THE ASSESSMENT OF FATIGUE-RELATED CHANGES IN STRIDE MECHANICS, VARIABILITY AND LONG-RANGE CORRELATIONS IN RECREATIONAL AND ELITE DISTANCE RUNNERS USING FOOT-MOUNTED INERTIAL SENSORS

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By
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Clemens Markus Brahms, candidate for the degree of Doctor of Philosophy in Kinesiology and Health Studies, has presented a thesis titled, *The assessment of fatigue-related changes in stride mechanics, variability and long-range correlations in recreational and elite distance runners using foot-mounted inertial sensors*, in an oral examination held on December 19, 2016. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

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*Via teleconference*
Abstract

This thesis was designed to assess stride mechanics, variability and long-range correlations during running, as well as their relationship with fatigue and skill level. For this purpose, three separate experiments were conducted. As a first step, it was established whether a simple hardware setup consisting of a wireless foot-mounted inertial measurement unit (IMU) was capable of accurately measuring individual stride length vectors during distance running. The results showed that the sensor-based method displayed excellent levels of agreement with a 3D motion capture system as the criterion. Subsequently, the same setup was used to track a set of gait variables in a group of elite and recreational runners during an exhaustive overground run. It was established that long-range correlations (LRCs) decreased over the run, while no significant changes were observed in the coefficients of variation (CV). Group differences were found in mean stride length, contact time and peak impact acceleration, stride time CV as well as peak impact acceleration FSI. A final study assessed the impact of a fatiguing drop jump protocol on joint stiffness, stride mechanics and measures of variability. As before, a group of elite and recreational distance runners were recruited for this experiment. It was found that joint stiffness was significantly reduced after the fatiguing jumps. Additionally, mean stride time, as well as LRCs in the stride time and stride length series were reduced in response to the jumps. Group differences existed in knee joint stiffness and mean stride length. Notable interaction effects indicated that elite and recreational runners reacted differently to the fatiguing jumps with respect to mean ankle joint stiffness and stride length. Together, this thesis demonstrates that long-range correlations serve as a potential marker of neuromuscular fatigue during prolonged running. It also confirms that IMUs are capable of tracking a variety of gait parameters across a range of different distance running speeds.

Keywords: distance running, fatigue, stride variability, inertial sensors, IMU
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# Contents

Abstract ii  
Acknowledgements iii  
Table of Contents iv  
List of Figures vii  
List of Tables xi  
List of Abbreviations xii  

1 Introduction 1  

2 Literature Review 7  

2.1 The Gait Cycle in Walking and Running 7  
2.2 Kinematics 8  
  2.2.1 Sagittal Plane Kinematics 10  
  2.2.2 Coronal Plane Kinematics 11  
  2.2.3 Transverse Plane Kinematics 11  
2.3 Kinetics 12  
  2.3.1 Ground Reaction Forces and Center of Pressure 12  
  2.3.2 Joint Forces, Moments and Power 15  
2.4 Functional Anatomy of Running 17  
2.5 Biomechanical Factors Affecting Running Technique 19  
  2.5.1 Running Speed 19  
  2.5.2 Footfall Patterns in Running 21  
  2.5.3 Skill Level 22
5 Study 2: Stride Mechanics and Variability over a Prolonged Run in Recreational and Elite Distance Runners

5.1 Research Design

5.2 Instrumentation and Test Procedures

5.3 Data Analysis

5.4 Statistical Analysis

5.5 Results

5.6 Discussion

5.7 Conclusion

6 Study 3: The Effects of a Fatiguing Jump Protocol on Joint Stiffness, Stride Kinematics, Variability and Long-Range Correlations in Recreational and Elite Distance Runners

6.1 Research Design

6.2 Instrumentation and Test Procedures

6.3 Data Analysis

6.4 Statistical Analysis

6.5 Results

6.6 Discussion

6.7 Conclusion

7 Limitations

8 Conclusion and Future Work

References
# List of Figures

3. Representative example of resultant acceleration signal recorded with a foot-mounted IMU during distance running.
4. Representative example of an angular velocity signal recorded with a foot-mounted IMU during distance running.
5. Velocity estimates derived from acceleration signal by integration with (solid line) and without (dotted line) applying regular ZUPTs. Figure adapted from Feliz, Zalama, and Garcia-Bermejo (2009). Pedestrian tracking using inertial sensors. *Journal of Physical Agents*, 3, 35-43.
6. IMU orientation and reflective markers attached to the foot.
7. Camera setup in the lab.
8. A scatterplot showing the relationship between the stride length estimates of the two different methods.
9. Bland-Altman plot comparing the two different methods to calculate stride length.
10. Between-method difference in stride length for each participant.
11. Resultant angular velocity during running. The bold line indicates the stance phases detected by the algorithm. Improper threshold tuning is shown to cause considerable stance detection errors.
12 Diagram showing the dimensions of the indoor track and the experimental setup.

13 Stride time, contact time and peak impact acceleration calculated from the resultant acceleration signal recorded by the foot-mounted IMU.

14 Mean stride length as a function of run duration. ■ = mean SL significantly different (p < 0.001) between groups.

15 Mean stride time as a function of run duration.

16 Mean $t_c$ as a function of run duration. ■ = mean $t_c$ significant difference (p < 0.001) between groups, * = significant difference (p = 0.041) between beginning and middle of the run.

17 Mean PIA as a function of run duration. ■ = significant difference (p < 0.001) between groups. * = significant difference (p = 0.045) between the beginning and middle of the run, ** = significant difference (p = 0.009) between the beginning and end of the run, *** = significant difference (p = 0.031) between the middle and end of the run.

18 Coefficients of variation for SL as a function of run duration.

19 Coefficients of variation for ST as a function of run duration. ■ = significant difference (p = 0.007) between groups.

20 Coefficients of variation for $t_c$ as a function of run duration.

21 Coefficients of variation for PIA as a function of run duration.

22 FSI $\alpha$ for SL as a function of run duration. * = significant difference (p < 0.001) between the beginning and middle of the run, ** = significant difference (p < 0.001) between the beginning and end of the run.

23 FSI $\alpha$ for ST as a function of run duration. * = significant difference (p < 0.001) between the beginning and middle of the run, ** = significant difference (p < 0.001) between the beginning and end of the run.
FSI $\alpha$ for PIA as a function of run duration. $^*$ = significant difference ($p < 0.001$) between the beginning and middle of the run, $^{**}$ = significant difference ($p < 0.001$) between the beginning and end of the run.

FSI $\alpha$ for $t_c$ as a function of run duration. $^*$ = significant difference ($p = 0.003$) between the beginning and middle of the run.

Example of stride time series over the course of the run.

Example of stride length series over the course of the run.

Representative example of stride length series for elite and recreational runners.

Mean stride length (a) and stride rate (b) of each participant as a function of running speed.

Representative example of stride time series for elite and recreational runners.


Calculation of joint stiffness for running. Stiffness ($k$) is represented by the slope of the dashed line.

AJS for the pre- and post-jump condition. $^*$ = significant main effect ($p < 0.001$) for run condition, $\lozenge$ = significant interaction effect for group x run condition ($p = 0.042$).

KJS for the pre- and post-jump condition. $^*$ = significant main effect ($p = 0.007$) for run condition, $\blacksquare$ = significant interaction effect for group ($p = 0.012$).

Mean SL for both groups before and after the fatiguing jump protocol. $\blacksquare$ = significant main effect ($p < 0.001$) for group.
36  Mean ST for both groups before and after the fatiguing jump protocol.  
    * = significant main effect (p < 0.001) for run condition  . . . . . . . 132
37  Stride time CV (a) and stride length CV (b) for both groups before  
    and after the fatiguing jump protocol. . . . . . . . . . . . . . . . . . . 133
38  FSI $\alpha$ calculated for SL for both groups before and after the fatiguing  
    jump protocol. * = significant main effect (p < 0.001) for run condition134
39  FSI $\alpha$ calculated for ST for both groups before and after the fatiguing  
    jump protocol. * = significant main effect (p < 0.001) for run condition135
List of Tables

1. Subject characteristics. ................................................. 64
2. Descriptive statistics of SL data. ....................................... 71
3. Subject characteristics of the different groups (Elite vs. Recreational). 89
4. Average values of descriptive parameters for the prolonged run. ........ 91
5. Mean values (± SD) of selected stride parameters during the prolonged run. ...................................................... 94
6. Coefficients of variation of selected stride parameters (± SD) during the prolonged run. ...................................................... 98
7. $\alpha$ (± SD) of selected stride parameters during the prolonged run. . . . 102
8. Characteristics of the different study groups (Elite vs. Recreational). . 128
9. Descriptives for the pre- and post-jump overground runs on the indoor track. ................................................................. 129
10. Values of the dependent variables for the pre- and post-jump condition. 136
## List of Abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Full Form</th>
</tr>
</thead>
<tbody>
<tr>
<td>3D</td>
<td>Three-dimensional</td>
</tr>
<tr>
<td>α</td>
<td>Fractal scaling exponent α</td>
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<tr>
<td>ACL</td>
<td>Anterior cruciate ligament</td>
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<tr>
<td>AJS</td>
<td>Ankle joint stiffness</td>
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<tr>
<td>ANOVA</td>
<td>Analysis of variance</td>
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<tr>
<td>ASIS</td>
<td>Anterior Superior Iliac Spine</td>
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<tr>
<td>cm</td>
<td>Centimeter</td>
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<tr>
<td>CNS</td>
<td>Central nervous system</td>
</tr>
<tr>
<td>COM</td>
<td>Center of mass</td>
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<tr>
<td>COP</td>
<td>Center of pressure</td>
</tr>
<tr>
<td>CV</td>
<td>Coefficient of variation</td>
</tr>
<tr>
<td>df</td>
<td>Degrees of freedom (statistics)</td>
</tr>
<tr>
<td>DFA</td>
<td>Detrended Fluctuation Analysis</td>
</tr>
<tr>
<td>DOF</td>
<td>Degrees of freedom (navigation)</td>
</tr>
<tr>
<td>DOMS</td>
<td>Delayed-onset muscle soreness</td>
</tr>
<tr>
<td>e.g.</td>
<td>Exempli gratia (for example)</td>
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<tr>
<td>EMG</td>
<td>Electromyography</td>
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<tr>
<td>η²</td>
<td>Eta squared</td>
</tr>
<tr>
<td>et al.</td>
<td>Et alia (and others)</td>
</tr>
<tr>
<td>etc.</td>
<td>Et cetera (and so forth)</td>
</tr>
<tr>
<td>F</td>
<td>Force</td>
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<tr>
<td>FFS</td>
<td>Forefoot strike</td>
</tr>
<tr>
<td>FSI</td>
<td>Fractal scaling index</td>
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<tr>
<td>g</td>
<td>Standard gravity; acceleration due to gravity</td>
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<tr>
<td>GHz</td>
<td>Gigahertz</td>
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<tr>
<td>GRF</td>
<td>Ground reaction force</td>
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h Hour
HR Heart rate
Hz Hertz
i.e. Id est (that is)
IEEE Institute of Electrical and Electronics Engineers
ICC Intraclass correlation coefficient
IMU Inertial Measurement Unit
INS Inertial integration
$k$ Stiffness
kg Kilogram
KJS Knee joint stiffness
km Kilometer
LRC Long range correlations
m Meter
MEMS Microelectromechanical systems
MFS Midfoot strike
mm Millimeter
ms Milliseconds
$N$ Newton
$p$ p-value
Pa Pascal
PDR Pedestrian dead reckoning
PIA Peak impact acceleration
PRS Preferred running speed
PSIS Posterior Superior Iliac Spine
$r$ Pearson’s $r$; correlation coefficient
rad Radian
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Definition</th>
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<tbody>
<tr>
<td>RFS</td>
<td>Rearfoot strike</td>
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<tr>
<td>RLOA</td>
<td>Ratios limit of agreement</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root mean squared error</td>
</tr>
<tr>
<td>RPE</td>
<td>Rate of perceived exertion</td>
</tr>
<tr>
<td>s</td>
<td>Seconds</td>
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<tr>
<td>SD</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>SEC</td>
<td>Series elastic component</td>
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<tr>
<td>SL</td>
<td>Stride length</td>
</tr>
<tr>
<td>SR</td>
<td>Stride rate</td>
</tr>
<tr>
<td>SSC</td>
<td>Stretch shortening cycle</td>
</tr>
<tr>
<td>ST</td>
<td>Stride time</td>
</tr>
<tr>
<td>$t_c$</td>
<td>Contact time</td>
</tr>
<tr>
<td>VO$_{2\text{max}}$</td>
<td>Maximal oxygen consumption</td>
</tr>
<tr>
<td>ZUPT</td>
<td>Zero-velocity update</td>
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1 Introduction

Distance running is the preferred form of physical activity for many people around the world. It has been estimated that about 30 million Americans regularly run in a competitive or recreational setting (Novacheck, 1998). As a fundamental form of human locomotion, running appears to be an effortless motor task. However, despite its apparent automaticity, running is a complex activity that is characterized by a coordinated effort between the musculoskeletal and nervous systems (Jordan, Challis, & Newell, 2007a).

Distance running performance is determined by different factors, some of which represent activity-induced fatigue processes. Although the underlying mechanisms of fatigue and its exact contributions to running performance are not well understood, fatigue appears to be a multifactorial phenomenon that fundamentally alters the mechanics and motor control of running (Bertram, Prebeau-Menezes, & Szarko, 2013). Factors associated with fatigue involve cardiovascular fitness (Whyte et al., 2000), the availability of energy substrates (Callow, Morton, & Guppy, 1986), local muscular damage (Appell, Soares, & Duarte, 1992), impaired neuromuscular control (Nicol, Komi, & Marconnet, 1991b), and other central mechanisms (Noakes, 2007).

These physiological factors have a direct effect on the fundamental parameters of running gait: stride length and stride rate (Hausswirth, Bigard, Berthelot, Thomaidis, & Guezennec, 1996; Place, Lepers, Deley, & Millet, 2004). Changes in these basic stride parameters are linked to other kinematic parameters, such as body segment angles (Clansey, Hanlon, Wallace, & Lake, 2012; Dutto, Levy, Lee, Sidthalaw, & Smith, 1997), ground reaction force characteristics, and stiffness characteristics (Hobara et al., 2010; Horita, Komi, & Kyröläinen, 1996). Additionally, variables associated with impact loading are known to change with fatigue (Clansey et al., 2012; Verbitsky, Mizrahi, Voloshin, & Treiger, 1998).
Most studies that look at the effects of fatigue on the biomechanics of running involve either recreational runners or elite endurance athletes. Only a few studies have focused on the differences that exist between runners of different skill and training levels (Bertram et al., 2013; Cavanagh, Pollock, & Landa, 1977). This is problematic because there is evidence to suggest that fatigue affects recreational and elite distance runners to varying degrees. For example, Bertram et al. (2013) have shown that lesser-trained runners experience fatigue at an earlier point in a race than elite distance runners. Consequently, lesser-skilled runners may experience a higher level of exertion and exhibit different changes in running technique in response to fatigue. Analyzing the differences that exist between these individuals could help make recommendations that aim at the optimization of stride mechanics to maintain consistent running performance.

The majority of studies that have involved prolonged running have been conducted in controlled laboratory environments. In biomechanics research, optical methods and force plate measurements have traditionally been used to analyze different aspects of running mechanics. However, the limited confines of the laboratory severely restrict the number of strides that can be recorded and used for further analysis. As a result, many studies in gait research involve treadmill conditions because this allows researchers to track movement for a prolonged period of time. Additionally, experiments that involve walking or running on a treadmill are able to control for running speed and ensure accurate tracking of the parameters of interest by using sophisticated biomechanical motion capture systems.

Although these methods have allowed researchers to investigate various aspects of running biomechanics, there is evidence to suggest that running under controlled conditions in the laboratory, particularly on a treadmill, differs considerably from running in an unrestricted overground scenario (Frishberg, 1983; Nigg, Cole, & Brüggemann, 1995). However, despite the great interest in the biomechanics of
distance running, there is a scarcity of research that has tried to obtain and analyze spatiotemporal parameters of running gait in an unrestricted environment. In recent years, advances in technology have led to the development of accurate, noninvasive and cost-effective microelectromechanical systems (MEMS) components that have a wide range of potential applications in biomechanics research. Among these, inertial measurement units (IMUs) are frequently used for the analysis of locomotor tasks. Most IMUs simultaneously collect data from a set of gyroscopes and accelerometers. Consequently, IMUs are capable of measuring accelerations and angular velocity along three orthogonal axes, thereby quantifying movement by six degrees of freedom. When securely attached to an individual, IMUs can provide valuable information about the characteristics of the stride pattern.

The placement of the IMU dictates the information provided about the movement. When attached near the body’s center of mass, the recorded signals represent the motion of the trunk. When placed at the distal part of the lower extremity, the recorded signals may be used to interpret segmental kinematics. IMUs may also be used to calculate a variety of gait events and stride parameters during walking and running (Angermann, Robertson, Kemptner, & M., 2010; Bichler et al., 2012; Feliz, Zalama, & Garcia-Bermejo, 2009; Jimenez, Seco, Prieto, & Guevara, 2009; Kobsar, Olson, Paranjape, Hadjistavropoulos, & Barden, 2014) or to measure the impact acceleration that is being exerted onto the body at ground contact (Mercer, Devita, Derrick, & Bates, 2003). Given their small size, versatility and accuracy, IMUs are effective biomechanical tools that are able to address and overcome some of the current limitations of biomechanical locomotor analysis in a confined laboratory setting.

In addition to measuring spatiotemporal gait parameters, IMUs are also capable of assessing the regularity and variability of movement. Like other physiological variables (such as heart rate), stride parameters vary over time and
change from one stride to the next, even when external conditions are controlled (Hausdorff, 2005). Studies conducted on the dynamics of walking have shown that healthy individuals usually exhibit a highly stable pattern of spatiotemporal characteristics (Terrier, 2003). Traditionally, a predictable structure of stride-to-stride fluctuations in the gait pattern is thought to indicate efficient motor control, while changes in neurological function associated with aging and certain disease states negatively influence the temporal persistence of the stride pattern (Hausdorff, 2007).

Although originally regarded as noise, it is now understood that stride-to-stride fluctuations (i.e. gait variability) play an important role in the control of human gait. Both linear and nonlinear aspects of these gait fluctuations can be calculated to assess the variability and temporal stability of the gait pattern. Linear measures, such as the standard deviation (SD) or the coefficient of variation (CV), relate to the central tendency of the gait pattern. They provide useful information about the overall level of dispersion and indicate how much a certain set of data fluctuates around its mean value. For example, the standard deviation of stride-to-stride fluctuations has been used to evaluate the quality of postural control during gait or limb asymmetries (Gabell & Nayak, 1984; Lord, Howe, Greenland, Simpson, & Rochester, 2011).

In contrast, nonlinear measures of gait variability identify the structure of the locomotor pattern, e.g. by assessing its temporal stability (Hamill, van Emmerik, Heiderscheit, & Li, 1999; Hausdorff, 2007). One particular class of nonlinear measures, which is based on the concept of fractal dynamics, assumes that stride-to-stride fluctuations in the gait pattern are not randomly distributed but are correlated with each other over long time spans. A method called detrended fluctuation analysis (DFA) can be used to analyze the persistence of these so-called long-range correlations (LRC) and indicate the level of dependency of a particular
gait cycle in the time series with other gait cycles. Like linear measures of gait variability, DFA offers insight into the control of gait. Additionally, it can determine the dynamic stability of the gait pattern by quantifying changes in fluctuations over time, regardless of their magnitude (Jordan, Challis, Cusumano, & Newell, 2009).

Based on recent advances in the field of sensor technology, there is a growing interest among researchers to explore the use of simple IMU-based systems in biomechanics and clinical research. Although several studies have assessed movement characteristics in relation to neuropathology and aging using IMUs (Hausdorff, 2007; Hausdorff et al., 1997), there is a scarcity of research investigating stride variability during unconstrained overground running. To date only one study has applied DFA to prolonged distance running and examined the relationship between stride-to-stride fluctuations and fatigue (Meardon, Hamill, & Derrick, 2011). These results indicate that prolonged running is associated with a significant decrease in LRCs that are present in the stride time interval. The authors also reported that the mean values of the analyzed parameters as well as linear measures of gait variability were not affected by fatigue. However, it is not known what causes the observed changes in gait dynamics and how they are linked to other biomechanical parameters. It is also unclear if differences exist in the way fatigue affects stride mechanics and gait dynamics in recreational and elite distance runners. To address the gaps identified in the literature, the following experiments were conducted as part of this dissertation:

1. As a first step, the concurrent validity of a foot-mounted IMU to calculate stride length for distance running was established. In particular, it was tested whether a pedestrian dead-reckoning (PDR) approach, which estimated stride length by integrating the inertial signals (accelerations and angular velocities), displayed high levels of absolute agreement with a 3D motion capture system that measured stride length using reflective markers.
2. Subsequently, the validated IMU configuration was used to track different stride parameters (e.g. stride length and stride time), as well as measures of variability and temporal stability over the course of a fatiguing run at a fixed, pre-determined running speed. This experiment was also designed to explore whether skill level had an effect on stride mechanics and different measures of stride pattern variability. In order to address this aspect, a group of elite distance runners and a group of recreational runners were recruited for this study. Based on the literature, it was hypothesized that a significant reduction in the strength of the LRCs would occur over the course of the run and that the observed changes would be more pronounced in the group of recreational runners.

3. Finally, a third study was conducted to investigate the effects of a fatiguing jump protocol on joint stiffness, stride kinematics and gait dynamics. It was expected that exhaustive stretch-shortening cycle (SSC) exercise would significantly reduce joint stiffness and also decrease the strength of LRCs during distance running. Similar to the previous experiment, a group of elite distance runners and a group of recreational runners were recruited to identify whether fatigue affects stiffness characteristics and gait dynamics differently in runners of different skill levels.
2 Literature Review

2.1 The Gait Cycle in Walking and Running

Walking and running gait are organized in a similar manner. Both forms of locomotion consist of a series of strides, each of which represents one full gait cycle. More precisely, the gait cycle is defined as the period from initial ground contact of one foot to the following initial contact of that same foot, during which each limb has a period of support and non-support (Öunpuu, 1994). These phases are referred to as stance phase and swing phase (Novacheck, 1998).

Despite their similarities, walking and running gait both have unique characteristics. Walking requires that at least one foot be in contact with the ground throughout the whole gait cycle. It is further characterized by short periods of double-support during which both feet are in contact with the ground. In contrast, running is defined by a lack of double support and involves the presence of a flight phase or double float (Novacheck, 1998). Whether a person becomes airborne during locomotion or not, is determined by the relative contribution of the stance phase to the gait cycle. Since a flight phase requires neither foot to be in contact with the ground, the stance phase in running must comprise less than 50% of the gait cycle (Öunpuu, 1994).

During running, the gait cycle can be further subdivided into a series of specific events and sub-phases. These include initial contact, absorption, midstance, propulsion, toe off, double float, initial swing, midswing, and terminal swing (see Figure 1). The gait cycle begins with a period of absorption after initial contact. This phase continues until midstance after which a period of propulsion occurs. Toe off marks the beginning of a period of double float, which extends into initial swing. Midswing, which occurs simultaneously with the stance phase of the contralateral leg, is characterized by a phase of single support, while the terminal swing coincides with a second short period of double float (Öunpuu, 1994). Running speed affects
the exact duration of the stance and swing phase and their respective sub-phases (K. R. Williams, 2000).

![Diagram of the gait cycle during running.](image)


2.2 Kinematics

The branch of biomechanics that deals with the description of human movement is termed kinematics. The primary parameters of interest in kinematics involve linear displacement, velocity and acceleration as well as its angular equivalents. Kinematics is not concerned with the internal or external forces that cause the observed motion (Winter, 2009).

Kinematic analyses in running often focus on the motion of body segments with respect to an external reference frame or relative to each other. However, sometimes researchers might also be interested in the motion of the body’s center of mass (COM) (K. R. Williams, 2000). When the position of the COM is visualized over the course of one full gait cycle, it becomes apparent that the vertical excursion exhibits an oscillating pattern, where the height of the body’s COM will reach a minimum during midstance and a maximum during the flight phase. This behavior fundamentally affects the way in which the system maintains movement efficiency.
and serves as a basis for biomechanical models describing the human body during running (Enoka, 2002).

The two basic kinematic parameters in running are stride length and stride rate. Both parameters represent the combined output of several other factors. For example, stride length comprises the distance the body travels during the stance and flight phase. Similarly, stride rate is the result of stance and flight time. These parameters are in turn influenced by various other biomechanical variables, such as takeoff height and angle, takeoff speed, vertical and horizontal takeoff velocity, as well as segmental kinematic and inertial parameters (J. P. Hunter, Marshall, & McNair, 2004). Although it is often thought that anthropometric variables, such as height or leg length are important determinants of SL, these parameters only correlate weakly at typical distance running speeds (Cavanagh & Kram, 1989).

Typical stride rates in long- and middle-distance running range from 1.4 Hz - 1.8 Hz. However, values greater than 2.3 Hz have been reported for elite sprinters (100 - 400 m) at maximal speed (Luhtanen & Komi, 1978). Distances longer than 800 m are generally accomplished with a relatively consistent frequency of 1.75 Hz (Hanon & Gajer, 2009). Runners also employ greater stride lengths during sprinting compared to long-distance running. Similar to stride rate, there appears to be relatively little variation in stride length in race distances greater than 800 m (Brüggemann & Glad, 1990; Scholich, 1978).

Increases in stride length and stride rate are accompanied by changes in segmental kinematics. This includes both the range of motion occurring about the joints as well as the interjoint coordination at the lower extremity. Since joint kinematics differ from person to person and are influenced by factors such as skill level and speed, their absolute values are of limited relevance (Novacheck, 1998). In order to allow for comparison between runners, values are often normalized and presented relative to the gait cycle (Enoka, 2002).
2.2.1 Sagittal Plane Kinematics. Most of the motion in running occurs in the sagittal plane. Consequently, the kinematics at the hip, knee and ankle joint in this plane have been studied extensively and are generally well-established.

The hip joint follows a basic sinusoidal pattern over the course of a full gait cycle. Although extension begins in the late swing phase, some degree of flexion exists when contact is made with the ground. During stance, the hip continuously extends until peak extension is reached immediately before toe off. In early swing, the hip begins to move into flexion, with peak values occurring in midswing. The second half of the swing is characterized by a gradual transition into extension, which prepares the limb for the upcoming ground contact. This strategy helps to prevent excessive deceleration at initial contact and reduces potentially injurious ground reaction forces that would occur if the foot was too far in front of the body’s COM (Novacheck, 1998).

Motion at the knee joint during running is characterized by two periods of flexion. The first period occurs during early stance and is the result of the vertical ground reaction force (GRF) acting on the lower extremity. In distance running, the knee flexes to approximately 45° in response to impact. During the later stage of the stance phase the knee extends slightly, until the knee joint reaches an angle of approximately 25° at toe off. This motion contributes to the vertical and anterior displacement of the COM. During the subsequent swing phase, a second period of flexion occurs, with the knee joint angle reaching approximately 90°. This movement aims at the reduction of the moment of inertia of the lower limb during swing and reduces energy cost (Novacheck, 1998).

Unlike the hip and the knee, greater interindividual variation exists with respect to ankle joint kinematics. This is because motion at the ankle is strongly influenced by the footfall pattern of the individual. The majority of distance runners exhibit a heel strike pattern when running at moderate speeds (Hasegawa,
Yamauchi, & Kraemer, 2007). In these individuals, the ankle plantarflexes after initial contact while runners who initiate contact with the midfoot or forefoot will experience dorsiflexion during early stance (K. R. Williams, 2000). Thus, runners may exhibit contrasting ankle joint motion during early stance.

2.2.2 Coronal Plane Kinematics. Compared to the sagittal plane, there is relatively little motion occurring in the coronal plane at the lower extremity. This is mainly due to strong ligamentous and osseous constraints (Neumann, 2010). For example, the ankle joint only allows plantar-/ and dorsiflexion due to the bony configuration of the talus and its fixed position between the tibia and fibula (Tortora & Derrickson, 2012). In the foot segment, however, pronation and supination occur in the coronal plane. In general, the foot pronates during the absorption phase and supinates during the later stages of the stance, when power is generated (K. R. Williams, 2000).

The knee, which is classified as a hinge joint, mainly allows movement in the direction of flexion and extension and is further restricted by the collateral and cruciate ligaments, as well as by the muscles located around the joint (Neumann, 2010). Despite these constraints, a small amount of adduction and abduction occurs at the knee during running (Enoka, 2002). Significantly greater motion in the coronal plane occurs at the hip joint. In general, the hip adducts during the early stance phase and moves into abduction in the subsequent swing phase. Hip motion is reciprocal to movement of the pelvis. By decoupling the large amount of lower extremity motion from the head and the trunk, this mechanism serves the purpose of keeping the head level, allowing balance and equilibrium to be maintained (Novacheck, 1998).

2.2.3 Transverse Plane Kinematics. Lower-extremity motion in the transverse plane involves joint rotations. Joint excursions in this plane suspectedly have important implications for movement efficiency and injury mechanisms. For
example, some degree of pelvic rotation also occurs naturally during running. More precisely, external rotation of the pelvis during initial contact assists the generation of propulsive forces, which helps to maintain speed. Since rotation of the pelvis is out-of-phase with rotation of the shoulder, this motion also helps to keep the center of mass stable in the sagittal plane (Novacheck, 1998).

In general, there is limited internal and external knee rotation when the knee is fully extended. However, when the knee exhibits less than 10° of flexion, the femur naturally rotates on the tibia in the medial direction (Neumann, 2010). Thus, if the femoral condyles or tibial plateau are shaped abnormally or if an individual lacks ligamentous restraints, they might be predisposed to greater rotational range of motion at the knee during dynamic loading (Boden, Breit, & Sheehan, 2009). Likewise, there is evidence to suggest that abnormal foot and hip mechanics contribute to increased rotational movements and higher incidences of knee pathologies (Hintermann & Nigg, 1998; Powers, 2010).

2.3 Kinetics

Kinetics is the branch of mechanics that is concerned with the forces that cause motion. It is based on Newton’s laws, which state that: a) objects are either at rest or move at a constant velocity unless they are acted upon by an external force; b) an external force acting on an object accelerates the object proportionally to its mass in the direction of the exerted force; and c) an object that exerts a force on a second object, experiences a force that is equal in magnitude and opposite in direction by the second body.

2.3.1 Ground Reaction Forces and Center of Pressure. Many movements involve the interaction of the body with the ground surface. Force plates are commonly used in biomechanics research because they are able to measure the ground reaction forces associated with these movements (Enoka, 2002). With
respect to running, the GRF represents the response of the support surface to the action of the moving system. Ground reaction forces are usually recorded along three orthogonal axes (vertical, anteroposterior and mediolateral). The resultant effect of these components corresponds to the acceleration experienced by the center of mass of the body (Enoka, 2002).

In reality, the GRF does not act on the body as a single vector. Rather it is distributed over large parts of the foot. The concept of pressure is used to describe the way in which force is distributed over an area (Pascal; 1 Pa = 1 N/m²). When interacting with the ground, the magnitude of the vertical GRF is equal to the sum of the pressure applied to the foot. The point of application of the resultant GRF vector corresponds to the center of pressure (COP). Runners exhibit a large interindividual variability in the distribution of pressure along the plantar surface. This variability is attributed to anatomical differences and individual running technique. For heel strikers, the COP is located at the posterior lateral aspect of the foot during initial contact. In the subsequent stance phase it shifts to the central region and over to the big toe. In runners who initiate contact with the midfoot, the COP moves from the lateral border of the midfoot to its center and then transitions towards the big toe (Enoka, 2002).

The vertical GRF component represents the reaction of the surface to the gravitational acceleration of the body mass and therefore reaches greater values than the other two components. The magnitude of the vertical GRF increases at higher running speeds (K. R. Williams, Cavanagh, & Ziff, 1987). Despite some invariant characteristics, the vertical GRF profile exhibits significant differences that depend on the running style of the individual. Most significantly, the vertical GRF is affected by different footfall patterns (Lieberman et al., 2010).

In heel striking individuals, a double-peaked pattern can be observed at typical distance running speeds (Cavanagh & Lafortune, 1980; Munro, Miller, &
Immediately after initial contact, the GRF profile exhibits a short and sharp impact peak, which reaches a magnitude of approximately $1.5 - 3 \times$ body weight (Lieberman et al., 2010; Munro et al., 1987). Subsequently, the force declines and transitions towards a local minimum, after which the force increases again and reaches another smooth and elongated peak. This so-called active peak reaches a magnitude of about $2.5 - 3 \times$ body weight and occurs somewhere between 35 to 50% of the stance phase (Hamill, Bates, Knutzen, & Sawhill, 1983; Munro et al., 1987). In contrast, the vertical GRF profiles of runners who initiate ground contact with the mid- or forefoot lack an initial impact peak (Lieberman et al., 2010). This has potential implications for running injuries because the magnitude and rate of impact loading have been repeatedly linked to overuse injuries, such as stress fractures (Milner, Ferber, Pollard, Hamill, & Davis, 2006; Nigg, Denoth, & Neukomm, 1981; Pohl, Hamill, & Davis, 2009).

No uniform GRF profile exists for the anteroposterior component of the ground reaction force in running. Depending on their technique, individuals might produce single-, double- and multiple-peaked patterns (Munro et al., 1987). However, the anteroposterior GRF curve generally follows a biphasic pattern. The initial phase, which represents a negative impulse, causes deceleration of the body’s COM because the force acts in the posterior direction. The second part of the anteroposterior curve represents a positive impulse, which acts in the direction of the intended displacement (Munro et al., 1987). The onset of the propulsion phase occurs roughly in the middle of the stance phase, independent of running speed (Hamill et al., 1983).

When running at constant speed, the braking and propulsion impulse will be equal in magnitude and opposite in direction. This implies that the net acceleration of the COM in the anteroposterior direction must equal zero (Munro et al., 1987). Since the magnitude of anteroposterior GRF increases with running speed, a larger
braking impulse occurs and needs to be compensated by a greater propulsive force. As a result, greater muscular effort is necessary to maintain a constant speed.

The mediolateral component of the GRF shows the greatest variability among runners (Munro et al., 1987). In comparison to the vertical and anteroposterior GRF components, the magnitude of the mediolateral force is relatively small, with normalized peak values reaching about $0.12 - 0.20 \times$ body weight (Cavanagh & Lafortune, 1980; Hamill et al., 1983). However, despite the large variability, the mediolateral GRF might be used to identify bilateral asymmetries (Munro et al., 1987).

2.3.2 Joint Forces, Moments and Power. When kinematic data is combined with anthropometric variables and force plate data (GRF, COP), it becomes possible to calculate parameters that provide information about joint torques and reaction forces. The biomechanical method by which these parameters are derived is known as inverse dynamics. For a detailed description of the inverse dynamic approach see Winter (2009). In running, large flexion and extension torques are generated at the ankle, knee and hip joint, which are used for repositioning of the limbs during the swing phase and for effective forward drive of the body’s center of mass during the stance phase (Novacheck, 1998).

At the knee, a flexor moment is generated in late swing, which counteracts passive knee extension and decelerates the forward movement of the leg. Upon initial contact, an extensor moment is produced to prevent collapse of the lower extremity (Winter, 1983). This extensor moment is greater in endurance running than it is in sprinting because lower running speeds involve a greater amount of knee flexion. Since the knee still moves into slight flexion during early stance, the extensors must contract eccentrically and a period of power absorption occurs (Winter, 1983). In the late stance phase, the knee extends and power is generated. After toe off, the knee extensors act again to absorb power and control flexion in the
early swing phase (Winter, 1983).

In heel striking individuals, an external plantarflexor moment is generated at the ankle following initial contact, which causes the forefoot to be lowered to the ground (Novacheck, 1998). A strong internal dorsiflexor moment is generated to counter this movement. In contrast, midfoot and forefoot strikers experience an external dorsiflexor moment at the ankle, which lowers the heel towards the ground. This demonstrates that the footfall pattern of the runner influences ankle joint kinetics, i.e. the way in which structures absorb and generate power (Novacheck, 1998). Regardless of the footfall pattern, the initial phase of power absorption at the ankle joint is followed by a period of power generation. At this point, a net plantarflexion moment is generated by concentric contraction of the triceps surae muscle group. The magnitude of the power that is absorbed and generated at the ankle joint depends on the running speed and impact forces (Novacheck, 1998).

In contrast to the knee and ankle joint, the action of the hip is very similar across the different forms of locomotion. In both walking and running, the hip extensors begin to generate power before initial contact occurs. This is continued through the first half of the stance phase. Afterwards, the hip flexors become increasingly activated and decelerate the backward motion of the lower extremity, which allows them to absorb power (K. R. Williams, 2000). The elastic energy stored in these structures is returned during the subsequent swing phase, which helps to pull the lower extremity forward and reposition it for the next stride (Novacheck, 1998; K. R. Williams, 2000).

Relatively little information exists about the joint kinetics in the coronal and transverse planes. The task of muscles and ligaments is mainly to minimize motion and to stabilize the joints (Neumann, 2010). At the proximal end of the lower extremity, the gluteal muscles generate a constant hip abductor moment, which helps to stabilize the pelvis in the coronal plane (Powers, 2010). During the first
half of the stance, the GRF falls medial to the hip and creates an external
adduction moment that has to be controlled by eccentric action of the hip
abductors. In the subsequent propulsion phase, the concentric contraction of the
abductors generates power at the hip (Novacheck, 1998). Small coronal plane
moments are also generated at the knee and ankle joints.

2.4 Functional Anatomy of Running

Muscle activity patterns in running are influenced by speed of locomotion and
the desired movement goal. Due to technological limitations it is impossible to
directly quantify the force generated by individual muscles, ligaments and other
tissues. However, given the assumption that muscles are the major source of power
generation and absorption in the body, generalized statements can be made about
how groups of muscles contribute to the movements occurring about a joint
(K. R. Williams, 2000). The muscle groups that generate a significant amount of
power in running include the hip extensors, i.e. the gluteus maximus and the
hamstrings, during the late swing phase and first half of the stance phase, the hip
flexors in the early swing phase, and the knee extensors, hip abductors, as well as
the ankle plantarflexors during the late stance phase (Novacheck, 1998).

After swing phase reversal and throughout early stance, the gluteus maximus
and hamstring muscles actively move the lower limb posteriorly by extending the
hip (see Figure 2). This observation is supported by the high electromyographic
(EMG) activity evident in these muscles before the foot makes contact with the
ground (K. R. Williams, 2000). In addition to the hip extensors, other prime
movers, such as the quadriceps, triceps surae, and tibialis anterior, also become
increasingly active during terminal swing (Öunpuu, 1994). There is evidence to
suggest that this strategy serves to adjust lower extremity stiffness in anticipation of
the high ground reaction forces that act on the system at foot strike (Komi, 2000).
EMG data further indicates that the knee extensors are highly active throughout the first half of the stance phase (see Figure 2). Since there is an increase in knee flexion during this time, these muscles contract eccentrically to attenuate impact loads and prevent excessive knee flexion. In the subsequent propulsion phase, the quadriceps and the triceps surae shorten to extend the knee and plantarflex the ankle, thereby accelerating the body’s COM in the vertical and anterior direction (Öunpuu, 1994). Simultaneously, the hip abductors (gluteus medius, gluteus minimus) generate tension to keep the pelvis level in the coronal plane and help provide a stable basis for the trunk (Novacheck, 1998). In the swing phase the hip flexors accelerate the lower limb in the anterior direction (see Figure 2). The amount of power generated by these muscles increases with running speed. The rectus femoris becomes active during midswing to prevent excessive posterior movement of the tibia when the knee is flexing (Öunpuu, 1994). Finally, there is also considerable activity in the various trunk, arm and shoulder muscles, which helps to minimize excursions of the COM during running and maintain movement efficiency. For example, Hinrichs (1990) note that activity in the arms and the shoulder girdle helps the runner to maintain a more constant horizontal velocity by counteracting the rotation of the pelvis that occurs in running.
2.5 Biomechanical Factors Affecting Running Technique

2.5.1 Running Speed. The running speed of an individual is the product of stride length and stride rate (Weyand, Sternlight, Bellizzi, & Wright, 2000). While stride length is defined as the distance travelled in meters between two consecutive footfalls of the same limb, stride rate refers to the number of strides taken per second (Hz). This relationship implies that a change in either stride length or stride rate produces a proportional change in running speed when the other variable remains constant (Weyand et al., 2000). In general, runners modify both stride length and stride rate when increasing their running speed (Luhtanen & Komi, 1978). However, in the lower range (4 - 7 m/s) speed is primarily modified by changes in stride length (Cavanagh & Kram, 1989), while increases in the near-maximal range (> 8 m/s) are predominantly achieved by higher stride rates (Mero & Komi, 1985). Depending on subject characteristics and the state of exertion, runners may choose different length-rate combinations to attain a given speed.
Most biomechanical variables in running change significantly as a function of running speed (Mero & Komi, 1985; Munro et al., 1987). Along with a general reduction in stride time, a decrease in stance or contact time ($t_c$) can be observed at faster running speeds (Brughelli, Cronin, & Chaouachi, 2011). While $t_c$ comprises approximately 60% of the gait cycle in walking, it decreases to approximately 35% in running and 20% in sprinting (Novacheck, 1998). Nilsson, Thorstensson, and Halbertsma (1985) further reported that swing time increases and decreases at slower and faster running speeds, respectively. A significant effect of speed on joint kinematics has also been documented. In general, higher speeds are associated with a greater dynamic range of motion at the ankle, knee and hip joint. Moreover, the point on the foot that initially touches the ground shifts from the heel towards the forefoot (Novacheck, 1998). This is supported by the observation that most individuals exhibit a heel strike pattern at typical distance running speeds, but switch to a midfoot or forefoot strike pattern when sprinting.

Speed has a significant effect on the forces that cause segmental motion and whole body movement during running. Vertical and horizontal GRF magnitudes are known to increase directly as a function of speed. Peak vertical GRFs have been reported to increase by 50 - 100%, while peak horizontal forces increase by more than 200% from slow (ca. 1.5 m/s) to moderate (ca. 6.5 m/s) running speeds (Nilsson et al., 1985). Brughelli et al. (2011) further note that peak horizontal GRF increases over the complete range of running speeds, while peak vertical GRF primarily increases at lower speeds and remains constant at speeds greater than 60%. The observation that the greatest changes in vertical GRF magnitude occurs in the lower speed range is also supported by other studies (Kuitunen, Komi, & Kyröläinen, 2002; Nummela, Keranen, & Mikkelsson, 2007).

Running speed has also been shown to influence the muscle activity of lower-extremity muscles. Surface EMG recordings revealed that faster speeds are
associated with an increased duration of active periods relative to the gait cycle, higher peak EMG magnitudes, as well as greater integrated EMG values (Mero & Komi, 1985).

### 2.5.2 Footfall Patterns in Running.

A fundamental component of running technique that determines how forces are generated and distributed throughout the body is the way in which a runner makes contact with the ground. Although there is no general agreement on how to define footfall patterns, runners are often classified as rearfoot (i.e., heel) strikers (RFS), midfoot strikers (MFS), or forefoot strikers (FFS) (Daoud et al., 2012). At typical distance-running speeds, about 80% of runners exhibit a RFS pattern, while about 12 - 30% of runners have been reported to prefer to make contact with the midfoot or the forefoot (Daoud et al., 2012; Larson et al., 2011).

Footfall patterns change as a function of running speed. In general, many runners will naturally switch from RFS to MFS or FFS when running speed is increased. In support of this view, Hasegawa et al. (2007) observed the relationship between foot strike pattern and performance during a half-marathon and found that the percentage of RFS was higher among slower runners. Conversely, the percentage of MFS increased among faster individuals. Other studies have shown that individual biomechanics, fatigue, lower-extremity stiffness and footwear affect the footfall patterns of distance runners (Hamill, Gruber, & Derrick, 2012; Larson et al., 2011; Lieberman et al., 2010).

Several studies suggest that a MFS or FFS pattern may be associated with a decreased risk of running injury and improved performance (Daoud et al., 2012; Lieberman et al., 2010; Romanov & Fletcher, 2007). The health-related effect has mainly been attributed to the absence of the initial impact peak in the vertical GRF profile (Lieberman et al., 2010). Although there is conflicting evidence regarding the effects of impact loads on overuse injury risk, recent research supports the view that
a RFS pattern may predispose individuals to a greater injury risk. A retrospective study that investigated the relationship between footfall pattern and injury rate found that runners who habitually RFS experienced approximately twice as many overuse injuries than runners who MFS or FFS (Daoud et al., 2012). Although a direct causal relationship cannot be inferred from this, the results are in accordance with other research that has suggested a strong link between impact loading characteristics and stress injury rates (Mizrahi, Verbitsky, & Isakov, 2000; Radin et al., 1973; Verbitsky et al., 1998).

Some researchers have proposed a causal relationship between footwear and overuse running injuries. For example, Nigg (1986) as well as Lieberman et al. (2010) state that excessive cushioning in running shoes may encourage a RFS pattern because they have been designed to dampen the impact in RFS and make it comfortable for runners to land on their heels. Although a runner may perceive less shock at ground contact, the magnitude of the vertical impact force in habitual RFS was reported to be approximately three times higher than for habitual FFS (Lieberman et al., 2010). Furthermore, running shoes with arch supports and high midsole stiffness have been associated with kinematic alterations (Hamill, Russell, Gruber, & Miller, 2011; Hardin & van den Bogert, 2004), weakness of the intrinsic muscles of the foot and decreased proprioceptive feedback (Robbins & Hanna, 1987).

2.5.3 Skill Level. In an effort to identify the main determinants of running performance, several studies have investigated the biomechanical differences between runners of different skill level and training status. For example, Cavanagh et al. (1977) analyzed sagittal plane kinematics of good and elite distance runners. They concluded that the two groups exhibited very similar running form, but noted that lesser-skilled runners displayed a greater degree of plantarflexion at the ankle joint during late stance, which caused an increase in stride length. It was assumed that this factor contributes to a running style that is less economical and has a
negative effect on performance. The observation that fast and slow runners do not differ considerably from each other with respect to their kinematics is consistent with other studies. A recent study that assessed changes in sagittal plane kinematics for fast and slow runners between the early and late stage of a marathon run demonstrated that all runners significantly changed their running form over the course of the run and that only small group-differences existed in the peak knee flexion angle during stance (Chan-Roper, Hunter, Myrer, Eggett, & Seeley, 2012). Siler and Martin (1991) also analyzed kinematic alterations between slow and fast runners during a fatiguing 10 km treadmill run. Although significant differences in stride length and dynamic range of motion at the hip and knee joint were found between groups, the authors noted that performance level did not affect the relative timing of kinematic alterations.

Different theories have been put forward regarding the mechanisms that influence running performance. Traditionally, it has been argued that individuals with longer limbs exhibit greater stride lengths, thus providing greater anterior displacement of the COM with every step (Jones & Lindstedt, 1993). Moreover, slender limbs with a higher proportion of fast-twitch muscle fibers are suspected to increase stride rate by allowing the runner to reposition their limbs more rapidly (van Ingen Schenau, de Koning, & de Groot, 1994). However, Weyand et al. (2000) argue that longer stride lengths and faster maximal speeds are primarily achieved by higher vertical ground reaction forces. They compared fast and slow runners and observed that top speed was reached whenever the decline in $t_c$ prevented a further increase in effective impulse, thus decreasing the time spent in double float to the minimum necessary to reposition the limb for the next step. Additionally, this study did not find significant differences between the minimum swing times of fast and slow runners. Based on their findings it was concluded that leg swing is primarily determined by passive elastic recoil, thus making it a relative invariant feature of
running mechanics (Weyand et al., 2000). These results are also supported by data from Cavanagh and Kram (1989), who investigated the effects of added mass and body dimensions on stride length and found that neither anthropometric variables, nor the mass of lower extremity segments were primary determinants of stride length.

K. R. Williams et al. (1987) reported that individual running form, as assessed by segmental kinematics, accounts for up to 54% of the variability of the energy cost of running. However, despite these large subject-specific differences, the information regarding the effect of training status and skill level on running economy remains inconclusive. Several studies have demonstrated that trained runners exhibit a more economical running form than untrained individuals (V. Billat, Flechet, Petit, Muriaux, & Koralsztein, 1999; Petray & Krahenbuhl, 1985; T. Smith, McNaughton, & Marshall, 1999). These authors suggest that better running economy is linked to a smaller vertical displacement of the COM during the gait cycle (Svedenhag & Sjodin, 1984). However, their results are challenged by other studies that found no differences in the metabolic cost of running between highly-trained, well-trained and untrained runners (Daniels, Oldridge, Nagle, & White, 1978; Pollock, Jackson, & Pate, 1980; Slawinski & Billat, 2004).

2.5.4 Treadmill vs. Overground Running. Many studies that investigated physiological and biomechanical variables during running have collected data under controlled conditions in the laboratory, with subjects running on a treadmill. However, a generalization of these findings to all running conditions may be problematic because the biomechanics of treadmill running have been shown to differ from those exhibited during overground running (Frishberg, 1983; Nigg et al., 1995; P. Riley et al., 2008).

For example, large differences in metabolic cost exist between treadmill and overground conditions. Frishberg (1983) reported that oxygen consumption during a
treadmill run was 36% less than that of a comparable overground running trial. The authors note that although the lack of air resistance in the laboratory setting may have contributed to the decreased energy requirements, the observed difference was too large to be caused by this factor. Likewise, Winter (1978) found large differences in work and energy calculations between running conditions and pointed out that in contrast to overground running, the average horizontal velocity of the COM during treadmill running is almost zero.

Frishberg (1983) further noted significant differences in shank and thigh kinematics between the two running conditions. Nigg et al. (1995) and van Ingen-Schenau (1980) observed that foot placement was significantly altered in the treadmill condition, with subjects adapting a flatter foot position during initial contact. Minor kinematic changes on the treadmill were also observed by other studies (P. Riley et al., 2008; Schache et al., 2001).

Different factors have been linked to the observed differences between treadmill and overground running. These include surface characteristics, which are known to influence the stiffness adjustment of the leg and in turn alter related biomechanical variables, such as impact acceleration, contact time, and ground reaction forces (Kerdok, Biewener, McMahon, Weyand, & Herr, 2002) as well as movement of the treadmill belt, which may reduce metabolic cost by actively driving the supporting leg backwards during the stance phase of running (Frishberg, 1983). Additionally, a familiarization effect, which has been observed after prolonged treadmill running, is suspected to cause changes in running biomechanics (Lavanska, Taylor, & Schache, 2005).

Running on a treadmill also forces individuals to maintain a constant speed, regardless of whether they become fatigued or not (Verbitsky et al., 1998). This is in contrast to overground running, where runners are likely to slow down after the onset of fatigue (Bertram et al., 2013). This constant ‘pacing’ likely influences the
nature of the biomechanical changes that naturally occur with the onset of fatigue and may explain the equivocal results reported in the literature.

Despite these results, other authors have reported only small or insignificant differences between treadmill and overground running. For example, P. Riley et al. (2008) reported similar kinematic and kinetic trajectories for both running conditions. Schache et al. (2001) found lumbopelvic kinematics to be similar on the treadmill when compared to the overground condition, whereas K. R. Williams (1985) noted a high level of agreement between the two conditions and stated that significant differences only occurred at speeds above 5 m/s.

2.5.5 The Stretch-Shortening Cycle. Muscle actions are traditionally described as being either isometric, concentric or eccentric. However, human movement rarely consists of isolated muscle contractions. The natural pattern of muscle function in most forms of locomotion is the stretch-shortening cycle (SSC), which is characterized by the coupling of an eccentric contraction (resulting from external forces, such as gravity) and a subsequent concentric contraction (van Ingen Schenau, Bobbert, & de Haan, 1997). Komi and Nicol (2000) further remarked that the SSC is characterized by preactivation of the muscles before an eccentric contraction occurs. This has been observed in running, where the triceps surae is activated before contact with the ground in an effort to better resist the impact force.

Together, these mechanisms provide a biomechanical advantage as they allow muscles to produce a greater amount of work, compared to an isolated concentric contraction (Cavagna, Saibene, & Margaria, 1965). Different underlying mechanisms have been suggested to contribute to this increase in muscle performance. For example, Cavagna et al. (1965) argued that this enhancement is primarily caused by elastic energy which is stored in the series-elastic component (SEC) of the muscle during lengthening and returned during the subsequent concentric contraction.
Since mechanical energy is described as the capacity to perform work, muscular performance is enhanced (Enoka, 2002). Another theory that has been put forward is that reflex mechanisms play a role in the potentiation of performance during the SSC. This assumption is made because the rapid change in muscle length and an immediate transition into the concentric phase generally favors the contribution of spindle-mediated reflex responses to muscle force generation (Komi, 2003). Although there has been some doubt regarding the functional significance of reflex contributions (van Ingen Schenau et al., 1997), there is sufficient evidence to suggest that reflexes assist in stiffness regulation of the muscle and thus increases the amount of elastic energy that can be stored in the series-elastic component (Komi, 2000). Despite these findings, the relative contribution of these mechanisms to force potentiation during SSC is not clear and may be subject-specific. It is reasonable to assume that no fixed scheme exists and that the exact role of each mechanism depends on the type of movement involved (Enoka, 2002).

### 2.5.6 Stiffness and Spring-Mass Behavior in Human Running.

Many intrinsic and extrinsic factors influence the mechanical behavior of the human body during running. An exact theoretical model would need to be very complex and take into consideration the viscoelastic properties of individual anatomical structures, such as muscles, ligaments and cartilage, as well as physiological factors; i.e. reflex contributions and muscle activation state (Latash & Zatsiorsky, 1993). However, several studies have demonstrated that human running can be accurately modeled by using a simple spring-mass system (Alexander, 1992; Blickhan, 1989; McMahon & Cheng, 1990). One fundamental component of this model is the stiffness of the leg spring, which has been shown to significantly affect the biomechanics of running (Dutto & Smith, 2002; Farley & González, 1996).

In the mechanical sense, the concept of stiffness is related to the property of a deformable body to store and return a certain amount of elastic energy. It is
described by Hooke’s law, which states that the force \( F \) required to deform an elastic body by some distance \( x \) is related to that distance and a constant factor \( k \), its stiffness:

\[
F = kx
\]

(1)

According to Hooke’s law the spring constant \( k \) describes the stiffness of an ideal mass-spring system, i.e. the spring must be massless and has a stiffness that is independent of displacement or velocity. Furthermore, the mass of the system is assumed to be concentrated at a point located at the end of the spring (Butler, Crowell, & Davis, 2003).

Many different methods exist by which lower extremity stiffness can be calculated. Depending on the context, researchers may choose to calculate vertical stiffness, leg stiffness or torsional/joint stiffness. Although all of these methods are based on the same principles, they might yield different results depending on the variables used to calculate stiffness. This needs to be taken into account when comparing the results of different studies (Butler et al., 2003).

Stiffness is inherently linked to the forces acting on the system. With respect to biomechanics, a certain level of musculoskeletal stiffness is needed to store and return elastic energy during activities involving the stretch-shortening cycle. When higher forces are exerted onto the system, for example when exercise intensity increases, the physiological response is an increase in stiffness (Farley, Blickhan, Saito, & Taylor, 1991; Granata, Padua, & Wilson, 2002). This is confirmed by studies that have analyzed leg spring stiffness at different running speeds. Arampatzis, Brüggemann, and Metzler (1999) as well as Kuitunen, Komi, and Kyröläinen (2002) both reported that stiffness increases at higher running speeds. Simulated models further corroborate this assumption (Seyfarth, Geyer, Günther, & Blickhan, 2002).

Stiffness in running also appears to be related to basic stride parameters. For
example, Farley and González (1996) found a positive linear relationship between stride rate and vertical stiffness. Other studies have repeatedly confirmed this relationship (Dutto & Smith, 2002; Granata et al., 2002). Furthermore, McMahon and Cheng (1990) observed that a "groucho running" style, which is characterized by increased knee flexion and a greater stride length (and consequently lower stride rate), was associated with decreased vertical stiffness. Likewise, a simulation study conducted by Derrick, Caldwell, and Hamill (2000) predicted decreases in leg stiffness with increased stride length.

Running economy is also at least partially influenced by stiffness of the musculoskeletal system. In general, a greater amount of vertical stiffness and leg stiffness has been associated with a lower metabolic cost of running (Dutto & Smith, 2002; Kerdok et al., 2002). In contrast, a decrease in stiffness may increase energy demands by inhibiting the potential to use stored elastic energy in the musculotendinous unit and during the late stance phase (Komi, 2000; Latash & Zatsiorsky, 1993). Since stiffness modification seems to be highly dependent on fatigue status and subject characteristics, large interindividual variability may distort the relationship between stiffness and running economy (I. Hunter & Smith, 2007).

Butler et al. (2003) proposed the idea of an optimal stiffness range that contributes to an economical and effective running technique. The authors present evidence that values below or above this range could generally increase the risk of overuse injuries, since they have been associated with abnormal loading characteristics and altered impact shock waves. More precisely, there is evidence to suggest that excessive stiffness causes higher impact loading rates, which are suspected to play a role in the etiology of bony injuries, such as stress fractures and knee osteoarthritis (Burr, Martin, Schaffler, & Radin, 1985; Grimston, Engsberg, & Kloiber, 1991). On the contrary, minimal stiffness may contribute to soft tissue
injuries by permitting excessive range of motion at the weight-bearing joints (Granata et al., 2002).

This differential perspective is further supported by studies that assessed the occurrence of injuries in runners with high and low arches. These authors found that high-arched runners, who exhibit higher stiffness and impact loading rates, are more likely to sustain bony injuries, while low-arched runners, who are characterized by lower stiffness and greater joint excursions, experience more soft tissue injuries (D. S. Williams, Davis, Scholz, & Hamill, 2004, 2001).

2.5.7 Impact Acceleration. Each foot strike in running produces an impact load that is transmitted as a shock wave through the body (Derrick, Hamill, & Caldwell, 1998). Under normal conditions, the musculoskeletal system is able to effectively attenuate and distribute these shock waves, thus reducing their amplitude and absorbing impact energy (Nigg et al., 1995). While a certain amount of loading is required to maintain optimal health of muscle, bone and other connective tissues (Korver, van de Stadt, Kiljan, van Kampen, & van der Korst, 1992; Stone, 1988), excessive impact loading may lead to tissue damage and play a role in the etiology of certain running injuries (Milner et al., 2006; Radin et al., 1973). Consequently, great interest exists in the factors that influence shock attenuation and the mechanisms by which the musculoskeletal system handles impact loads (Milner et al., 2006; Radin et al., 1973; A. Voloshin & Wosk, 1982).

Impact characteristics are typically measured by an accelerometer that is attached to a bony prominence of the lower extremity (Mercer et al., 2003; Mizrahi, Verbitsky, Isakov, & Daily, 2000; Verbitsky et al., 1998). Common parameters of interest include impact magnitude as well as the rate of loading. In order to evaluate shock attenuation, a second accelerometer is required, which is usually attached to the head of the individual. To quantify attenuation, the obtained signals must be processed and compared to each other. A large difference in impact
magnitude between the signals measured at the leg and head is indicative of effective shock attenuation (Abt et al., 2011; Derrick et al., 2000; Mercer, Vance, Hreljac, & Hamill, 2002).

Both impact loading and shock attenuation are complex mechanisms that are affected by multiple factors. For example, lower extremity geometry during initial contact can alter the impact magnitude (Challis, 2001). More precisely, the spatial orientation of the lower extremity segments is known to modify stiffness, which in turn affects impact loading (Derrick et al., 2000, 1998). This is also supported by results from McMahon, Valiant, and Frederick (1987), who found that greater knee flexion angles at impact are associated with reduced lower-extremity stiffness and increased shock attenuation.

Running speed also significantly affects shock attenuation. Although increased speed results in higher magnitudes of impact accelerations (Shorten & Winslow, 1992), the ability of the body to attenuate impacts is also enhanced (Mercer et al., 2002). Furthermore, Derrick et al. (1998) report that shock attenuation is affected by concurrent changes in stride rate and stride length at constant running speeds. Based on these results, subsequent studies have independently manipulated stride rate and stride length and found that only changes in stride length, but not stride rate, affect shock attenuation (Mercer et al., 2003). A possible explanation for this effect is that stride length alterations are related to changes in lower extremity geometry at initial contact (Chan-Roper et al., 2012; Mizrahi, Verbitsky, Isakov, & Daily, 2000), which may affect stiffness and impact loading (Derrick et al., 1998).

Additionally, external factors, such as shoe design and surface characteristics are also suspected to influence impact loading characteristics and shock attenuation (Bigelow, Elvin, Elvin, & Arnoczky, 2013; Butler, Hamill, & Davis, 2007; Cook, Kester, Brunet, & Haddad, 1985; Feehery, 1986).
2.6 Fatigue in Running

Prolonged running depends on the generation of continuous muscular effort. When metabolic and mechanical processes in active muscles become increasingly intense, a drop in work capacity can be observed. This marks the onset of muscular fatigue, which is defined as a reduction in the force generating capacity of the active muscles that occurs after prolonged and vigorous activity (Fitts, 1996).

Fatigue is a complex phenomenon. It involves multiple underlying processes that contribute to the observed decrease in muscular performance. The two major categories that are used to classify these processes are central and peripheral fatigue (Nicol & Komi, 2011). Central fatigue refers to a decreased neural drive from the central nervous system (CNS), i.e. a reduction in efferent commands to the contracting muscle (Bigland-Ritchie, Johansson, Lippold, Smith, & Woods, 1983). This mechanism has recently been linked to the inhibitory effects of serotonin, which binds to extrasynaptic receptors on α-motorneurons (Cotel, Exley, Cragg, & Perrier, 2013). In contrast, the term peripheral fatigue is commonly used to describe any impairment that occurs distal to the neuromuscular junction (Komi & Nicol, 2000). Contributing factors include the depletion of energy substrates (Kirkendall, 1990), accumulation of potassium and hydrogen ions in the extracellular space (DeLuca, 1997), and altered peripheral feedback (Garland & Kauffman, 1995). In particular, prolonged muscular contraction may lead to the accumulation of metabolites, specifically hydrogen ions, in the skeletal muscle tissue, which decreases the susceptibility of contractile proteins to calcium, thereby impairing the conduction of the action potential along the sarcolemma (DeLuca, 1997).

A variety of methods have been used to analyze fatigue. While some researchers track cardiovascular parameters during prolonged running (Mizrahi, Verbitsky, Isakov, & Daily, 2000), it is common to assess the maximal voluntary contraction (MVC) of a certain muscle before and after a bout of exercise.
(Kuitunen, Avela, Kyröläinen, Nicol, & Komi, 2002; Nicol, Komi, & Marconnet, 1991c). Other methods involve the analysis of an EMG signal, such as tracking the mean or median frequency, the amplitude of a triggered M-wave or observing shifts in the power spectrum of the recording (DeLuca, 1997). The variety of assessment techniques used in the literature complicates the generalization of findings.

### 2.6.1 Effects of Fatigue on Kinematics

Many biomechanical parameters in running are interrelated and known to affect each other. Since fatigue impairs neuromuscular function, it becomes evident that exhaustive exercise can fundamentally change the kinematics of running. Under normal conditions, runners choose a preferred combination of stride rate and stride length for a given speed at which impact loads are effectively attenuated (Mercer et al., 2002) and running economy is optimized (Cavanagh & Williams, 1982). In contrast, fatigued runners naturally decrease their running speed, which in turn has an effect on both stride length and stride rate (Bertram et al., 2013).

Despite some common trends, the observed changes in running kinematics are highly individual and appear to be influenced by subject characteristics and study design (Dutto & Smith, 2002; Nicol, Komi, & Marconnet, 1991a). Several studies have reported that prolonged running is associated with a decrease in stride length and a simultaneous increase in stride rate (Hausswirth et al., 1996; Kyröläinen et al., 2000). Furthermore, Place et al. (2004) noted a linear decrease in stride length along with a proportional decrease in stride duration over a five-hour treadmill run.

In contrast, a recent study that monitored running kinematics at different points of a marathon found that stride length increased between the early and late stages of the run, while stride rate decreased (Chan-Roper et al., 2012). Furthermore, I. Hunter and Smith (2007) reported that trained runners significantly decreased their stride rate at the end of a 60-minute treadmill run. Since speed was controlled in this experiment, the results imply that stride length must have
increased simultaneously. These results are also corroborated by other experiments involving treadmill conditions (Candau et al., 1998; Mizrahi, Verbitsky, Isakov, & Daily, 2000; Verbitsky et al., 1998).

Other studies have reported inconsistent trends in the changes that occur in basic stride parameters under fatiguing conditions. Dutto and Smith (2002) observed individual changes in stride rate during a treadmill run to exhaustion, with some participants exhibiting increases and other decreases in stride rate. Nicol et al. (1991a) found that although runners consistently exhibited clear signs of fatigue over the course of a marathon (as indicated by changes in integrated EMG and by a decrease in running speed) no effects were visible in any kinematic variables. The authors attributed the absence of an effect to a great variability in individual running patterns and opposite trends in fatigue-induced kinematic alterations.

Several studies have reported that contact time ($t_c$) increases with progressive fatigue (Chan-Roper et al., 2012; Derrick, Dereu, & McLean, 2002; Elliott & Roberts, 1980). There is evidence to suggest that this increase results from the inability to effectively utilize elastic energy stored in the muscle-tendon apparatus (Komi, 2000) and from a reduction in lower extremity stiffness (Mercer et al., 2002). This information has important implications for performance because contact time has repeatedly been linked to the energy cost of running (Chapman et al., 2012; Kram & Taylor, 1990; T. J. Roberts, Kram, Weyand, & Taylor, 1998).

Studies that have investigated the effects of fatigue on joint kinematics have yielded equivocal results. For example, experiments involving exhaustive running have shown that the onset of fatigue is associated with decreased ankle dorsiflexion at touchdown and increased rearfoot motion (Clansey et al., 2012; Dutto et al., 1997; Elliott & Ackland, 1981). Fatigue in running has further been associated with increased knee flexion immediately before initial contact and a more extended knee during early stance (Mizrahi, Verbitsky, Isakov, & Daily, 2000). Moreover, the
dynamic range of motion at the hip changes during fatigued running (Chan-Roper et al., 2012), which has been linked to an increased amount of trunk flexion (Elliott & Roberts, 1980; Hausswirth, Bigard, & Guezennec, 1997). In contrast, Abt et al. (2011) have investigated the timing of several kinematic parameters, including ankle pronation and knee flexion, before and after a brief exhaustive run and did not find any significant effects of fatigue on kinematics.

In summary, no clear relationship has been established yet between the level of fatigue and running kinematics. Although some general trends can be observed, the fatigue response in running appears to be highly individual. Runners may be able to effectively compensate for the impairment of neuromuscular function and maintain performance, i.e. running speed, despite exhibiting significant changes in running form.

### 2.6.2 Effects of Fatigue on Kinetics.

The ability to attenuate high forces is regarded as a major function of the neuromuscular system (Nigg & Liu, 1999). Among the different mechanisms that influence impact loading, active regulation of muscle tension is most significantly affected by fatigue (Radin, 1986). Simulated models support the view that the amount of co-contraction around a joint, which determines joint stiffness, has a large effect on impact loading characteristics (Bobbert, Yeadon, & Nigg, 1992; Gerritsen, van den Bogert, & Nigg, 1995). Consequently, fatigue may play an important role in the development of overuse running injuries, via its effect on abnormal joint loading in combination with altered kinematics (Christina, White, & Gilchrist, 2001).

The literature yields conflicting results regarding the effects of exhaustive running on ground reaction forces. Although early research suggested that the magnitude of vertical impact force increases with fatigue (Dickinson, Cook, & Leinhardt, 1985), several studies have contested this view. For example, studies that analyzed kinetic adaptations in SSC performance after a marathon observed
decreases in average vertical forces during the braking phase (Komi, Hyvärinen, Gollhofer, & Mero, 1986; Nicol et al., 1991a). Likewise, ultra-distance running has been shown to induce significant changes in spring-mass behavior and cause decreases in vertical GRF peaks (Degache et al., 2013; Morin, Tomazin, Edouard, & Millet, 2011). Clansey et al. (2012) reported that vertical loading rates but not impact magnitudes were affected by a fatiguing treadmill run.

It has been proposed that impact attenuation may occur purposefully via modulation of muscle stiffness in an effort to adapt a safer running style and reduce the potentially harmful effects of high repetitive impact loads (Morin et al., 2011). Prior to these findings, Christina et al. (2001) found that the fatigue response during SSC activity was muscle-specific. Their results showed that localized fatigue of the ankle dorsiflexors caused greater vertical loading rates while leaving GRF magnitudes unaffected. In contrast, fatigue of the ankle invertors did not have any effects on GRF characteristics. To further elucidate the effects of lower-extremity muscle fatigue on vertical GRF, Zadpoor and Nikooyan (2012) conducted a meta-analysis on the available literature and concluded that both impact and active vertical GRF peaks, as well as vertical GRF loading rate do not change significantly in running as a result of fatigue. Some researchers suspect that differences between studies may exist because the premature onset of cardiovascular fatigue forces the participants to terminate prolonged exercise before neuromuscular fatigue and associated mechanical changes become detectable (Abt et al., 2011).

2.6.3 Effects of Fatigue on SSC Performance and Stiffness.

2.6.3.1 SSC Fatigue. As previously described, the SSC represents a model from which the complex muscle actions during cyclic locomotion, such as running, can effectively be studied. It is also a powerful method to investigate fatigue because it integrates mechanical, neural and metabolic processes by generating a common output (Nicol & Komi, 2011). Fatigue responses during SSC
exercise are highly individual and depend on the type of exercise, its intensity and volume. In general, SSC fatigue causes reversible damage of muscle tissue and considerably affects stiffness regulation, reflex activity, as well as muscle mechanics (Komi, 2000).

Research involving long-duration SSC fatiguing exercise, such as continuous running, has shown that altered kinematics may reflect purposeful adjustments to fatigue rather than being indicative of impaired muscle function (Kyröläinen et al., 2000; Nicol et al., 1991a). Therefore, it has been suggested that higher-intensity loading, e.g. drop jumps, repeated sprints etc., should be combined with long-lasting SSC exercises to reveal true deterioration of neuromuscular function (Komi & Nicol, 2000).

Different methods and protocols have been used to study the fatigue-induced changes of exhaustive SSC exercise. While some studies observed the fatigue response during the course of exercise (Bertram et al., 2013; Chan-Roper et al., 2012), others performed specific performance tests before and after exercise (Christina et al., 2001; Morin et al., 2011). Often, researchers compare measures of neuromuscular performance as well as kinematic, kinetic and EMG variables, in order to isolate the different aspects of SSC-fatigue (Nicol et al., 1991b, 1991c). A common method used to quantify fatigue is to stop the ongoing SSC activity at certain points and perform intermittent tests. The obtained values are then compared against baseline in order to assess the progression of fatigue. For example, Nicol et al. (1991b, 1991c) used a marathon protocol and had the participants perform several maximal and submaximal tests after every 10 km.

Exhaustive SSC exercise has several acute effects on neural activation and muscle force production. Using a continuous running protocol and intermittent tests, Place et al. (2004) monitored the MVC capacity of runners during a 5 hour treadmill run at typical distance running speeds. Their findings suggest that knee
extensor force potential was significantly depressed during the late stages of the run. The authors also concluded that both central activation failure and peripheral mechanisms contributed to the impairment of neuromuscular function.

Significant decreases in MVC of lower extremity muscles have also been shown to occur during marathon performance (Nicol et al., 1991b), ultra-distance running (G. P. Millet et al., 2002; Saugy et al., 2013) and intermittent exercise (Girard, Lattier, Maffiuletti, Micallef, & Millet, 2008). Based on existing results, G. Y. Millet and Lepers (2004) compared the drop in force generating capacity in running with that of a prolonged non-SSC cycling exercise. The results showed that SSC activity induced a significantly higher amount of fatigue than a cycling protocol of similar volume and intensity. In addition to voluntary activation levels, exhaustive SSC fatigue is associated with a significant reduction in stretch-reflex sensitivity (Avela, Kyröläinen, & Komi, 1999; Horita et al., 1996).

Using a high-intensity rebound protocol, Horita et al. (1996) showed that prolonged SSC exercise required a significant increase in muscular effort during the push-off phase. This has been associated with higher metabolic costs and is thought to lead to failure to generate work over time (Gollhofer, Komi, Miyashita, & Aura, 1987). These results are corroborated by Nicol et al. (1991b, 1991c) who found that the tolerance of the participants to impact loading decreased progressively over a marathon run and that greater muscular work was required to compensate for this effect in the subsequent push-off phase.

Repetitive SSC action has been shown to affect lower-extremity muscles in different ways. For example, Regueme, Nicol, Barthèlemy, and Grélot (2005) reported that a reduction in EMG activity during preactivation occurs in the early stages of prolonged SSC activity. However, the authors also note that this effect could be linked to an increased efficiency of the rebound technique and consequently may not be fatigue-related. It has also been reported that EMG activity of the
ankle plantarflexors decreases significantly during the subsequent braking and push-off phase (Horita, 2000). In contrast, knee extensor EMG activity increases steadily over the course of exercise, which may indicate a greater reliance on active force generation by this muscle group and the simultaneous decrease in SSC efficacy (Nicol & Komi, 2011).

In summary, all of these results support the view that SSC fatigue involves the intricate coupling between muscle damage, reduced reflex sensitivity and impaired stiffness regulation. More precisely, deteriorated muscle function causes a reduced tolerance to impact loading, which in turn negatively affects the utilization of elastic energy. This loss of elastic potential requires the muscles to generate more work during the push-off phase and eventually causes a reduction in performance.

2.6.3.2 Stiffness. Stiffness is a critical determinant of the spring-mass behavior in SSC activities (see Section 2.5.6). In general, the stiffness of a joint is affected by the passive mechanical properties of the surrounding tissues as well as by the activation state of the muscles acting across a joint. It is well established that muscle and connective tissues have viscous properties and change their stress-strain characteristics in response to repeated mechanical stimuli. This history-dependent behavior of tissue is known as thixotropy (Proske, Morgan, & Gregory, 1993). In muscle tissue, however, thixotropy is not only dependent on the passive molecular arrangement, but also on the amount of crossbridges that form between the contractile proteins, i.e. its activation state. The fact that crossbridges are the mechanical result of repetitive neural stimuli supports the notion that stiffness is affected by voluntary and reflex-mediated muscular contractions (Avela & Komi, 1998a).

It has repeatedly been reported that with progression of fatigue there is a concomitant decrease in stiffness. For example, Rabita, Couturier, Dorel, Hausswirth, and Le Meur (2013) demonstrated that an exhaustive run at VO$_{2\text{max}}$
caused a significant reduction in leg-spring stiffness. Likewise, fatigue has also been reported to reduce vertical stiffness (Girard, Micallef, & Millet, 2011; Hobara et al., 2010), tendon stiffness (Kubo, Kanehisa, Kawakami, & Fukunaga, 2001) as well as stiffness of the lower extremity joints (Horita et al., 1996; Kuitunen, Avela, et al., 2002). In contrast, several other studies have reported that stiffness remained unaltered despite the progression of fatigue (I. Hunter & Smith, 2007; Meur et al., 2013).

Fatigue-induced stiffness alterations have been linked to kinematic and kinetic changes in running. For example, Dutto and Smith (2002) analyzed changes in spring-mass characteristics during a treadmill run to exhaustion and found that for most runners both vertical and leg stiffness decreased significantly over the course of the run. The authors also found that this decrease was correlated with the observed changes in stride rate and thus suspected a causal relationship. This theory is supported by data from Girard et al. (2011), who also found that changes in stride rate were strongly correlated with a reduction in vertical stiffness. Hobara et al. (2010) reported that vertical stiffness was significantly correlated with running velocity and stride rate during a maximal 400 m sprint. In contrast, no relationship existed between vertical stiffness and stride length. The authors further note that leg stiffness was uncorrelated with any of the analyzed kinematic parameters.

The underlying mechanisms that are responsible for the stiffness alterations remain a subject for discussion. While some authors have argued that the loss in stiffness is due to a change in the viscoelastic properties of the musculotendinous unit (Kubo et al., 2001), other researchers assume that impairment of the contractile mechanism is primarily responsible for the decreased stiffness (Avela & Komi, 1998a). The equivocal results in the literature may be caused by the various equipment (force plates vs. video) and fatigue protocols (overground vs. treadmill; duration and intensity) employed by researchers. Moreover, some studies have used
cardiovascular parameters to track fatigue (Dutto & Smith, 2002; Rabita et al., 2013), while others used measures related to local muscular performance (Kuitunen, Avela, et al., 2002; Nicol et al., 1991b). It is apparent that these methods assess different levels of fatigue and thus may yield different results regarding stiffness alterations. Additionally, stiffness alterations have been shown to be highly subject specific (Dutto & Smith, 2002; I. Hunter & Smith, 2007).

2.6.4 Effects on Impact Acceleration and Shock Attenuation.

Dynamic loading on the musculoskeletal system has repeatedly been assessed using body-mounted accelerometers. Since impact loads are transmitted through the body as a shock wave, the detected signal can provide information about how fatigue affects the impact acceleration and shock attenuation during running.

Several authors have found magnitudes of impact acceleration to increase with fatigue (Clansey et al., 2012; Mizrahi, Verbitsky, Isakov, & Daily, 2000; Verbitsky et al., 1998; A. S. Voloshin, Mizrahi, Verbitsky, & Isakov, 1998). For example, Mizrahi, Verbitsky, and Isakov (2000) documented that a fatiguing treadmill run caused significant increases in impact accelerations and concurrently changed running kinematics (decreased stride rate, decreased knee flexion). The authors hypothesized that these kinematic alterations in combination with altered impact loading might be associated with a higher risk of stress fractures. Derrick et al. (2000) also observed significant changes in running kinematics and increased impact accelerations with fatigue. However, it was argued that the altered impact loading characteristics do not pose a higher injury risk because the observed alterations in kinematics caused a decrease in effective mass, which may have decreased impact forces. This idea is supported by studies that have directly measured GRF parameters during prolonged running (Degache et al., 2013; Morin et al., 2011; Nigg et al., 1995).

Other authors report that impact accelerations in running are unaffected by
fatigue (Abt et al., 2011; Mercer et al., 2003). However, Mercer et al. (2003) found that although impact peaks at the tibia did not increase with fatigue, less shock was attenuated. Potential reasons for the inconclusive results might be the use of various test protocols as well as different standards by which fatigue is assessed. Some authors have used prolonged running conditions, while others employed brief repetitive runs. Fatigue in running has been assessed by measuring cardiovascular parameters like VO$_{2\text{max}}$, by lactate, electromyography or by changes in biomechanical characteristics.

**2.6.5 Effects of Fatigue on Movement Variability.** Only a few studies have investigated the effects of prolonged exercise and fatigue on the variability and regularity of movement patterns in running. Using a trunk mounted accelerometer, Le Bris et al. (2006) looked at stride regularity and stride asymmetry by analyzing the similarity of anteroposterior and mediolateral accelerations, during an exhaustive run at VO$_{2\text{max}}$. It was reported that the regularity of anteroposterior accelerations decreased significantly between successive strides, thus indicating a decline in the periodicity of the running cycle. Some authors have argued that this decline in regularity is associated with a greater incidence of jerky movements and unsmooth stride patterns (Hreljac, 2000; Menz, Lord, & Fitzpatrick, 2003). This is further supported by Gazeau, Koralsztein, and Billat (1997), who observed that runners who maintained stable movement patterns during a maximal aerobic speed test were able to significantly delay the point of fatigue. Verkerke, Ament, Wierenga, and Rakhorst (1998) examined step times, foot position and step width during a fatiguing treadmill run and reported a significant increase in the variance of these parameters that occurred with the onset of fatigue, as identified by blood lactate concentrations. Despite these insights, little is known about how fatigue affects long-range correlations and nonlinear measures of variability during walking and running. Studies involving repetitive upper body reaching movements and
standing postural control observed that fatigue caused a reduction in the strength of long-range correlations (Corbeil, Blouin, Bégin, Nougier, & Teasdale, 2003; Gates & Dingwell, 2008). Gates and Dingwell (2008) further noted that increased peak forces and greater movement errors occurred during the later stages of the protocol. Furthermore, Meardon et al. (2011) reported that long-range correlations decrease in a linear fashion during prolonged overground running. The authors analyzed the temporal structure of the stride interval with a tibia-mounted accelerometer and demonstrated that the runners’ stride pattern became less predictable with fatigue.

2.7 Gait Variability

Human walking and running are complex motor tasks that are realized by a coordinated effort of the neuromuscular system (Jordan et al., 2007a). More specifically, locomotion arises from the coupling of different neural control mechanisms that act together to produce a rhythmic-patterned output (Jordan, Challis, & Newell, 2006). The mechanical consequence of this output is an adaptable, yet stable, gait pattern. However, despite its remarkable regularity, human locomotion exhibits a natural degree of fluctuation, i.e. basic stride parameters change from one stride to the next, even when external conditions are controlled (Hausdorff, 2005). Although a small amount of variability is inherent in all physiological variables and can be considered a sign of good adaptability (Hausdorff, 2005), increased variability has been linked to impaired motor control and certain movement pathologies (Hausdorff, 2007).

2.7.1 Linear Gait Dynamics. The magnitude of stride-to-stride fluctuations, i.e. gait variability, is commonly assessed in biomechanics and motor control research because it can help to understand how movement is regulated under normal conditions. Moreover, variability can provide information about how age- and health-related factors affect the consistency of human locomotor patterns.
Another potential benefit of measuring gait variability is its sensitivity to changes that cannot be detected and represented by traditional parameters, such as average velocity or joint angles. This indicates that human gait can be altered by internal or external factors, even if no change occurs in major biomechanical variables (Hausdorff, 2007). Variability has been assessed in different spatiotemporal parameters of gait, such as stride time (Hausdorff et al., 2001), stride length (Blin, Ferrandez, & Serratrice, 1990), as well as double-support time and step width (Gabell & Nayak, 1984; Owings & Grabiner, 2004). The parameter that is most commonly used to assess gait variability is stride time. One the one hand, this is because it is a meaningful parameter that integrates all phases and events of the gait cycle and can be regarded as the common output variable of the locomotor system (Beauchet, Allali, Berrut, & Dubost, 2007). On the other hand, it can easily and accurately be assessed with a variety of tools.

Depending on the parameter in question, gait variability can provide information about the rhythmicity of motion (e.g. stride time variability), postural control (e.g. step width variability) (Gabell & Nayak, 1984), or asymmetry (e.g. differences in variability between the lower extremities) (Lord et al., 2011).

Statistically, the variability of a certain parameter is assessed by calculating the standard deviation or the coefficient of variation from a previously recorded time series. For a sample of the parameter $x$ with $N$ data points, i.e. \{x_1, ..., x_N\}, the SD provides an estimate of the absolute amount of variability present in the data set. It is measured in the same units as the original data and represents the square root of the variance.

$$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} (x_i - \bar{x})^2}$$

The CV is defined as the ratio of the SD to the mean. In contrast to the standard deviation, the CV yields a dimensionless number, expressed as a percentage that is
independent of the unit of the collected data.

\[ CV = \frac{s}{\bar{x}} \times 100 \]  

The CV is often preferred to express variability since it allows for the comparison between data sets with different units or largely varying means. It also has the advantage of being insensitive to the magnitude of variability because it expresses the magnitude of a data set in relation to its level of variability (Moe-Nilssen, 2010). On the other hand, the CV is sensitive to changes when the mean is small and might therefore not be suited for all gait variables.

As stated before, a normal gait pattern is usually associated with small amounts of variability. CV values of approximately 4% have been reported for the stride interval in running of healthy adults (Jordan et al., 2006). With respect to linear measures of variability it appears that increased stride-to-stride fluctuations, i.e. greater variability, are indicative of an aging or unhealthy motor control system (Auvinet, Chaleil, & Barrey, 1999; Moe-Nilssen & Helbostad, 2004). Possibly, this is the case because lower variability is thought to reflect a high degree of rhythmicity and less adaptability (Hausdorff, 2007).

### 2.7.2 Nonlinear Gait Dynamics.

Both the standard deviation and coefficient of variation have limited explanatory value because they only refer to the amount of variability and do not provide information about the structure of variability in a given time series (Jordan et al., 2006). In contrast, some nonlinear measures are able to quantify changes in these fluctuations over time, regardless of their magnitude (Jordan et al., 2009).

Studies conducted on the dynamics of gait have shown that healthy individuals usually exhibit a very stable pattern of spatiotemporal characteristics (Terrier, 2003). In particular, a predictable structure of stride-to-stride fluctuations
is thought to be representative of a high degree of motor control (Meardon et al., 2011). In contrast, changes in neurological function associated with aging and certain disease states negatively affect stability (Hausdorff, 2007).

To determine the temporal characteristics of gait fluctuations, a fractal-like scaling index (FSI) can be calculated for a data set presented in the time-domain. The index expresses whether the variability demonstrates the characteristics of random, white noise or if it contains a pattern that is indicative of a certain degree of self-similarity on a large time-scale. In general, persistent patterns show that long-range correlations (LRCs) are present in time-series. They signify the dependence of any particular data point on other points at a considerable temporal distance (Hausdorff, 2007). This dependence has been shown to decay over time in a fractal-like fashion.

LRCs are commonly reported for the stride time interval during walking and running (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995; Jordan et al., 2006; Kobsar et al., 2014). However, LRCs have also been calculated for stride length, step length and step interval, vertical impulse, duration of contact and other kinetic parameters (Jordan, Challis, & Newell, 2007b). Complex mathematical models are required to assess the stride-to-stride fluctuations of cyclic motion. One common method, called detrended fluctuation analysis, represents the long-range correlations observed in time-series signals by a scaling exponent called $\alpha$. A signal where all data points are completely random and uncorrelated results in an $\alpha$ value of 0.5. Persistent long-range correlations will yield an $\alpha$ between 0.5 and 1.0 (Hausdorff, 2007). Healthy young individuals exhibit $\alpha$ values anywhere from 0.6 - 1.0 in the time series of different gait variables (Hausdorff et al., 1997, 1995; Jordan et al., 2007b; Terrier, Turner, & Schutz, 2005).

The validity of DFA has been questioned by some researchers. For example, Maraun, Rust, and Timmer (2004) criticize that fractal characteristics are
impossible to determine for finite sets of data, such as gait trials. Furthermore, Damouras, Chang, Sejdić, and Chau (2010) point out that no standards exist regarding the range of window sizes and number of strides recorded for DFA. The fact that these factors differ significantly between studies and are known to affect the value of $\alpha$, complicates inter-study comparisons. In contrast, several studies have confirmed the validity of DFA with other nonlinear models. These validation techniques include the Hurst exponent, power spectrum analysis as well as autoregressive methods (Crevecoeur, Bollens, Detrembleur, & Lejeune, 2010; Delignieres & Torre, 2009; Gao, Hu, Tung, Cao, & Sarshar, 2006). To avoid misinterpretation, some authors have recommended that DFA should be used exclusively to assess LRCs in the finite time series, such as gait trials (Bollens, Crevecoeur, Nguyen, Detrembleur, & Lejeune, 2010).

Different guidelines and recommendations for DFA can be found in the literature. For example, Hausdorff et al. (1997) suggest that gait parameters should be recorded for a minimum of 5 minutes when LRCs are to be calculated. Pierrynowski et al. (2005) investigated the reliability of the DFA method and found that a longer total recording time yielded higher intra-class coefficients and suggested that the collected data should consist of four 3 minute, three 6 minute or two 8 minute walking trials. Recently, Damouras et al. (2010) formulated more specific guidelines and proposed that for a data set of length $N$, a box size range of $[16, N/9]$ should be chosen. They also recommend that a minimum of 600 strides should be recorded to estimate $\alpha$ with an accuracy of $\pm 0.1$.

### 2.7.3 Nonlinear Dynamics in Walking and Running

The majority of research investigating LRCs in human gait involves speed-controlled walking trials. In one of the earliest studies, Hausdorff et al. (1995) found that LRCs were present in the stride interval of young healthy men. Subsequent studies that employed walking protocols of different lengths and speeds confirmed these
observations. Their results show that LRCs are present in gait trials consisting of up to several thousand steps (Hausdorff et al., 2001, 1996).

LRCs further appear to be influenced by locomotor speed. Hausdorff et al. (1996) calculated $\alpha$ for slow, preferred and fast walking speeds. They found preferred walking speed was associated with the lowest values of $\alpha$. These results are in line with Jordan and Newell (2008) who analyzed the strength of LRCs over a range of speeds (80 - 120% of preferred running speed) during a treadmill run. The authors found consistent LRCs and observed that they followed a U-shaped pattern, with the lowest values occurring at preferred running speed (PRS).

No satisfactory explanation exists for why preferred locomotor speeds are associated with the lowest values of $\alpha$ and different arguments have been put forward regarding the meaning and interpretation of LRCs. Contrary to these results, other studies have shown that low values of $\alpha$ are associated with a higher risk of falls (Giladi, Herman, Reider-Groswasser, Gurevich, & Hausdorff, 2005), aging of the neuromuscular system, as well as certain neurological disorders (Hausdorff et al., 1997). In other words, LRCs of physiological signals may be indicative of a healthy and adaptable locomotor system but may also be linked to certain pathological changes and impaired motor control (Hausdorff, 2007). These examples demonstrate the complex relationship between gait variables and nonlinear measures of variability. It further implies that a more differentiated perspective on LRCs and other measures of gait variability might be necessary. In this regard, Brach, Berlin, Vanswearingen, Newman, and Studenski (2005) have proposed the idea of an optimal window for LRCs and state that values for $\alpha$ should range between the extremes of white and brown noise. However, other nonlinear measures of gait variability seem to behave differently. For example, Beauchet et al. (2007) state that higher Lyapunov exponents may reflect increased adaptability.

Only a small number of studies have investigated nonlinear aspects of
variability in running gait. For example, Hamill et al. (1999) used a dynamical systems approach to investigate lower extremity running injuries and found that runners with patellofemoral pain showed less variability in the continuous relative phase (CRP) patterns of lower extremity couplings than healthy individuals. Jordan et al. (2006) were the first to investigate LRCs in human running. The authors reported that LRCs were speed-dependent and followed a U-shaped distribution, with the lowest correlations occurring at PRS. The authors hypothesized that PRS is associated with a higher number of dynamical degrees of freedom (i.e. the number of combinations of stride length and stride rate resulting in the same speed) and thus represents a lower biological stress than faster or slower running speeds. Follow-up studies detected the presence of LRCs in other biomechanical variables of running gait and confirmed the U-shaped pattern of LRCs across a range of running speeds (Jordan et al., 2007a, 2007b). Another study recently investigated the effects of skill level on nonlinear fluctuations via DFA in the gait cycle of running. Although the authors did not confirm the U-shaped relationship between running speed and the strength of LRCs, they showed that trained runners exhibited significantly lower values of $\alpha$ (Nakayama, Kudo, & Ohtsuki, 2010). A recent study found that various measures of gait dynamics differed significantly between treadmill and overground running (Lindsay, Noakes, & McGregor, 2014). In particular, treadmill running was characterized by a more ordered control, as indicated by a higher scaling index $\alpha$, compared to overground runs performed at identical speeds. The authors conclude that runners on a treadmill were constrained to a greater degree and required increased voluntary control to complete the locomotor task. To date, only one study has investigated the effects of fatigue on the fractal-like nature of running gait. Meardon et al. (2011) analyzed stride-time variability in healthy and previously injured individuals. While no significant group or fatigue effects were found for linear measures of variability, DFA, as quantified by
α, significantly decreased over time, thus rendering stride time less predictable. Furthermore, injured runners exhibited lower values of α than their healthy counterparts. The authors concluded that fatigue was associated with a higher degree of movement errors and altered complexity.

2.8 Inertial Measurement Units

Various tools and techniques exist by which the biomechanics of locomotion can be assessed. One alternative to traditional methods, such as force plates and camera-based motion capture systems, involves the use of body-mounted inertial measurement units (IMUs), which typically contain accelerometers and gyroscopes.

Accelerometers are inertial sensors that provide information about linear acceleration. The most common sensor types include strain gauge, capacitative, piezoelectric, and piezoresistive accelerometers (Kavanagh & Menz, 2008). Conceptually, accelerometers act as spring-mass systems and derive acceleration based on the relationship between Newton’s 2nd law of motion and Hooke’s law (Godfrey, Conway, Meagher, & O’Laighin, 2008):

\[ F = ma = kx \]  

When a tensile or compressive force is applied to a linear spring-mass system, a reactive force \( F \) that is proportional to the displacement of the mass \( m \) is generated by the spring. Provided that spring stiffness \( k \) and mass \( m \) are invariant, the resultant acceleration can be calculated by solving Equation 4 for \( a \):

\[ a = \frac{kx}{m} \]  

Despite some variations in technical details, all accelerometers operate by generating an electrical signal that is proportional to the magnitude of the
experienced acceleration (Kavanagh & Menz, 2008). Different methods exist by which accelerometers can be calibrated, the most common of which includes the use of gravity. When being aligned in the vertical direction, gravity acts with an acceleration of 9.81 m/s\(^2\) along an axis. Consequently, the magnitude of the electrical output measured in this situation must be equal to 1 g (Kavanagh & Menz, 2008).

Gyroscopes are inertial sensors that measure angular velocity about an axis of rotation. They are able to provide information regarding the pitch, yaw and roll characteristics of the sensor. The relative orientation of the sensor can be estimated by integrating the obtained angular velocity signals. Local coordinates can subsequently be transformed into a global frame of reference with the help of rotational matrices or quaternions (Fischer, Sukumar, & Hazas, 2013).

While early IMUs only quantified linear acceleration along a single axis, newer models usually contain three accelerometers and three gyroscopes that are aligned orthogonally along three axes. When attached to an object, modern IMUs are capable of fully quantifying its movement in three-dimensional space (i.e. six degrees of freedom). In biomechanics research, body-fixed IMUs have several advantages over traditional motion capture methods. In addition to the low cost, they can be used to collect data outside of a laboratory setting. This is particularly important in gait research as the biomechanics of walking and running may be affected by environmental constraints. The small size and wireless capabilities of modern IMUs allows individuals to move freely and without any restrictions, which may improve the quality of the obtained data. Recent advances in microelectronics and biomedical signal processing have enabled researchers to record data for several hours or even days (Kavanagh & Menz, 2008).

2.8.1 Inertial Measurement Units in Gait Analysis. IMUs have been used to analyze the temporal structure of cyclic motion in swimming (Barber &
Barden, 2014), provide feedback in weightlifting (Sato, Smith, & Sands, 2009), track physical activity behavior (Troiano et al., 2008) and predict the risk of falls in an elderly population (Menz, Lord, & Fitzpatrick, 2005). Additionally, IMUs are frequently used for gait analysis. Depending on the attachment site and placement of the sensor, IMUs are able to provide information about specific gait events and spatiotemporal stride parameters (Kobsar et al., 2014; E. Martin, 2011; Moe-Nilssen, 1998a). While many studies employ a trunk-mounted setup (Kobsar et al., 2014; Moe-Nilssen, 1998a; Zijlstra, 2003), IMUs have also been attached to the lower extremity (Lafortune, Henning, & Valiant, 1995; Sabatini, Martelloni, Scapellato, & Cavallo, 2005) or the head (Kavanagh, Morrison, James, & Barrett, 2006; Menz et al., 2003). When mounted to the lower trunk (approximately at the level of L3/L4) an IMU quantifies the motion of the total body COM along the anteroposterior, vertical and mediolateral axes and therefore represents the integrated motor output during locomotion (Zijlstra, 2003). In contrast, leg- or foot-mounted IMUs can be used to measure impact loading characteristics as well as stride parameters, such as contact time or stride length (J. B. Lee, James, Ohgi, & Yamanaka, 2012; Mizrahi, Verbitsky, Isakov, & Daily, 2000; Strohrmann, Harms, Kappeler-Setz, & Tröster, 2012).

In order to make meaningful inferences based on IMU signals, a high degree of accuracy compared to accepted methods (i.e. videography, force plates etc.) must be present with respect to the measured variables. However, valid kinematic parameters, in particular velocity and position estimates, are hard to obtain because high-frequency noise in physiological time-series amplifies when inertial signals are integrated or differentiated (Winter, 2009). Although filtering is able to attenuate noise and mitigate this amplification effect, it also reduces the power of the recorded signals.

Despite these limitations, trunk acceleration and GRF signals show a similar
structure for walking and running. This is expected, considering the relationship between $F$ and $a$ as expressed by Newton’s 2nd law of motion. In particular, vertical accelerations exhibit a strong biphasic pattern during running, with the first sharp peak corresponding to the maximum impact load experienced during early stance and a second peak representing the thrust maximum achieved during active push-off. A local minimum occurring between these two peaks indicates a short period of unloading during midstance (Auvinet et al., 2002). Noticeable agreement also exists between the anteroposterior acceleration curves and the respective component of the GRF. In general, anteroposterior accelerations exhibit a bimodal pattern in running. A period of negative acceleration (directed posteriorly) during the early stance phase is caused by the braking impulse upon initial contact, while the subsequent phase of positive acceleration corresponds to the propulsive impulse (in the anterior direction) during active push-off (Auvinet et al., 2002).

Inertial signals can also be used to obtain information about basic stride parameters, such as stride rate/stride time. Many sensor-based methods involve the identification of invariant periodic features of the acceleration or gyroscope signals. For example, Mercer et al. (2003) determined the time between successive vertical impact peaks and subsequently calculated stride rate as the inverse of this time interval, i.e. stride time. Other authors have counted the number of zero-crossings in the anteroposterior accelerations to estimate stride time (Neville, Wixted, Rowlands, & James, 2010). Based on the correct identification of initial contact and toe off, additional variables such as contact time and swing time can be determined. Various methods exist by which the exact timing of these incidents are defined. For example, Strohrmann et al. (2012) used a threshold value of $2\ g$ to identify the instant at which ground contact occurred. Other studies have defined initial contact as the point at which large peaks occur either in the vertical or anteroposterior direction (J. B. Lee, Mellifont, & Burkett, 2010; Purcell, Channells, James, &
Barrett, 2005). In addition to estimating different aspects of stride kinematics, IMUs have been used to classify foot strike patterns (Strohrmann et al., 2012), measure gait symmetry (Brach et al., 2011) and running speed (Neville et al., 2010).

The measurement of spatiotemporal gait parameters has mostly been validated for walking. For example, Zijlstra (2003) compared kinematic variables obtained from a back-mounted triaxial accelerometer with data acquired from a force-plate mounted treadmill. The results showed that the measured stride times were almost identical and only varied within a range of 2 to 15 ms. Using vertical acceleration signals, the authors indirectly estimated step length and walking speed by combining accelerometric and anthropometric data (leg length). Similarly, Hartmann, Murer, de Bie, and de Bruin (2009) determined the concurrent validity of a trunk-mounted accelerometer system with a force-plate walkway system in elderly adults during level walking and demonstrated excellent levels of agreement for walking speed, cadence and step duration. Lower intra-class correlation coefficients (ICC) were reported for parameters of variability (step length, step duration). Kobsar et al. (2014) reported that a waist-mounted accelerometer is able to accurately measure stride time, its standard deviation and fractal dynamics during level overground walking.

It has also been established that IMU-derived estimates of basic spatiotemporal parameters display a high level of reliability. For example, Henriksen, Lund, Moe-Nilssen, Bliddal, and Danneskiold-Samsøe (2004) investigated the test-retest reliability of trunk accelerations as a measure of balance in walking and standing. The reported ICC value ranged from 0.77 - 0.96, while measurement errors were 0.007 - 0.01 \( g \) for mean accelerations; 0.009 m for step lengths; 0.022 m for stride lengths and 1.644 steps/min for cadence (Henriksen et al., 2004). These results are similar to those of Moe-Nilssen (1998b), who reported ICCs ranging from 0.79 - 0.94 for walking on an even and uneven surface. Hartmann, Luzi, Murer,
de Bie, and de Bruin (2009) determined the intra- and interrater reliability of selected gait parameters obtained from trunk accelerations by calculating ICC, CV and ratios limit of agreement (RLOA) and noted excellent reliability (as shown by large ICCs and small CVs/ RLOAs) for walking speed, cadence and step duration. However, the reliability of gait variability was reported to be only moderate with deficient ICCs and large CVs and RLOAs.

![Figure 3](image_url)

*Figure 3.* Representative example of resultant acceleration signal recorded with a foot-mounted IMU during distance running.

Efforts have also been made to validate the use of a trunk-mounted triaxial accelerometer to identify events and phases of running gait. J. B. Lee et al. (2010) found a high level of agreement for stride, step and stance time between the values obtained by inertial sensing and those recorded with an infrared camera system. The authors reported that the data was within 95% limits of agreements over a wide range of running speeds (10 - 19 km/h). Hausswirth (2009) as well as Heiden and Burnett (2008) reported that an accelerometer-based sensor mounted to the foot yielded similar levels of validity and reliability compared to an optical sensor system and force-plate measurements. Heiden and Burnett (2008) further compared the accuracy of initial contact and toe off between hip and foot mounted accelerometers and found that a significant lag was present in the data recorded at the hip.
Wixted, Billing, and James (2010) compared trunk accelerations with synchronously collected data from in-shoe pressure sensors during a 1500 m run. They reported that pressure sensor data allowed the framing of the acceleration signal, which made it possible to estimate the basic events of the gait cycle (initial contact, toe off) from the COM accelerations. Likewise, Auvinet et al. (2002) noted consistencies between trunk acceleration curves and ground reaction force profiles at distance running speeds.

Accelerometer-based inertial-measurement units have also been used for the identification of consistent gait parameters during sprint running. However, Bergamini et al. (2012) reported inconsistencies in the detection of initial contact and toe off from trunk-acceleration signals. In contrast, a 95% limit of agreement for these measures was achieved by processing simultaneously recorded gyroscope signals. These results demonstrate that the combination of data from different inertial sensors greatly improves the reliability and validity of IMU-derived spatiotemporal gait parameters. Figure 3 and 4 illustrate the resultant acceleration and angular velocity signals recorded by a foot-mounted IMU during overground running.

![Figure 4](image_url). Representative example of an angular velocity signal recorded with a foot-mounted IMU during distance running.
Despite the versatility of body-mounted IMUs, the direct estimation of running velocity and individual stride length vectors poses a challenging problem. Theoretically, the recorded accelerations can be combined with signals obtained by magnetometers and gyroscopes to determine the direction and magnitude of displacement over time. In practice, however, these methods are very sensitive to drifting of the signal, which leads to the accumulation of significant error over time (E. Martin, 2011). Some researchers have developed novel IMU-based algorithms to estimate running speed. For example, Yang, Mohr, and Li (2011) combined gyroscope and accelerometer data from a shank-mounted IMU. Using a treadmill to verify their results, the authors reported root-mean-square error of 4.1% for their estimates. Likewise, Hausswirth (2009) reported excellent levels of validity and a high level of agreement between the speed calculated by a foot-mounted uniaxial accelerometer and treadmill running speed. The accuracy of stride length estimates can also be significantly improved (< 5% error) when double-integration of the acceleration signal is combined with a zero-velocity reference in the gait cycle for a sensor mounted to the distal end of the leg (Jimenez et al., 2009). This method overcomes the problem of signal drifting by restarting the integration process after each step and resetting movement velocity to zero during stance (Rong, Jianzhong, Ming, & Xiangfeng, 2007). These so-called pedestrian dead-reckoning approaches offer a viable alternative to traditional camera-based methods for estimating stride length (Jimenez et al., 2009). Although research has shown that stride length for walking can be estimated with a high degree of accuracy, none of these approaches have been properly validated for running.
3 Purpose and Objectives

Human walking and running are complex motor tasks that are realized by a coordinated effort of the neuromuscular system (Jordan et al., 2007a). Although the gait pattern of healthy individuals is generally very stable, it exhibits a natural degree of fluctuation (Hausdorff, 2005). Interestingly, research has shown that these fluctuations do not occur randomly but rather exhibit high temporal stability as signified by persistent long-range correlations (LRCs) (Hausdorff et al., 1995). It has been suggested that these patterned fluctuations offer insight into the control of gait and convey information about the way cyclic movement is organized (Hausdorff, 2005). Despite these findings, however, very little is known about the mechanisms that govern the emergence of LRCs during running as well as their functional relevance. Moreover, LRCs have been shown to change with fatigue but the exact mechanism responsible for these changes is still undetermined.

One of the main reasons for this research gap is that sophisticated biomechanical tools, such as 3D-motion capture systems or force plates are only capable of recording a small number of consecutive strides. As a result, many researchers have used treadmill protocols to overcome this limitation. However, studies have shown that running on a treadmill is biomechanically different from unconstrained overground running (Nigg et al., 1995; P. Riley et al., 2008). With respect to gait dynamics research has shown that treadmill locomotion is less variable (Frenkel-Toledo et al., 2005) and more locally stable (Dingwell, Cusumano, Cavanagh, & Sternad, 2001) compared to overground locomotion. Additionally, Lindsay et al. (2014) demonstrated that treadmill running resulted in more persistent LRCs.

Given the limitations of existing methods to collect a large number of consecutive strides and to improve our understanding of stride pattern fluctuations during unconstrained running, this thesis was designed to investigate the sensitivity
and applicability of LRCs to assess fatigue and their relevance for health and performance using a simple foot-mounted IMU. In particular, the goal was to identify factors that account for the changes in measures of self-similarity in response to exhaustive exercise. Concomitantly, this thesis sought to determine the effects of skill level on running mechanics and different measures of variability under different fatiguing conditions.

In order to achieve these overall objectives, it was necessary to analyze LRCs for both the temporal and spatial dimension of the stride pattern. This required that stride length, which had not previously been assessed during unconstrained running, had to be estimated with high accuracy prior to conducting any experiments involving prolonged running. From a research perspective, detailed knowledge about SL is important for coaches, clinicians and researchers alike because together with SR it determines running speed. Moreover, individual SL vectors represent the integrated output of different biomechanical determinants and as such can provide valuable insight into the control of running gait. Therefore, the purpose of the first study of this thesis was to determine whether a simple IMU configuration could provide valid estimates for stride length over a range of typical distance running speeds. Based on successful attempts to estimate walking distance using pedestrian dead-reckoning (PDR) approaches (Angermann et al., 2010) it was expected that a running-specific multi-threshold, zero-velocity update (ZUPT) algorithm would be capable of accurately estimating individual stride length vectors.

In line with the overall objectives of this thesis, a subsequent experiment was then conducted to explore changes in both spatial (SL) and temporal gait parameters (ST, CT), their variability and LRCs during an exhaustive run. This was necessary because only a small number of studies have previously investigated LRCs for running and most existing studies involved treadmill protocols. Although research suggests that factors such as fatigue (Meardon et al., 2011) and skill level
(Nakayama et al., 2010) may cause changes in LRCs during running, the exact nature of this relationship and its potential causes remain unknown. Most importantly, it is not known whether fatigue affects all dimensions of the stride pattern to the same degree. It was hypothesized that the strength of LRCs would decrease during the run, while linear measures of variability would not be affected by fatigue. It was also expected that elite distance runners would be able to maintain more persistent levels of LRCs during the run compared to recreational runners.

After gathering insights into the nature and time-course of fatigue-related changes in the stride pattern and associated LRCs, it was intended to obtain further information about the potential mechanisms responsible for the emergence of patterned fluctuations in the stride pattern. Considering the relationship between fatigue and joint stiffness (Horita et al., 1996; Kuitunen, Avela, et al., 2002; Rabita et al., 2013) as well as the suspected link between fatigue and LRCs (Gates & Dingwell, 2008; Meardon et al., 2011), there is a need to analyze the effects of varying joint stiffness on stride pattern LRCs. To date, however, no study has looked at how fatiguing high-intensity SSC exercise affects the stride pattern variability and LRCs. Therefore, the third and final study of this thesis was designed to examine the relationship between fatiguing high-intensity SSC exercise, joint stiffness, stride mechanics and LRCs in elite and recreational runners. It was hypothesized that a decrease in joint stiffness would be associated with reduced LRCs, while linear measures of variability would remain unaffected. Furthermore, it was expected that both joint stiffness and LRCs would decrease to a lesser degree in competitive distance runners.
4 Study 1: Concurrent Validity of a Foot-Mounted IMU to Estimate Stride Length in Running

Stride length is a fundamental variable of human gait that represents the integrated output of various biomechanical determinants. Together with stride rate, stride length determines the speed at which the body moves during walking and running. Due to a lack of alternatives that are capable of continuously and accurately assessing spatial parameters in an unconstrained setting, stride length has traditionally been measured with force plates or camera-based systems in the laboratory, either by recording a few isolated strides or on a treadmill. Consequently, studies that have investigated stride characteristics during prolonged overground locomotion were limited to focusing on temporal aspects of the stride pattern (i.e., stride time, contact time etc.) or indirectly making inferences about its spatial dimension. However, in order to obtain a complete picture of the stride pattern and to allow researchers to conduct more complex time series analyses (i.e. DFA) of parameters that have been hard to study during continuous locomotion, accurate information regarding stride length is necessary.

Since the development of feasible and accurate MEMS components, several studies have tried to estimate stride length and positional data using body-mounted sensors (Bichler et al., 2012; Feliz et al., 2009; Jimenez et al., 2009; E. Martin, 2011). Often sensor algorithms are based on or include Global Positioning System (GPS), ultrasound, or radio signals (Bichler et al., 2012; Jimenez, Seco, Prieto, & Roa, 2005; Ogris et al., 2012; Siegle, Stevens, & Lames, 2013). Systems based on IMUs offer a powerful alternative to beacon technologies because they can operate without relying on a pre-installed infrastructure. The term Pedestrian Dead Reckoning (PDR) is used to describe the process of solving the problem of localization and object tracking by calculating displacement and orientation vectors via integration of the recorded inertial signals, i.e. triaxial accelerations and angular
velocities (Bichler et al., 2012; Feliz et al., 2009; Jimenez et al., 2009; Kim, Jang, Hwang, & Park, 2004). Although the theoretical model allows for the exact assessment of spatial gait variables, such as stride length, the process is complicated by measurement errors and accumulated noise that occur in practice. Since an accurate estimation of the velocity, position and orientation vectors depends on exact knowledge of the initial values, noise will induce substantial drift errors over time, which are exacerbated during the integration process (Fischer et al., 2013).

Several studies have demonstrated that this drift error can be greatly reduced when so-called zero-velocity updates (ZUPT) are periodically applied during the integration process (Angermann et al., 2010; Bichler et al., 2012; Feliz et al., 2009; Jimenez et al., 2009). In particular, ZUPTs involve resetting the velocity reading to zero whenever the IMU is known to be stationary, which corrects for the accumulation of errors generated by noise. Consequently, this method requires accurate knowledge about the points in time where the velocity of the sensor can be assumed to be equal to zero. In walking and running, ZUPTs have been successfully applied during the stance phase of each gait cycle when an IMU is securely mounted to the foot (see Figure 5). This approach has been shown to greatly improve the accuracy of algorithms aiming at object tracking and stride length estimation (Angermann et al., 2010; Bichler et al., 2012; Feliz et al., 2009; Jimenez et al., 2009).

4.1 Research Design

Although the performance of ZUPT-based PDR algorithms has repeatedly been tested for walking (Feliz et al., 2009; Jimenez et al., 2009; E. Martin, 2011), only a few studies have tested their performance during running. For example, Angermann et al. (2010) tested the accuracy of different PDR algorithms by calculating the cumulative distance traveled during a short indoor run and found that an approach considering both the accelerations and turn rates of a
foot-mounted IMU yielded the best results. The authors also note that the observed position errors were higher compared to slow walking. In a similar experiment, Bichler et al. (2012) assessed the performance of an algorithm that combined IMU and GPS data to derive different stride parameters, including stride length, during overground running. The results showed that the sensor estimates were in good agreement with those produced by a simple videography system. However, the authors also noted that the accuracy varied across running speeds. Despite these initial attempts to estimate spatial parameters in an unconstrained setting, no study has explicitly assessed the concurrent validity of a single foot-mounted IMU to estimate individual stride length vectors for running. Therefore, the purpose of this study was to determine whether a simple IMU configuration can provide valid estimates for stride length during distance running. In particular, the concurrent validity of a novel sensor-based existing algorithm was tested using class 3 intraclass correlation coefficients (ICC) with a 3D-camera motion capture system (T-Series, Vicon, Denver, CO) as the criterion. It was hypothesized that good levels of agreement would exist between the sensor and camera-based methods for individual
stride length vectors. Participants were selected so that a wide range of anthropometric characteristics (e.g. height, weight, leg length) were represented in the sample. Subject characteristics are reported in Table 1. In order to be included in the study, participants were not allowed to have any current medical or pre-existing health conditions that could be exacerbated by the testing procedures. The study was approved by the university’s ethics review board. Prior to enrollment, all participants signed a University of Regina Ethics Board approved consent form.

Table 1
Subject characteristics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>$M \pm SD$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>22.3 (±1.5)</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>175.2 ± 23.1</td>
</tr>
<tr>
<td>Leg Length (cm)</td>
<td>80.56 ± 4.36</td>
</tr>
<tr>
<td>Bodymass (kg)</td>
<td>76.04 ± 3.19</td>
</tr>
</tbody>
</table>

$M =$ mean, $SD =$ standard deviation

4.2 Instrumentation and Test Procedures

Eleven young healthy adults (female = 4; male = 7) volunteered to participate in this study. A 9 degree of freedom IMU, consisting of a gyroscope, accelerometer and magnetometer (Xsens, MTw), was secured to the right foot of each participant. The sensor was firmly attached using the shoe’s laces and adhesive tape (see Figure 6b). It was oriented longitudinal along the foot, so that anteroposterior motion was detected along the x-axis, mediolateral motion along the y-axis and vertical motion along the z-axis (see Figure 6a). The exact position and orientation of the sensor did not need to be determined because the running-specific sensor algorithm depends only on the magnitude of the detected gyroscope and acceleration signals, which were transformed into a global coordinate system. All sensor data were recorded at 100 Hz.
Prior to the experiment, a wireless connection had to be established between the sensor and a docking station, which was connected to a laptop. In accordance with the manufacturer’s recommendations, the sensor was kept still while connecting to the station. Afterwards, several slow movements were executed with the sensor in order to warm up the filter. The wireless communication protocol used by the inertial system operated in the 2.4 GHz range and was based on IEEE 802.15.4 standard. To avoid potential interference with devices such as WiFi routers, a channel with a center frequency of 2.450 GHz or 2.475 GHz was selected (“MTw User Manual,” 2013). The system used in this study has a reported wireless transmission range of approximately 50 m in an unobstructed indoor setting. Given the dimensions of the biomechanics lab, this range was deemed sufficient to ensure the continuous recording of inertial data. For a detailed description of the technical specifications, inbuilt filters, wireless configuration and recommended workflow see (“MTw User Manual,” 2013).

![IMU orientation and reflective markers attached to the foot.](image)

*Figure 6.* IMU orientation and reflective markers attached to the foot.

Three reflective markers were attached to the right foot of the participants to track the position of the foot with the camera system during the running trials (Figure 6b). One marker was placed directly onto the IMU in the area of the mid-foot. Additional markers were placed on the heel and on the second metatarsal
head of the foot, respectively. The markers attached to the front and the back of
the shoe provided redundant information regarding the foot’s position that was only
used in case the mid-foot marker became obstructed or detached during the runs.
All marker positions were recorded at 100 Hz. After the participants were equipped
with the sensor and reflective markers, they performed twenty individual 10 m runs
through the previously calibrated space of the 3D camera motion capture system
(see Figure 7). The participants were instructed to naturally vary their speed
between trials. During each trial, 1 - 3 full strides were recorded and used for
further analysis. In order to identify the beginning and end of each trial,
participants were asked to stand still outside of the calibrated camera volume for 5
seconds and to initiate each run with their left foot. This also ensured that the first
footfall recorded by both the camera system and the foot-mounted IMU always
occurred with the right foot, which allowed for synchronization of the strides for
further analysis.

Figure 7. Camera setup in the lab.
4.3 Data Analysis

Custom programs written in MATLAB (v. R2012a, The MathWorks, Natick, MA) were used to process and analyze the recorded IMU signals. In particular, this study employed a modified version of the algorithm proposed by Angermann et al. (2010) and Fischer et al. (2013), who used inertial integration (INS) with zero-velocity updates (ZUPT) at stance detections in combination with Kalman Filtering to solve the problem of pedestrian navigation. This approach has been shown to perform well over a range of locomotor speeds. However, the reliability and concurrent validity of this PDR approach to estimate individual stride length values in running has not been established.

Fischer et al. (2013) outlined the individual steps of the algorithm as follows:

1. Critical parameters, such as sampling rate, gravitational acceleration, as well as different thresholds are defined before the main loop of the program is initiated.

2. The raw signal components are imported to the program.

3. The orientation of the IMU is estimated by integration of the gyroscope signals.

4. Accelerations are transformed from the local coordinate system, i.e. sensor frame, to the global coordinate system, i.e. navigation frame.

5. The gravitational component is subtracted from the acceleration signals.

6. The acceleration values are integrated to obtain velocity estimates.

7. The calculated velocities are integrated to obtain position estimates.

8. A Kalman filter prediction estimates the error covariance.
9. The stance phase detection algorithm determines when the sensor is stationary.

10. When stance is detected, a Kalman Filter update is applied by estimating velocity, position and orientation errors.

11. The Kalman filter update corrects the error covariance.

12. A zero-velocity update is applied to correct velocity, position and orientation estimates.

13. The algorithm generates the position output.

14. Individual stride length vectors are calculated by subtracting the position of the foot at sample $k-1$ from the position at step $k$.

   In this experiment, stance was declared when the resultant angular velocity was less than 3.5 rad/s and simultaneously the resultant acceleration was between 0.3 and 1.7 g. More detailed information regarding the method is provided in Angermann et al. (2010) and Fischer et al. (2013).

   The marker coordinates recorded by the motion capture system were digitized and processed in the motion capture software (Nexus, v.1.8, Vicon Motion System, UK). Actual SL was defined as the horizontal displacement of the mid-foot marker at foot contact between subsequent footfalls. Marker trajectories were low-pass filtered using a fourth-order Butterworth filter with a cutoff frequency of 10 Hz. The processed data were exported as a txt file in order to allow for further analysis. Custom software written for MATLAB was used to extract the position of the right foot during each stance phase. For the camera-based method, stance was defined as occurring whenever the horizontal velocity of the mid-foot marker was below a pre-defined threshold of 0.2 m/s. The positional data for the entire stance phase was averaged to obtain a single representative value. After the stride length values
for both the camera and the sensor-based system were determined by the respective programs, strides were manually matched to allow for a direct comparison of the methods.

4.4 Statistical Analysis

In order to establish the accuracy of the foot-mounted IMU in measuring stride length in comparison with the 3D-camera system, the absolute level of agreement between the two methods (camera vs. sensor) was assessed using an intraclass correlation coefficient. More specifically, a model 3 ICC was used because there are no methods of interest other than those described in the previous section (no random selection from a pool of different methods). Since reliability was calculated from a series of individual measurements, a (3,1) ICC was computed. This specific type of ICC is designed for two-way mixed single measures and quantifies the agreement between two methods on a particular dependent variable. Based on the convention proposed by Shrout and Fleiss (1979), ICCs less than 0.4 were considered poor, ICCs between 0.4 and 0.75 were considered fair to moderate and ICCs greater than 0.75 were considered excellent. In addition to the ICC, the Pearson product-moment correlation coefficient was calculated to quantify the strength and direction of the linear relationship between the camera and the sensor-based stride length estimates.

4.5 Results

The participants completed 162 runs through the calibrated camera volume of the lab. During these runs, 331 strides were recorded by the camera system and included in the analysis. The IMU-based stride length algorithm successfully identified all of the strides that were recorded by the camera system.

Based on the strides recorded from the 11 individuals that participated in the study, the Pearson product-moment correlation coefficient showed that there was an
excellent correlation between the 3D motion capture system and the IMU-system for the measurement of stride length \((r = 0.961, n = 331, p < 0.001)\). The scatterplot in Figure 8 shows the results. The mean stride length values and standard deviations calculated by the IMU-based method \((2.592 \pm 0.276)\) were strikingly similar to those recorded by the camera-based system \((2.623 \pm 0.272)\). The mean absolute error of the sensor-based method was 0.05 m (2.01%) compared to the ground truth, i.e. the 3D motion capture system. The root mean squared error of the two methods was 0.083 m. A single measures class 3 intraclass correlation coefficient revealed excellent levels of absolute agreement \((\text{ICC}(3,1) = 0.955, df = 330, p < 0.001)\) between the two methods (Camera vs. IMU) on the measure of stride length. The upper and lower bounds of the 95% confidence interval were 0.927 and 0.970, respectively.
Table 2
Descriptive statistics of SL data.

<table>
<thead>
<tr>
<th>Variable</th>
<th>n</th>
<th>M (m)</th>
<th>SD (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SL Overall</td>
<td>331</td>
<td>2.61</td>
<td>0.27</td>
</tr>
<tr>
<td>SL Camera</td>
<td>331</td>
<td>2.62</td>
<td>0.27</td>
</tr>
<tr>
<td>SL Sensor</td>
<td>331</td>
<td>2.59</td>
<td>0.28</td>
</tr>
</tbody>
</table>

$M = \text{mean}, SD = \text{standard deviation}$

The Bland-Altman plot shown in Figure 9 shows that the mean difference in stride length estimation between the methods was -0.032 m, which indicates a small bias of the sensor-based algorithm to underestimate stride length. The 95% limits of agreement of the between-method difference in stride length were calculated to be 0.118 m and -0.183 m, respectively. A linear regression with the difference in stride length as the dependent variable and mean stride length as the independent variable further corroborated the findings that no significant trends existed in the between-method difference for different stride lengths ($p = 0.350$). Consequently, the null hypothesis, which stated that there was no proportional bias in mean stride length, was accepted.

4.6 Discussion

The purpose of this study was to determine whether a single foot-mounted IMU was capable of producing valid stride length estimates during distance running. As evidenced by the high ICC, the experiment showed that excellent levels of agreement were obtained between the sensor and camera-based methods (ICC(3,1) = 0.955, $p < 0.001$). The accuracy of the sensor algorithm was also confirmed by the high correlation coefficient ($r = 0.961$, $p < 0.001$) and the absence of any significant trends in the difference between methods. Together the results of the statistical analyses indicate that a single foot-mounted IMU exhibits high concurrent validity with a 3D-camera motion capture system as the criterion.
Figure 9. Bland-Altman plot comparing the two different methods to calculate stride length.

Despite the positive results, it was noted that the accuracy of the sensor-based method varied between participants. Although this study did not investigate the causes of these inconsistencies, it is reasonable to suggest that running speed as well as individual aspects of running technique, e.g. foot strike patterns, determine the signal characteristics, which, in turn, may have affected the accuracy of the stride length algorithm. Figure 10 illustrates the between-method differences in stride length for all eleven participants.

The calculated position estimates and stride length vectors depend largely on correct identification of the stance phases because ZUPTs are applied at each of these points (Zhao, Brahms, Gerhard, & Barden, 2015). This study employed a stance phase detection algorithm based on static thresholds, which were determined by visual inspection of several running trials. An approach considering both the
Figure 10. Between-method difference in stride length for each participant.

turn rates and the acceleration readings to detect stance was shown to yield better results over a range of walking and running speeds than approaches based on accelerometer or gyroscope readings alone (Angermann et al., 2010; Fischer et al., 2013). However, one of the general shortcomings of threshold-based approaches is their sensitivity to changes in gait patterns, running surfaces, sensor placement and running speed (Angermann et al., 2010; Bichler et al., 2012). By design, the method works better when the foot remains relatively stationary during stance compared to when it is moving (pronation/ supination, plantarflexion/dorsiflexion) while being in contact with the ground. Although foot strike patterns were not monitored during the running trials, it is reasonable to assume that runners who initiated ground contact with the fore- or midfoot exhibited different acceleration and angular velocity profiles compared to runners who initiate ground contact with the rearfoot (Strohrmann, Harms, Tröster, Hensler, & Müller, 2011). More specifically, runners with a FFS/MFS pattern dorsiflex the foot during the early stance phase.
and subsequently move into plantarflexion, as opposed to a sequence of plantarflexion, dorsiflexion, plantarflexion in runners who display a RFS pattern. Furthermore, running speed, which has also been shown to influence the duration and stability of the stance phase (Bichler et al., 2012; Strohrmann et al., 2011) may have been a confounding factor.

Stance detection errors may affect the stride length calculation in two different ways. One the one hand, by producing false negatives, i.e. deletion errors, which lead to the overestimation of stride length vectors and result in the accumulation of signal drift. In particular, this may occur when the signal is not stationary during the stance phase because in these situations the threshold-based stance detection mechanism may fail and subsequently continues to integrate the inertial signals even though the stride is already completed. The negative effects of stance phase deletion errors on pedestrian navigation have been discussed in more detail elsewhere (Angermann et al., 2010; Bichler et al., 2012; Jimenez et al., 2009).

![Figure 11](image)

*Figure 11.* Resultant angular velocity during running. The bold line indicates the stance phases detected by the algorithm. Improper threshold tuning is shown to cause considerable stance detection errors.

On the other hand, stance phase insertion errors, i.e. false positives, may occur between two subsequent stance phases. These errors cause stride length to be underestimated because the time interval between subsequent ZUPTs is reduced. Although making the stance detection algorithm more selective by lowering the
gyroscope and acceleration thresholds will reduce insertion errors, the risk of deletion errors increases simultaneously. Consequently, thresholds were manually tuned to establish the values that work best across subjects. To correct for the effects of the remaining insertion errors, a condition proposed by Angermann et al. (2010) was added to the algorithm, which stated that stride length vectors must exceed a certain distance (0.75 m) in order to be valid. For stride lengths below this threshold, the last ZUPT was declared to be a false positive and the algorithm continued with the integration process until the next ZUPT was applied. Figure 11 shows the occurrence of stance detection errors for a sample run as a result of an improperly tuned algorithm. In this experiment, no insertion or deletion errors occurred within the 331 strides that were recorded and included in the analysis. This was achieved by meticulous fine-tuning of the stride length algorithm and by extracting only two or three strides performed at a constant running speed from each trial. However, occasionally inconsistencies were observed immediately at the beginning or end of the short linear run, i.e. when runners accelerated or decelerated. This suggests that although the proposed method performs well for strides performed at a constant speed, it may not be suited for locomotion involving abrupt changes in directions.

In summary, it is likely that the performance of the stride length algorithm was affected by factors such as running speed and individual variations of running technique. This is also consistent with other studies that have shown that features such as foot strike patterns and locomotor speed affect the accuracy of pedestrian navigation (Angermann et al., 2010). To minimize these effects, participants were instructed to accelerate quickly and maintain a constant speed while running through the calibrated 3D camera space. The participants were also asked to run and initiate ground contact as they would do normally during a continuous overground run. Although a simple threshold-based stance detection procedure was
able to correctly identify all strides recorded by the camera, an additional correction mechanism was added to the sensor-based algorithm (i.e. the condition that a stride length vector must exceed 0.75m in order for a new ZUPT to be applied) in order to avoid stance insertion errors.

4.7 Conclusion and Future Work

For research purposes in biomechanics, stride length has been hard to measure using inertial sensors in field conditions. This study has demonstrated that individual stride length vectors can accurately be determined with a single foot-mounted sensor during distance running. The presented method has great potential for high-precision, real-time monitoring of stride length and other spatial gait variables during continuous running and provides researchers with the opportunity to apply more complex time series analyses, such as DFA, to parameters that have thus far been hard to study in an unconstrained overground running scenario. The studies presented in Sections 5 and 6 expand upon the results of this experiment by tracking stride length, its variability and LRCs during continuous overground running. The results of this study are also highly relevant for distance runners, coaches and clinicians who are interested in tracking stride length for the purpose of optimizing performance and exploring factors related to running injuries. The method proposed in this paper offers a highly accurate and cost-effective alternative to existing biomechanical tools that require a complex setup and are restricted to laboratory settings.
5 Study 2: Stride Mechanics and Variability over a Prolonged Run in
Recreational and Elite Distance Runners

It is well established that fatigue has profound effects on running mechanics (Chan-Roper et al., 2012; Derrick et al., 2002; Dutto & Smith, 2002; Elliott & Ackland, 1981). Traditionally, these effects have been assessed by tracking the mean values, as well as the standard deviation and coefficient of variation of certain biomechanical variables over time (Derrick et al., 2002; Dutto & Smith, 2002; Owings & Grabiner, 2003, 2004; Queen, Gross, & Liu, 2006). Some researchers, however, have argued that these measures only represent one dimension of fatigue and are insensitive to subtle changes that arise within the neuromuscular system (Hausdorff, 2005; Jordan et al., 2006; Meardon et al., 2011).

Studies have shown that under normal conditions healthy individuals exhibit very stable movement patterns during walking and running (Terrier, 2003). However, like any other physiological variable the basic gait parameters change from one stride to the next, even when external conditions are controlled (Hausdorff, 2005, 2007; Jordan et al., 2006, 2007a). Rather than occurring randomly, the observed fluctuations exhibit varying degrees of temporal stability and show characteristics of self-similarity. While there is evidence to suggest that a certain amount of fluctuation is indicative of a high degree of motor control and adaptability (Hausdorff, 2005, 2007; Meardon et al., 2011), abnormal values have been associated with aging and certain disease states (Hausdorff, 2007).

The characteristics of these patterned fluctuations can be assessed by calculating what is known as the fractal scaling index (FSI) for a given physiological time-series, such as gait data derived from a series of strides. The mathematical procedure which is used to calculate the FSI is called detrended fluctuation analysis (DFA). The DFA yields a scaling exponent $\alpha$, which represents the degree to which stride-to-stride fluctuations exhibit characteristics of both noise and meaningful
non-random temporal patterns. With respect to walking and running, $\alpha$ signifies the degree to which one particular stride in an existing data set is correlated with strides that occur at a considerable temporal distance. Although these so-called long-range correlations (LRCs) are most commonly assessed using the stride time interval (Hausdorff et al., 1995; Jordan et al., 2006), they have also been found to exist in other gait variables, such as stride length and certain variables of impact loading (Jordan et al., 2007b).

While most studies have looked at LRCs during level walking, only a small number of studies have focused on nonlinear fluctuations during distance running. For example, Jordan et al. (2006, 2007a, 2007b), who investigated LRCs during treadmill running, reported that the value of $\alpha$ was speed-dependent and followed a U-shaped distribution, with the weakest LRCs occurring at preferred running speeds. A study conducted by Nakayama et al. (2010), which investigated the effects of skill level on LRCs, showed that trained runners exhibited significantly lower values of $\alpha$ compared to untrained individuals during a treadmill run over a range of typical distance running speeds. However, these findings may not be valid for overground running and there is a scarcity of research that has investigated changes in stride pattern variability and LRCs due to fatigue during unconstrained overground running. Meardon et al. (2011) tracked LRCs and linear measures of gait variability in a group of healthy and previously injured runners using a body-fixed inertial sensor and found that for both groups $\alpha$ significantly decreased over time, while linear measures of variability remained unaffected. It was concluded that stride time becomes less predictable over the course of a fatiguing overground run. The authors further reported that injured runners exhibited lower values of $\alpha$ compared to their healthy counterparts. However, the effects of fatigue on LRCs during exhaustive running have not yet been confirmed.

Based on these results, the purpose of the present study was twofold. The first
objective was to investigate changes in the variability and LRCs of various spatiotemporal gait parameters during a prolonged run by using a single, foot-mounted IMU. Since it has been reported that fatigue affects elite distance runners and recreational runners differently (Bertram et al., 2013), a second objective was to determine the extent to which skill level had an effect on running kinematics, including the coefficient of variation of different stride parameters as well as LRCs of the stride pattern.

It was hypothesized that a significant reduction in the strength of the LRCs (as indicated by $\alpha$) would occur over the course of the run. In contrast, it was expected that no significant changes would occur in the mean values of selected stride parameters and linear measures of variability, i.e. coefficient of variation. It was also expected that elite distance runners would maintain more stable levels of $\alpha$ during the run than recreational runners.

5.1 Research Design

The proposed study employed a two-way repeated-measures design, with skill level (elite vs. recreational) as between-subject factor and run duration (normalized and subdivided into three categories) as the within-subject factor. The sample involved a group of elite distance runners as well as a group of individuals that had never undergone training specific to distance running.

Both groups participated in the same experimental protocol, i.e. a prolonged overground running trial to fatigue, performed at an individual running speed. Like any prolonged activity, continuous running depends on the generation of tension in the active muscles. However, when metabolic and mechanical demands surpass a muscle’s work capacity, a decrease in performance will occur. Reduced exercise intensity, e.g. slower running speed, is an expected result of fatigue, which can be assessed with simple tools (Bertram et al., 2013). Given the lack of existing
methods to directly measure neuromuscular aspects of fatigue during unconstrained overground running, this study employed a model of voluntary exhaustion to signify fatigue. More specifically, fatigue was defined as the inability to maintain a previously established running speed.

Elite distance runners \( n = 16 \) were recruited from the University of Regina Cougars Track and Field and Cross-Country teams. All subjects in this group were required to have performed regular distance running between 4 and 7 days per week for more than 2 years and must have competed at a provincial or intercollegiate level within the preceding year. Furthermore, a personal best time of 21:30 min (women) and 17:30 min (men) for the 5000 m was required in order to be classified as an elite distance runner. These times were established in accordance with the team requirements for the university track and field team. Exclusion criteria for this group included a race time for the 5000 m above the specified threshold; any history of lower-extremity surgery in the past 24 months; any history of running-related injuries that caused discontinuation of running for more than 7 days; any other neuromuscular or cardiovascular pathology; or any other medical condition that could potentially be worsened by prolonged running.

The group of recreational runners \( n = 16 \) consisted of young, healthy adults. These participants were not allowed to have had any training specific to competitive distance running. However, recreational running for a time of up to 3 hours per week was allowed. Furthermore, in order to be included in this group, individuals had to possess the ability to run at a comfortable pace for a minimum of 15 minutes. The health-related exclusion criteria were identical to those of the elite distance running group. Prior to enrollment, all participants signed a consent form that had previously been approved by the University of Regina Ethics Board.

Since the effort required to maintain a specific speed differs between individuals, the running speed for each participant was normalized and defined
relative to an individual marker of performance. Therefore, participants were asked to complete the fatiguing run at their current 5000 m race pace. This value had been estimated based on the desired range of distances to be covered during the prolonged run as well as on the minimum number of strides necessary to perform calculations required for the DFA (> 1200). In order to determine the individual running speeds, recreational runners completed a 5000 m all-out run at least 5 days prior to performing the actual experimental protocol. The elite distance runners completed a 5000 m time trial as part of their training in the past month and did not have to undergo the testing protocol prior to the prolonged run. For these individuals running velocity corresponded to their self-reported 5000 m race pace.

5.2 Instrumentation and Test Procedures

This study employed the sensor configuration and attachment protocol described in Section 4.2. The system used in this study has a reported wireless transmission range of approximately 50 m in an unobstructed indoor setting. Given the dimensions of the indoor track, it was estimated that this range would be sufficient to ensure the recording of inertial data at every point around the track. This assumption was confirmed after conducting several test runs with the IMU around the track before the beginning of the data collection process. Figure 12 demonstrates the equipment setup that produced the most stable results during the test runs.

Since LRCs have been shown to change as a function of running speed (Jordan et al., 2007a), the pace of each runner was tracked during the experiment. For this purpose, participants were equipped with a wrist-worn running computer, a heart rate sensor, which was strapped around their chest, and an associated footpod, which was attached to their left foot (RS300X, Polar, Kempele, Finland). This system continuously monitored heart rate, speed and distance covered and triggered
an audible alarm once a participant left the tolerable speed range (± 5% of designated running speed). It was previously used to control for speed in a similar study (Meardon et al., 2011) and was shown to yield valid and reliable data (Hausswirth, 2009).

Calibration of the running computer and the associated foot pod was performed according to the instructions of the manufacturer. This required the participants to run a certain predefined distance at a self-selected running speed. After standing still for several seconds, participants started the calibration procedure by pushing the start/stop button on the wrist-worn running computer and initiated the run with their left leg, i.e. the side to which the commercial footpod was attached. For the calibration, participants ran for a distance of 1100 m on the outermost lane of the indoor track. Since one lap around this lane of the
track equaled 218 m, the participants needed to complete five full laps and an additional distance of 10 m. The researcher stood next to the track and indicated the point at which the runners had to come to a full stop after the required distance was covered. After completing the run, the participants had to stand still and wait for 15 seconds, so the data could be transmitted from the footpod to the wrist-worn computer. The calibration run also served as a warm up for the experimental protocol. However, if participants indicated that they wanted to perform additional warm-up activities, they were given the opportunity to do so, provided that these activities were non-fatiguing. During the run, the quality of the wireless connection between the foot-mounted IMU and the dock station over the range of the indoor track as well as the characteristics of the inertial signal were monitored. If abnormalities were detected, the position of the sensor on the foot was improved and the radio channel was changed.

Following the warm up, the researcher reset the running computer and started recording the inertial signals from the wireless foot-mounted IMU. Subsequently, participants positioned themselves at the starting line on the outermost lane of the indoor track in preparation for the fatiguing run. After counting down, the researcher and the participant simultaneously started to time the run, on a stop watch and the running computer respectively. The participants then initiated the run on their left leg and ran around the track in a counterclockwise direction until they felt they could no longer maintain the predetermined speed. This was indicated by repeatedly hearing the audible alarm of the running computer.

5.3 Data Analysis

Before conducting any further analysis, the raw data collected by the foot-mounted IMU was pre-processed and reduced. The first minute of every run was excluded to remove potential inconsistencies in the signal that may have
occurred due to an irregular running pace before the participants found their predetermined running speed. Furthermore, a custom-written MATLAB program was used to assess the periodicity of the inertial signals. Aperiodic or weak periodic sections that may have occurred due to weak signal reception or aberrant movements were excluded from the analysis. After the preprocessing procedures, custom programs written in MATLAB (v. R2012a, The MathWorks, Natick, MA) were used to process and analyze the raw data collected with the foot-mounted IMU.

The following dependent variables were calculated from the raw data using MATLAB scripts:

1. **Stride time (ST)** was defined as the interval between two subsequent footfalls of the same foot. The stance identification was based on the resultant acceleration signal. Individual stride times were found by subtracting the absolute time of subsequent strides (see Figure 13).

2. **Contact time** ($t_c$) was defined as the time between initial contact and toe off of one individual step. Contact time corresponds to the stance phase of the cycle. Previous studies have shown that a single foot-mounted sensor is able to identify these events accurately over a wide range of running speeds (10 - 19 km/h) and that high levels of agreement (95%) exist between stance time as assessed by inertial sensing, infrared motion capture and force plate data (J. B. Lee et al., 2010). In accordance with previous research, the events of initial contact and toe off were determined from the resultant acceleration signal, using a method that combined peak extraction and thresholding. In particular, large positive peaks in the acceleration profile indicate initial contact, while a smaller peak immediately after a short stationary period signifies the end of the stance phase (J. B. Lee et al., 2010). Figure 13 shows the events of initial contact and toe-off.
3. **Stride length (SL)** was also estimated based on a pedestrian dead-reckoning approach with ZUPTs applied during each stance phase. For more details regarding instrumentation and data analysis see Section 4.3.

4. **Peak impact acceleration (PIA)** as defined by the magnitude of the local maximum occurring during early stance was calculated from the resultant acceleration signal (see Figure 13).

![Figure 13](image)

*Figure 13.* Stride time, contact time and peak impact acceleration calculated from the resultant acceleration signal recorded by the foot-mounted IMU.

The duration of the run (i.e. total run time) for each participant was normalized from 0% to 100% and divided into three intervals (beginning = 0-33%, middle = 34-66%, and end = 67-100%) of equal length. Mean, coefficient of variation and LRCs represented by the fractal scaling index ($\alpha$) of the dependent variables were calculated for each subject and interval respectively. To investigate the effects of skill level, group averages for elite and recreational runners were calculated from the individual subject values.
The coefficient of variation was calculated as described in Section 2.7.1 to assess the magnitude of variability in the kinematic parameters of interest. LRCs in the stride parameters were calculated using detrended fluctuation analysis. As stated previously, DFA maps the self-similarity of fluctuations in a time-series signal. Different methods exist that vary with respect to the box windows used in the calculation of the scaling exponent $\alpha$.

Hausdorff et al. (1995) stated that the first step of the DFA procedure consists of integration of the time series ($N$ data points). This is shown by Equation 6:

$$y(k) = \sum_{i=1}^{k}[S(i) - S_{ave}]$$

Equation 6

where $S(i)$ is the $i$th sample of the time series and $S_{ave}$ is the average value of the time series. After the integration process, the obtained data were divided into box-sizes of length ($n$). Next, a trend line was applied to each individual box using the least squares method. The next step was to detrend the data series by subtracting the $y$-coordinate $y_n(k)$ of the data in each box from the integrated time series $y(k)$. The average fluctuation $F(n)$, which is a function of the box size, was calculated using Equation 7:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_n(k)]^2}$$

Equation 7

Subsequently, the calculation in Equation 7 was repeated for different box sizes ranging from 4 to $N/4$, where $N$ is the number of collected strides. This step was done to establish a relationship between $F(n)$ and $n$. The observed power law indicates the presence of scaling as seen in a linear regression between $F(n)$ and $n$ on a double-log graph. The slope of this line, relating log $F(n)$ to log $n$ on the double-log graph, was expressed as the scaling exponent $\alpha$.

Additionally, each runner’s maximal heart rate was estimated using the
nonlinear method known as the Tanaka formula (Tanaka, Kevin, & Douglas, 2001):

\[ HR_{\text{max}} = 208 - (0.7 \times \text{age}) \] (8)

The heart rate of each participant was collected continuously during the run. Average heart rates for each interval were calculated as a percentage of \( HR_{\text{max}} \). This was done in order to track the individual level of exertion during cardiovascular performance.

5.4 Statistical Analysis

The study had two main objectives. First, it was designed to investigate the effects of a prolonged overground run to fatigue on kinematic stride parameters and different measures of variability using a single foot-mounted IMU. The second objective was to determine whether fatigue affected the stride kinematics of elite distance runners and recreational runners to the same degree or if differences existed in the onset and time-course of fatigue as indicated by the dependent variables. Consequently, the two independent variables specified in this study were group (elite vs. recreational) and run duration interval (Beginning = 0 - 33% vs. Middle = 34 - 66% vs. End = 67 - 100%).

Independent sample t-tests were performed on each of the following subject characteristics: age (years), body mass (kg), training volume (hours) and height (cm). Additional independent sample t-tests were conducted to check for group differences regarding the characteristics of the prolonged run: average running speed (m/s), average heart rate during the run (% of max. HR), distance covered (km), run duration (minutes), as well as rate of perceived exertion (RPE) immediately after completion of the run. Before the independent t-tests, all data sets were assessed for normality and log-transformed if necessary. Homoscedasticity was assessed using Levene’s test for equality of variances.
A two-way repeated measures (mixed) ANOVA was conducted for each of the dependent variables (mean stride time, mean stride length, mean contact time, mean impact acceleration, CV stride time, CV stride length, CV contact time, CV impact acceleration, \( \alpha \) stride time, \( \alpha \) stride length, \( \alpha \) contact time, \( \alpha \) impact acceleration) to examine the effect of the within-subject independent variable (run duration [3 levels]) and the between-subject independent variable (group [2 levels]). In addition to examining the main effects for both skill level and run duration, this analysis also provided information about potential interaction effects. Before conducting the main analysis, all data sets were assessed for normality using the Shapiro-Wilks test. Non-normally distributed data were log transformed before conducting any further analysis. Sphericity was assessed using Mauchly’s test. In case the assumption of sphericity was violated, the procedure described by Girden (1992) was applied, who recommended applying the Huynh-Feldt correction in case \( \varepsilon > 0.75 \) and the more conservative Greenhouse-Geisser correction for situations where \( \varepsilon < 0.75 \).

If the ANOVA revealed a significant main effect for group on any of the dependent variables, no post-hoc test needed to be conducted. However, if a significant main effect was found for run duration, a post-hoc Bonferroni correction (\( p = 0.05 \)) was used to identify which intervals of the run (beginning, middle or end) were significantly different from each other.

5.5 Results

The average age of the elite runners (21.2 years) was significantly different (\( p < 0.001 \)) from that of the recreational group (26.8 years). The reported training volume, expressed in hours spent running per week, for the group of elite runners (9.31 hrs) was significantly higher (\( p < 0.001 \)) than for recreational runners (2.34 hrs). Mean body mass for the group of elite runners (63.4 kg) was also significantly lower (\( p = 0.028 \)) than that of the recreational runners (71.6 kg). Height was not
Table 3
*Subject characteristics of the different groups (Elite vs. Recreational).*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>21.19 (± 2.99)</td>
<td>26.81 (± 4.82)</td>
<td>0.001*</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>175.56 (± 8.70)</td>
<td>174.45 (± 7.44)</td>
<td>0.697</td>
</tr>
<tr>
<td>Bodymass (kg)</td>
<td>63.42 (± 9.51)</td>
<td>71.59 (± 10.49)</td>
<td>0.028*</td>
</tr>
<tr>
<td>Training Volume (hours)</td>
<td>9.31 (± 2.190)</td>
<td>2.34 (± 0.84)</td>
<td>&lt; 0.001*</td>
</tr>
</tbody>
</table>

* Indicates significant difference between groups (p ≤ 0.05)

significantly different between groups. Subject characteristics are summarized in Table 3.

The elite runners completed the experiment at a significantly greater average running speed (4.45 m/s) than the recreational runners (3.54 m/s). The duration of the run was also significantly different, with elite runners and recreational runners stopping after an average time of 19.8 minutes and 26.2 minutes respectively. There were no significant group differences with respect to the distance covered, average heart rate during the run (expressed as percentage of the estimated maximal heart rate), or rate of perceived exertion, as indicated on the Borg scale. Table 4 summarizes the descriptive characteristics of the fatiguing run for both groups.

Mean SL during the beginning, the middle part, as well as the end was 3.01 m, 3.01 m and 3.01 m respectively for the group of elite distance runners, while the mean values for the recreational group were 2.46 m, 2.46 m and 2.46 m respectively. A two-way repeated measures ANOVA revealed a significant main effect for group F(1, 30) = 17.499, p < 0.001, η² = 0.368 on mean stride length. In contrast, neither the main effect for run duration F(1.472, 44.169) = 0.048, p = 0.908, η² = 0.002 nor the interaction effect of group × run duration F(1.472, 44.169) = 0.106, p = 0.839, η² = 0.004 reached statistical significance. Figure 14 shows the mean stride length for both the elite and recreational runners as a function of run duration.

Mean ST during the beginning, middle and the end of the run was 698 ms,
Figure 14. Mean stride length as a function of run duration. ■ = mean SL significantly different (p < 0.001) between groups.

Figure 15. Mean stride time as a function of run duration.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Running Speed (m/s)</td>
<td>4.45 (± 0.39)</td>
<td>3.54 (± 0.51)</td>
<td>&lt; 0.001*</td>
</tr>
<tr>
<td>Run Duration (min)</td>
<td>19.83 (± 3.35)</td>
<td>26.18 (± 6.28)</td>
<td>0.002*</td>
</tr>
<tr>
<td>Run Distance (km)</td>
<td>4.80 (± 1.46)</td>
<td>5.38 (± 1.02)</td>
<td>0.204</td>
</tr>
<tr>
<td>% of HR&lt;sub&gt;max&lt;/sub&gt;</td>
<td>90.93 (± 3.32)</td>
<td>92.33 (± 5.17)</td>
<td>0.383</td>
</tr>
<tr>
<td>RPE (Borg Scale)</td>
<td>15.77 (± 1.09)</td>
<td>16.36 (± 1.36)</td>
<td>0.248</td>
</tr>
</tbody>
</table>

* Indicates significant difference between groups (p ≤ 0.05)

696 ms and 695 ms respectively for the group of elite distance runners, while the mean values for the recreational group were 710 ms, 711 ms and 708 ms respectively. A two-way repeated measures ANOVA did not reveal any significant main effect for group F(1, 30) = 0.840, p = 0.367, η² = 0.027 or run duration F(1.288, 38.640) = 1.710, p = 0.200, η² = 0.054. The interaction effect of group × run duration F(1.288, 38.640) = 0.355, p = 0.610, η² = 0.012 did not reach statistical significance. Figure 15 shows the mean stride time for both the elite and recreational runners as a function of run duration.

Mean t<sub>c</sub> for the three run intervals were 147 ms (beginning), 148 ms (middle) and 148 ms (end) for the group of elite distance runners. In contrast, the mean t<sub>c</sub> for the recreational group was 171 ms, 172 ms and 173 ms respectively. A two-way repeated measures ANOVA revealed a significant main effect for group F(1, 30) = 31.504, p < 0.001, η² = 0.512 as well as for run duration F(1.356, 40.670) = 4.589, p = 0.028, η² = 0.133 on the measure of mean t<sub>c</sub>. The interaction effect of group × run duration F(1.356, 40.670) = 0.029, p = 0.924, η² = 0.001 was not statistically significant. Bonferroni adjusted pair-wise comparisons revealed that mean t<sub>c</sub> differed significantly between the beginning and the middle of the run (p = 0.041). However, there was no significant change between any of the other sections. Figure 16 shows the mean t<sub>c</sub> for both the elite and recreational runners as a function of run duration.
Figure 16. Mean $t_c$ as a function of run duration. ■ = mean $t_c$ significant difference ($p < 0.001$) between groups, * = significant difference ($p = 0.041$) between beginning and middle of the run.

Mean PIA during the beginning, middle and the end of the run were 197 m/s$^2$, 201 m/s$^2$ and 204 m/s$^2$ respectively for the group of elite distance runners, while the mean impact acceleration values for the recreational group were 158 m/s$^2$, 160 m/s$^2$ and 161 m/s$^2$ respectively. A two-way repeated measures ANOVA revealed a significant main effect for group $F(1, 30) = 16.063$, $p < 0.001$, $\eta^2 = 0.349$. There was also a significant main effect for run duration $F(1.297, 38.905) = 8.916$, $p = 0.003$, $\eta^2 = 0.229$. In contrast, the interaction effect for group $\times$ run duration did not reach statistical significance $F(1.297, 38.905) = 1.481$, $p = 0.237$, $\eta^2 = 0.047$. Bonferroni adjusted pair-wise comparisons showed that the beginning differed significantly from the middle ($p = 0.045$) and the end ($p = 0.009$) of the run. Additionally, the difference between the middle and the end was statistically significant ($p = 0.031$). Figure 17 shows the mean resultant impact acceleration of
Figure 17. Mean PIA as a function of run duration. ■ = significant difference (p < 0.001) between groups. * = significant difference (p = 0.045) between the beginning and middle of the run, ** = significant difference (p = 0.009) between the beginning and end of the run, *** = significant difference (p = 0.031) between the middle and end of the run.

The stride length CV for the beginning, middle and end section was 4.34%, 4.30% and 4.78% respectively for the group of elite distance runners. The mean CV values for the recreational group were 4.05%, 3.80% and 3.98% respectively. A two-way repeated measures ANOVA showed that there were no significant main effects for run duration F(1.293, 38.783) = 1.218, p = 0.290, \( \eta^2 = 0.039 \) or for group F(1, 30) = 1.860, p = 0.183, \( \eta^2 = 0.058 \). No significant interaction effect for group \( \times \) run duration F(1.293, 38.783) = 0.708, p = 0.440, \( \eta^2 = 0.023 \) was found. Figure 18 shows the mean coefficients of variation for stride length for both the elite and

the foot during initial stance for both the elite and recreational runners as a function of run duration. Table 5 summarizes the descriptive statistics for the mean values of the analyzed gait parameters.
Table 5
Mean values (± SD) of selected stride parameters during the prolonged run.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>Total (± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stride time (ms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>698 (± 46)</td>
<td>710 (± 40)</td>
<td>704 (± 42)</td>
</tr>
<tr>
<td>Middle</td>
<td>696 (± 46)</td>
<td>711 (± 38)</td>
<td>703 (± 42)</td>
</tr>
<tr>
<td>End</td>
<td>695 (± 45)</td>
<td>708 (± 39)</td>
<td>701 (± 42)</td>
</tr>
<tr>
<td>Stride length (m)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>3.01 (± 0.39)</td>
<td>2.46 (± 0.34)</td>
<td>2.74 (± 0.34)</td>
</tr>
<tr>
<td>Middle</td>
<td>3.01 (± 0.43)</td>
<td>2.46 (± 0.33)</td>
<td>2.74 (± 0.47)</td>
</tr>
<tr>
<td>End</td>
<td>3.01 (± 0.42)</td>
<td>2.46 (± 0.31)</td>
<td>2.74 (± 0.46)</td>
</tr>
<tr>
<td>Contact time (ms)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>147 (± 8)</td>
<td>171 (± 16)</td>
<td>159 (± 18)</td>
</tr>
<tr>
<td>Middle</td>
<td>148 (± 8)</td>
<td>172 (± 15)</td>
<td>160 (± 17)</td>
</tr>
<tr>
<td>End</td>
<td>148 (± 8)</td>
<td>173 (± 16)</td>
<td>160 (± 18)</td>
</tr>
<tr>
<td>Peak impact acc. (m/s²)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>197.36 (± 20.30)</td>
<td>158.07 (± 38.39)</td>
<td>177.72 (± 36.21)</td>
</tr>
<tr>
<td>Middle</td>
<td>200.91 (± 19.37)</td>
<td>159.62 (± 36.42)</td>
<td>180.27 (± 35.54)</td>
</tr>
<tr>
<td>End</td>
<td>203.91 (± 18.77)</td>
<td>160.82 (± 34.87)</td>
<td>182.36 (± 35.18)</td>
</tr>
</tbody>
</table>

*Figure 18.* Coefficients of variation for SL as a function of run duration.
The stride time CV for the beginning, middle and end section was 1.32%, 1.30% and 1.36% respectively for the group of elite distance runners, while the mean CV values for the recreational group were 1.59%, 1.57% and 1.59% respectively. A two-way repeated measures ANOVA did not find a significant main effect for run duration $F(2, 60) = 0.855, p = 0.430, \eta^2 = 0.028$. However, there was a significant main effect for group $F(1, 30) = 8.499, p = 0.007, \eta^2 = 0.221$. The interaction effect for group $\times$ run duration $F(2, 60) = 0.197, p = 0.797, \eta^2 = 0.007$ did not reach statistical significance. Figure 19 shows the mean coefficients of variation for stride time for both the elite and recreational runners as a function of running time.

The contact time CV for the beginning, middle and end section was 4.06%, 3.96% and 4.05% respectively for the group of elite distance runners, while the CV values for the recreational group were 4.46%, 4.33% and 4.45% respectively. A
Figure 20. Coefficients of variation for $t_c$ as a function of run duration.

Figure 21. Coefficients of variation for PIA as a function of run duration.
two-way repeated measures ANOVA did not reveal a significant main effect for run duration $F(1.449, 43.459) = 1.945, p = 0.165, \eta^2 = 0.061$ or group $F(1, 30) = 1.681, p = 0.205, \eta^2 = 0.053$. There was no interaction effect $F(1.449, 43.459) = 0.031, p = 0.931, \eta^2 = 0.001$. Figure 20 shows the mean coefficients of variation for contact time for both the elite and recreational runners as a function of running time.

The peak impact acceleration CV for the beginning, middle and the end sections was 14.88%, 15.05% and 15.17% respectively for the group of elite distance runners, while the corresponding mean CV values for the recreational group were 15.98%, 15.81% and 15.87%. No significant main effects were found for run duration $F(1.350, 40.496) = 0.126, p = 0.799, \eta^2 = 0.004$ or group $F(1, 30) = 0.977, p = 0.331, \eta^2 = 0.032$. There was no significant interaction effect $F(1.350, 40.496) = 0.616, p = 0.484, \eta^2 = 0.020$. Figure 21 shows the mean coefficients of variation for peak impact acceleration for both the elite and recreational runners as a function of run duration. Table 6 summarizes the descriptive statistics for the coefficients of variation of the analyzed gait parameters.

Mean $\alpha$ values for stride length were 0.89 (beginning), 0.74 (middle) and 0.77 (end) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.91, 0.81 and 0.77 respectively. A two-way repeated measures ANOVA revealed a significant main effect for run duration $F(2, 60) = 21.512, p < 0.001, \eta^2 = 0.418$. In contrast, the main effect for group $F(1, 30) = 1.009, p = 0.323, \eta^2 = 0.033$ as well as the interaction effect for group $\times$ run duration $F(2, 60) = 1.408, p = 0.252, \eta^2 = 0.045$ did not reach statistical significance. Pairwise comparisons with Bonferroni adjustments revealed that the $\alpha$ of stride length differed significantly between the beginning and the middle of the run ($p < 0.001$) as well as between the beginning and the end of the run ($p < 0.001$). However, there was no significant change between the middle and end of the run. Figure 22 shows the mean $\alpha$ values for stride length for both the elite and
Table 6
Coefficients of variation of selected stride parameters (± SD) during the prolonged run.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>Total (± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CV Stride time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>1.32 (± 0.18)</td>
<td>1.59 (± 0.31)</td>
<td>1.45 (± 0.29)</td>
</tr>
<tr>
<td>Middle</td>
<td>1.30 (± 0.13)</td>
<td>1.57 (± 0.34)</td>
<td>1.43 (± 0.29)</td>
</tr>
<tr>
<td>End</td>
<td>1.36 (± 0.19)</td>
<td>1.59 (± 0.38)</td>
<td>1.47 (± 0.32)</td>
</tr>
<tr>
<td>CV Stride length</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>4.34 (± 1.32)</td>
<td>4.05 (± 1.58)</td>
<td>4.20 (± 1.44)</td>
</tr>
<tr>
<td>Middle</td>
<td>4.30 (± 1.17)</td>
<td>3.80 (± 1.18)</td>
<td>4.05 (± 1.18)</td>
</tr>
<tr>
<td>End</td>
<td>4.78 (± 1.35)</td>
<td>3.98 (± 1.16)</td>
<td>4.38 (± 1.30)</td>
</tr>
<tr>
<td>CV Contact time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>4.06 (± 0.54)</td>
<td>4.46 (± 1.07)</td>
<td>4.26 (± 0.86)</td>
</tr>
<tr>
<td>Middle</td>
<td>3.96 (± 0.53)</td>
<td>4.34 (± 1.06)</td>
<td>4.14 (± 0.84)</td>
</tr>
<tr>
<td>End</td>
<td>4.05 (± 0.57)</td>
<td>4.46 (± 1.27)</td>
<td>4.25 (± 0.99)</td>
</tr>
<tr>
<td>CV peak impact acc.</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>15.87 (± 2.42)</td>
<td>15.98 (± 2.65)</td>
<td>15.43 (± 2.56)</td>
</tr>
<tr>
<td>Middle</td>
<td>15.05 (± 2.45)</td>
<td>15.80 (± 2.80)</td>
<td>15.43 (± 2.61)</td>
</tr>
<tr>
<td>End</td>
<td>15.17 (± 2.16)</td>
<td>15.87 (± 2.65)</td>
<td>15.52 (± 2.41)</td>
</tr>
</tbody>
</table>

Figure 22. FSI $\alpha$ for SL as a function of run duration. * = significant difference (p < 0.001) between the beginning and middle of the run, ** = significant difference (p < 0.001) between the beginning and end of the run.
Figure 23. FSI $\alpha$ for ST as a function of run duration. * = significant difference ($p < 0.001$) between the beginning and middle of the run, ** = significant difference ($p < 0.001$) between the beginning and end of the run.

Mean $\alpha$ values for stride time were 0.86 (beginning), 0.74 (middle) and 0.75 (end) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.84, 0.71 and 0.73 respectively. A two-way repeated measures ANOVA revealed a significant main effect for run duration $F(2, 60) = 28.536, p < 0.001, \eta^2 = 0.487$ but not for group $F(1, 30) = 0.358, p = 0.554, \eta^2 = 0.012$. There was no significant interaction effect for group $\times$ run duration $F(2, 60) = 0.075, p = 0.928, \eta^2 = 0.002$. Pairwise comparisons with Bonferroni adjustments revealed that $\alpha$ stride time differed significantly between the beginning and the middle of the run ($p < 0.001$) as well as between the beginning and the end of the run ($p < 0.001$). However, there was no significant change between the middle and end of the run. Figure 23 shows the mean $\alpha$ values for stride time for both the elite and recreational runners as a function of run duration.
Mean ($\alpha$) values for peak impact acceleration were 0.59 (beginning), 0.52 (middle) and 0.52 (end) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.64, 0.58 and 0.58 respectively. A two-way repeated measures ANOVA revealed a significant main effect for run duration $F(1.823, 54.292) = 17.099$, $p < 0.001$, $\eta^2 = 0.363$ as well as for group $F(1, 30) = 11.364$, $p = 0.002$, $\eta^2 = 0.275$. There was no significant interaction effect for group $\times$ run duration $F(1.823, 54.292) = 0.232$, $p = 0.774$, $\eta^2 = 0.008$. Pairwise comparisons with Bonferroni adjustments revealed that the $\alpha$ of peak impact acceleration differed significantly between the beginning and middle of the run ($p < 0.001$) as well as between the beginning and end of the run ($p < 0.001$). However, there was no significant change between the middle and end of the run. Figure 24 shows the mean $\alpha$ values for peak impact acceleration for both the elite and
recreational runners as a function of run duration. Table 7 summarizes the $\alpha$ values observed over the course of the run.

Figure 25. FSI $\alpha$ for $t_c$ as a function of run duration. * = significant difference ($p = 0.003$) between the beginning and middle of the run.

Mean ($\alpha$) values for contact time were 0.67 (beginning), 0.61 (middle) and 0.62 (end) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.69, 0.63 and 0.66 respectively. A two-way repeated measures ANOVA revealed a significant main effect for run duration $F(2, 60) = 6.449$, $p = 0.003$, $\eta^2 = 0.177$ but not for group $F(1, 30) = 1.736$, $p = 0.198$, $\eta^2 = 0.055$. There was no significant interaction effect for group $\times$ run duration $F(2, 60) = 0.048$, $p = 0.953$, $\eta^2 = 0.002$. Pairwise comparisons with Bonferroni adjustments revealed that the $\alpha$ of contact time differed significantly between the beginning and the middle of the run ($p = 0.003$). However, there was no significant difference between any of the other run intervals. Figure 25 shows the mean $\alpha$ values for contact time for both the elite and recreational runners as a function of run duration.
Table 7
α (± SD) of selected stride parameters during the prolonged run.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>Total (± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>α stride time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>0.86 (± 0.09)</td>
<td>0.84 (± 0.11)</td>
<td>0.85 (± 0.10)</td>
</tr>
<tr>
<td>Middle</td>
<td>0.74 (± 0.11)</td>
<td>0.71 (± 0.14)</td>
<td>0.73 (± 0.12)</td>
</tr>
<tr>
<td>End</td>
<td>0.75 (± 0.12)</td>
<td>0.73 (± 0.14)</td>
<td>0.74 (± 0.13)</td>
</tr>
<tr>
<td>α stride length</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>0.89 (± 0.15)</td>
<td>0.91 (± 0.14)</td>
<td>0.90 (± 0.14)</td>
</tr>
<tr>
<td>Middle</td>
<td>0.74 (± 0.12)</td>
<td>0.81 (± 0.10)</td>
<td>0.77 (± 0.12)</td>
</tr>
<tr>
<td>End</td>
<td>0.77 (± 0.08)</td>
<td>0.77 (± 0.13)</td>
<td>0.77 (± 0.11)</td>
</tr>
<tr>
<td>α contact time</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>0.67 (± 0.09)</td>
<td>0.69 (± 0.07)</td>
<td>0.68 (± 0.08)</td>
</tr>
<tr>
<td>Middle</td>
<td>0.61 (± 0.07)</td>
<td>0.63 (± 0.06)</td>
<td>0.62 (± 0.07)</td>
</tr>
<tr>
<td>End</td>
<td>0.62 (± 0.08)</td>
<td>0.66 (± 0.11)</td>
<td>0.64 (± 0.10)</td>
</tr>
<tr>
<td>α peak impact acceleration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Beginning</td>
<td>0.59 (± 0.08)</td>
<td>0.64 (± 0.09)</td>
<td>0.62 (± 0.09)</td>
</tr>
<tr>
<td>Middle</td>
<td>0.52 (± 0.05)</td>
<td>0.58 (± 0.08)</td>
<td>0.55 (± 0.07)</td>
</tr>
<tr>
<td>End</td>
<td>0.52 (± 0.04)</td>
<td>0.58 (± 0.05)</td>
<td>0.55 (± 0.05)</td>
</tr>
</tbody>
</table>

5.6 Discussion

The purpose of this study was to investigate the effects of a prolonged distance run on stride parameters and gait variability in recreational and elite distance runners using a single foot-mounted IMU. In particular, the means, coefficients of variation and α values of stride time, stride length, contact time as well as peak impact acceleration of the foot were calculated. It was hypothesized that α would decrease significantly over the course of the run while no significant changes were expected to be observed in the CV. It was further hypothesized that elite runners would exhibit less changes in LRCs than recreational runners.

Our results show that the mean values for stride length (p = 0.908) and stride time (p = 0.200) did not change significantly over time. Figure 26 shows a typical stride time series over the course of the experiment. This is in contrast to existing research that has reported changes in these parameters during prolonged treadmill...
and overground running (Bertram et al., 2013; Kyröläinen et al., 2000; Place et al., 2004). Studies involving overground running have often reported a decrease in running speed with progressive fatigue (Bertram et al., 2013; Nicol et al., 1991b). Since running speed is the product of both SL and SR, it seems likely that the changes reported in the literature are often a direct result of the fatigue-related decreases in running speed. Thus, it is likely that the constant levels of stride length and stride time that were observed in this experiment resulted from the fact that the participants were paced with a wearable running computer. This observation is also in accordance with Cavanagh and Williams (1982) and Mercer et al. (2002), who reported that runners choose a preferred combination of SR and SL for a given speed. Likewise, Meardon et al. (2011), who performed a similar experiment and measured average stride time over the course of a fatiguing run, did not find any
significant changes in stride time. Consequently, the present results support the notion that runners have a tendency to maintain a relatively constant SL/SR ratio during prolonged overground running, even under fatiguing conditions.

![Figure 27. Example of stride length series over the course of the run.](image)

In contrast to stride time and stride length, peak impact acceleration increased significantly over the course of the run ($p = 0.003$, $\eta^2 = 0.229$). These results are in accordance with other studies that have found impact acceleration to increase during exhaustive running (Clansey et al., 2012; Derrick et al., 2000; Mizrahi, Verbitsky, Isakov, & Daily, 2000; Verbitsky et al., 1998; A. S. Voloshin et al., 1998). It is likely that peak impact acceleration was influenced by the external constraints of the experiment, i.e. by having participants maintain their speed despite increasing levels of exertion. In this regard, Gates and Dingwell (2008) demonstrated that individuals experienced significantly greater peak forces during the late stages of a
repetitive movement task. Interestingly, the authors also noted that biomechanical changes only occurred in such a way that the goal-relevant features of the task, i.e. maintaining movement speed, were preserved. Since the primary goal of this experiment was to maintain running speed for as long as possible, the increase in peak impact acceleration could have resulted from limiting potential compensatory movement strategies that may otherwise occur naturally in response to fatigue, e.g. decreasing running speed. (Bertram et al., 2013; Kyröläinen et al., 2000).

Physiologically and mechanically, impact loading characteristics are known to be affected by altered stiffness regulation in the lower limb via changes in muscle preactivation levels, altered limb configuration at touchdown or a combination of these factors (Derrick et al., 2000, 1998). For example, Challis (2001) demonstrated that lower extremity geometry during initial contact influenced impact loading during running. This is also supported by McMahon et al. (1987), who found that greater knee flexion angles at impact are associated with reduced lower-extremity stiffness and increased shock attenuation. It is reasonable to assume that the observed increase in peak impact acceleration resulted from a combination of different fatigue-related mechanisms, which in turn were influenced by the external constraints of the experiment.

Runners also increased their contact time over the course of the run ($p = 0.028, \eta^2 = 0.133$). This is consistent with other research that reported a progressive increase of contact time with fatigue (Chan-Roper et al., 2012; Derrick et al., 2002; Elliott & Roberts, 1980). Longer contact time has been associated with the inability to effectively utilize elastic energy stored in the muscle-tendon apparatus (Komi, 2000). More specifically, neuromuscular fatigue increases $t_c$ via joint stiffness reduction (Mercer et al., 2002). Contact time has also repeatedly been linked to the energy cost of running (Chapman et al., 2012; Kram & Taylor, 1990; T. J. Roberts et al., 1998). Based on these studies, the increase in contact time may
indicate the tendency of the runners to expend more energy at the end of the run compared to the beginning.

![Figure 28](image)

**Figure 28.** Representative example of stride length series for elite and recreational runners.

There was a significant main effect for group with respect to mean stride length \((p < 0.001)\), mean contact time \((p < 0.001)\) as well as mean peak impact acceleration \((p < 0.001)\). The observed magnitudes of effect sizes were large, with \(\eta^2\) values ranging from 0.349 (peak impact acceleration) to 0.512 \((t_c)\). More specifically, the group of elite runners consistently produced longer stride lengths, shorter contact times as well as higher peak impact accelerations (see Table 5).

Most biomechanical variables in running change significantly as a function of running speed (Cavanagh & Kram, 1989; Luhtanen & Komi, 1978; Mero & Komi, 1985). In particular, Shorten and Winslow (1992) reported higher magnitudes of impact accelerations at greater running speeds. Moreover, Brughelli et al. (2011) observed decreases in stance or contact time \((t_c)\) at faster running speeds. As expected, there was a significant difference between groups with respect to running
speed \( (p < 0.001) \). On average, elite runners performed the experiment at a speed of 4.45 m/s compared to 3.54 m/s in the recreational group. Based on this evidence, it is reasonable to conclude that elite runners demonstrated greater peak impact acceleration, shorter contact times and greater stride lengths because they ran faster. Given the fact that elite runners had a significantly lower body mass than recreational runners, the observed difference in absolute peak impact acceleration becomes even more relevant. Figure 28 shows the stride length series of a recreational and an elite runner during the overground run.

The mean values of stride time (and consequently stride rate) did not exhibit a significant group effect \( (p = 0.367) \). This seemingly contradicts reports that faster running speeds are linked to increases in both stride length and stride rate. However, it must be considered that the main determinant of speed in the submaximal range \((3\text{-}7 \text{ m/s})\) is stride length (Luhtanen & Komi, 1978; Weyand et al., 2000). In contrast, stride time (and consequently stride rate) remains constant at typical distance running speeds and only increases when a runner approaches their maximal velocity (Bertram et al., 2013; Cavanagh & Kram, 1989; Mero & Komi, 1985; Weyand et al., 2000). Given the results of previous studies, the linear relationship between running speed and the two basic stride parameters SL and SR was analyzed using Pearson’s \( r \). As expected, very high correlations existed between mean SL and running speed for all run intervals \((\text{Beg} = 0.891, \text{Mid} = 0.883, \text{End} = 0.866)\), while SR was not significantly correlated with running speed \((\text{Beg} = 0.129, \text{Mid} = 0.133, \text{End} = 0.124)\). Figure 29a and 29b illustrate the average stride rate and stride length values of each participant as a function of running speed. In light of existing evidence, the present experiment demonstrates that faster runners achieved greater speeds by taking longer strides while exhibiting stride rates that are similar to those of the recreational runners. It is likely that the ability to run with a greater stride length results from the high volume of
Figure 29. Mean stride length (a) and stride rate (b) of each participant as a function of running speed.
specialized training that elite runners perform throughout their career.

In agreement with the hypothesis, run duration (i.e. time) did not have a significant effect on the CV for any of the analyzed stride parameters. This is consistent with results from Meardon et al. (2011), who reported that stride time variability did not increase during a prolonged overground run. Moreover, other studies have shown that movement patterns of young healthy adults exhibit a small degree of variability during walking and running. In contrast, the gait patterns of older adults or individuals that suffer from certain neurological disorders have been associated with greater amounts of variability (Auvinet et al., 1999; Moe-Nilssen & Helbostad, 2004). The presented findings support the hypothesis that linear measures of variability, such as the CV, are not sensitive to fatigue-related changes in the gait pattern.

![Figure 30](image-url)

*Figure 30.* Representative example of stride time series for elite and recreational runners.

Skill level did not have a significant effect on the CVs for stride length, contact time and peak impact acceleration. However, the CV for stride time did exhibit a
significantly large effect for group (p = 0.007, \( \eta^2 = 0.221 \)). More specifically, the stride time CV was significantly smaller for the elite runners than for the recreational runners. This is in accordance with reports from Nakayama et al. (2010) and Slawinski, Demarle, Koralsztein, and Billat (2001), who demonstrated significantly lower stride time variability in trained endurance athletes compared to untrained individuals. Figure 30 shows the different magnitudes of stride time variability in recreational and elite runners. As is evident from Table 4, the elite group spent an average of 9.31 hours per week running, compared to 2.43 hours in the recreational group. It is highly likely that the observed group differences are linked to the high volume of specialized training performed by the competitive runners. A large number of studies have demonstrated that movement patterns become more consistent as a result of extensive practice. For example, Button, Macleod, Sanders, and Coleman (2003) reported greater movement consistency of upper extremity motion in the basketball free throw with increasing skill level. Likewise, Darling and Cooke (1987), Fujii, Kudo, Ohtsuki, and Oda (2009), T. Lee, Swinnen, and Verschueren (1995) observed that trajectory variability, relative phase alterations, as well as the variability of tapping interval in drumming decreased significantly in response to extended practice.

Surprisingly, lower CV values for the elite group were only found in the stride time interval but not in any other stride parameters. One possible explanation is that stride rate is a critical determinant of energy expenditure during running and therefore has a particular functional relevance to running performance. For example, Cavanagh and Williams (1982) reported that the metabolic cost of running for a given running speed is minimized at a particular SR. In this sense, the larger CV observed in the recreational runners may indicate that these individuals deviated to a greater degree from the most economical SR and consequently ran less efficiently. In contrast, elite runners ran at a more steady pace (as indicated by a
lower CV), which minimized the metabolic cost of running and allowed them to perform at a greater relative intensity. Based on these observations and existing reports from the literature, it is highly likely that stride time CV is an important marker of skill level and running economy in running.

Although some researchers have assessed LRC for ST during running (Jordan et al., 2006; Meardon et al., 2011; Nakayama et al., 2010), the present experiment was the first to assess LRCs for SL, contact time and peak impact acceleration during a fatiguing overground run. Consistent with the hypothesis, it was found that LRCs decreased significantly over the course of the run for all stride parameters. There was a medium effect size for \( t_c \) \( \alpha \) (\( p = 0.003, \eta^2 = 0.177 \)), while the effect sizes for stride length \( \alpha \) (\( p < 0.001, \eta^2 = 0.418 \)), stride time \( \alpha \) (\( p < 0.001, \eta^2 = 0.487 \)) and peak impact acceleration \( \alpha \) (\( p = 0.001, \eta^2 = 0.363 \)) were all found to be large. Across groups, stride length \( \alpha \) decreased from 0.90 at the beginning of the run to 0.77 in the middle segment, while no change occurred between the middle and end of the run. Stride time \( \alpha \) was 0.85 in the beginning and dropped to 0.73 in the intermediate run interval. It remained relatively constant for the rest of the run, reaching a value of 0.74 in the final run interval. Contact time and peak impact acceleration \( \alpha \) were 0.68 and 0.62 respectively at the beginning as well as 0.62 (contact time) and 0.55 (peak impact acceleration) in the middle segment. No significant changes occurred in these parameters between the middle and end run interval. The LRCs of all investigated parameters followed the same pattern: After initially displaying high relative values, \( \alpha \) decreased sharply after the first run interval and remained stable for the rest of the run. The percentage decrease in \( \alpha \) between the first two run intervals ranged from 14.4% (stride length) to 9.1% (contact time). A strong reduction in \( \alpha \) at an early stage was also reported by Meardon et al. (2011), who assessed LRCs in the stride time interval during an exhaustive overground run. This observation is particularly noteworthy because the
drop occurred well before the point of complete exertion was reached.

Currently, the exact meaning of LRCs during locomotion is still subject to ongoing debate. Given that LRCs represent the degree of interdependency between individual data points within a time series, weaker LRCs during running generally indicate that the stride pattern becomes more random and consequently less predictable (Jordan et al., 2007a). The majority of studies support the idea that a reduction in $\alpha$ reflects the inability to maintain a stable motor output. For example, reduced LRCs have been associated with neurological diseases, such as Huntington’s or Parkinson’s disease (Goldberger et al., 2002; Hausdorff et al., 1997). Moreover, older individuals are known to exhibit lower values of $\alpha$ during walking compared to healthy, young adults (Kobsar et al., 2014). On the other hand, researchers have proposed that lower values of $\alpha$ could be linked to increased flexibility and adaptability of the neuromuscular system (Jordan et al., 2006, 2007a, 2007b; Nakayama et al., 2010). Under this premise, lower values of $\alpha$ may indicate an increase in the dynamical degrees of freedom, which provides an individual with more solutions to execute a certain stride (Jordan et al., 2007a; Nakayama et al., 2010). However, the fact that all of these experiments involved treadmill running questions the significance of these results for unconstrained overground running.

Although the exact mechanisms that govern the emergence of LRCs in the stride pattern remain elusive, the present experiment has clearly shown that $\alpha$ is reduced as fatigue increases. Based on existing models of the physiological fatigue response, it is reasonable to assume that reduced LRCs in the stride pattern reflect a loss of system flexibility rather than increased adaptability. This has important implications for health and performance because it potentially enables researchers to monitor the persistence of gait parameters in real time and identify the point at which the stride pattern reaches a critical level of irregularity. Sophisticated algorithms that combine information regarding stride-to-stride fluctuations with
traditional biomechanical parameters could have the potential to effectively monitor the accumulated training load and subsequently reduce the risk of overuse injuries. Nonetheless, further research is needed to elucidate the meaning of LRCs in the control of human movement and its complex interaction with aspects such as skill level, fatigue and disease.

This experiment has also demonstrated that LRCs are present in gait variables other than stride time and that stride-to-stride fluctuations can be measured with a single foot-mounted IMU. This confirms reports by Jordan et al. (2007a), who found persistent LRCs in variables such as stride/step time, stride/step length, contact time and different GRF variables during treadmill running. However, although LRCs were present in all of the analyzed stride parameters, the level of alpha differed substantially between variables. The highest LRCs were found to exist in stride length and stride time, with mean values of 0.81 and 0.77 respectively across groups. In contrast, the average $\alpha$ for contact time was significantly lower (0.65). The least persistent LRCs were found to exist in peak impact acceleration (0.57). Mathematically, persistent long-range correlations will result in an $\alpha$ value that ranges between 0.5 and 1.0. Studies have also shown that healthy young individuals exhibit $\alpha$ values anywhere between 0.6 and 1.0 in the time series of different gait variables (Hausdorff, 2007; Jordan et al., 2007a). In contrast, completely random and uncorrelated time series produce an $\alpha$ value of 0.5 (Hausdorff et al., 1997, 1995; Jordan et al., 2007b; Terrier et al., 2005). While the values of $\alpha$ for ST, SL and contact time are similar to those reported in other studies, LRCs in peak impact acceleration were substantially lower and approached the range that is characteristic of white noise. The observation that the level of $\alpha$ was variable-dependent suggests that the mechanism responsible for the emergence of LRCs does not affect all biomechanical variables to the same degree. Consequently, parameters that are more random and less self-organized, e.g. peak impact acceleration, are limited in
their ability to offer insight in the control mechanisms responsible for the temporal organization of gait.

In contrast to other parameters, the LRCs of peak impact acceleration exhibited a main effect for group. Since this study is the first to calculate $\alpha$ for peak impact acceleration from a foot-mounted IMU, this observation should be interpreted with caution. It must also be considered that $\alpha$ levels of peak impact acceleration were substantially lower than those of the other stride parameters, which signifies a greater random component within the time series and further complicates its interpretation. The fact that no group differences were found in other parameters suggests that persistent LRCs are an inherent feature of human locomotion but do not show in all aspects of the gait pattern. Additional research is required to elucidate the relationship between skill level and LRCs and different classes of biomechanical variables.

When interpreting the results of this study, it is important to mention that elite distance runners differed from recreational runners with respect to certain subject and performance characteristics. Most importantly, elite runners completed the run at a significantly faster speed than recreational runners ($p < 0.001$), which was expected given the larger aerobic capacity and smaller body mass. In order to allow the comparison of the individual data, the intensity at which the experimental run was completed had to be normalized. Therefore, running speed for each participant was chosen based on an individual marker of performance, i.e. their most recent 5k race pace, and monitored during the run. It was also confirmed that the level of fatigue experienced during the experiment was similar across participants. For this purpose, heart rate was recorded during the run and participants were asked to indicate their perceived level of exertion immediately after completing the protocol (see Table 4 and Appendix G).

The recreational group ran for a significantly longer time than the elite
runners ($p = 0.002$). This difference is most likely a direct result of the experimental protocol: Participants were instructed to run at their all-out 5k race pace. Based on this constraint, runners were expected to reach complete exertion after approximately 5000 m. Since faster runners are able to cover a greater distance in less time, the elite group reached the point of exhaustion earlier than recreational runners. As is evident from Table 4, both groups covered a comparable distance ($p = 0.204$) and achieved similar levels of exertion at the end of the run (0.248).

5.7 Conclusion

The present experiment established that elite and recreational runners increased their mean $t_c$ and peak impact acceleration over the course of a fatiguing run, while no significant changes were observed in mean ST and SL. Significant main effects for group existed for the mean values of SL, $t_c$ and peak impact acceleration. It is likely that these differences were linked to the different running speeds at which the groups completed the experiment. The results of this study also demonstrate that persistent LRCs are present in gait parameters other than stride time during overground running. The $\alpha$ values for stride length and stride time indicated a high degree of temporal persistence, while $t_c$ and peak impact acceleration $\alpha$ exhibited lower values. For SL, ST and $t_c$, the observed range of $\alpha$ is comparable to those reported by previous studies (Hausdorff, 2007; Jordan et al., 2006, 2007a, 2007b; Meardon et al., 2011; Nakayama et al., 2010). It was further shown that LRCs decreased significantly during the overground run, while the magnitude of variability of the measured gait parameters remained constant. A possible explanation is that $\alpha$ marks the onset of fatigue, which might have important clinical and performance-related implications and open new ways to study fatigue during continuous exercise. For example, individual $\alpha$-thresholds might be used to indicate when a runner’s stride pattern reaches a critical level of inconsistency. Future
research should explore if this information can help to reduce the accumulative impact load and assist in preventing certain overuse injuries. LRCs did not differ significantly between recreational and elite runners, which supports the assumption that the mechanisms responsible for the emergence of LRC in the stride pattern are not influenced by skill level and the high volume of training completed by the elite distance runners. However, recreational and elite runners differed with respect to their stride time CV, which suggests that it could be used as an indicator of skill level in distance running. Given the potential benefits of wearable sensors for movement analysis, the present study also demonstrated that a simple IMU-based system is capable of measuring fatigue-related changes of different stride parameters, their variability and LRCs in runners of different skill levels. This work could potentially be extended to develop tools that allow athletes, coaches or clinicians to obtain valuable information about running performance in real-time.
Prolonged distance running requires continuous muscular effort and eventually leads to a decrease in performance. Although the underlying mechanisms of fatigue and their effects on biomechanics are subject to ongoing debate, fatigue is known to be a multifactorial phenomenon. High-intensity stretch-shortening cycle (SSC) exercise, such as jumping, is an effective method to study fatigue because rather than representing an isolated model, it takes into consideration mechanical, neural and metabolic factors (Nicol & Komi, 2011). Research has established that SSC fatigue induces delayed onset muscle soreness (DOMS), affects reflex activity, as well as muscle mechanics and stiffness regulation of the neuromuscular system (Komi, 2000; Kyröläinen et al., 2000; Nicol et al., 1991b, 1991c).

Many intrinsic and extrinsic factors influence the mechanical behavior of the human body during running. However, several studies have demonstrated that human running can be accurately simulated by a simple spring-mass model, which is based on the property of a deformable body to store and return elastic energy (Alexander, 1992; Blickhan, 1989; McMahon & Cheng, 1990). A fundamental determinant of the spring-mass behavior in running is the stiffness of the leg spring. (Dutto & Smith, 2002; Farley & González, 1996). In particular, the stiffness of a joint is affected by the mechanical properties of the surrounding passive structures as well as by the activation state of the muscles acting across that joint. It has repeatedly been reported that joint stiffness decreases with progression of fatigue (Horita et al., 1996; Kuitunen, Avela, et al., 2002; Rabita et al., 2013).

Fatigue-induced stiffness alterations have been linked to kinematic and kinetic changes in running. For example, studies that have analyzed spring-mass characteristics during exhaustive running found that decreases in stiffness were
correlated with changes in basic stride parameters (Dutto & Smith, 2002; Girard et al., 2011; Rabita et al., 2013).

During walking and running, long range correlations (LRCs) are thought to represent the temporal stability of the stride pattern (Hausdorff et al., 1997; Jordan et al., 2007a). In a given data set, LRCs indicate the degree to which one particular stride is correlated with other strides in the time series, even when they occur at a considerable temporal distance. Early studies have shown that certain diseases of the central nervous system, such as Huntington’s or Parkinson’s disease, cause deterioration of LRCs during walking (Frenkel-Toledo et al., 2005; Hausdorff et al., 1997). Moreover, imposing external constraints on the CNS, for example by pacing a walk with a metronome, has been shown to reduce the strength of LRCs. Based on this research, it has traditionally been thought that LRCs represent patterns that emerge within the central nervous system.

In contrast, other researchers have argued that persistent stride-to-stride fluctuations are the result of sensory feedback rather than representing highly complex self-governing processes. For example, studies have demonstrated that the strength of LRCs is affected by the quality of visual and proprioceptive feedback (Collins & DeLuca, 1995; M. Riley, Balasubramaniam, & Turvey, 1997). In support of these findings, Gates, Dingwell, and Su (2007) applied different levels of sensory noise and feedback to a simple bipedal model with passive dynamic characteristics and were able to reproduce persistent LRCs in the simulated stride time series. Another study involving repetitive upper extremity reaching tasks showed that LRCs in movement speed and timing errors approached the range of uncorrelated, white noise ($\alpha = 0.5$) after the onset of muscle fatigue, while the goal-relevant features of the motor output, i.e. the accuracy of the movements, were maintained (Gates & Dingwell, 2008). Additionally, a study involving exhaustive distance running demonstrated that prolonged neuromuscular effort caused a reduction of
LRCs in the stride time interval (Meardon et al., 2011).

Considering the relationship between fatigue and joint stiffness (Horita et al., 1996; Kuitunen, Avela, et al., 2002; Rabita et al., 2013) as well as the suspected link between fatigue and LRCs (Gates & Dingwell, 2008; Meardon et al., 2011), there is a need to analyze the effects of varying joint stiffness on stride pattern LRCs. To date, however, no study has looked at how fatiguing high-intensity SSC exercise affects the stride pattern variability. Consequently, this experiment employed a fatiguing jump protocol to induce potential changes in joint stiffness, stride kinematics, variability and LRCs during distance running. It was hypothesized that a localized fatigue-response, as indicated by a decrease in joint stiffness, would be associated with less temporal stability, i.e. reduced levels of $\alpha$, while linear measures of variability would remain unaffected.

A second objective of this study was to determine if a prolonged SSC protocol affected the stride kinematics, variability and LRCs to a similar degree in a group of elite distance runners and recreational runners. It was expected that both joint stiffness and $\alpha$ would decrease to a lesser degree in the elite group compared to the recreational group after completing the jump protocol.

6.1 Research Design

This study employed a two-way repeated measures design with skill level (elite vs. recreational) and condition (pre-fatigue vs. post-fatigue) serving as independent variables. It further involved two different experimental groups. One group consisted of elite distance runners, while the other group contained individuals that had not undergone training specific to distance running. Both groups participated in the same experimental protocol, i.e. a fatiguing SSC protocol consisting of drop jumps and countermovement jumps, that attempted to reduce ankle joint stiffness (AJS) and knee joint stiffness (KJS). Prior to enrollment, all individuals provided
written consent in order to participate in the study.

Elite distance runners ($n = 16$) were recruited from the University of Regina track and cross-country teams. All subjects in this group were required to have performed regular distance running between 4 and 7 days per week for more than 2 years and competed at a provincial or intercollegiate level within the preceding year. Furthermore, a personal best of 21:30 minutes (women) and 17:30 minutes (men) for the 5000 m was required in order to be classified as an elite distance runner. These times were established in accordance with the team requirements for the university track and field team. Exclusion criteria for this group included a race time for the 5 km that was above the specified threshold; any history of lower-extremity surgery in the past 24 months; any history of running-related injuries that caused discontinuation of running for more than 7 days; any other neuromuscular or cardiovascular pathology; or any other medical condition that could potentially be worsened by prolonged running.

The group of recreational runners ($n = 16$) consisted of young, healthy adults. These participants did not have any training specific to distance running. However, recreational running for a time of up to 3 hours per week was allowed. Furthermore, in order to be included in this group, individuals had to possess the ability to run at a comfortable pace for a minimum of 15 minutes. The health-related exclusion criteria were identical to those of the elite distance running group. Recruitment occurred through university e-mail and poster advertisements. Prior to enrollment, all participants signed a consent form that had previously been approved by the University of Regina Ethics Board.

### 6.2 Instrumentation and Test Procedures

Participants were equipped with a wireless, 9 degree of freedom IMU, consisting of a gyroscope, accelerometer and magnetometer (Xsens, MTw) on their
right foot. The IMU set-up and preparation procedures were identical to those described in Sections 4.2 and 5.2.

In addition to the IMU, participants were equipped with a wrist-worn running computer, a heart rate sensor, which was strapped around their chest, and an associated footpod, which was attached to their left foot (RS300X, Polar, Kempele, Finland). This system continuously monitored heart rate, speed and distance covered during the run. It has previously been used to control for running speed (Meardon et al., 2011) and was shown to yield valid and reliable data (Hausswirth, 2009).

Calibration of the running computer and the associated foot pod was performed according to the instructions of the manufacturer. This required the participants to run a certain predefined distance at a self-selected running speed. After standing still for several seconds, participants started the calibration procedure by pushing the start/stop button on the wrist-worn running computer and initiating the run with their left leg, i.e. the side to which the commercial footpod was attached. For the calibration, participants ran for a distance of 1100 m on the outermost lane of the indoor track. Since one lap in this lane was 218 m, the participants were asked to complete five full laps and an additional distance of 10 m. The researcher stood next to the track and indicated the point at which the runners had to come to a full stop after the required distance was covered. After completing the run, the participants had to stand still and wait for 10-15 seconds, so the data could be transmitted from the footpod to the wrist-worn computer. The calibration run also served as a warm up for the experimental protocol. However, if participants indicated that they wanted to perform additional warm-up activities, they were given the opportunity to do so, provided that these activities were non-fatiguing. During the warm-up run, the quality of the wireless connection between the foot-mounted IMU and the docking station over the range of the indoor
track as well as the characteristics of the inertial signal were monitored. If abnormalities were detected, the position of the sensor on the foot was improved and the radio channel was changed.

Following the warm up, the researcher reset the running computer and started recording the inertial signals from the wireless foot-mounted IMU. Subsequently, participants positioned themselves at the starting line on the outermost lane of the indoor track. Participants were instructed to run in a counterclockwise direction at a steady, comfortable running speed for a period of 8 minutes. This time interval has been used previously to establish LRCs in running (Jordan et al., 2006) and is above the minimum time of 6 minutes, which was recommended by Hausdorff (2007). After a brief countdown, the researcher and the participant simultaneously started timing the run, on a stop watch and the running computer respectively. The researcher controlled the running speed of the participants by monitoring each individual lap time and providing instructions as required.

After completing the overground run, participants went to the biomechanics lab (Figure 7), which was located in close proximity to the indoor track, to assess ankle and knee joint stiffness at baseline, i.e. before performing the fatiguing SSC protocol, using GRF and 3-D motion capture data. As a first step, the following anthropometric variables were measured: body mass, height, as well as leg length, knee width, and ankle width of both legs. Subsequently, reflective markers (5 mm) were placed on both lower limbs as well as on the pelvis. All markers were placed according to the plug-in gait configuration (Figure 31): heel, distal head of the second metatarsal, lateral malleolus, lower third of the lateral surface of the tibia, lateral epicondyle of the knee, lower third of the lateral surface of the thigh, posterior superior iliac spine (PSIS) and anterior superior iliac spine (ASIS). Immediately before applying the markers, the sites were cleaned with alcohol swabs and shaved if necessary. Afterwards, the anthropometric data was entered into the
motion capture software (Nexus v.1.8, Vicon, Denver, CO) in order to create a kinematic model for each participant. Next, a static calibration trial was recorded, which required the participants to stand still and maintain the anatomical position for about 1 - 3 seconds.

After applying the markers, each participant performed a series of 10 - 15 short (15 m) runs through the calibrated volume of the 3D motion capture system (T-Series, Vicon, Denver, CO), with the specific goal of hitting a force-plate (AMTI, Watertown, MA) with their right foot during each trial. Participants were asked to replicate the speed at which they previously performed the overground run. To obtain representative data they were further instructed to run naturally and avoid adjusting their stride in order to hit the force plate. To maximize the chances of correctly hitting the force plate, an optimal starting position was determined for each participant based on a series of practice runs. This position was marked on the
floor with adhesive tape. Following the runs, all subjects completed a fatiguing jump protocol that attempted to reduce joint stiffness by decreasing the level of muscular co-contraction in the ankle and knee joints. In order to minimize cardiovascular and maximize localized fatigue, this study employed a short-duration jump protocol instead of long-duration SSC exercise. High-intensity fatiguing SSC exercise has been used before to induce significant reductions in stiffness (Avela & Komi, 1998b; Kuitunen, Avela, et al., 2002; Nicol, Komi, Horita, Kyröläinen, & Takala, 1996).

Before performing the fatiguing jumps, participants were dropped from progressively greater starting heights to determine their optimal drop height, i.e. the height that produced the best vertical jump performance. Maximal jump height was calculated based on the vertical displacement of the right ASIS marker compared to its height during the static calibration trial. The fatigue protocol of this study was similar to that described by Kuitunen, Avela, et al. (2002). It consisted of 100 single maximal drop jumps from the optimal drop height, with one jump being performed every 5 seconds. The participants stood on a box and took a step forward with their right foot, thereby initiating free fall. They were instructed to land with both feet simultaneously and rebound quickly, while trying to jump as high as possible. After each jump, participants immediately turned around and stepped back onto the box using a small pedestal.

After completing the drop jumps, participants were asked to continuously jump in place with maximal effort until they could no longer reach 70% of their maximal jump height. Height was assessed with the motion capture system. The researcher previously calculated the 70% threshold based on the displacement of the right ASIS marker during the maximal jump performance. For all jumps, the use of arms to increase jump height was prevented by holding a light stick, which was placed across the participants’ shoulders.

Within five minutes after completing the jumps, participants performed
another set of 10-15 short (15 m) runs through the calibrated space of the 3D motion capture system to reevaluate knee, ankle and leg stiffness. If any markers became detached during the jumps, they were reapplied before the runs. In this case, another short calibration trial had to be performed. About ten minutes after the jump protocol, stride kinematics, variability and LRCs were reassessed with the foot mounted IMU during another 8-minute overground run on the indoor track. To ensure that the running speed was identical to that of the pre-jump condition, the average running speed of the baseline run was entered into the running computer. Once participants increased or decreased their running speed out of a tolerable range (± 5% average running speed at baseline), the computer triggered an audible alarm, thereby notifying the participants to adjust their running speed.

6.3 Data Analysis

Before conducting any further analysis, the raw data collected by the foot-mounted IMU was preprocessed and reduced. The first minute of every overground run was removed to avoid potential inconsistencies in the signals that may have occurred due to an irregular running pace before the participants found their predetermined running speed. Furthermore, a custom-written MATLAB program was used to assess the periodicity of the inertial signals. Aperiodic or weak periodic sections that may have occurred due to weak signal reception or aberrant movements were excluded from the analysis.

After the preprocessing procedures, custom programs written in MATLAB (v. R2012a, The MathWorks, Natick, MA) were used to process and analyze the data collected with the foot-mounted IMU. The following dependent variables were calculated using MATLAB scripts:

1. **Stride time** was defined as the interval between two subsequent footfalls of the same foot. The stance identification was based on the resultant
acceleration signal. Individual stride times were found by subtracting the absolute time of subsequent strides.

2. **Stride length** was estimated using a pedestrian dead-reckoning approach with ZUPTs applied during each stance phase. For more details regarding instrumentation and data analysis see Section 4.3.

The coefficient of variation was calculated as described in Section 2.7.1 to assess the magnitude of variability for both ST and SL. LRCs for ST and SL of running were evaluated using the DFA procedure described in Section 5.3.

Only complete 15 m trials that were within the appropriate speed range (±10% of average running speed of the overground running trials) were used to calculate joint moments and angle data. Running speed for a given trial was determined by averaging the horizontal velocity of the right ASIS marker.

Ground-reaction forces were sampled at 1000 Hz. Kinematic data was collected at 100 Hz. According to the recommendations of Kristianslund, Krosshaug, and van den Bogert (2012), kinematic data and ground-reaction forces were filtered using a fourth-order Butterworth low-pass filter with an identical cut-off frequency of 15 Hz. Afterwards, sagittal plane joint angles and moments were calculated for the ankle and knee using an inverse dynamics approach (Vicon Nexus 2). Joint moments and joint kinematics of the valid running trials were averaged to calculate AJS and KJS for each participant (Dutto & Smith, 2002).

As proposed by Farley, Houdijk, Van Strien, and Louie (1998), joint stiffness for the ankle and knee \((k)\) was determined by calculating the slope of a regression line through the joint moment versus joint angle data (see Figure 32):

\[
k_{\text{joint}} = \frac{\Delta M}{\Delta \theta}
\]

where \(\Delta M\) = change in joint moment and \(\Delta \theta\) = change in joint angle.
Figure 32. Calculation of joint stiffness for running. Stiffness \((k)\) is represented by the slope of the dashed line.

Additionally, each runner’s maximal heart rate was estimated using the Tanaka formula shown in Equation 8. Heart rate was collected continuously during the overground runs and calculated as a percentage of the maximal heart rate. This was done in order to estimate the level of cardiovascular exertion during the pre- and post-jump overground runs.

6.4 Statistical Analysis

Independent samples t-tests between the two groups were performed for each of the following variables: age (years), body mass (kg), height (cm) and leg length (cm). Additionally, paired samples t-tests were conducted to assess differences between the pre- and post-jump condition: average running speed of the overground runs (m/s), average heart rate during the overground runs, average speed of the running trials that were used to calculate joint stiffness (m/s). A two-way repeated measures ANOVA was conducted for each of the dependent variables (AJS, KJS,
mean stride time, mean stride length, CV stride time, CV stride length, α stride time, α stride length) to examine the effect of the within-subject independent variable (pre-jump vs. post-jump [2 levels]) and the between-subject independent variable (group [2 levels]). In addition to examining the main effects for both skill level and condition, the ANOVA also provided information about potential interaction effects. Before conducting any statistical tests, all data sets were assessed for normality using the Shapiro-Wilks test. If necessary, non-normally distributed data was log transformed before conducting any further analysis. Homoscedasticity was assessed using Levene’s test for equality of variances.

6.5 Results

Table 8

<table>
<thead>
<tr>
<th>Variable</th>
<th>Elite (± SD)</th>
<th>Recreational (± SD)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>22.56 (± 3.31)</td>
<td>27.81 (± 4.72)</td>
<td>0.001*</td>
</tr>
<tr>
<td>Height (cm)</td>
<td>176.94 (± 8.01)</td>
<td>171.88 (± 8.36)</td>
<td>0.090</td>
</tr>
<tr>
<td>Bodymass (kg)</td>
<td>64.19 (± 9.54)</td>
<td>69.52 (± 11.87)</td>
<td>0.172</td>
</tr>
<tr>
<td>Leg Length (cm)</td>
<td>82.81 (± 3.79)</td>
<td>79.68 (± 5.51)</td>
<td>0.071</td>
</tr>
</tbody>
</table>

* Indicates significant difference between groups (p ≤ 0.05)

Independent samples t-tests revealed that there was a significant age difference between the two groups. Elite runners had a mean age of 22.56 (± 3.31) years, while recreational runners were 27.81 (± 4.72) years on average. Elite runners performed the overground runs as well as the linear runs in the lab at a significantly greater running speed than recreational runners. However, the average running speeds of the overground runs did not differ significantly from the speeds of the linear runs in the biomechanics lab across participants for the pre- and post-jump condition. Paired samples t-tests further revealed that mean heart rate during the overground run was significantly higher after the participants had completed the fatiguing jump protocol compared to the pre-jump condition. Subject
Table 9  
Descriptives for the pre- and post-jump overground runs on the indoor track.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-Jump (± SD)</th>
<th>Post-Jump (± SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Running Speed Lab (m/s)</td>
<td>3.80 (± 0.38)</td>
<td>3.86 (± 0.39)</td>
</tr>
<tr>
<td>Elite</td>
<td>4.13 (± 0.47)</td>
<td>4.19 (± 0.49)</td>
</tr>
<tr>
<td>Recreational</td>
<td>3.48 (± 0.28)(^a)</td>
<td>3.53 (± 0.29)(^a)</td>
</tr>
<tr>
<td>Running Speed Track (m/s)</td>
<td>3.59 (± 0.44)</td>
<td>3.64 (± 0.49)</td>
</tr>
<tr>
<td>Elite</td>
<td>3.85 (± 0.38)</td>
<td>3.91 (± 0.43)</td>
</tr>
<tr>
<td>Recreational</td>
<td>3.33 (± 0.32)(^a)</td>
<td>3.36 (± 0.32)(^a)</td>
</tr>
<tr>
<td>% of HR(_{max}) (track run)</td>
<td>80.53 (± 5.35)</td>
<td>85.48 (± 5.80)(^b)</td>
</tr>
<tr>
<td>Elite</td>
<td>78.33 (± 5.79)</td>
<td>82.92 (± 6.47)</td>
</tr>
<tr>
<td>Recreational</td>
<td>82.72 (± 3.92)(^a)</td>
<td>88.04 (± 3.70)(^a)</td>
</tr>
</tbody>
</table>

\(^a\) Indicates significant difference between groups \((p \leq 0.05)\).

\(^b\) Indicates significant difference between conditions \((p \leq 0.05)\).

characteristics and the descriptive statistics for the pre- and post-jump test procedures are shown in Table 8 and Table 9, respectively.

Elite runners exhibited mean AJS values of 0.133 Nm/kg/° (pre-jump) and 0.127 Nm/kg/° (post-jump), while the mean ankle stiffness of the recreational group was 0.153 Nm/kg/° and 0.136 Nm/kg/° respectively (Figure 33). A two-way repeated measures ANOVA revealed a significant ordinal interaction effect (i.e. lines have similar trend but do not cross) for group × condition F(1,30) = 4.508, \(p = 0.042\), \(\eta^2 = 0.131\), suggesting that the jump protocol affected the AJS of elite and recreational runners to a different degree. There was also a significant main effect for condition F(1,30) = 20.011, \(p < 0.001\), \(\eta^2 = 0.400\) but not for group F(1,30) = 0.558, \(p = 0.461\), \(\eta^2 = 0.018\). Follow up paired samples t-tests showed that the recreational group exhibited a significant difference in AJS between the pre- and post-jump condition \((p < 0.001)\), while AJS did not differ significantly between conditions in the elite group \((p = 0.162)\).

Elite runners exhibited mean KJS values of 0.092 Nm/kg/° (pre-jump) and 0.090 Nm/kg/° (post-jump), while the mean KJS of the recreational group was
Figure 33. AJS for the pre- and post-jump condition. * = significant main effect (p < 0.001) for run condition, ♦ = significant interaction effect for group x run condition (p = 0.042)

Figure 34. KJS for the pre- and post-jump condition. * = significant main effect (p = 0.007) for run condition, ■ = significant interaction effect for group (p = 0.012)
0.070 Nm/kg/° and 0.065 Nm/kg/° respectively (Figure 34). A two-way repeated measures ANOVA revealed a significant main effect for condition $F(1,30) = 8.380, p = 0.007, \eta^2 = 0.218$ and for group $F(1,30) = 7.228, p = 0.012, \eta^2 = 0.194$. However, the interaction effect for group $\times$ condition did not reach significance $F(1,30) = 2.027, p = 0.165, \eta^2 = 0.063$. Follow up paired samples t-tests showed that the recreational group exhibited a significant difference in KJS between the pre- and post-jump condition ($p = 0.004$), while KJS did not differ significantly between conditions in the elite group ($p = 0.358$).

![Figure 35](image)

**Figure 35.** Mean SL for both groups before and after the fatiguing jump protocol. ■ = significant main effect ($p < 0.001$) for group

Mean stride length during the overground run at baseline was 2.69 m and 2.32 m for the group of elite and recreational runners, respectively. The mean values for the post-jump condition were 2.71 m and 2.27 m respectively. A two-way repeated measures ANOVA revealed a strong but non-significant trend of the interaction effect for group $\times$ condition $F(1,27) = 4.152, p = 0.051, \eta^2 = 0.133$. There was also a significant main effect for group $F(1,27) = 14.185, p < 0.001, \eta^2 = 0.344$ on mean
Figure 36. Mean ST for both groups before and after the fatiguing jump protocol. * = significant main effect (p < 0.001) for run condition

Stride length. In contrast, no significant main effect was found for condition F(1,27) = 0.694, p = 0.412, η² = 0.025. Follow up paired samples t-tests showed that mean stride length was not significantly different between the pre- and post-jump condition for either the elite (p = 0.332) or the recreational group (p = 0.1).

The group of elite runners decreased their stride time from 0.715 s at baseline to 0.706 s in the post-jump condition, while the group of recreational runners decreased their stride time from 0.701 s (pre-jump) to 0.692 s (post-jump). A two-way repeated measures ANOVA revealed a significant main effect for test condition on mean stride time F(1,27) = 24.606, p < 0.001, η² = 0.477. In contrast, the main effect for group F(1,27) = 0.003, p = 0.957, η² < 0.001 as well as the interaction effect for group × condition F(1,27) = 0.621, p = 0.438, η² = 0.022 was non-significant. Figures 35 and 36 show the mean SL and ST values (pre-jump vs. post-jump) for both the elite and recreational runners.

Furthermore, a two-way repeated measures ANOVA was conducted to
Figure 37. Stride time CV (a) and stride length CV (b) for both groups before and after the fatiguing jump protocol.
investigate the effects of the independent variables on the magnitude of variability as measured by the coefficient of variation. The CV of stride length before the jumps were 4.12% and 3.85% for the elite and recreational runners respectively, while the CV values for the post-jump condition were 4.06% (elite) and 4.13% (recreational). Neither the main effect for group \( F(1,27) = 0.260, p = 0.614, \eta^2 = 0.01 \) nor the main effect for condition \( F(1,27) = 0.002, p = 0.832, \eta^2 = 0.001 \) reached significance. No significant interaction effect was found \( F(1,27) = 0.636, p = 0.432, \eta^2 = 0.023 \).

The stride time CV before the jumps was 1.49% and 1.55% for the elite and recreational runners respectively, while the CV values for the post-jump condition were 1.43% (elite) and 1.47% (recreational). Neither the main effect for condition \( F(1,27) = 2.578, p = 0.120, \eta^2 = 0.087 \) nor the main effect for group \( F(1,27) = 0.253, p = 0.619, \eta^2 = 0.009 \) reached significance. There was no significant interaction effect \( F(1,27) = 0.028, p = 0.868, \eta^2 = 0.001 \). Figures 37a and 37b show the CVs for stride time and stride length as a function of fatigue condition.

![Figure 37](image.png)

Figure 38. FSI \( \alpha \) calculated for SL for both groups before and after the fatiguing jump protocol. * = significant main effect (\( p < 0.001 \)) for run condition.
Mean $\alpha$ values for stride length were 0.92 (pre-jump) and 0.84 (post-jump) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.94 and 0.85 respectively. A two-way repeated measures ANOVA revealed a significant main effect for condition $F(1,27) = 45.930, p < 0.001, \eta^2 = 0.630$ but not for group $F(1,27) = 0.138, p = 0.713, \eta^2 = 0.005$. There was no significant interaction effect for group $\times$ condition $F(1,27) = 0.212, p = 0.649, \eta^2 = 0.008$.

Mean $\alpha$ values for stride time were 0.81 (pre-jump) and 0.72 (post-jump) for the group of elite distance runners, while the mean $\alpha$ values for the recreational group were 0.82 and 0.75 respectively. A two-way repeated measures ANOVA revealed a significant main effect for condition $F(1,27) = 45.312, p < 0.001, \eta^2 = 0.627$ but not for group $F(1,27) = 0.384, p = 0.540, \eta^2 = 0.014$. There was no significant interaction effect for group $\times$ condition $F(1,27) = 2.079, p = 0.161, \eta^2 = 0.072$. Figures 38 and 39 show the mean values of $\alpha$ for stride time and stride length.
as a function of fatigue condition.

6.6 Discussion

The purpose of this study was to evaluate the effects of a fatiguing jump protocol on stride time and stride length, the variability of these parameters as expressed by the CV and LRCs during distance running. Moreover, the study
investigated whether recreational and elite runners were affected to the same degree by the jumps or if differences existed between groups with respect to their fatigue response. Based on existing literature and the results described in Section 5, it was hypothesized that $\alpha$ would be reduced significantly after the jumps, while the magnitude of variability, as measured by the CV, would remain unaffected by fatigue. It was also hypothesized that elite distance runners would experience less decrease in joint stiffness and $\alpha$ than recreational runners.

In general, AJS ($p < 0.001, \eta^2 = 0.4$) and KJS ($p = 0.007, \eta^2 = 0.218$) decreased significantly in response to the jumping protocol, which indicates that high-intensity SSC exercise was effective in generating fatigue in the muscles of the lower extremities. Previous research has established a link between changes in neuromuscular performance, stiffness modification and repetitive SSC action. For example, Nicol et al. (1991b, 1991c) reported reduced levels of maximal voluntary contraction, decreased force output and a lowered tolerance to stretch loads after a fatiguing SSC protocol. Avela and Komi (1998b) demonstrated reduced stiffness of the tendomuscular complex and decreased reflex sensitivity in the quadriceps and soleus muscles after a high-intensity drop jump protocol. Furthermore, submaximal SSC exercise has been shown to cause a reduction in joint stiffness at the knee joint (Horita et al., 1996). The underlying mechanisms governing muscle (and consequently joint) stiffness regulation involve changes in the number of active crossbridges (i.e. muscle activation), altered reflex sensitivity as well as decreased central drive to the muscle cells (Avela & Komi, 1998a; Kuitunen, Avela, et al., 2002). Additionally, the accumulation of metabolites, i.e. hydrogen ions, is known to impair cross-bridge cycling and force generation (Green, 1997). Although neuromuscular fatigue was not assessed directly in this study, it is likely that repetitive jumping reduced AJS and KJS by impairing the level of force generation.

Statistical analysis also revealed a significant main effect for group on KJS.
Figure 34 shows that elite runners (0.086, ± 0.005 Nm/kg/°) exhibited higher overall KJS values than recreational runners (0.072 ± 0.005 Nm/kg/°) across test conditions. In contrast, there was no significant main effect for group on AJS, indicating that the reported values were similar across groups. Arampatzis et al. (1999) systematically investigated the contribution of different joints to leg spring stiffness and demonstrated that faster running speeds were primarily associated with increases in KJS but not AJS. Based on these results, it is possible that the significant group effect on KJS was mainly due to the greater running speeds at which elite runners performed the linear overground runs in the laboratory. Physiologically, the greater KJS of the elite group could be explained by a stronger cocontraction of the leg muscles, which resulted from the intensive training performed by this cohort.

There was also a significant interaction effect (p = 0.042, η² = 0.131) on AJS. Follow up paired samples t-tests revealed a significant decrease in AJS for recreational runners (p < 0.001), but not in the elite group (p = 0.162), which suggests that recreational runners were affected to a greater degree by the fatiguing jumps. Specialized training, such as plyometric exercise, has been shown to increase overall lower extremity stiffness (Cornu, Silveira, & Goubel, 1997; Spurrs, Murphy, & Watsford, 2002). Additionally, Hobara et al. (2010) showed that endurance-trained athletes exhibited greater joint stiffness during a bilateral hopping task compared to untrained individuals. Therefore, it is likely that the specialized training performed by the elite runners improved the fatigue resistance of the muscles responsible for modulating AJS. The absence of an interaction effect on KJS indicates that training influences stiffness modulation only under certain conditions or that maintaining stiffness at the knee is less important than at the ankle in running. Future research is required to explain the relationship between skill level and joint specific stiffness modulation. In summary, the results of this
study support the view that elite and recreational runners differ with respect to the stiffness modulation in the lower extremity in response to fatiguing SSC action. However, while elite runners exhibited greater KJS, their AJS was similar to that of the recreational runners, suggesting that the effects of skill level and training on lower extremity stiffness are joint-specific.

A mixed ANOVA with follow-up t-tests revealed that mean SL was not significantly different between the pre- and post-jump condition for either the elite (p = 0.332) or the recreational group (p = 0.1). This indicates that the fatiguing jump protocol did not have a substantial effect on mean SL during an overground run at a self-selected, submaximal running speed, which is in agreement with previous experiments (see Section 5). However, the non-significant trend of the interaction effect (p = 0.051, $\eta^2 = 0.133$) indicated that the groups tended to react slightly different to the fatiguing jump protocol. In particular, elite runners increased their SL by 0.02 m on average in the post-jump run, while recreational runners decreased their SL by 0.05 m, which suggests that skill level may influence the way the jump protocol affected mean SL. Given this observation, it is reasonable to suggest that the null hypothesis was incorrectly accepted to be true (i.e. Type II error).

In contrast, a significant main effect for condition existed on mean ST. Follow-up paired samples t-tests showed that mean ST was significantly different between the pre- and post-jump condition for both the elite (p = 0.004) and the recreational group (p = 0.003), demonstrating that participants in general exhibited higher stride rates during the post-jump run compared to baseline. The absence of a significant interaction effect further confirms that elite and recreational runners alike decreased ST in response to high-intensity jump protocol. These results are supported by studies that found runners to increase SR under fatiguing conditions (Hausswirth, 2009; Kyröläinen et al., 2000; Place et al., 2004).
Statistical analysis further revealed a significant group effect on mean SL (p<0.001, $\eta^2 = 0.344$) but not mean ST (p = 0.957). Consistent with the results presented in Section 5.5, trained runners exhibited significantly greater stride lengths in both conditions than recreational runners (see Table 10). It is evident that stride length was the main factor responsible for the group differences that were observed in running speed. This view is supported by Cavanagh et al. (1977) and Weyand et al. (2000). Furthermore, the results discussed in Section 5.6 showed that running speed was strongly correlated with SL but not with ST. Since all participants performed this experiment at a self-selected, comfortable distance running speed, it appears reasonable that ST was similar across participants. Together, the results show that the elite group ran faster by taking longer strides, while maintaining stride rates that were similar to those of recreational runners. Greater SLs are likely a result of the specialized training that the elite runners perform on a regular basis. Elite runners were highly efficient at preserving the goal-relevant features of the stride pattern (i.e. constant levels of SL and ST), which is plausible given that the main characteristic of expert performance in distance running is to maintain running speed, even after the onset of fatigue.

In accordance with the hypothesis, the magnitude of variability of SR and SL did not change in response to fatiguing jumps. This is demonstrated by the persistent CVs for both ST (p = 0.120) and SL (p = 0.614) across the two different conditions. The magnitude of variability has previously been shown to be unaffected by increasing levels of exertion during running (Meardon et al., 2011). Likewise, the experiment described in Section 5 did not find any effects of prolonged overground running on the CV calculated for stride time, stride length, contact time and impact magnitude. Although factors such as aging and certain neuropathologies (i.e. Huntington’s or Parkinson’s disease) have been shown to increase gait variability (Auvinet et al., 1999; Hausdorff et al., 1997; Moe-Nilssen & Helbostad, 2004), the
presented findings support the view that the stride pattern of young, healthy adults remains at the same level of consistency, even after the onset of fatigue.

No group differences were observed with respect to the coefficient of variation for both ST and SL. Although the average stride time CV was slightly lower for elite runners, the main effect for group on stride time CV was not statistically significant (p = 0.619). This contradicts Nakayama et al. (2010), who reported lower stride time variability in trained runners compared to untrained individuals during treadmill running, and the results presented in Section 5, which showed that elite distance runners displayed significantly lower stride time CVs (p = 0.007; η² = 0.221) during a prolonged overground run compared to recreational runners.

These differences may be linked to the implementation of different study designs and varying nature of fatigue experienced by the participants. More specifically, the intermittent character of the exercise and the time spent on preparation for the post-jump run could have caused the participants to recover to a certain degree after the fatiguing jumps. Furthermore, the present experiment required that all participants performed the overground runs at a comfortable, self-selected running speed, while those described in Section 5 required the participants to run at a much greater intensity to complete exertion. It is possible that skill-related differences in variability become smaller when runners are allowed to choose the optimal conditions for a locomotor task themselves, while skill-level may have a more significant effect on variability when external conditions impose a bigger physiological stress and consequently are far from optimal. It is left to future studies to investigate the effects of skill level on the variability of stride parameters in relation to varying levels of exercise intensity.

There was a significant main effect for test condition on α ST (p < 0.001, η² = 0.630) as well as on α SL (p < 0.001, η² = 0.627). This suggests that LRCs changed significantly in response to the fatiguing, high-intensity SSC exercise. Across
participants, the average decrease in $\alpha$ was 9.86% and 9.93% for stride time and stride length, respectively. The absence of any interaction effect confirms that the jump protocol affected the temporal organization of the stride pattern to a similar degree in recreational and elite runners. The magnitude of the reduction was consistent with the decrease observed in Section 5 but slightly less than the values reported by Meardon et al. (2011) during a prolonged overground run to exhaustion. In this experiment, $\alpha$ was found to be within the range of 0.5 to 1.0, which indicated the presence of persistent LRCs in the time series of both stride time and stride length.

The exact meaning of long-range stride-to-stride fluctuations in the stride pattern has not yet been determined. Some researchers have argued that higher levels of stride-to-stride fluctuations are associated with flexible and adaptable neuromuscular control (Jordan et al., 2006, 2007a; Nakayama et al., 2010). Mathematically, reduced LRCs signify a decreased dependency between individual strides within a given time series (Jordan et al., 2006), which could provide an individual with more possibilities to execute a certain stride (i.e. higher degrees of freedom). On the other hand, the majority of existing research suggests that lower levels of $\alpha$ are associated with abnormal motor control, injury and certain neurological diseases (Hausdorff et al., 1997; Meardon et al., 2011; Stergiou, Harbourne, & Cavanaugh, 2006). It has also been established that injured runners exhibit weaker LRCs during prolonged overground running compared to non-injured runners (Meardon et al., 2011). There is also an ongoing debate regarding the possible origins of LRCs in cyclic movement patterns. While some research suggests that localized muscle fatigue affects LRCs during repetitive tasks (Gates & Dingwell, 2008), other authors argue that a decrease in LRCs during locomotion mainly results from compromised or altered motor control mechanisms that originate within the CNS (Hausdorff et al., 2001, 1997). The latter theory is
corroborated by studies that have discovered LRCs in the dynamics of respiration and heart rate variability (Goldberger et al., 2002; Peng et al., 2002).

Although the origin of LRCs in basic stride parameters is not known, the present findings show that LRCs in the stride pattern are reduced in a fatigued state. Given the possible link between peripheral fatigue and changes in LRCs (Gates et al., 2007; Meardon et al., 2011), it was anticipated that altered mechanical properties of the musculoskeletal system, such as joint stiffness, would influence its dynamic behavior and the ability to self-organize. This seems to be supported by the observation that both joint stiffness and LRCs decreased significantly in response to the fatiguing jumps. To gain a more complete picture, the linear relationship of the observed changes in these parameters was assessed using Pearson’s $r$. However, statistical analysis did not reveal any significant correlations. This suggests that LRCs and joint stiffness alterations represent different dimensions of fatigue and that the magnitude of their change is not linearly related. Furthermore, these results support the view that the mechanism responsible for the emergence of LRCs in the stride pattern is not caused by peripheral mechanical characteristics of the locomotor system but rather depends on central factors. Given these results, $\alpha$ has the potential to act as a marker of central neuromuscular fatigue. However, future studies that involve larger cohorts are necessary to systematically identify and rule out factors that cause LRCs during running gait.

The statistical analysis did not reveal any significant effects for skill level on either $\alpha$ ST ($p = 0.540$) or $\alpha$ stride length ($p = 0.713$). The absence of any group or interaction effect is consistent with the findings presented in Section 5. However, Nakayama et al. (2010), who analyzed the strength of LRCs in the stride interval of competitive and recreational distance runners, found that recreational runners exhibited higher values of $\alpha$, even after correcting for the effects of varying running speeds. The authors speculate that lower values of $\alpha$ in elite distance runners may
be indicative of an optimization strategy that aims at increasing the dynamical degrees of freedom of the stride pattern. It is important to mention that Nakayama et al. (2010) analyzed LRCs during treadmill running and used a sample that only consisted of 14 participants for their experiment. Given the small sample size and the potential constraints that may have been imposed on the stride dynamics by the treadmill, their results do not simply apply to experiments involving unconstrained overground running.

Our results suggest that exhaustive high-intensity SSC exercise caused ST and SL $\alpha$ to behave similarly across groups. This indicates that the mechanism responsible for decreasing the fractal-like patterns of basic stride parameters is independent of any physiological adaptation that may have occurred in response to specialized training performed by the elite runners. However, given the scarcity of research in this area and the conflicting results, there is a need for future research to systematically investigate the relationship between skill level and LRCs of basic stride parameters during running.

Certain aspects have to be considered when interpreting the results of the present experiment. For example, paired samples t-tests revealed that runners performed the post-jump run at a significantly higher heart rate compared to baseline ($p < 0.001$). Across groups, participants performed the overground run in the unfatigued state at 80.53% ($\pm$ 5.35) of their maximal heart rate, compared to 85.48% ($\pm$ 5.80) in the post run. It was estimated that on average participants performed jumps for approximately ten minutes. Consequently, it was expected that the fatiguing SSC protocol induced a certain degree of cardiovascular exertion. It is also possible that reduced joint stiffness lowered the participants’ ability to utilize elastic energy in the concentric phase of the SSC and forced them to use greater muscular effort, consequently increasing the load on the cardiovascular system.

Additionally, the observation that participants exhibited significantly higher
stride rates but similar stride length in the post-run is unexpected, since running speed, as the product of SL and SR, did not differ significantly between the pre- and post-jump condition. However, despite the significant main effect of condition on stride time and its large effect size ($\eta^2 = 0.477$), the mean difference in stride time across participants was only 9 ms. Given the inverse relationship between stride time and stride rate, participants increased their stride frequency from 1.41 Hz in the unfatigued state to 1.43 Hz in the post-jump condition. It is safe to assume that these significant, yet small, differences in ST did not have a significant effect on the measured speeds at which participants completed the pre- and post-jump overground run.

6.7 Conclusion

This study demonstrated that a high-intensity SSC protocol, consisting of a fatiguing series of jumps, was effective in generating a local fatigue response, as indicated by reduced knee and ankle joint stiffness. Across groups, participants significantly decreased their ST after completing the SSC protocol, while maintaining relatively constant levels of SL. It was also noted that participants exhibited lower levels of $\alpha$ in a fatigued state, while leaving the magnitude of variability, i.e. CV, unaffected. Elite runners took significantly longer strides but exhibited stride rates that were comparable to those of the recreational runners. Consequently, the elite group performed the overground run at a significantly greater running speed. No significant group effects were found with respect to the magnitude of variability or $\alpha$. In conclusion, fatiguing high-intensity SSC exercise was shown to affect mean ST, lower extremity joint stiffness as well as LRCs in elite and recreational runners when running at a comfortable, self-selected speed on an indoor track. The results suggest that $\alpha$ may serve as a potential indicator of neuromuscular fatigue and possibly signifies changes in the spring-mass behavior.
during running. It was also demonstrated that LRCs can be assessed with a simple hardware setup, consisting of a single foot-mounted IMU. In the future, this work could be extended by connecting sensors to mobile end-user devices, thus offering a simple and convenient way to monitor stride kinematics, variability and fatigue-related changes in gait dynamics in real time. Potentially, data collected from large cohorts could be used to identify fatigue thresholds and gait patterns that are associated with a greater risk of injury.
7 Limitations

There were several limitations that should be considered when interpreting the results of this thesis:

1. The results of all three studies only apply to a population that has characteristics similar to those of the participants that were recruited for this study (e.g. age range, training, skill level and health status). In particular, the results may not apply to runners with a history of running injury.

2. Although the sample sizes that were initially estimated using an a-priori power analysis were achieved for all studies, the cohorts were relatively small. This factor may have reduced the statistical power and increased the likelihood of error.

3. The gender ratio was different in the cohorts of all three studies. Consequently, any interaction that may have occurred due to gender remains undetermined. Furthermore, a confounding effect of gender on the outcome variables cannot be ruled out.

4. The validation of the stride length algorithm in Study 1 involved several short linear runs. It was assumed that this method would work equally well for prolonged continuous overground running, but the method has not been validated for this specific condition.

5. The excellent levels of agreement between the two stride length methods reported in Study 1 were achieved by manually tuning the thresholds of the recorded angular velocity and acceleration signals. Although this approach worked well for a small number of participants, the use of alternative approaches, e.g. adaptive thresholds, should be considered when applying the method to larger cohorts.
6. One of the assumptions of Study 1 was that the velocity of the foot was zero during stance. Although the high accuracy of sensor-based stride length vectors suggests that the induced drift error was very small and potentially negligible for most applications, the degree to which factors such as running speed and individual foot strike patterns affected this assumption is unknown.

7. Study 2 assumed that exhaustion, as defined by the inability to maintain a pre-determined running speed, is associated with a high amount of fatigue. Despite the fact that the model of voluntary exhaustion is frequently used in biomechanical research it does not allow for any inferences to be drawn with regard to the neuromuscular processes underlying fatigue.

8. With regard to the previous point, it should also be recognized that the participants’ motivation, well-being, and current physical condition may have influenced the level of perceived exertion at the end of the run and consequently affected the point at which the experiment was terminated.

9. The effects of controlling for speed during overground running on measures of self-similarity and variability are not known. It is possible that this condition imposed notable constraints on the participants, which in turn may have altered their stride pattern.

10. The methods for calculating contact time, stride time and peak impact acceleration in Study 2 and 3 were not validated against a gold standard, i.e. force plate 3-D motion capture. Algorithms were based on approaches used by previous studies.

11. It is not known if the frequency with which the inertial data was sampled had an effect on the accuracy of the stride parameter estimates, particularly LRCs. Measures of self-similarity require that stride-to-stride fluctuations be
recorded with high temporal resolution. A sampling frequency of 100Hz caused notable quantization for ST at the 10ms level. Although kinematic data for running is frequently collected at 100Hz, it is not known if a higher sampling frequency would have resulted in the same levels of LRCs.

12. Similar to study 2, neuromuscular aspects of fatigue were not assessed directly in Study 3. Instead, this experiment was based on the assumption that severe exertion is associated with a substantial amount of fatigue.

13. Although an effort was made to minimize any variation in the rest periods between the testing procedures, the time between the fatiguing jump protocol and the post-test procedures varied to a small extent between participants. This was due to unforeseen events, such as detached camera markers, which required a quick recalibration of the marker model.

14. Participants were instructed to perform all pre- and post-jump overground runs at a self-selected comfortable pace. Although no significant differences in overall running speed were found with respect to these runs, individual variations in running speed cannot be ruled out.
8 Conclusion and Future Work

The present thesis adds a number of important findings to the existing literature and raises further questions about underlying physiological mechanisms of gait control, as well as clinical and performance-related applications. As such, it may serve as the basis for future research that investigates the complex interactions between fatigue, skill level and the structure of stride-to-stride fluctuations in running.

Firstly, it was demonstrated that SL can be predicted with high accuracy by a simple, non-invasive sensor configuration consisting of a single foot-mounted IMU. From a research and performance perspective, detailed knowledge about SL is crucial for coaches, clinicians and researchers alike because together with SR it determines running speed. Moreover, individual SL vectors represent the integrated output of different biomechanical determinants and as such can provide valuable insight into the control of running gait.

In the past, SL during overground running has often been assessed in a confined laboratory setting using stationary high-precision camera systems. However, this method is not suited for detecting changes that may occur in the stride pattern during prolonged running because it only allows for a small number of consecutive strides to be recorded. For continuous running, researchers were traditionally restricted to using treadmills and applying the known relationship between running speed, SR and SL to calculate an average SL value for a certain time interval. Although this method has helped researchers understand how runners modify running speed (Cavanagh & Kram, 1989; Weyand et al., 2000), it is not capable of detecting stride-to-stride fluctuations and consequently does not offer any insight into the control of running gait. Additionally, research has shown that the biomechanics of treadmill running differ from those exhibited during overground running (Frishberg, 1983; Nigg et al., 1995; P. Riley et al., 2008). Likewise, LRCs
during running are thought to differ significantly between treadmill and overground conditions, possibly due to the greater constraints imposed on the locomotor system by ‘pacing’ of the treadmill belt (Lindsay et al., 2014).

The limitations of existing methods used to calculate SL and the lack of studies that have explicitly focused on SL in running emphasized the need to systematically test the performance of an IMU-based algorithm to calculate SL during running. The sensor-based method was found to be valid in its assessment of stride length when compared to a 3-D camera system (ICC(3,1) = 0.955, p < 0.001). Due to the inability to continuously monitor stride length during running using cameras, the performance of the sensor method was tested by repeatedly recording a small number of consecutive strides. Although this approach yielded excellent results, its accuracy during prolonged overground running is not yet known. Consequently, future research should make an effort to validate the performance of PDR algorithms to calculate individual stride length vectors during running using alternative approaches. This could potentially be achieved with synchronization between body-fixed sensors and force plates.

One of the reasons for the excellent performance of this method was the frequent application of ZUPTs. However, this approach depended on the correct identification of each stance phase. Although our results suggest that individual running technique influenced the performance of the stance detection algorithm, these aspects were not subject to investigation. Thus, future work needs to determine the sensitivity of SL algorithms to aspects such as foot strike patterns and running speed. Overall, this experiment is highly relevant within the field of gait biomechanics and running research because it expands the existing set of variables that can be monitored during continuous running. In addition to providing detailed knowledge about SL, the excellent performance of the IMU-based algorithm will also enable researchers to conduct other, more sophisticated analyses of a
continuous SL series, for example by tracking the coefficient of variation and the fractal-scaling index $\alpha$ under various conditions.

Although fatigue is a well-studied phenomenon, prior to the current thesis, no research had been done to track both spatial and temporal stride parameters, their variability and LRCs during exhaustive overground running in a cohort of recreational and elite runners. After validating the use of a simple IMU-configuration to determine SL, a series of stride parameters, including their CV and LRCs were tracked over the course of a fatiguing run at a fixed, pre-determined running speed. While participants maintained constant levels of SR and SL, LRCs of all investigated parameters decreased as a function of running time ($p \leq 0.003$). In contrast, no changes were observed in linear measures of variability ($p \leq 0.126$). Mean peak impact acceleration ($p = 0.003$) and contact time ($p = 0.028$) also increased over the course of the run for both groups.

Interestingly, $\alpha$ did not decline linearly over the course of the run but exhibited a sharp decrease after the first run interval, which confirms previous reports from Meardon et al. (2011). Although it is likely that participants had already experienced a certain degree of exertion at this stage, it is safe to state that they were still far from the point of being unable to maintain the required speed. One possible explanation for this behavior is that $\alpha$ indicates the early onset of fatigue during locomotion. Future research should systematically examine the response of LRCs to increasing levels of exertion and also use a larger number of time intervals for which $\alpha$ is calculated. This may help to further elucidate the role of LRCs in locomotion in relation to fatigue.

Group comparison revealed that elite runners demonstrated greater stride lengths ($p < 0.001$), shorter ground contact time ($p < 0.001$), greater peak impact acceleration ($p < 0.001$) and lower stride time CV ($p < 0.007$) than recreational runners. In contrast, no group differences were found with respect to the strength of
LRCs. This supports the idea that the mechanisms responsible for the emergence of LRCs in the stride pattern are a general characteristic of the motor control system, which is unaffected by skill level and the high volume of training completed by the elite distance runners. However, similar experiments using different cohorts, e.g. injured vs. non-injured, are necessary to better understand the role of $\alpha$ and its effects on the motor control system.

A fundamental assumption of this experiment was that fatigue is associated with the inability to preserve a constant work output, i.e. maintain running speed. While this model is commonly used in the literature, it does not provide insight into the physiological processes that govern the fatigue response in the working muscle. In order to learn about the processes that are potentially responsible for the decrease in LRCs during exhaustive exercise, future studies need to apply methods that directly assess neuromuscular fatigue. Furthermore, the effects of controlling for speed on measures of self-similarity and variability during a fatiguing run are not known. As a result, future work needs to quantify the extent to which external constraints during overground running affect the strength of LRCs and determine the degree to which the results differ from treadmill running.

To further examine the potential link between neuromuscular fatigue, joint mechanics and LRCs, a high intensity SSC activity was tested to determine the extent to which it affected the stiffness characteristics of the ankle and knee joints, basic stride parameters as well as gait dynamics during distance running. Joint stiffness was significantly reduced after the fatiguing jumps ($p < 0.007$) in both groups. Furthermore, detrended fluctuation analysis of the stride time and stride length series revealed that levels of $\alpha$ decreased in response to the jump protocol ($p < 0.001$) in elite and recreational runners. However, a comparison of the observed changes in joint stiffness and LRCs did not yield any significant correlations, which corroborates the view that these factors represent different dimensions of fatigue.
and that LRCs in the stride pattern originate within the central nervous system. Although this view is also supported by other studies, future research should investigate true indicators of neuromuscular fatigue in combination with joint stiffness to identify the mechanisms that are responsible for the reduction of LRCs.

It must also be pointed out that the findings of the third study differed from those of study 2 in certain aspects. For instance, it was observed that mean stride time changed only in response to the fatiguing jumps but not during the exhaustive overground run. In contrast, group differences in stride time CV were only observed during exhaustive running (section 5). Possibly, some of these discrepancies are linked to differences in study design. For example, running speed in the second experiment was equivalent to an individual all-out 5000 m pace. This implies that the relative intensity of the run was higher compared to the third study, where participants had to run at a comfortable, self-selected pace for 8 minutes. Additionally, the second experiment used a prolonged continuous run to exert the participants, while Study 3 employed a short high-intensity jump protocol. Given the equivocal results, precise evaluation is recommended to examine the effects of varying levels of exercise intensity on different stride parameters. Furthermore, other factors were not investigated or controlled for in the experiments and consequently may have had an effect on the outcome of the studies. These aspects include but are not limited to: muscle morphology, availability of energy substrates, individual running technique, as well as sex.

In summary, the present thesis adds valuable insight into how fatigue and skill level affect various stride parameters, their variability and LRCs during unconstrained running. The proposed IMU-configuration was found to be capable of tracking various stride parameters, including mean stride length, CV and LRCs, which are important measures in the analysis of running gait. The fact that these parameters can be accurately calculated with an IMU demonstrates the great
potential for biomechanics research and clinical applications. One of the key findings of this thesis was that LRCs changed in response to exhaustive stretch-shortening exercise, i.e. prolonged running and jumping, while linear measures of variability, such as the coefficients of variation were insensitive to this process. It was also established that recreational and elite runners exhibited similar levels of $\alpha$ across conditions, which suggests that the mechanism responsible for the occurrence of LRCs in the stride pattern is unaffected by skill level or training. These findings could act as a vantage point for future research that aims at analyzing gait patterns under natural conditions. For example, future research could use non-linear approaches to effectively quantify the training loads for distance runners. When being used to derive sophisticated parameters of gait dynamics, such as LRCs, sensor algorithms have the potential to become an important tool for runners, which may help to monitor the training loads and subsequently reduce the risk of overuse injuries.
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Appendix A

Ethics Approval Forms

PRINCIPAL INVESTIGATOR
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Regina, SK S4P 2R7

DEPARTMENT
Kinesiology and Health Studies

REB#
2014-174

SUPERVISOR
Dr. John Barden – Kinesiology and Health Studies

FUNDER(S)
Unfunded

TITLE
Concurrent Validity of Body-Fixed IMUs to Estimate Stride Length and Stride-to-Stride Fluctuations in Running

APPROVAL OF
Consent Form
Information Sheet
Poster

APPROVED ON
October 16, 2014

RENEWAL DATE
October 16, 2015

Full Board Meeting
Delegated Review

CERTIFICATION
The University of Regina Research Ethics Board has reviewed the above-named research project. The proposal was found to be acceptable on ethical grounds. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to this research project, and for ensuring that the authorized research is carried out according to the conditions outlined in the original protocol submitted for ethics review. This Certificate of Approval is valid for the above time period provided there is no change in experimental protocol, consent process or documents.

Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair for Research Ethics Board consideration in advance of its implementation.

ONGOING REVIEW REQUIREMENTS
In order to receive annual renewal, a status report must be submitted to the REB Chair for Board consideration within one month of the current expiry date each year the study remains open, and upon study completion.
Please refer to the following website for further instructions: [http://www.uregina.ca/research/REB/mpin.shtml](http://www.uregina.ca/research/REB/mpin.shtml)


Dr. Larena Hoeber, Chair
University of Regina
Research Ethics Board

Please send all correspondence to:
Office for Research, Innovation and Partnership
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Dr. John Barden - Kinesiology and Health Studies

Unfunded

Variability of Stride Kinematics and Impact Loading Characteristics During a Prolonged Run in Recreational and Elite Distance Runners

February 5, 2015  
February 5, 2016

Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair for Research Ethics Board consideration in advance of its implementation.

Please refer to the following website for further instructions: http://www.uregina.ca/research/REB/main.shtml

Dr. Larena Hoeber, Chair  
University of Regina  
Research Ethics Board
PRINCIPAL INVESTIGATOR
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SUPERVISOR
Dr. John Barden - Kinesiology and Health Studies

FUNDER(S)
Unfunded

TITLE
The Effects of Stiffness Modification on Variability and Running Mechanics in Recreational and Elite Distance Runners

APPROVAL OF
Application for Behavioural Research Ethics Review
Consent Form
Information Sheet
Poster

APPROVED ON
February 5, 2015

RENEWAL DATE
February 5, 2016

CERTIFICATION
The University of Regina Research Ethics Board has reviewed the above-named research project. The proposal was found to be acceptable on ethical grounds. The principal investigator has the responsibility for any other administrative or regulatory approvals that may pertain to this research project, and for ensuring that the authorized research is carried out according to the conditions outlined in the original protocol submitted for ethics review. This Certificate of Approval is valid for the above time period provided there is no change in experimental protocol, consent process or documents.

Any significant changes to your proposed method, or your consent and recruitment procedures should be reported to the Chair for Research Ethics Board consideration in advance of its implementation.

ONGOING REVIEW REQUIREMENTS
In order to receive annual renewal, a status report must be submitted to the REB Chair for Board consideration within one month of the current expiry date each year the study remains open, and upon study completion.

Please refer to the following website for further instructions: http://www.uregina.ca/research/REB/main.shtml

Dr. Larena Hoeber, Chair
University of Regina
Research Ethics Board

Please send all correspondence to:
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Appendix B

Consent Form Study 1

CONSENT FORM

Concurrent Validity of Body-Fixed IMUs to Estimate Stride Length and Stride-to-Stride Fluctuations in Running

Principal Investigators:

Clemens M. Brahms
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Dr. John Barden
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Phone: (306) 585-4629
E-mail: john.barden@uregina.ca

To be completed by the participant:

Have you read and received a copy of the attached Information Sheet?  Yes  No
Do you understand the benefits and risks involved in taking part in this research study?  Yes  No
Have you had an opportunity to ask questions regarding the study?  Yes  No
Do you understand that you are free to refuse to participate or withdraw from the study at any time?  Yes  No
Has the issue of confidentiality been explained to you?  Yes  No
If you are currently a student in a class of one of the investigators:

Do you understand that participation will not result in favorable treatment in class?  Yes  No
Are you currently between the ages of 20 and 35?  Yes  No

This study was explained to me by: ___________________________

I agree to take part in this study.

_________________________  __________________________  __________________________
Signature of participant  Date  Witness

_________________________  __________________________
Printed Name  Printed Name

I believe that the person signing this form understands what is involved in the study and voluntarily agrees to participate.

_________________________  __________________________
Signature of Investigator Date  Date

This project has been approved by the Research Ethics Board of the University of Regina. If you have any questions or concerns about your rights or treatment as a research participant, you may contact the Chair of the University Research Ethics Board by phone at 585-4775 or by e-mail at research.ethics@uregina.ca. Should you have any questions or wish to discuss the procedures or objectives of the study, please contact Clemens Brahms via phone (306) 216-6847 or e-mail (brahms2c@uregina.ca).

THE INFORMATION SHEET MUST BE ATTACHED TO THIS CONSENT FORM AND A COPY GIVEN TO THE RESEARCH PARTICIPANT
Appendix C

Information Sheet Study 1

Clemens M. Brahms
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Dr. John Barden
Faculty of Kin. & Health Studies
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PURPOSE OF THE STUDY:
The purpose of this study is to determine whether body-mounted sensors can provide valid estimates for stride length (SL) during distance running. In particular, the accuracy of two existing methods will be tested with a camera system as the criterion.

BACKGROUND:
Stride length is an important variable of running. It can be precisely assessed with force plates or cameras. Since the advent of cost-effective and accurate inertial sensors, several studies have tried to estimate SL by attaching these sensors to the body (Jimenez et al., 2009; Martin, 2011). However, this is difficult because small errors will add up over time. Additionally, most studies have tried to determine SL during walking on a flat surface. To the best of our knowledge, no study exists that has examined the precision of body-mounted sensors to calculate SL and its variability for running.

PROCEDURE:
An inertial sensor will be placed on your right foot. It will be firmly attached using the shoe’s laces and adhesive tape. Additionally, you will be equipped with a small accelerometer, which will be secured to your lower back region with a waist-belt. Once equipped with these sensors, you will be asked to perform a series of twenty short runs (approx. 10m) through a calibrated camera space. You will also be asked to naturally vary your running speed between trials. The time required to collect the data will be approximately 20-30 minutes.

RISKS/BENEFITS:
There are no known risks associated with the short runs. The sensors used in this project are attached to the body in a way that they do not interfere with your natural movements. You will be able to stop running on your own account at any point during the experiment. Your participation will help to develop a tool that is able to accurately measure stride length in running. This tool could be used to improve running technique and detect injury.

CONFIDENTIALITY/FREEDOM TO WITHDRAW:
Group averages rather than individual data will be reported. If it becomes necessary to report individual data, an anonymous subject code and trial number will be used. Individual subject codes (e.g., Subject 1a) will be the only reference to any presentation of individual data. Only the investigators will have access to participant information. Investigators will not directly identify any participants in the study. Participation is strictly voluntary. You are free to withdraw from the study at any time. Data from this study will not be used in future studies without approval from an ethics committee.

If you have any questions about the study or wish to provide comments about the research and its procedure, please contact Clemens Brahms at (306) 551-9155 or via e-mail at brahms2c@uregina.ca; or Dr. John M. Barden at (306) 585-4629 or via e-mail at john.barden@uregina.ca.
Appendix D

Consent Form Study 2

D

CONSENT FORM

Variability of Stride Kinematics and Impact Loading Characteristics During a Prolonged Run in Recreational and Elite Distance Runners

Principal Investigators:

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To be completed by the participant:

Have you read and received a copy of the attached Information Sheet? Yes No
Do you understand the benefits and risks involved in taking part in this research study? Yes No
Have you had an opportunity to ask questions regarding the study? Yes No
Do you understand that you are free to refuse to participate or withdraw from the study at any time? Yes No
Has the issue of confidentiality been explained to you? Yes No
If you are currently a student in a class of one of the investigators:
Do you understand that participation will not result in favorable treatment in class? Yes No
Do you understand that no negative consequences will result from not choosing to participate? Yes No

This study was explained to me by: ____________________________

I agree to take part in this study.

_________________________ ___________
Signature of participant Date

_________________________ ___________
Printed Name

I believe that the person signing this form understands what is involved in the study and voluntarily agrees to participate.

_________________________ ___________
Signature of Investigator Date

This project has been approved by the Research Ethics Board of the University of Regina on _________. If you have any questions or concerns about your rights or treatment as a research participant, you may contact the Chair of the University Research Ethics Board by phone at 585-4775 or by e-mail at research.ethics@uregina.ca. Should you have any questions or wish to discuss the procedures or objectives of the study, please contact Clemens Brahms by phone (306) 551-9155 or e-mail (brahms2c@uregina.ca).

THE INFORMATION SHEET MUST BE ATTACHED TO THIS CONSENT FORM AND A COPY GIVEN TO THE RESEARCH PARTICIPANT
Appendix E

Information Sheet Study 2

INFORMATION SHEET

Variability of Stride Kinematics and Impact Loading Characteristics During a Prolonged Run in Recreational and Elite Distance Runners

Principal Investigators:
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PURPOSE OF THE STUDY:
This project is designed to investigate the relationship between gait variability and running mechanics under fatiguing conditions using body-mounted sensors. It will also assess the extent to which these relationships differ between recreational and competitive distance runners.

BACKGROUND:
Prolonged distance running requires continuous effort and eventually causes muscle fatigue. It has been shown that this can fundamentally alter the running mechanics of an individual. Measures of variability and temporal stability convey important information about the control of gait and have been reported to change with fatigue. However, these results are still preliminary and require further investigation.

PROCEDURE:
Wireless sensors will be securely attached to your trunk and foot. Additionally, you will also be equipped with a heart rate monitor and an associated footpod that monitors speed and triggers an audible alarm when running speed changes significantly. Once equipped with the sensors, you will be asked to complete a fatiguing run at a constant, predetermined running speed on an indoor running track. The run will end when your running speed repeatedly drops below a pre-defined, individualized threshold. The estimated time requirement for participation in this study will be 60-75 minutes.

RISKS/BENEFITS:
There are no known risks associated with the overground running trials. The body-mounted sensors used in this project are attached in a way that will not interfere with your natural movements. You might experience some discomfort and considerable exhaustion at the end of the run. Guidance in terms of medical assistance will be provided to you prior to the test protocol. There is also a small risk of over-exertion. If your perceived exertion is becoming severe, you can terminate the run on your own account at any point during the experiment. Your participation will help to develop a potentially important screening tool to detect signs of fatigue and overtraining, which could lead to more efficient methods for injury prevention.

CONFIDENTIALITY/FREEDOM TO WITHDRAW:
Group averages rather than individual data will be reported. If it becomes necessary to report individual data, the data will be referred to by an anonymous subject code and trial number. Individual subject codes (e.g., Subject 1a) will be the only reference to any presentation of individual data. Only the investigators will have access to participant information. There are no circumstances that would require the investigators to directly identify any participants in the study. Participation is strictly voluntary and you are free to withdraw from the study at any time. You can request that your data will be deleted after participation in the study. Data from this study will not be used in future studies without further approval from an ethics committee.
Appendix F
Participant Intake Form Study 2

**STUDY INTAKE FORM**

Stride Kinematics, Impact Loading Characteristics and Variability over a Prolonged Run in Recreational and Elite Distance Runners

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<td></td>
</tr>
<tr>
<td>Are you over 35 years of age?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Do you have any medical condition that could be worsened by prolonged running?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Have you had surgery or any running related injury or in the past 6 months that prevented you from training for more than 7 days?</td>
<td></td>
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</tr>
<tr>
<td>How many hours, on average, do you run per week?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are you currently a competitive distance runner?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Age:  ___________  Height:  ___________

Gender:  ___________  Weight:  ___________

Participant Number:  ___________

What is your most recent 5k time?  ___________

How many hours, on average, do you run per week?  ___________
### Appendix G

**RPE / Borg Scale**

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<tr>
<td>7</td>
<td>EXTREMELY LIGHT</td>
</tr>
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<td>8</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>VERY LIGHT</td>
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</tr>
<tr>
<td>12</td>
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</tr>
<tr>
<td>13</td>
<td>SOMewhat HARD</td>
</tr>
<tr>
<td>14</td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>HARD (HEAVY)</td>
</tr>
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<td>19</td>
<td>EXTREMELY HARD</td>
</tr>
<tr>
<td>20</td>
<td>MAXIMAL EXERTION</td>
</tr>
</tbody>
</table>
Appendix H

Consent Form Study 3

The Effects of Stiffness Modification on Variability and Running Mechanics in Recreational and Elite Distance Runners

Principal Investigators:

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Regina, SK S4S 0A2
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E-mail: john.barden@uregina.ca

To be completed by the participant:

Have you read and received a copy of the attached Information Sheet? Yes No
Do you understand the benefits and risks involved in taking part in this research study? Yes No
Have you had an opportunity to ask questions regarding the study? Yes No
Do you understand that you are free to refuse to participate or withdraw from the study at any time? Yes No
Has the issue of confidentiality been explained to you? Yes No
If you are currently a student in a class of one of the investigators: Do you understand that participation will not result in favorable treatment in class? Yes No
Are you currently between the ages of 18 and 35? Yes No

This study was explained to me by: __________________________

I agree to take part in this study.

_________________________ __________________________
Signature of participant Date Witness

_________________________ __________________________
Printed Name Date Printed Name

I believe that the person signing this form understands what is involved in the study and voluntarily agrees to participate.

_________________________ __________________________
Signature of Investigator Date

This project has been approved by the Research Ethics Board of the University of Regina. If you have any questions or concerns about your rights or treatment as a research participant, you may contact the Chair of the University Research Ethics Board by phone at 585-4775 or by e-mail at research.ethics@uregina.ca. Should you have any questions or wish to discuss the procedures or objectives of the study, please contact Clemens Brahms by phone (306) 551-9155 or e-mail (brahms2c@uregina.ca).

THE INFORMATION SHEET MUST BE ATTACHED TO THIS CONSENT FORM AND A COPY GIVEN TO THE RESEARCH PARTICIPANT.
Appendix I

Information Sheet Study 3

I

UNIVERSITY OF REGINA

Faculty of Kinesiology and Health Studies

INFORMATION SHEET

The Effects of Stiffness Modification on Variability and Running Mechanics in Recreational and Elite Distance Runners

Principal Investigators:

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PURPOSE OF THE STUDY:

This project is designed to test whether fatigue-induced alterations in leg and joint stiffness are associated with changes in movement variability during running. It will also investigate whether altered joint stiffness has similar effects on measures of stride pattern self-similarity in both elite distance runners and recreational runners.

BACKGROUND:

Although it is generally thought that self-similar patterns emerge within the central nervous system, there is evidence to suggest that these so-called long-range correlations (LRCs) present in gait variables may have biomechanical origins. It has further been established that prolonged stretch-shortening cycle exercise, such as hopping and jumping, causes a reduction in the force generating capacity of the active muscles and fundamentally alters the biomechanics of running. In order to elucidate the meaning of LRCs in running gait, this study will investigate the relationship between fatigue-induced alterations in stiffness and movement variability. A second objective of this study will be to determine whether altered joint stiffness has similar effects on LRCs in both elite distance runners and recreational runners.

PROCEDURE:

After a short warm-up, reflective markers will be placed on your lower extremity to track leg movements. Subsequently, you will be asked perform a 2-minute run on a force-plate mounted treadmill. All runs in this experiment will be performed at your preferred running speed. After the short run, you will complete an 8-minute overground run on a running track while wearing a waist-mounted accelerometer. Following this pre-test, participants will participate in a jumping protocol which will consist of 100 single drop jumps from a predetermined height, with one jump being performed every 5 seconds. After this series of jumps, you will be asked to continuously jump in place until you feel you can no longer continue. For all jumps, you will be asked to keep your hands placed firmly against your waist to prevent the use of your arms to increase jump height.

Upon completion of the protocol, you will again be equipped with reflective markers and asked to perform another 2-minute run on the force-plate mounted treadmill to re-evaluate knee, ankle and leg stiffness. Subsequently, LRCs will be re-assessed using the body-mounted accelerometer on a running track. The total time requirement for participation in this study will be approximately 60 minutes.

RISKS/BENEFITS:

There are no known risks associated with the overground running trials. The body-mounted sensors used in this project will be attached in a way that will not interfere with your natural movements. You might experience some discomfort and considerable exhaustion at the end of the jumping protocol. Participants who are unaccustomed to repetitive jumping might also experience some degree muscle soreness or overexertion. Guidance in terms of medical assistance will be provided to you prior to the test protocol. If your perceived exertion is becoming severe, you can stop running or jumping on your own account at any point during the experiment. Your participation will help to develop a potentially important screening tool for running injuries, which could lead to more efficient methods for injury prevention.
Appendix J

Participant Intake Form Study 3

STUDY INTAKE FORM

The Effects of Stiffness Modification on Variability and Running Mechanics in Recreational and Elite Distance Runners

<table>
<thead>
<tr>
<th>Question</th>
<th>YES</th>
<th>NO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Are you under 18 years of age?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are you over 35 years of age?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Do you have any medical condition that could be worsened by the procedures described on the information sheet?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Have you had surgery or any injury or in the past 6 months that prevented you from running/training for more than 7 days?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>How many hours, on average, do you run per week?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are you currently a competitive distance runner?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Age: ___________ Height: ___________

Gender: ___________ Weight: ___________

Participant Number: ___________

How many hours, on average, do you run per week? ___________