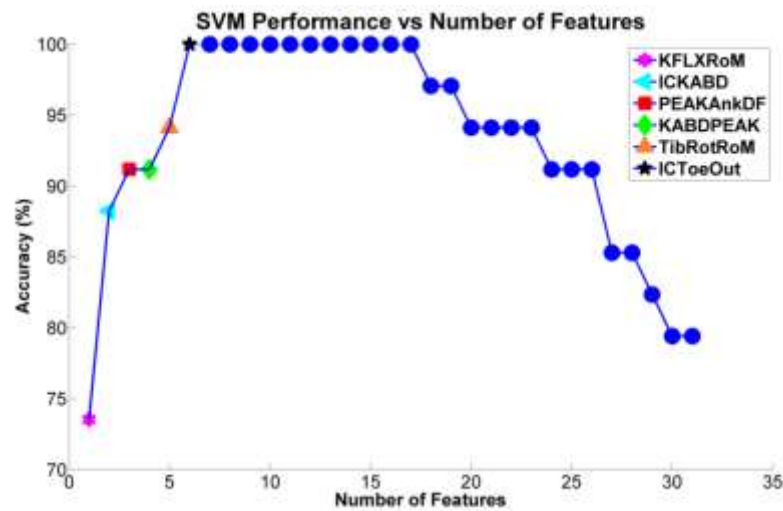


Figure 4-10. Performance of the SVM classifier using linear kernel on the number of features. The best performance was achieved with 6 features: KFLXRoM, ICKABD, PEAKAnkDF, KABDPEAK, TibRotRoM and ICToeOut.

The first two features (ICKABD and KFLXRoM) that were selected as well as the decision boundary (linear and polynomial) are shown in the 2D scatter plot (Figure 4-11).

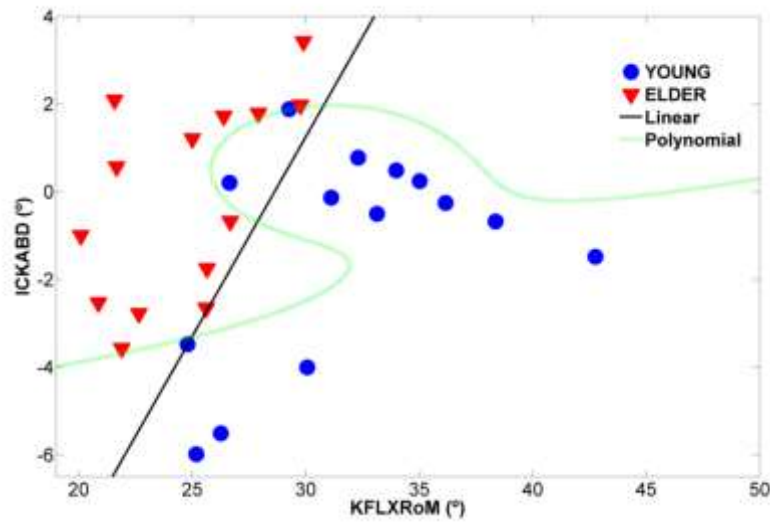


Figure 4-11. Scatter plot graph showing the distribution of the best two discriminating features (KFLXRoM (horizontal axis) and ICKABD (vertical axis)) and the separating line (hyperplane) with linear and polynomial ($d=3$) kernel SVM.

4.4 Discussion

This classification approach has demonstrated that the SVM algorithm can distinguish young and elderly runners using running kinematic data. We have previously reported differences between age groups when each feature was compared using an inferential statistics approach (Fukuchi and Duarte, 2008). However, the present results suggest that some features contain strong discriminatory information since the SVM approach required only 6 features for maximum accuracy. When more than 18 features were added, the classification performance deteriorated, thus indicating that the remaining features were highly correlated to the first selected ones. This characteristic of overfitting has also been reported in previous studies and is attributed to the redundancy of information (Begg and Kamruzzaman, 2005; Wu and Wang, 2008).

The linear kernel performed best with a maximal CAR of 91% ($C=1$). The RBF was the worst performer with a maximal CAR of 50% ($C=100$) (Figure 4-9). This suggests that the dataset was linearly separable and the use of more complex kernel did not enhance but bring more variance and impaired the generalization performance of the SVM. In fact, Lai et al. (2009b) reported similar behavior when gait kinematic variables from subjects with and without PFPS were used as input in their model. Therefore the C -parameter should be carefully selected to achieve the best performance for a given kernel. Hence, the linear kernel might be a suitable option since it is the simplest and the computationally fastest to solve the optimization problem. Moreover, the use of other kernel types makes the interpretation of the separating plane very difficult due to the transformation of the original variables to higher dimensions.

The forward feature selection algorithm consistently selected KFLXRoM and ICKABD regardless of the kernel method adopted. In fact, maximum separation of 88.2% was achieved when these features were combined alone. It is important to highlight that this type of features selection algorithm is highly dependent in the order that the variables are selected and other implementations have been proposed in the literature (Chan et al., 2002). Future research is necessary to assess the consistency of this set of selected features in discriminating age groups based on gait biomechanics data.

The distribution of the subjects' data in the 2D scatter plot (Figure 4-11) also demonstrates the ability to accurately discriminate young and elderly runners using this feature combination; and confirms that the first selected features were indeed very discriminative. The KFLXRoM exhibited the most significant difference ($p<0.001$) when age groups were compared in our previous study (Fukuchi and Duarte, 2008). Furthermore, a decrease in KFLXRoM among older runners has been reported in other studies (Bus, 2003; Karamanidis and Arampatzis, 2005).

Therefore, feature selection can detect potential candidate features as well as function to avoid redundant information.

4.5 Conclusion

The SVM method was used to detect ageing effects in running kinematics with an accuracy rate comparable with a previous findings (Begg and Kamruzzaman, 2005). Moreover, this method has demonstrated 100% accuracy when the algorithm was trained with suitably fewer selected kinematic features. Given that there is a higher incidence of injuries among older runners, future clinical applications using the SVM approach are envisioned to investigate the relationship between movement patterns and injury development. However, future prospective studies are required to answer this question.

4.6 Summary

This study assessed the performance of a novel data analysis technique to discriminate young and older runners with respect to biomechanical gait patterns. The results demonstrated that the SVM can successfully classify young and older runners based solely on discrete gait kinematic variables. In addition, the classification performance achieved a 100% accuracy rate when a subset of discriminating variables was used for classification. However, the limited sample size and confounder variables such as height, weight and shoes, may have influenced the main outcome measure (age). Moreover, while gait kinematic variables have been used to detect age-related changes in locomotion, previous research has shown that joint kinetic and ground reaction force data are also very important to understand gait adaptations as a result of biological ageing. Therefore, our next study will provide a more in-depth assessment of the classification

performance of the SVM when considering a more representative set of data (including joint kinetics and GRF data) of a larger sample size of both age groups.

Chapter 5: Effects of exercise on muscle strength, flexibility and gait biomechanics in older runners quantified by a machine learning approach: a randomized controlled trial

5.1 Introduction

There has been an increased participation of older individuals in running races in the last decade (Jokl et al., 2004). However, the increased rate of injuries among older runners has also been observed (McKean et al., 2006). Despite the fact that muscle weakness and lack of flexibility have been suggested to cause biomechanical changes in the older population (McGibbon, 2003), we have recently found limited association between clinical and biomechanical factors in younger and older runners (see chapter 3). This conflicting evidence may be due to the within- and between-subject variability of the older runners investigated. In most studies, the age groups were not matched in terms of demographic characteristics such as height, mass, BMI and mileage, which limited the external validity of previous findings (Bus, 2003; Fukuchi and Duarte, 2008; Fukuchi et al., 2011; Karamanidis and Arampatzis, 2005; Lilley et al., 2011).

Regardless of these limitations, both muscle strengthening and flexibility exercises have been widely recommended to counteract the effects of ageing (Chodzko-Zajko et al., 2009) as well as to prevent running injuries (Johnston et al., 2003). The effects of those exercises on running gait patterns remain controversial. Previous studies have reported positive changes in gait biomechanics following exercise intervention in either healthy (Snyder et al., 2009) or injured runners (Earl and Hoch, 2011). For example, Snyder, Earl et al. (2009) and Earl and Hoch (2011) reported little-to-no changes in running biomechanical variables of interest following an 8-week strengthening program for specific hip muscles in young healthy runners and runners with PFPS. Other studies have also reported a lack of association between clinical

and biomechanical factors following exercise intervention (Ferber et al., 2011; Pohl et al., 2012). The conflicting evidence may be partially explained by the univariate statistical approach employed in these studies, which does not consider the complexity of the data such as high-dimensionality and complex non-unique correlations and variability. A more robust technique that confronts these challenges is necessary.

Support Vector Machines have been recently used for biomechanics research to solve classification problems (Fukuchi et al., 2011). In brief, SVM aims to find an optimal separation between groups by learning patterns from typical data (see 4.2.3 in chapter 4 for a detailed description). SVM serves to determine combinations of variables that provide optimal dichotomous separation between groups and attempts to minimize over-fitting the model based on the training data. Moreover, SVM approaches are less sensitive to misclassification error or data points that do not belong to the underlying distribution (or are not support vectors). SVM approaches have also demonstrated a promising ability to quantitatively assess joint function following an intervention (Silver et al., 2006).

We conducted two independent studies. For the first study, our aim was to assess the ability of the SVM to classify age-groups of runners based on a number of clinical and biomechanical variables. For the second study, we investigated the effects of exercise intervention in older runners and potential changes in these clinical and gait biomechanical factors through a randomized controlled trial (RCT) study. We hypothesized that (1) SVM would accurately classify younger and older runners based on a subset of either clinical or biomechanical variables; (2) strengthening exercises would be more effective in altering the position of the older runners relative to the SVM-hyperplane and subsequently move them over or towards the side of the hyperplane populated by the younger runners; and (3) the SVM-

hyperplane distance would provide a representative estimate of the overall pattern change following the intervention, thereby demonstrating the potential of the SVM classification for other clinical research applications.

5.2 Methods

5.2.1 Study Design and Setting

The first study was an observational cross-sectional controlled laboratory study with two groups of subjects (young and older runners). The subjects in the older group were extracted from a larger sample of older subjects involved in the RCT study (study 2) and they were chosen to match the characteristics of the young group with respect to body mass, body height, BMI and weekly training hours.

The second study was a prospective, single-centre, RCT with a three group parallel design investigating the effect of exercises (stretching and strengthening) with respect to a control group. Assessments were performed at baseline and at 8-weeks. Ethics approval was obtained from the Conjoint Health Research Ethics Board of the University of Calgary (# 23344); and written informed consent was obtained from each participant prior to the initial data collection. The study was conducted at the Running Injury Clinic at the University of Calgary, Canada; and was registered at clinicaltrials.gov (NCT01574794).

5.2.2 Eligibility criteria and recruitment

Recreational runners with no injuries were considered for both studies. The participants had to be between 20-35 years (study 1) and 55-75 years (studies 1 and 2) to be considered eligible. Participants were excluded if they had: 1) lower extremity injury within the last 3

months; 2) surgery to the lower extremity within the last 8 months; 3) head injury/vestibular disorder within the last 6 months; and 4) inability to speak or read English. All participants were familiar and comfortable with running on a treadmill. Participants were recruited from local races and posted flyers between April and December 2012.

5.2.3 Power analysis

To determine the study sample size, a priori power analysis was conducted in G-power 3.1 (Faul et al., 2007). Considering we used a mixed factorial ANOVA approach to test the hypothesis that no difference across groups would be observed, the following parameters were assumed for the power analysis computation: a conservative effect size of 0.3, as this would represent a small effect (Cohen, 1988), $\alpha=0.05$; $\beta=0.20$; 3 groups of intervention (between factor) and 2 measurements (within factor). We found that a minimum of 30 runners per group were necessary to appropriately power this study. To account for 15% dropout rate, we chose to recruit 35 runners per group.

5.2.4 Participant screening

Upon recruitment, potential participants were informed about the eligibility criteria and the commitment to participate in the study. A poster flyer also outlined the eligibility criteria. Potential participants were then asked to visit the clinic for an appointment where they were screened. A certified athletic therapist (AT) screened any potential participants using a questionnaire to ensure the participants addressed the eligibility criteria.

5.2.5 Randomization

A minimization procedure (Scott et al., 2002) was adopted to optimize balance across groups for the factors of age, sex, BMI, overall flexibility and strength. The flexibility measures that were taken at the baseline were averaged across muscle groups to represent the subject's overall flexibility. Likewise, the strength measures taken at the baseline were averaged across muscle groups was considered the overall strength for each subject. These values were then used in the minimization procedure. The participants were randomly allocated to strengthening exercises group (STG), flexibility exercises group (FXG) or control group (CTG) after the baseline measures were performed.

5.2.6 Blinding

A research coordinator managed the concealed randomization procedure. The results of the randomization were stored electronically and the allocation sequence as well as any other content related to the randomization procedure were concealed. Although the exercise program was unsupervised, the first and the subsequent weekly appointments were carried out by another certified AT who could not, by definition, be blinded. Nonetheless, the participants were blinded to the investigators' hypotheses. Given that the participants were allocated only after the baseline measures were taken, they were therefore, double-blinded at baseline and single-blinded in the post-testing. Although they were not fully aware about the study hypotheses, the participants and the exercise supervision personnel could not feasibly be blinded to group assignment after the randomization procedure. However, the main study outcomes were measured by a blinded assessor through objective measures.

5.2.7 Exercise Intervention

The exercise programs were developed by the principal investigator based on both consultation with other health practitioners (physiotherapists (PT) and certified ATs) and commonly used exercises reported in the literature recommended for recreational runners. Participants allocated into the STG performed progressive resistance exercise training and the exercises included bilateral hip, knee and ankle strengthening exercises generally recommended in clinical practice, involving both open and closed-kinetic chain exercises (see APPENDIX D for a detailed description). The strengthening exercises were performed for three sets of 15 repetitions (4-6 sec/repetition) with approximately 30 seconds of rest between sets. For some of the strengthening exercises, elastic bands (Theraband; Hygenic Corporation, Akron, OH) were used as an external resistance method since it is feasible to use in a home-based exercise program. The resistance that this band provided was graded qualitatively upon colour ranging from light (yellow) to heavy (gold) and the initial loads were determined by the AT during the first appointment according to the participants' ability in performing the required exercises.

During the first visit, the participants had a chance to perform as many repetitions as they wanted to familiarize themselves with the movements and to determine their dosage. In addition, the participants were required to record their perceived exertion for each exercise on an intensity rating of 5-8 on a 10-point exertion scale (Colado et al., 2012) in the end of the exercise session (APPENDIX D). Instructions were given to the participants describing the desired way to move their legs as well as how they should adjust the resistance according to the exertion scale. At each subsequent appointment, participants were re-assessed and the appropriate adjustment to the resistance was made when necessary. During the first and for each of the weekly appointments, the AT ensured that the participants were performing the exercises properly.

The participants allocated in the FXG performed bilaterally static stretching exercises for their lower extremity muscle groups including hip flexors, hamstrings, iliotibial band, hip internal rotators, hip external rotators, hip adductors, quadriceps and triceps surae. Detailed description and illustrations of the stretching exercises are demonstrated in APPENDIX D. The participants were asked to slowly stretch their targeted muscle groups until a position of mild discomfort was achieved (Thompson et al., 2010). At this position, they were instructed to hold the position for approximately 15-30 seconds. The participants were asked to perform three consecutive stretching exercises for each flexibility exercise, six days/week for 8-weeks, taking 15-20 seconds break and alternating legs. Similar to the strengthening group, the participants in the FXG group received an individual initial orientation session wherein the participants had a chance to perform and familiarize themselves with the stretches with assistance from the AT and they also reported back to the clinic on a weekly basis to ensure they were doing the stretches properly.

Subjects in the control group did not receive any instructions regarding any exercises during the 8-week period. Nonetheless, they were strongly advised to not engage in any new exercise program during the intervention period.

To enhance adherence to the exercise programs, the participants in the STG and FXG received a comprehensive illustrated exercise booklet (APPENDIX D). The exercise booklet included contact information of the clinic and of the study personnel, a detailed outline and instructions of the exercise program including pictures, and a daily log (APPENDIX D). Each participant was also asked to check off the exercises they performed each day. At the weekly appointments, the participants' exercise booklet was reviewed, the exercise progressions were monitored, and participant's exercise progression feedback was noted.

All participants, including the CTG, were strongly encouraged to keep the overall volume of their weekly training consistent and refrain from any new exercise programs prior to commencement of the study and over the course of the 8-week intervention period.

5.2.8 Dependent and Independent Variables

5.2.8.1 Study 1

For the young and older comparison and to determine the age-related SVM classification, a discriminant vector and bias of the SVM-hyperplane that yielded the best classification rate was obtained. In the present study a linear kernel was adopted to allow a functional interpretation of the contribution of the individual variables to group differences.

A 10-fold cross-validation approach was used to determine the best parameters for the SVM model and to assess the generalizability of the algorithm. The original data set was randomly divided into 10 subsets; and nine subsets were used to train the model and the remaining 1 subset was used to test. This procedure was repeated until all subsets were used to test the model and the average classification accuracy rate (CAR) across testing subsets was used to assess the classification ability. The cross-validation procedure has been deemed a robust method to determine the SVM model accuracy prediction as long as the training sample is representative of the true population distribution that is being tested (Duda et al., 2001). All the SVM models were trained over a range of penalty parameters ($C=[0.1,1,10,100,1000]$), similarly to our previous study (chapter 4), to determine which one yielded the best generalization. The lower the C , the softer the decision boundary becomes, thus allowing misclassifications without deteriorating the classification performance. Therefore, the parameter C determines the tradeoff between margin maximization and misclassification rates.

First, we obtained the overall CAR of the age groups separately using gait biomechanical, strength and flexibility variables (Figure 5-1). Second, we investigated further classification improvements using a forward feature selection algorithm, where a combination of features was used to train the SVM such that they enhance the CAR. As such, each SVM model derived a subset of features that yielded the best-combined CAR for each variable type. The best subset for each group of features was then combined with features selected from other variable types to assess whether any further CAR could be achieved. Therefore, we obtained one SVM model for each variable type (biomechanics, strength and flexibility) and one last model that combined the best set of features from each type as depicted in Figure 5-1.

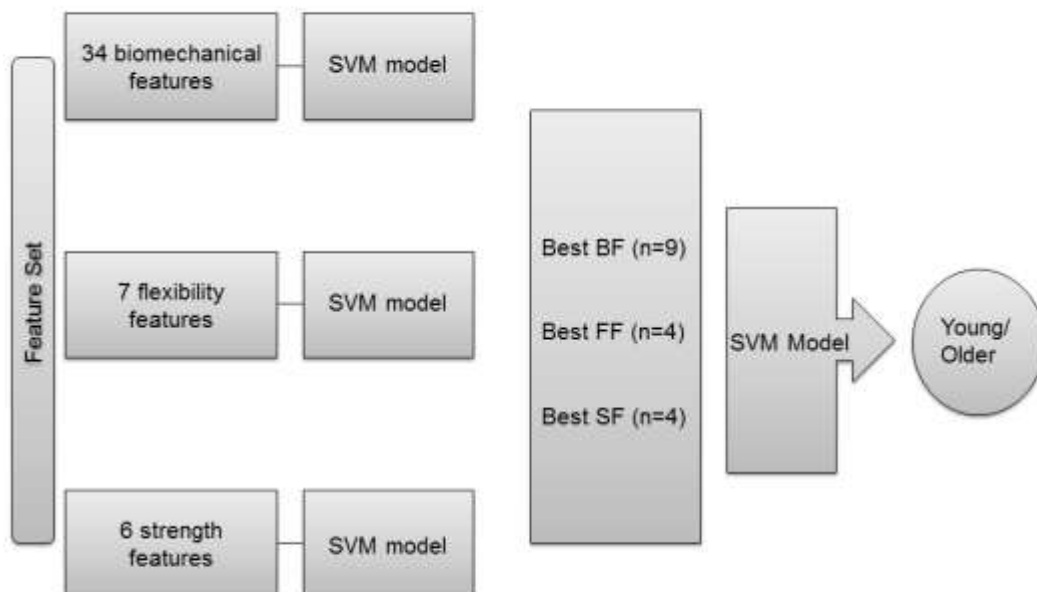


Figure 5-1. Flow diagram of the SVM classification process of young and older runners.

5.2.8.2 Study 2

The independent variables for the RCT study were exercise type (STG, FXG and CTG) and time (before and after the 8-week intervention); and the dependent variables were gait biomechanical and clinical variables. A separate analysis was conducted for gait biomechanical and clinical measures which were considered primary and secondary outcome measures in this study, respectively. Considering that there were several dependent variables to be included in the analysis, the perpendicular distance from each data point to the SVM-hyperplane was quantified and represented the overall function score of each participant in the corresponding condition analyzed.

5.2.9 Primary and Secondary Outcomes

The perpendicular distance from the participants' data to the SVM-hyperplane was calculated in high-dimensional space corresponding to the subset of gait biomechanical variables selected from the study 1 (section 5.2.8.1). A separate SVM model was trained for muscle strength and flexibility data.

5.2.10 Baseline Data Collection

Demographic information was collected during the initial visit and included age, gender, body mass, body height and weekly running training hours.

5.2.10.1 Muscle Strength and Flexibility Measurements

The right leg was used as the test extremity for muscle strength and flexibility measures. Maximal voluntary isometric muscle strength testing was performed on the following muscle groups: hip abductors (HABDS), hip extensors (HEXTS), knee extensors (KEXTS), ankle

plantar-flexors (APFS) and hip external rotators (HERS). Muscle force was measured using a HHD (Nicholas MMT, Lafayette Instruments, Lafayette, USA) and non-elastic adjustable straps (Figure 5-2). The straps were anchored to the testing bed and the subjects performed each test by pushing into the dynamometer and against the strap. Hence, it was expected that this procedure removed any potential for tester strength or experience to influence the assessment. In all strength measures, the participants were asked to maximally push against the dynamometer by moving the joint toward the instructed direction for 5 seconds. One practice trial and three experimental trials were performed, with 15 seconds of rest in between. The mean force (N) of the three MVICs trials was then normalized as a percentage of body weight.

The HABDS and HERS were tested similarly to Snyder et al. (2009). The HABDS was tested with the participant in a side-lying position with the test leg facing upward. The HHD was placed 5 cm proximally to the knee joint line and it was secured to the leg using a strap that surrounded the leg and table (Figure 5-2a). The HEXTS test was performed with the subject lying in prone with the right knee in 90° of flexion (Figure 5-2b). The HHD was placed 5 cm proximal to the popliteal fold and it was secured to the leg using a strap that surrounded the leg and table. The KEXTS was tested similarly to Reese (2012) with the participants in a seated position with their hips and knees in 90° of flexion (Figure 5-2c). The tested lower leg was then positioned at 60° relative to the horizontal and the HHD was placed 5 cm above the midpoint between lateral and medial malleoli. An inclinometer was used to ensure that the tested lower leg was always at the same starting position angle. The APFS was measured with the participants in a prone position with their foot positioned beyond the edge of the testing bed and the ankle in a neutral position. The tester stabilized the subjects' shank so that any movement of the participant's leg relative to the testing bed was minimized (Figure 5-2d). The HERS was tested

with the participants seated with their hips and knees in 90° of flexion. The HHD was placed 5 cm above the medial malleolus and secured by a strap around the ankle that was anchored to a table leg (Figure 5-2e).

Joint ROM measures were taken by using either a universal goniometer or a digital inclinometer (Pro 360 digital protractor; SmartTool Technology, Inc, Oklahoma City, OK, USA). The hip adduction ROM (HADDROM) was tested with the subjects in side-lying position, pelvis and shoulder aligned along the vertical plane, and the knee extended (Figure 5-3a). The examiner stabilized the pelvis with one hand while the other hand moved the thigh of the tested limb (the top limb) into hip flexion, abduction, and extension and then lowers the limb into adduction until it stopped via soft-tissue stretch or from posterior rotation of the pelvis, or both (Figure 5-3a). Hip extension (HEXTROM) was measured with the participants lying in supine with the hip joint positioned over the edge of the exam table. The subject was then asked to bring and hold their contralateral limb to their chest such that the hip and knee remained in a flexed position (Figure 5-3b). To quantify the joint ROM, the inclinometer was then placed at the mid-point between the anterior superior iliac spine and patella, along the longitudinal axis of the lateral and anterior aspect of the thigh to measure HADDROM and HEXTROM, respectively (Ferber et al., 2010). Hip external rotation (HERROM) (Figure 5-3c) and hip internal rotation (HIRROM) (Figure 5-3d) were assessed while the subjects were seated with their hips and knees at 90° while the tester passively moved the lower leg towards the desired direction (Norkin and White, 2003). The axis of the goniometer was placed at the knee joint with the fixed arm in a vertical direction, which was determined visually, towards the ground and the movable arm along the participants' test leg (Norkin and White, 2003). Ankle dorsiflexion ROM was tested using a goniometer with the participants lying prone on the test bed and the tester passively

moved the ankle into dorsiflexion. The axis of the goniometer was positioned at the lateral malleolus, the fixed arm was aligned to the fibula and the movable arm aligned to the fifth metatarsal. Ankle dorsiflexion ROM was assessed similarly to Johanson et al. (2008) with the knee both extended and flexed at 90° to better isolate gastrocnemius (AGASROM) and soleus (ASOLROM) muscle flexibility, Figure 5-3e and Figure 5-3f, respectively. The hip flexion (HFLXROM) was measured through a straight leg raise test. The participant's hip was passively moved into flexion while keeping the knee in full extension (Figure 5-3g). An inclinometer was then placed in the anterior aspect of the thigh to quantify the available ROM. Intra-class correlation coefficient (ICC 2,1) ranged from 0.60 to 0.87 and from 0.71 to 0.96 for the flexibility and strength measures, respectively; thus indicating good to excellent reliability in the clinical measurements (Shrout and Fleiss, 1979).



Figure 5-2. Participant's position for isometric strength test: (a) hip abductors, (b) hip extensors, (c) knee extensors, (d) ankle plantar flexors, (e) hip external rotators.



Figure 5-3. (a) hip adduction, (b) hip extension, (c) hip external rotation, (d) hip internal rotation, (e) ankle gastrocnemius, (f) ankle soleus, (g) hip flexion.

5.2.10.2 Biomechanical Measures

For the biomechanical analysis, the participants were requested to run at a speed of 2.7 m/s on an instrumented treadmill (Bertec, Columbus, OH, USA). The running speed was chosen to allow for a more direct comparison with the only study that attempted to relate levels of muscle strength and gait biomechanics in older runners (Karamanidis and Arampatzis, 2005). The participants first had an accommodation period on the treadmill for about three minutes. All participants wore standard, neutral shoes (Nike Air Pegasus, Nike, Portland, OR, USA) provided by our laboratory.

Biomechanical data were collected using an eight camera Vicon MX3 (Vicon Motion Systems, Oxford, UK) motion analysis system. A combination of anatomical and tracking markers was used to determine the position and orientation of the segments in three-dimensional space (Figure 5-4). This kinematic gait model has displayed good reliability and a detailed description of the model can be found in previous studies (Pohl et al., 2010; Pohl et al., 2012).

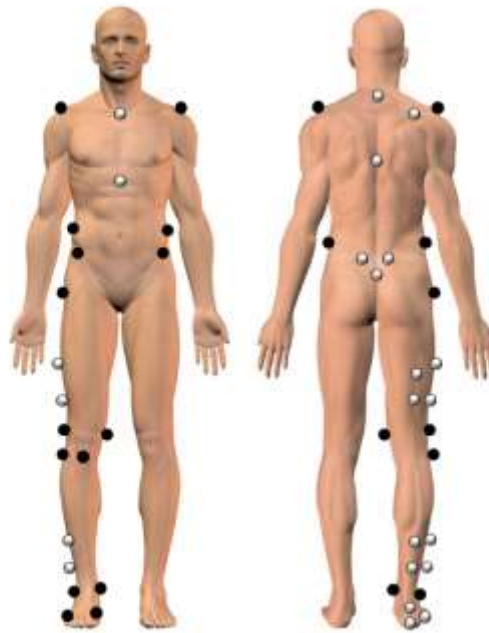


Figure 5-4. Marker set protocol used in this study depicting anatomical (black) and technical (white) markers used in the study.

Following a standing calibration trial, the anatomical markers were removed and the subjects ran on the treadmill. The kinematic data for ten footfalls were collected at a sample rate of 200 Hz and the GRF data were collected at 1000 Hz. The heel strike and toe off were determined when the vertical GRF crossed a 40 N threshold level. After residual analysis, raw marker trajectory data and GRF data were filtered using a fourth order low-pass Butterworth filter with cut-off frequencies of 10 Hz and 50 Hz, respectively (Winter, 2005). Three-dimensional hip, knee, and ankle joint angles were calculated using cardan angles with the distal segment expressed relative to the proximal segment. The net internal joint moments and joint powers were calculated using a standard inverse dynamics approach and they were resolved in a joint coordinate system. Joint power was calculated as the product of the torque and angular velocity at each joint. Joint impulse and joint work were computed as the area under the moment-time and power-time curves, respectively. The joint kinetic and the GRF variables were normalized by subject's body mass. A detailed description of the biomechanical variable calculation is offered in APPENDIX A. In addition, the centre of pressure (COP) of the force platforms was calibrated to minimize errors in the COP location using procedures detailed in APPENDIX B.

Visual 3D software (C-motion Inc, Germantown, MD, USA) was used to filter the marker and GRF data and to calculate joint kinematics and kinetics. Joint angles, joint moments and powers were normalized to the stance phase over 101 data points. Individual and group mean parameters were obtained using in-house algorithms developed in Matlab 7.12 (Mathworks Inc, Natick, MA, USA). The average time-distance parameters and average plots of kinematic and

kinetic parameters were obtained from the 10 footfalls. For a better characterization of the older runners' gait pattern, we selected variables commonly reported previously (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). Excursion angles (difference between maximal and minimal values) were obtained for all joints in all three planes of motion. The maximal loading rate, the magnitude of the impact peak and the active peak of the vertical GRF, and the magnitude of the breaking and propulsion peaks of the horizontal GRF were also quantified.

5.2.11 Machine Learning Approach

A machine learning algorithm (SVM) was first trained to identify patterns from young and older runners. In brief, the SVM algorithm (Vapnik, 1998) determines an optimal separating hyperplane which generates the maximum margin of separation between dichotomous datasets (young vs. older) considering all combinations of variables. To find the optimal decision boundary, the SVM relies on the information provided by only the data points that are close to the decision boundary (support vectors). Hence, the data points that are not close to the boundary are ignored, which makes SVM less prone to noisy data. In addition, the SVM has a user-specified penalty parameter that defines the trade-off between margin width and misclassification rate. Therefore, SVM have a soft margin and the user can determine how many and how far data points can cross the decision boundary. Based on these parameters, the SVM aim is generalization rather than over-fitting of the model to the training dataset making its ability to detect prospective data higher as compared to other algorithms (a detailed description of the SVM algorithm can be found in chapter 4, section 4.2.3).

To determine the clinical and biomechanical age-related adaptations, we first trained the SVM model using example data of 35 young and 35 older runners which was the same sample that we analysed in chapter 3 using traditional statistical methods. To better characterize the older runners' gait pattern, we selected variables commonly reported in previous studies (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). The model that yielded the best overall classification accuracy rate in discriminating age-groups was obtained and a number of input parameters were tested to investigate which combination of variables would result in the best overall classification approach. Input parameters that were tuned were: kernel type, penalty parameter **C** and cross-validation procedure. For clinical measures, a separate SVM model was trained considering 6 muscle strength and 7 flexibility original variables. A forward feature selection algorithm was used to reduce the dimensionality of the gait biomechanical variables. This method creates a subset of features and then subsequently adds one new feature at a time, choosing the subset that best increases the classification accuracy (Kohavi and John, 1997). Hence, gait biomechanical variables that retained the best combined classification accuracy were identified.

The first SVM model obtained using data from young and older runners was used to determine which exercise program would affect the position of an older runner relative to the SVM-separating hyperplane. By using the decision boundary parameters obtained in the previous step: **w** (the discriminant vector) and **b** (the perpendicular distance from the plane to the origin), we calculate the orthogonal distance from each data point in the 3 groups (strength, flexibility and control) before and after exercise using Equation 5.1 (Silver et al., 2006). This metric provided a representative score of the overall pattern change following intervention, by capturing the combined influence of the dependent variables.

$$d_i = \frac{[\langle w, x_i \rangle + b]}{\|w\|} \quad \text{Equation 5.1}$$

5.2.12 Statistical Analysis

The statistical analysis was conducted on a *per protocol* basis using R software 2.15.1 (R Foundation, Vienna, Austria). The normality assumption of the dependent variables was assessed through the Levene's test followed by a 3X2 mixed factorial ANOVA to assess the differences, if any, in the orthogonal distance to the SVM-hyperplane, at a significance level of 0.05. Between group independent factors (type of intervention) with three levels (STG, FXG and CTG) and a repeated measures factor (time) with two levels (pre- and post-intervention) were used. If a main effect was found, simple effects with Tukey's honestly significance difference (HSD) correction to reduce the chance of Type I error was performed (Knudson, 2009a).

5.3 Results

5.3.1 Study 1

The demographics information (Table 3-1) and the descriptive statistics (Table 3-2, Table 3-3, Table 3-4 and Table 3-5) of the young and older runners that were analyzed in this study can be found in section 3.2 of chapter 3.

The best overall CAR, when all features were included, was 85% for flexibility measures, 86% for muscle strength measures and 73% for gait biomechanical measures. These CARs were achieved when the SVM was trained using a linear kernel and 10, 0.1 and 1 were the respective penalty parameters (C).

The CAR was further enhanced when only features that retained the best discrimination ability, which was determined by the feature selection algorithm, were included. For flexibility

measures the combination of ASOLROM, AGASROM, HERROM and HFLXROM yielded a CAR of 87%. The distribution of young and older runners, considering only the first three flexibility measures selected (ASOLROM, AGASROM and HERROM) is shown in Figure 5-5. For the strength measures, the combined information of APFS, HABDS, HIRS and HEXTS yielded a CAR of 90%. The distribution of young and older runners, considering only the first three strength measures selected (APFS, HABDS and HIRS) is shown in Figure 5-6. For gait biomechanical measures, the optimal CAR of 89% was achieved when 9 out of 34 variables were included in the following sequence: Tho/Pel IR-ER excursion, Hip ADD-ABD excursion, Maximal GRF vertical loading rate, Ankle positive work, Knee ER Impulse, Ankle DF-PF excursion, GRF vertical active peak, Ankle ADD-ABD excursion and Ankle PF impulse. It can also be noticed a steady decrease in classification accuracy rate when more than 11 biomechanical variables were used, thus indicating some of the features presented redundant information and poorly linear separability (Figure 5-7). The distribution of young and older runners, considering only the first three biomechanical measures selected (Tho/Pel IR-ER, Hip ADD-ABD excursion) is shown in Figure 5-8.

In addition, when the best discriminant features of each type of measured variables (4 flexibility, 4 strength and 9 biomechanics) were combined and used for classification ($C=0.1$), the overall CAR was 89%, compared to the overall CAR of 85%, 86% and 73% that were obtained for flexibility, strength and biomechanics, respectively. However, the best performance of the SVM was achieved when a subset of features from the optimal combined sets were selected. Specifically, when APFS, Hip ADD-ABD excursion, HERROM, Tho/Pel IR-ER excursion, Ankle DF-PF excursion and HIRS were used for classification, the SVM model yielded a CAR of 94% (Figure 5-9). The first three selected features corresponded to one

strength, one flexibility and one biomechanical variable are demonstrated in the scatterplot of Figure 5-10.

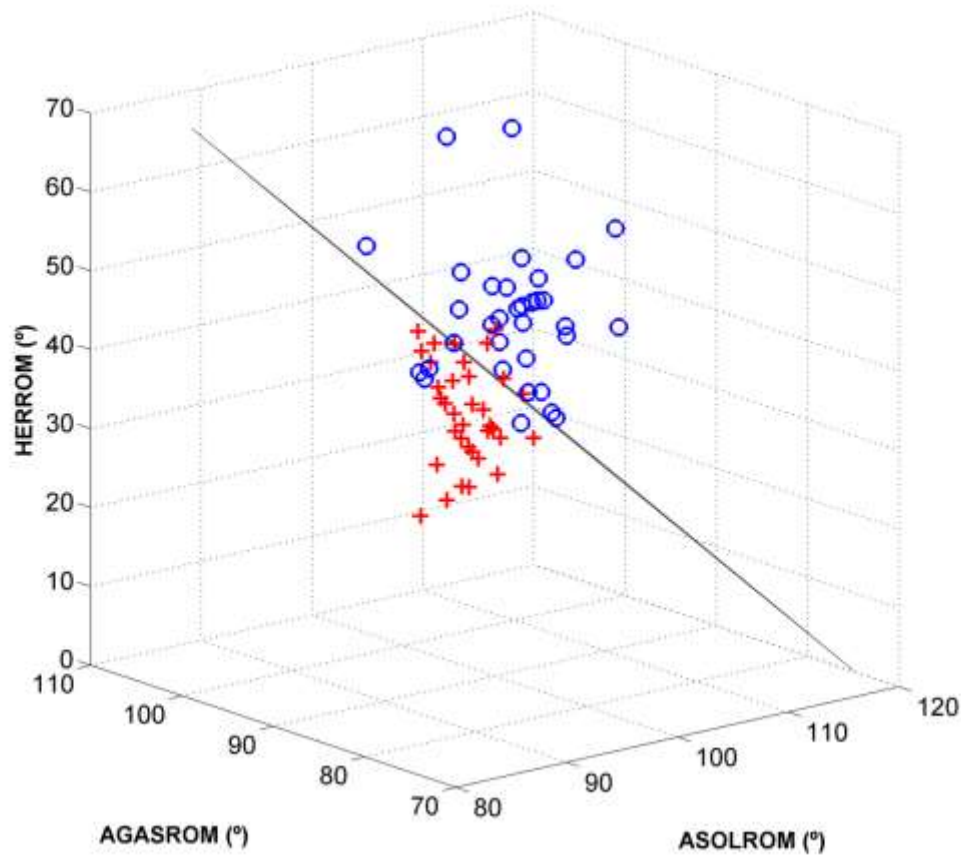


Figure 5-5. 3D scatter plot of the three best flexibility variables (AGASROM, ASOLROM and HERROM) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of flexibility features.

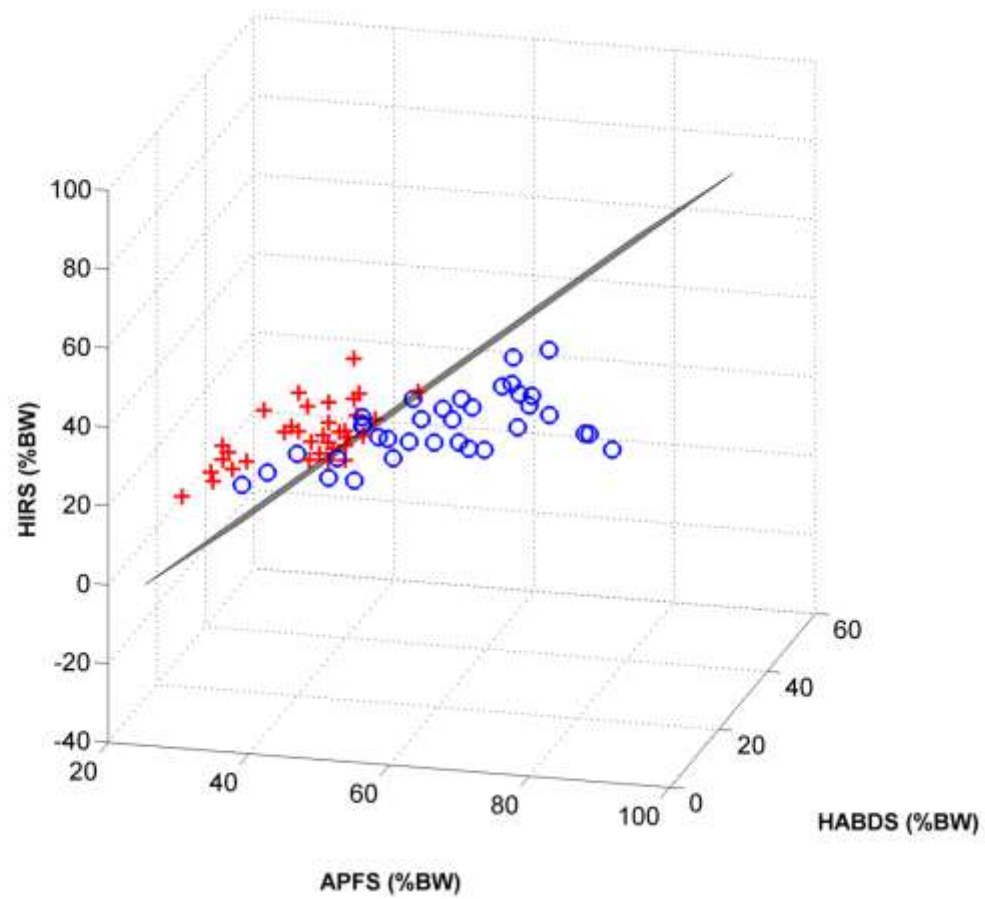


Figure 5-6. 3D scatter plot of three best muscle strength variables (APFS, HABDS and HIRS) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of strength features.

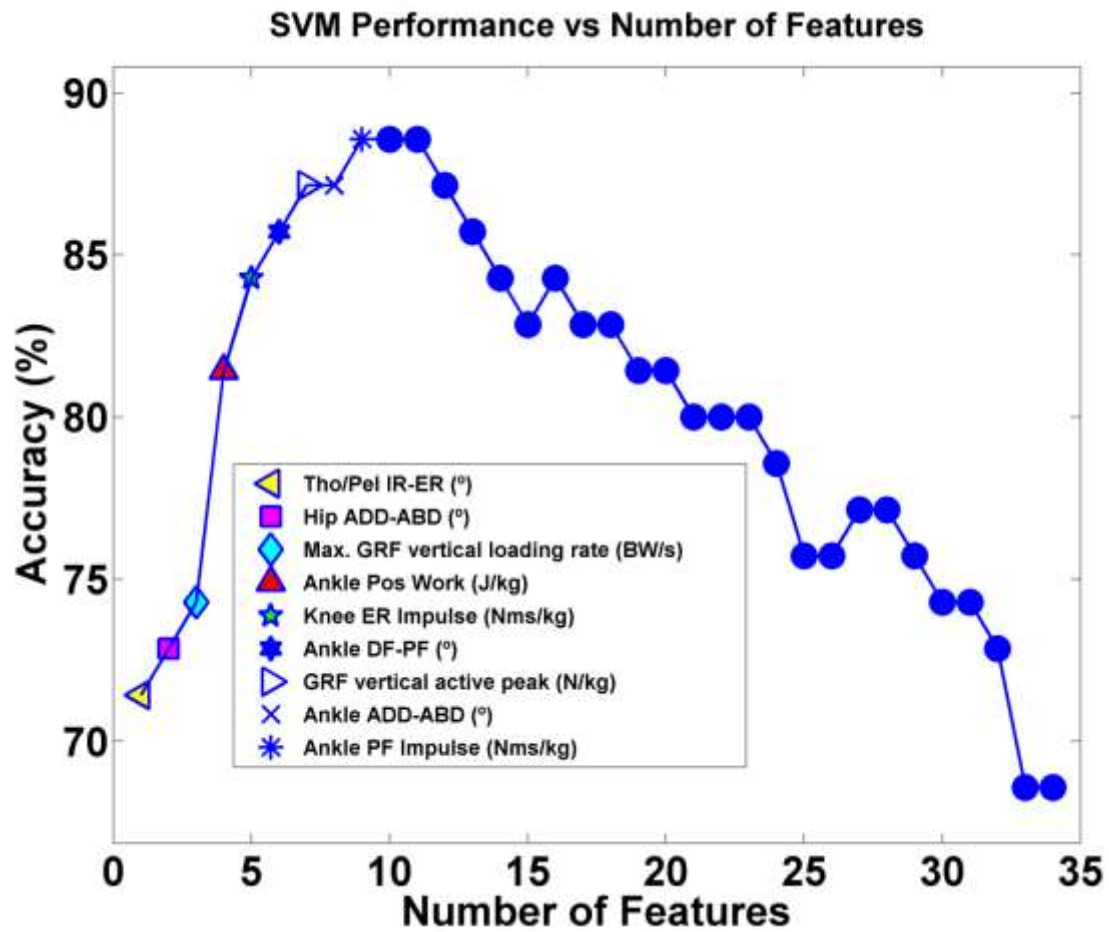


Figure 5-7. Performance of the SVM classifier on the number of gait biomechanical features.

The best performance (89%) was achieved with 9 features.

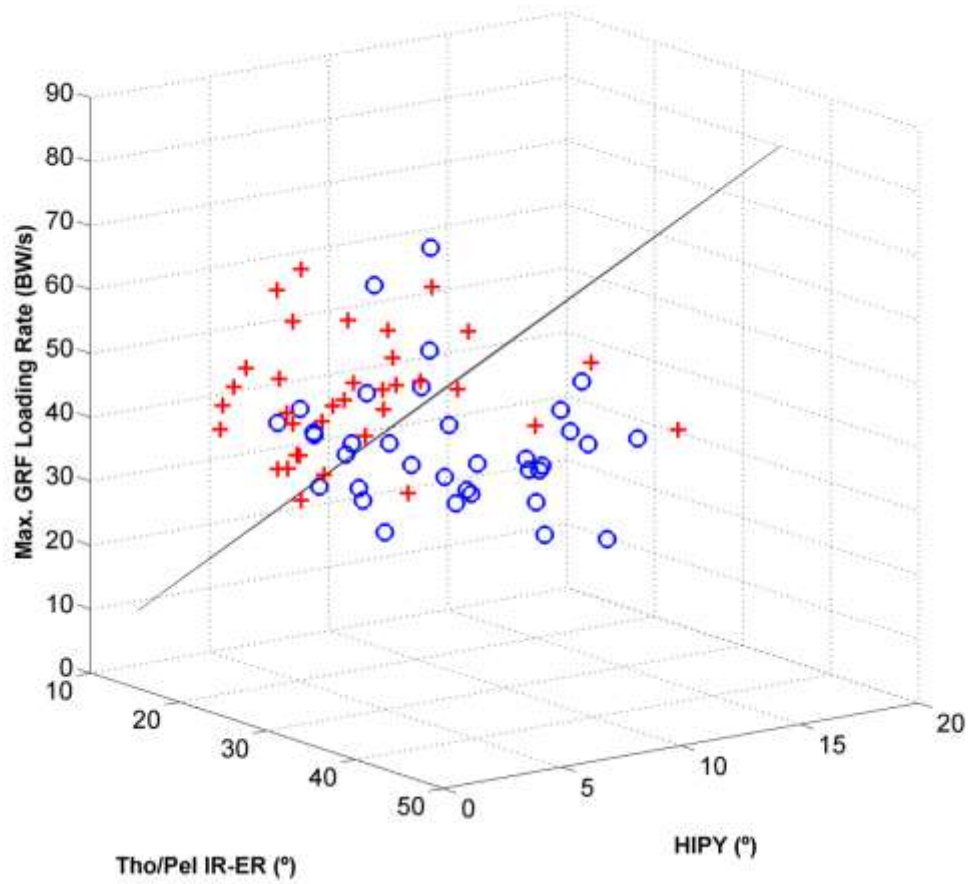


Figure 5-8. 3D scatter plot of best three biomechanical variables (Tho/Pel IR-ER, Hip ADD-ABD excursion and Max GRF loading rate) depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of biomechanical features.

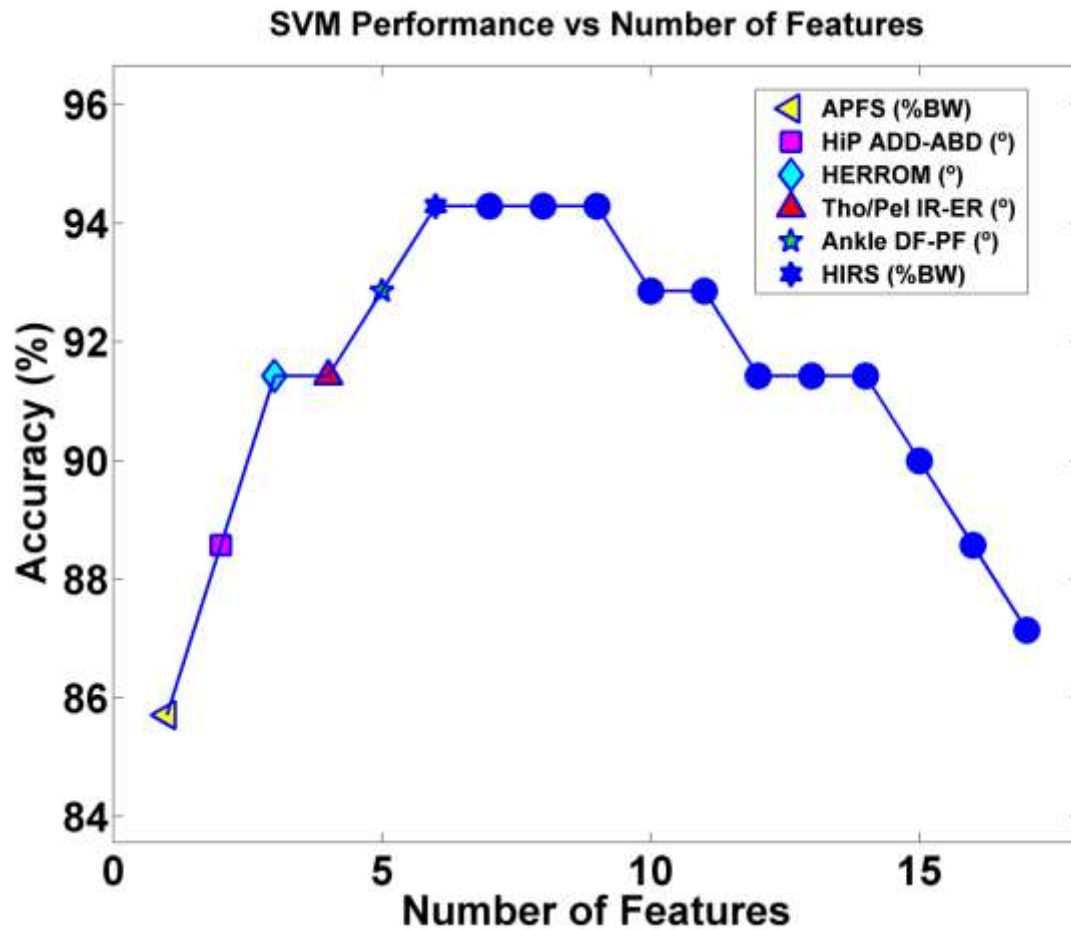


Figure 5-9. Performance of the SVM classifier using linear kernel on the number of features. The best performance (94%) was achieved with 6 features selected from the subset of 4 flexibility, 4 strength and 9 biomechanical variables.

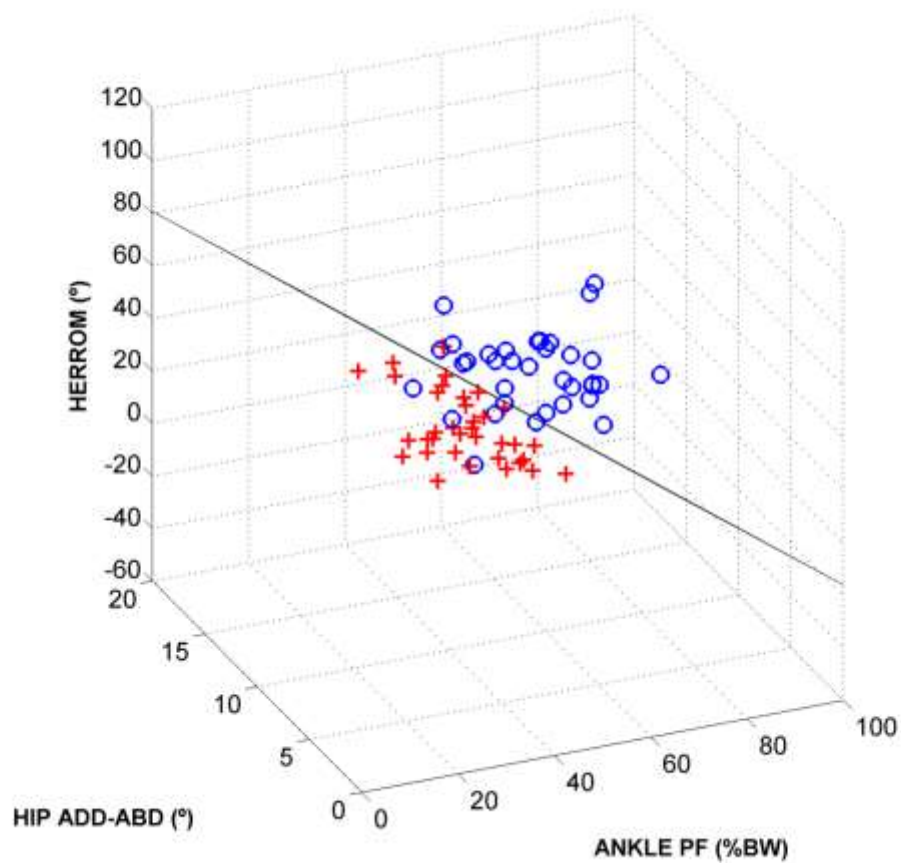


Figure 5-10. 3D scatter plot of APFS, HIP ADD-ABD and HERROM depicting the distribution of subjects, the SVM hyperplane and the discriminative power of the combination of these features.

5.3.2 Study 2

A total of 223 participants were initially contacted between March 2012 and September 2012. Of those that responded to initial contact, 74 did not meet the exclusion criteria and 44 declined to participate. Therefore, 105 participants, meeting the study eligibility criteria were randomized into one of three groups. The minimization allocation procedure resulted in 36, 34

and 35 older runners allocated to the STG, FXG and CTG, respectively (Figure 5-11). Of the 105, 93 returned for their 8-week follow up appointment resulting in a retention rate of 88.7%. Twelve subjects did not return for their post-intervention appointments and they withdrew from the study at different time periods and due to a variety of reasons outlined in Figure 5-11. In addition, data from two subjects could not be analyzed due to technical problems. Therefore, 91 subjects were included in the final analysis (33 in the STG, 31 in the FXG and 27 in the CTG). A trial participant flow diagram is included in Figure 5-11.

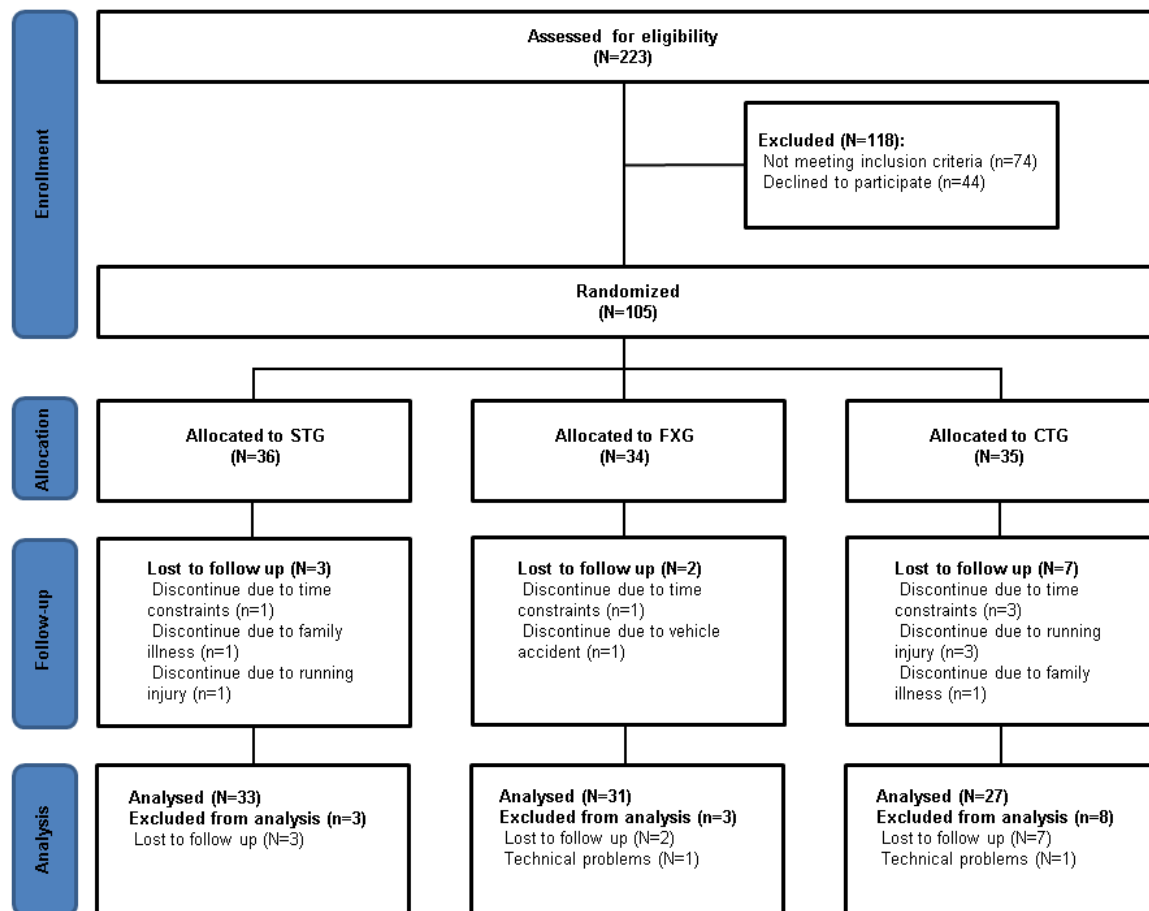


Figure 5-11. Flow diagram of the participants through the phases of the randomized controlled trials of three groups.

5.3.2.1 Baseline Data

Baseline characteristics, including demographics, and baseline data are presented in Table 5-1. The results from one-way ANOVA demonstrated that the groups were similar ($P>0.05$) in terms of demographic characteristics and the variables used to allocate the subject in the groups.

Table 5-1. Demographics information at the baseline data collection.

Variable	STG	FXG	CTG	F ratio	p-value
Demographics					
Age (years)	59.81 (4.75)	59.82 (4.03)	59.91 (3.64)	0.01	0.99
Body mass (kg)	72.72 (13.43)	72.26 (11.46)	72.49 (12.15)	0.01	0.99
Body height (cm)	171.92 (10.29)	172.00 (8.76)	172.35 (8.43)	0.02	0.98
BMI (kg/cm ²)	24.45 (3.15)	24.31 (2.51)	24.33 (3.27)	0.02	0.98
Experience (Years)	18.89 (15.21)	16.38 (13.59)	15.11 (12.42)	0.68	0.51
Weekly running training hours	3.72 (1.77)	4.68 (3.27)	4.12 (2.37)	1.23	0.30

5.3.2.2 Primary Analysis

The *per protocol* analysis included only the subjects that finished the study and the orthogonal distance of each data point to the corresponding SVM hyperplane was analyzed separately for strength, flexibility and gait biomechanical variables. This distance was also measured using a SVM model with the best combined set of clinical and biomechanical variables. This individual analysis derived four measures as follows: strength score, flexibility score, biomechanical score and combined score and they were the dependent variables in this study.

The normality of the variances among groups was addressed by qualitatively examining the distribution of the outcome variables through boxplots and histograms; and quantitatively by the Levene's test. The Levene's test yielded the following results: $P=0.01$; $P=0.73$; $P=0.86$ and $P=0.37$ for biomechanical, strength, flexibility and the combination of variables scores, respectively. The null hypothesis that the variances among groups were not different in the conditions tested was supported for the majority of the variables tested.

Biomechanical Features

Nine gait biomechanical features were included in this analysis. The combination of these features yielded the best CAR to detect young and older patterns (see results of study 1). The main effect of type of exercise on biomechanical score yielded a F ratio of $F(2,88) = 1.06$, $p = 0.349$, $\eta^2=0.024$ indicating that the mean change score across groups were not different. There were no main effects on either factor time ($F(2,1) = 0.25$, $p = 0.619$, $\eta^2=0.002$) and no interaction between group and time ($F(2,88) = 0.25$, $p = 0.619$, $\eta^2=0.002$). The average and standard deviation of the biomechanical score for the analysed groups are provided in Figure 5-12.

A detailed summary of the joint kinematics (Table 5-2 and Figure 5-13), joint moment impulses (Table 5-3 and Figure 5-14), joint work (Table 5-4 and Figure 5-15) and GRF (Table 5-5 and Figure 5-16) variables are presented.

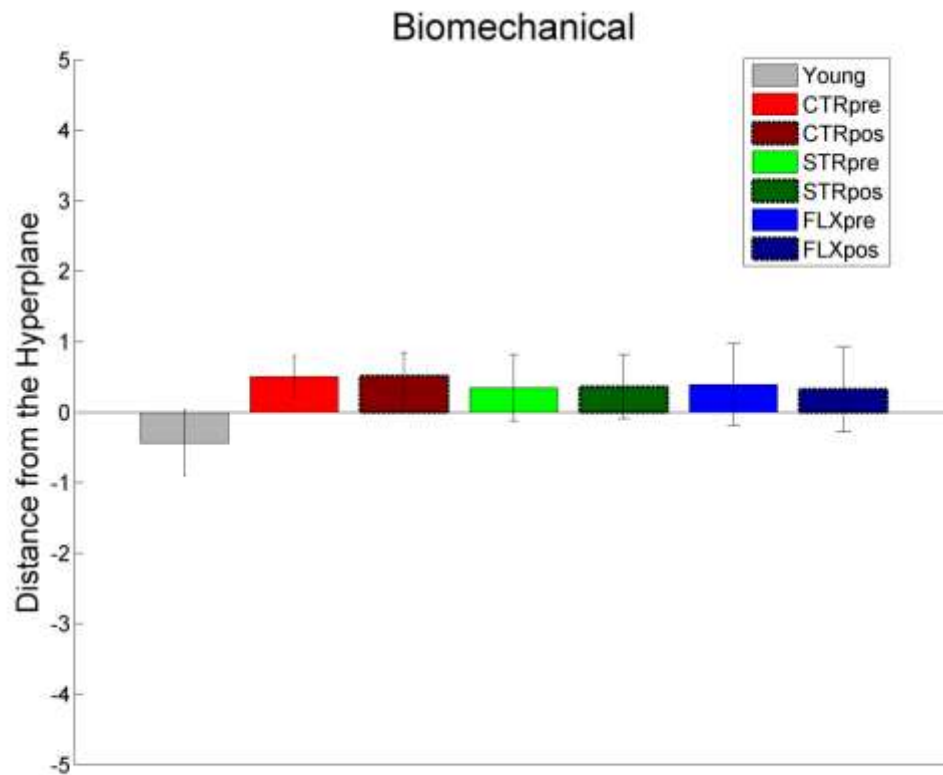


Figure 5-12. Average distance from the hyperplane before and after 8 weeks of exercise intervention for biomechanical measures. The distance was measured in nine dimensional space.

Table 5-2. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint kinematic variables in Study 2.

Variable		STG					FXG					CTG				
		PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
Joint excursion (°)																
Hip	FLX-EXT	36.9	37.4	0.5	0.3	0.7	38.5	38.2	-0.3	-0.2	-0.3	37.9	37.3	-0.6	-0.4	-0.9
	ADD-ABD	7.3	7.1	-0.2	-0.1	-0.2	7.5	7.6	0.1	0.1	0.1	7.7	7.5	-0.2	-0.1	-0.3
	IR-ER	12.0	12.0	-0.1	0.0	-0.1	12.6	12.6	0.0	0.0	0.0	11.7	12.7	1.0	0.6	1.5
Knee	EXT-FLX	28.0	28.2	0.2	0.1	0.3	27.8	27.7	0.0	0.0	-0.1	26.9	26.6	-0.3	-0.2	-0.4
	ADD-ABD	6.9	7.0	0.1	0.1	0.2	7.1	7.2	0.1	0.1	0.2	6.6	7.5	0.9	0.6	1.3
	IR-ER	13.0	13.3	0.4	0.2	0.5	11.8	12.6	0.8	0.5	1.1	12.0	13.1	1.0	0.6	1.5
Ankle	DF-PF	34.7	35.2	0.6	0.4	0.8	35.5	35.9	0.4	0.3	0.5	34.4	35.4	1.1	0.7	1.5
	INV-EV	10.7	10.9	0.2	0.1	0.2	9.7	10.4	0.7	0.5	1.0	10.4	10.6	0.2	0.1	0.3
	ADD-ABD	12.1	12.0	-0.1	-0.1	-0.1	11.1	10.8	-0.3	-0.2	-0.5	12.4	11.9	-0.5	-0.3	-0.7
Tho/Pel	EXT-FLX	9.5	9.7	0.2	0.1	0.2	8.9	9.3	0.4	0.2	0.5	8.9	9.3	0.4	0.2	0.5
	IPSI-CONTRA	13.3	13.8	0.5	0.3	0.7	12.6	13.4	0.8	0.5	1.0	13.5	13.6	0.1	0.0	0.1
	IR-ER	19.2	20.9	1.6	1.1	2.2	19.5	20.5	1.1	0.7	1.5	18.9	19.8	0.9	0.5	1.2

Table 5-3. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint moment impulse variables in Study 2.

	STG					FXG					CTG				
Variable	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
Joint Moment Impulse (Nms/kg)															
Hip EXT	-0.5	-0.5	0.0	0.0	0.0	-0.5	-0.5	0.0	0.0	0.0	-0.5	-0.5	0.0	0.0	0.0
Hip ABD	-1.0	-1.0	0.0	0.0	0.0	-0.9	-0.8	0.1	0.1	0.2	-0.9	-0.9	0.0	0.0	0.0
Hip ER	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
Knee EXT	0.7	0.8	0.0	0.0	0.1	0.7	0.7	0.0	0.0	0.0	0.7	0.7	0.0	0.0	0.0
Knee ABD	-0.3	-0.3	0.0	0.0	0.0	-0.3	-0.2	0.0	0.0	0.0	-0.2	-0.3	0.0	0.0	0.0
Knee ER	-0.1	-0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0
Ankle PF	-1.5	-1.5	0.0	0.0	0.0	-1.5	-1.4	0.0	0.0	0.1	-1.4	-1.4	0.0	0.0	0.0
Ankle INV	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0	0.1	0.1	0.0	0.0	0.0
Ankle EV	-0.1	-0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0	-0.1	-0.1	0.0	0.0	0.0
Ankle ABD	-0.3	-0.3	0.0	0.0	0.0	-0.3	-0.2	0.0	0.0	0.0	-0.3	-0.3	0.0	0.0	-0.1
Support moment	2.6	2.5	0.0	0.0	0.0	2.5	2.5	-0.1	-0.1	-0.1	2.5	2.4	0.0	0.0	-0.1

Table 5-4. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the joint work variables in Study.

	STG					FXG					CTG				
Variable	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
Joint Work (J/kg)															
Hip positive work	0.8	0.7	0.0	0.0	0.0	0.7	0.7	0.0	0.0	0.0	0.7	0.7	0.0	0.0	0.0
Hip negative work	-0.6	-0.6	-0.1	-0.1	-0.1	-0.7	-0.7	0.1	0.1	0.1	-0.7	-0.7	0.0	0.0	0.1
Knee positive work	1.1	1.2	0.1	0.1	0.1	1.1	1.1	0.0	0.0	0.0	1.1	1.1	0.0	0.0	0.0
Knee negative work	-1.2	-1.2	0.0	0.0	-0.1	-1.3	-1.2	0.1	0.1	0.1	-1.2	-1.2	0.0	0.0	0.0
Ankle positive work	2.6	2.6	0.0	0.0	0.0	2.6	2.5	-0.1	-0.1	-0.1	2.5	2.5	0.0	0.0	0.0
Ankle negative work	-1.9	-1.9	0.0	0.0	0.0	-1.9	-1.8	0.1	0.1	0.2	-1.8	-1.8	0.0	0.0	0.0

Table 5-5. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the GRF variables in Study.

Variable		STG					FXG					CTG				
		PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
GRF																
(N/kg)	Braking peak	-0.3	-0.3	0.0	0.0	0.0	-0.3	-0.3	0.0	0.0	0.0	-0.3	-0.2	0.0	0.0	0.0
	Propulsion peak	0.2	0.2	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.0	0.2	0.2	0.0	0.0	0.0
	Impact peak	1.6	1.6	0.0	0.0	0.0	1.6	1.6	0.0	0.0	0.0	1.6	1.6	0.0	0.0	0.0
	Active peak	2.2	2.2	0.0	0.0	0.0	2.2	2.2	0.0	0.0	0.0	2.2	2.1	0.0	0.0	0.0
(BW/s)	Loading Rate	40.7	41.0	0.3	0.2	0.5	43.4	42.3	-1.2	-0.7	-1.6	44.5	43.5	-1.0	-0.6	-1.5

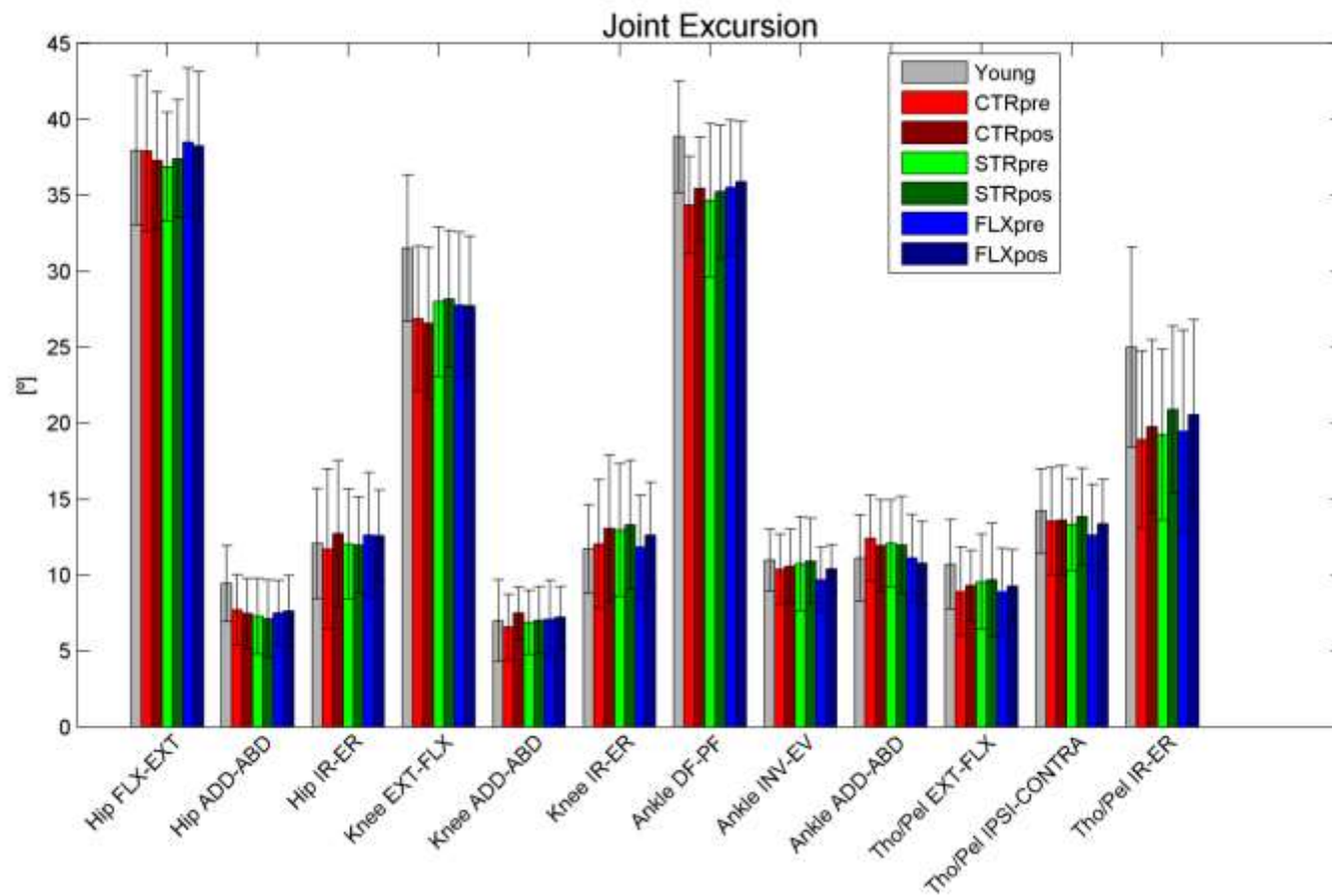


Figure 5-13. Mean and SD of the joint excursion angles for young and intervention groups before and after 8 weeks.

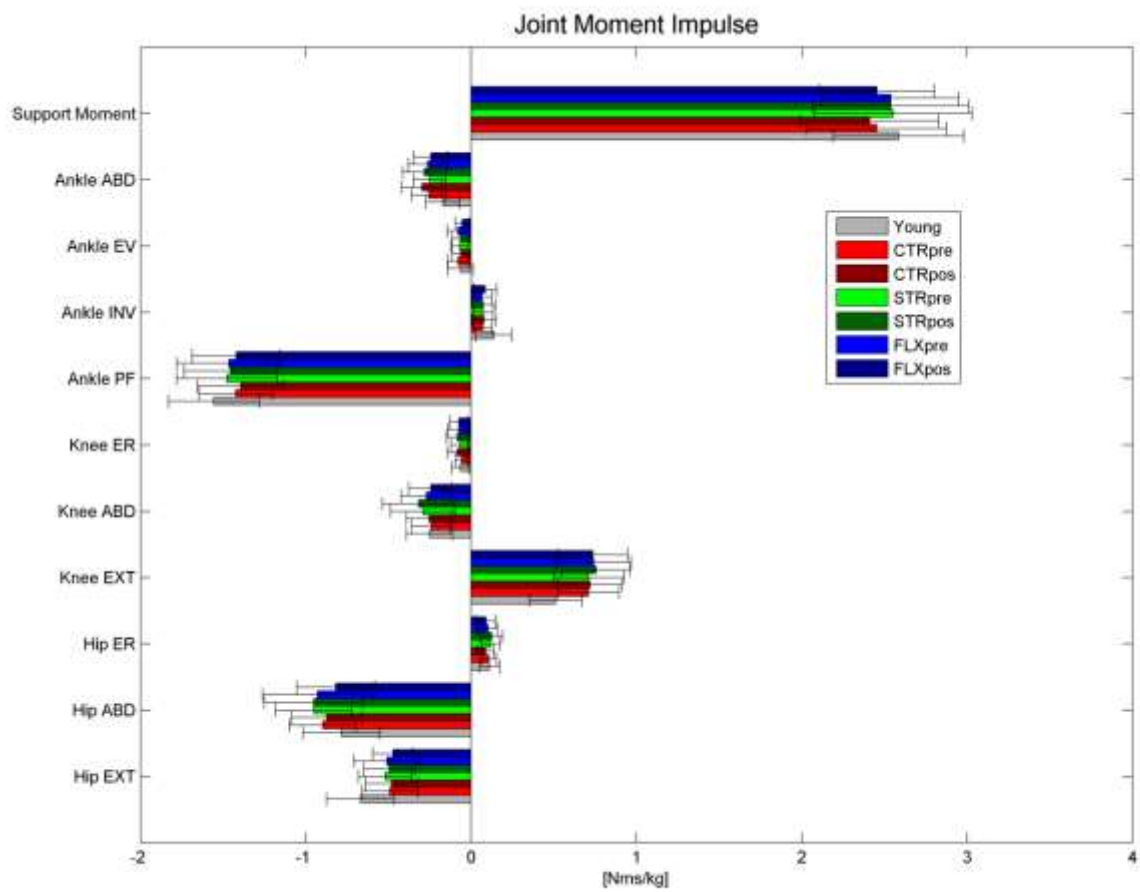


Figure 5-14. Mean and SD of the joint angular impulse variables for young and intervention groups before and after 8 weeks.

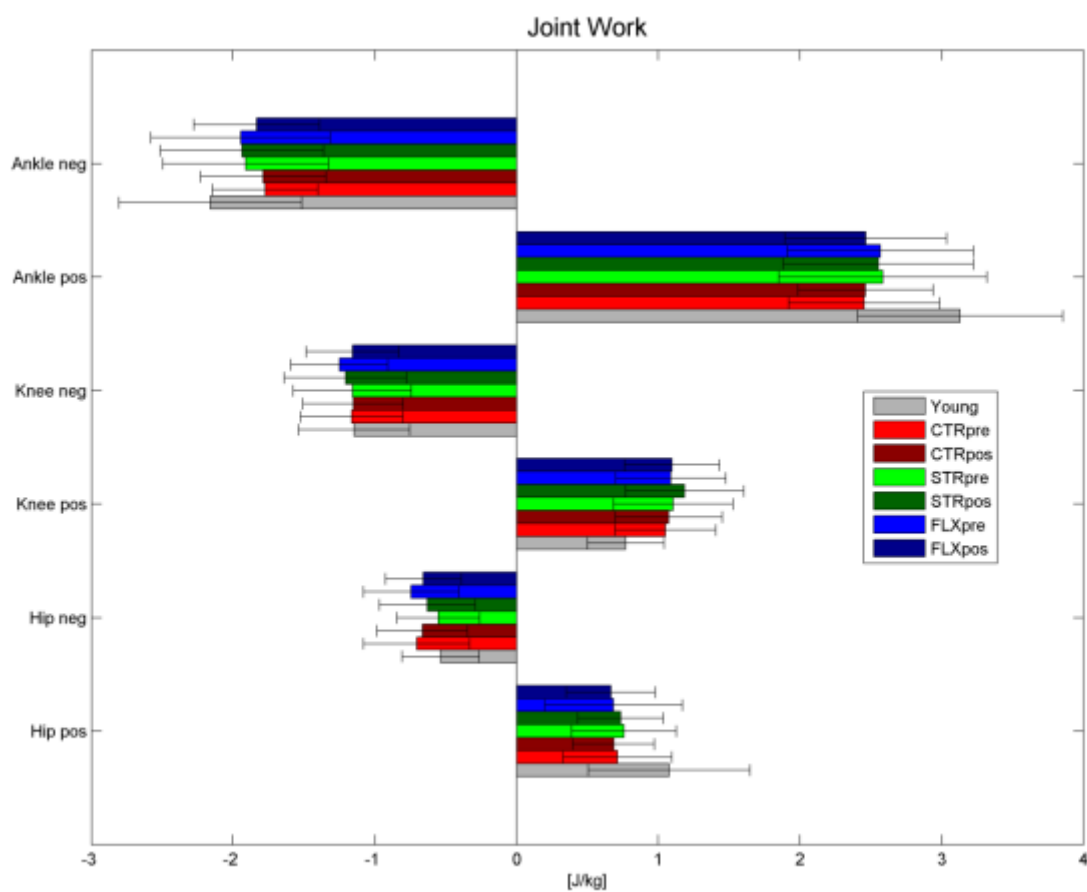


Figure 5-15. Mean and SD joint work for young and intervention groups before and after 8 weeks.

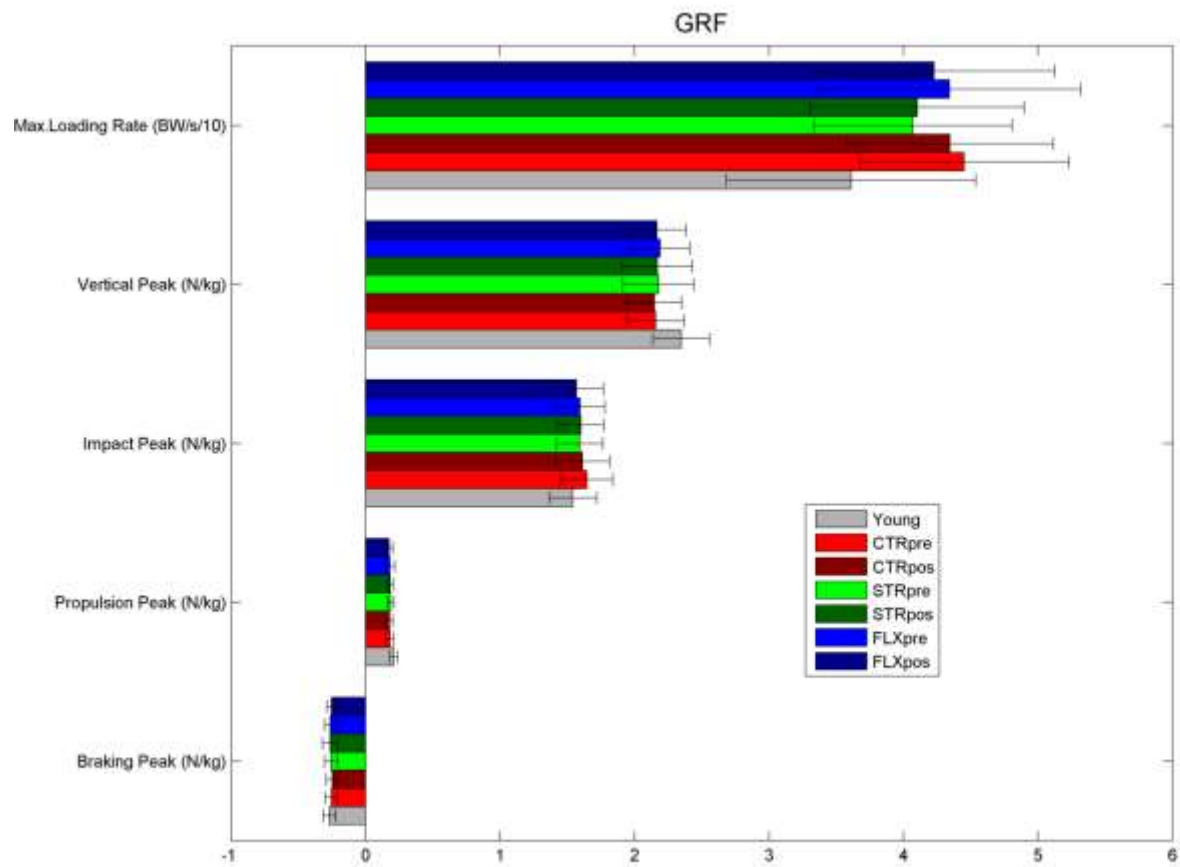


Figure 5-16. Mean and SD of the GRF variables for young and intervention groups before and after 8 weeks.

Strength Features

Six muscle strength measures were taken and the summary of the descriptive statistics and the mean and standard deviation are demonstrated in Table 5-6 and Figure 5-18. All muscle MVIC measures were included to calculate the orthogonal distance from the hyperplane and corresponded to the strength score of the individual subjects. The main effect of type of exercise on the strength score yielded a F ratio of $F(2,88) = 0.52$, $p = 0.592$, $\eta^2=0.011$ indicating that the mean change score across groups were not different. There were no main effects on either factor time ($F(2,1) = 3.94$, $p = 0.051$, $\eta^2=0.043$) or interaction between group and time ($F(2,88) = 2.02$, $p = 0.138$, $\eta^2=0.044$). The average and standard deviation of the strength score, computed in six dimensional-space, for each of the analysed groups are demonstrated in Figure 5-17.

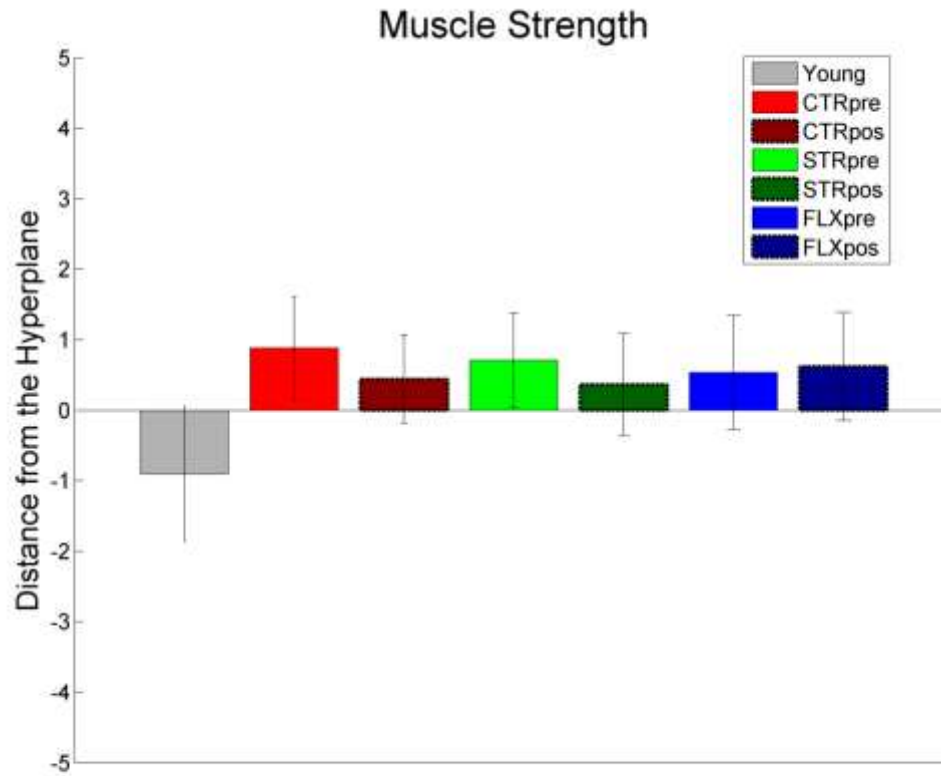


Figure 5-17. Average distance from hyperplane before and after exercise intervention for 6 MVIC variables. The distance was measured in six dimensional space.

Table 5-6. Mean values pre and post intervention, mean change, 95%CI of the change (Low-Up) for the MVIC measures.

	STG					FXG					CTG				
MVIC (%BW)	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
HABDS	31.6	31.4	-0.1	-0.1	-0.2	30.9	29.3	-1.7	-1.1	-2.3	30.2	30.4	0.2	0.1	0.3
HEXTS	23.7	21.2	-2.5	-1.6	-3.4	24.1	20.3	-3.7	-2.4	-5.1	22.8	20.4	-2.4	-1.5	-3.4
APFS	37.7	41.5	3.9	2.5	5.3	38.3	38.3	0.0	0.0	0.0	35.2	40.4	5.1	3.1	7.2
HERS	16.8	15.1	-1.7	-1.1	-2.4	16.8	14.4	-2.3	-1.5	-3.2	16.2	14.4	-1.8	-1.1	-2.6
HIRS	18.2	17.4	-0.8	-0.5	-1.1	17.1	17.3	0.2	0.1	0.3	17.6	16.9	-0.7	-0.4	-1.0
KEXTS	42.2	40.9	-1.4	-0.9	-1.9	42.6	39.1	-3.6	-2.3	-4.9	41.4	40.3	-1.1	-0.7	-1.5

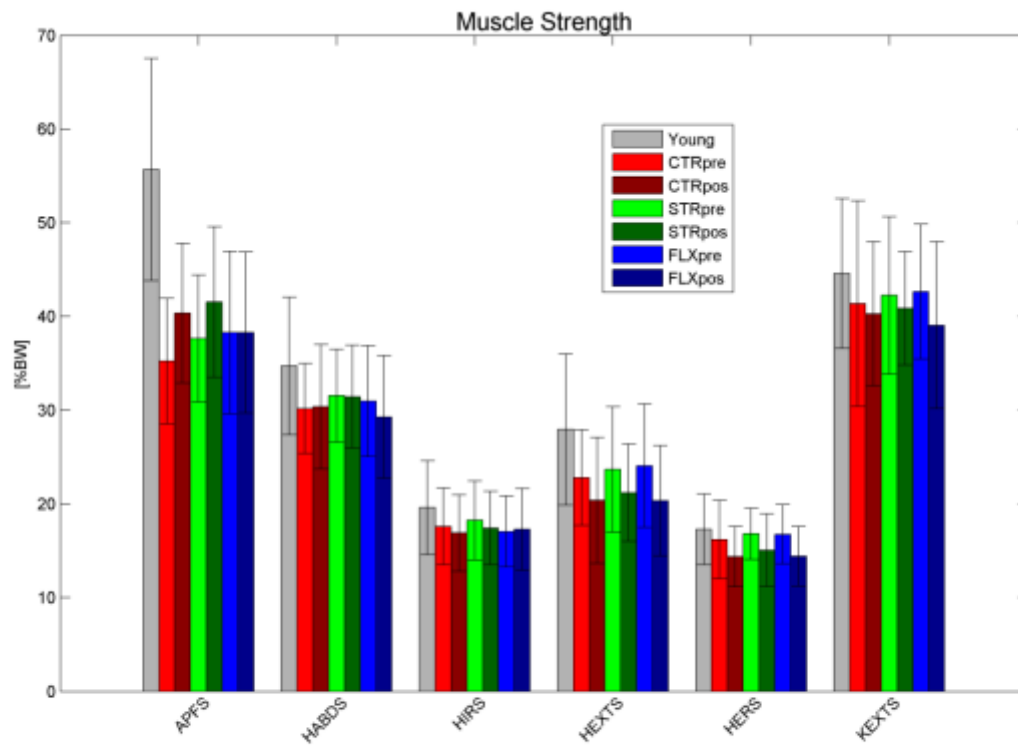


Figure 5-18. Mean and SD of strength measures for young and intervention groups before and after 8 weeks.

Flexibility Features

Similarly to the strength measures, all the flexibility features were included in the calculation, and corresponded to an overall flexibility score. The main effect of type of exercise on the flexibility score yielded a F ratio of $F(2,88) = 0.99$, $p = 0.377$, $\eta^2=0.022$ indicating that the mean change score across groups were not different. There were no main effects on either factor time ($F(2,1) = 2.37$, $p = 0.127$, $\eta^2=0.027$) or interaction between group and time ($F(2,88) = 0.31$, $p = 0.732$, $\eta^2=0.007$). The average and standard deviation of the flexibility score, computed in seven dimensional-space, for each of the analysed groups are demonstrated in Figure 5-19. A detailed summary of the descriptive statistics flexibility measures are presented in Table 5-7 and Figure 5-20.

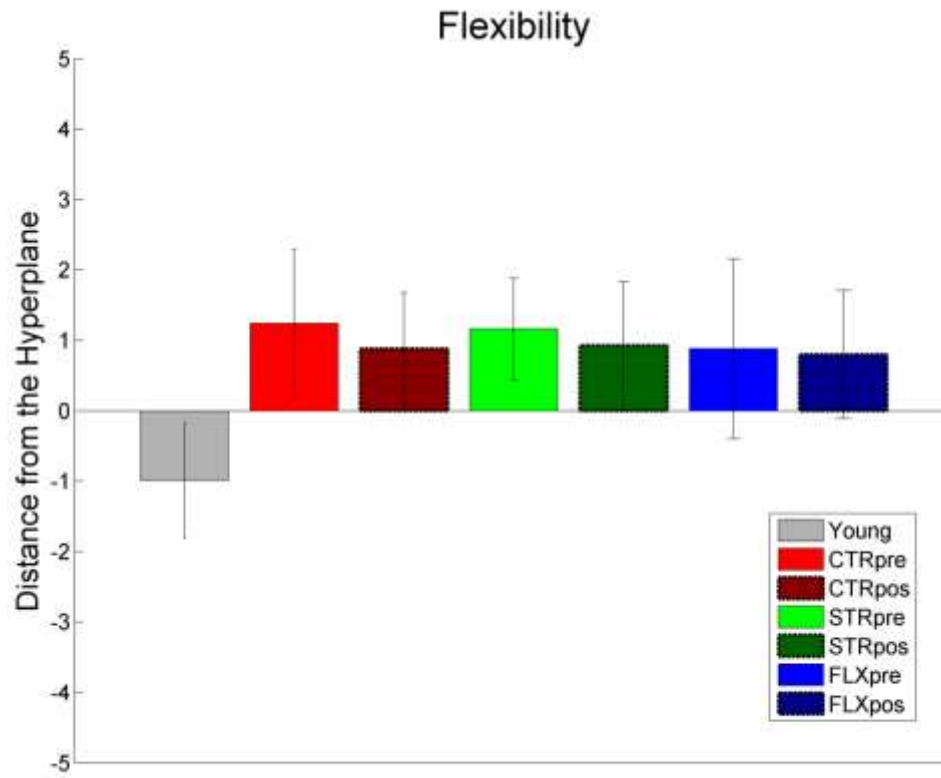


Figure 5-19. Average distance from hyperplane before and after exercise intervention for 7 flexibility measures. The distance was measured in seven dimensional space.

Table 5-7. Mean values pre and post intervention, mean change, 95% CI of the change (Low-Up) for the flexibility measures.

	STG					FXG					CTG				
ROM (°)	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up	PreM	PostM	Change	Low	Up
HEXTROM	-17.3	-19.2	-2.0	-1.3	-2.7	-16.6	-21.7	-5.1	-3.2	-7.0	-17.7	-20.4	-2.8	-1.7	-3.9
HADDROM	-26.3	-29.1	-2.7	-1.8	-3.7	-27.6	-29.2	-1.7	-1.1	-2.3	-26.1	-29.0	-2.9	-1.8	-4.1
HFLXROM	76.4	77.7	1.3	0.9	1.8	76.5	86.4	9.9	6.3	13.6	78.4	83.7	5.3	3.2	7.5
AGASROM	88.1	90.3	2.3	1.5	3.1	89.5	91.3	1.7	1.1	2.4	89.6	92.2	2.7	1.6	3.7
ASOLROM	96.1	99.4	3.4	2.2	4.6	98.8	99.8	1.0	0.6	1.4	96.6	99.9	3.3	2.0	4.6
HERROM	35.6	33.8	-1.8	-1.1	-2.4	35.2	34.9	-0.4	-0.2	-0.5	36.4	35.1	-1.3	-0.8	-1.8
HIRROM	35.8	35.8	0.1	0.0	0.1	35.3	38.3	3.0	1.9	4.1	35.6	38.7	3.1	1.9	4.4

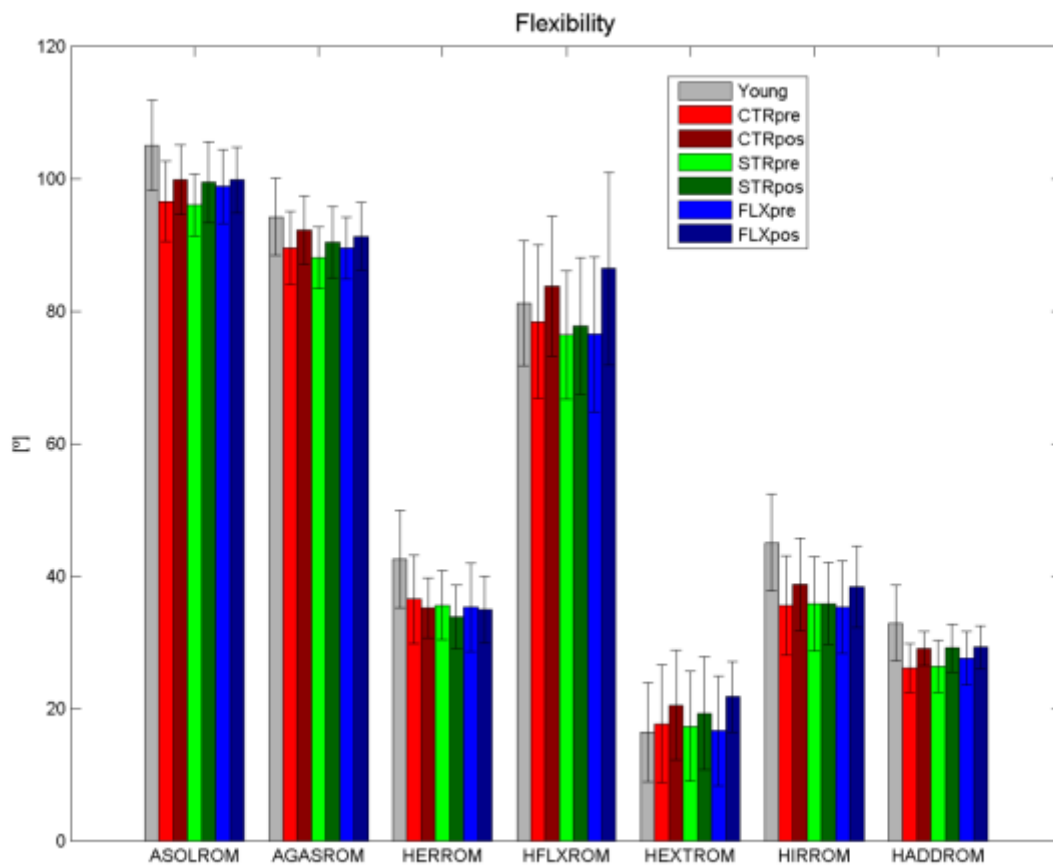


Figure 5-20. Mean and SD of flexibility measures for young and intervention groups before and after 8 weeks.

Combination of Features

In addition to the individual variable types (flexibility, strength and biomechanics), the orthogonal distance considering an optimal combination of feature types was also calculated (see section 5.2.8.1). A total of 6 features that yielded the best discrimination ability to the SVM were used to compute this distance. The main effect of type of exercise on the functional score yielded and F ratio of $F(2,88) = 0.14$, $p = 0.865$, $\eta^2=0.003$ indicating that the mean change score across groups were not different. The main effect for time presented an F ratio of $F(2,1) = 7.13$, $p = 0.009$, $\eta^2=0.074$, indicating that there was difference in scores after 8 weeks of exercise intervention. Simple effects revealed that the mean score changed significantly for STG and CTG but not for FXG after 8 weeks. The time factor was determined to be the most important factor affecting the dependent variables and accounted for 7.4% of the variance in the SVM-hyperplane distance. The average distance to the hyperplane revealed that both STG and CTG shifted significantly toward the young group but this was not observed for the FXG. There was no interaction effect between group and time factors ($F(2,88) = 0.44$, $p = 0.647$, $\eta^2=0.009$).

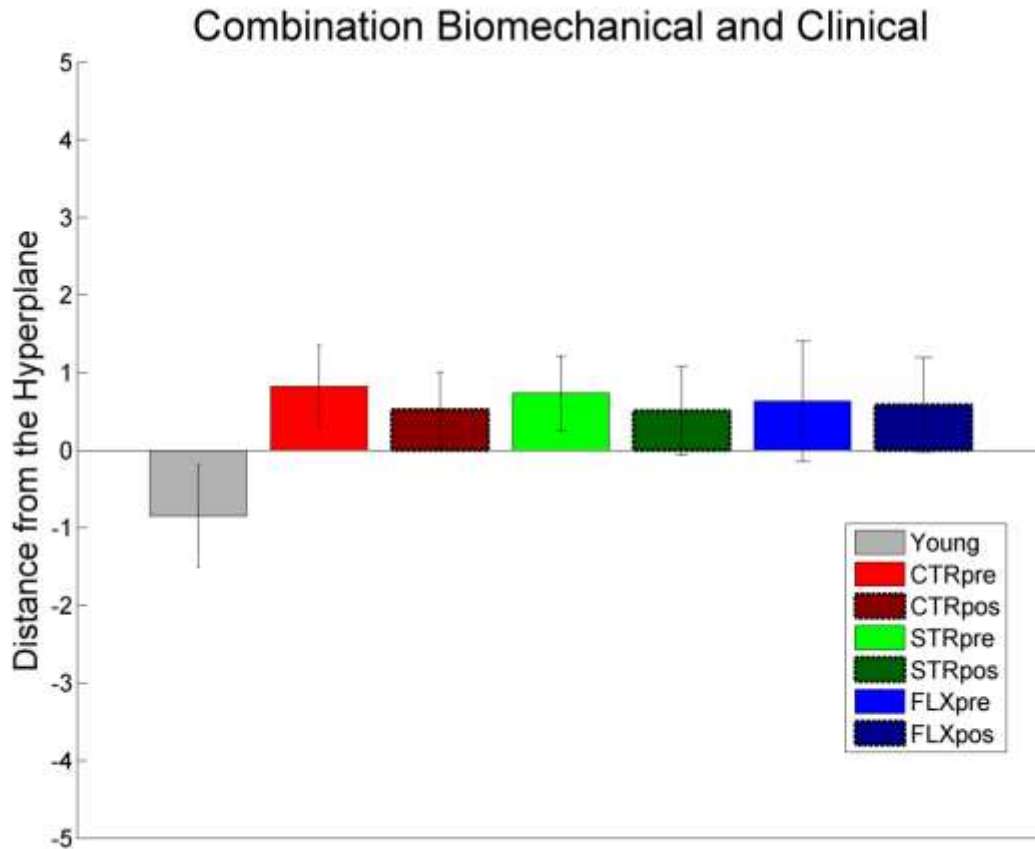


Figure 5-21. Average distance from hyperplane before and after exercise intervention for the combined set of variables (clinical and biomechanical) measures. The distance was measured in six dimensional space.

5.3.2.3 Participants Adherence and Exercise Load

On average, participants performed 5.8(0.7) and 6.1(0.8) days per week of strengthening and stretching exercises, respectively. No significant difference was found ($p=0.233$) between STG and FXG with respect to the frequency that the exercises were performed. In addition, the participants attended, on average, 7.0(1.2) and 6.7(1.3) sessions during their 8 week program

($p=0.340$). These results suggest that the participants in the intervention exercise groups dedicated the same amount of time and received similar instructions during their program. For the strengthening group the participants were asked to record their perceived exertion at the end of the exercise day. On average, the participants in the STG reported 6.2 (1.3) in a 10-point exertion scale, thus indicating that they were within the recommended range (5 to 8). Although no scale was used to monitor the dosage of the stretching exercises for the participants allocated in the FXG, their exercise booklet was reviewed and the AT ensured that the exercises were performed with the proper dosage in a weekly basis.

5.4 Discussion

5.4.1 Study 1

The aim of this study was to further examine the classification performance of the SVM in detecting the age group of runners considering a larger sample and more representative variables; and to yield a model that was further assessed to quantify exercise intervention. The results of the present study support that an SVM-approach is able to discriminate age group membership based on selected gait biomechanical variables. In addition, the performance of the SVM was further enhanced when a selected combination of biomechanical and clinical variables were included. The overall CAR was over 80% for clinical measures (85% flexibility and 86% strength) but only 73% for biomechanical features. Therefore, these results indicate that some gait biomechanical features contain redundant information or poor discriminative information, thus impairing the SVM performance. This hypothesis was supported by the fact that the relative classifier performance enhanced substantially (89% vs. 73%, or 16% improvement) when only discriminant gait features (9 out of 34) were used to train the SVM algorithm. In contrast, little-to-no improvement in CAR was observed for both strength (87% vs. 85%) and flexibility (90% vs. 86%) measures when only combinations of discriminant features were used to train the classifier. In fact, the individual clinical measures were generally more discriminant (see Chapter 3) and the set of measures was also smaller when compared to biomechanical variables. Thus it was expected that the overall CAR with the original clinical set of variables would provide good discrimination as opposed to using only the biomechanical features. Nonetheless, a CAR of 89% was obtained when the best set of each variable type (4 flexibility, 4 strength and 9 biomechanics) were input into the SVM model for training (see the steps to obtain this result in the flow diagram shown in Figure 5-1). This CAR was further enhanced and reached the

maximum CAR of 94% when only variables, from this best set of 17 variables, that retained most combined discriminative information were employed through the feature selection algorithm. The first three features selected (APFS, Hip ABD-ADD excursion and HERROM) corresponded to each of the variable types analyzed (strength, biomechanics and flexibility, respectively), thus highlighting the importance to consider different types of variables to achieve the best discrimination.

We had previously observed that a reduced set of biomechanical variables enhanced the classifier performance (Fukuchi et al., 2011). However, in this study the SVM was trained only with gait kinematic variables to predict age group in a cohort of young and older runners who were not as well matched as the current study. Considering that the young and older runners in the current study were well matched in terms of possible confounders such as height, mass, BMI and weekly training hours, the discriminative quality of this algorithm has many potential applications in clinical settings. For example, in light of the reported increased rate of injuries among older runners, the early detection of atypical gait patterns and its association with musculoskeletal changes may help design optimal intervention to alter these patterns. With validation, the SVM score derived in this study could be considered for inclusion in functional scoring systems and the results of the present study suggest that the SVM is a robust method to predict age group membership based on an optimal set of clinical and gait biomechanical variables. The results of this study also encourage the use of SVM to prospectively identify older runners, who present altered movement patterns, and to identify younger runners who exhibit clinical and biomechanical factors more similar to older runners.

5.4.2 Study 2

The goal of the current RCT was to determine which exercise type was effective in altering gait biomechanical patterns in older runners towards the young runners. With the overarching hypothesis that older runner patterns are atypical, and given the high volume of data typically used in biomechanical research studies, we used the SVM model to derive a score (orthogonal distance to the SVM hyperplane) based on an optimal combination of variables. The results indicate that this single value can potentially serve as a functional score to monitor the progression of any intervention in both research and clinical settings. However, the applicability of this score in identifying improvement in either strength or flexibility following an intervention program is limited.

Contrary to our hypothesis, an 8-week program of either stretching or muscle strengthening had no effect on the SVM score for either clinical or biomechanical variables. Despite the fact that strengthening and flexibility exercises have been widely recommended to both counteract the ageing effects and to prevent running injuries (Chodzko-Zajko et al., 2009; Johnston et al., 2003), the effects of such exercises on movement patterns remain poorly understood.

Few clinical trials have attempted to investigate the effects of these exercises on running mechanics and presented contradictory findings. Earl and Hoch (2011) and Snyder, et al. (2009) reported some positive changes in running gait biomechanics along with increased muscle strength following a hip strengthening exercise program in both younger healthy and injured runners with PFPS. Although these authors suggested that changes in biomechanics were a result of changes in muscle strength, the use of univariate inferential statistical methods limited their conclusion. In addition, the lack of a control group limits the internal validity of their findings.

In contrast, Ferber, et al. (Ferber et al., 2011) and Willy and Davis (Willy and Davis, 2011) utilized a control group of younger runners but did not find any effect on discrete knee abduction kinematics despite a reported 33% increase in hip abductor muscle strength for runners with PFPS. Similarly, Davis Hammonds, et al. (2012) found no change in running mechanics despite increased flexibility following acute hamstring stretching exercises in healthy young athletes. However, these aforementioned studies did not utilize an RCT design making any direct comparison with our results difficult.

Contrary to previous studies, we chose to investigate the effects of general exercises as opposed to targeting a specific muscle group. We also chose to investigate the overall effect of these exercises on an SVM score as opposed to assessing the individual biomechanical variables separately. Therefore, our results may not be comparable to previous literature. As biological ageing does not primarily affect a particular muscle group, the use of more general, as compared to specific exercises, were thought to be more appropriate for this population. However, the lack of effect of exercises observed in the present study suggests that general exercises of a single type (strengthening or stretching) may not be sufficient to alter gait mechanics but rather a combination of strengthening and flexibility exercises would be recommended. Future studies need to address this question.

Several strengths are apparent in this study compared to previous literature including large sample of subjects, low dropout, inclusion of both clinical and biomechanical measures, and assessment of an SVM functional score. Although, the exercise programs were home-based, the adherence of the participants was comparable between exercise groups. In addition, the weekly appointment with the certified AT helped ensure the exercises were performed consistently among participants. Furthermore, the combined information provided by both

clinical and biomechanical measures allowed for the understanding of potential underlying mechanisms of running-related injuries among older runners.

Regardless of these strengths, several limitations in the present study are acknowledged. First, the participants in the control group did not receive any intervention exercise and therefore were not required to visit the clinic on a weekly basis. Although, they were strongly recommended to not engage in any new exercise program as well as maintaining the same training levels, these individuals were not closely monitored as compared to the participants in the STG and FXG. Discrete clinical and biomechanical variables were used to assess the intervention. Hence, some temporal information may have been lost for the gait biomechanical variables. We chose to analyze discrete since the chosen variables have been commonly reported and are considered to be biomechanical risk factors for injuries. Future research needs to explore whether the inclusion of continuous time dependent biomechanical and clinical variables would provide further understanding.

5.5 Conclusion

The SVM classifier trained with a representative and reduced set of biomechanical and clinical features and with a large sample of matched young and older runners accurately predicted age group membership using a machine learning approach. In addition, the functional SVM score reduced the complexity of the analysis to a single value that represents the overall pattern change. The results of the RCT, however, demonstrated no significant effect of improvements in strength or flexibility on biomechanical patterns. Future studies involving different exercise programs and temporal analysis of biomechanical and clinical variables are

encouraged. Moreover, a validation of the SVM classifier with a more comprehensive data set and its functional score need to be further explored.

Chapter 6: Summary and Future Directions

The major focus of this dissertation was to investigate age-related gait biomechanical adaptations and the robustness of these adaptations to exercise commonly prescribed to older individuals and runners. Four main research questions were addressed in this study using a traditional and a novel data analysis approach. The results of these individual studies are presented and summarized following their aims.

6.1 Describe the clinical (strength and flexibility) and biomechanical adaptations in older runners and examine the association between them.

The effects of biological ageing have been previously investigated in only limited sample sizes and not including clinical measures, although these studies have suggested that there is an association between clinical and gait biomechanical adaptations by assuming, for example, that the older group of runners were less flexible and weaker than the younger group. In addition, these studies have also assumed that a possible correlation between these variables would exist without establishing a cause and effect relationship.

The older runners in our study indeed demonstrated an overall reduction in flexibility and muscle strength compared to matched young runners. Furthermore, atypical gait biomechanics were observed. In particular, some of these gait patterns have been observed in young runners that sustained injuries both retrospectively (Hreljac, 2004) and prospectively (Stefanyshyn et al., 2006). In addition, the results of this study further support previous findings that older runners operate less joint power and propulsion force; and have reduced ROM during running. While these findings indicate a potential association of gait biomechanics with reduced muscle strength

and flexibility, we found a poor relationship between these variables in most of the correlation analysis.

From this study it was shown that biological ageing affects clinical and biomechanical factors in runners, but the association between these factors was poor.

6.2 Determine the ability of a machine learning algorithm (SVM) to discriminate age groups (young and elderly) based on gait kinematics parameters and a reduced set of discriminant variables.

Traditional data analysis methods have been challenged by the multiple dependent variables generated in gait biomechanical studies (Chau, 2001a; Knudson, 2009b). The interpretation of the findings is a daunting task due to the complexity of the interrelationship among variables as observed in chapter 3. The use of a more sophisticated method to deal with this problem was, therefore, identified and needed to be explored.

We explored the ability of an emerging data analysis technique (SVM) in discriminating young and elderly runners based on gait variables. SVM accurately discriminate age groups based on gait kinematic variables. In addition, the classifier performance was outstanding when only fewer selected features were used to train the classifier.

The results showed that SVM was capable of accurately classifying runners according to their age group and was able to identify a reduced set of biomechanical variables while retaining important discriminative information. Hence, the results encourage the use of SVM for other research and clinical applications to solve classification problems. Research should consider

SVM in their arsenal of data analysis when the use of classical methods is impaired by the presence of multiple dependent complex variables.

6.3 Determine what subset of variables (clinical, biomechanical or both) yields an optimal combined discrimination between age-groups with a more comprehensive set of variables and larger sample size.

Previous studies that attempted to determine age-related gait changes had to deal with a large number of variables contrasted with a small sample and number of between-group differences. Hence, following the encouraging results obtained in chapter 4, we further explored the prediction ability of the SVM in detecting older gait patterns considering a more comprehensive set of variables in a larger matched sample of young and older runners.

The SVM was trained with different types and combinations of clinical and biomechanical variables aiming to enhance classification performance, since previous studies only examined these variables in isolation or with simple correlation analysis. The results yielded the identification of an optimal set of variables corresponding to a combination of different variable types, thus indicating that not only biomechanical variables (as observed in chapter 4) but also strength and flexibility measures were important for classification.

6.4 Determine what type of exercise intervention (strengthening and stretching) most effectively influences the identified features.

Despite the current popularity of the use of gait analysis in clinical settings, few studies have investigated the effects of intervention in modifying gait patterns. Previous research using this tool as an outcome measure has struggled to deal with multiple dependent variables.

A SVM-based score was calculated based on a combination of gait variables that optimally discriminate young and older runners. The relative position of the older runners before and after intervention provided its overall gait pattern change due to the intervention. Therefore, the SVM-score may be promising metric to summarize gait patterns.

The results yielded no significant effects of the exercises on gait biomechanical patterns. Similarly, the overall muscle strength and flexibility remained unchanged following exercises. From the results of this study, muscle strengthening or flexibility exercises in isolation did not benefit older runners in changing their gait pattern.

6.5 Limitations and future directions

One of the main limitations of this study was that the sample consisted of only injury free runners. However, considering the existence of previous studies suggesting ageing as a risk factor for injuries it is reasonable to assume that older runners with atypical gait were at higher risk. In addition, older individuals tend to be more cautious and only those that are asymptomatic continue to run, therefore, they are missed in surveys which would underestimate the true injured older population. In fact, this observation has previously been made (Matheson et al., 1989). We are unaware of any study that has determined gait biomechanical risk factors for running-related injuries in older runners. Therefore, a prospective study where injury free older runners are analyzed and followed for a substantial amount of time and the injury incidence is registered is highly desired.

Although encouraging, the results of the SVM in chapter 4 and 5 need to be interpreted with caution. In chapter 4 we conducted a preliminary assessment of the ability of the classifier in predicting group membership and its performance was surprisingly outstanding. However, we used only gait kinematic variables for the knee and ankle joints and, therefore these data might be insufficient to characterize the phenomenon of ageing. Following the results obtained in chapter 4, we assessed the SVM with a different sample of matched subjects and more comprehensive data and found that its performance was not as good, thus indicating that the classifier performance is highly dependent on the sample and the data that are being used. The use of static measures of flexibility and strength as opposed to functional assessments may also have limited the application of these findings. Debate still exists in clinical practice as to which measurement (for example, isometric or isokinetic) is of greater functional assessment value. Similarly, the use of discrete gait biomechanical variables as opposed to whole time series patterns may have impaired the analysis since temporal information was lost. To our knowledge, no studies have included both clinical and gait biomechanical measures, considering all the information contained in time series curves, to portray older running gait patterns. In light of the promising ability of the SVM to accurately detect gait patterns observed in this study, this classifier deserves further testing considering the abovementioned data set.

The SVM-based derived score, proposed in chapter 5 requires validation before its clinical application. Once a prospective study is conducted and the SVM is trained with exemplary data of healthy and injured older runners, the SVM-based score could be validated by quantifying the relative position of an injured runner before and after intervention compared to the score obtained by the validated functional scale. Similarly, the score derived from clinical measures could also be validated against well-grounded strength and flexibility scores.

The sample sizes used to compare age groups as well as to determine the effects of exercises were the largest ever employed compared to previous studies (Bus, 2003; Fukuchi and Duarte, 2008; Karamanidis and Arampatzis, 2005; Lilley et al., 2011). However, it is noteworthy that these samples could have been insufficient to draw conclusions about both ageing and exercise effects on movement patterns due to the larger variability, particularly in gait variables. Since SVM has demonstrated to outperform other algorithms in dealing with large data sets, future work using a large data base, including injured and non-injured older runners, are welcomed and necessary.

It is possible that the accommodation period (3 minutes) and the duration of the running trials (approximately 15 minutes) on the treadmill were not sufficient for both the adaptations with ageing and the effects of exercise interventions arise. A split belt instrumented treadmill (Bertec, Columbus, OH, USA) was used in the studies described in chapter 3 and chapter 5, but they were asked to run over a single belt to prevent that they land on both force platforms at the same time. The belt was narrower and the instrumented treadmill was higher compared to other available treadmills but none of the participants reported to have any problems during the experimental procedures.

References

- Abate, M., Schiavone, C., Pelotti, P. and Salini, V.** (2010). Limited Joint Mobility in Diabetes and Ageing: Recent Advances in Pathogenesis and Therapy. *International Journal of Immunopathology and Pharmacology* **23**, 997-1003.
- Allard, P.** (1997). Three-dimensional analysis of human locomotion. Chichester, England ; New York: J. Wiley.
- Alnaqeeb, M. A., Al Zaid, N. S. and Goldspink, G.** (1984). Connective tissue changes and physical properties of developing and ageing skeletal muscle. *J Anat* **139** (Pt 4), 677-89.
- Astephen, J. L., Deluzio, K. J., Caldwell, G. E., Dunbar, M. J. and Hubley-Kozey, C. L.** (2008). Gait and neuromuscular pattern changes are associated with differences in knee osteoarthritis severity levels. *J Biomech* **41**, 868-76.
- Barton-Davis, E. R., Shoturma, D. I. and Sweeney, H. L.** (1999). Contribution of satellite cells to IGF-I induced hypertrophy of skeletal muscle. *Acta Physiol Scand* **167**, 301-5.
- Begg, R. and Kamruzzaman, J.** (2005). A machine learning approach for automated recognition of movement patterns using basic, kinetic and kinematic gait data. *J Biomech* **38**, 401-8.
- Bell, A. L., Brand, R. A. and Pedersen, D. R.** (1989). Prediction of Hip-Joint Center Location from External Landmarks. *Human Movement Science* **8**, 3-16.
- Bell, A. L., Pedersen, D. R. and Brand, R. A.** (1990). A comparison of the accuracy of several hip center location prediction methods. *Journal of Biomechanics* **23**, 617-21.
- Brown, W. F.** (1972). A method for estimating the number of motor units in thenar muscles and the changes in motor unit count with ageing. *J Neurol Neurosurg Psychiatry* **35**, 845-52.
- Bus, S. A.** (2003). Ground reaction forces and kinematics in distance running in older-aged men. *Med Sci Sports Exerc* **35**, 1167-75.
- Canada, S.** (2012). The Canadian Population in 2011: Age and Sex, (ed. S. Canada). Ottawa: Minister of Industry.
- Cappozzo, A., Catani, F., Croce, U. D. and Leardini, A.** (1995). Position and orientation in space of bones during movement: anatomical frame definition and determination. *Clin Biomech (Bristol, Avon)* **10**, 171-178.
- Cavagna, G. A., Legramandi, M. A. and Peyre-Tartaruga, L. A.** (2008). Old men running: mechanical work and elastic bounce. *Proc Biol Sci* **275**, 411-8.
- Chan, K., Lee, T. W., Sample, P. A., Goldbaum, M. H., Weinreb, R. N. and Sejnowski, T. J.** (2002). Comparison of machine learning and traditional classifiers in glaucoma diagnosis. *IEEE Trans Biomed Eng* **49**, 963-74.
- Chan, Y. Y., Fong, D. T., Chung, M. M., Li, W. J., Liao, W. H., Yung, P. S. and Chan, K. M.** (2010). Identification of ankle sprain motion from common sporting activities by dorsal foot kinematics data. *J Biomech* **43**, 1965-9.
- Chang, A., Hurwitz, D., Dunlop, D., Song, J., Cahue, S., Hayes, K. and Sharma, L.** (2007). The relationship between toe-out angle during gait and progression of medial tibiofemoral osteoarthritis. *Ann Rheum Dis* **66**, 1271-5.
- Chau, T.** (2001a). A review of analytical techniques for gait data. Part 1: Fuzzy, statistical and fractal methods. *Gait Posture* **13**, 49-66.

- Chau, T.** (2001b). A review of analytical techniques for gait data. Part 2: neural network and wavelet methods. *Gait Posture* **13**, 102-20.
- Chodzko-Zajko, W. J. P. D. F., Proctor, D. N. P. D. F., Fiatarone Singh, M. A. M. D., Minson, C. T. P. D. F., Nigg, C. R. P. D., Salem, G. J. P. D. F. and Skinner, J. S. P. D. F.** (2009). Exercise and Physical Activity for Older Adults. *Medicine & Science in Sports & Exercise* **41**, 1510-1530.
- Christiansen, C. L.** (2008). The effects of hip and ankle stretching on gait function of older people. *Arch Phys Med Rehabil* **89**, 1421-8.
- Cohen, J.** (1988). Statistical power analysis for the behavioral sciences. Hillsdale, N.J.: L. Erlbaum Associates.
- Colado, J. C., Garcia-Masso, X., Triplett, T. N., Flandez, J., Borreani, S. and Tella, V.** (2012). Concurrent validation of the OMNI-resistance exercise scale of perceived exertion with Thera-band resistance bands. *J Strength Cond Res* **26**, 3018-24.
- Cortes, C. and Vapnik, V.** (1995). Support-Vector Networks. *Machine Learning* **20**, 273-297.
- Davis Hammonds, A. L., Laudner, K. G., McCaw, S. and McLoda, T. A.** (2012). Acute lower extremity running kinematics after a hamstring stretch. *J Athl Train* **47**, 5-14.
- de Boer, M. D., Maganaris, C. N., Seynnes, O. R., Rennie, M. J. and Narici, M. V.** (2007). Time course of muscular, neural and tendinous adaptations to 23 day unilateral lower-limb suspension in young men. *J Physiol* **583**, 1079-91.
- DeVita, P. and Hortobagyi, T.** (2000). Age causes a redistribution of joint torques and powers during gait. *J Appl Physiol* **88**, 1804-11.
- Dierks, T. A., Manal, K. T., Hamill, J. and Davis, I. S.** (2008). Proximal and distal influences on hip and knee kinematics in runners with patellofemoral pain during a prolonged run. *J Orthop Sports Phys Ther* **38**, 448-56.
- Dirks, A. J. and Leeuwenburgh, C.** (2005). The role of apoptosis in age-related skeletal muscle atrophy. *Sports Med* **35**, 473-83.
- Duda, R. O., Hart, P. E. and Stork, D. G.** (2001). Pattern classification. New York: Wiley.
- Earl, J. E. and Hoch, A. Z.** (2011). A proximal strengthening program improves pain, function, and biomechanics in women with patellofemoral pain syndrome. *Am J Sports Med* **39**, 154-63.
- Edman, A. C., Lexell, J., Sjostrom, M. and Squire, J. M.** (1988). Structural diversity in muscle fibres of chicken breast. *Cell Tissue Res* **251**, 281-9.
- Enoka, R. M.** (1988). Muscle strength and its development. New perspectives. *Sports Med* **6**, 146-68.
- Enoka, R. M.** (2008). Neuromechanics of human movement. Champaign, IL: Human Kinetics.
- Eskofier, B. M., Kraus, M., Worobets, J. T., Stefanyshyn, D. J. and Nigg, B. M.** (2012). Pattern classification of kinematic and kinetic running data to distinguish gender, shod/barefoot and injury groups with feature ranking. *Comput Methods Biomech Biomed Engin* **15**, 467-74.
- Faul, F., Erdfelder, E., Lang, A. G. and Buchner, A.** (2007). G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav Res Methods* **39**, 175-91.

- Faulkner, J. A., Larkin, L. M., Claflin, D. R. and Brooks, S. V.** (2007). Age-related changes in the structure and function of skeletal muscles. *Clin Exp Pharmacol Physiol* **34**, 1091-6.
- Ferber, R., Kendall, K. D. and Farr, L.** (2011). Changes in knee biomechanics after a hip-abductor strengthening protocol for runners with patellofemoral pain syndrome. *J Athl Train* **46**, 142-9.
- Ferber, R., Kendall, K. D. and McElroy, L.** (2010). Normative and critical criteria for iliotibial band and iliopsoas muscle flexibility. *J Athl Train* **45**, 344-8.
- Ferri, A., Scaglioni, G., Pousson, M., Capodaglio, P., Van Hoecke, J. and Narici, M. V.** (2003). Strength and power changes of the human plantar flexors and knee extensors in response to resistance training in old age. *Acta Physiol Scand* **177**, 69-78.
- Fiatarone, M. A., O'Neill, E. F., Ryan, N. D., Clements, K. M., Solares, G. R., Nelson, M. E., Roberts, S. B., Kehayias, J. J., Lipsitz, L. A. and Evans, W. J.** (1994). Exercise training and nutritional supplementation for physical frailty in very elderly people. *N Engl J Med* **330**, 1769-75.
- Fields, K. B.** (2011). Running Injuries - Changing Trends and Demographics. *Current Sports Medicine Reports* **10**, 299-303.
- Frey, D., Schneider, C., Xu, L., Borg, J., Spooren, W. and Caroni, P.** (2000). Early and selective loss of neuromuscular synapse subtypes with low sprouting competence in motoneuron diseases. *J Neurosci* **20**, 2534-42.
- Frontera, W. R., Hughes, V. A., Fielding, R. A., Fiatarone, M. A., Evans, W. J. and Roubenoff, R.** (2000). Aging of skeletal muscle: a 12-yr longitudinal study. *J Appl Physiol* **88**, 1321-6.
- Frontera, W. R., Hughes, V. A., Lutz, K. J. and Evans, W. J.** (1991). A cross-sectional study of muscle strength and mass in 45- to 78-yr-old men and women. *J Appl Physiol* **71**, 644-50.
- Fukuchi, R. K. and Duarte, M.** (2008). Comparison of three-dimensional lower extremity running kinematics of young adult and elderly runners. *J Sports Sci* **26**, 1447-54.
- Fukuchi, R. K., Eskofier, B. M., Duarte, M. and Ferber, R.** (2011). Support vector machines for detecting age-related changes in running kinematics. *J Biomech* **44**, 540-2.
- Gajdosik, R. L., Vander Linden, D. W., McNair, P. J., Williams, A. K. and Riggin, T. J.** (2005a). Effects of an eight-week stretching program on the passive-elastic properties and function of the calf muscles of older women. *Clin Biomech (Bristol, Avon)* **20**, 973-83.
- Gajdosik, R. L., Vander Linden, D. W., McNair, P. J., Williams, A. K. and Riggin, T. J.** (2005b). Effects of an eight-week stretching program on the passive-elastic properties and function of the calf muscles of older women. *Clinical Biomechanics* **20**, 973-983.
- Gajdosik, R. L., Vander Linden, D. W. and Williams, A. K.** (1999). Influence of age on length and passive elastic stiffness characteristics of the calf muscle-tendon unit of women. *Phys Ther* **79**, 827-38.
- Garber, C. E., Blissmer, B., Deschenes, M. R., Franklin, B. A., Lamonte, M. J., Lee, I. M., Nieman, D. C. and Swain, D. P.** (2011). American College of Sports Medicine position stand. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: guidance for prescribing exercise. *Med Sci Sports Exerc* **43**, 1334-59.

- Grau, S., Krauss, I., Maiwald, C., Axmann, D., Horstmann, T. and Best, R.** (2011). Kinematic classification of iliotibial band syndrome in runners. *Scand J Med Sci Sports* **21**, 184-9.
- Grimston, S. K., Nigg, B. M., Hanley, D. A. and Engsberg, J. R.** (1993). Differences in ankle joint complex range of motion as a function of age. *Foot Ankle* **14**, 215-22.
- Good, E. S. and Suntay, W. J.** (1983). A joint coordinate system for the clinical description of three-dimensional motions: application to the knee. *J Biomech Eng* **105**, 136-44.
- Guillet, C., Auguste, P., Mayo, W., Kreher, P. and Gascan, H.** (1999). Ciliary neurotrophic factor is a regulator of muscular strength in aging. *J Neurosci* **19**, 1257-62.
- Hakkinen, K., Alen, M., Kallinen, M., Newton, R. U. and Kraemer, W. J.** (2000). Neuromuscular adaptation during prolonged strength training, detraining and re-strength-training in middle-aged and elderly people. *Eur J Appl Physiol* **83**, 51-62.
- Hakkinen, K., Kraemer, W. J., Kallinen, M., Linnamo, V., Pastinen, U. M. and Newton, R. U.** (1996). Bilateral and unilateral neuromuscular function and muscle cross-sectional area in middle-aged and elderly men and women. *J Gerontol A Biol Sci Med Sci* **51**, B21-9.
- Hakkinen, K. and Pakarinen, A.** (1994). Serum hormones and strength development during strength training in middle-aged and elderly males and females. *Acta Physiol Scand* **150**, 211-9.
- Hakkinen, K., Pastinen, U. M., Karsikas, R. and Linnamo, V.** (1995). Neuromuscular performance in voluntary bilateral and unilateral contraction and during electrical stimulation in men at different ages. *Eur J Appl Physiol Occup Physiol* **70**, 518-27.
- Hanavan, E. P., Jr.** (1964). A Mathematical Model of the Human Body. Amrl-Tr-64-102. *AMRL TR*, 1-149.
- Hreljac, A.** (2004). Impact and overuse injuries in runners. *Med Sci Sports Exerc* **36**, 845-9.
- Hsu, T. C., Wang, C. L., Tsai, W. C., Kuo, J. K. and Tang, F. T.** (1998). Comparison of the mechanical properties of the heel pad between young and elderly adults. *Arch Phys Med Rehabil* **79**, 1101-4.
- Hudson, Z. and Darthuy, E.** (2009). Iliotibial band tightness and patellofemoral pain syndrome: a case-control study. *Man Ther* **14**, 147-51.
- Hunter, S. K., Thompson, M. W., Ruell, P. A., Harmer, A. R., Thom, J. M., Gwinn, T. H. and Adams, R. D.** (1999). Human skeletal sarcoplasmic reticulum Ca²⁺ uptake and muscle function with aging and strength training. *J Appl Physiol* **86**, 1858-65.
- James, B. and Parker, A. W.** (1989). Active and passive mobility of lower limb joints in elderly men and women. *Am J Phys Med Rehabil* **68**, 162-7.
- Janssen, I., Heymsfield, S. B. and Ross, R.** (2002). Low relative skeletal muscle mass (sarcopenia) in older persons is associated with functional impairment and physical disability. *J Am Geriatr Soc* **50**, 889-96.
- Jenkins, J. and Beazell, J.** (2010). Flexibility for runners. *Clin Sports Med* **29**, 365-77.
- Johanson, M., Baer, J., Hovermale, H. and Phouthavong, P.** (2008). Subtalar joint position during gastrocnemius stretching and ankle dorsiflexion range of motion. *J Athl Train* **43**, 172-8.

- Johnston, C. A., Taunton, J. E., Lloyd-Smith, D. R. and McKenzie, D. C.** (2003). Preventing running injuries. Practical approach for family doctors. *Can Fam Physician* **49**, 1101-9.
- Jokl, P., Sethi, P. M. and Cooper, A. J.** (2004). Master's performance in the New York City Marathon 1983-1999. *Br J Sports Med* **38**, 408-12.
- Karamanidis, K. and Arampatzis, A.** (2005). Mechanical and morphological properties of different muscle-tendon units in the lower extremity and running mechanics: effect of aging and physical activity. *J Exp Biol* **208**, 3907-23.
- Kerrigan, D. C., Xenopoulos-Oddsson, A., Sullivan, M. J., Lelas, J. J. and Riley, P. O.** (2003). Effect of a hip flexor-stretching program on gait in the elderly. *Arch Phys Med Rehabil* **84**, 1-6.
- Kjaer, M.** (2004). Role of extracellular matrix in adaptation of tendon and skeletal muscle to mechanical loading. *Physiol Rev* **84**, 649-98.
- Knudson, D.** (2009a). Significant and meaningful effects in sports biomechanics research. *Sports Biomech* **8**, 96-104.
- Knudson, D.** (2009b). Stretch-induced strength deficits are likely significant. *Med Sci Sports Exerc* **41**, 479; author reply 480.
- Kohavi, R. and John, G. H.** (1997). Wrappers for feature subset selection. *Artificial Intelligence* **97**, 273-324.
- Komi, P. V.** (2003). Strength and power in sport / edited by Paavo V. Komi. Osney Mead, Oxford ; Malden, MA: Blackwell Science.
- Korhonen, M. T., Cristea, A., Alen, M., Hakkinen, K., Sipila, S., Mero, A., Viitasalo, J. T., Larsson, L. and Suominen, H.** (2006). Aging, muscle fiber type, and contractile function in sprint-trained athletes. *J Appl Physiol* **101**, 906-17.
- Kovanen, V.** (1989). Effects of ageing and physical training on rat skeletal muscle. An experimental study on the properties of collagen, laminin, and fibre types in muscles serving different functions. *Acta Physiol Scand Suppl* **577**, 1-56.
- Kovanen, V. and Suominen, H.** (1988). Effects of age and life-long endurance training on the passive mechanical properties of rat skeletal muscle. *Compr Gerontol A* **2**, 18-23.
- Kuno, H., Suzuki, N., Akataki, K., Mita, K., Yasubayashi, M. and Ito, M.** (1998). Geometrical analysis of hip and knee joint mobility in cerebral palsied children. *Gait Posture* **8**, 110-116.
- Lai, D. T., Begg, R. K. and Palaniswami, M.** (2009a). Computational intelligence in gait research: a perspective on current applications and future challenges. *IEEE Trans Inf Technol Biomed* **13**, 687-702.
- Lai, D. T., Levinger, P., Begg, R. K., Gilleard, W. L. and Palaniswami, M.** (2009b). Automatic recognition of gait patterns exhibiting patellofemoral pain syndrome using a support vector machine approach. *IEEE Trans Inf Technol Biomed* **13**, 810-7.
- Leardini, A., Biagi, F., Merlo, A., Belvedere, C. and Benedetti, M. G.** (2011). Multi-segment trunk kinematics during locomotion and elementary exercises. *Clin Biomech (Bristol, Avon)* **26**, 562-71.
- Levinger, P., Lai, D. T., Begg, R. K., Webster, K. E. and Feller, J. A.** (2009). The application of support vector machines for detecting recovery from knee replacement surgery using spatio-temporal gait parameters. *Gait Posture* **29**, 91-6.

- Lexell, J., Taylor, C. C. and Sjostrom, M.** (1988). What is the cause of the ageing atrophy? Total number, size and proportion of different fiber types studied in whole vastus lateralis muscle from 15- to 83-year-old men. *J Neurol Sci* **84**, 275-94.
- Lilley, K., Dixon, S. and Stiles, V.** (2011). A biomechanical comparison of the running gait of mature and young females. *Gait Posture* **33**, 496-500.
- Lopopolo, R. B., Greco, M., Sullivan, D., Craik, R. L. and Mangione, K. K.** (2006). Effect of therapeutic exercise on gait speed in community-dwelling elderly people: a meta-analysis. *Phys Ther* **86**, 520-40.
- Macaluso, A. and De Vito, G.** (2004). Muscle strength, power and adaptations to resistance training in older people. *Eur J Appl Physiol* **91**, 450-72.
- Magnusson, S. P., Beyer, N., Abrahamsen, H., Aagaard, P., Neergaard, K. and Kjaer, M.** (2003). Increased cross-sectional area and reduced tensile stress of the Achilles tendon in elderly compared with young women. *J Gerontol A Biol Sci Med Sci* **58**, 123-7.
- Malliaras, P., Cook, J. L. and Kent, P.** (2006). Reduced ankle dorsiflexion range may increase the risk of patellar tendon injury among volleyball players. *Journal of Science and Medicine in Sport* **9**, 304-9.
- Marti, B., Vader, J. P., Minder, C. E. and Abelin, T.** (1988). On the epidemiology of running injuries. The 1984 Bern Grand-Prix study. *Am J Sports Med* **16**, 285-94.
- Matheson, G. O., Macintyre, J. G., Taunton, J. E., Clement, D. B. and Lloyd-Smith, R.** (1989). Musculoskeletal injuries associated with physical activity in older adults. *Med Sci Sports Exerc* **21**, 379-85.
- McClay, I. and Manal, K.** (1997). Coupling parameters in runners with normal and excessive pronation. *Journal of Applied Biomechanics* **13**, 109-124.
- McClay, I. and Manal, K.** (1998a). A comparison of three-dimensional lower extremity kinematics during running between excessive pronators and normals. *Clin Biomech (Bristol, Avon)* **13**, 195-203.
- McClay, I. and Manal, K.** (1998b). A comparison of three-dimensional lower extremity kinematics during running between excessive pronators and normals. *Clinical Biomechanics* **13**, 195-203.
- McGibbon, C. A.** (2003). Toward a better understanding of gait changes with age and disablement: neuromuscular adaptation. *Exerc Sport Sci Rev* **31**, 102-8.
- McGill, S. M., Yingling, V. R. and Peach, J. P.** (1999). Three-dimensional kinematics and trunk muscle myoelectric activity in the elderly spine - a database compared to young people. *Clin Biomech (Bristol, Avon)* **14**, 389-95.
- McKean, K. A., Landry, S. C., Hubley-Kozey, C. L., Dunbar, M. J., Stanish, W. D. and Deluzio, K. J.** (2007). Gender differences exist in osteoarthritic gait. *Clin Biomech (Bristol, Avon)* **22**, 400-9.
- McKean, K. A., Manson, N. A. and Stanish, W. D.** (2006). Musculoskeletal injury in the masters runners. *Clin J Sport Med* **16**, 149-54.
- Mellin, G.** (1990). Decreased joint and spinal mobility associated with low back pain in young adults. *J Spinal Disord* **3**, 238-43.
- Miyazaki, T., Wada, M., Kawahara, H., Sato, M., Baba, H. and Shimada, S.** (2002). Dynamic load at baseline can predict radiographic disease progression in medial compartment knee osteoarthritis. *Ann Rheum Dis* **61**, 617-22.

- Morse, C. I., Thom, J. M., Davis, M. G., Fox, K. R., Birch, K. M. and Narici, M. V.** (2004). Reduced plantarflexor specific torque in the elderly is associated with a lower activation capacity. *Eur J Appl Physiol* **92**, 219-26.
- Mountrakis, G., Im, J. and Ogole, C.** (2011). Support vector machines in remote sensing: A review. *Isprs Journal of Photogrammetry and Remote Sensing* **66**, 247-259.
- Narici, M. V. and Maffulli, N.** (2010). Sarcopenia: characteristics, mechanisms and functional significance. *Br Med Bull* **95**, 139-59.
- Narici, M. V., Maffulli, N. and Maganaris, C. N.** (2008). Ageing of human muscles and tendons. *Disabil Rehabil* **30**, 1548-54.
- Narici, M. V., Maganaris, C. and Reeves, N.** (2005). Myotendinous alterations and effects of resistive loading in old age. *Scand J Med Sci Sports* **15**, 392-401.
- Narici, M. V., Maganaris, C. N., Reeves, N. D. and Capodaglio, P.** (2003). Effect of aging on human muscle architecture. *J Appl Physiol* **95**, 2229-34.
- Newman, A. B., Arnold, A. M., Naydeck, B. L., Fried, L. P., Burke, G. L., Enright, P., Gottdiener, J., Hirsch, C., O'Leary, D. and Tracy, R.** (2003). "Successful aging": effect of subclinical cardiovascular disease. *Arch Intern Med* **163**, 2315-22.
- Newman, A. B., Simonsick, E. M., Naydeck, B. L., Boudreau, R. M., Kritchevsky, S. B., Nevitt, M. C., Pahor, M., Satterfield, S., Brach, J. S., Studenski, S. A. et al.** (2006). Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability. *JAMA* **295**, 2018-26.
- Newsholme, S. J., Lexell, J. and Downham, D. Y.** (1988). Distribution of fibre types and fibre sizes in the tibialis cranialis muscle of beagle dogs. *J Anat* **160**, 1-8.
- Nigg, B. M., Cole, G. K. and Nachbauer, W.** (1993). Effects of arch height of the foot on angular motion of the lower extremities in running. *Journal of Biomechanics* **26**, 909-16.
- Noble, W. S.** (2006). What is a support vector machine? *Nature Biotechnology* **24**, 1565-1567.
- Noehren, B., Hamill, J. and Davis, I.** (2012). Prospective Evidence for a Hip Etiology in Patellofemoral Pain. *Med Sci Sports Exerc.*
- Nonaka, H., Mita, K., Watakabe, M., Akataki, K., Suzuki, N., Okuwa, T. and Yabe, K.** (2002). Age-related changes in the interactive mobility of the hip and knee joints: a geometrical analysis. *Gait Posture* **15**, 236-43.
- Nordin, M. and Frankel, V. H.** (2012). Basic biomechanics of the musculoskeletal system. Philadelphia: Wolters Kluwer/Lippincott Williams & Wilkins Health.
- Norkin, C. C. and White, D. J.** (2003). Measurement of joint motion : a guide to goniometry. Philadelphia: F.A. Davis.
- Nott, C. R., Zajac, F. E., Neptune, R. R. and Kautz, S. A.** (2010). All joint moments significantly contribute to trunk angular acceleration. *J Biomech* **43**, 2648-52.
- Novacheck, T. F.** (1998). The biomechanics of running. *Gait Posture* **7**, 77-95.
- Paffenbarger, R. S., Jr., Hyde, R. T., Wing, A. L., Lee, I. M., Jung, D. L. and Kampert, J. B.** (1993). The association of changes in physical-activity level and other lifestyle characteristics with mortality among men. *N Engl J Med* **328**, 538-45.
- Patten, C. and Kamen, G.** (2000). Adaptations in motor unit discharge activity with force control training in young and older human adults. *Eur J Appl Physiol* **83**, 128-43.

- Persch, L. N., Ugrinowitsch, C., Pereira, G. and Rodacki, A. L. F.** (2009). Strength training improves fall-related gait kinematics in the elderly: A randomized controlled trial. *Clinical Biomechanics* **24**, 819-825.
- Pijnappels, M., Reeves, N. D., Maganaris, C. N. and van Dieen, J. H.** (2008). Tripping without falling; lower limb strength, a limitation for balance recovery and a target for training in the elderly. *J Electromyogr Kinesiol* **18**, 188-96.
- Pohl, M. B., Lloyd, C. and Ferber, R.** (2010). Can the reliability of three-dimensional running kinematics be improved using functional joint methodology? *Gait Posture* **32**, 559-63.
- Pohl, M. B., Patel, C., Wiley, J. P. and Ferber, R.** (2012). Gait biomechanics and hip muscular strength in patients with patellofemoral osteoarthritis. *Gait Posture*.
- Radford, J. A., Burns, J., Buchbinder, R., Landorf, K. B. and Cook, C.** (2006). Does stretching increase ankle dorsiflexion range of motion? A systematic review. *Br J Sports Med* **40**, 870-5; discussion 875.
- Ramsey, D. K. and Wretenberg, P. F.** (1999). Biomechanics of the knee: methodological considerations in the in vivo kinematic analysis of the tibiofemoral and patellofemoral joint. *Clin Biomech (Bristol, Avon)* **14**, 595-611.
- Reese, N. B.** (2012). Muscle and sensory testing. St. Louis, Mo.: Elsevier.
- Reeves, N. D., Maganaris, C. N. and Narici, M. V.** (2003). Effect of strength training on human patella tendon mechanical properties of older individuals. *J Physiol* **548**, 971-81.
- Reeves, N. D., Narici, M. V. and Maganaris, C. N.** (2004a). Effect of resistance training on skeletal muscle-specific force in elderly humans. *J Appl Physiol* **96**, 885-92.
- Reeves, N. D., Narici, M. V. and Maganaris, C. N.** (2004b). In vivo human muscle structure and function: adaptations to resistance training in old age. *Exp Physiol* **89**, 675-89.
- Richards, J. G.** (1999). The measurement of human motion: A comparison of commercially available systems. *Human Movement Science* **18**, 589-602.
- Roach, K. E. and Miles, T. P.** (1991). Normal hip and knee active range of motion: the relationship to age. *Phys Ther* **71**, 656-65.
- Robertson, D. G. E.** (2004). Research methods in biomechanics. Champaign, Ill.: Human Kinetics.
- Rodacki, A. L., Souza, R. M., Ugrinowitsch, C., Cristopoliski, F. and Fowler, N. E.** (2009). Transient effects of stretching exercises on gait parameters of elderly women. *Man Ther* **14**, 167-72.
- Rosenberg, I. H.** (1997). Sarcopenia: origins and clinical relevance. *J Nutr* **127**, 990S-991S.
- Rubinstein, S. and Kamen, G.** (2005). Decreases in motor unit firing rate during sustained maximal-effort contractions in young and older adults. *J Electromyogr Kinesiol* **15**, 536-43.
- Savelberg, H. H., Verdijk, L. B., Willems, P. J. and Meijer, K.** (2007). The robustness of age-related gait adaptations: can running counterbalance the consequences of ageing? *Gait Posture* **25**, 259-66.
- Schölkopf, B. and Smola, A. J.** (2002). Learning with kernels: support vector machines, regularization, optimization, and beyond. Cambridge, MA: MIT Press.
- Scott, G., Menz, H. B. and Newcombe, L.** (2007). Age-related differences in foot structure and function. *Gait Posture* **26**, 68-75.

- Scott, N. W., McPherson, G. C., Ramsay, C. R. and Campbell, M. K.** (2002). The method of minimization for allocation to clinical trials. a review. *Control Clin Trials* **23**, 662-74.
- Short, K. R., Bigelow, M. L., Kahl, J., Singh, R., Coenen-Schimke, J., Raghavakaimal, S. and Nair, K. S.** (2005). Decline in skeletal muscle mitochondrial function with aging in humans. *Proc Natl Acad Sci U S A* **102**, 5618-23.
- Shrout, P. E. and Fleiss, J. L.** (1979). Intraclass correlations: uses in assessing rater reliability. *Psychol Bull* **86**, 420-8.
- Silver, A. E., Lungren, M. P., Johnson, M. E., O'Driscoll, S. W., An, K. N. and Hughes, R. E.** (2006). Using support vector machines to optimally classify rotator cuff strength data and quantify post-operative strength in rotator cuff tear patients. *J Biomech* **39**, 973-9.
- Snyder, K. R., Earl, J. E., O'Connor, K. M. and Ebersole, K. T.** (2009). Resistance training is accompanied by increases in hip strength and changes in lower extremity biomechanics during running. *Clin Biomech (Bristol, Avon)* **24**, 26-34.
- Spoor, C. W. and Veldpaus, F. E.** (1980). Rigid body motion calculated from spatial co-ordinates of markers. *J Biomech* **13**, 391-3.
- Stathokostas, L., Little, R. M., Vandervoort, A. A. and Paterson, D. H.** (2012). Flexibility training and functional ability in older adults: a systematic review. *J Aging Res* **2012**, 306818.
- Stefanyshyn, D. J., Stergiou, P., Lun, V. M., Meeuwisse, W. H. and Worobets, J. T.** (2006). Knee angular impulse as a predictor of patellofemoral pain in runners. *Am J Sports Med* **34**, 1844-51.
- Taaffe, D. R., Henwood, T. R., Nalls, M. A., Walker, D. G., Lang, T. F. and Harris, T. B.** (2009). Alterations in muscle attenuation following detraining and retraining in resistance-trained older adults. *Gerontology* **55**, 217-23.
- Tabary, J. C., Tabary, C., Tardieu, C., Tardieu, G. and Goldspink, G.** (1972). Physiological and structural changes in the cat's soleus muscle due to immobilization at different lengths by plaster casts. *J Physiol* **224**, 231-44.
- Taunton, J. E., Ryan, M. B., Clement, D. B., McKenzie, D. C., Lloyd-Smith, D. R. and Zumbo, B. D.** (2002). A retrospective case-control analysis of 2002 running injuries. *Br J Sports Med* **36**, 95-101.
- Taunton, J. E., Ryan, M. B., Clement, D. B., McKenzie, D. C., Lloyd-Smith, D. R. and Zumbo, B. D.** (2003). A prospective study of running injuries: the Vancouver Sun Run "In Training" clinics. *Br J Sports Med* **37**, 239-44.
- Thompson, W. R., Gordon, N. F. and Pescatello, L. S.** (2010). ACSM's guidelines for exercise testing and prescription. Philadelphia: Lippincott Williams & Wilkins.
- Tomlinson, B. E. and Irving, D.** (1977). The numbers of limb motor neurons in the human lumbosacral cord throughout life. *J Neurol Sci* **34**, 213-9.
- Trappe, S., Godard, M., Gallagher, P., Carroll, C., Rowden, G. and Porter, D.** (2001). Resistance training improves single muscle fiber contractile function in older women. *Am J Physiol Cell Physiol* **281**, C398-406.
- Trappe, S., Williamson, D., Godard, M., Porter, D., Rowden, G. and Costill, D.** (2000). Effect of resistance training on single muscle fiber contractile function in older men. *J Appl Physiol* **89**, 143-52.
- Tuite, D. J., Renstrom, P. A. and O'Brien, M.** (1997). The aging tendon. *Scand J Med Sci Sports* **7**, 72-7.

- Van Looy, S., Verplancke, T., Benoit, D., Hoste, E., Van Maele, G., De Turck, F. and Decruyenaere, J.** (2007). A novel approach for prediction of tacrolimus blood concentration in liver transplantation patients in the intensive care unit through support vector regression. *Crit Care* **11**, R83.
- Van Sint Jan, S.** (2007). Color atlas of skeletal landmark definitions : guidelines for reproducible manual and virtual palpations. Edinburgh ; New York: Churchill Livingstone/Elsevier.
- Vandervoort, A. A., Chesworth, B. M., Cunningham, D. A., Paterson, D. H., Rechnitzer, P. A. and Koval, J. J.** (1992a). Age and sex effects on mobility of the human ankle. *J Gerontol* **47**, M17-21.
- Vandervoort, A. A., Chesworth, B. M., Cunningham, D. A., Rechnitzer, P. A., Paterson, D. H. and Koval, J. J.** (1992b). An outcome measure to quantify passive stiffness of the ankle. *Can J Public Health* **83 Suppl 2**, S19-23.
- Vapnik, V. N.** (1998). Statistical learning theory. New York, NY: Wiley & Sons.
- Viidik, A.** (1982). Lectures on gerontology. London ; New York: Academic Press.
- Wachtel, E., Maroudas, A. and Schneiderman, R.** (1995). Age-related changes in collagen packing of human articular cartilage. *Biochim Biophys Acta* **1243**, 239-43.
- Wearing, S. C., Smeathers, J. E., Urry, S. R., Hennig, E. M. and Hills, A. P.** (2006). The pathomechanics of plantar fasciitis. *Sports Med* **36**, 585-611.
- Willcox, B. J., He, Q., Chen, R., Yano, K., Masaki, K. H., Grove, J. S., Donlon, T. A., Willcox, D. C. and Curb, J. D.** (2006). Midlife risk factors and healthy survival in men. *JAMA* **296**, 2343-50.
- Willy, R. W. and Davis, I. S.** (2011). The effect of a hip-strengthening program on mechanics during running and during a single-leg squat. *J Orthop Sports Phys Ther* **41**, 625-32.
- Wilson, B. C., Downham, D. Y., Lexell, J. and Sjoström, M.** (1988). Some probability models for diagnosing neurogenic disorders. *IMA J Math Appl Med Biol* **5**, 167-79.
- Winter, D. A.** (2005). Biomechanics and motor control of human movement. Hoboken, New Jersey: John Wiley & Sons.
- Wu, G., Siegler, S., Allard, P., Kirtley, C., Leardini, A., Rosenbaum, D., Whittle, M., D'Lima, D. D., Cristofolini, L., Witte, H. et al.** (2002). ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion--part I: ankle, hip, and spine. International Society of Biomechanics. *J Biomech* **35**, 543-8.
- Wu, J. and Wang, J.** (2008). PCA-based SVM for automatic recognition of gait patterns. *J Appl Biomech* **24**, 83-7.
- Zadpoor, A. A. and Nikooyan, A. A.** (2011). The relationship between lower-extremity stress fractures and the ground reaction force: a systematic review. *Clin Biomech (Bristol, Avon)* **26**, 23-8.
- Zatsiorsky, V. M.** (1998). Kinematics of human motion. Champaign, IL: Human Kinetics.
- Zatsiorsky, V. M.** (2002). Kinetics of human motion. Champaign, IL: Human Kinetics.

APPENDIX A : Reference frame convention, joint kinematics and joint kinetics calculations

Kinematics

To determine the three-dimensional (3D) kinematics of the human body during running, each anatomical segment was modeled as a rigid body with six degrees of freedom (DoF). The position and orientation of each segment was defined based on the anatomic planes and axes which, in turn, will be determined using markers placed on specific anatomical landmarks. In the present study, the position and orientation of each segment were quantified during the movement through the position of the superficial anatomical landmarks. The Calibration Anatomical System Technique (CAST) protocol proposed by Cappozzo et al. (1995) was adopted in this study in order to minimize the experimental errors. In this protocol, during the dynamic trials (running) the anatomical markers were not tracked; and the position of a cluster of markers (technical markers) in a rigid shell attached on the segment will be tracked instead. Considering each segment as a rigid body, the relative position of the anatomical markers, in that particular segment, and the technical markers would not change. Thus, it is possible to determine mathematically the position of each anatomical marker solely based on the technical markers (see Cappozzo et al. (Cappozzo et al., 1995) for a more detailed description about CAST). After the static calibration the anatomical markers can then be removed from the segments and the dynamic trials recorded without these markers.

The landmarks represent bony regions that were located through palpation. The landmarks were located according to the instruction found in Van Sint Jan (2007).

Segment reference frame convention

Foot segment

For the foot anatomical coordinate system (ACS), the x-axis was parallel to the floor and ran from the distal posterior heel marker through the midpoint of the first and fifth metatarsal heads (MIDMT). The z-axis was the cross product between the x-axis and the line joining the distal (RHED) and proximal (RHEP) posterior heel markers with its positive direction to the right. The y-axis was the cross-product of the z-axis and x-axis with its positive direction upwards (Figure A-1).

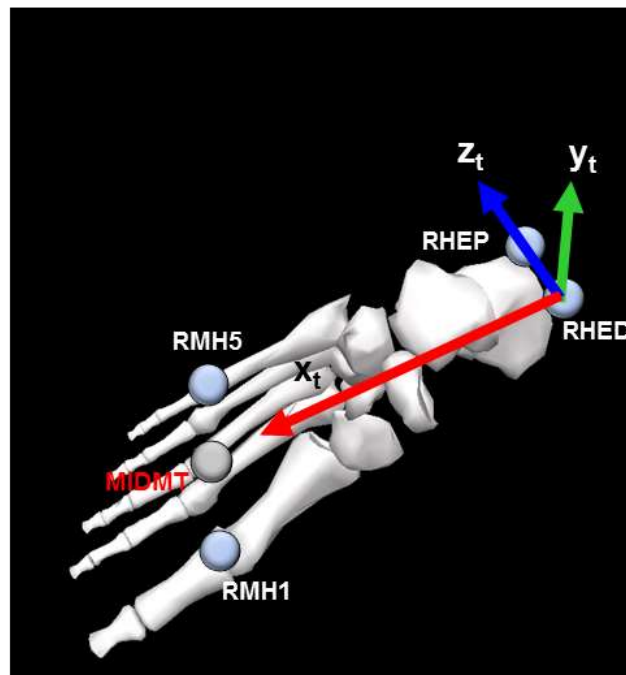


Figure A-1. Anatomical landmarks and reference frame convention of the foot segment.

Shank segment

The x-axis of the shank ACS was orthogonal to the plane formed by head of fibula (HF), ankle joint centre (AJC) and lateral malleolus (LM) and its positive direction pointing to anterior. The z-axis was orthogonal to x-axis and lied in the plane formed by HF, AJC and LM, and its positive direction pointed to the right. The y-axis was the cross-product of the z- and x-axes with its positive direction upwards (Figure A-2).

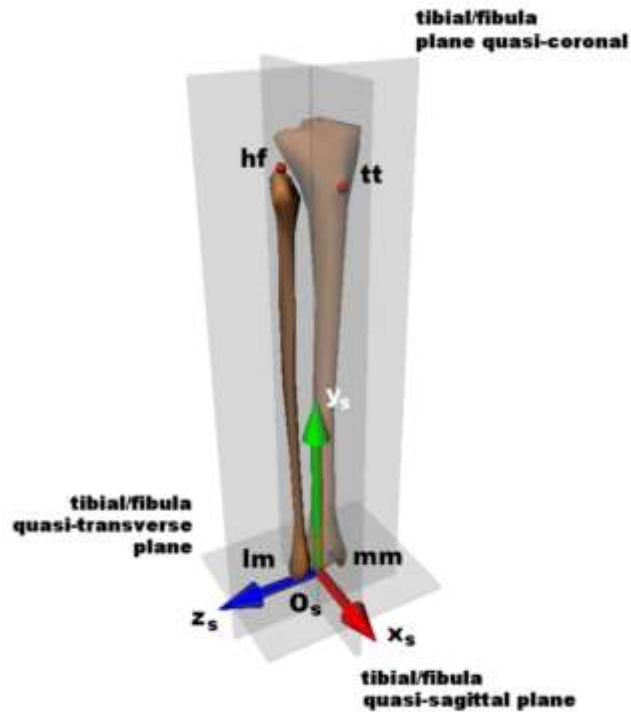


Figure A-2. Anatomical landmarks and reference frame convention of the shank segment (Van Sint Jan, 2007).

Thigh segment

The y-axis of the thigh ACS was oriented as the line joining the hip joint centre (HJC) and knee joint centre (KJC) with its positive direction proximal. The z-axis was perpendicular to the y-axis and lied in the plane formed by HJC, ME and LE with its positive direction pointing right. The x-axis was then defined as the cross-product between y-axis and z-axis and its positive direction is pointing forward (Figure A-3).

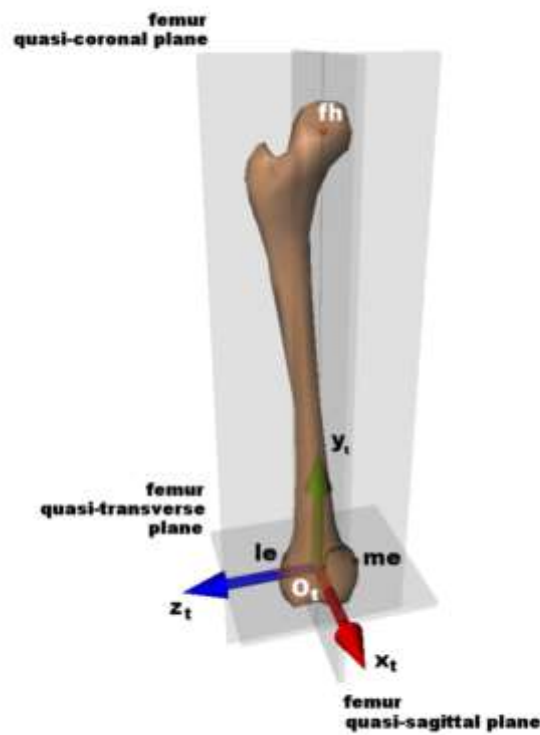


Figure A-3. Anatomical landmarks and reference frame convention of the thigh segment (Van Sint Jan, 2007).

Pelvic segment

The origin of the pelvis segment coordinate system is defined as the mid-point between the ASIS markers. The y-axis is orthogonal to the plane formed by both ASIS and the mid-point of the right and left PSIS markers and its positive direction pointing upwards. The z-axis is defined from the ORIGIN towards the right ASIS, therefore it is orthogonal to y-axis and its positive direction pointing to the right. The x-axis is then the cross product of the y-axis and z-axis and its positive direction pointing anterior (Figure A-4).

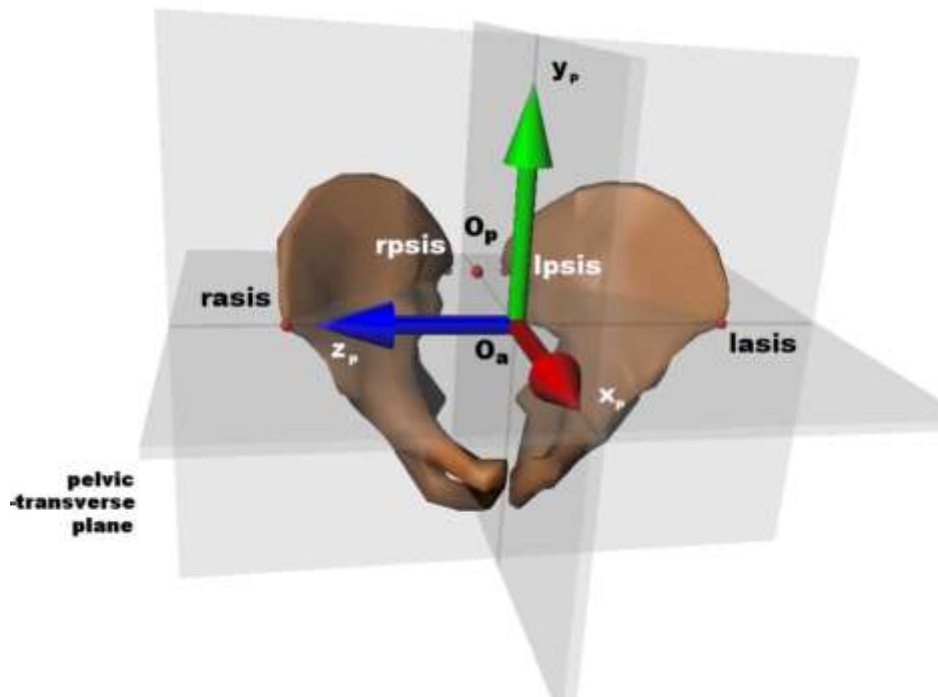


Figure A-4. Anatomical landmarks and reference frame convention of the pelvic segment (Van Sint Jan, 2007).

Thorax segment

The anatomical landmarks to define the trunk segments were the second thoracic vertebrae (T2), midpoint between the inferior angles of most caudal points of the scapulae (MAI), xiphoid process (PX) and the deepest point of incisura jugularis (IJ). The origin of the thorax reference frame was set in the centroid of the T2, MAI, IJ and PX markers. The z-axis was orthogonal the plane formed by PX, MAI and T2 and its positive direction pointed to the right. The y-axis was oriented as the line joining MAI and T2 and its positive direction pointed upwards. The x-axis was the cross-product of the y-axis and z-axis and its positive direction was anterior (Figure A-5).

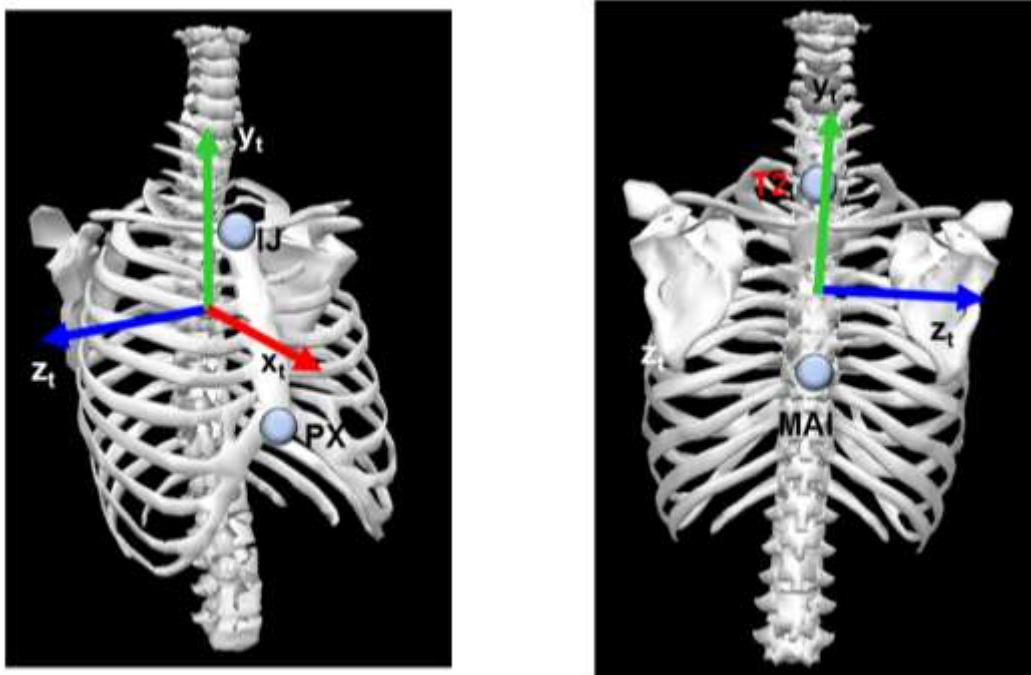


Figure A-5. Anatomical landmarks and reference frame convention of the trunk segment (Leardini et al., 2011).

Joint Angles

The human body consists of several segments connected to each other by joints. To interpret data from human body motion, joint coordinate systems (JCS) need to be defined. Once the segment and joint reference systems were defined, the rotations in the three planes of motions of the ankle, knee, hip and Tho/Pel joints were computed using the Cardan (or Euler) sequence adopting the following convention: the first rotation was described occurring in the medio-lateral axis (z-axis, perpendicular to the sagittal plane) who defines the flexion-extension movement; the third rotation will be described around the longitudinal axis (y-axis, perpendicular to the transverse plane) which defines the internal/external rotations; and the second rotation will be described around an axis perpendicular to the previous ones, which in the anatomic position represents the anterior-posterior axis (x-axis, perpendicular to the frontal plane) where the abduction/adduction occurs. This convention is simply defined as Z-X-Y convention and it is frequently used to describe the lower extremity rotations (Cappozzo et al., 1995; Grood and Suntay, 1983; Wu et al., 2002; Zatsiorsky, 1998). For instance, the knee flexion-extension angle is defined around the medio-lateral axis of the thigh (z-axis), the internal-external rotation around the vertical axis of the shank (y-axis) and the adduction-abduction around the floating axis which is mutually perpendicular to z-axis of the proximal and y-axis of the distal segments as shown in Figure A-6. It is necessary to define this convention to describe the rotations in the three-dimensional space since the three-dimensional angles are not commutative, thus the definition of axis and the order of description of the angles would interfere in the values of those angles (Zatsiorsky, 1998).

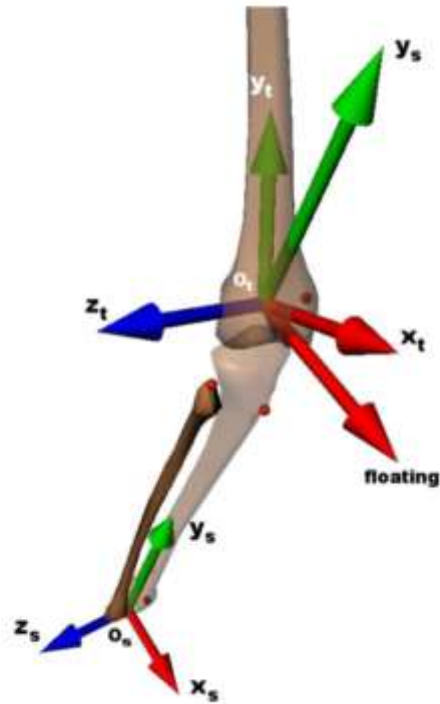


Figure A-6. Segment coordinate systems of the thigh and shank and the resulting knee JCS (Grood and Suntay, 1983; Van Sint Jan, 2007).

The origin of the JCS is usually located in the joint centres. In addition, the accurate joint centre location is important to calculate the joint moments which will be discussed in the next session. The KJC was computed as the mean distance of the epicondyles of the femur. Finally, the HJC location was determined by a predictive method (Bell et al., 1989) based on the distance between ASIS (distASIS) according to the Equation A-1.

$$\text{HJC} = (0.36 * \text{distASIS}, -0.19 * \text{distASIS}, -0.3 * \text{distASIS}) \quad \text{Equation A-1}$$

Joint Moments

The mechanical loads (forces and moments) about the musculoskeletal system were determined based on an inverse dynamic approach as demonstrated in the diagram in Figure A-7 .

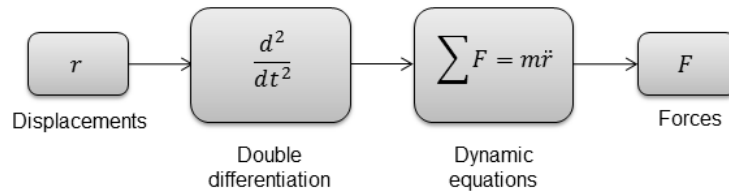


Figure A-7. Diagram showing the inverse dynamics workflow approach. Adapted from Zatsiorsky (2002).

In a broad sense, this approach adopted a physical-mathematical model of the human body and experimental measures of:

- external forces (in such case, the ground reaction force (GRF) via force platforms);
- position, velocity and acceleration of the body (via motion capture system);
- inertial parameters of each segment estimated from an anthropometric model (segment masses from Dempster's model (Winter, 2005) and geometry from Hanavan's model (Hanavan, 1964)).

Therefore, the forces that produce a given motion can be determined.

Once these variables were measured or estimated, we can then apply Newton/Euler equations Equation A-2 and Equation A-3 to solve the unknown variables (internal forces and moments).

For instance, the forces and torques acting in each segment are represented in the free body diagram (FBD) (Figure A-8). Therefore, we can determine the proximal joint force considering the FBD shown in Figure A-8 by Equation A-2:

$$\sum \vec{F} = m\vec{a} \quad \text{Equation A-2}$$

$$\vec{F}_{\text{prox}_i} = m\vec{a}_i - m\vec{g} - \vec{F}_{\text{EXT}_i}$$

Likewise, the joint moments about the proximal joint can be calculated by Equation A-3 (Robertson, 2004).

$$\sum \vec{M} = I \times \vec{\alpha} \quad \text{Equation A-3}$$

$$\vec{M}_{\text{prox}_i} = I_i \alpha_i - (\vec{r}_{p_i} \times \vec{F}_{\text{prox}_i}) - (\vec{r}_{d_i} \times \vec{F}_{\text{dist}_i}) - \vec{M}_{\text{dist}_i}$$

Note that for the foot segment, the \vec{M}_{dist_i} is the GRF moment vector and, therefore, the moments about the horizontal axes are usually assumed to be zero and the only moment acting on the foot is the free moment about the vertical axis.

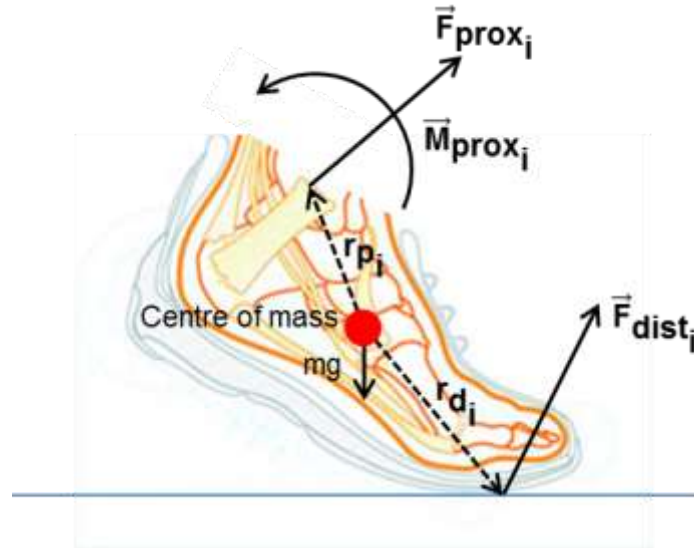


Figure A-8. FBD of one foot segment demonstrating the forces and moments acting in the segment during propulsion phase of running. Adapted from Robertson (2004).

The necessary condition to use this approach was that the number of unknown variables was equal or fewer than the number of equations. This condition was addressed in two ways: first, joint forces and moments (e.g. forces and moments produced by each tendon, ligament and bone) were pooled as resultant force and moment (net force and net moment), resulting in a unique force and unique moment for each joint. This procedure decreases considerably the number of unknown variables. However the tradeoff is the impossibility of more detailed description about the individual contribution for the resultant joint forces and joint moments. The calculation began with one segment where the forces and moments acting in the extremity of the segment are known (e.g. foot segment in Figure A-8). Hence, for this segment, there was only one joint (the proximal end) where we did not know the resultant force and moment, thus, there were only two unknown variables. According to second Newton's law we have two equations for this segment and these equations can be solved as a determined system.

Angular impulse

The joint moment impulse represents the cumulative twisting load experienced on the joint during stance phase of running (Stefanyshyn et al., 2006). It was obtained by integrating the area under the joint moment curve or by multiplying the load with the length of time that was applied as demonstrated in Equation A-4 and Figure A-9.

$$\text{Imp} = \int_{t_1}^{t_2} M \, dt \quad \text{Equation A-4}$$

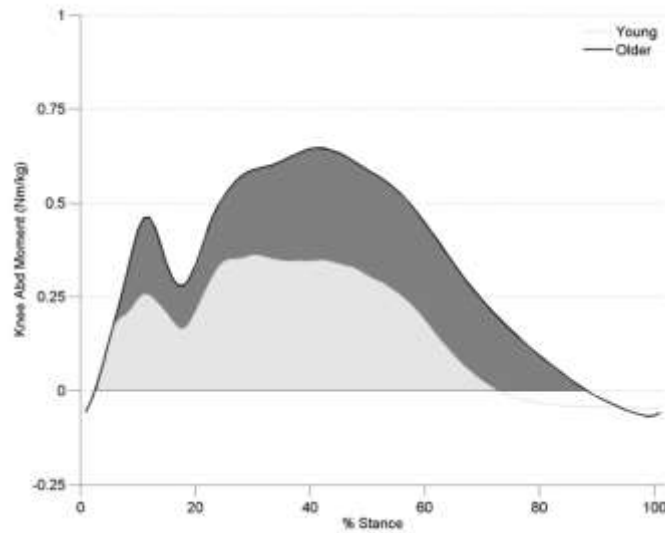


Figure A-9. Time-series curves of knee abduction moment patterns. The shaded area represents the joint moment impulse experienced by young (grey) and older (black) runners.

Joint Power

The joint power was defined as the product of the net moment of force (calculated through inverse dynamics analysis described above) and the relative angular velocity of the two segments intersected by the analyzed joint (Robertson, 2004) as demonstrated in Equation A-5.

$$\text{Power} = M(\omega_{\text{prox}} - \omega_{\text{dist}}) \quad \text{Equation A-5}$$

Joint Work

Power is the rate of work done (Winter, 2005). Therefore, the joint work was obtained by integrating the joint power over a period of time according to Equation A-6 and illustrated in Figure A-10.

$$\text{Work} = \int_{t_1}^{t_2} \text{Power} \, dt \quad \text{Equation A-6}$$

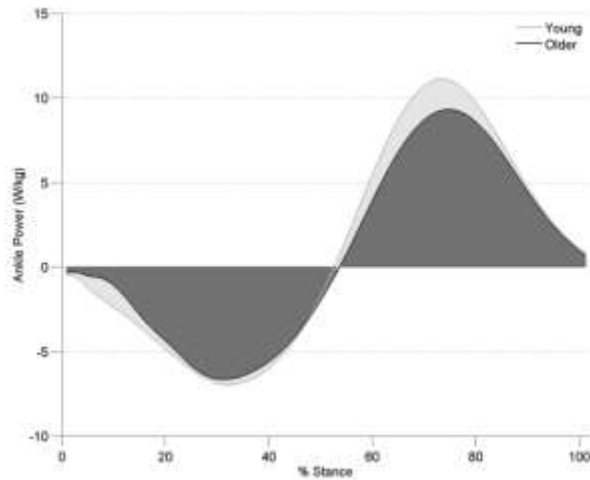


Figure A-10. Time series curves depicting positive and negative ankle joint work in young and older runners.

APPENDIX B :Instrumented treadmill calibration

Centre of Pressure (COP) Calibration

To estimate the joint loadings (through the use of inverse dynamics approach discussed earlier) it was necessary to combine data from different sources such as GRF (force platforms), kinematic (motion capture system) and anthropometric data. Hence, there were many sources of errors that may have contributed to inaccuracy and inconsistency in the estimation of joint moments. Although, GRF data are usually the most accurate and reliable source of data, these data would likely be more affected by errors when instrumented treadmills are used. Therefore, the use of this type of equipment demands proper calibration procedures in order to ensure the COP location is the most accurate and reliable as possible.

To assess and correct the location of the COP we used a machined rigid calibration rod (MTD-2, Motion Laboratory Systems, Baton Rouge, LA) that had a pointed tip at each end and five spherical retroreflective markers on it (Figure B-1). This rod was designed in a way that we could apply forces on the force platform with negligible applied moment of a force couple since we used a loading bar along with a base-plate that contained conical depressions (dimples). GRF and kinematic data were then simultaneously collected while the investigator applied force through the bar pivoting about the tip mounted in the base plate. Hence, the COP could be obtained both in the laboratory (COP_{LAB}), through the tip of the MTD-2; and force plate (COP_{FP}) coordinate systems.

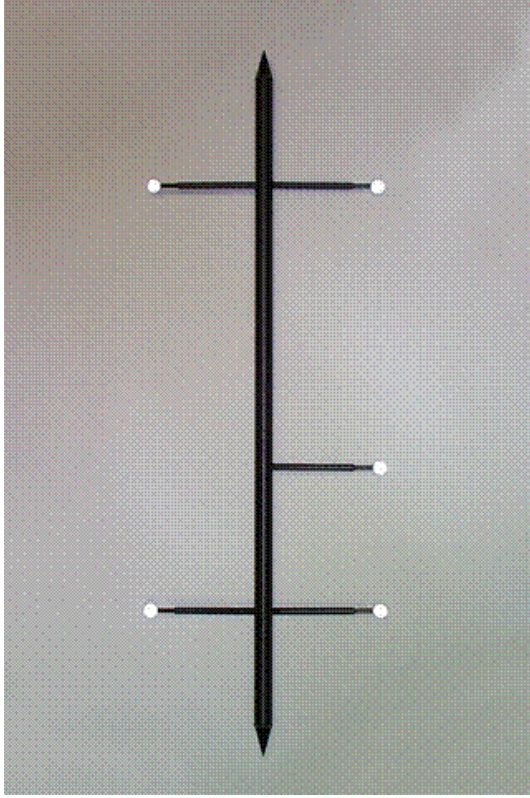


Figure B-1. MTD-2 calibration rod and an illustration of the calibration procedure.

The calibration procedure was performed every day that a study participant had their data collected. Six calibration trials were performed for each force platform and the COP_{LAB} was deemed the gold standard COP location as demonstrated in Figure B-2. Then, the values obtained for each of these trials were used to compute the optimized transformation between the laboratory and force platform coordinate system using a least-squares method (Spoor and Veldpaus, 1980) by minimizing the error expression in Equation B-1.

$$\sum_{n=1}^6 [COP_{FP} - (RCOP_{LAB} + L)]^2$$

Equation B-1

The obtained optimized rotation (R) and translation (L) matrices were then used to correct the COP location (Equation **B-2**) and the error could be estimated as shown in Table B-1 and Figure B-2.

$$\text{COP}_{\text{LABcorrected}} = \text{RCOP}_{\text{FP}} + \text{L} \quad \text{Equation B-2}$$

The corrected relative position and orientation of the force plate coordinate system to the laboratory coordinate system could also be calculated and used for the inverse dynamics approach.

Table B-1. Mean ($\pm 1\text{SD}$) COP location error of six trials across calibration days for the right and left force platforms.

	Right	Left
Accuracy (mm)	2.13 \pm 0.63	2.09 \pm 1.09

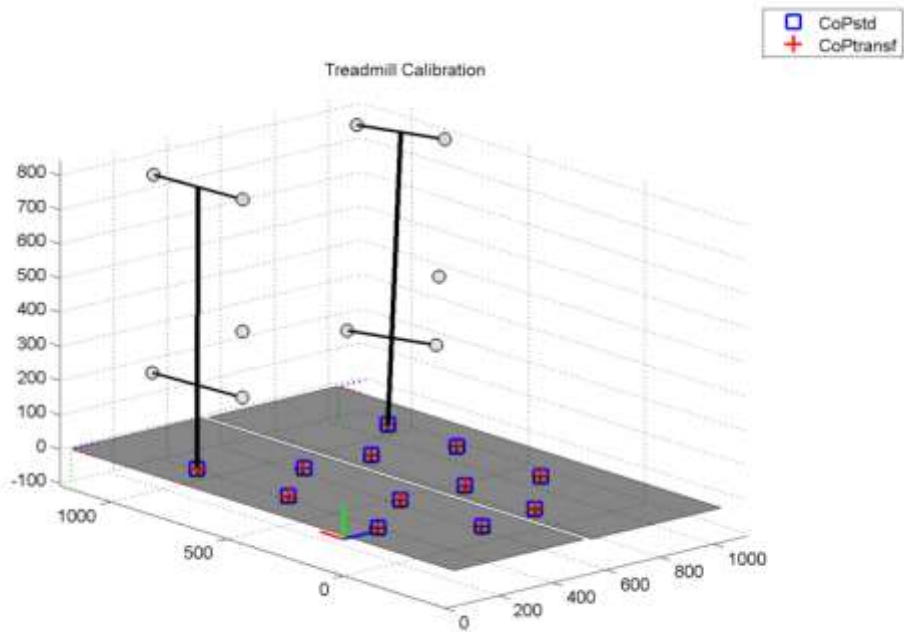


Figure B-2. Average position of the markers outfitted on the MTD-2 calibration rod and the average location of the tip of the rod (COP_{std}) and the corrected COP location (COP_{transf}) for one data collection day.

Motion capture system error

The accuracy of the motion capture system could also be concurrently verified based on the position of the five markers outfitted in the MTD-2 rod. Five distances were calculated through the motion capture system. The measured distances along with the values provided by the manufacturer that were used in the comparisons are shown in Figure B-3.

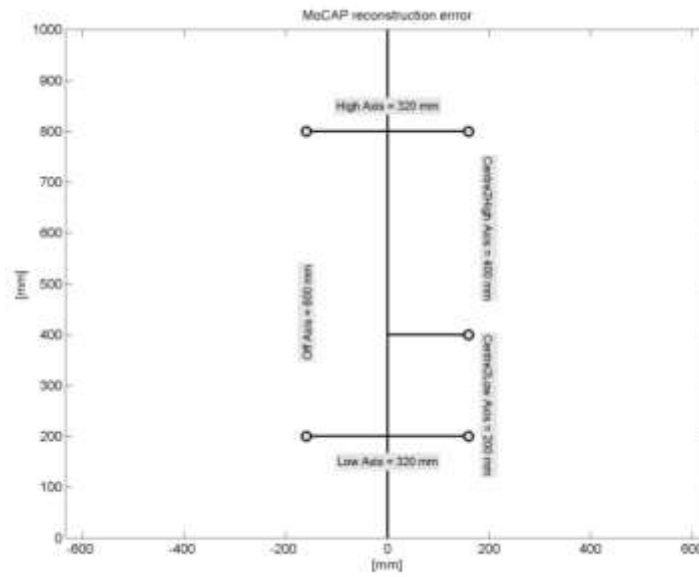


Figure B-3. Selected distances between markers outfitted in the MTD-2 calibration rod to calculate the motion capture (MoCAP) system reconstruction error.

Hence, the known distances were used to estimate the motion capture reconstruction error for six trials and for every day that a participant had their data collected. The results are demonstrated in Table B-2.

Table B-2. Reconstruction error of the motion capture system.

Distance	Right (mm)	Left (mm)
High Axis	2.41±0.39	2.49±0.39
Low Axis	2.69±0.31	2.68±0.34
Off Axis	1.56±0.92	1.60±0.97
Centre2High Axis	2.29±0.56	2.30±0.61
Centre2Low Axis	0.82±0.28	0.86±0.63

APPENDIX C : Support Vector Machine algorithm workflow

All the calculations involving the Support Vector Machines approach to analyze data in chapter 4 and chapter 5 of this thesis were undertaken in Matlab 7.12 (Mathworks Inc, Natick, MA, USA), mainly using functions available in the Bioinformatics toolbox (v. 3.2). A core function was programmed by the author of this thesis to embody the algorithm outlined in the workflow by modifying `svmtrain`, `svmclassify`, and their sub-functions to allow the cross-validation and the feature selection procedures. In addition, an implementation was made to yield the perpendicular distance of the data points to the hyperplane by using the parameters (**w**, **b**) obtained by the SVM model. Moreover, the `classperf` function was used to calculate the classification accuracy rate (CAR).

The workflow in Figure C-1 depicts the steps taken to obtain the SVM model by classifying young and older runners (described in study 1 of chapter 5) and to measure the effects of exercise intervention in the randomized controlled trials study (study 2 of chapter 5).

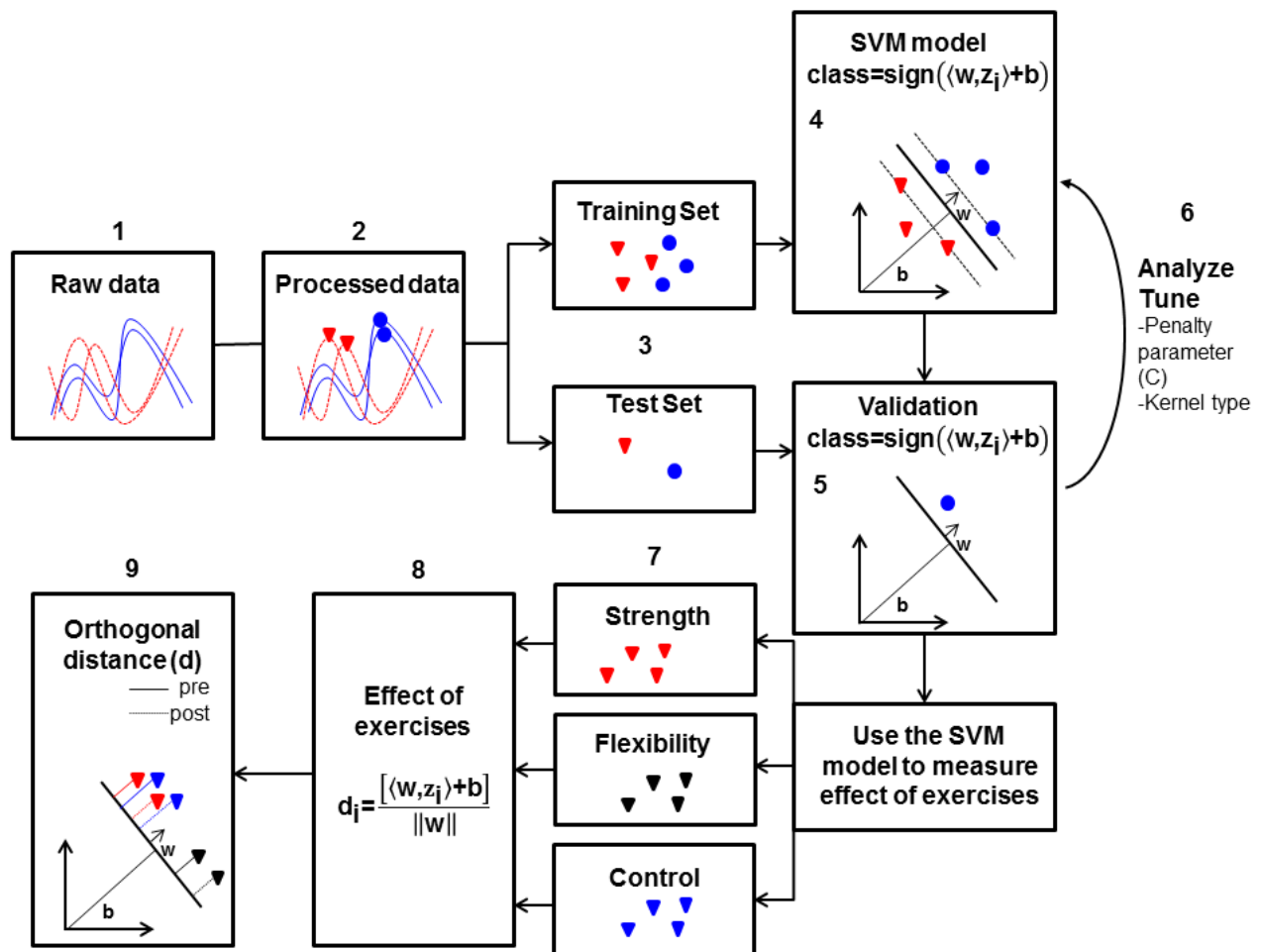


Figure C-1. SVM model workflow utilized to classify young and older runners and to quantify the effects of exercise intervention (RCT study).

Table C-1. Description of the steps taken to obtain the classification of young and older runners and to quantify the effects of exercise intervention.

Procedure	Description
1 Raw data	3D gait kinematics, kinetics and ground reaction forces (GRF) time-series curves, maximal isometric voluntary contraction (MVIC) and static flexibility measures.
2 Processed data	Discrete variables extracted from time-series curves averaged across trials. Averaged MVIC across trials and static flexibility measures.
3 Cross-validation procedure	The data were partitioned in k subsets and k-1 subsets were used to train the SVM and the remaining was used to test. In this study a k=10 was used.
4 Learning process	The SVM learns patterns in a supervised learning process (i.e. a supervisor labels the input data).
5 Testing process	The generalization ability of the SVM model is evaluated by the number of correctly classified data points in the testing set.
6 Analyze and Tune	Based on the results of the testing procedure, the SVM classifier can be tuned based on some parameters such as penalty parameter (C) and kernel methods to enhance classification.
7 Randomization	Once the best SVM model is determined based on young and older runners, a bigger cohort of older runners were then randomly assigned to the intervention groups.
8 SVM-based score	The perpendicular distances of the older runners to the SVM-hyperplane, before and after exercise, were then calculated to summarize the muscle strength, flexibility and gait function as a single value.
9 Effects of exercises examination	The score derived from the SVM-model was then used to compare the effects of intervention across groups.

APPENDIX D : Exercise intervention programs

Group One: Strengthening based exercises

Exercise Log Book Intervention Group 1

ID#: _____

General Comments:

With advancing age, structural and functional deterioration occurs in most physiological systems, even in the absence of discernible disease. One of the most remarkable changes in the musculoskeletal system is the loss of muscle (sarcopenia) followed by muscle weakness that occurs during middle and old age. Therefore, muscle strengthening exercises have been widely recommended to counterbalance the effects of aging.

Procedures:

Please perform the exercises following the descriptions in this booklet. You will be required to visit the Running Injury Clinic once a week to update the progression of the exercises and to make sure that the exercises have been properly done. All unilateral exercises should be performed on both sides and you should alternate legs between sets.

The exercises will be performed in 3 sets of 15 repetitions. Allow at least 30 seconds recovery between each set. Speed of movement should be slow and controlled, 2-3 seconds at the start of the movement, and 2-3 seconds at the end of the movement.

The pictures below simply show the technique in which the exercises should be performed. However, the resistance that should be met during the exercise is particular for each participant. Every exercise has to result in exertion perception at the end of the last repetition. In particular, the exercise should cause a perceived exertion scale (PES) of 5-8 on a 10-point scale where zero means “extremely easy” and ten means “extremely hard” (Colado et al., 2012). In case you perceive a smaller or a higher resistance at the end of a set, the resistance should be adjusted until you meet the requirements. You will receive instruction on how to manipulate the resistance during your weekly appointments at the Running Injury Clinic.

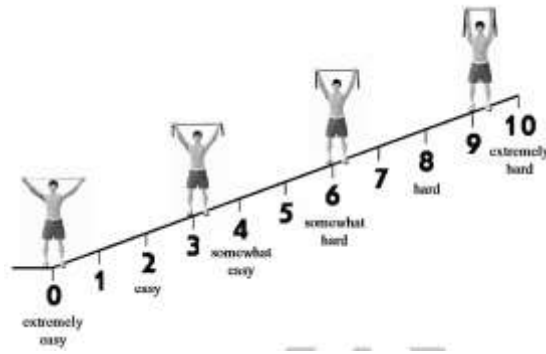




Figure 1. OMNI- Resistance Exercise Scale of perceived exertion with Thera-Band® resistance bands Colado et al. (2012).

The exercises are listed below according to the weeks that they should be done. In addition, at the end of each week, please mark the days of the week that you perform the full set of exercises. In case you could not do any exercise listed, you should leave the box unchecked and write down which number corresponds to that particular exercise.

In addition to this booklet, videos demonstrating how to perform the exercises are posted on the following website: <https://sites.google.com/site/runhealthyaging/>. By clicking on the link “Intervention Group 1” you will be redirected to the login page. If you already have a Google account (i.e.: Gmail) just log in using your username and password, otherwise you will need to create a new account. To do so, click the sign up button in the top-right corner of the page and you will be prompted to provide your username (you may want to use your current e-mail address i.e.: healtholder@hotmail.com) and password (please, create one that you will recall). Now, you should be able to navigate through the website and watch the videos of the exercises. If you need further assistance do not hesitate to contact Reginaldo K. Fukuchi (e-mail: r.fukuchi@ucalgary.ca).

Weeks 1-2 – Dates:



1. Sidelying Hip Abduction

Start		Finish	
			

Instructions:

Lying on your side. Move the top leg upwards, keeping knee straight and hip forward. 2 seconds up and 2 seconds down, control the motion throughout.



2. Calf Raises

Start		Finish	
			

Instructions:

Place both feet on the ground shoulder width apart. Rise up onto toes. 2 seconds up and 2 seconds down, control the motion throughout.

3. Full Squat



Start		Finish	
			

Instructions:



Place both feet on the ground shoulder width apart with knees fully extended. Slowly flex your knees and squat down until the thighs are parallel with the ground. Once you achieve that position return to the starting position. 2 seconds down and 2 seconds up, control the motion throughout.

Weeks 1-2 – Dates:



4. Half Lunge

Start		Finish	
			
<p>Instructions:</p> <p>Place both feet on the ground shoulder width apart. Step out of this position with one leg, lunge down to 45° then stand up. 2 seconds down and 2 seconds up, control the motion throughout. Switch legs and repeat.</p>			

5. Hip Internal Rotators



Start		Finish	
			
<p>Instructions:</p> <p>Loop the band and securely attach one end of the loop to a fixed object near the floor. Sit with the exercising side away from the attachment, and place your ankle inside the other end of the loop. Rotate your ankle outward, keeping your knee pointing forward. 2 seconds out and 2 seconds in, control the motion throughout.</p>			

6. Hip External Rotators

Start		Finish	
			
<p>Instructions:</p> <p>Loop the band and securely attach one end of the loop to a fixed object near the floor. Sit with the exercising side closest to the attachment, and place your ankle inside the other end of the loop. Rotate your ankle inward, keeping your knee pointing forward. 2 seconds in and 2 seconds out, control the motion throughout.</p>			

Weeks 1-2 – Dates:

7. Hip Extensors

Start		Finish	
			
<p>Instructions: Loop the band and securely attach one end of the loop to a fixed object near the floor. Place your ankle inside the other end of the loop and stand facing the attachment. Place opposite foot beside band. Move involved leg backwards, keeping knee and trunk straight. 2 seconds backward and 2 seconds forward, control the motion throughout.</p>			

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 1

☐ Monday ☐ Tuesday ☐ Wednesday ☐ Thursday ☐ Friday ☐ Saturday ☐ Sunday

Please record your overall weekly PES (0-10): _____

WEEK 2



☐ Monday ☐ Tuesday ☐ Wednesday ☐ Thursday ☐ Friday ☐ Saturday ☐ Sunday

Please record your overall weekly PES (0-10): _____



Notes:

Week 3-4 – Dates:



1. Lateral Step-up (Hip hike)

Start		Finish	
			
<p>Instructions:</p> <p>Standing on stool or step with outside foot hanging off the edge while keeping both knees straight, relax hip so that the outside leg hangs past the step towards the ground. Hike the hip so that the involved foot crosses the level of the stool. 2 seconds down and 2 seconds up, control the motion throughout.</p>			

2. Calf Raises on Step





Start		Finish	
			
<p>Instructions:</p> <p>Place both feet on a step shoulder width apart. Rise up onto toes and completely down just below the level of the step. 2 seconds up and 2 seconds down, control the motion throughout.</p>			

3. One-Leg Half Squat





Start		Finish	
			
<p>Instructions:</p> <p>Place both feet on the ground shoulder width apart with knees fully extended. Lift one leg off the ground while squatting down with the opposite leg to 45°. 2 seconds down and 2 seconds up, control the motion throughout while keeping your arms out in front.</p>			

Week 3-4 – Dates:



4. Hip Internal Rotators

Start		Finish	
			
<p>Instructions: Stand with involved leg externally rotated at 45° and the band around the front of your waist. Move the involved leg forward while internally rotating, keeping knee straight or with slight “soft knee”. 2 seconds forward and 2 seconds back, control the motion throughout.</p>			

5. Hip External Rotators



Start		Finish	
			
<p>Instructions: Stand with feet side by side and the band around the back of your waist. Move the involved leg backward while externally rotating, keeping knee straight or with a slight “soft knee”. Tap toe down at 160°, control the motion throughout.</p>			

6. Lateral Step Down

Start		Finish	
			
<p>Instructions: Use a 6-10 inch step. Step up on to the side edge of the step with one foot. With the other foot hanging off the side of the step, step down, lightly touch the floor, and return to standing. Control the motion throughout.</p>			

Week 3-4 – Dates:

7. Half Lunges with Resistance

Start		Finish	
			
<p>Instructions: Loop the band around your leg slightly above the knees. Place both feet on the ground shoulder width apart. Step out of this position with one leg, lunge down to 45° and back up and return to the starting position. 2 seconds down and 2 seconds up, control the motion throughout. Repeat the sets stepping out with the opposite leg.</p>			

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 3

☐ Monday ☐ Tuesday ☐ Wednesday ☐ Thursday ☐ Friday ☐ Saturday ☐ Sunday

Please record your overall weekly PES (0-10): _____

WEEK 4



☐ Monday ☐ Tuesday ☐ Wednesday ☐ Thursday ☐ Friday ☐ Saturday ☐ Sunday

Please record your overall weekly PES (0-10): _____



Notes:

Week 5-6 – Dates:



1. Hip Abduction

Start		Finish	
			
<p>Instructions: Loop the band around your ankle, and stabilize the other end of the band to a stationary object near the floor. Keep your knees straight and move leg outward. Keep your back straight, and avoid leaning or bending over. 2 seconds out and 2 seconds in, control the motion throughout.</p>			

2. One-Leg Calf Raises





Start		Finish	
			
<p>Instructions: Place one foot on the ground. Rise up onto toes. 2 seconds up and 2 seconds down, control the motion throughout.</p>			

3. One-Leg Half Squat





Start		Finish	
			
<p>Instructions: Place both feet on the ground shoulder width apart with knees fully extended. Lift one leg off the ground while squatting down with the opposite leg to 45°. 2 seconds down and 2 seconds up, control the motion throughout while keeping your arms out in front.</p>			

Week 5-6 – Dates:



4. Hip Internal Rotators

Start		Finish	
			
<p>Instructions:</p> <p>Stand with involved leg externally rotated at 45° and the band around the front of your waist. Move the involved leg forward while internally rotating, keeping knee straight or with slight “soft knee”. 2 seconds forward and 2 seconds back, control the motion throughout.</p>			

5. Hip External Rotators

Start		Finish	
			
<p>Instructions:</p> <p>Stand with feet side by side and the band around the back of your waist. Move the involved leg backward while externally rotating, keeping knee straight or with a slight “soft knee”. Tap toe down at 160°, control the motion throughout.</p>			

6. Full Lunge

Start		Finish	
			
<p>Instructions:</p> <p>Place both feet on the ground shoulder width apart. Step out of this position with one leg, lunge down until the thigh is parallel with the ground, stand back up and return to the starting position. 2 seconds down and 2 seconds up, control the motion throughout. Switch legs and repeat.</p>			

Week 5-6 – Dates:

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 5

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

Please record your overall weekly PES (0-10): _____

WEEK 6



<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

Please record your overall weekly PES (0-10): _____



Notes:

Week 7-8 – Dates:



1. Gluteus Medius

Start		Finish	
			
<p>Instructions:</p> <p>Place opposite leg in front of band. Move involved leg back to 45 degree angle, keeping knee straight. 2 seconds out and 2 seconds in, control the motion throughout.</p>			

2. One-Leg Calf Raises on Step





Start		Finish	
			
<p>Instructions:</p> <p>Place one foot on the edge of a step at shoulder width. Rise up onto toes and completely down past the level of the step. 2 seconds down and 2 seconds up, control the motion throughout.</p>			

3. One Leg Full Squat





Start		Finish	
			
<p>Instructions:</p> <p>Place both feet on the ground shoulder width apart with knees fully extended. Lift one leg up off the ground while squatting down with the opposite leg until the thigh is parallel with the ground (90°). 2 seconds down and 2 seconds up, control the motion throughout while keeping your arms out in front.</p>			

Week 7-8 – Dates:



4. Hip Internal Rotators

Start		Finish	
			
<p>Instructions:</p> <p>Stand with involved leg externally rotated at 45° and the band around the front of your waist. Move the involved leg forward while internally rotating, keeping knee straight or with slight “soft knee”. 2 seconds forward and 2 seconds back, control the motion throughout.</p>			

5. Hip External Rotators

Start		Finish	
			
<p>Instructions:</p> <p>Stand with feet side by side and the band around the back of your waist. Move the involved leg backward while externally rotating, keeping knee straight or with a slight “soft knee”. Tap toe down at 160°, control the motion throughout.</p>			

6. Full Lunge with resistance

Start		Finish	
			
<p>Instructions:</p> <p>Loop the band around your leg slightly above the knees. Place both feet on the ground shoulder width apart. Step out of this position with one leg, lunge down until the thigh is parallel with the ground (90°), stand back up and return to the starting position. 2 seconds down and 2 seconds up, control the motion throughout. Repeat the repetitions stepping out with the opposite leg.</p>			

Week 7-8 – Dates:

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 7

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

Please record your overall weekly PES (0-10): _____

WEEK 8

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

Please record your overall weekly PES (0-10): _____

Notes:

Group Two: Stretching based exercises

**Exercise Log Book
Intervention Group 2**

ID#: _____

General Comments:

With the aging process the loss of range of motion as a result of the tendon inflexibility is known and widely reported in the literature. This loss of flexibility may compromise the ability of the individuals to perform physical activities such as long distance running. However this loss is modifiable through flexibility exercises according to some studies. There has been evidence that flexibility training improves muscle performance. In addition, stretching exercises have been demonstrated to be effective to decrease both the frequency and severity of injuries. The exercises below were designed according to the scientific literature and to the guidelines of exercise testing and prescription of the American College of Sports Medicine.

Procedures:

The stretching exercises should be performed in the following way: slowly stretch the muscle groups until you reach a position of mild discomfort (*“The following stretching exercises should be performed to the limits of discomfort within the range of motion, but no further. This will be perceived as the point of mild tightness without discomfort.”* (Thompson et al., 2010)). Hold that position for 15-30 seconds. Take a 15-20 second break between repetitions. Repeat the same procedure at least 3 consecutive times.



The series of stretching exercises must be done at least 6 days/week over the next 8 weeks. The exercises are listed below according to the weeks that they should be done. In addition, at the end of each week, please mark the days of the week that you perform the full set of exercises. In case you could not do any exercise listed, you should leave the box unchecked and write down which number corresponds to that particular exercise.

You will be asked to visit the Running Injury Clinic every other week to ensure that you are performing the exercises properly. In addition, joint range of motion tests will be performed to record any changes in muscle length.



In addition to this booklet, videos demonstrating how to perform the exercises are posted on the following website: <https://sites.google.com/site/runhealthyaging/>. By clicking on the link “Intervention Group 2” you will be redirected to the login page. If you already have a Google account (i.e.: Gmail) just log in using your username and password, otherwise you will need to create a new account. To do so, click the sign up button in the top-right corner of the page and you will be prompted to provide your username (you may want to use your current e-mail address i.e.: healthholder@hotmail.com) and password (please, create one that you will recall). Now, you should be able to navigate through the website and watch the videos of the exercises. If you need further assistance do not hesitate to contact Reginaldo K. Fukuchi (e-mail: r.fukuchi@ucalgary.ca).

Weeks 1-2 – Dates: _____



1. Iliotibial Band (ITB) Standing Stretch

Start		Finish	
			
<p>Instructions:</p> <p>Place opposite foot across involved foot and in front. Lean away from involved side pushing hip outwards. Switch legs and repeat.</p>			

2. Quadriceps Stretch



Start		Finish	
			
<p>Instructions:</p> <p>Grasp ankle of the leg you want to stretch and pull towards buttock. Keep the knee in alignment with the hip and shoulder. Switch legs and repeat.</p>			

3. Hamstring Stretch - Seated



Start		Finish	
			
<p>Instructions:</p> <p>Sit with one leg bent and involved leg straight. Lean forward over involved leg to stretch the hamstrings. Switch legs and repeat.</p>			

Weeks 1-2 – Dates: _____



4. Soleus Stretch

Start		Finish	
			
Instructions: Place involved heel as close to wall as possible. Bend knees to feel stretch in Achilles tendon. Switch legs and repeat.			

5. Gastrocnemius Stretch



Start		Finish	
			
Instructions: Place involved heel as close to wall as possible. Lean forward and with knee straight stretch will be felt in calf muscle. Switch legs and repeat.			

6. Hip Internal Rotator Stretch - Seated

Start		Finish	
			
Instructions: Place soles of feet together. Push knees towards floor with elbows and bend forward at the hips. Switch legs and repeat.			

Weeks 1-2 – Dates: _____

7. Hip Flexor Stretch - Standing

Start	Finish
	
<p>Instructions: Place involved limb behind and lean forward slowly while pushing your hips forward and keeping your back and back knee straight. Switch legs and repeat.</p>	

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 1

☐ Monday
 ☐ Tuesday
 ☐ Wednesday
 ☐ Thursday
 ☐ Friday
 ☐ Saturday
 ☐ Sunday



WEEK 2

☐ Monday
 ☐ Tuesday
 ☐ Wednesday
 ☐ Thursday
 ☐ Friday
 ☐ Saturday
 ☐ Sunday



Notes:

Weeks 3-4 – Dates: _____



1. Iliotibial Band (ITB) Stretch – Lying

Start	Finish
	
<p>Instructions: Lying down, bring involved knee and thigh across body and pull gently with opposite hand to stretch. Switch legs and repeat.</p>	

2. Quadriceps Stretch – Sidelying



Start	Finish
	
<p>Instructions: Lay on your side. Grasp ankle of the leg you want to stretch and pull towards buttock. Place opposite (bottom) foot over top of the involved (top) knee. Switch legs and repeat.</p>	

3. Hamstring Stretch - Lying



Start	Finish
	
<p>Instructions: Lying on back with a towel or inelastic band around your foot. Stretch hamstring straight back and then to each side. Hold each position for 15-30 seconds. Switch legs and repeat.</p>	

Weeks 3-4 – Dates: _____



4. Soleus Stretch

Start			Finish		
					
Instructions: Place involved heel as close to wall as possible. Bend knees to feel stretch in Achilles tendon. Switch legs and repeat.					

5. Gastrocnemius Stretch



Start			Finish		
					
Instructions: Place involved heel as close to wall as possible. Lean forward and with knee straight stretch will be felt in calf muscle. Switch legs and repeat.					

6. Hip Internal Rotator Stretch – Lying

Start			Finish		
					
Instructions: Lying down, place soles of feet together and let knees fall towards floor. Switch legs and repeat.					

Weeks 3-4 – Dates:

7. Hip Flexor Stretch – Kneeling

Start	Finish
	
<p>Instructions: Place involved limb behind and lean forward slowly pushing hips forward while keeping back straight. Switch legs and repeat.</p>	

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 3

☐ Monday
 ☐ Tuesday
 ☐ Wednesday
 ☐ Thursday
 ☐ Friday
 ☐ Saturday
 ☐ Sunday

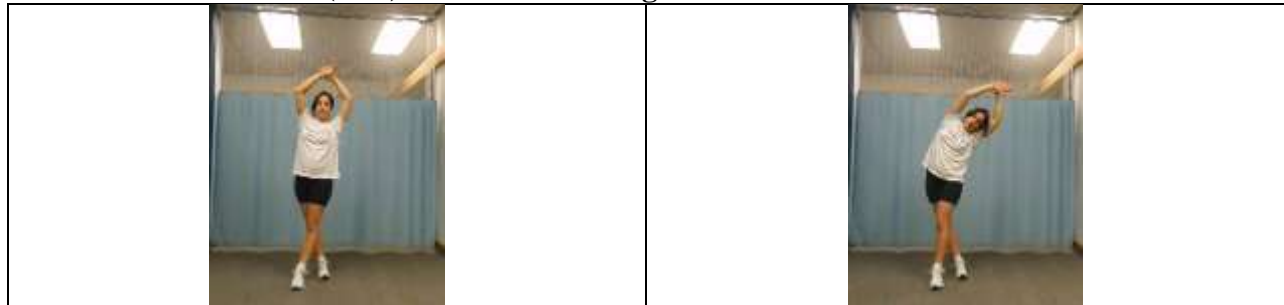
WEEK 4

☐ Monday
 ☐ Tuesday
 ☐ Wednesday
 ☐ Thursday
 ☐ Friday
 ☐ Saturday
 ☐ Sunday

Notes:

Weeks 5-6 – Dates: _____

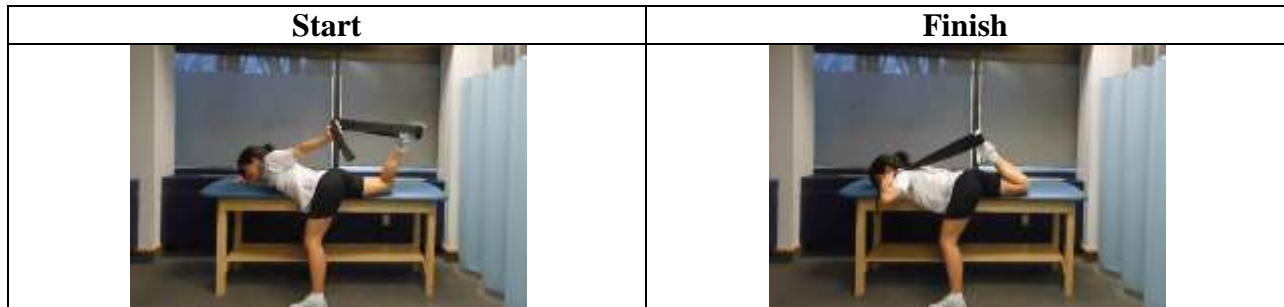
1. Iliotibial Band (ITB) Stretch - Standing



Instructions:

Place opposite foot across involved foot and in front. Grab the wrist of the involved side while you lean away pushing hip outwards and pulling the wrist upward. Switch legs and repeat.

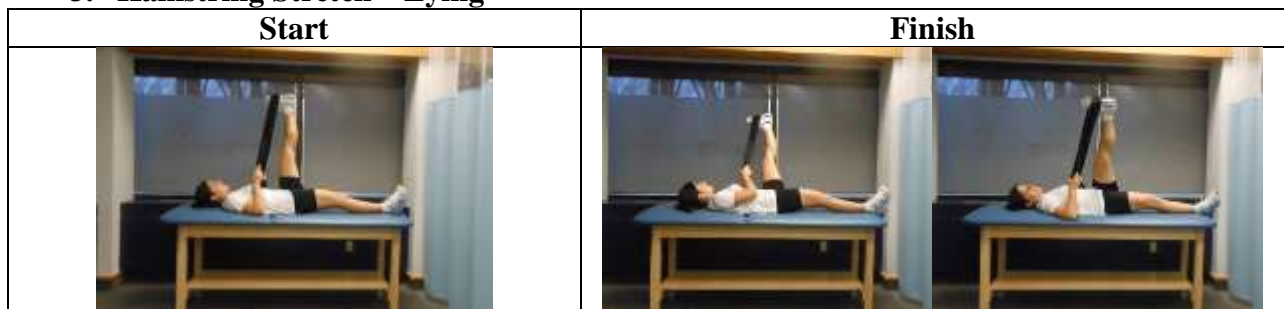
2. Rectus Femoris Stretch



Instructions:

Stabilize pelvis with the involved leg on table. Use a towel or inelastic band to stretch front of hip. Switch legs and repeat.

3. Hamstring Stretch – Lying





Instructions:



Lying on back with a towel or inelastic band around your foot. Stretch hamstrings straight back and then to each side. Hold each position for 15-30 seconds. Switch legs and repeat.

Weeks 5-6 – Dates: _____



4. Gastrocnemius/Soleus Stretch

Start	Finish
	
<p>Instructions: A towel can be placed under the medial arch to help maintain subtalar neutral. Place involved heel away from the wall. Bend the uninvolved knee and lean forward. Keep back leg straight. Stretch will be felt in the calf muscle. Switch legs and repeat.</p>	

5. Hip External Rotator Stretching



Start	Finish
	
<p>Instructions: Sitting with knees at 90 degree angles. Lean forward to 12 o'clock. Switch legs and repeat.</p>	

6. Hip Internal Rotation Stretching

Start	Finish
	
<p>Instructions: Sitting with knees at 90 degree angles. Lean backward to 6 o'clock. Switch legs and repeat.</p>	

Weeks 5-6 – Dates: _____

7. Hip Flexor Stretch – Kneeling

Start	Finish
	
<p>Instructions: Place involved limb behind and lean forward slowly pushing hips forward while keeping back straight. Switch legs and repeat.</p>	

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 5

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday



WEEK 6

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday



Notes:

Weeks 7-8 – Dates: _____



1. Iliotibial Band (ITB) Stretch - Foam Roller

Start	Finish
	
<p>Instructions: Lay on side with foam roller positioned just above knee. Roll slowly until roller is positioned just below hip and back up. Repeat 5 times in each leg.</p>	

2. Hip External Rotator Pigeon Stretch



Start	Finish
	
<p>Instructions: Cross involved leg underneath your body and lean forward over the knee. Place opposite leg straight back to optimize stretch. Switch legs and repeat.</p>	

3. Hip Flexor Stretch - Kneeling



Start	Finish
	
<p>Instructions: Place involved limb behind and lean forward slowly pushing hips forward while keeping back straight. Switch legs and repeat.</p>	

Weeks 7-8 – Dates: _____



4. Hip External Rotator Stretching

Start		Finish	
			
Instructions: Sitting with knees at 90 degree angles. Lean forward to 12 o'clock. Switch legs and repeat.			

5. Hip Internal Rotation Stretching





Start		Finish	
			
<p>Instructions: Sitting with knees at 90 degree angles. Lean backward to 6 o'clock. Switch legs and repeat.</p>			

6. Active Hamstring Stretch



Start		Finish	
			
<p>Instructions:</p> <p>Bend your involved hip up to 90 degrees and grasp behind knee. Straighten knee to activate quadriceps and stretch hamstrings. Switch legs and repeat.</p>			

Weeks 7-8 – Dates: _____

7. Calf Muscles Stretch – Variations

Start		Finish			
					
<p>Instructions: To stretch the different fibres in the calf muscle you can change the angle of your foot on the ground. Place involved heel away from the wall. Bend the uninvolved knee and lean forward. Keep back leg straight. Hold each position for 15-30 seconds. Switch legs and repeat.</p>					

8. Adductor Muscle Stretch - Wall

Start		Finish	
			
<p>Instructions: Sit on the floor with your legs extended and your feet touching a wall. Sit tall and shuffle your buttocks toward the wall as you push your straight legs farther apart. Bend your knees before you back up to the initial position.</p>			

Weeks 7-8 – Dates: _____

Compliance: Check the box if you completed the FULL set of exercises for that respective day

WEEK 7

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

WEEK 8

<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday

Notes:
