EVALUATION OF STRIDE VARIABILITY BETWEEN EXPERIENCED AND NOVICE RUNNERS DURING A PROLONGED RUN

by

MO, Shiwei

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DEPARTMENT OF HEALTH AND PHYSICAL EDUCATION

SUPERVISORY AND EXAMINING COMMITTEE

Shiwei Mo, candidate for the degree of Doctor of Philosophy in Health and Physical Education, has presented a thesis titled, **Evaluation of Stride Variability between Experienced and Novice Runners during a Prolonged Run,** in an oral examination held on October 4, 2018. The following committee members have found the thesis acceptable in form and content, and that the candidate demonstrated satisfactory knowledge of the subject material.

External Examiner I:	Professor LU Weijia, William, The University of Hong Kong
External Examiner II:	*Dr. KONG Pui Wah, Nanyang Technological University
External Examiner III:	*Dr. TREMBLAY Luc, University of Toronto
Principle Supervisor:	Professor CHOW Hung Kay, Daniel, Department of Health and Physical Education
Committee Member:	Dr. CHEUNG Pui Yee, Peggy, Department of Health and Physical Education
Committee Member:	Dr. Sun Fenghua, Bob, Department of Health and Physical Education
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Shiwei Mo

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Abstract

The objectives of this dissertation were to evaluate the accuracy of using inertial measurement unit (IMU) for gait events prediction during overground running and investigate effects of running experience and fatigue on stride-to-stride variability during a prolonged treadmill run. The entire study consisted of three parts. The first part evaluated the accuracy of three typical IMU-based methods for gait events prediction during an overground run. The S-method, placing the IMU at the shoe instep and analysing the resultant acceleration, produced the most accurate initial contact prediction with mean absolute difference of 4.7 (4.1) ms. The M-method, placing the IMU at the shank and analysing the vertical acceleration, produced the most accurate toe-off prediction with mean absolute difference of 7.0 (3.5) ms. The MS-method—a combination of the S- and M-methods—provided the most accurate stance time estimation with mean percentage difference of 3.8% (1.6%), and mean absolute differences of 9.1 (4.2) ms during jogging and 8.8 (3.5) ms during running.

The second part investigated stride interval dynamics of both experienced and novice runners while performing a 31-min treadmill run at their individual anaerobic threshold speeds. The scaling exponent alpha of the detrended fluctuation analysis and coefficient of variance were used to quantify the complexity and variability of the stride interval dynamics, respectively. A U-shape trend of the alpha was observed for both the experienced and novice runners, but the two groups presented slight differences in both the alpha and the coefficient of variance. Both the experienced and novice runners regulated the stride interval complexity to maintain the run at anaerobic threshold speed. The experienced runners also regulated the stride interval variability.

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The final part investigated lower-limb coordination pattern and variability during a 31-min treadmill run. Lower-limb coordination pattern and variability during the stance phase at the beginning, middle, and end of the run were quantified using a modified vector coding technique. Running experience and progressive fatigue had significant interactions on the coordination patterns for the hip–knee and pelvis–thigh couplings. The experienced runners exhibited a higher percentage of in-phase motion for the pelvis–thigh and knee–ankle couplings, whereas the novice runners exhibited a higher percentage of distal dominant motion for the pelvis–thigh coupling and anti-phase motion for the hip–knee coupling during mid-stance. The experienced runners exhibited more variability in the hip–knee and shank–foot couplings, whereas the novice runners had more variability in hip, knee, and thigh motions. The experienced and novice runners adapted to fatigue through different lower-limb coordination patterns. The experienced runners demonstrated larger variability for segment/joint coupling motions and the novice runners exhibited larger variability for single segment/joint motions.

In conclusion, this dissertation demonstrated that initial contact and toe-off could be most accurately predicted by identifying the local peak resultant acceleration measured by the foot IMU and the minimum vertical acceleration measured by the shank IMU during overground running, and different gait regulation strategies for adapting to progressive fatigue between the experienced and novice runners during treadmill running at anaerobic threshold speed.

Keywords: anaerobic threshold, distance run, inertial measurement unit, variability

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Table of Contents

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List of Abbreviations

ABD/ADD	Abduction/adduction
α	Scaling exponent alpha
AD	Absolute difference
AP	anteroposterior
AT	Anaerobic threshold
CoV	Coefficient of variance
CV	Coordination variability
DFA	Detrended fluctuation analysis
e.g.	Exempli gratia
ER	Experienced runners
et al.	Et alia
etc.	Et cetera
FLEX/EXT	Flexion/extension
g	Acceleration due to gravity
GRF	Ground reaction force
IC	Initial contact
IMU	Inertial measurement unit
INT/EXT ROT	Internal/external rotation
MAD	Mean absolute difference
ML	Mediolateral

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MRD	Mean relative difference
NR	Novice runners
PAR-Q	Physical Activity Readiness Questionnaire
Q_1	25th percentile
Q_3	75th percentile
r	Pearson's *r*; correlation coefficient
RD	Relative difference
RPE	Rating of perceive exertion
RRIs	Running-related injuries
SD	Standard deviation
ST	Stance time
3D	Three-dimensional
TO	Toe-off
$\dot{V}_E/\dot{V}_{O_2}$	Ratio of ventilation to oxygen consumption
%D	Percentage difference

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List of Figures

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List of Tables

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List of Units

cm	Centimetre
Hz	Hertz
h	Hour
kg	Kilogram
kg/m^2	Kilogram per square metre
km	Kilometre
km/h	Kilometre per hour
m	Metre
m/s	Metre per second
min	Minute
ms	Milliseconds
mm	Millimetre
mmol/L	Millimoles per litre
N	Newton
s	Second
°	Degree

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Chapter 1: Introduction

1.1 Rationale and Justifications of This Study

Distance running has become extremely popularity worldwide. However, instances of running-related injuries (RRIs) have increased remarkably, particularly for novice runners, who face the highest risk of RRIs (Kluitenberg et al., 2015). The most prevalent sites of RRIs are in the lower limbs (Lopes et al., 2012; Tschopp & Brunner, 2017; van Gent et al., 2007), and the reported incidence of lower-limb RRIs (e.g., patellofemoral pain and iliotibial band syndrome) varies from 11% to 92.4% in the literature (Kluitenberg et al., 2015; van Gent et al., 2007).

Understanding running mechanics is necessary for RRIs prevention. Numerous studies (Breine et al., 2017; Hreljac et al., 2000; Lieberman et al., 2010; McClay & Manal, 1997; Stergiou et al., 1999; van der Worp et al., 2016; Zhang et al., 2017) have investigated the running mechanics with the aim of identifying biomechanical factors which may contribute to developing an RRI, such as foot strike pattern and running shoes (Breine et al., 2017; Lieberman et al., 2010; van der Worp et al., 2016; Zhang et al., 2017). These studies are based on cognitive theory to motor control and therefore mostly aimed to identify the invariant characteristics of gait patterns during running and focused on average values. To date, limited insights have been gained into the relationship between running mechanics and RRIs (Ferber et al., 2009). Dynamical systems theory has been recently used to understand the mechanics of developing an RRI (Bartlett et al., 2007; Davids et al., 2003; Hamill et al., 2012). According to the dynamical systems theory, the variability between strides (also called stride-to-stride variability or stride variability in this

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dissertation) during running, which was traditionally treated as noise, was regarded as a by-product of long-range dynamics (Chau et al., 2001).

The stride variability refers to two types, variability at task execution level, such as coordination variability, and variability at task outcome level, such as stride interval variability (Davids et al., 2003; Hamill et al., 2012). Both reflects the flexibility of the locomotor system to adapt to constraints imposed by the ever-changing environment (Davids et al., 2003). The stride variability may help to reduce the risk of developing an RRI because the impact loading during landing per stride can be distributed over a relatively broader area among different structures of the human body, thereby reducing the cumulative load (or stress) applied to a specific structure (e.g., knee joint) during a running session (Bartlett et al., 2007; Bertelsen et al., 2017; Gabbett, 2016). In support of this theory, numerous studies (Hamill et al., 1999; Lilley et al., 2018; Miller et al., 2008) found a lower variability for the injured group (e.g., patellofemoral pain and iliotibial band syndrome) compared with the healthy control group.

However, running performance is negatively affected when the stride variability is excessively high due to less efficiency (Belli et al., 1995). Moreover, in accordance with the cognitive theory to motor control, the stride variability may represent aberrant neuromuscular control (Schmidt, 2013); consequently, excessively high stride variability may result in poorly controlled motion and cause excessive stress and RRIs (Hamill et al., 2012). In support of this theory, many studies (Edwards et al., 2017; Hein et al., 2012; Kipp & Palmieri Smith, 2012) demonstrated a higher variability for the injured group (e.g., chronic ankle instability and iliotibial band syndrome) compared with the healthy control group. There may exist an ‘optimal window’ for the stride

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variability during running (Hamill et al., 2012), and within this range, one would both reduce the risk of developing an RRI and avoid negative effects on running performance. Nevertheless, defining the 'optimal window' is currently difficult because the characteristics of the stride-to-stride variability in healthy runners, such as in runners with different years of running experienced during a prolonged run, remain unclear and require further study.

Studies have investigated running mechanics primarily through the analysis of isolated joints and segments and the measurements of discrete parameters at specific gait events, such as initial contact and toe-off. Coordination is goal-directed and refers to the performer's employment of an individualised approach to adapt to specific constraints during task execution, such as running (Davids et al., 2003). Because running is a complex motor skill that involves multiple joints and segments, investigating the coordination for the joint and segment coupling motions, instead of the isolated joints and segments, may be more informative. Although different methods, such as modified vector coding technique and continuous relative phase, have been proposed to quantify the coordination (van Emmerik et al., 2004), the coordination pattern for the lower-limb joint and segment coupling motions of healthy runners during running is yet to be understood.

Lack of running experience and progressive fatigue are two typical risk factors of RRIs. Both were reported to affect the running mechanics (Bazuelo-Ruiz et al., 2018; Clansey et al., 2012; Derrick et al., 2002; de Ruiter et al., 2014; Hreljac, 2000; Slawinski & Billat, 2004; Winter et al., 2017). However, evidences regarding the effect of running experience and fatigue on the running mechanics are equivocal. Some studies (e.g., Bazuelo-Ruiz et al., 2018; Clansey et al., 2012; Derrick et al., 2002) identified significant alterations in kinematics (e.g., knee flexion and

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rearfoot eversion) and/or impacts (e.g., peak tibial axial accelerations, shock attenuation, and loading rate) after an exhaustive run while others (e.g., Abt et al., 2011; Winter et al., 2017) demonstrated no changes. Higher step rate and/or shorter step length were identified for the experienced (or trained) runners in some studies (e.g., de Ruiter et al., 2014; Gómez-Molina et al., 2017) while for novice (or untrained) runners in others (e.g., Slawinski & Billat, 2004). A few studies (Maas et al., 2017; Strohrmann et al., 2012) have reported the interactions of running experience and fatigue on running kinematics; Maas et al. (2017) demonstrated a significant group-by-fatigue interaction effect for peak trunk forward lean angle, which increased only for the novice runners, and for hip abduction during mid-swing, which increased for the novice runners and decreased for the competitive runners; Strohrmann et al. (2012) observed that the beginners revealed a more pronounced increase in the trunk forward lean as well as more variations throughout the 45-min exhaustive run and the experts maintained the trunk posture relatively unchanged throughout the run. To date, no study has investigated the interrelationship between running experience, fatigue, and the stride variability; the characteristics of the stride variability of runners who exhibit different degrees of experience during a prolonged running remain unknown.

Inertial measure unit (IMU) was proposed to be an alternative of the traditional, expensive, laboratory-based instrumentations, such as video-based motion capture system. Because of its advantage, particularly under ecological environments, IMU is becoming popular in running-related studies (Agresta et al., 2018; Benson et al., 2018; Meardon et al., 2011; Norris et al., 2014; Muro-de-la-Herran et al., 2014; Tao et al., 2012; Strohrmann et al., 2012). One promising application of IMU is to predict gait events (e.g., initial contact, toe-off), which are critical in

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gait analysis. Numerous gait events prediction methods on basis of using IMU have been proposed (Lee et al., 2010; Mercer et al., 2003; Strohrmann et al., 2012). For these methods, the IMU was usually placed at different body locations, such as trunk (Lee et al., 2010), shank (Mercer et al., 2003), and foot (Strohrmann et al., 2012), and different signals were processed, such as anteroposterior acceleration (Lee et al., 2010), vertical acceleration (Mercer et al., 2003), and resultant acceleration (Strohrmann et al., 2012). However, the accuracy for the gait events prediction varied greatly, such as 0.4 – 147 ms for initial contact prediction and 3.1 – 34 ms for toe-off prediction (González et al., 2010; Hanlon & Anderson, 2009; Heiden & Burnett, 2008; Jasiewicz et al., 2006; Mansfield & Lyons, 2003; Selles et al., 2005). Due to different references (e.g., force platform system, video-based motion capture system, footswitch system) being used to validate the proposed methods and no comparison study being conducted, it remains unknown which IMU-based method produced the most accurate prediction of gait events during running.

1.2 Objectives and Hypotheses

The overarching objectives of the present study were (i) to evaluate the accuracy of different IMU-based methods for gait events prediction during overground running, and (ii) to investigate the effects of running experience and progressive fatigue on the stride variability during a prolonged run in terms of stride interval variability and variability for lower-limb joint and segment coupling motions and single joint and segment motions.

The present study firstly evaluated three typical IMU-based methods for gait events prediction and stance time estimation during overground running (Chapter 3). The aims of this part were (i)

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to understand the accuracy of different IMU-based methods for gait events prediction and stance time estimation during overground running, and (ii) to identify the most accurate method for gait events prediction and stance time estimation during overground running. It was hypothesized that the most accurate method for gait events prediction would be the one with the IMU being positioned closer to the ground.

The present study then investigated the stride interval dynamics of both experienced and novice runners during a prolonged treadmill run (Chapter 4). The study aims of this part were (i) to understand the characteristics of the stride interval dynamics during the prolonged treadmill run, (ii) to identify differences in the stride interval dynamics between the experienced and novice runners, and (iii) to investigate the interactions of running experience and fatigue on the stride interval dynamics. It was hypothesized that (i) the stride interval dynamics would change with progressive fatigue for both the experienced and novice runners, and (ii) the changes would be different between the two groups.

At the end, the present study investigated the variability for the lower-limb joint and segment coupling motions and single joint and segment motions of both experienced and novice runners during a prolonged treadmill run (Chapter 5). The study aims of this part were (i) to understand the characteristics of the coordination variability and single joint/segment variability during the prolonged treadmill running, (ii) to identify differences in the coordination variability and single joint/segment variability between the experienced and novice runners; and (iii) to gain insights into the interactions of running experience and progressive fatigue on the coordination variability and single joint/segment variability. It was hypothesized that (i) coordination variability and

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single joint/segment variability for both the experienced and novice runners would change with progressive fatigue, and (ii) the experienced runners, due to years of running practice, would display greater coordination variability and less single joint/segment variability compared with the novice runners.

1.3 Significance of The Thesis

Through comparing and evaluating different IMU-based method, it could gain more insights into the accuracy of different IMU-based methods for gait events prediction during overground running. In addition, it would better understand effects of the IMU position on the prediction accuracy, which may serve as reference for future study in determining the location where the IMU should be placed. Finally, it would determine a relatively accurate method for predicting gait events during running, which may show the potential applications in wearable products.

Through investigating the stride variability during a prolong run and comparing the differences between runners with different years of running experience, it could gain more insights into gait regulation of the locomotor system with progressive fatigue, and it could provide better understanding of the effects of long-term running practice on gait regulation. In addition, the study findings may serve as evidences for interpreting stride variability during running and could be applied to educate runners for performance promotion and RRIs prevention.

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1.4 Outline of The Thesis

This dissertation consisted of five chapters, which focused on the current, highly-debatable topic about the application of IMU and stride variability during running. The whole study consisted of three parts, and a flow chart is presented (Figure 1.1).

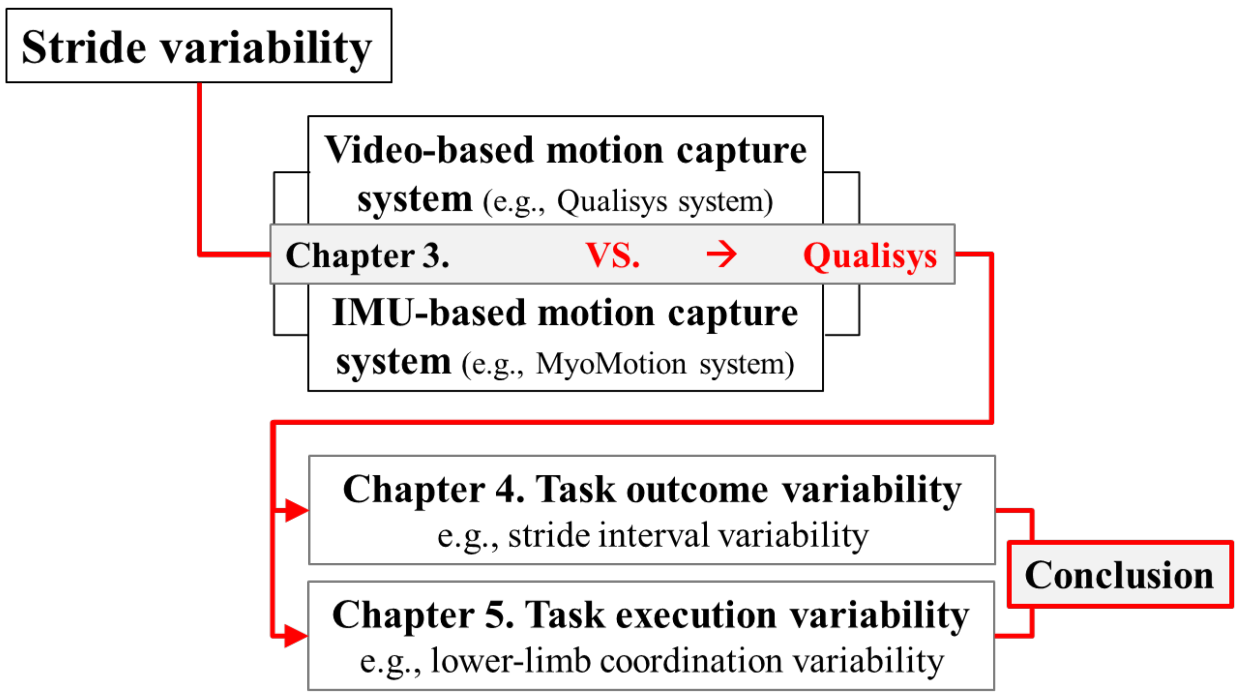

Figure 1.1. Flow chart of the thesis.

In ***Chapter 1***, the rationale and justifications of the present study are elucidated at the beginning. The purposes and hypotheses are proposed. Finally, the contents of each chapter are summarised.

In ***Chapter 2***, a comprehensive literature review is presented. Firstly, the popularity of distance running and the high incidence of RRIs are summarised. A theoretical framework is then

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presented to illustrate the aetiology of developing an RRI, and the related risk factors of RRIs are listed. Studies about the stride variability and RRIs are reviewed from the perspectives of task execution and outcome levels. Finally, the applications of IMU are discussed, and related studies are reviewed.

In ***Chapter 3***, the accuracy of different IMU-based approaches for gait events (initial contact and toe-off) prediction and stance time estimation during overground running at two speed conditions are evaluated and compared. The study objectives are (i) to understand the accuracy of each IMU-based method for initial contact and toe-off prediction and stance time estimation, (ii) to identify the most accurate method of using IMU to predict initial contact and toe-off and estimate stance time during overground running, and (iii) to serve as a reference for future running studies regarding where IMU should be positioned on the human body.

In ***Chapter 4***, variability and complexity of the stride interval for both experienced and novice runners during a prolonged treadmill running at their individual anaerobic threshold speeds are analysed. The study objectives are (i) to understand how the locomotor system regulates gait pattern during progressive fatigue, and (ii) to ascertain whether years of running experience could induce differences in the stride interval dynamics, particularly at the anaerobic threshold intensity level.

In ***Chapter 5***, coordination pattern and coordination variability for the lower-limb joint and segment coupling motions were compared between experienced and novice runners during a prolonged treadmill run at their individual anaerobic threshold speeds. The objectives are (i) to

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add to the knowledge and understanding of lower-limb joint and segment coordination pattern and coordination variability in healthy runners, and (ii) to gain insight into the interrelationships between running experience, progressive fatigue, and running mechanics.

In ***Chapter 6***, an overall summary is presented: appropriate IMU-based algorithms for initial contact and toe-off prediction and stance time estimation are demonstrated; and interactions of running experience and progressive fatigue on running mechanics referring to kinematic pattern for a single lower-limb joint and segment, coordination pattern for the lower-limb joint and segment coupling motions, and the stride variability (variability for a single joint and segment, coordination variability for the lower-limb joint and segment coupling motions, and stride interval variability) are summarised. The applications of the current findings for future studies are addressed.

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Chapter 2: Literature Review

2.1 Distance Running and Running-Related Injuries

2.1.1 Popularity of distance running

Distance running has become one of the most popular physical activities worldwide. According to the 2010 Annual Report of the National Sporting Goods Association (www.nsga.org), nearly 35.5% of Americans chose distance running as their preferred form of physical activity. The 2013 report estimated the number of marathon finishers in Europe to be 1,600,000 (Scheerder et al., 2015). In 2014, approximately 28,000 running events were held in the United States of America, with nearly 19,000,000 event finishers (Running USA, 2015). In 2016, the three major running events in Australia, namely the Gold Coast Airport Marathon, the Melbourne Marathon Festival, and the Sydney Running Festival, saw 24,214, 24,410, and 26,886 participants, respectively. Distance running has always attracted participants, and the number of participants in distance races is continually increasing. In Hong Kong, the number of participants in the Standard Chartered Hong Kong Marathon increased 74 times over the past two decades, growing from 1,000 in 1997 to 74,000 in 2016 (Hong Kong Amateur Athletic Association, 2016).

2.1.2 High incidence of running-related injuries

Although distance running is a lifelong physical activity and is known to be an excellent method to promote one’s physical and mental health, the prevalence of running-related injuries (RRIs) among distance runners is very high. Abt et al. (2011) observed that the incidents of RRIs increased with the popularity of distance running and the continually increasing number of

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participants. The RRI rate reported in the literature varies from 11% to 92.4% (Kluitenberg et al., 2015; van Gent et al., 2007), and most RRIs are related to the lower limbs (Lopes et al., 2012; Tschopp & Brunner, 2017; van der Worp et al., 2016; van Gent et al., 2007).

2.2 A Theoretical Framework of Developing Running-Related Injuries

An individual develops an RRI when the cumulative load applied to a specific structure (e.g., knee joint) exceeds the load capacity of the structure (Bertelsen et al., 2017; Hreljac, 2005), which is defined as the threshold load (Figure 2.1). During a running session, the cumulative load applied to a specific structure depends on the total number of strides and the load per stride (Bertelsen et al., 2017):

$$\sum(load) = \sum_{1}^{N}(Load_{stride})$$

where $\sum(load)$ is the cumulative load applied to the structure during the running session; $Load_{stride}$ is the load applied to the structure per stride; and N is the total number of strides during the running session. The load per stride is dependent on the magnitude and distribution of the load.

The load magnitude is the sum of the external force and muscle contraction force. The external force usually refers to the ground reaction force, and was mostly analysed in the literature. The larger is the load magnitude, the higher the risk of developing an RRI. Numerous studies have examined the factors related to the load magnitude and how these factors affect the load magnitude. Different methods have been proposed for RRIs prevention through a reduction in load magnitude. For example, the load magnitude is affected by factors such as (i) running shoes

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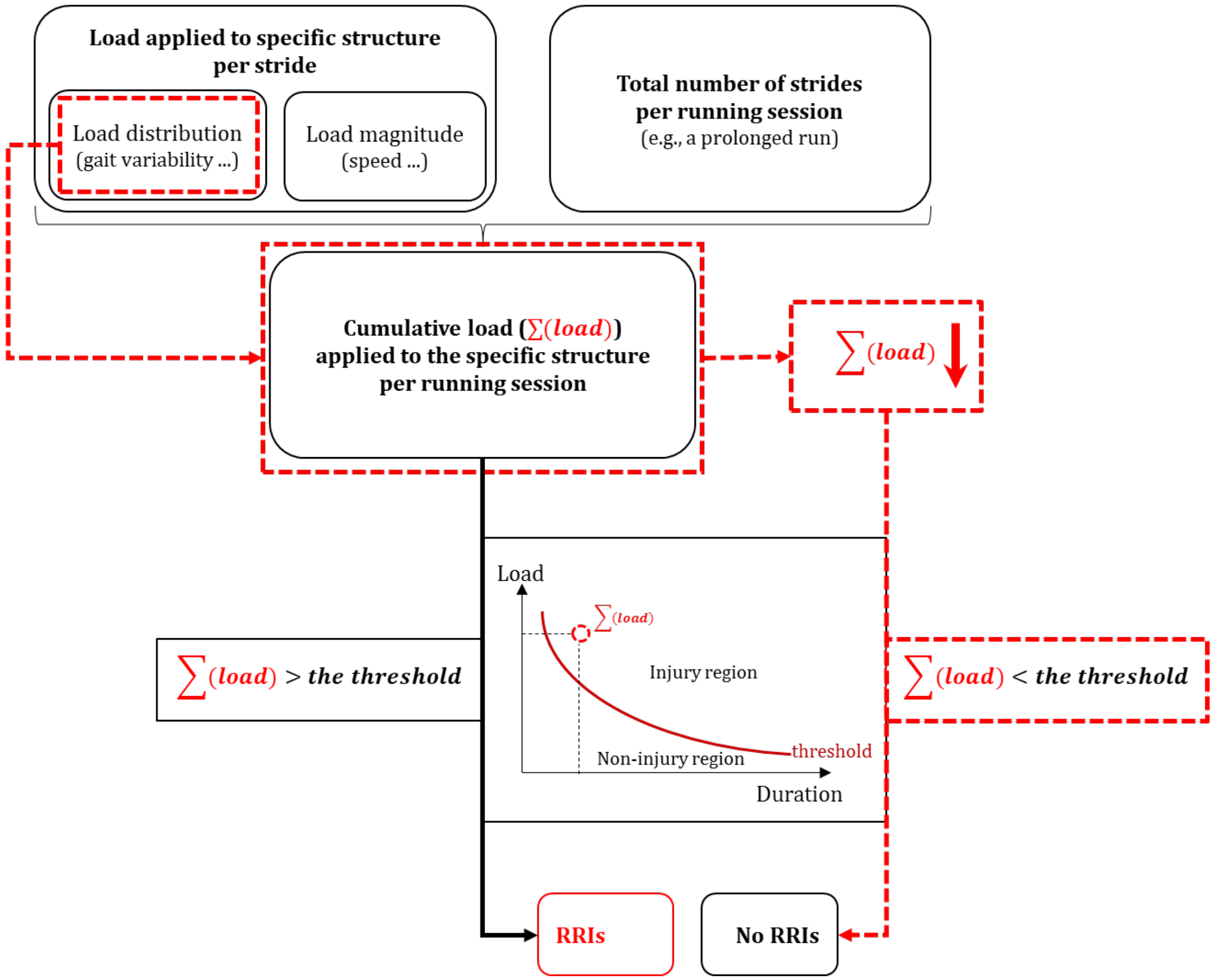

Figure 2.1. A schematic of the development of running-related injuries. (Adopted and redrawn based on Bartlett et al., 2007; Bertelsen et al., 2017; Blanch & Gabbett, 2016; Gabbett et al., 2016; Hamill et al., 2012). $\sum(load)$ represents the cumulative load applied to a specific structure during a running session, which is calculated using the load per stride and the total number of strides during a running session; the threshold load represents the maximum load that the specific structure can withstand without developing a running-related injury.

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and foot strike patterns, because the impact loading may be altered (Baltich et al., 2015; Breine et al., 2017; Knapik et al., 2016; Lieberman et al., 2010; van der Worp et al., 2016; Willy & Davis, 2014; Zhang et al., 2017); (ii) the runner's body weight (Malisoux et al., 2017; Sainton et al., 2015); (iii) running speed (Hobara et al., 2012; Thomson et al., 2017); (iv) progressive fatigue (García-Pérez et al., 2014; Mercer et al., 2003; Mizrahi et al., 2000, 2001); and (v) previous RRIs (van der Worp et al., 2016). Interventions for RRIs prevention usually include modifying these factors, such as rearfoot strike to midfoot or forefoot strike (Lieberman et al., 2010; Zhang et al., 2017). Nevertheless, the incidence of RRIs remains extremely high.

Load distribution refers to how the load per stride is distributed over the specific structure, which is influenced by many factors, such as foot strike patterns (Almeida et al., 2015), cadence (Heiderscheit et al., 2011; Lenhart et al., 2014; Schubert et al., 2014), stride length (Schubert et al., 2014; Willson et al., 2014, 2015), running shoes (Bergstra et al., 2015; Firminger & Edwards, 2016; Warne et al., 2014), running surface (e.g., hardness, material, gradient) (Wang et al., 2012; Willy et al., 2016), and alterations induced in running kinematics and kinetics.

The total number of strides for a specific running session depend on the running speed and cadence or stride length. Ideally, to complete a running distance (L) at a constant speed and cadence or stride length, the total number of strides (N) for the running session is computed using the following formula:

$$N = \frac{L}{speed} \times cadence = \frac{L}{stride\ length}$$

Winter et al. (2017) indicated that during a prolonged run, the cadence and stride length usually changes with progressive fatigue. Moreover, runners with different years of running experience

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were found to use different freely-chosen cadence (or step frequency) and stride length during running (de Ruiter et al., 2014; Hunter et al., 2017).

The threshold load of the specific structure is the maximum load that the structure is capable of withstanding without developing an RRI. The capability of the structure may be enhanced through years of running practice because the human body can positively adapt to the impact loading. However, it may deteriorate because of training errors, such as 'too much, too soon, too fast, too often, and too little rest' (Pribut, 2008). In addition, the human body cannot maintain any capability at the same level throughout a prolonged run due to the lack of time for restoration and progressive fatigue (Gabbett, 2016; Hreljac, 2005; Soligard et al., 2016), which may, therefore, lead to a decrease in the threshold load. Currently, quantifying the degree of the decrease in the threshold load is difficult because it is dependent on the characteristics of a specific structure (e.g., sensitivity to the impact loading per stride), the magnitude of the impact loading of previous strides, running experience, fatigue status, and previous injuries (Hamann et al., 2014; Ni et al., 2013).

2.3 Stride-to-Stride Variability and Running-Related Injuries

Running is a cyclical movement and its basic unit is stride, which is defined as the interval between two consecutive initial contacts for the same foot (Dugan & Bhat, 2005; Novacheck, 1998). Each stride comprises a landing phase, from initial contact to toe-off, and a flight phase. During the landing phase, the human body experiences great impact loading, which is considered the key factor in developing an RRI.

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During running, a certain amount of changes between strides are recorded regardless of the running experience and performance level of the runner. The stride-to-stride variability is generated because the biological system has many degrees of freedom, exceeding the minimum necessary for accomplishing a given task (Davids et al., 2003; Newell & Vaillancourt, 2001), and during task execution (e.g., running), the locomotor system is required to deal with the redundant degrees of freedom (Davids et al., 2003). Traditionally, researchers mainly focused on the invariant characteristics of the running pattern, and the small variances between strides are usually viewed as noises and ignored. Interventions are mostly designed to eliminate the stride variability and maintain a consistent running pattern for both performance promotion and RRIs prevention. Recently, researchers have found that the stride variability is functional, which reflects the flexibility and adaptability of the locomotor system (Bartlett et al., 2007; Davids et al., 2003). Wheat (2005) even proposed a 'variability–RRIs hypothesis' and believed that 'the decrease of the stride variability would increase the risk of developing an RRI'. The stride variability can be categorised into variability at task outcome level, such as stride interval variability, and variability at task execution level, such as coordination variability. To understand the mechanics of RRIs, both kinds of variability have been analysed in the literature.

2.3.1 Task outcome variability

Stride interval variability during running presents in a fractal-like manner with long-range correlations (Jordan et al., 2006, 2007), which means that the stride interval dynamics during running is predictable (a given stride interval is statistically dependent on that occurring over many different timescales). The long-range correlations, quantified using the fractal scaling index, such as the detrended fluctuation analysis (DFA) scaling exponent alpha, has been found

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to be affected by RRIs. However, conflicting findings have been reported about the effects of RRIs on the stride interval dynamics during running: Mann et al. (2015a) reported that runners with RRIs displayed a larger DFA scaling exponent alpha than healthy runners, whereas Meardon et al. (2011) observed that injured runners displayed a smaller DFA scaling exponent alpha than their healthy counterparts. The inconsistent findings of these two studies may be due to differences in the participants and in the experimental design (e.g., treadmill run vs. overground run; 2-min run vs. exhaustive run), because the stride interval dynamics are affected by numerous factors, such as runners' fatigue status (Fuller et al., 2017; Mann et al., 2015b; Meardon et al., 2011), running experience (Nakayama et al., 2010), running speed (Jordan et al., 2006, 2007; Lindsay et al. 2014), running surface (Lindsay et al. 2014), foot strike pattern, and running shoes (Fuller et al., 2016; Mann et al., 2015b). Nevertheless, both Mann et al. (2015a) and Meardon et al. (2011) have reported no differences in the magnitude (standard deviation and coefficient of variance) of the stride interval variability between injured runners and healthy counterparts; this is inconsistent with the data reported in other studies (Brown et al., 2009; McGrath et al., 2017). They observed that injured participants (e.g., with chronic functional ankle instability) presented larger movement variability (e.g., foot roll angle, ankle frontal plane movement) while performing dynamic tasks, such as running and stop-jump manoeuvre. Various factors may cause inconsistent results, such as task difficulty and variable of interest (James et al., 2000) and fatigue (Cortes et al., 2014; Paquette et al., 2017). To date, the relationship between RRIs and the variability at the task outcome level remains unclear.

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2.3.2 Task execution variability

Research has ascertained a link between coordination variability and RRIs (Barlett et al., 2007; Hamill et al., 2012). In the literature about RRIs, Wheat's 'variability–RRIs hypothesis' has been supported by numerous studies, which have noted that injured runners (with symptoms of patellofemoral pain, or iliotibial band syndrome, or other types of RRIs) displayed lower coordination variability for the joint/segment couplings of interest than that of the healthy counterparts (Hamill et al., 1999; Heiderscheit, 2000; Heiderscheit et al., 2002; Lilley et al., 2018; Miller et al., 2008; Seay et al., 2011). For example, Lilley et al. (2018) noted that the participants with chronic ankle instability displayed lower coordination variability for the lower limb joint couplings (knee–ankle, hip–ankle) during jogging than their healthy counterparts; Seay et al. (2011) observed that participants with low back pain had lower coordination variability for the pelvis–trunk coupling compared with the healthy controls during running. The coordination variability is believed to provide a level of flexibility for the adaptation of constraints and impact absorption during running; a decrease in the coordination variability indicates 'loss of complexity' (Lipsitz, 2002) or reduction of degrees of freedom in the locomotor system, which leads to the increase of the cumulative load applied to a specific structure because the impact loading distributed over a restricted surface of tissue among limited structures (Bartlett et al., 2007; Bertelsen et al., 2017). However, studies have also reported conflicting findings. Hafer et al. (2017) observed no differences in the coordination variability for the lower limb segment couplings between runners with iliotibial band syndrome and healthy runners during an exhaustive run; Seay et al. (2014) reported no differences in the coordination variability for the trunk bend–twist between participants with and without low back pain; Miller et al. (2008) observed that runners with iliotibial band syndrome presented a lager coordination

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variability for the knee flexion/extension–foot abduction/adduction than noninjured runners during an exhaustive run.

The conflicting findings about the relationship between RRIs and coordination variability may be because different methods have been used to quantify the coordination variability. In the literature, modified vector coding technique and continuous relative phase have been mostly used to quantify coordination variability. For the modified vector coding technique method, a coupling angle is calculated only through the angular displacement of the joint/segment of the coupling of interest; for the continuous relative phase method, a phase angle is obtained based on the angular displacement and velocity of the joint/segment of the coupling of interest (van Emmerik et al., 2004). Moreover, this may be caused by because lower limb coordination variability during running is affected by numerous factors, such as running experience (Floría et al., 2018), progressive fatigue (Brown et al., 2016; Dierks et al., 2010; Hafer et al., 2017; Miller et al., 2008), anatomical structure (e.g., the quadriceps angle) (Heiderscheit et al., 1999), gender, aging (Boyer et al., 2017), and cadence (Hafer et al., 2016).

2.3.3 Section summary

Stride-to-stride variability and RRIs may share a relationship, and numerous studies have provided evidence to support the ‘variability–RRIs hypothesis’ (Wheat, 2005). However, views on this hypothesis remain inconsistent. There still exist several questions. Equivocal evidences were reported in previous studies that both increased and decreased stride variability may lead to RRIs. The cause–effect relationship—that is, whether stride variability is the cause or the effect of RRIs—is unknown. Running performance would be negatively affected if stride variability is

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excessively high, which means an optimal stride variability level (Stergiou et al., 2006) or range (Hamill et al., 2012) may exist. In addition, whether and how this optimal range can be quantified warrant investigation. Findings related to the effects of RRIs on stride variability are conflicting in the literature, which further complicates the interpretation of stride variability. Stride variability is reported to be affected by numerous factors, such as running speed, running surface, aging, and foot strike pattern, and findings about the effects are inconsistent in the literature. Moreover, researchers have yet to properly understand the characteristics of the stride variability of healthy runners; for example, the characteristics of the stride variability of runners who exhibit different degrees of running experience during a prolonged run.

2.4 Application of Inertial Measurement Unit

Inertial measurement unit (IMU) is a type of miniature, integrated sensor package consisting of accelerometers, gyroscopes, and magnetometers. In the literature, alterative terms—such as magnetic and inertial measurement unit, magnetic angular rate and gravity sensor, micro-electro-mechanical sensor, attitude and heading reference system—have also been used. IMU has become an alternative to the expensive, laboratory-based instrumentations (e.g., infrared motion capture system and force platform system), particularly under unconstrained environmental conditions. Utilising IMU for gait analysis has become a promising trend (Benson et al., 2018; Muro-de-la-Herran et al., 2014; Tao et al., 2012; TarniŢă, 2016), and numerous studies have used IMU to investigate gait patterns during running (Agresta et al., 2018; Meardon et al., 2011; Norris et al., 2014; Strohrmann et al., 2012).

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2.4.1 Gait event prediction

In the literature, numerous IMU-based methods have been proposed to predict gait events, such as initial contact and toe-off, and details of some representative studies are presented in Table 2.1. The proposed methods present differences in IMU position, prediction algorithm, target signal, and data processing approach. Overall, IMU is commonly positioned at the lower trunk, shank, or foot. The prediction algorithm refers to '(modified) peak detection', 'zero crossing detection', or 'flat zone detection'. Target signal refers to the anteroposterior, mediolateral, vertical, and resultant accelerations, or angular velocity. The raw data profile or data profile filtered through infinite impulse response, finite impulse response, and wavelet transform are used.

Most researchers have stated that the proposed methods can correctly identify the gait events; however, the accuracy of these methods for the prediction of gait events varied widely. Regardless of the IMU position, prediction algorithm, target signal, or data processing approach, the accuracy of the IMU-based method for the prediction of gait events was affected by the locomotion type (walk or run) and speed, and gait pathology (Ben Mansour et al., 2015; Khandelwal, & Wickström, 2016, 2017; Trojaniello et al., 2014, 2015). Because different gold standards (e.g., footswitch, force platform, three-dimensional motion capture system) and experimental designs (e.g., participant with or without gait pathology, walk or run) have been utilised in the literature, identifying which method provides the most accurate prediction of gait events is difficult. To the author's best knowledge, no existing systematic review or comparison study refers to the IMU position, prediction algorithm, target signal, and data processing method. Therefore, no supporting evidence exists to serve as a reference regarding which method should

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be chosen. Furthermore, the specificity, sensitivity, and robustness of the proposed IMU-based methods for the prediction of gait events have rarely been reported, which may restrict the application of these methods in real-life environments that require long-term and real-time prediction of gait events.

Gait temporal parameters, such as stride interval, step time, and stance time, are basic parameters for quantifying gait pattern, and can also be estimated through IMU. However, the level of estimation accuracy relies on the predicted gait events. For instance, Trojaniello et al. (2014) reported utilised five IMU-based methods and reported errors of 2%–4% for stride interval estimation, 2%–8% for step time estimation, and 3%–10% for stance time estimation during walking; Ben Mansour et al. (2015) observed that the root mean squared errors for the four IMU-based methods were 5–47 ms for stride interval estimation, 7–53 ms for step time estimation, and 18–57 ms for stance time estimation during walking at five speeds. In addition to the gait temporal parameters estimation, IMU has also been used to estimate other gait parameters, such as stride length (Bugané et al., 2012; Köse et al., 2012; Peruzzi et al., 2011) and locomotion speed (Li et al., 2010; Yang et al., 2011, 2012).

Although the development of wearable technology has allowed for the use of IMU to estimate numerous gait parameters, their accuracy remains questionable. Many proposed methods have been tested only under well-controlled conditions. In addition, validation studies are required to identify the accuracy of those IMU-based methods for the estimation of gait parameters in real-life environments for both healthy and pathological populations.

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Table 2.1. Details of methods of using inertial measurement unit for the prediction of gait events.

	IMU		Prediction method	Gait	Events	Gait parameters	Gold standard
	Position	**Target signal**					
Aminian et al., 2002	Shank	Angular velocity (ML)	Peak detection	Walk	IC, TO	Stance time	Foot switch
Auvinet et al., 2002	Trunk	Acceleration (AP, vertical)	Peak detection	Run	IC, TO	-	Video
Bergamini et al., 2012	Trunk	Angular velocity	Peak detection	Run	IC, TO	Stride & stance time	Force platform, video
Boutaayamou et al., 2017	Foot	Acceleration (vertical)	Peak detection, zero crossing detection	Walk	IC, TO	Stride, stance & swing time	3D motion capture system
Bugané et al., 2012	Trunk	Acceleration (AP)	Peak detection	Walk	IC	Stride, step, stance & swing time, stride & step length	3D motion capture system
de Ruiter et al., 2014	Foot	Acceleration (not mentioned)	Not mentioned	Run	IC, TO	Stance time	not mentioned
González et al., 2010	Trunk	Acceleration (AP, vertical)	Zero crossing detection	Walk	IC, TO	-	Force platform
Greene et al., 2010	Shank	Angular velocity (ML)	Peak detection	Walk	IC, TO	Stride, step, stance & swing time	3D motion capture system
Hanlon & Anderson, 2009	Shank, foot	Acceleration (AP, vertical)	Peak detection	Walk	IC	-	Force platform
Heiden & Burnett, 2008	Shank	Acceleration (vertical)	Peak detection	Run	IC, TO	-	Force platform
Jasiewicz et al., 2006	Shank, foot	Acceleration (AP, vertical), angular velocity	Peak detection, zero crossing detection	Walk	IC, TO	-	Foot switch
Khandelwal, & Wickström, 2016, 2017	Foot	Acceleration (resultant)	Peak detection	Walk, run	IC, TO	-	Foot switch
Kitagawa & Ogihara, 2016	Foot	Acceleration, angular velocity	Peak detection, flat zone detection	Walk	IC, TO	Stride length, foot clearance	3D motion capture system
Köse et al., 2012	Trunk	Acceleration (AP, vertical)	Peak detection	Walk	IC, TO	Step length	Video
Lee et al., 2010	Trunk	Acceleration (AP)	Peak detection	Run	IC, TO	Stride, step & stance time	Force platform
Mansfield & Lyons, 2003	Trunk	Acceleration (AP)	Zero crossing detection	Walk	IC	-	Foot switch
Masci et al., 2013	Trunk	Acceleration (vertical)	Peak detection	Run	IC, TO	Stance time	-

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Table 2.1. (Continued)

McCamley et al., 2012	Trunk	Acceleration (vertical)	Peak detection	Walk	IC, TO	Stride & step time	Force platform
McGrath et al., 2012	Shank	Angular velocity (ML)	Peak detection	Walk, run	IC, TO	Stride, stance & swing time	3D motion capture system
Mercer et al., 2003; García-Pérez et al., 2014; Kawabata et al., 2013; Purcell et al., 2006	Shank	Acceleration (vertical)	Modified peak detection	Run	IC, TO	-	-
Norris et al., 2016	Shank	Acceleration (ML, vertical)	Zero crossing detection, peak detection	Run	IC, TO	Stride time	-
Rueterbories et al., 2014	Foot	Acceleration (resultant)	Peak detection	Walk	IC, TO	Stance & swing time	Foot switch
Sabatini et al., 2005	Foot	Angular velocity	Flat zone detection	Walk	IC, To	Stance & swing time, walking speed, incline	Foot switch
Selles et al., 2005	Shank	Acceleration (vertical)	Peak detection	Walk	IC, TO	Stance time	Force platform
Storm et al., 2016	Trunk, shank	Acceleration	Peak detection	Walk	IC, TO	Stride, step & stance time	Pressure insole
Strohrmann et al., 2012; Bailey & Harle, 2015	Foot	Acceleration (resultant)	Peak detection	Run	IC, TO	Stride & stance time	Video, 3D motion capture system
Watari et al., 2016	Trunk	Acceleration (not mentioned)	-	Run	-	Stance time, vertical oscillation	Force platform; 3D motion capture system
Willemsen et al., 1990a	Shank	Acceleration (vertical)	Peak detection	Walk	IC, TO	-	Foot switch
Yang et al., 2011	Shank	Acceleration (AP), Angular velocity	Zero crossing detection	Run	IC, TO	Running speed	3D motion capture system
Zijlstra & Hof, 2003	Trunk	Acceleration (AP)	Peak detection & zero crossing detection	Walk	IC	Stride time	Force platform

AP, anteroposterior; IC, initial contact; ML, mediolateral; TO, toe-off; 3D, three-dimensional

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2.4.2 Kinematic measurement

Willemsen et al. (1990b) used IMU to estimate joint kinematics for the first time. Lately, many IMU-based motion capture systems have been developed and extensively used in research (Agresta et al., 2018; Strohrmann et al., 2012). The root mean squared error reported by the vendor of the commercially available IMU systems is less than 1° under static condition and 2° under dynamic condition for absolute (segment orientation angle) and relative (joint angle) measurements. However, validation studies found that the errors were larger when the IMU systems were used in real applications (Table 2.2). Regardless of the influences caused by IMU-to-segment axis misalignment, the accuracy of utilising IMU for segmental and joint kinematic measurements were affected by numerous factors, such as the rotation speed (Cutti et al., 2006; Lebel et al., 2013, 2017) and type and duration of motion (Brodie et al., 2008; Cutti et al., 2006; Lebel et al., 2015, 2017; Liu et al., 2009). To date, no validation studies have investigated the variations of IMU accuracy during running. In additional, the IMU accuracy was affected by magnetic field disturbances due to the use of the magnetometer (de Vries et al., 2009; Robert- Lachaine et al., 2017b; Roetenberg et al., 2007). Several approaches, such as camera pose estimation algorithm, have been proposed to compensate for these disturbances (Bergamini et al., 2014; Lebel et al., 2018; Roetenberg et al., 2007). However, how the IMU accuracy changes over time during a prolonged run remains unknown, and whether those proposed correction methods improve the IMU accuracy during a prolonged run is unclear.

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Table 2.2. Accuracy of inertial measurement unit for measuring joint and segment angles.

	IMU system	Motion	Test apparatus, body location	Measurement	Gold standard	Evaluation variable	Accuracy
Blair et al., 2018	Xsens MVN	Football kicking	Pelvis & bilateral lower limbs	Segment & joint angle	3D motion capture system	Percentage error	0.2%–5.8%
Brennan et al., 2011	Inertia-Link by Microstrain Inc., VT	Mimic 3D joint rotation	An instrumented gimbal	Joint angle	True values	RMSE	FLEX/EXT: 3.2°; ABD/ADD: 3.4°; INT/EXT ROT: 2.9°
Brodie et al., 2008	Xsens MT9	Pendulum motion	A wooden pendulum	3D orientation angle	Two high-speed video cameras	RMSE	8.5°–11.7°; Maximum: 30°
Cooper et al., 2009	Self-built IMU	Knee FLEX/EXT	Shank & thigh	Knee FLEX/EXT angle	3D motion capture system	RMSE	0.7°–3.4°
Cutti et al., 2006	Xsens MT9	Static & dynamic	A rigid plate	3D orientation angle	True values	RMSE	Static: 0.0°– 0.3° Dynamic:5.4°–11.6°
Favre et al., 2008	Self-built IMU	Hip motion with standing posture, & walk	Shank & thigh	Knee joint angle	The Liberty magnetic tracking device	RMSE	FLEX/EXT: 1.5°; ABD/ADD: 1.7°; INT/EXT ROT: 1.6°
Godwin et al., 2009	Xsens MTx	Static, quasistatic, dynamic	A rotating block; a dynamic pendulum	3D orientation angle	3D motion capture system	RMSE	Quasistatic: 0.3°–0.7° Dynamic: 1.9°–3.5°
Harms et al., 2010	ETH orientation sensor	Arm motion with sitting posture	Arm	3D orientation angle	Xsens	RMSE	Roll angle: 6.1°; Pitch angle: 2.6°; Yaw angle: 18.1°
Liu et al., 2009	Self-built IMU	Static, straight walk	Mechanical arms; Thigh	Thigh angle	3D motion capture system	RMSE	Static: 0.8°–1.7° Walk: 2.4°–4.9°
Mayagoitia et al., 2002	Accelerometers & gyroscopes	Treadmill walk	Shank & thigh	Shank & knee angle, angular velocity	3D motion capture system	Percentage error	Shank angle: 1.9%–5.2%; Knee angle: 11.5%–14.8%
Picerno et al., 2008	Xsens MTx	Upright posture, walk	Pelvis & lower limb	3D joint angle	3D motion capture system	RMSE	**Upright posture** FLEX/EXT: 1.3°–1.9°; ABD/ADD: 3.0°–5.7°; INT/EXT ROT: 6.3°–8.3°; **Walk** FLEX/EXT: 0.8°–1.9°; ABD/ADD: 1.5°–2.8°; INT/EXT ROT: 1.8°–3.6°

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Table 2.2. (Continued)

Robert-Lachaine et al., 2017a	Xsens MVN	Manual material handling task	Full body	3D joint angle	3D motion capture system	RMSE	3.2°–40.2°
Takeda et al., 2009	Self-built IMU	Walk	Pelvis, bilateral lower limbs	3D joint angle	3D motion capture system	RMSE	4.1°–10.3°
Zhang et al., 2013	Xsens MVN	Level walk, stair walk	Pelvis, bilateral lower limbs	3D joint angle	3D motion capture system	RMSE	Level walk: 1.8°–5.1°; Stair descent: 1.4°–6.7°; Stair ascent: 1.6°–5.2°
Lebel et al., 2013, 2015	Xsens MTx	Mimic 3D joint rotation	An instrumented gimbal	Absolute & relative angle	3D motion capture system	Mean error	**Orientation angle** Static: –0.3° (2.8°); Slow motion: 1.0°; **Relative (joint) angle** Slow motion: 1.8°–3.1°
	Inertial Lab OSv3						**Orientation angle** Static: –0.5° (3.3°); Slow speed: 2.0°; **Relative (joint) angle** Slow motion: 4.3°–7.3°
	APDM Opal						**Orientation angle** Static: –0.01° (2.9°); Slow motion: 1.2°; **Relative (joint) angle** Slow motion: 2.5°–6.3°
Lebel et al., 2016	Inertial Lab OSv3	Timed up and go	Trunk and bilateral lower limbs	3D joint angle	3D motion capture system	RMSE	**Sit:** 0.7°–3.4°; **Sit-to-stand:** 2.1°–5.8°; **Walk:** 3.5°–14.3°; **Turn:** 3.8°–15.2°; **Turn-to-sit:** 3.9°–12.5°
Lebel et al., 2017	Inertial Lab OSv3	Timed up and go	Full body	3D segment & joint angle	3D motion capture system	RMSE	**Segment angle** Static: 0.9°–8.0°; Walk: 1.6°–8.9°; Turn: 1.3°–6.8°; **Joint angle** Static: 1.5°–6.4°; Walk: 3.3°–20.6°; Turn: 3.4°–23.5°

RMSE, root mean squared error; FLEX/EXT, flexion/extension; ABD/ADD, abduction/adduction; INT/EXT ROT, internal/external rotation; 3D, three-dimensional

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2.4.3 Applications in running studies

The use of IMU in running-related studies have mainly focused on the following topics:

- **Shock absorption**. Numerous studies (Castillo & Lieberman, 2018; García-Pérez et al., 2014; Giandolini et al., 2016; Kawabata et al., 2013; Mercer et al., 2003, 2010; Mizrahi et al., 2000, 2001) have utilised IMU to investigate the characteristics of impact shock during running and to understand the effects of different factors (e.g., progressive fatigue, speed, stride length, and foot strike pattern) on shock attenuation. These studies have mainly analysed the acceleration file provided by IMUs that were positioned at the distal aspect of tibia, lower trunk, and head.

- **Running gait pattern**. Agresta et al. (2018) investigated lower limb running kinematics with several IMUs being positioned at lower limbs and explored the relationship between running kinematics and experience of running practice. Strohrmann et al. (2012) investigated running gait pattern by analysing gait spatiotemporal parameters and running kinematics measured by IMUs positioned on the entire body (head, trunk, upper limbs, and lower limbs) and tried to understand the effects of progressive fatigue. Meardon et al. (2011) investigated stride interval time series during a prolonged run through an IMU positioned at the shank.

- **Outdoor running monitor**. IMU has been used to gain information throughout a training course or running race (marathon) (Auvinet et al., 2002; Giandolini et al., 2015; Reenalda et al., 2016). This provides valuable information to coaches and runners for running performance promotion and RRI prevention.

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- **Others**. IMU was also used to estimate energy expenditure during running (Wixted et al., 2007), to analyse running gait using a data-driven approach (Strohrmann et al., 2012b), and to provide real-time feedback for RRI prevention (Crowell et al., 2010; Crowell & Davis, 2011).

2.4.4 Section summary

IMU has been extensively used in running-related studies and can be used to predict spatiotemporal gait parameters and measure running kinematic. However, further research is required to improve its accuracy and reliability. Furthermore, although wearable technology is believed to play an influential role in RRIs prevention, to date, most sports-related applications only include the function to count steps or estimate running distance. This data is insufficient for injury prevention, and future studies are required to gain insights into the meaning of the data provided by IMU, which is a core element of wearable technology. IMU has the advantage of collecting data under unconstrained environmental conditions for a long period. However, no appropriate methods have been developed to process the obtained big data. Some researchers have analysed IMU-based data through machine learning-based methods (e.g., support vector machine), for example, to identify fatigue-induced changes in walking gait (Baghdadi et al., 2018), classify muscle fatigue during walking (Zhang et al., 2014), and determine pulmonary function status based on walking gait data provided by IMU (Cheng et al., 2017; Juen et al., 2014). However, extensive research is required before these methods are applied in running-related studies for RRIs prevention in real-life environments.

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2.5 Summary

Stride variability is functional. Stride variability may share a link with RRIs. However, equivocal evidences were reported that both reduced and increased stride variability may lead to RRIs. Stride variability within an 'optimal window' may reduce the risk of developing an RRI. Moreover, as these findings are on basis of only comparing injured and uninjured runners, it is still unknown the stride variability is the cause or the effect of RRIs. There are some studies investigate the stride variability in healthy runners, and stride variability was found to be affected by many factors, such as age, sex, footwear, running speed. Understanding of the stride variability in healthy runners remains limited.

Although IMU is becoming popular in running studies, there are still many unsolved issues, such as the measuring accuracy. One important implication of IMU is to predict gait events, and many IMU-based methods were proposed. However, the prediction accuracy among these methods varied greatly. There remains no comparison study to identify a relatively accurate IMU-based method during running. Another application of IMU is to measure kinematic. However, the measuring accuracy is still arguable, particularly poor accuracy was reported under dynamical condition.

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Chapter 3: Accuracy of Three IMU-Based Methods for Gait Events Prediction

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3.1 Introduction

Analysing running gait is of importance to understand the mechanics of running-related injuries (RRIs) and improving running performance. Gait temporal parameters, such as stance time (ST) and stride interval, are basic parameters for quantifying gait alterations (Trojaniello et al., 2014). Stride interval is also considered a key parameter within running biomechanics because it contributes to running efficiency and performance (Gindre et al., 2016). To obtain gait temporal parameters, accurately determining gait events, such as initial contact (IC) and toe-off (TO), is a requirement.

Recently, because of the advantages of long-term outdoor measurements and limited cost and invasiveness, inertial measurement unit (IMU) has been extensively used in running studies (Agresta et al., 2018; Benson et al., 2018; Norris et al., 2014, 2016; Strohrmann et al., 2012), which has led to the need to process IMU-based data in an appropriate approach. In the literature, numerous algorithms that refer to different IMU positions have been proposed to predict IC and TO (Bergamini et al., 2012; Boutaayamou et al., 2017; Chapman et al., 2012; González et al., 2010; Khandelwal et al., 2017; Lee et al., 2010; McGrath et al., 2012; Mercer et al., 2003;

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Strohrmann et al., 2012; Trojaniello et al, 2014). However, the accuracy of these IMU-based methods that were used to predict IC and TO are questionable; for example, the reported errors vary from 0.4 to 147.0 ms for IC prediction and from 3.1 to 34.0 ms for TO prediction (González et al., 2010; Hanlon & Anderson, 2009; Heiden & Burnett, 2008; Jasiewicz et al., 2006; Mansfield & Lyons, 2003; Selles et al., 2005). In the literature, IMU has been positioned at different locations (e.g., foot, shank, and lower trunk), and the accuracy for IC and TO prediction has been evaluated on the basis of a 'gold standard' provided by different instrumentations, such as force platforms, high-speed motion capture systems, and footswitches; this makes a direct comparison of the accuracy of these IMU-based methods impossible.

The acceleration profile was analysed to predict gait events in most proposed algorithms (Boutaayamou et al., 2017; Chapman et al., 2012; Hanlon & Anderson, 2009; Khandelwal & Wickström, 2017; Lee et al., 2010; Mercer et al., 203; Strohrmann et al., 2012; Trojaniello et al, 2014). Three IMU-based methods (see **3.2.3**) are typically used in running-related studies (Chapman et al., 2012; Lee et al., 2010; Mercer et al., 203; Norris et al., 2016; Strohrmann et al., 2012), among which, the IMU is positioned at the lower trunk, shank, or foot, and the anteroposterior (AP), vertical, or resultant acceleration profile is processed. However, the accuracy of the three methods for gait events prediction has never been compared.

The accuracy of IC and TO predictions may be also affected during running at different speeds because the acceleration profile is related to the running speed. Research has reported indirect evidence: the error of estimated STs, which were calculated using IC and TO, was 0 (12) ms during jogging, 2 (3) ms during running, 1 (1) ms during sprinting (Purcell et al., 2006), 16–25

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ms during running at slow, natural, and fast speeds (Lee et al., 2010), and 26–103 ms during walking at speeds from 0.5 m/s to 1.75 m/s (Zijlstra & Hof, 2003).

Therefore, in this part of the present study, the accuracy of different IMU-based methods for IC and TO predictions and ST estimation was comparatively evaluated during overground running at two different speeds. The study aims of this part were (i) to understand the accuracy of different IMU-based methods for gait events prediction and stance time estimation during overground running, (ii) to gain information about effects of IMU positions on the prediction accuracy during overground running, and (iii) to identify the most accurate method for gait events prediction and stance time estimation during overground running. It was hypothesized that the most accurate method for gait events prediction would be the one with the IMU being positioned closer to the ground.

3.2 Methods

3.2.1 Participants

Four female and seven male recreational runners participated in the present study. The mean (standard deviation, SD) age, height, and body mass were 25.5 (4.2) years, 168.3 (9.1) cm, and 58.8 (5.3) kg, respectively. The participants were given a brief introduction about the whole procedure of the experimental protocol and provided informed consent prior to data collection. This study was approved by the Ethics Committee of The Education University of Hong Kong (Ref: No. 2015-2016-0346).

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3.2.2 Experimental protocol

The participants were required to run on a 10-m walkway at their preferred jogging speeds (3.1 (0.1) m/s) and distance running race speeds (4.1 (0.3) m/s) in a random order. For each speed condition, the participant was required to perform at least ten running trials (10–14 trials), and the clean steps of the successful trials were processed and analysed. The clean step was defined as that during which the participant landed with the entire foot on one of three force platforms, whereas the successful trial was defined as that during which the participants did not make any obvious changes in stride length before and after the landing (Hreljac & Marshall, 2000).

Using a force platform system (Bertec, FP4060-07, USA) and an IMU-based motion capture system (MyoMotion, Noraxon, USA), respectively, three-dimensional (3D) ground reaction force (GRF) and acceleration were collected simultaneously. The force platform system contains three force platforms (overall length by width = 1.8 m × 0.4 m) that were aligned and embedded in the middle of the walkway. The GRF were acquired at 2000 Hz and low-pass filtered using a second-order Butterworth filter at 70 Hz (Bergamini et al., 2012). The IMU system consists of a set of 16 IMUs and a packed analysis software (MR3 v3.8.6, Noraxon, USA) (Figure 3.1). Each IMU encompasses a tri-axial accelerometer, gyroscope, and magnetometer, and the specifications are presented in Table 3.1. Five IMUs were used in the present study and were affixed to the lower trunk and bilateral shanks and feet (Figure 3.2). The pelvis IMU was affixed to the lumbosacral joint level, and the shank IMUs were positioned at the anteromedial distal aspect of the tibias using elastic straps. Using flat bracelet housings and tightly interlacing them with the shoelaces, the foot IMUs were positioned at the instep of shoes. Prior to each trial, the

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participants were required to stand statically for 30 s to calibrate the IMUs. The acceleration was acquired at 200 Hz.

The participants wore their own athletic shoes. At the beginning of each trial, the participants were instructed to perform a vertical jump on one of the three force platforms. The IMU and force platform systems were synchronised by matching the time of the vertical jump (Lee et al., 2010; Mo & Chow, 2018; Storm et al., 2016). During the test, to avoid any potential targeting on the force platforms, the participants were instructed to focus on a picture placed at around eye level height at the end of the walkway. Before the running test, the participants were provided sufficient time to familiarise themselves with the instrumentations and the testing procedures.

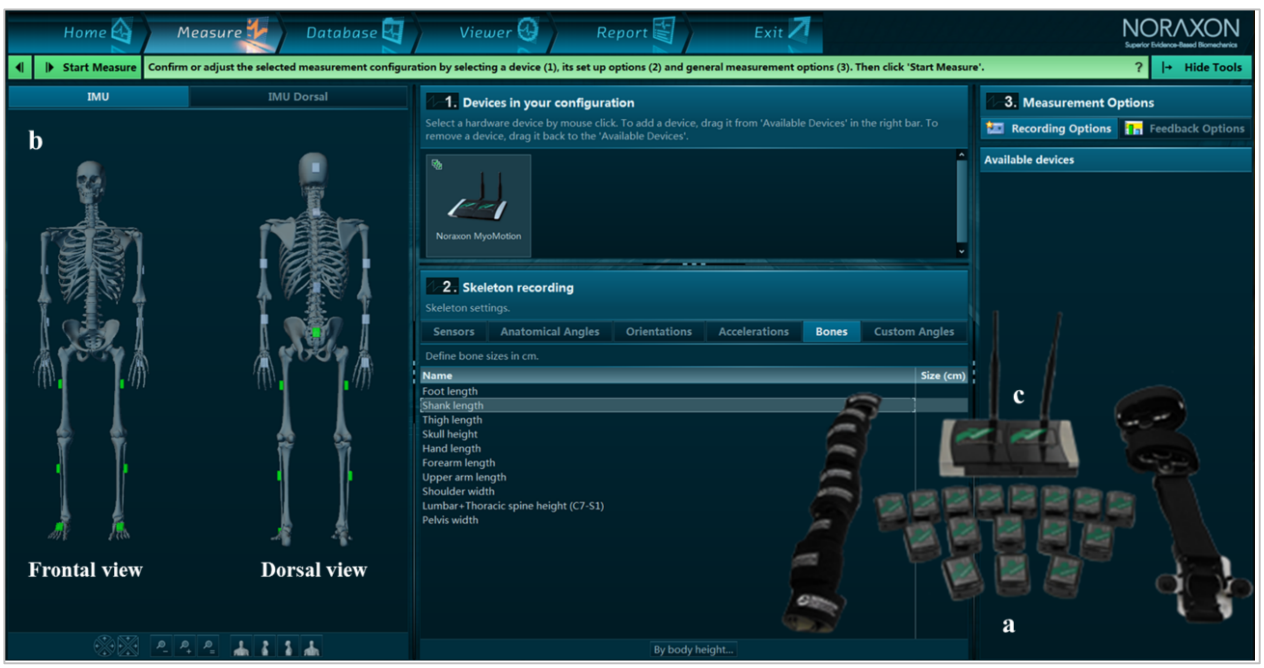

Figure 3.1. The inertial measurement unit motion capture system. A full package of 16 IMUs (a), interface with 3D avatar of the software module (b) and a wireless receiver (c).

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Table 3.1. Specifications of the inertial measurement unit.

	Inertial measurement unit (IMU)*		
Dimensions	37.6 mm x 52 mm x 18.1 mm		
Weight	34 grams		
Static accuracy	± 0.4 degree		
Dynamic accuracy	± 1.2 degrees		
Sampling rate	200 Hz		
Sensor elements	**Accelerometer**	**Gyroscope**	**Magnetometer**
Data	Acceleration	Angular velocity	Magnetic field
Scale	± 16 g	± 2000 degrees/second	± 1.9 Gausses
Noise	$110\mu g/\sqrt{Hz}$	0.03 degrees/second/$\sqrt{Hz}$	
Internal sampling rate	800 Hz	220 Hz	800 Hz

g = acceleration due to gravity

*, Noraxon Website. Available from: http://www.noraxon.com

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Figure 3.2. Locations of the inertial measurement units. The foot IMUs were affixed to the instep of the shoes using flat bracelet housings and were interlaced tightly using the shoelaces. The shank IMUs were affixed to the anteromedial distal aspect of the tibias using elastic straps. The pelvis IMU was affixed to the lumbosacral joint level using an elastic strap.

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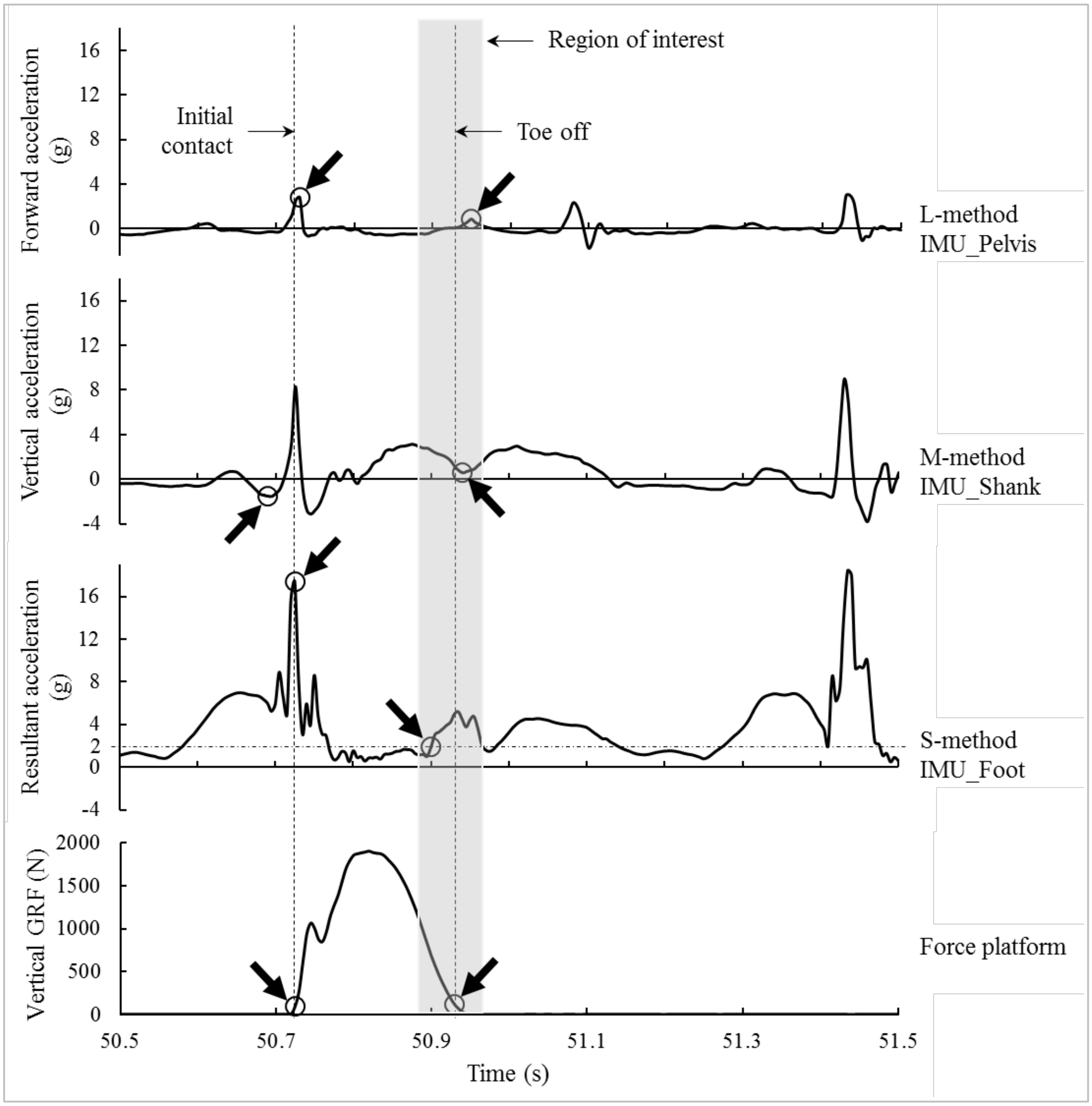

Figure 3.3. Methods for initial contact and toe-off prediction. For the L-method, IC was defined as the instant corresponding to the peak anteroposterior acceleration; TO was defined as the peak in the region of interest after the IC. For the M-method, IC was defined as the instant corresponding to the minimum value before the peak vertical acceleration; TO was defined as the minimum value in the region of interest after the IC. For the S-method, IC was defined as the instant corresponding to the peak resultant acceleration, and TO was defined using a threshold of 2 g in the region of interest after the IC. For the force platform method, IC was defined as the instant when the vertical ground reaction force > 10 N; TO was defined as the instant when the vertical ground reaction force < 25 N.

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3.2.3 Three IMU-based methods

Three typical IMU-based methods, which were widely used to predict IC and TO events in previous running-related studies (Chapman et al., 2012; García-Pérez et al., 2014; Kawabata et al., 2013; Lee et al., 2010; Mercer et al., 2003; Norris et al., 2016; Strohrmann et al., 2012), were evaluated in this part of the current study. The details of the three methods are as follows:

- In the first method (Lee et al., 2010), called the L-method in the present study, the AP acceleration profile from the IMU affixed to the lower trunk is analysed. The L-method defines IC as the instant corresponding to the positive peak of the acceleration profile, and TO as the instant corresponding to the maximum value in the region of interest after the IC (Figure 3.3). The advantage of this method is that the bilateral ICs and TOs can be identified using only one IMU.

- In the second method (Mercer et al., 2003), called the M-method in the present study, the vertical acceleration profile from the IMU affixed to the distal aspect of the tibia is processed. The M-method is a type of modified 'peak detection' method. IC is defined as the instant corresponding to the minimum value before the positive peak of the acceleration profile, and TO is defined as the instant corresponding to the minimum value in the region of interest after the IC (Figure 3.3). The M-method has been extensively used to investigate landing impact and shock attenuation during running (García-Pérez et al., 2014; Kawabata et al., 2013; Mercer et al., 2010) because the site where the IMU positioned contained the least soft tissue. Therefore, the IMU may provide impact data that most accurately reflects the real impact to the human body.

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- In the third method (Strohrmann et al., 2012), called the S-method in the present study, entails an analysis of the resultant acceleration profile obtained from the IMU positioned at the foot (or shoe). The S-method defines IC as the instant corresponding to the peak of the resultant acceleration, and TO is determined on the basis of a threshold of 2 g (g = acceleration due to gravity) in the region of interest after the IC (Figure 3.3). Using the resultant acceleration profile, the S-method minimizes the prediction errors caused by the misalignment of axes (Rueterbories et al., 2014; Khandelwal & Wickström, 2016).

3.2.4 Gait events prediction

The IC and TO timings were identified using both the force-platform-based method and the IMU-based methods (L-, M-, and S-method). For the force-platform-based method (Figure 3.3), the IC timing was determined as the instant when the vertical GRF exceeded 10 N; the TO timing was identified as the instant when the vertical GRF fell below 25 N after the IC (Bergamini et al., 2012; Hunter et al., 2004, 2005). The timings of IC and TO in the IMU-based methods used in the present study are as follows (Figure 3.3): for the L-method, the IC timing was determined as the instant of the positive peak of the AP acceleration, and the TO timing was defined as the instant of the maximum value of the AP acceleration in the region of interest after the IC (Lee et al., 2010); for the M-method, the IC timing was identified as the instant of the minimum value before the peak vertical acceleration, and the TO timing was determined as the instant of the minimum value of the peak vertical acceleration in the region of interest after the IC (Mercer et al., 2003); for the S-method, the IC timing was determined as the instant of the peak resultant acceleration, and the TO timing was defined as the instant when the resultant acceleration in the region of interest after the IC exceeded 2 g (Strohrmann et al., 2012). Therefore, for the accuracy of IC and TO prediction, three IMU-based methods (L-, M-, and S-

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method) were evaluated on basis of the reference ICs and TOs obtained using the force-platform-based method.

3.2.5 Stance time estimation

STs were estimated on the basis of the obtained IC and TO timings predicted using the force-platform-based method, L-, M-, and S-method. In addition, considering that the S-method produced the most accurate IC and the M-method produced the most accurate TO, a method (namely MS-method in the present study), which combined the M-method for TO prediction and the S-method for IC prediction, was used to estimate STs as well. Therefore, for the accuracy of ST estimation, four IMU-based methods (L-, M-, S-, and MS-method) were evaluated on basis of the reference STs obtained using the force-platform-based method.

3.2.6 Data processing and analysis

The IC and TO timings and estimated STs through the force-platform-based method were taken as references. Both relative difference (RD) and absolute difference (AD) for the IC and TO timings and estimated ST were computed with respect to the references for evaluating the accuracy of the IMU-based methods for IC and TO prediction and ST estimation.

For the IC and TO prediction, the RD was defined as the arithmetic difference between the predicted timings using the IMU-based methods (T_{IMU}) and the reference timings (T_{REF}):

$$RD = T_{IMU} - T_{REF}$$

Positive values indicated time lag, which is the predicted ICs and TOs occurred after the reference events; and negative values meant time lead, which is the predicted ICs and TOs

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occurred before the reference events (Hanlon & Anderson, 2009; Hreljac & Marshall, 2000; McGrath et al., 2012). The AD was the absolute value of RD, which measured the magnitude of difference regardless of direction (Bergamini et al., 2012; Hanlon & Anderson, 2009; Hreljac & Marshall, 2000):

$$AD = |T_{IMU} - T_{REF}|$$

For the ST estimation, the RD and AD were computed between the estimated STs using the IMU-based methods (ST_{IMU}) and the reference STs (ST_{REF}):

$$RD = ST_{IMU} - ST_{REF}$$

$$AD = |ST_{IMU} - ST_{REF}|$$

A positive value of RD indicated longer time, which means that the estimated ST was longer than the reference ST; and a negative value of RD indicated shorter time, which means that the estimated ST was shorter than the reference ST. In additional, the percentage difference (%D) was also computed using the following formula (McGrath et al., 2012; Trojaniello et al., 2014):

$$\%D = \left|\frac{ST_{IMU} - ST_{REF}}{ST_{REF}}\right| \times 100$$

To evaluate the accuracy for the IC and TO prediction, and ST estimation, 10 clean steps were processed for each participant at each speed condition. The mean relative difference (MRD), the mean absolute difference (MAD), and the mean %D were obtained by averaging the RD, AD, and %D of the 10 clean steps, respectively.

The data analysis was conducted using a statistical software (SPSS version 21.0, IBM Inc., Chicago, IL, USA). The MRD and MAD of the IC and TO predictions and ST estimation for

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each IMU-based method at each speed condition were described in mean (SD). The two-way (methods and speeds) repeated-measures analysis of variance with Bonferroni-corrected post hoc comparison was performed to examine differences in the ST estimation. Correlations between the estimated STs and the references were identified using the Pearson correlation coefficient (r). Normality tests were performed on the RD of the IC and TO predictions and ST estimation with the Shapiro-Wilk test. For the nonnormally distributed dataset, a Friedman test was performed to examine the effect of different methods and speeds, and Wilcoxon signed-rank tests were conducted to determine the differences between methods and between speeds.

3.3 Results

Table 3.2 presents the MRD and MAD for the IC and TO predictions and ST estimation. The M-method earlier remarkably predicted the IC with MRD of –27.4 (15.5) ms; the S-method earlier significantly predicted the TO with MRD of –42.9 (15.8) ms; and therefore, led to the ST estimation being longer (MRD: 35.5 (24.5) ms) and shorter (MRD: –40.4 (20.1) ms) than the references, respectively. Overall, the S- and M-methods presented the minimum MAD for the IC and TO predictions, respectively, whereas the MS-method produced the minimum MAD for the ST estimation.

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Table 3.2. Mean relative difference and mean absolute different for the initial contact and toe-off predictions and stance time estimation during jogging and running.

Variables	Prediction methods	IC prediction		TO prediction		ST estimation	
		Jogging	Running	Jogging	Running	Jogging	Running
Mean relative difference (ms)	L-method	–2.6 (4.9)	5.6 (5.0)	7.7 (9.9)	9.3 (12.7)	10.3 (8.9)	4.6 (12.1)
	M-method	–38.0 (10.7)	–17.0 (11.7)	0.0 (4.2)	1.4 (8.4)	38.0 (9.4)	32.9 (34.1)
	S-method	–7.3 (3.3)	3.2 (4.8)	–32.1 (13.1)	–46.8 (8.0)	–24.7 (14.8)	–56.0 (9.6)
	MS-method	—	—	—	—	7.3 (6.2)	–1.3 (7.1)
Mean absolute difference (ms)	L-method	9.0 (2.0)	6.2 (4.6)	15.2 (5.0)	20.3 (8.2)	15.9 (4.7)	18.7 (7.5)
	M-method	19.5 (6.5)	17.4 (11.0)	5.1 (2.1)	8.8 (3.7)	39.4 (8.0)	30.9 (18.9)
	S-method	5.2 (3.4)	4.2 (4.7)	25.0 (7.5)	27.6 (7.6)	29.3 (11.5)	34.2 (10.4)
	MS-method	—	—	—	—	9.1 (4.2)	8.8 (3.5)

For the IC and TO prediction: +, time lag; −, time lead;

For the ST estimation: +, longer time; −, shorter time

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Table 3.3 presents the STs estimated using different methods for each speed condition. No interaction between methods and speeds on the estimated STs were evident ($F = 4.2$, $p = 0.068$). The estimated STs were significantly affected by both methods and speeds ($F = 140.1$, $p < 0.001$; $F = 49.3$, $p < 0.001$). Significant differences were observed in estimated STs between using the IMU-based methods and using the force-platform-based method (all $p < 0.05$), with an exception being between the MS-method and the force-platform-based method ($p = 0.079$). The MS-method presented a mean %D of less than 5% for the ST estimation. A higher correlation between the estimated STs was noticed using the MS-method and the references during both jogging ($r = 0.95$) and running ($r = 0.86$).

The RDs of the IC and TO predictions and ST estimation were nonnormally distributed (Figure 3.4). Significant differences were observed between each pair of the IMU-based methods (all $p < 0.05$), and no statistical differences were evident between jogging and running in the RDs for the TO prediction using the L- and M-methods ($p = 0.46$ and 0.24, respectively) and the RDs for the ST estimation using the L-method ($p = 0.067$).

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Table 3.3. Mean of the estimated stance times using different methods, mean percentage difference for the stance time estimation, and the Pearson correlation coefficient with relation to the reference stance times.

Estimation methods	Estimated stance time (s)		Mean percentage difference (%)		Pearson correlation coefficient (*r*)	
	Jogging	Running	Jogging	Running	Jogging	Running
Reference	0.253 (0.010)	0.215 (0.007)	—	—	—	—
L-method	0.263 (0.015)	0.220 (0.018)	6.3 (1.8)	8.7 (3.7)	0.830*	0.891*
M-method	0.291 (0.015)	0.248 (0.039)	15.6 (3.0)	17.3 (14.1)	0.776*	0.738*
S-method	0.228 (0.023)	0.159 (0.014)	11.9 (4.8)	26.6 (4.3)	0.880*	0.740*
MS-method	0.260 (0.014)	0.214 (0.012)	3.6 (1.5)	4.1 (1.8)	0.952*	0.860*

*, $p < 0.05$

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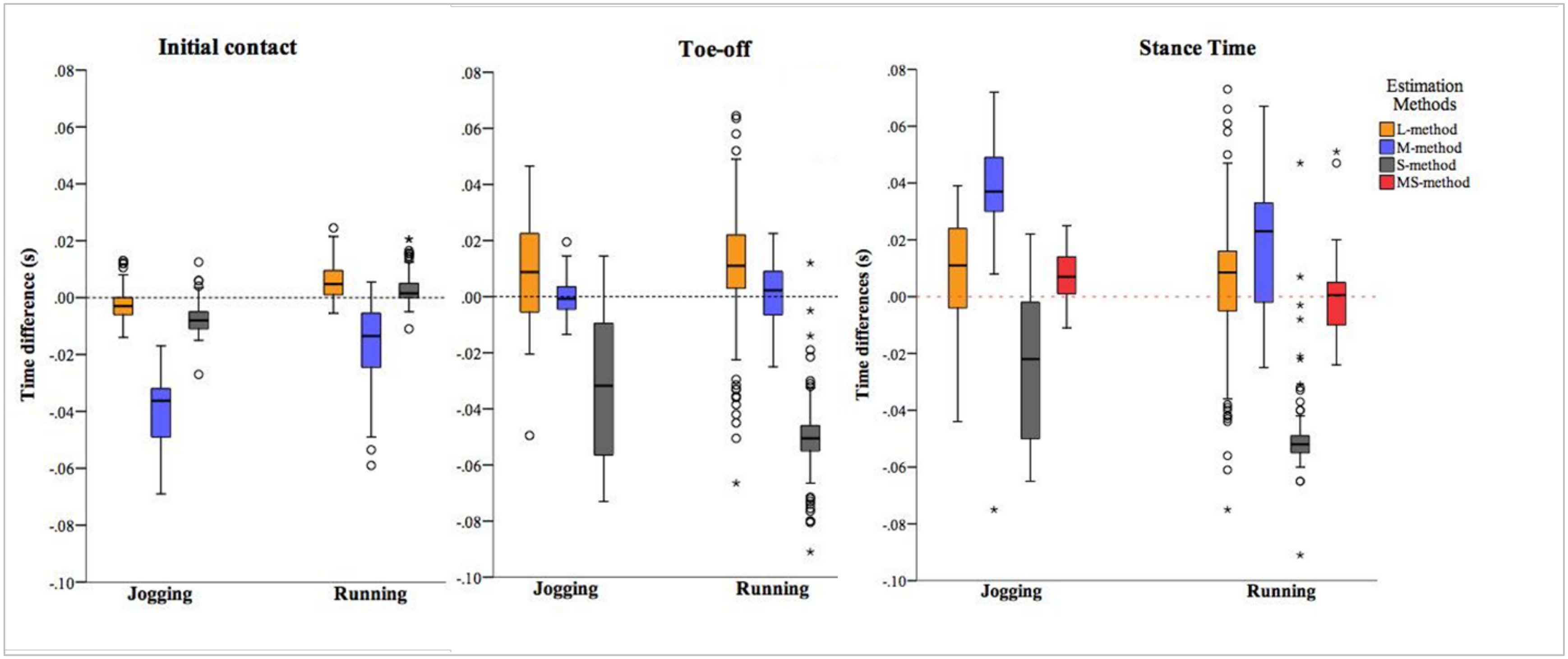

Figure 3.4. Minimum, 25th percentile (Q_1), median, 75th percentile (Q_3), and maximum RDs for the initial contact and toe-off predictions and stance time estimation during jogging and running events.

Median, the thick horizontal line in the box; Q_1, the lower edges of the box; Q_3, the upper edges of the box; the minimum value (the smallest nonoutlier value), the lower whiskers; the maximum value (the largest nonoutlier value), the upper whiskers. Values larger than $Q_3 + 1.5 \times (Q_3 - Q_1)$ or smaller than $Q_1 - 1.5 \times (Q_3 - Q_1)$ are viewed as outliers, which are represented with circles; values larger than $Q_3 + 3 \times (Q_3 - Q_1)$ or smaller than $Q_1 - 3 \times (Q_3 - Q_1)$ are regarded as extreme outliers, which are represented with asterisks.

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3.4 Discussion

Gait events (IC and TO) during running can be predicted using IMU-based methods because a connection exists between the gait events and specific features of the acceleration profiles measured by IMU. Time lags were reported during the transmission of the peak impacts from the collision point to the upper trunk (Lucas-Cuevas et al., 2017), which may lead to alterations in the accuracy of the prediction of gait events when the IMU is positioned at different locations (e.g., foot, shank, and pelvis).

3.4.1 Accuracy of initial contact prediction

Heiden and Burnett (2008) reported a strong positive correlation (r^2 = 0.997) in the time lag and the distance from the IMU location to the collision point; the time lag became longer when the IMU was positioned further from the collision point. Therefore, in the present study, the S-method exhibited the minimum AD with MAD of 4.7 (4.1) ms for the IC prediction because the IMU was positioned at the foot instep, which was remarkably smaller than the previously reported 65 (5) ms (Heiden & Burnett, 2008). In that study (Heiden & Burnett, 2008), the ICs during overground running were predicted using an IMU that was positioned near the ankle joint level. In the present study, the AD for the IC prediction was within the range (0.42–147.0 ms) that was reported by the studies that have analysed walking gait (González et al., 2010; Hanlon & Anderson, 2009; Jasiewicz et al., 2006; Mansfield & Lyons, 2003; Selles et al., 2005). In these studies, either the acceleration profile or the angular velocity profile along with different data processing approaches were used, and references were provided by different instrumentations along with different sampling rates. To minimise the effects of time lag, for the L-method, the

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IMU was positioned at the lumbosacral level, and the AP acceleration profile was processed; for the M-method, the IMU was positioned at the shank level, and the minimum vertical acceleration before the positive peak was determined instead of the positive peak. However, both methods presented large event prediction errors with a considerably earlier IC prediction (RD: –27.4 (15.5) ms) by the M-method, and a relatively larger AD for the IC prediction by the L-method in comparison to that by the S-method.

The accuracy of both the L-method and S-method for the IC prediction was influenced by running speed. In comparison to the L-method, the S-method exhibited an earlier IC prediction during jogging; however, the S-method exhibited a shorter time delay during running. Overall, when compared with the L- and M-methods, the S-method presented less variances during both jogging and running.

3.4.2 Accuracy of toe-off prediction

TO is of importance in running gait analysis and is the final contact event of the landing phase during running, which represents the end of foot propulsion. In addition to estimating gait temporal parameters, TO is also a critical event in RRI studies (Kindred et al., 2011; Miller et al., 2008). Nevertheless, the accuracy of the TO prediction during running has seldom been compared when different IMU-based methods were used. The M-method exhibited the most accurate TO prediction with an AD of 7.0 (3.5) ms, which is considerably smaller than the reported 15 (2) ms (Heiden & Burnett, 2008), and is within the range of 3.11–34.0 ms that was reported by the studies analysing walking gait (González et al., 2010; Jasiewicz et al., 2006; Selles et al., 2005). The TO can be accurately predicted from the shank vertical acceleration

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profile because knee and hip joints flex at the TO, and therefore, produce an abrupt upward and forward shank movement (Dugan & Bhat, 2005). The L-method presented a comparably large AD (17.7 (7.1) ms) for the TO prediction; the IMU positioned at the lower trunk was close to the centre of the body mass, and the AP acceleration profile obtained by that IMU may be minimally influenced, because during running, runners are prone to reducing the oscillation of the centre of body mass to improve running efficiency (Novacheck, 1998). For the S-method, TOs were predicted on the basis of a threshold of 2 g, which may be inappropriate because it produced a larger AD (26.3 (7.5) ms). A possible explanation is that the resultant acceleration from the foot IMU may be bigger than 2 g because the heel-off and foot propulsion occurred before TO. In additional, compared with the other two methods, the M-method also presented less variances for the TO prediction at both speed conditions.

3.4.3 Accuracy of stance time estimation

Regarding the advantages of using the S- and M-methods to predict gait events, the MS-method presented the most accurate ST estimation with a mean %D of 3.8% (1.6%), which is considerably smaller than the data (5.9%–22.4%) reported by McGrath et al. (2012). In McGrath et al. (2012), the STs were estimated on the basis of the angular velocity profile, the running tests were conducted on the treadmill, and the reference data were obtained through a gyroscope-based method and two kinematic-based methods (200 Hz). The results of the present study also indicated a high correlation between the estimated STs and the references at both speed conditions (r = 0.95 during jogging and 0.86 during running), which are similar to the data (r = 0.93) reported by Lee et al. (2010). In Lee et al. (2010), the IMU was positioned at the pelvis level, and the reference data were obtained through a high-speed motion capture system (100

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Hz). Using the MS-method, the ADs for the ST estimation were 9.1 (4.2) ms during jogging and 8.8 (3.5) ms during running, which are significantly smaller than the data (125 (15) ms for amateur athletes and 105 (10) ms for elite athletes) reported by Bergamini et al. (2012), and larger than the data (0 (12) ms during jogging, 2 (3) ms during running and 1 (1) ms during sprinting) reported by Purcell et al. (2006). It should be noted that sprinting as well as data profiles of acceleration, angular velocity, and second derivative of angular velocity were analysed, and the references provided by different instrumentations (high-speed camera at 300 Hz and force platform at 200 Hz) were used in Bergamini et al. (2012); the IMU was positioned at the shank level, and the data were acquired at 250 Hz in Purcell et al. (2006). Compared with the other three methods (L-, M-, and S-methods), the MS-method exhibited smaller RDs and less variances for the ST estimation during both jogging and running. In summary, the MS-method produced a comparably accurate ST estimation and is, therefore, recommended. However, the limitation is that the MS-method requires at least four IMUs to gain bilateral data.

3.5 Limitations

The present study had several limitations. Firstly, ST was the only gait temporal parameter that was assessed; more informative results could have been obtained if other gait temporal parameters, such as stride interval, step time, and flight time, were also assessed. Secondly, the overground running tests were conducted in the laboratory (concrete surface), and quite a few steps were acquired (e.g., one or two steps per trial). Significant variations were observed in peak GRF and knee kinematic between overground and treadmill running (Riley et al., 2008), and peak pressure and ST were reported to be changed with running surfaces (rubber, asphalt,

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concrete, and grass) (Tessutti et al., 2012); therefore, the findings should be applied with caution to other running surfaces and treadmill running. Thirdly, a comparison study uses public gait databases, such as the MAREA gait database, may provide more insights into the performance of the three IMU-based methods in different outdoor environments. Fourthly, the three IMU-based methods were evaluated only under two running speed conditions. Future studies can evaluate their performance at more different running speeds, such as from walking to sprinting, because speed-induced changes in foot strike patterns (e.g., rearfoot, midfoot, and forefoot strike) may affect the accuracy (Leitch et al., 2011). In addition, because of the short running distance (10 m), it was impossible to ensure the participant completed the run at a constant speed. Future studies should minimise the effects caused by acceleration and deceleration in each trial. Furthermore, numerous studies (Lieberman et al., 2010; Zhang et al., 2017) have demonstrated the effects of foot strike pattern on landing impact, which therefore leads to alterations in the acceleration profiles. Future study is suggested to investigate the effects of foot strike pattern on the accuracy of using IMU-based methods for gait events prediction. Lastly, the reliability, such as how the researcher placing the IMU on the participant, is unknown. Effects of this reliability on the prediction accuracy should be addressed in future work.

3.6 Summary

In conclusion, the S-method produced the most accurate IC prediction, the M-method produced the most accurate TO prediction during overground running, and the MS-method produced the most accurate ST estimation during overground running. Therefore, during field running, to obtain the most accurate IC events, the IMU should be placed at the foot instep and the resultant

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acceleration should be processed to identified the local peak value; to obtain the most accurate TO, the IMU should be placed at the distal aspect of the tibia and the vertical acceleration should be processed to identify the local minimum in the region of interest after the IC; to obtain the most accurate ST, two IMUs are suggested and should be separately placed at foot and shank.

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Chapter 4: Stride Interval Variability during a Prolonged Treadmill Run

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4.1 Introduction

Stride interval, which is defined as the duration between the initial contacts (ICs) of two consecutive landings of the same foot during running (Hollman et al., 2011), is regarded as a 'final output' of the locomotor system (Hausdorff, 2007). Stride interval is a key parameter within running biomechanics due to its contribution to running efficiency and performance (Gindre et al., 2016). Typically, variability within the stride interval time series has been viewed as noises or errors in the gait performance, and linear approaches, such as standard deviation (SD) and coefficient of variation (CoV), have been typically employed to quantify the magnitude of the stride interval variability occurring around the average value (Stergiou & Decker, 2011). However, these methods do not provide information about the structure or temporal organisation of the stride interval variability, which reflects how the locomotor system self-organises to adapt to constraints due to ever-changing environments (Harbourne & Stergiou, 2009; Hausdorff, 2005). With the application of nonlinear methods, such as the detrended fluctuation analysis (DFA) in gait analysis (Chau, 2001), researchers have observed and confirmed that the stride interval variability during running exhibits a fractal-like manner with long-range correlations

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(Jordan et al., 2006, 2007), indicating that the stride interval is predictable and correlated regardless of the time point in the longitudinal stride interval time series.

Stride interval variability in trained runners (Nakayama et al., 2010), and the effects of health status (Mann et al., 2015a; Meardon et al., 2011), running speed (Jordan et al., 2006; Lindsay et al., 2014), fatigue (Fuller et al., 2017; Mann et al., 2015b; Meardon et al., 2011), footwear, and foot strike pattern (Fuller et al., 2016; Mann et al., 2015b) on stride interval variability have been investigated. However, the characteristics of the stride interval variability that are exhibited during a prolonged run by runners with varying degrees of experience remain unknown.

Therefore, in this part of the present study, variability within the stride interval time series between experienced runners and novice runners was compared during a 31-min treadmill run at a constant running speed that corresponded to their individual anaerobic threshold (AT) level. The objectives were (i) to understand the characteristics of the stride interval dynamics during the prolonged treadmill running and to understand how the locomotor system regulates gait patterns in progressive fatigue during a prolonged run, (ii) to identify differences in the stride interval dynamics between the experienced and novice runners and to ascertain whether years of running experience can induce performance differences, especially at the AT intensity level, and (iii) to investigate the interactions of running experience and fatigue on the stride interval dynamics. It was hypothesized that (i) the stride interval dynamics would change with progressive fatigue for both the experienced and novice runners, and (ii) the changes would be different between them.

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4.2 Methods

4.2.1 Experimental design

A two-way repeated-measures design with mixed samples were adopted to investigate the effects of running experience and progressive fatigue on the stride interval dynamics. Two groups of participants (experienced and novice runners) were recruited and performed a preliminary running test for determining their AT speeds and a 31-min treadmill running at their AT speeds.

4.2.2 Participants

Sample Size

The sample is estimated using G*Power on basis of a previous relevant study which examined the impact of running condition (overground run and treadmill run) and running speed (Lindsay et al., 2014) on stride interval dynamics. Running condition by speed interaction and main effects of running condition were evident for the stride interval complexity (Partial Eta Squared, $\eta^2 = 0.05$ and 0.21, respectively). Assuming that similar effects will be obtained in this part of the study, a sample of 11 participants per group is required to achieve a power of 80% and a significance level at $p = 0.05$. Considering 20% attrition of the effect size, 14 participants per group will be required. To ensure the generalizability of the results yielded from this part of study, 17 participants per group will be required.

Participant Recruitment

The participants of this study were recruited within the university and from local communities through advertisements (posters and informational flyers) and verbal invitations. The respondent

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was enrolled in the present study if she/he (i) volunteered to participate in this study; (ii) was in the age range of 18-40 years; (iii) did not experience any running-related injuries (RRIs) in the past six months; and (iv) had no known cardiovascular diseases or any other diseases that would prevent their participation in strenuous physical activities. Totally, 72 respondents (23 females and 49 males) enrolled in this study. The enrolled respondents were required to complete the revised Physical Activity Readiness Questionnaire (PAR-Q, Canadian Society for Exercise Physiology, 2002. www.csep.ca/forms) and a medical history questionnaire prior to performing in the running experiment. A pre-participation screening was conducted by an experienced researcher, and the respondent was excluded if she/he (i) answered with 'YES' to one or more questions of the PAR-Q; or (ii) had any obvious anatomical abnormities, such as genu valgum, genu varum, or flat feet. Eventually, 42 enrolled respondents met the inclusion criteria, and considering that some participants may withdraw from the study, all the 42 respondents were included in this part of the study.

Participant Grouping

The 42 participants were grouped into experienced and novice runners. To qualify as an experienced runner, one must (i) be a recreational distance runner, 'who run and train, week in and week out, at levels far in excess of that required for basic physical fitness, yet stand no realistic chance of winning, or doing well in any distance race' (Allen-Collinson & Hockey, 2007; Shipway & Holloway, 2016; Smith, 1998); and (ii) do regular running training (≥3 times per week and ≥60 min per time) with a minimum weekly running distance of 20 miles for at least 2 years (Hunter et al., 2017). To qualify as a novice runner, (i) one must 'have no regular running experience within the previous 12 months' (Buist et al., 2007, 2010; Kluitenberg et al., 2015;

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Nielsen et al., 2013), or (ii) a beginner, 'who had no prior running training and not being involved in regular sporting activities (Moore et al., 2012), or had run for less than 5 km/week (Strohrmann et al., 2012)', or (iii) one may do running practice irregularly and be active in other sport activities. Finally, 20 participants (6 females and 14 males) were grouped in experienced runner group and 22 participants (5 females and 17 males) in novice runner group.

Participants Description

During the test, 3 female experienced runners and 5 novice runners quitted from the present study after the preliminary test. Eventually, there were 17 participants for both groups. Overall information for each group was summarized (Table 4.1).

The participants received a brief introduction about the study, such as its purpose and the procedures of the experimental protocol, and provided signed informed consent prior to participating in the present study. The present study was approved by the Human Research Ethics Committee of The Education University of Hong Kong (Ref: No. 2015-2016-0346).

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Table 4.1. **Descriptiveness, anthropometry, training, and psychophysiological characteristics of the participants.**

		Experienced runners	Novice runners
Gender		3 females, 14 males	2 females, 15 males
Age (years)		24.9 (6.4)	23.8 (4.7)
Height (cm)		170.3 (6.1)	173.1 (8.0)
Body mass (kg)		63.4 (9.5)	62.8 (10.4)
Body mass index (kg/m^2)		21.8 (2.3)	20.9 (2.3)
AT speed (km/h)		12.6 (1.3)	11.1 (0.8)
Running experience		8.5 years (from 4 to 20 years)	< 6 months
Weekly running volume		> 30 km	-
Best time for 5-km race		20.5 min (from 16 to 22 min)	-
Blood lactate accumulation (mmol/L)	Pre-test	1.3 (0.8)	1.3 (0.5)
	Post-test	8.0 (2.0)	7.4 (1.5)
Self-reported RPE score	Pre-test	7.6 (2.1)	7.2 (1.2)
	Post-test	17.5 (0.9)	18.3 (0.9)

AT, anaerobic threshold; RPE, rating of perceived exertion

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4.2.3 Experimental protocol

The experimental protocol consisted of two parts: a preliminary test to determine the AT speed for each participant and a main test to collect stride interval time series data.

The Preliminary Test

Each participant was required to perform an incremental load running protocol (Figure 4.1), which was adopted from a previous study by Mizrahi et al. (2000). The participants ran at an initial running speed of 8.0 km/h, and the running speed was increased by 1.0 km/h every 2 min until reaching a maximum running speed of 15.0 km/h. The test was stopped immediately if a participant could not continue before they reached the maximum running speed. In the present study, the 34 participants completed the preliminary running test.

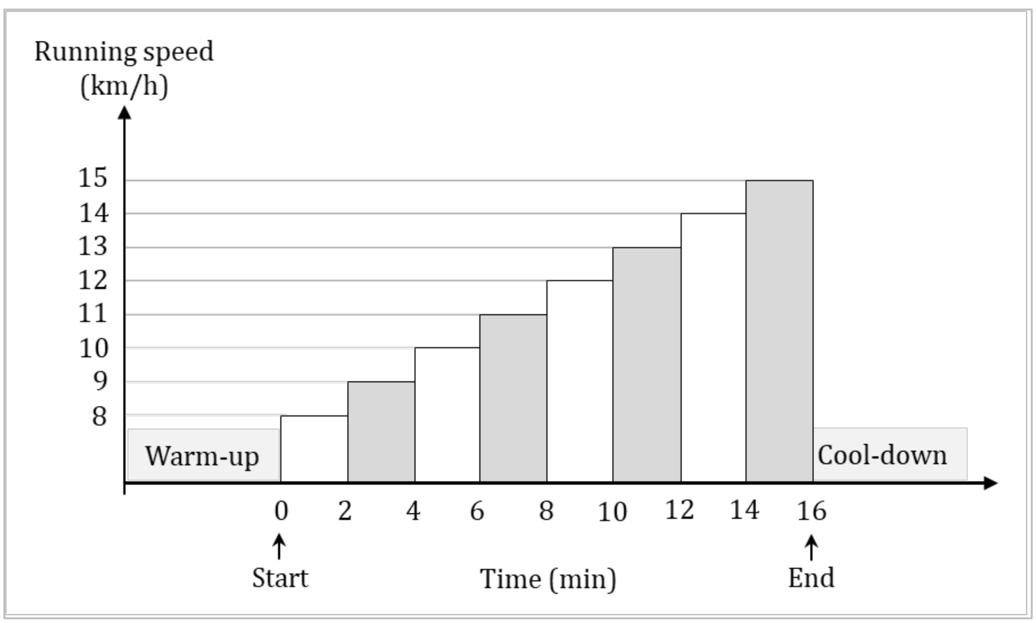

Figure 4.1. The incremental load running protocol during the preliminary test.

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During the running test, each participant was asked to wear a mouthpiece, which was attached to a turbine device, and their breathing gas was continuously sampled and analysed in real time using a metabolic gas analyser (Cortex Metalyzer 3B, Germany). Prior to each measurement, the gas analyser was calibrated using reference gases and a standard syringe. Breath-by-breath, gas exchange data were obtained, and the ventilatory equivalent for oxygen, which was defined as the ratio of ventilation to oxygen consumption ($\dot{V}_E/\dot{V}_{O_2}$), was calculated by averaging the breath-by-breath data at a time span of 30 s. The participant's AT was determined as the turning point when the $\dot{V}_E/\dot{V}_{O_2}$ displayed a nonlinear steep increase (Ghosh, 2004). This noninvasive method to determine an individual's AT was proposed and justified by Wasserman et al. (1973), and has been widely used in the literature (Ghosh, 2004; Mizrahi et al., 2000, 2001). The running speed corresponding to the AT level was defined as the participant's AT speed (Figure 4.2) (Mizrahi et al., 2000, 2001). Overall, the mean (SD) AT speed was 12.6 (1.3) km/h and 11.1 (0.8) km/h for the experienced runners and novice runners, respectively.

The preliminary test was conducted on a treadmill (Pulsar, h/p/cosmos, Germany; Running surface: 1900 mm × 650 mm; Belt speed: 0–40 km/h; Elevation: –25% to 25% grade) with a minimum gap of 48 h prior to the main test. Each participant was provided sufficient time to warm-up and cool-down in the preliminary test.

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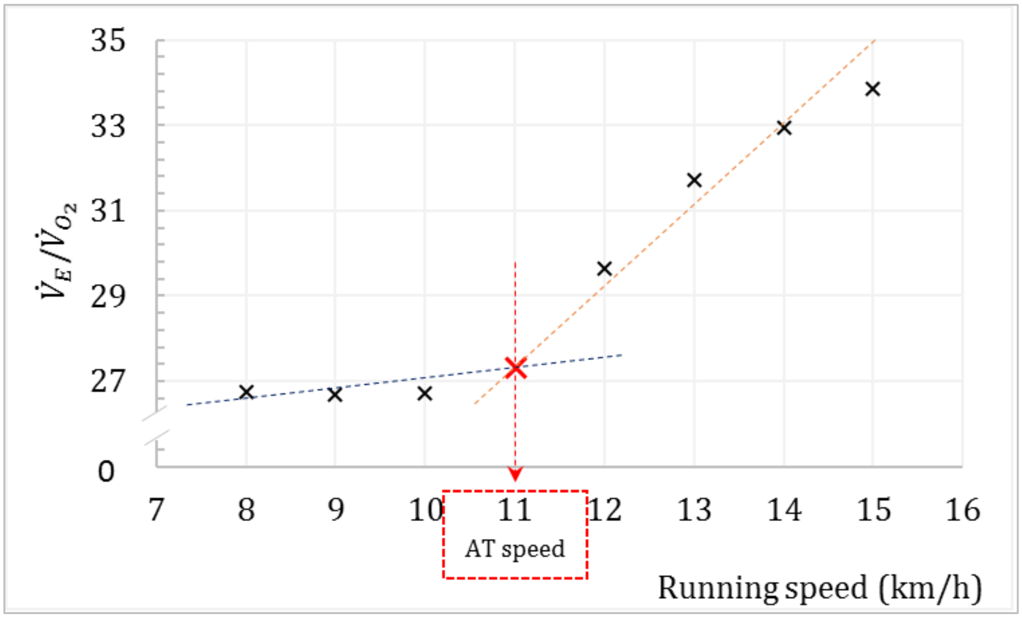

Figure 4.2. Determining anaerobic threshold speed.

For this participant, the anaerobic threshold speed was 11.0 km/h.

$\dot{V}_E/\dot{V}_{O_2}$, ratio of ventilation to oxygen consumption.

The Main Test

The participants were asked to perform a run at their individual AT speed for 31 min on a treadmill (GE Marquette 2000, USA). Before the treadmill run, two reflective markers were affixed separately on bilateral heels (middle of the heel cup of the shoe). Using a motion capture system (Qualysis Inc., Sweden), three-dimensional displacements of heel markers were continuously recorded at a sampling rate of 200 Hz throughout the treadmill run. The motion capture system was calibrated before each measurement and the reported errors were within 0.5 mm. Using a lactate meter (Nova Biomedical Corp., USA) and Borg's rating of perceive exertion (RPE) scale (6–20 points), respectively, each participant's blood lactate accumulation level and perceived exertion state were measured prior to and immediately after the treadmill run. To monitor the progression of fatigue, the participant was also required to report their RPE score

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every 5 min during the treadmill run. The participants wore their own running shoes and were provided sufficient time to warm-up and cool-down.

4.2.4 Data processing and analysis

A video analysis of each participant's foot strike pattern revealed that the participants were rearfoot strikers (heel hits the ground first during landing). The data were processed using Matlab (Mathworks Inc., USA). The present study analysed data regarding the vertical displacement of the right heel marker. The 31-min data were initially filtered using a zero-lag, second-order Butterworth low-pass filter at a cut-off frequency of 7 Hz. The ICs were predicted as the local minimum of the vertical displacements (Figure 4.3) (Fellin et al., 2010). This IC prediction method has been widely used in the literature (Alton et al., 1998; Cappellini et al., 2006; Dingwell et al., 2001; Hunter et al., 2005). The stride interval time series was obtained by locating ICs. To minimise the effects of the start-up and end, the stride interval time series data of the initial and last 30 s were excluded from the analysis. The remaining 30-min data were equally divided into six intervals (TI1, TI2, TI3, TI4, TI5, and TI6). The number of strides for each interval was from 401 to 488 for the participants.

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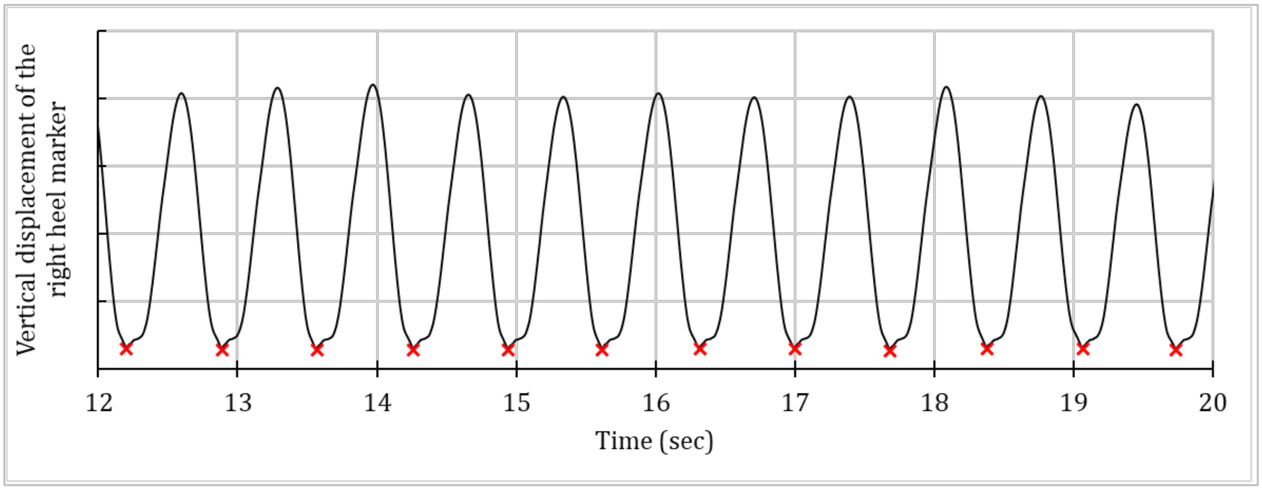

Figure 4.3. Determining initial contacts.

× is the local minimum of the vertical displacements of the right heel marker, which is viewed as initial contact.

To investigate the effects of the progression of fatigue, the stride interval data were processed separately for the six intervals. The mean stride interval was computed by averaging all the stride intervals. The stride interval variability was quantified by calculating CoV, which was used to evaluate the overall distribution characteristics of the stride interval time series. The variability within the stride interval time series was also analysed using DFA, which yielded a scaling exponent alpha (α) to quantify the internal structure characteristics of the stride interval time series (e.g., long-range correlations of the stride interval variability).

Detrended Fluctuation Analysis

The DFA estimates the scaling exponent alpha of the time series dataset ($(SI_i)_{i=1}^{N}$) through the following steps (Damouras et al., 2010):

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1) To integrate the dataset's deviations with its mean ($\overline{SI}$), and generate a new time series dataset, $X_i = \sum_{j=1}^{i}\left[SI_j - \overline{SI}\right]$, for $i = 1, 2, \cdots, N$.
2) The new dataset ($(X_i)_{i=1}^{N}$) is divided into m non-overlapping boxes with equal length (n) for each box. $n = \left\lfloor \frac{N}{m} \right\rfloor$, where n takes the largest integer value.
3) A linear least squares line is fitted to the data within each box. The sequence of the fitted lines constitutes the trend series ($[(X_n)_i]_{i=1}^{(n\times m)}$). $(n\times m)$ is the total number of data points falling within the boxes, where $(n\times m) \leq N$.
4) To calculate the average fluctuation ($F(n)$) of the integrated series X around the trend series (X_n) using the following formula:

$$F(n) = \sqrt{\frac{\sum_{i=1}^{(n\times m)}(X_i - (X_n)_i)^2}{(n\times m)}}$$

5) Steps 2–4 are repeated over a range of different box sizes (n_k) to obtain a range of fluctuations $F(n_k)$. In the present study, $16 \leq n_k \leq \left\lfloor \frac{N}{9} \right\rfloor$, where $\left\lfloor \frac{N}{9} \right\rfloor$ is the largest integer function (Damouras et al., 2010).
6) To plot the log of average fluctuation ($\log F(n_i)$) versus the log of the box size ($\log n_i$), where $i = 1, 2, \cdots, k$. A linear least squares line is fitted to the data, and the slope of the fitted line is estimated as the scaling exponent alpha.

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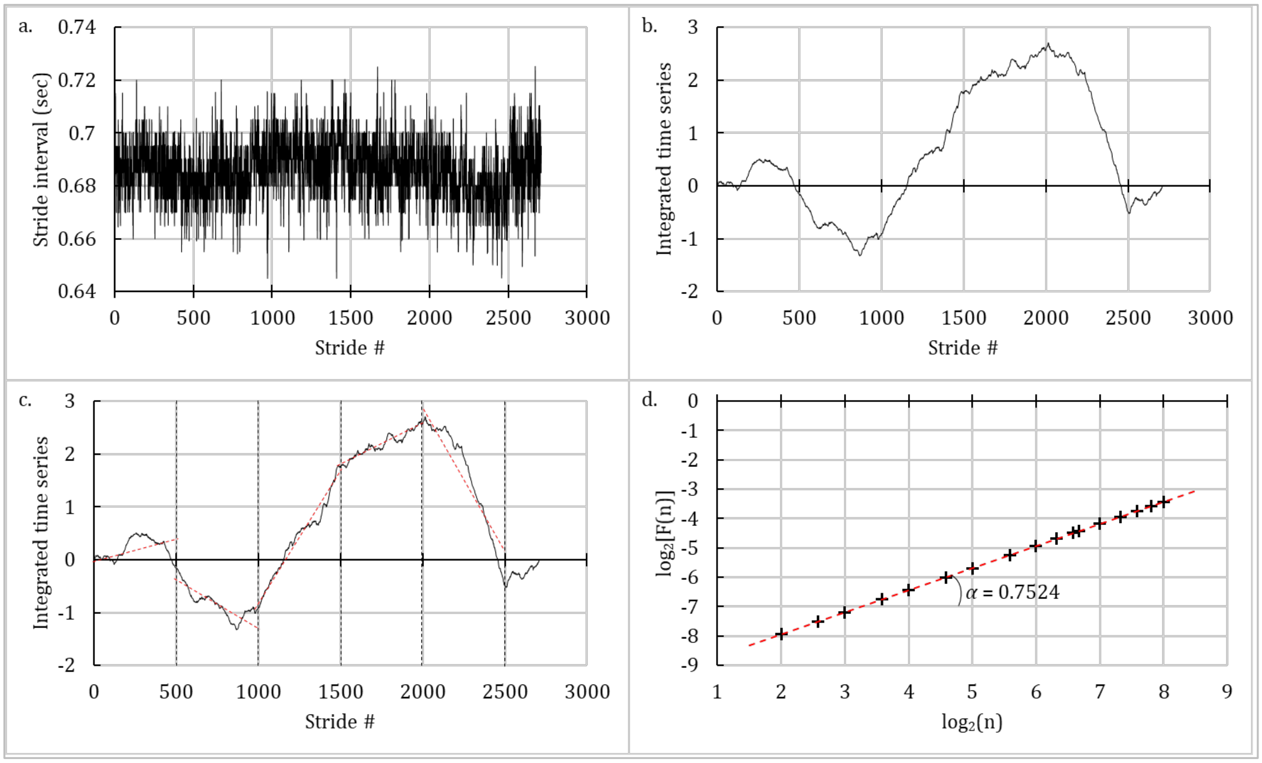

Figure 4.4. Estimating the scaling exponent alpha using the detrended fluctuation analysis. (a.) raw stride interval time series dataset; (b.) to integrate a raw dataset and generate a new time series dataset; (c.) to divide the new dataset into five boxes by dashed vertical lines, to fit a linear least squares line (dash line) within each box; (d) to plot the log of average fluctuation $F(n)$ versus the log of the box size *n* (dash line represents the linear least squares line). In this example, the estimated scaling exponent alpha is 0.75.

The aforementioned six steps to estimate the scaling exponent alpha (α) are illustrated in Figure 4.4. $0 < \alpha < 0.5$ indicates anti-correlation (e.g., a given short stride interval is likely to be followed by a long stride interval and vice versa); $\alpha = 0.5$ indicates a random walk; and $0.5 < \alpha \leq 1.0$ indicates persistent long-range correlations (e.g., any given stride interval is statistically dependent on those occurring over many different timescales).

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Statistical Analysis

The data were analysed using a statistical software (SPSS version 21.0, IBM Inc., Chicago, IL, USA). The descriptive results are presented as mean (SD). Independent sample *t*-tests were conducted to determine differences in age, height, body mass, body mass index, and AT speed between the groups. A two-way (groups: experienced runners vs. novice runners; time: 6 intervals) repeated-measures analysis of variance was performed to determine any differences in mean stride interval, and CoV and alpha of stride interval. Post hoc comparisons were performed on the basis of the Least Significant Difference test. The significance level was set at $p < 0.05$.

4.3 Results

The results indicate that the two groups showed no evident differences regarding age ($p = 0.50$, $d = 0.24$), body mass ($p = 0.74$, $d = 0.11$), height ($p = 0.11$, $d = 0.57$), and body mass index ($p = 0.20$, $d = 0.45$). The AT speed of experienced runners (12.6 (1.3) km/h) was significantly faster than that of novice runners (11.1 (0.8) km/h) ($p < 0.001$, $d = 0.1.5$). Prior to the treadmill run, the blood lactate accumulation levels of experienced and novice runners were 1.3 (0.8) mmol/L and 1.3 (0.5) mmol/L, respectively, and the self-reported RPE scores were 7.6 (2.1) and 7.2 (1.2), respectively. After performing the treadmill run at their individual AT speed for 31 min, both experienced and novice runners reached an intensity level of ‘very hard’ with a self-reported RPE score of 17.5 (0.9) and 18.3 (0.9), respectively. The blood lactate was significantly accumulated and reached 8.0 (2.0) mmol/L for experienced runners and 7.4 (1.5) mmol/L for novice runners. The mean stride interval, CoV and alpha of stride interval are presented in Table 4.2.

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Table 4.2. Mean (SD) stride interval, coefficient of variation (CoV) and scaling exponent alpha of stride interval for experienced and novice runners at each interval.

	Groups	TI1	TI2	TI3	TI4	TI5	TI6	Interaction effect	Group effect	Time effect
Stride interval (s)	**Experienced runners**	0.694 (0.04)	0.695 (0.05)	0.698 (0.05)	0.700 (0.04)	0.700 (0.04)	0.699 (0.04)	$F = 1.50$, $p = 0.20$, $\eta^2 = 0.09$, power=0.50	$F = 3.49$, $p = 0.08$, $\eta^2 = 0.18$, power=0.42	$F = 9.16$, $p < 0.001$, $\eta^2 = 0.36$, power=1.00
	Novice runners	0.707 (0.03)	0.716 (0.03)	0.721 (0.03)	0.721 (0.03)	0.720 (0.03)	0.719 (0.03)			
CoV (%)	**Experienced runners**	1.43 (0.50)	1.37 (0.37)	1.39 (0.53)	1.41 (0.67)	1.53 (0.60)	1.60 (0.78)	$F = 4.14$, $p = 0.002$, $\eta^2 = 0.21$, power=0.95	$F < 0.001$, $p = 0.99$, $\eta^2 < 0.001$ power=0.05	$F = 1.12$, $p = 0.34$, $\eta^2 = 0.07$ power=0.23
	Novice runners	1.53 (0.33)	1.47 (0.24)	1.44 (0.27)	1.46 (0.31)	1.38 (0.28)	1.41 (0.33)			
alpha	**Experienced runners**	0.74 (0.07)	0.69 (0.05)	0.68 (0.05)	0.67 (0.09)	0.76 (0.09)	0.75 (0.10)	$F = 5.95$, $p < 0.001$, $\eta^2 = 0.27$ power=0.99	$F = 2.7$, $p = 0.12$, $\eta^2 = 0.14$, power=0.34	$F = 8.21$, $p < 0.001$, $\eta^2 = 0.34$, power=1.00
	Novice runners	0.72 (0.07)	0.74 (0.08)	0.65 (0.07)	0.64 (0.10)	0.66 (0.08)	0.69 (0.08)			

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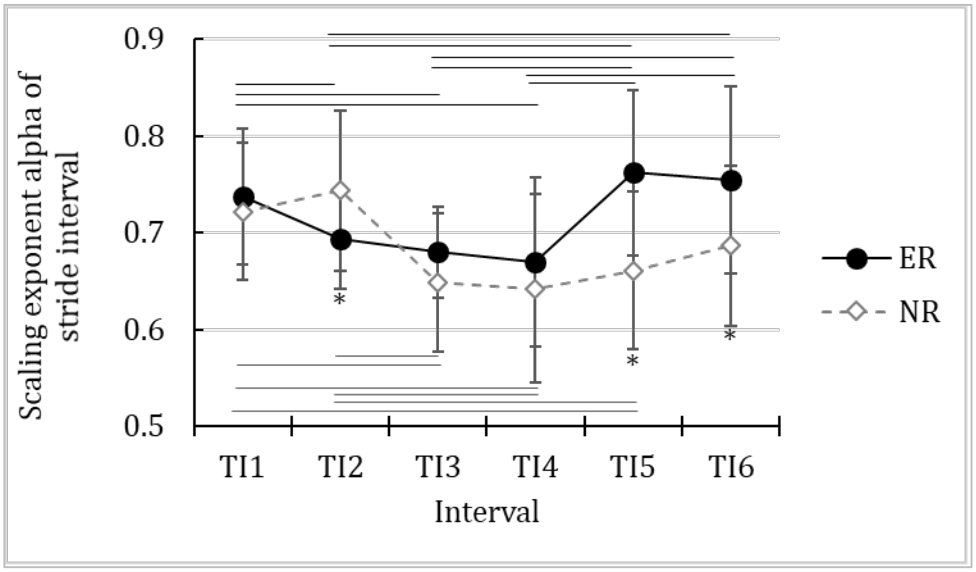

Figure 4.5. The scaling exponent alpha of stride interval throughout the 31-min treadmill run.

ER, experienced runners; NR, novice runners; *, ER vs. NR, *p* < 0.05;

———— (in black), significant differences between paired intervals for experienced runners, *p* < 0.05;

———— (in grey), significant differences between paired intervals for novice runners, *p* < 0.05.

For the scaling exponent alpha (α) of stride interval, the significant group by time interaction ($F = 5.95$, $p < 0.001$, $\eta^2 = 0.27$, power = 0.99), time effect ($F = 8.21$, $p < 0.001$, $\eta^2 = 0.34$, power = 1.00), and no group effect ($F = 2.70$, $p = 0.12$, $\eta^2 = 0.14$, power = 0.34) were evident. The alpha of stride interval for both the experienced ($F = 7.83$, $p < 0.001$, $\eta^2 = 0.33$, power = 1.00) and novice runners ($F = 6.57$, $p < 0.001$, $\eta^2 = 0.29$, power = 1.00) changed over time in a nonlinear trend, which was observed to be a roughly U-shape but was slightly different between them (Figure 4.5). For the experienced runners, the alpha of stride interval significantly decreased at

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the beginning (TI1 vs. TI2, TI1 vs. TI3, TI1 vs. TI4: p = 0.016, 0.020, 0.014, respectively), maintained constant in the middle (TI2 vs. TI3, TI2 vs. TI4, TI3 vs. TI4: p = 0.26, 0.29, 0.65, respectively), and significantly increased at the end of the 31-min run (TI4 vs. TI5, TI4 vs. TI6: p = 0.001, 0.002, respectively). For the novice runners, the alpha of stride interval remained unchanged at the beginning (TI1 vs. TI2: p = 0.37), significantly decreased in the middle (TI2 vs. TI3, TI2 vs. TI4: p = 0.001, 0.002, respectively), and exhibited an increase trend at the end of the 31-min run (TI4 vs. TI5, TI4 vs. TI6: p = 0.31, 0.070, respectively). The results indicate no difference between the groups regarding the alpha of stride interval at TI1, TI3, and TI4 (p = 0.53, 0.15, and 0.40, respectively), whereas the alpha of stride interval for the experienced runners was significantly smaller than that of the novice runners at TI2 (p = 0.043) and larger at TI5 and TI6 (p = 0.001 and 0.035, respectively).

For CoV of stride interval, significant group by time interaction (F = 4.14, p = 0.002, η^2 = 0.21, power = 0.95), and no group (F < 0.001, p = 0.99, η^2 < 0.001, power = 0.05) and time effect (F = 1.12, p = 0.34, η^2 = 0.07, power = 0.23) were evident. *Post-hoc* comparisons revealed that throughout the 31-min run CoV of stride interval greatly varied for the experienced runners (F = 2.78, p = 0.023, η^2 = 0.15, power = 0.81) and maintained relatively constant for the novice runners (F = 1.56, p = 0.22, η^2 = 0.09, power = 0.37) (Figure 4.6). CoV of stride interval of the experienced runners decreased at the beginning (TI1 vs TI2: p = 0.038), maintained in the middle (TI2 vs TI3, TI2 vs TI4, TI3 vs TI4, p = 0.15, 0.27, and 0.66, respectively), and significantly increased at the end of the 31-min run (TI4 vs TI6: p = 0.001). No group differences in CoV of stride interval were evident for each interval (TI1, TI2, TI3, TI4, TI5, and TI6: p = 0.49, 0.15, 0.73, 0.79, 0.33, and 0.36, respectively).

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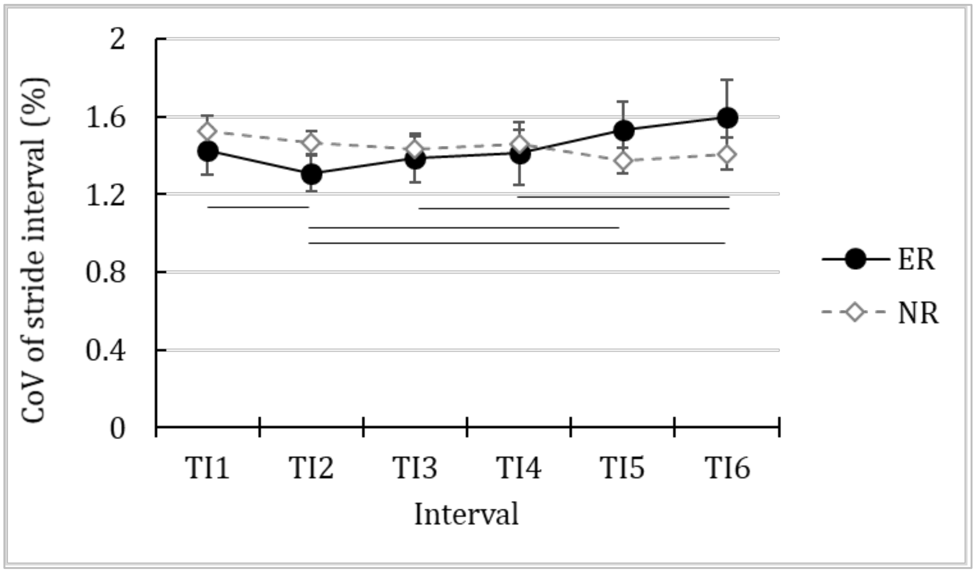

Figure 4.6. The coefficient of variance of stride interval throughout the 31-min treadmill run.

ER, experienced runners; NR, novice runners;

________ , significant differences between paired intervals for experienced runners, *p* < 0.05.

For the stride interval, no group by time interaction ($F = 1.50$, $p = 0.20$, $\eta^2 = 0.09$, power = 0.50) and group effect ($F = 3.49$, $p = 0.08$, $\eta^2 = 0.18$, power = 0.42), and significant time effect were evident ($F = 9.16$, $p < 0.001$, $\eta^2 = 0.36$, power = 1.00). The mean stride interval nonlinearly increased over time (Figure 4.7).

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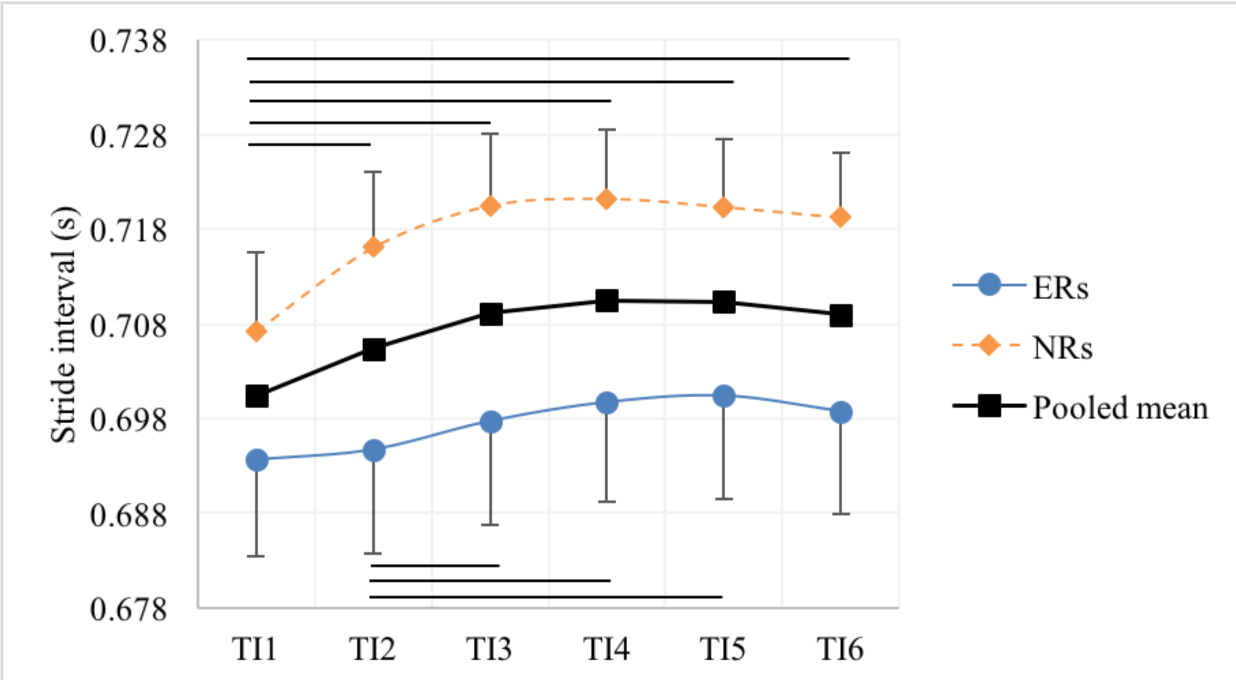

Figure 4.7. Mean (SD) of stride interval throughout the 31-min treadmill run.

________ , significant differences between paired intervals for pooled mean, *p* < 0.05.

4.4 Discussion

The main purpose of this part was to investigate the effects running experience and progressive fatigue on the stride interval dynamics and identify differences in the stride interval dynamics between the experienced and novice runners. It was hypothesized that the stride interval dynamics would change with progressive fatigue for both the experienced and novice runners but differently. Consistent to the hypothesis, the results revealed that both the stride interval variability and alpha of the stride interval were changed over running time for both groups; additionally, differences in both the stride interval variability and alpha of the stride interval were demonstrated between the two groups.

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The AT speed of experienced runners was faster than that of novice runners; this may be due to years of running practice (Ghosh, 2004; Hughes et al., 2018). Participants from both groups were at the same relative physiological intensity level as they ran at their individual AT speed. After the 31-min treadmill run, the participants were fatigued, because of significantly increased blood lactate accumulation level and self-reported RPE scores.

4.4.1 Complexity of the stride interval

The long-range correlations of stride interval were evaluated using the scaling exponent alpha, which indicates organisations of the locomotor system. Accordingly, the larger the alpha, the stronger the strength of the long-range correlations are, which is that the stride interval time series displayed a more predictable pattern, and the locomotor system is less flexible. The alpha of stride interval in the present study ranged from 0.55 to 0.80, which were slightly smaller than those reported in the literature: 0.75–0.80 for trained runners and 0.85–0.90 for nonrunners in Nakayama et al. (2010); the mean value of 0.96 for noninjured runners and 0.79 for injured runners in Meardon et al. (2011); 0.84–0.86 for overground run and 0.98–1.04 for treadmill run (Lindsay et al., 2014). The relatively smaller value of the alpha of stride interval in the present study might have resulted from interactions of fatigue, running experience, and AT speed because previous studies have reported that the alpha was affected by running speed (Jordan et al., 2006, 2007; Mann et al., 2015a), health and training status (Mann et al., 2015a, b; Meardon et al., 2011), and running surface (Lindsay et al., 2014).

In the present study, the alpha of stride interval for both experienced and novice runners changed with time in a roughly U-shape trend, which was inconsistent to Meardon et al. (2011). In their

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study, both healthy trained runners (n = 9) and trained runners with RRIs (n = 9) performed exhaustive runs at their self-reported 5-km race pace (variation of 5%) on an indoor track. It was observed that the alpha of stride interval decreased with time in a nonlinear trend, and significantly reduced in the middle and at the end of the exhaustive run, but no differences were observed between them (Meardon et al., 2011). The difference in running surfaces (treadmill vs. overground) (Lindsay et al., 2014) may contribute to the inconsistent results in the present study and Meardon et al. (2011). In addition, speed fluctuations may be another contributor because redundancy within the locomotor system is displayed by coupling stride interval, stride length, and speed in a specific manner. Dingwell and Cusumano (2010) observed that the locomotor system regulated stride interval and stride length simultaneously to minimise stride-to-stride fluctuations in speed when one was required to walk at a constant speed.

In the present study, the alpha graphs were slightly different between experienced and novice runners because they probably adapted to the progression of fatigue differently during a prolonged treadmill run at AT speed. Because of highly controlled running gait, the alpha of stride interval was relatively larger at the beginning of the 31-min treadmill run, which is viewed as the adaptation stage. Because of the increased flexibility of the locomotor system, the alpha of stride interval reduced in the middle of the run, which is regarded as the stable stage. With the progression of fatigue, the alpha of stride interval depended on increased needs to control running gait and adjust alterations in running kinematics (e.g., reduced joint range of motion, less competent in foot and leg landing positioning) (Winter et al., 2017) as well as increased antagonist muscle activation (Corbeil et al., 2003). Therefore, the present study observed that the alpha of stride interval for novice runners, compared with that of experienced runners, remained

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unchanged at the initial 10 min (TI1 and TI2) because they may require a longer duration to adapt to the treadmill run at AT speed. At the end of the 31-min run, the participants became fatigued; the alpha of stride interval for experienced runners increased significantly and reached almost the same level as the beginning due to the increased need to control running gait at a fatigued state, whereas the alpha of stride interval for novice runners increased slightly and was smaller than it was at the beginning due to the increased need to adjust alterations in running kinematics and antagonist muscle activation at a fatigued state. In the middle stable stage, differences in the alpha of stride interval were also observed; the alpha of stride interval for experienced runners was maintained at the same level for a longer duration (TI2, TI3, and TI4) because experienced runners may enhance tolerance to fatigue due to years of running practice, whereas the alpha of stride interval for novice runners was maintained for a relatively shorter duration (TI3 and TI4) because of less tolerance to fatigue.

Nakayama et al. (2010) reported that the alpha of stride interval for trained runners were smaller than that of nonrunners. In their study, the participants ran for only 10 min and they did not progress to fatigue. Consistent with the findings of the aforementioned study (Nakayama et al., 2010), the alpha of stride interval for experienced runners in the present study was significantly smaller than that of novice runners at TI2 (both ER and NR were at a nonfatigued state), although a larger alpha was found in ER than NR at TI5 and TI6 (both ER and NR were at a fatigued state). These findings confirmed the interaction of running experience and fatigue on running gait that were reported in previous studies (Maas et al., 2017; Strohrmann et al., 2012), and demonstrated the necessity to interpolate the alpha of stride interval within the context of the

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control process involved and the inherent biomechanical and neuro-motor redundancies available (Dingwell & Cusumano, 2010).

Although some studies have reported that fatigue affects motor control (Corbeil et al., 2003; Meardon et al., 2011), the results of the post hoc analysis indicated no differences in the alpha of stride interval between TI1 and TI6 for both experienced and novice runners, which is consistent with the findings of Fuller et al. (2017) and Mann et al. (2015b). In the aforementioned two studies, 10 trained male runners and 26 trained runners were fatigued after a 14-day heavy training (Mann et al., 2015b) and a prolonged running bout (Fuller et al., 2017), respectively; however, no differences were observed in the alpha of stride interval before and after fatigue. It should be noted that these findings might not be representative enough because the data were only collected for 5 min at fixed speeds (8 km/h, 10.5 km/h, and 13 km/h) (Fuller et al., 2017) or 2 min at preferred speed (Mann et al., 2015b).

4.4.2 Variability of the stride interval

The magnitude of the stride interval variability was quantified using CoV in the present study, which was in the range of 1%–3% in the literature (Fuller et al., 2016, 2017; Jordan et al., 2006; Mann et al., 2015a; Meardon et al., 2011; Nakayama et al., 2010). The CoV of stride interval had no statistical difference between experienced and novice runners; however, Nakayama et al. (2010) reported that trained runners displayed a smaller magnitude of stride interval variability than nonrunners. In the aforementioned study, they attributed these results to running training because long-term specific practice can reduce variability (Newell & Corcos, 1993). The effect of running speed should also be considered but interpreted with caution because inconsistent

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findings were reported in previous studies, such as the stride interval variability being larger (Fuller et al., 2017; Jordan et al., 2006, 2007) or unchanged (Fuller et al., 2016; Lindsay et al., 2014; Mann et al., 2015a) at slower running speed conditions; the variability of foot strike angle was larger (Mann et al., 2015a) or smaller (Paquette et al., 2017) at slower running speed conditions. Therefore, the differences in running experience, AT speed and progression of fatigue may jointly account for the results of the present study.

Regarding the effects of a prolonged run on stride interval variability at AT speed, experienced and novice runners exhibited different trends. Consistent with the findings of Meardon et al. (2011), novice runners displayed larger variability but maintained relatively constant throughout the 31-min run. For experienced runners, the CoV of stride interval changed with time in a roughly U-shape trend: it decreased at the beginning, maintained constant in the middle, and increased at the end of the run. The experienced runners may have employed an increasingly adaptive strategy during the prolonged run at AT speed, such as trying different strategies to determine an optimal one, thereby inducing a relatively larger variability at the initial exploration period (TI1); maintaining the optimal strategy during the middle stage (TI2, TI3, and TI4) and reducing variability; and at the end of the run, increasing variability due to fatigue. Overall, in comparison to novice runners, experienced runners can regulate stride-to-stride variability to adapt to the progression of fatigue during a prolonged run at AT speed.

4.4.3 Stride interval

The experienced runners were previously reported to run with faster cadence and shorter step length than the novice runners at the same speed or physiological intensity (de Ruiter et al.,

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2014; Gómez-Molina et al., 2017), indicating shorter stride intervals for the experienced runners. In Nakayama et al. (2010), trained runners were found to run with a shorter stride interval than nonrunners, and Nakayama et al. (2010) explained that faster speeds are a major contributor. In line with these studies, the present study also observed that the experienced runners displayed a shorter stride interval than the novice runners but did not indicate statistical difference (p = 0.080). A possible explanation is that the running experience and speed difference between the experienced and novice runners in the present study were insufficient to indicate statistical significance. In addition, unlike the running protocol (10-min treadmill run) employed by Nakayama et al. (2010), the present study compared the stride interval data throughout the 31-min treadmill run, which may have averaged out the significance.

Stride interval significantly increased at the end of the 31-min treadmill run. The findings of previous studies for stride interval were inconsistent; some studies reported an increase (Chan-Roper et al., 2012), whereas others indicated a decrease (Kim et al., 2018), or indicated no change (Mann et al., 2015b; Meardon et al., 2011) in a fatigued state. Various factors may account for such inconsistencies, namely, speed fluctuation due to the overground run (Chan-Roper et al., 2012; Meardon et al., 2011) and short running duration (Mann et al., 2015b). Furthermore, running speed depends on both stride length and stride interval (consisting of step interval, stance time, and swing time). The coupling between these spatiotemporal parameters may vary with the progression of fatigue. Based on the associations between running efficiency, stride interval (or cadence), and stride length (de Ruiter et al., 2014; Gómez-Molina et al., 2017), future studies are recommended to investigate methods of improving running efficiency at AT speed by controlling cadence.

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4.5 Limitations

Several limitations of this study should be mentioned. Firstly, the current findings may be partially attributable to the speed differences. In future work, reprocessing the data and considering the running speed as co-variance are strongly suggested. Secondly, Lindsay et al. (2014) have demonstrated that running on different surfaces (treadmill vs. overground) affected the stride interval variability. All running tests were conducted on the treadmill under the laboratory environment because it is impossible to maintain the running speed at a constant level during field running. Experiments conducted under ecological environments may be more meaningful. As gait events can be accurately predicted using IMU (Chapter 3), therefore, stride interval can be easily obtained using IMU, which makes it possible to collect stride interval data during distance running. Future work should focus on outdoor running, such as road marathon. IMU-based methods were proposed to estimate the stride/step speed, length (Yang et al., 2011, 2012; Kitagawa & Ogihara, 2016; Sabatini et al., 2005), which may solve the speed fluctuation issue during running under ecological environment. Finally, the present study did not collect sufficient data regarding the participants' daily running practice (e.g., intensity level); whether experienced runners had been exposed to AT intensity level more frequently than novice runners in their daily running practice remains unknown.

4.6 Summary

The present study demonstrated a roughly U-shape trend in the scaling exponent alpha of stride interval for both the experienced and novice runners during a 31-min treadmill run at AT speed;

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differences in both long-range correlations and the magnitude of stride interval variability were evidenced between the experienced and novice runners. The results of this study provide insights into how the locomotor system adapts to the progression of fatigue and evidence of the benefits of years of running experience on motor control. Although both the experienced and novice runners could regulate stride interval complexity to maintain AT speed throughout the 31-min run, the experienced runners also regulated stride interval variability to keep running at AT speed.

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Chapter 5: Lower-limb Coordination Variability during a Prolonged Treadmill Run

Manuscript 'Mo, S., & Chow, D. H. K. Differences in lower limb coordination and coordination variability between novice and experienced runners during a prolonged treadmill run at anaerobic threshold speed.' has been submitted to the *Journal of Sports Sciences*.

5.1 Introduction

Understanding running mechanics is critical for preventing running-related injuries (RRIs). RRIs are multifactorial and involve different sites of the lower limbs. Running is a complex motor skill that engages multiple lower limb joints and segments. Therefore, analysing lower limb coordination is of importance. Some studies (Brown et al., 2016; Hamill et al., 1999; Heiderscheit et al., 2002; Miller et al., 2008) have investigated lower limb coordination in participants with RRIs, and have observed that abnormal lower limb joint and segment coordination may increase the risk of developing an RRI (DeLeo et al., 2004). Although some studies have examined lower limb coordination in healthy individuals (Boyer et al., 2014; Dierks & Davis, 2007; Floría et al., 2018; Hafer et al., 2016), because coordination is goal-directed and refers to that the performer uses individualised manner to satisfy specific constraints during task execution (Davids et al., 2003), patterns of the lower limb coordination in runners with different degrees of experience that are exhibited during a prolonged run remain unknown.

Gait variability, such as stride interval variability, has been analysed to gain insight into the locomotor control during running. In the literature, the variability of lower limb coordination has

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also been investigated (Hafer et al., 2016, 2017; Heiderscheit et al., 2002; Hein et al., 2012; Lilley et al., 2018; Miller et al., 2008), and researchers have ascertained an association between coordination variability (CV) and RRIs (Bartlett et al., 2007; Hamill et al., 2012). CV was even considered a parameter for distinguishing between runners with RRI and healthy runners (Hein et al., 2012). Runners with RRIs typically presented lower CV in comparison to their healthy counterparts (Heiderscheit et al., 2002; Lilley et al., 2018; Miller et al., 2008). High CV can reduce the risk of RRIs because the loading induced by landing during running can be distributed over a broad area of tissue (Bartlett et al., 2007; Hamill et al., 2012). Nonetheless, excessively high CV may reduce running performance because of less running efficiency. Therefore, runners have been encouraged to maintain a moderate level of CV (Hamill et al., 2012). Although researchers contend that an optimal window of CV exists for both reducing the risk of RRIs and avoiding negatively affecting running performance (Hamill et al., 2012), defining this window is difficult because some characteristics of healthy runners remain unclear, such as the effects of running experience and fatigue on CV.

The lack of running experience and progression of fatigue are regarded as two common risk factors that contribute to RRIs. To date, findings regarding the effects of running experience and fatigue on running mechanics are inconsistent (Agresta et al., 2018; Schmitz et al., 2014; Winter et al., 2017). Some studies (Brown et al., 2016; Dierks et al., 2010; Floría et al., 2018; Hafer et al., 2017; Miller et al., 2008) have investigated the influences of running experience and fatigue on running mechanics from the aspect of lower limb coordination and CV; however, they were analysed separately even though running experience and fatigue have been reported to interact in the motion of individual joints and segments (Maas et al., 2017; Strohrmann et al., 2012). In

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addition, anaerobic threshold (AT) speed is viewed as one of the best physiological indicators of running performance; runners have been encouraged to practice at or slightly above AT speed to improve running performance. However, in the literature, lower limb coordination and CV have only been analysed when the runners performed a running test at their individual comfortable speed (e.g., 2.6–3.38 m/s) (Dierks et al., 2010; Floría et al., 2018), or at a relatively slow fixed speed (e.g., 3.35 ± 10% m/s) (Brown et al., 2016).

Therefore, in this part of the study, the characteristics of lower limb coordination pattern and CV in the sagittal plane were analysed when both experienced runners and novice runners performed a prolonged run at their individual AT speed on a treadmill. The aim of this part of the study was to add to the knowledge and understanding of lower limb coordination pattern and CV in healthy runners and gain insights into the interrelationships between running experience, fatigue, and running mechanics.

5.2 Methods

5.2.1 Experimental design

A two-way repeated-measures design with mixed samples were adopted to investigate the influence of running experience and fatigue on lower limb coordination pattern and CV. Two groups of participants were recruited and performed a preliminary running test (16 min with an incremental load protocol) and a main running test (31 min at AT speed).

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5.2.2 Participants

The 34 participants who participated in the running test of the Chapter 4 were also included in this part of study. Due to data lost (e.g., markers missing or lost) during data collection and withdrawal of some participants, 9 more participants were recruited and to ensure 17 participants per group. All participants were grouped into experienced runner group and novice runner group using the same methods as that in Chapter 4. Details can be found in sub-section of '*Participants Grouping*' in Chapter 4 (pp. 57-58).

The experienced runner group consisted 17 recreational runners (3 females) who had been running regularly for 8.5 years (varied from 4 to 20 years), had a minimum weekly running distance of 30 km, and had attended at least one distance running race (self-reported best time for a 5-km race ranged from 16 to 22 min). The novice runner group consisted 17 participants (1 females), who had been running regularly for fewer than 6 months. The mean (standard deviation, SD) age, height, body mass, and body mass index for the experience runner group were 24.5 (5.5) years, 170.8 (6.7) cm, 63.7 (10.1) kg, and 21.7 (2.3) kg/m^2, respectively, whereas that of the novice runner group was 22.5 (3.3) years, 173.5 (6.0) cm, 62.6 (7.3), and 20.8 (2.5) kg/m^2, respectively.

The participants reported no RRI during the previous six months, and provided informed consent after receiving a brief introduction about the objectives of the study and procedures of the experimental protocol. The Human Research Ethics Committee of The Education University of Hong Kong approved the present study (Ref: No. 2015-2016-0346).

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5.2.3 Experimental protocol

The present study consisted of a preliminary running test and a main running test. The preliminary running test aimed to determine each participant's AT speed. Briefly, each participant was asked to finish an incremental load running protocol with an initial speed of 8 km/h and an increment of 1 km/h every 2 min until they reached the maximum speed of 15 km/h. The AT speed was defined as the running speed that corresponded to the onset of the nonlinear steep increase of the ratio of ventilation to oxygen consumption, which was calculated using breath-by-breath data (Metalyzer 3B, Cortex, Germany). The experimental protocol and approach to determine the AT speed are presented in detail in Chapter 4 under Section 4.1.3.

The main running test was performed after a minimum gap of 48 h from the preliminary running test and aimed to obtain each participant's running kinematic data during a 31-min treadmill run at his or her AT speed.

5.2.4 Data collection

During the 31-min treadmill run, three-dimensional (3D) kinematic data of the pelvis and bilateral lower limbs were continuously acquired at a sampling rate of 200 Hz.

Instruments

A motion capture system (Qualysis Inc., Sweden), which consists of eight infrared cameras (Oqus 7+, Qualysis Inc., Sweden), a video camera (Oqus 210c, Qualysis Inc., Sweden), and a packed software (Qualysis Track Manager, Qualysis Inc., Sweden), was used to collect the 3D kinematic data. The eight infrared cameras were positioned around the treadmill, and had a

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capture volume of around 3.0 m × 2.0 m × 2.0 m in the laboratory (Figure 5.1). The capture volume was calibrated using a standard T-shaped calibration wand with two retroreflective markers before each measurement. The reported error of the motion capture system was controlled within 0.5 mm. The packed software was used to perform the system calibration, as well as marker capture, identification, pre-processing, and data preparation. The marker trajectory data were exported and saved in the .c3d format for further processing conducted in the Visual 3D (C-Motion Inc., USA).

The global coordinate system in the present study was the same as the one recommended by the International Society of Biomechanics (Sheehan & Mitiguy, 1999; Wu & Cavanagh, 1995). The three axes were the X-, Y-, and Z-axis. The X-axis was the progression direction and pointed forward; the Y-axis was the vertical direction and pointed upward; and the Z-axis was the medical-lateral direction and pointed to the right.

Marker Placement

A set of 38 retroreflective markers (at a radius of 7 mm) were used in the present study, and were categorised into three types: anatomical marker (A) (which were removed after the static calibration trial), tracking marker (T), and anatomical and tracking marker (A/T). The marker set was adopted from Cappozzo et al. (1995), and the attaching locations were determined based on guidelines by van Sint Jan (2007). The markers were affixed to the pelvis and bilateral thighs, shanks, and feet (Figure 5.2). Clusters with four tracking markers on a standard rigid shell were affixed firmly to the lateral side of bilateral thighs and shanks using an elastic strap. Detailed information, such as name, type, and placement, for each marker is presented in Table 5.1.

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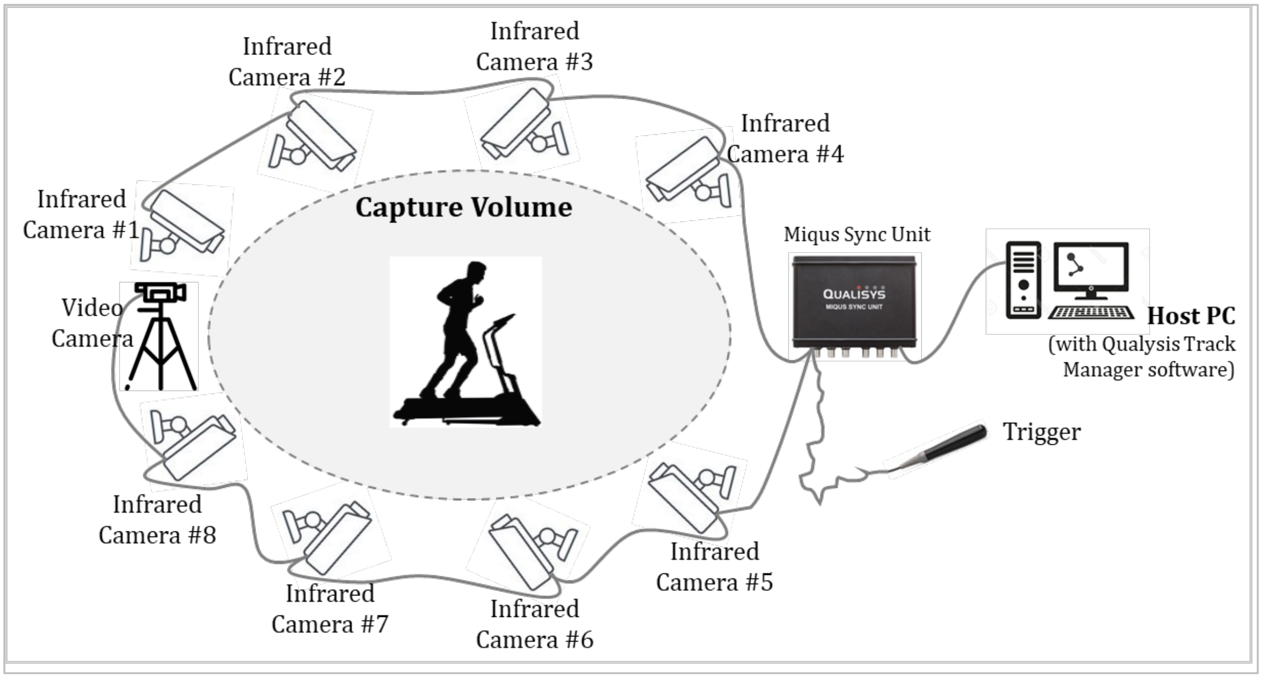

Figure 5.1. Experimental setup.

Marker Capture

Prior to performing the 31-min treadmill run, a static trial was captured for 30 s. During the static trial, each participant was asked to stand on the treadmill with their feet shoulder width apart and their arms crossing on their chest. After the static trial, ten anatomical markers (R_GT, L_GT, R_KNEE_LAT, L_KNEE_LAT, R_KNEE_MED, L_KNEE_MED, R_ANKLE_LAT, L_ANKLE_LAT, R_ANKLE_MED, and L_ANKLE_MED) were removed, and the remaining 28 tracking makers were captured throughout the 31-min treadmill run. The participants wore their own running shoes and sufficient time was provided for them to warm-up and cool-down.

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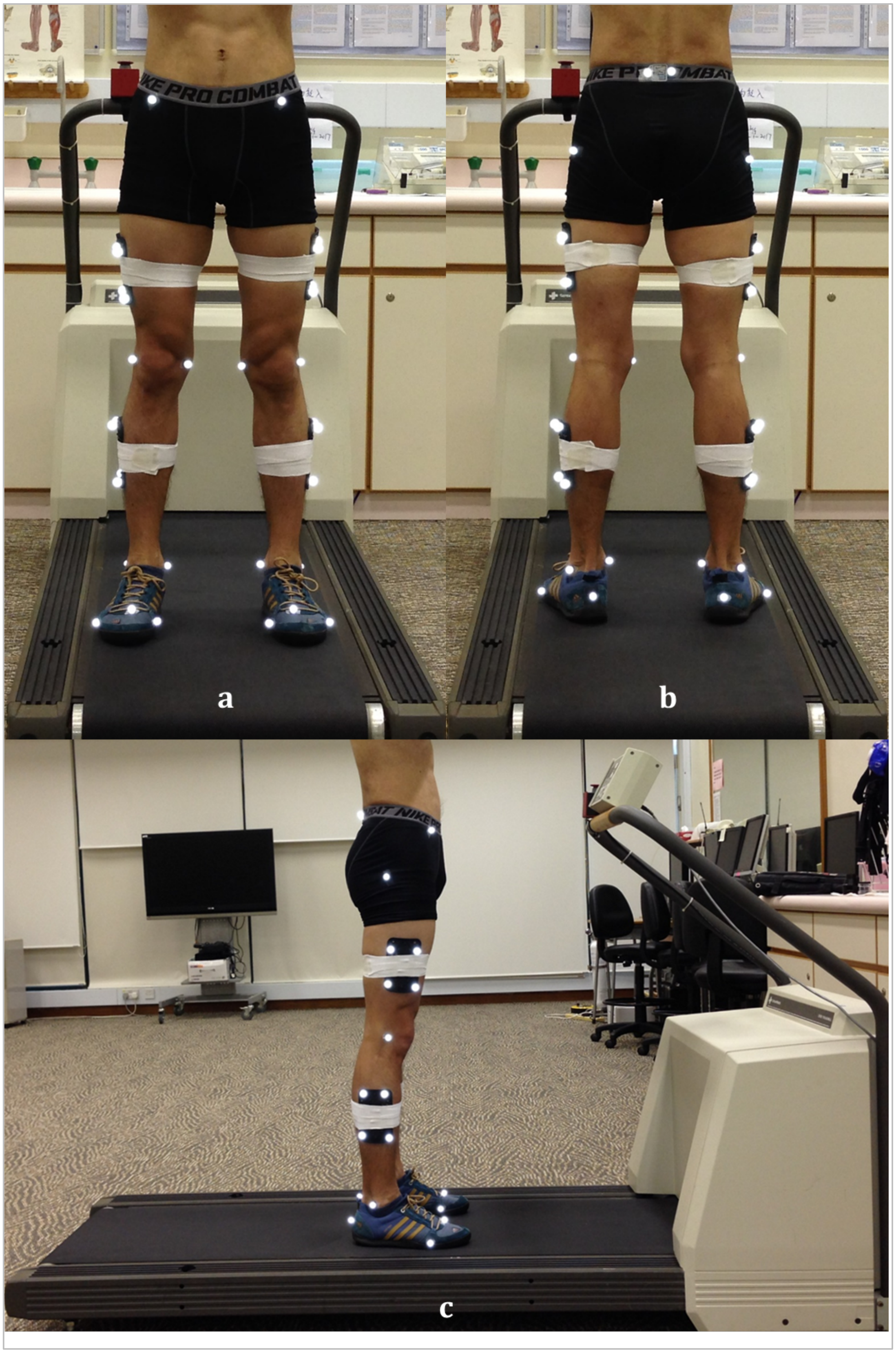

Figure 5.2. Marker placement. Front view (a), back view (b), and side view (c).

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Table 5.1. Details of marker placement.

#	Marker Label	Maker Type	Maker Name/Location
1	R_ASIS	A/T	Right anterior superior iliac spine
2	R_PSIS	A/T	Right posterior superior iliac spine
3	R_GT	A	Prominence of right greater trochanter
4	RTH1	T	Right thigh cluster marker #1 (top anterior)
5	RTH2	T	Right thigh cluster marker #2 (bottom anterior)
6	RTH3	T	Right thigh cluster marker #3 (bottom posterior)
7	RTH4	T	Right thigh cluster marker #4 (top posterior)
8	R_KNEE_LAT	A	Right lateral epicondyle
9	R_KNEE_MED	A	Right medial epicondyle
10	RSK1	T	Right shank cluster marker #1 (top anterior)
11	RSK2	T	Right shank cluster marker #2 (bottom anterior)
12	RSK3	T	Right shank cluster marker #3 (bottom posterior)
13	RSK4	T	Right shank cluster marker #4 (top posterior)
14	R_ANKLE_LAT	A	Prominence of the right lateral malleolus
15	R_ANKLE_MED	A	Prominence of the right medial malleolus
16	R_HEEL	A/T	Prominence of the right calcaneus (shoe heel cup)
17	R_FOOT_LAT	A/T	The 5th metatarsal head of right foot
18	RFM2	A/T	The 2nd metatarsal head of right foot
19	R_FOOT_MED	A/T	The 1st metatarsal head of right foot
20	L_ASIS	A/T	Left anterior superior iliac spine
21	L_PSIS	A/T	Left posterior superior iliac spine
22	L_GT	A	Prominence of left greater trochanter
23	LTH1	T	Left thigh cluster marker #1 (top anterior)
24	LTH2	T	Left thigh cluster marker #2 (top posterior)
25	LTH3	T	Left thigh cluster marker #3 (bottom posterior)
26	LTH4	T	Left thigh cluster marker #4 (top anterior)
27	L_KNEE_LAT	A	Left lateral epicondyle
28	L_KNEE_MED	A	Left medial epicondyle
29	LSK1	T	Left shank cluster marker #1 (top anterior)
30	LSK2	T	Left shank cluster marker #2 (top posterior)
31	LSK3	T	Left shank cluster marker #3 (bottom posterior)
32	LSK4	T	Left shank cluster marker #4 (top anterior)
33	L_ANKLE_LAT	A	Prominence of the left lateral malleolus
34	L_ANKLE_MED	A	Prominence of the left medial malleolus
35	L_HEEL	A/T	Prominence of the left calcaneus (shoe heel cup)
36	L_FOOT_LAT	A/T	The 5th metatarsal head of left foot
37	LFM2	A/T	The 2nd metatarsal head of left foot
38	L_FOOT_MED	A/T	The 1st metatarsal head of left foot

A, anatomical marker; T, tracking marker; A/T, anatomical/tracking marker

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5.2.5 Data processing and analysis

The raw marker trajectory data were processed using Visual 3D (C-Motion, Inc., Rockville, MD) and Matlab (MathWorks, Inc., USA). The foot strike pattern of each participant was identified through video analysis, and the participants were determined as rearfoot strikers. The 3D marker displacement data for 60 s were extracted from each participant's right lower limb from the beginning, middle, and end of the 31-min run, and were low-pass filtered at 7 Hz using a second-order Butterworth filter. Initial contact (IC) was determined by identifying the local minimum of the vertical displacement of the heel marker (Fellin et al., 2010), and toe-off (TO) was defined as the local minimum of the knee flexion/extension angle after IC using a pattern recognition algorithm (Fellin et al., 2010). The methods for IC and TO detection have been justified by Fellin et al. (2010), and have been commonly used in the literature (Alton et al., 1998; Cappellini et al., 2006; Dingwell et al., 2001; Hunter et al., 2005).

Joint and segment kinematic data were reported following the ISB recommendations (Wu & Cavanagh, 1995; Wu et al., 2002). 3D joint (hip, knee, and ankle) angles were computed using the Cardan angles (Z–X–Y) (Cappozzo et al., 1995; Wu & Cavanagh, 1995; Wu et al., 2002), with the joint angles being expressed as the distal segment relative to the proximal segment: the first rotation was around the medial-lateral axis (Z-axis, being perpendicular to the sagittal plane), which defines the movement of flexion-extension; the third rotation was around the proximal-distal axis (Y-axis, being perpendicular to the transverse plane), which defines the movement of internal-external rotation; and the second rotation was around the axis perpendicular to the Z- and Y-axes, which represents the anterior-posterior axis (X-axis, being perpendicular to the frontal plane), which defines the movement of abduction-adduction. The 3D

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segment (pelvis, thigh, shank, and foot) orientation angles were computed with respect to the global coordinate system. As motion in the sagittal plane is essential to running performance, data of joint (hip, knee, and ankle) angles and segment (pelvis, thigh, shank, and foot) orientation angles in the sagittal plane were, therefore, extracted and further processed to evaluate running kinematic patterns and lower limb coordination.

The stance phase of the middle 10 strides for each interval (beginning, middle, and end of the 31-min run) was analysed and time-normalised to 100%. The running kinematic pattern was evaluated using discrete parameters, which were peak angle, angle at IC and TO, range of motion, and time to peak angle. The data were averaged across the 10 strides of each interval for each participant. SD across the 10 strides for each parameter was computed to quantify the variability of the running kinematic pattern.

Using the coupling angle, which was computed using the modified vector coding technique (Figure 5.3), lower limb coordination was evaluated (Brown et al., 2016; Change et al., 2008; Hafer et al., 2016, 2017). Briefly, an angle-angle plot was initially constructed with a proximal segment or joint angle ($\theta_{proximal}$) on the horizontal axis and the distal segment or joint angle on the vertical axis (φ_{distal}). The coupling angle ($\varnothing$) was defined as the angle relative to the right horizontal line formed by the vector of connecting two adjacent time points for each stance phase using the following formula:

$$\emptyset_{(i,j)} = \tan^{-1}\frac{(\varphi_{distal})_{(i,j+1)} - (\varphi_{distal})_{(i,j)}}{(\theta_{proximal})_{(i,j+1)} - (\theta_{proximal})_{(i,j)}}, where\ i = 1, 2, \ldots, 10; j = 0, 1, \ldots, 100$$

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The coupling angle $\varnothing$ was 0°–360°, and j represented the percentage of the i^{th} stance phase. The couplings of interest in the present study were hip–knee flexion/extension, knee–ankle flexion/extension, pelvis–thigh sagittal plane rotation, thigh–shank sagittal plane rotation, and shank–foot sagittal plane rotation, which were commonly used in the literature (Floría et al., 2018; Hafer et al., 2016, 2017; Hafer & Boyer, 2017; Heiderscheit et al., 2002). The coordination pattern, which indicated the relative rotation direction of the two segments or joints of the coupling of interest, was divided into the following four categories (Chang et al., 2008; Hafer et al., 2016):

- In-phase motion, $22.5° < \varnothing < 67.5°$ or $202.5° < \varnothing < 247.5°$, both segments or joints rotated simultaneously in the same direction;
- Anti-phase motion, $112.5° < \varnothing < 157.5°$ or $292.5° < \varnothing < 337.5°$, the two segments or joints simultaneously rotated in opposite directions;
- Proximal motion phase, $0° < \varnothing < 22.5°$ or $157.5° < \varnothing < 202.5°$ or $337.5° < \varnothing < 360°$, the proximal joint or segment rotated while the other was fixed; and
- Distal motion phase, $67.5° < \varnothing < 112.5°$ or $247.5° < \varnothing < 292.5°$, the distal joint or segment rotated while the other was fixed.

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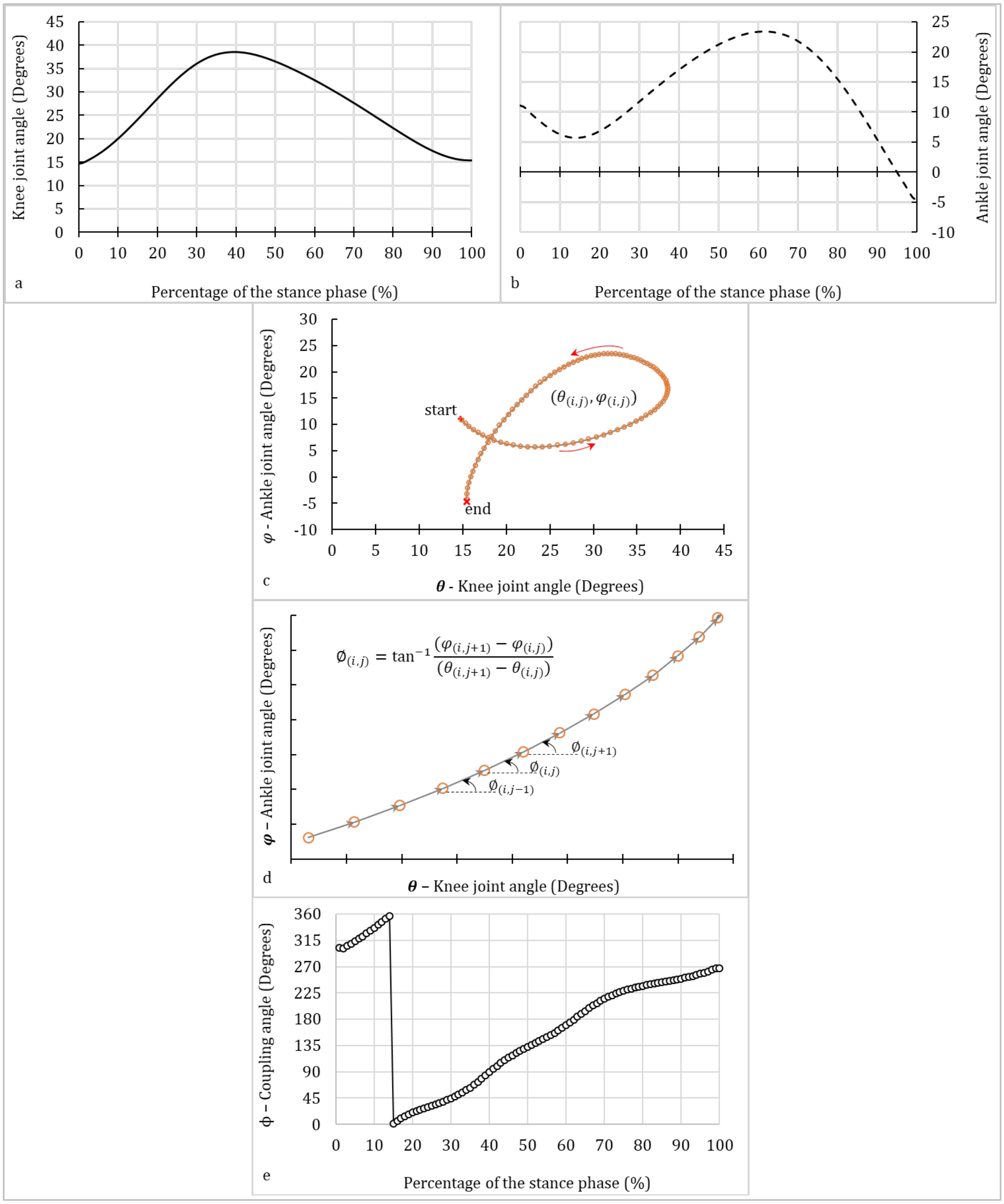

Figure 5.3. Illustration of steps for calculating coupling angle during the stance phase. Raw data of knee joint angle (a) and ankle joint angle (b) during stance phase; a phase plane of knee–ankle coupling (c); examples of calculating coupling angle (d); and coupling angles during the stance phase for the knee–ankle coupling (e).

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Based on other studies (Floría et al., 2018; Hein et al. 2012; Perry & Burnfield, 2010), the stance phase was divided into four subphases on the basis of different function roles: the loading stance, defined as the initial 20% of the stance phase; the mid-stance, from 21% to 50% of the stance phase; the terminal stance, from 51% to 80% of the stance phase; and the pre-swing, the final 20% of the stance phase. The frequency of each coordination pattern across the stance phase and the four subphases were computed and described as percentage of stance phase (Chang et al., 2008; Hafer et al., 2016; Hein et al., 2012) and then averaged across the 10 strides at each interval for each participant to quantify various functional demands during the 31-min run. The SD of the coupling angle at each percentage of the stance phase was computed across the 10 strides to quantify CV (Floría, 2018; Hafer et al., 2016, 2017). The SD was averaged across the stance phase and the four subphases at each interval for each participant to describe the CV.

Statistical Analysis

The data were analysed using a statistical software (SPSS version 21.0, IBM Inc., Chicago, IL, USA). Differences regarding age, body mass, height, body mass index, and AT speed between the groups were analysed using independent sample *t*-tests. Running speed affected the results, and a significant difference in AT speed was evident between the groups ($p < 0.001$); therefore, a two-way (groups: experience and novice runners; time: beginning, middle, and end) repeated-measures analysis of covariance examined the differences in running kinematic patterns and variability, coordination patterns, and CV after eliminating the variances attributable to running speed. Post hoc comparisons were conducted on the basis of the least significant difference criterion. The statistical significance level was set at $p = 0.05$.

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5.3 Results

The results indicate no differences between the groups regarding age ($p = 0.50$), height ($p = 0.11$), body mass ($p = 0.74$), and body mass index ($p = 0.20$). The AT speed of experienced runners was 12.8 (1.2) km/h, which was faster than the 11.0 (0.7) km/h speed of novice runners ($p < 0.001$). Before the run, the blood lactate accumulation levels of experienced and novice runners were 1.4 (0.7) mmol/L and 1.2 (0.5) mmol/L, respectively, and the self-reported RPE scores were 7.8 (2.0) and 7.3 (1.2), respectively. After the 31-min run, the blood lactate accumulation levels reached 7.7 (2.1) mmol/L for experienced runners and 7.3 (1.3) mmol/L for novice runners, and the RPE scores were 17.5 (1.0) and 18.2 (0.6), respectively.

The results also indicated that no group by time interactions were discerned for the parameters of running kinematic patterns, except the time to peak hip angle ($F = 4.15$, $p = 0.020$, $\eta^2 = 0.42$; Figure 5.4), which was similar between experienced and novice runners at the beginning of the 31-min run, but remained relatively constant for novice runners and significantly decreased for experienced runners during the 31-min run. The results indicate the absence of group and time effects on running kinematic patterns.

According to the study results, no group by time interactions were revealed, but significant group effects for the variability of single joint and segment motions were evident. Compared with novice runners, experienced runners exhibited significantly smaller variabilities in peak hip angle ($F = 4.71$, $p = 0.038$, $\eta^2 = 0.43$; Figure 5.5a), peak knee angle ($F = 9.30$, $p = 0.005$, $\eta^2 = 0.63$; Figure 5.5b), peak thigh angle ($F = 10.38$, $p = 0.003$, $\eta^2 = 0.55$; Figure 5.5c), and thigh angle at

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IC ($F = 6.35$, $p = 0.017$, $\eta^2 = 0.47$; Figure 5.5d). A time effect was only evident for the variability of the knee angle at TO ($F = 3.31$, $p = 0.043$, $\eta^2 = 0.40$), but post hoc comparisons did not indicate significant differences.

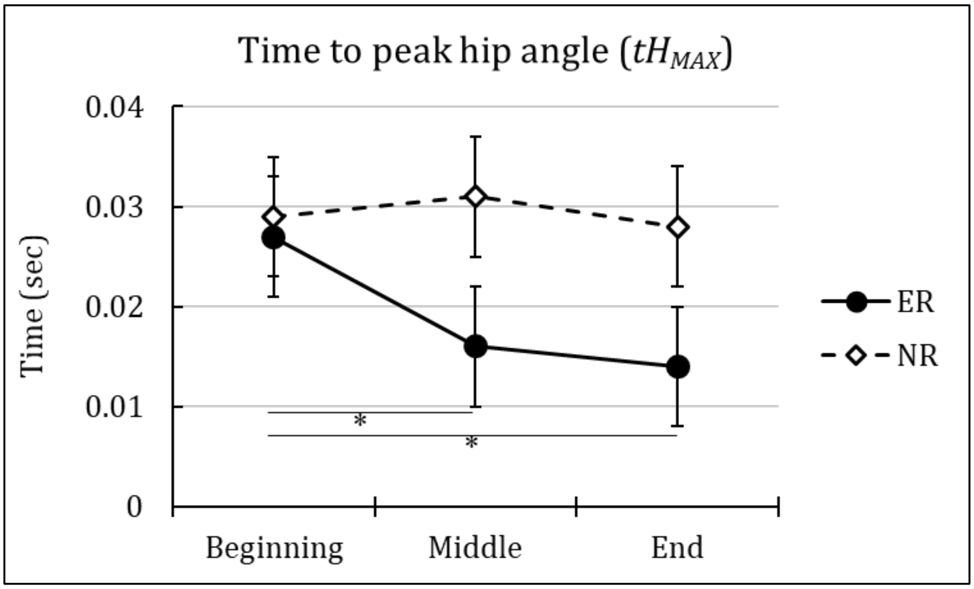

Figure 5.4. Group by time interaction on the time to peak hip angle during the 31-min run. ER, experienced runners; NR, novice runners;

***, *p* < 0.05.**

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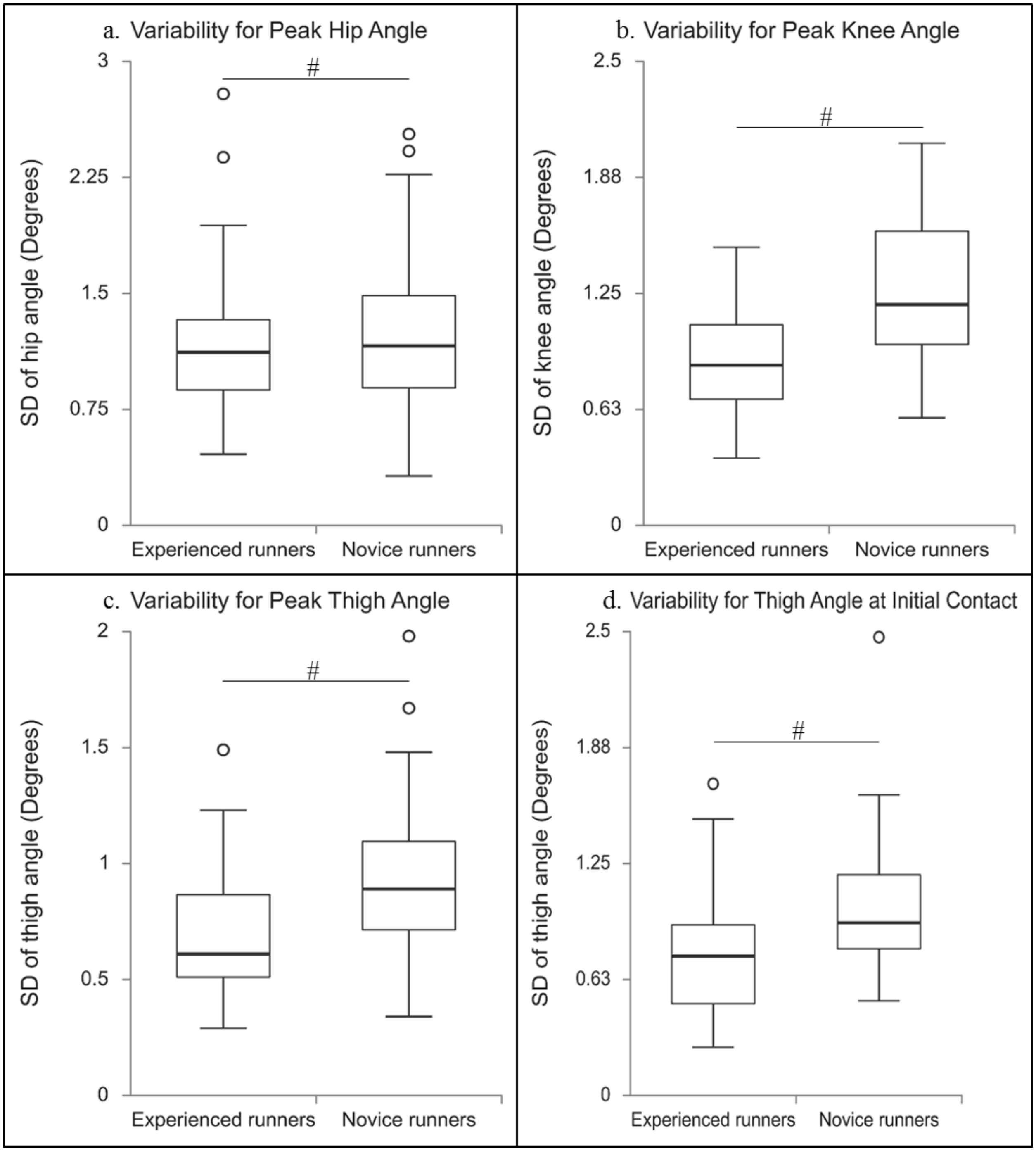

Figure 5.5. Variability for single segment and joint motions during the 31-min run.

#, experienced runners vs novice runners, *p* < 0.05.

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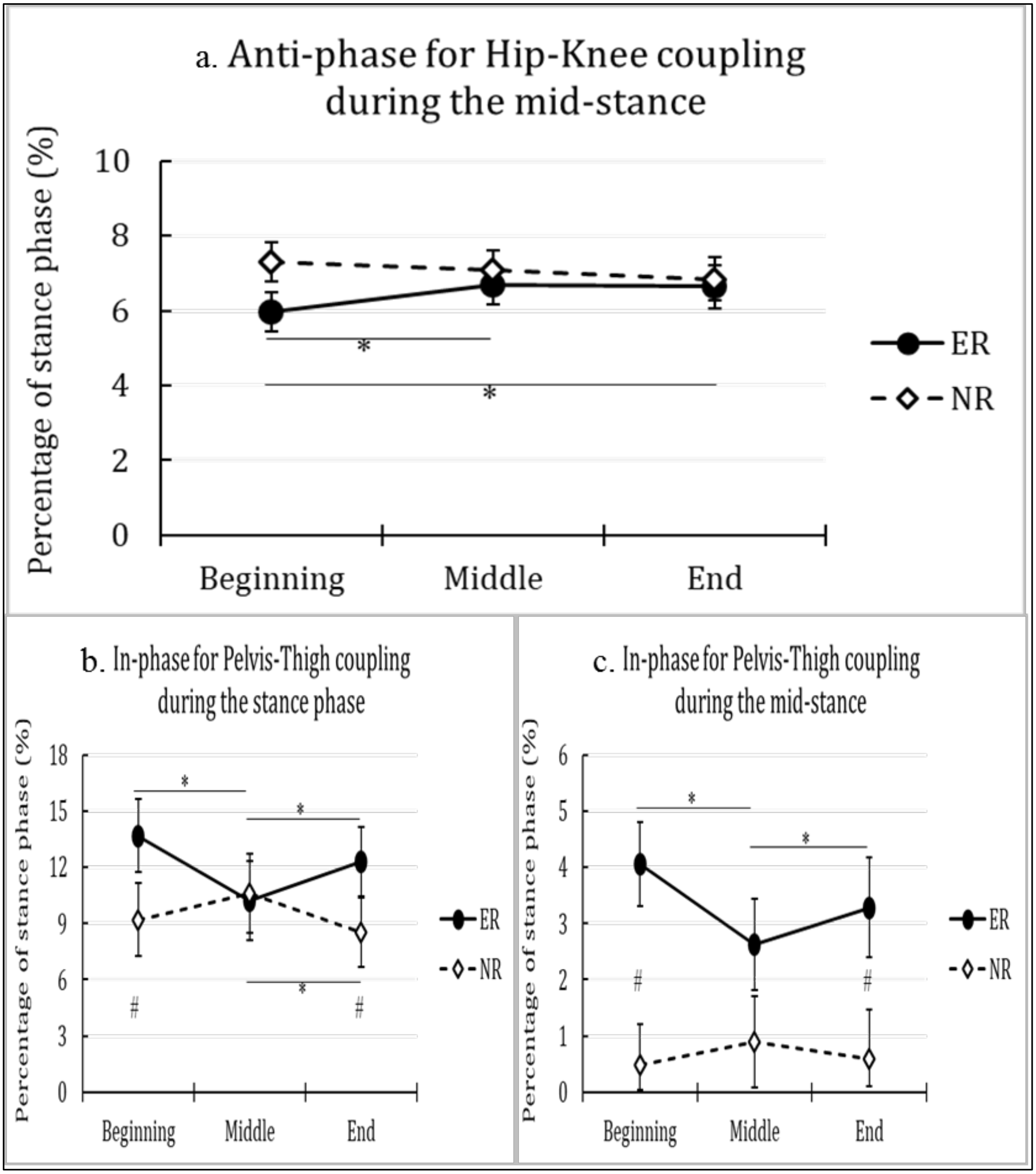

Figure 5.6. Coordination pattern for the hip–knee coupling (a) and pelvis–thigh coupling (b) during the 31-min run.

ER, experienced runners; NR, novice runners;

***, $p < 0.05$.**

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For lower limb coordination pattern, significant group by time interactions were evident: anti-phase motion for the hip–knee flexion/extension during the mid-stance (F = 4.06, p = 0.022, η^2 = 0.42); in-phase motion for the pelvis–thigh sagittal plane rotation during the stance phase (F = 3.80, p = 0.028, η^2 = 0.41) and during the mid-stance (F = 4.32, p = 0.018, η^2 = 0.42). For the hip–knee coupling, the percentage of anti-phase motion during the mid-stance for experienced runners was less than novice runners at the beginning, and significantly increased with time for experienced runners and maintained relatively unchanged throughout the 31-min run for novice runners (Figure 5.6a). For the pelvis–thigh coupling, the percentage of in-phase motion during the stance phase (Figure 5.6b) and the mid-stance (Figure 5.6c) for experienced runners was higher than that for novice runners; during the 31-min run it decreased in the middle and increased at the end for experienced runners but initially increased then decreased for novice runners.

The results indicate significant time effects for lower limb coordination patterns. For the pelvis–thigh coupling, the pelvis motion phase during the stance phase increased significantly with time (F = 4.16, p = 0.020, η^2 = 0.42; Figure 5.7a). The thigh motion phase for the thigh–shank coupling during the mid-stance (F = 3.77, p = 0.041, η^2 = 0.41; Figure 5.7b) and the shank motion phase for the shank–foot coupling during the stance phase (F = 3.61, p = 0.048, η^2 = 0.40) increased with time, but post hoc comparisons revealed no significant differences for the shank–foot coupling.

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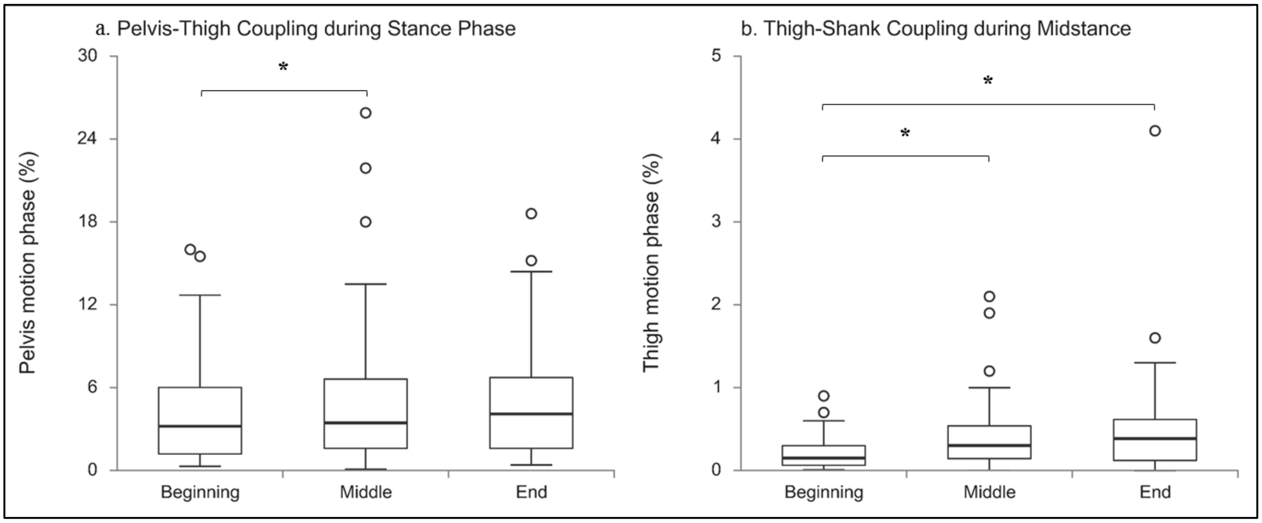

Figure 5.7. Coordination pattern for the pelvis–thigh coupling (a) and thigh–shank coupling (b) during the 31-min run.

***, p < 0.05**

The results indicate significant group effects for lower limb coordination patterns. Compared with novice runners, experienced runners displayed a higher percentage of knee motion phase for the hip–knee coupling during the mid-stance ($F = 5.61$, $p = 0.024$, $\eta^2 = 0.45$; Figure 5.8a), in-phase motion for the knee–ankle coupling during the mid-stance ($F = 4.61$, $p = 0.040$, $\eta^2 = 0.43$; Figure 5.8b), pelvis motion phase for the pelvis–thigh coupling during the stance phase ($F = 9.09$, $p = 0.005$, $\eta^2 = 0.63$; Figure 5.8c), the loading stance ($F = 8.32$, $p = 0.007$, $\eta^2 = 0.51$; Figure 5.8d), and the mid-stance ($F = 4.63$, $p = 0.039$, $\eta^2 = 0.43$; Figure 5.8e), but a lower percentage of ankle motion phase for the knee–ankle coupling during the mid-stance ($F = 4.22$, $p = 0.048$, $\eta^2 = 0.45$; Figure 5.9a), and thigh motion phase for the pelvis–thigh coupling during the stance phase ($F = 4.49$, $p = 0.042$, $\eta^2 = 0.13$; Figure 5.9b) and mid-stance ($F = 7.20$, $p = 0.012$, $\eta^2 = 0.49$; Figure 5.9c).

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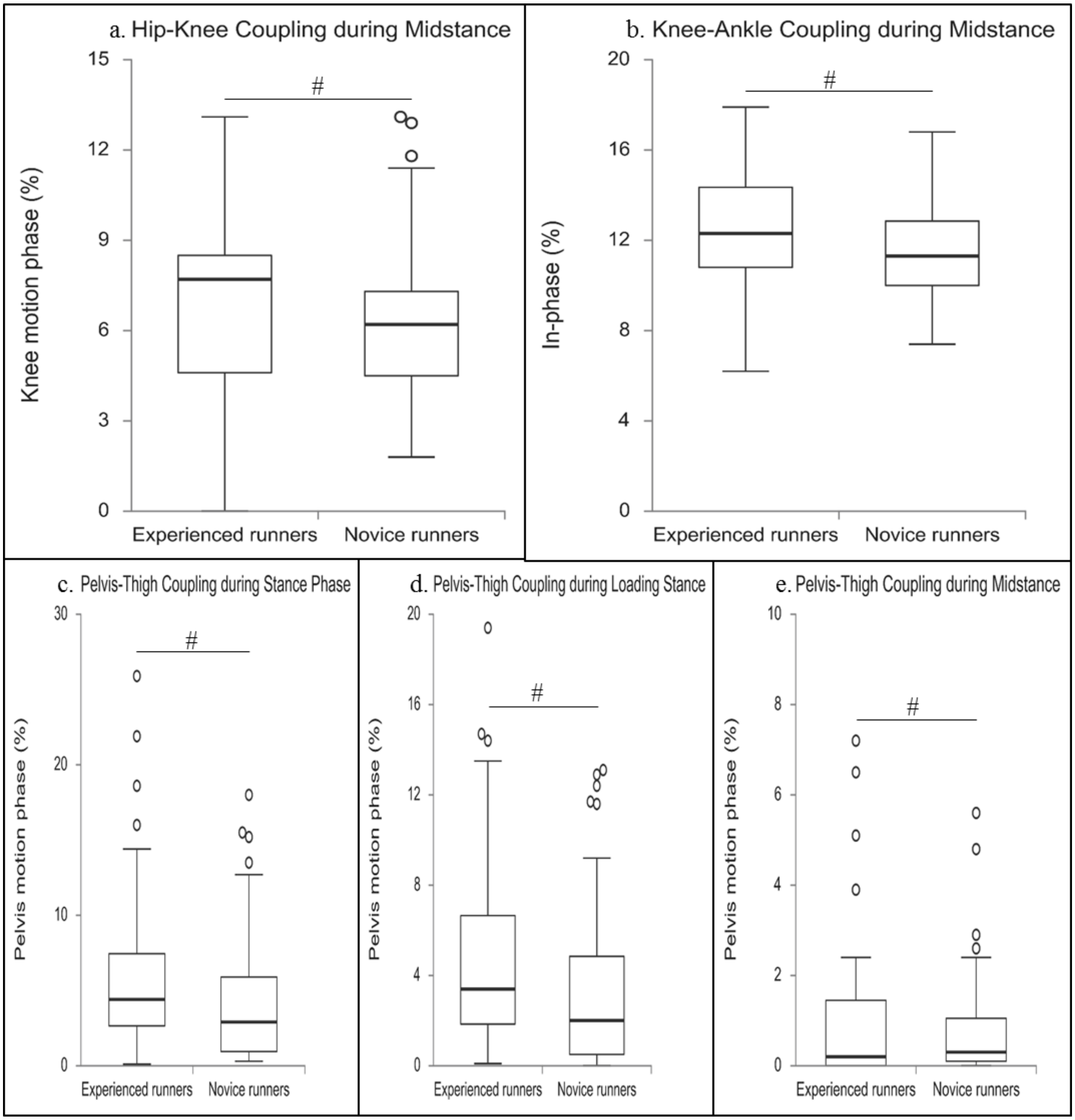

Figure 5.8. Coordination pattern for the hip–knee coupling (a), knee–ankle coupling (b), and pelvis–thigh coupling (c-d) during the 31-min run.

#, experienced runners vs novice runners, $p < 0.05$.

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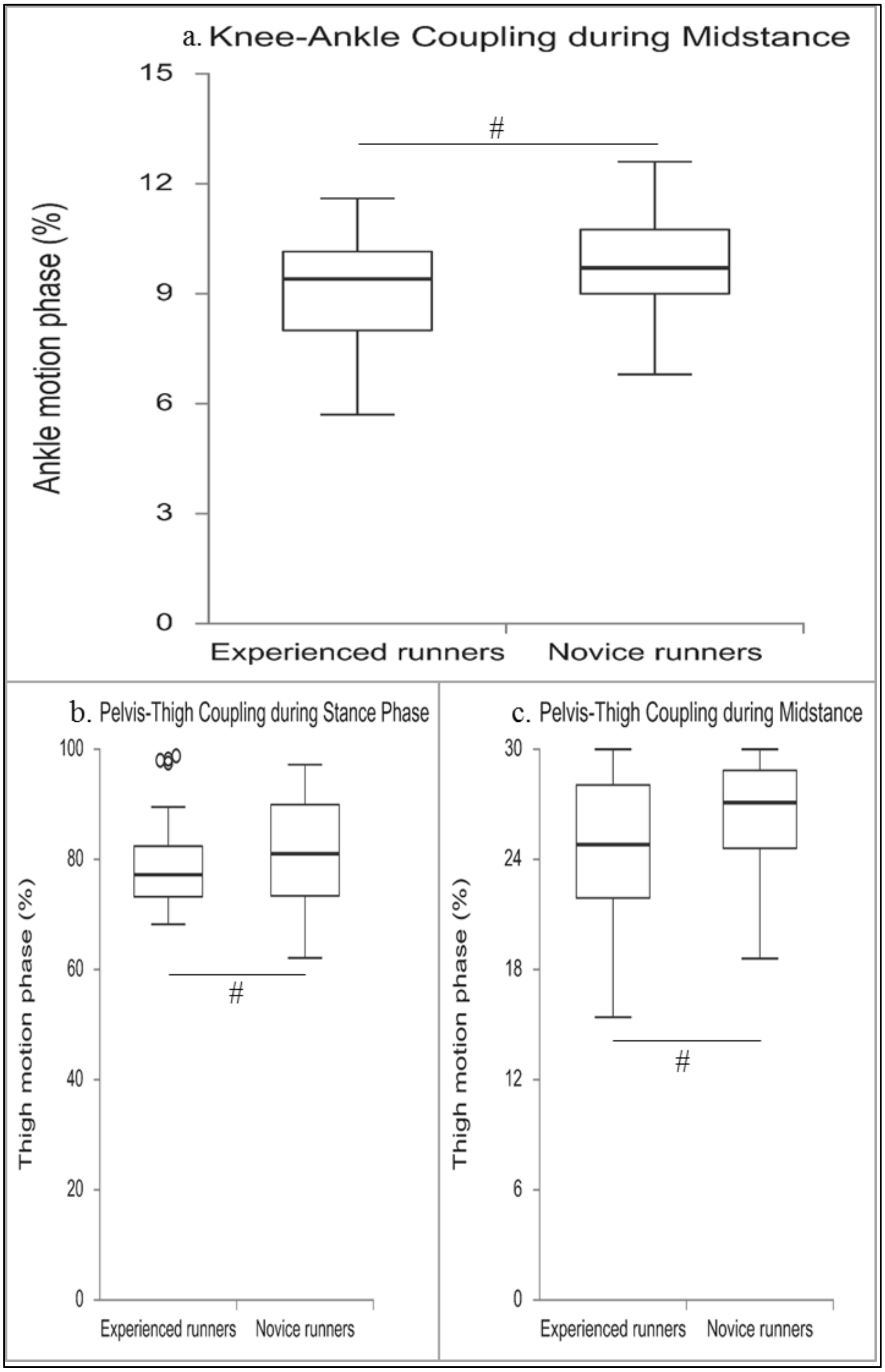

Figure 5.9. Coordination pattern for the knee–ankle coupling (a) and pelvis–thigh coupling (b, c) during the 31-min run.

#, experienced runners vs novice runners, *p* < 0.05.

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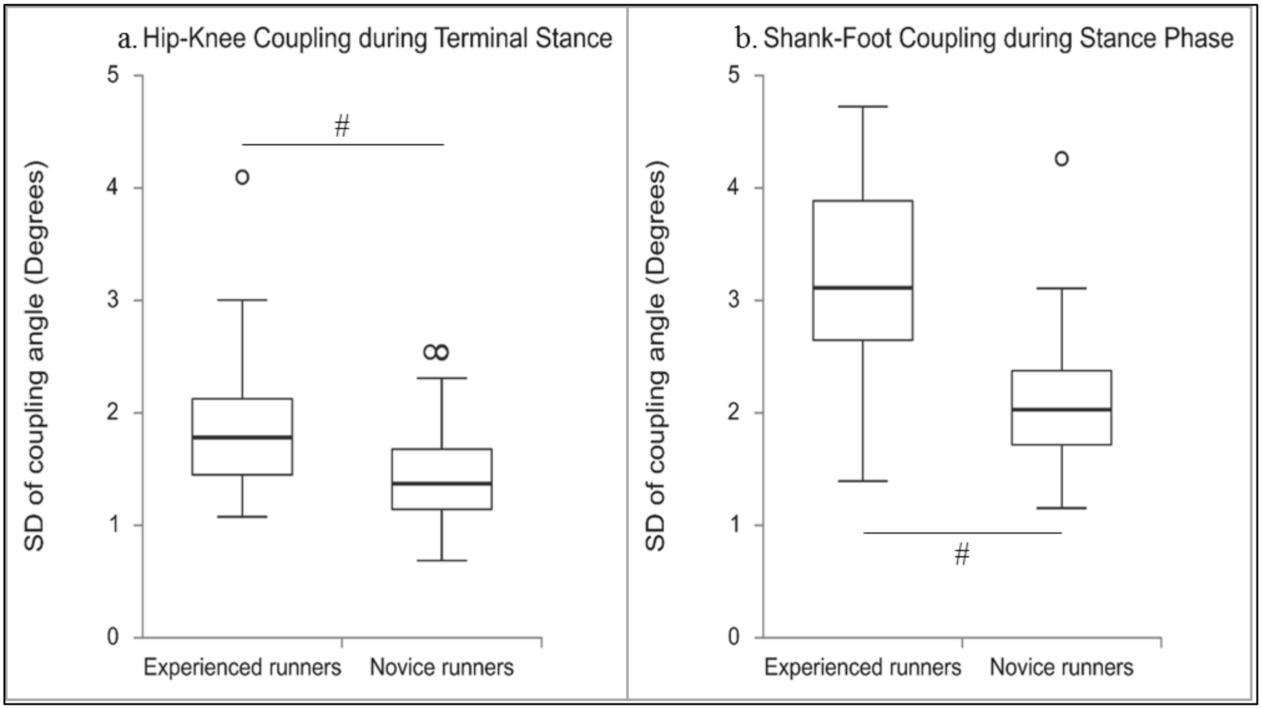

Figure 5.10. Coordination variability for the hip–knee coupling (a) and shank–foot coupling (b) during the 31-min run.

#, experienced runners vs novice runners, $p < 0.05$.

According to the study results, no group by time interaction or time effect was evident for CV. Although no group effects were evident for CV, significances were observed for some parameters. Overall, compared with novice runners, experienced runners exhibited more CV for the hip–knee flexion/extension during the terminal stance ($F = 4.82$, $p = 0.036$, $\eta^2 = 0.44$; Figure 5.10a) and the shank–foot sagittal plane rotation during the stance phase ($F = 4.46$, $p = 0.043$, $\eta^2 = 0.33$; Figure 5.10b).

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5.4 Discussion

This study investigated running mechanics by examining lower limb coordination patterns and CV when experienced and novice runners performed a prolonged treadmill run at AT speed. The results demonstrated the presence of group by time interactions on lower limb coordination patterns, and significant group differences in joint and segment kinematic variability and CV.

5.4.1 Interactions of running experience and fatigue

The ankle joint and knee joint play dominant roles in shock attenuation during the landing in running; however, the hip joint flexion also helps to absorb impact (Dugan & Bhat, 2005; Schache et al., 1999). In the present study, the time to peak hip joint flexion exhibited no difference between experienced and novice runners at the beginning of the 31-min run, but it significantly reduced over time for experienced runners and remained relatively unchanged for novice runners. This indicates that experienced runners adapt more favourably to the progression of fatigue than novice runners, perhaps because experienced runners could adjust their hip joint motion to improve shock absorption. However, a significant interaction was only observed for the peak hip joint flexion.

Regarding lower limb coordination, at the beginning of the 31-min run, experienced runners exhibited a higher percentage of in-phase motion for the pelvis–thigh coupling during the stance phase and the mid-stance but a lower percentage of anti-phase motion for the hip–knee coupling during the mid-stance than novice runners. Because impact absorption relies on coordinated joints and segments, more in-phase motion could improve efficiency during shock attenuation

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but more anti-phase motion could worsen it. The results indicate no difference between experienced and novice runners for the anti-phase motion for the hip–knee coupling during the mid-stance at the end of the 31-min run, but experienced runners nevertheless displayed more in-phase motion for the pelvis–thigh coupling during the stance phase and the mid-stance than novice runners in a fatigued state. To date, no study has reported any interactions between running experience, fatigue, and coordination patterns; however, interactions have been reported for the motion of joints and segments (Maas et al., 2017; Strohrmann et al., 2012). For example, novice runners revealed more changes in the hip joint abduction and more trunk forward leaning in a fatigued state compared with experienced runners (Maas et al., 2017; Strohrmann et al., 2012). These study findings have demonstrated the benefits of years of running experience that may have enabled the locomotor system of those in experienced runners to gain better adaptation to progressive fatigue.

5.4.2 Effects of running experience

The present study displayed no differences in joint and segment kinematic patterns between experienced and novice runners, which is consistent with the findings of a previous study (Agresta et al., 2018). The trunk and lower limb kinematic data were acquired from 100 runners with different degrees of running experience in that study (Agresta et al., 2018), and they discerned no significant correlation between running experience and kinematic patterns. However, the present study ascertained significant differences in the lower limb coordination pattern between experienced and novice runners; experienced runners displayed less ankle motion phase but more in-phase motion for the knee–ankle coupling during the mid-stance and less thigh motion phase but more pelvis motion phase for the pelvis–thigh coupling compared

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with novice runners, which was partially consistent with the findings reported by Floría et al. (2018); they observed that runners revealed less in-phase motion for the knee–ankle coupling and more in-phase motion for the hip–knee coupling compared with nonrunners. In the aforementioned study (Floría et al., 2018), coordination was quantified using the continuous relative phase, which was calculated using both angular velocity and displacement, and they did not eliminate the effects induced by running speed, because the running speed of runners was faster (3.4 ± 0.4 m/s) than that of nonrunners (2.8 ± 0.2 m/s). The contradictory results in Floría et al. (2018) and the present study might be because coordination is a goal-directed behaviour (Davids et al., 2003). The same coordination pattern may be inappropriate for the overall stance phase because the four subphases (the loading stance, the mid-stance, the terminal stance, and the pre-swing) have different functional roles during landing in running. Therefore, experienced and novice runners may exhibit unique lower limb coordination patterns during running, which was dependent on specific functional divisions of the stance phase and couplings of interest (joint coupling or segment coupling).

Furthermore, experienced runners displayed less variability in the segment and joint kinematic than novice runners. This may be attributable to years of running practice causing optimised running kinematic patterns and reduced variances. A consistent finding that has been reported in another study indicates that trained runners exhibited less variability in stride interval than nonrunners (Nakayama et al., 2010). However, only the variability at task outcome level was investigated in that study. The variability at task execution level, such as CV, is differently interpolated, and is seen as being linked to adaptability and flexibility of the locomotor system (Hamill et al., 2012): more CV indicates more flexibility during task execution, such as running.

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The present study determined that compared with novice runners, experienced runners displayed more CV of the hip–knee coupling during the terminal stance and the shank–foot coupling during the stance phase, which may indicate higher flexibility for experienced runners during landing; this flexibility may reduce the risk of developing RRIs (Hamill et al., 2012). Another study (Floría et al., 2018) reported inconsistent findings that nonrunners exhibited a moderate increase in CV compared with runners; however, effects attributable to running speed differences were not eliminated.

5.4.3 Effects of fatigue

The lower limb coordination patterns were strongly affected by fatigue, which was evident in increased pelvis motion phase for the pelvis–thigh coupling in the stance phase and thigh motion phase for the thigh–shank coupling in the mid-stance in a fatigued state. In the literature, lower limb coordination was reported to be maintained unchanged in a fatigued state (Dierks et al., 2010; Brown et al., 2016), but fatigue induced significant changes in the motion of hip joint. In the two studies, the coordination of joint couplings of interest were quantified using joint timing, a discrete time-point parameter (Dierks et al., 2010) and continuous relative phase, a parameter involving both angular displacement and velocity information (Brown et al., 2016); these methods are quite different from the modified vector coding technique method employed in the present study. Nevertheless, similar to the aforementioned studies, fatigue-induced changes around the hip joint were observed in the present study (the pelvis–thigh coupling), which may indicate that runners adapt to the progression of fatigue by adjusting the motion of the proximal joint or segment closer to the core area (hip, pelvis, and thigh). Increasing supporting evidence

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has been reported in the literature; fatigue-induced changes have been identified in trunk and hip motion (Koblbauer et al., 2014; Maas et al., 2017; Strohrmann et al., 2012).

The present study discerned no differences in CV between fatigued and nonfatigued states for both experienced and novice runners. Miller et al. (2008) observed that CV remained relatively constant during an exhaustive run for both healthy runners and runners with iliotibial band syndrome. However, Hafer et al. (2017) reported that CV was increased for runners with iliotibial band syndrome and reduced for healthy runners in a fatigued state. In that study (Hafer et al., 2017), five participants developed pain at the end of the prolonged run, which might have affected their results. To date, no convincing evidences support the contention that runners regulate CV to adapt to the progression of fatigue.

5.5 Limitations

The present study had some limitations. Firstly, the present study only involved joint and segment motions in the sagittal plane because kinematic data of the transverse and frontal planes was reported to be less reliable than the data of the sagittal plane (Ferber et al., 2002; Kadaba et al., 1989; Simon et al., 2006) and motion in the sagittal plane is the dominant movement with the largest range of motion during running and is tightly linked to both running performance (Gittoes & Wilson, 2010) and RRIs. Studies to analyse the lower-limb joint and segment couplings motions in all planes are suggested in the future in terms of gaining more insights into the association between RRIs and the coordination and CV for the lower-limb joint and segment coupling motions. But the data quality should be carefully controlled during data collection, such

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as the reflective markers being positioned on the participants by an investigator with years of 3D gait analysis marker placement experience (Sinclair et al., 2014). Secondly, the running test was conducted only at each participant's AT speed, which may limit the application of the current findings to the running at a different speed, such as preferred running speed. In addition, treadmill and overground are the two most common running environments. All the tests in the present study were conducted on the treadmill. Unlike that the running speed can be adjusted to one's fatigue level during the overground running, all participants were forced to maintain their AT speeds throughout the treadmill running. Although the running patterns are generally similar between the two running situations, numerous studies have demonstrated significant differences in kinematics, kinetics, muscle activation, and physiological response (e.g., cardiometabolic demands) between treadmill and overground running (Edwards et al., 2017; Firminger et al., 2018; Lindsay et al., 2014; Nigg et al., 1995; Panascì et al., 2017; Riley et al., 2008; Wank et al., 1998). It is unclear if similar results will be obtained during overground running. As studies of investigating lower-limb joint and segment coupling motion were conducted on treadmill (Hafer et al., 2016, 2017; Miller et al., 2008) or overground (Boyer et al., 2017; Brown et al., 2016; Dierks & Davis, 2007) in laboratory condition, a comparison study is suggested in the future in terms of understanding if there are any differences in coordination and CV for the lower-limb joint and segment coupling motions between treadmill and overground running. Furthermore, significances were evident for a few parameters, which may be partly due to the grouping methods. The grouping criteria in this study led to great variance in running experience within each group, such as 4 to 20 years for the experienced runner group, which may therefore induce great variations in results between subjects. More rigorous grouping methods would be used in future studies. Finally, a longitudinal study may provide better understanding of the effects of

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running experience on lower limb coordination and CV, and waveform analysis such as statistical parametric mapping and higher orders of coordination analysis, such as continuous relative phase would be considered in future work.

5.6 Summary

Both fatigue and running experience affected lower limb coordination patterns. Experienced and novice runners displayed different lower limb coordination patterns during the prolonged treadmill run at AT speed: more in-phase motion for the pelvis–thigh and the knee–ankle couplings during the mid-stance for experienced runners, and more thigh motion phase for the pelvis–thigh and anti-phase motion for the hip–knee coupling during the mid-stance for novice runners. With the progression of fatigue, experienced runners adapted by altering the motion of the proximal joints and segments (e.g., hip, pelvis, and thigh) with larger CV, and novice runners adapted by adjusting the motion of the distal joints and segments (e.g., shank, ankle, and foot), displaying larger variability in hip, knee, and thigh kinematic. The results of this part of the study demonstrate that different strategies were used by the experienced and novice runners during performing a prolonged run.

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Chapter 6: Conclusion and Future Work

In this doctoral dissertation, three methods of using inertial measurement unit (IMU) for gait events prediction during overground running were firstly evaluated, and then effects of running experience and progressive fatigue on the stride variability during a prolonged treadmill run were investigated. The following sections elaborate to how this research closes to some of the research gaps highlighted in Chapter 1. In addition, where possible, findings are translated into practical implications, considerations and take home message for the broader community, including researchers, practitioners, coaches, and runners.

6.1 Key Findings and Practical Implications

6.1.1. Accuracy of three IMU-based methods for gait events prediciton

The first conclusion of this doctoral dissertation is that both initial contact (IC) and toe-off (TO) can be predicted using IMU-based methods. This comparison study added to the current body of knowledge with respect to using IMU for gait events prediction during running. Previously, the IMU-based method was proposed and validated independently, and there were no comparison study to determine which method produces a comparably accurate prediction during running. Here, this work determined that the IC event during running can be most accurately predicted when the IMU was placed at the body position closer to the ground (e.g., foot instep) through identifying the local peak of the measured resultant acceleration; and the TO event can be most accurately predicted when the IMU was placed at the distal shank through identifying the local

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maximum of the measured vertical (or axial) acceleration after the IC event. Based on these findings, a practical implication for researchers and industry is that:

- The relevant methods can be used to improve accuracy of running gait analysis through providing more accurate IC and TO prediction during distance running under ecological environments, such as road marathon.
- Considering that IMU is one of the core elements in many wearable products (e.g., smart shoes), the algorithms can also be used to running-related Applications, and therefore improving the accuracy of estimating relevant parameters, such as estimating running distance, speed, and energy consumption during daily running practice.

6.1.2. Stride interval variability during a prolonged treadmill run

By analysing the stride interval time series during a prolonged treadmill run, (i) that the scaling exponent alpha of the stride interval changed in a roughly U-shape trend over running time for both experienced and novice runners was demonstrated; and (ii) differences in both the complexity and variability within the stride interval time series between the experienced and novice runners were observed. These findings demonstrated how the locomotor system adapts to progressive fatigue and the benefits of years of running practice on the locomotor control. Both the experienced and novice runners can regulate the stride interval complexity to maintain a constant running speed (e.g., anaerobic threshold speed) throughout the prolonged run, however, the experienced runners also regulated the stride interval variability.

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6.1.3. Lower-limb coordination variability during a prolonged treadmill run

The lower limb coordination pattern was affected by both fatigue and running experience. The lower limb coordination pattern during a prolonged treadmill run was different between experienced and novice runners: the experienced runners presented more in-phase motion for the pelvis–thigh sagittal rotation and the knee–ankle flexion/extension during the mid-stance of the landing phase; the novice runners exhibited more thigh motion phase for the pelvis–thigh sagittal rotation and anti-phase motion for the hip–knee flexion/extension during the mid-stance of the landing phase. The experienced runners adapted the progressive fatigue through altering motion of the proximal joint and segments (e.g., hip, pelvis, and thigh) and presenting larger coordination variability; the novice runners adapted the progressive fatigue by adjusting the motion of the distal joint and segments (e.g., ankle, shank, and foot) and displaying large kinematic variability of individual joints and segments (e.g., hip joint, knee joint, thigh segment). On the basis of the findings that the experienced and novice runners can maintain a constant speed (e.g., anaerobic threshold speed) throughout the prolonged run through different strategies, the novice runners are encouraged to include training exercises to enhance lower limb coordination during daily running practice.

6.2 Limitations of The Thesis

All results presented in this doctoral dissertation should be interpreted in light of certain constraints and limitations.

- For the first part of the study (Chapter 3), the comparison study were conducted in a laboratory. Due to a short running distance (10 m) and only 3 force platforms, limited

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steps were analysed, and only one temporal parameter—stance time—was estimated and evaluated.

- The IMU attaching method may produce errors and contribute to the results. For the comparison study (Chapter 3), attaching IMU (distal shank and lower trunk) through the elastic belt or placing IMU to the shoe instep may attenuate accelerations in comparison to that being directly attached to the skin. In addition, although all IMU attaching work was done by one investigator in this study, the experience of the investigator may contribute to the prediction error.
- Effects of other factors, such as foot strike pattern, were not discussed. For the comparison study (Chapter 3), all participants were rearfoot strikers. It is unknown if similar results could be gained during running with forefoot strike pattern.
- For controlling the running speed at one's anaerobic threshold level, all running tests in Chapter 4 and 5 were conducted on treadmill, and only one speed was investigated.
- The participant grouping methods in Chapter 4 and 5 led to great within-group variance of running experience, which may affect the results. Only basic information about running experience (e.g., weekly running volume, years of running, etc.) were collected in this study.
- Due to time limit, only motions in the sagittal plane were analysed. Stance time instead of the entire gait cycle (stance & swing phases) was addressed in Chapter 5. It would more informative if motions in all three planes and the entire gait cycle were analysed.
- More insights may be gained if waveform analysis (e.g., statistical parametric mapping) and higher orders of coordination analysis (e.g., continuous relative phase) were also considered during data processing and analysis in Chapter 5.

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6.3 Future Work

This doctoral dissertation about the stride variability of experienced and novice runners during a prolonged run generates many questions. What is the relationship between the task outcome variability (e.g., stride interval variability) and task execution variability (e.g., coordination variability for the joint and segment coupling motions)? How does the variability at task execution level contribute to the task outcome variability? Is this relationship affected by the running experience and fatigue? Considering that greater coordination variability being observed for the experience runners in comparison to the novice runners, how does this observation connect to the reported lower rate of running-related injuries (RRIs) for the experienced runners compared to the novice runners? As the running speed was controlled and all running tests were conducted on the treadmill, can similar results be obtained during distance running under ecological environments, such as road marathon? The magnitude and scope of these questions open up a large opportunity for future research. The dissertation here ends off by listing some interesting topics which will be addressed in future studies.

- The accuracy of IMU for kinematic measures under dynamical environments is still arguable. Future work will address this gap and find methods to improve the measuring accuracy of IMU.
- Only three typical IMU-based methods were evaluated during the overground run for a short distance in the present study. In future studies, the accuracy should be assessed during a prolonged overground run across different terrains (different gradients, different hardness such as grass, rubber, and concrete), as well as the robustness, specificity and sensitivity of utilising the IMU-based method for gait events prediction and gait temporal

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parameters estimation, particularly for real-time calculation. In addition, because the participants were rearfoot strikers, future studies should also consider the effects of foot strike pattern on the accuracy of the IMU-based methods for gait events prediction.

- All running tests in this doctoral dissertation were conducted in laboratory. Future studies should focus on distance running under ecological environments, e.g., road marathon.
- The lower limb coordination pattern and CV were evaluated only in the sagittal plane in the present study. Couplings of interest referring to motions in all three planes are recommended to gain more insights into mechanics of developing an RRI.
- The doctoral dissertation investigated the stride variability from both task execution and outcome levels. However, the correlation between them remains unknown. Future work will also address this gap.
- A longitudinal study is suggested to investigate the effects of running experience on the landing consistency during a prolonged run. For example, tracking a group of novice runners and comparing the landing consistency at different stages during the period of gaining running experience (e.g., before receiving a regular running practice, and three, six, and twelve months after receiving a regular running practice).
- Running data were acquired under a well-controlled condition (treadmill run at a constant speed) in the present study. Running data from a field run (e.g., road marathon race) are more informative.

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References

Abt, J. P., Sell, T. C., Chu, Y., Lovalekar, M., Burdett, R. G., & Lephart, S. M. (2011). Running kinematics and shock absorption do not change after brief exhaustive running. *Journal of Strength and Conditioning Research*, *25*(6), 1479-1485. DOI: 10.1519/JSC.0b013e3181ddfcf8.

Agresta, C. E., Peacock, J., Housner, J., Zernicke, R. F., & Zendler, J. D. (2018). Experience does not influence injury-related joint kinematics and kinetics in distance runners. *Gait & Posture*, *61*, 13-18. DOI: 10.1016/j.gaitpost.2017.12.020.

Allen-Collinson, J., & Hockey, J. (2007). 'Working out' identity: Distance runners and the management of disrupted identity. *Leisure Studies*, *26*(4), 381-398.

Almeida, M. O., Davis, I. S., & Lopes, A. D. (2015). Biomechanical differences of foot-strike patterns during running: a systematic review with meta-analysis. *Journal of Orthopaedic & Sports Physical Therapy*, *45*(10), 738-755. DOI: 10.2519/jospt.2015.6019.

Alton, F., Baldey, L., Caplan, S., & Morrissey, M. C. (1998). A kinematic comparison of overground and treadmill walking. *Clinical Biomechanics*, *13*(6), 434-440.

Aminian, K., Najafi, B., Büla, C., Leyvraz, P. F., & Robert, P. (2002). Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. *Journal of Biomechanics*, *35*(5):689-699.

Auvinet, B., Gloria, E., Renault, G., & Barrey, E. (2002). Runner's stride analysis: comparison of kinematic and kinetic analyses under field conditions. *Science & Sports*, *17*(2), 92-94.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Baghdadi, A., Megahed, F. M., Esfahani, E. T., & Cavuoto, L. A. (2018). A machine learning approach to detect changes in gait parameters following a fatiguing occupational task. *Ergonomics*, *61*(8), 1116-1129. DOI: 10.1080/00140139.2018.1442936.

Bailey, G. P., & Harle, R. K. (2015). Measuring temporal parameters of gait with foot mounted IMUs in steady state running. In *Proceedings of the 3rd International Congress on Sport Sciences Research and Technology Support* (Vol. 1, pp. 24-33).

Baltich, J., Maurer, C., & Nigg, B. M. (2015). Increased vertical impact forces and altered running mechanics with softer midsole shoes. *PLOS ONE*, *10*(4), e0125196. DOI: 10.1371/journal.pone.0125196.

Bartlett, R., Wheat, J., & Robins, M. (2007). Is movement variability important for sports biomechanics? *Sports Biomechanics*, *6*(2), 224-243. DOI: 10.1080/14763140701322994.

Belli, A., Lacour, J. R., Komi, P. V., Candau, R., & Denis, C. (1995). Mechanical step variability during treadmill running. *European journal of Applied Physiology and Occupational Physiology*, *70*(6), 510-517.

Ben Mansour, K., Rezzoug, N., & Gorce, P. (2015). Analysis of several methods and inertial sensors locations to assess gait parameters in able-bodied subjects. *Gait & Posture*, *42*(4), 409-414. DOI: 10.1016/j.gaitpost.2015.05.020.

Benson, L. C., Clermont, C. A., Bošnjak, E., & Ferber, R. (2018). The use of wearable devices for walking and running gait analysis outside of the lab: a systematic review. *Gait & Posture*, *63*, 124-138. DOI: 10.1016/j.gaitpost.2018.04.047.

Bergamini, E., Picerno, P., Pillet, H., Natta, F., & Thoreux, P. (2012). Estimation of temporal parameters during sprint running using a trunk-mounted inertial measurement unit. *Journal of Biomechanics*, *45*(6), 1123-1126. DOI: 10.1016/j.jbiomech.2011.12.020.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Bergamini, E., Ligorio, G., Summa, A., Vannozzi, G., Cappozzo, A., & Sabatini, A. M. (2014). Estimating orientation using magnetic and inertial sensors and different sensor fusion approaches: Accuracy assessment in manual and locomotion tasks. *Sensors*, *14*(10), 18625-18649. DOI: 10.3390/s141018625.

Bergstra, S. A., Kluitenberg, B., Dekker, R., Bredeweg, S. W., Postema, K., van den Heuvel, E. R., ... & Sobhani, S. (2015). Running with a minimalist shoe increases plantar pressure in the forefoot region of healthy female runners. *Journal of Science and Medicine in Sport*, *18*(4), 463-468. DOI: 10.1016/j.jsams.2014.06.007.

Bertelsen, M. L., Hulme, A., Petersen, J., Brund, R. K., Sørensen, H., Finch, C. F., ... & Nielsen, R. O. (2017). A framework for the etiology of running- related injuries. *Scandinavian Journal of Medicine & Science in Sports*, *27*(11), 1170-1180. DOI: 10.1111/sms.12883.

Bezuelo-Ruiz, B., Durá-Gil, J. V., Palomares, N., Medina, E., & Llana-Belloch, S. (2018). Effect of fatigue and gender on kinematics and ground reaction forces variables in recreational runners. *PeerJ*, *6*, e4489. DOI: 10.7717/peerj.4489.

Blair, S., Duthie, G., Robertson, S., Hopkins, W., & Ball, K. (2018). Concurrent validation of an inertial measurement system to quantify kicking biomechanics in four football codes. *Journal of Biomechanics*, *73*, 24-32. DOI: 10.1016/j.jbiomech.2018.03.031.

Blanch, P., & Gabbett, T. J. (2016). Has the athlete trained enough to return to play safety? The acute: chronic workload ratio permits clinicians to quantify a player's risk of subsequent injury. *British Journal of Sports Medicine*, *50*(8), 471-475. DOI: 10.1136/bjsports-2015-095445.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Boutaayamou, M., Denoël, V., Brüls, O., Demonceau, M., Maquet, D., …, & Garraux, G. (2017). Algorithm for temporal gait analysis using wireless foot-mounted accelerometers. *Communications in Computer and Information Science*, *690*, 236-254.

Boyer, K. A., Freedman Silvernail, J., & Hamill, J. (2014). The role of running mileage on coordination patterns in running. *Journal of Applied Biomechanics*, *30*(5), 649-654. DOI: 10.1123/jab.2013-0261.

Boyer, K. A., Freedman Silvernail, J., & Hamill, J. (2017). Age and sex influences on running mechanics and coordination variability. *Journal of Sports Sciences*, *35*(22), 2225-2231. DOI: 10.1080/02640414.2016.1265139.

Brennan, A., Zhang, J., Deluzio, K., & Li, Q. (2011). Quantification of inertial sensor-based 3D joint angle measurement accuracy using an instrumented gimbal. *Gait & Posture*, *34*(3), 320-323. DOI: 10.1016/j.gaitpost.2011.05.018.

Breine, B., Malcolm, P., Van Caekenberghe, I., Fiers, P., Frederick, E. C., & De Clercq, D. (2017). Initial foot contact and related kinematics affect impact loading rate in running. *Journal of Sports Sciences*, *35*(15), 1556-1564. DOI: 10.1080/02640414.2016.1225970.

Brodie, M. A., Walmsley, A., & Page, W. (2008). Dynamic accuracy of inertial measurement units during simple pendulum motion. *Computer Methods in Biomechanics and Biomedical Engineering*, *11*(3), 235-242. DOI: 10.1080/10255840802125526.

Brown, C. N., Padua, D. A., Marshall, S. W., & Guskiewicz, K. M. (2009). Variability of motion in individuals with mechanical or functional ankle instability during a stop jump maneuver. *Clinical Biomechanics*, *24*(9), 762-768. DOI: 10.1016/j.clinbiomech.2009.07.001.

Brown, A. M., Zifchock, R., A., Hillstrom, H. J., Song, J., & Tucker, C. A. (2016). The effects of fatigue on lower extremity kinematics, kinetics, and joint coupling in symptomatic female

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

runners with iliotibial band syndrome. *Clinical Biomechanics*, *39*, 84-90. DOI: 10.1016/j.clinbiomech.2016.09.012.

Bugané, F., Benedetti, M. G., Casadio, G., Attala, S., Biagi, F., Manca, M., & Leardini, A. (2012). Estimation of spatial-temporal gait parameters in level walking based on a single accelerometer: validation on normal subjects by standard gait analysis. *Computer Methods and Programs in Biomedicine*, *108*(1), 129-37. DOI: 10.1016/j.cmpb.2012.02.003.

Buist, I., Bredeweg, S. W., Lemmink, K. A., Pepping, G. J., Zwerver, J., van Mechelen, W., & Diercks, R. L. (2007). The GRONORUN study: Is a graded training program for novice runners effective in preventing running related injuries? Design of a randomized controlled trial. *BMC Musculoskeletal Disorders*, *8*, 24. DOI: 10.1186/1471-2474-8-24.

Buist, I., Bredeweg, S. W., Lemmink, K. A., van Mechelen, W., & Diercks, R. L. (2010). Predictors of running-related injuries in novice runners enrolled in a systematic training program: A prospective cohort study. *The American Journal of Sports Medicine*, *38*(2), 273-80. DOI: 10.1177/0363546509347985.

Cappellini, G., Ivanenko, Y. P., Poppele, R. E., & Lacquaniti, F. (2006). Motor patterns in human walking and running. *Journal of Neurophysiology*, *95*(6), 3426-3437. DOI: 10.1152/jn.00081.2006.

Cappozzo, A., Catani, F., Croce, U. D., & Leardini, A. (1995). Position and orientation in space of bones during movement: anatomical frame definition and determination. *Clinical Biomechanics*, *10*(4), 171-178.

Castillo, E. R., & Lieberman, D. E. (2018). Shock attenuation in the human lumbar spine during walking and running. *Journal of Experimental Biology*, *221*(Pt 9), pii: jeb177949. DOI: 10.1242/jeb.177949.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Chang, R., van Emmerik, R., & Hamill, J. (2008). Quantifying rearfoot-forefoot coordination in human walking. *Journal of Biomechanics*, *41*(14), 3101-3105. DOI: 10.1016/j.jbiomech.2008.07.024.

Chan-Roper, M., Hunter, .I, Myrer, J. W., Eggett, D. L., & Seeley, M. K. (2012). Kinematic changes during a marathon for fast and slow runners. *Journal of Sports Science & Medicine*, *11*(1), 77-82.

Chapman, R. F., Laymon, A. S., Wilhite, D. P., Mckenzie, J. M., Tanner, D. A., & Stager, J. M. (2012). Ground contact time as an indicator of metabolic cost in elite distance runners. *Medicine and Science in Sports and Exercise*, *44*(5), 917-925. DOI: 10.1249/MSS.0b013e3182400520.

Chau, T. (2001). A review of analytical techniques for gait data. Part 1: neural network and wavelet methods. *Gait & Posture*, *13*(1), 49-66.

Cheng, Q., Juen, J., Bellam, S., Fulara, N., Close, D., Silverstein, J. C., & Schatz, B. (2017). Predicting pulmonary function from phone sensors. *Telemedicine and e-Health*, *23*(11), 913-919. DOI: 10.1089/tmj.2017.0008.

Clansey, A. C., Hanlon, M., Wallace, E. S., & Lake, M. J. (2012). Effects of fatigue on running mechanics associated with tibial stress fracture risk. *Medicine and Science in Sports and Exercise*, *44*(10), 1917-1923. DOI: 10.1249/MSS.0b013e318259480d.

Cooper, G., Sheret, I., McMillan, L., Siliverdis, K., Sha, N., …, & Howard, D. (2009). Inertial sensor-based knee flexion/extension angle estimation. *Journal of Biomechanics*, *42*(16), 2678-2685. DOI: 10.1016/j.jbiomech.2009.08.004.

Corbeil, P., Blouin, J. S., Bégin, F., Nougier, V., & Teasdale, N. (2003). Perturbation of the postural control system induced by muscular fatigue. *Gait & Posture*, *18*(2), 92-100.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Cortes, N., Onate, J., & Morrison, S. (2014). Differential effects of fatigue on movement variability. *Gait & Posture*, *39*(3), 888-893. DOI: 10.1016/j.gaitpost.2013.11.020.

Crowell, H. P., Milner, C. E., Hamill, J., & Davis, I. S. (2010). Reducing impact loading during running with the use of real-time visual feedback. *Journal of Orthopaedic & Sports Physical Therapy*, *40*(4), 206-213. DOI: 10.2519/jospt.2010.3166.

Crowell, H. P., & Davis, I. S. (2011). Gait retraining to reduce lower extremity loading in runners. *Clinical Biomechanics*, *26*(1), 78-83. DOI: 10.1016/j.clinbiomech.2010.09.003.

Cutti, A. G., Giovanardi, A., Rocchi, L., & Davalli, A. (2006). A simple test to assess the static and dynamic accuracy of an inertial sensors system for human movement analysis. In *Conference Proceedings of IEEE Engineering in Medicine and Biology Society* (pp. 5912-5915).

Damouras, S., Chang, M. D., Sejdić, E., & Chau, T. (2010). An empirical examination of detrended fluctuation analysis for gait data. *Gait & Posture*, *31*(3), 336-340. DOI: 10.1016/j.gaitpost.2009.12.002.

Davids, K., Glazier, P., Araújo, D., & Bartlett, R. (2003). Movement systems as dynamical systems: the functional role of variability and its implications for sports medicine. *Sports Medicine*, *33*(4), 245-260.

de Ruiter, C. J., Verdijk, P. W., Werker, W., Zuidema, M. J., & de Haan, A. (2014). Stride frequency in relation to oxygen consumption in experienced and novice runners. *European Journal of Sport Science*, *14*(3), 251-258. DOI: 10.1080/17461391.2013.783627.

de Vries, W. H., Veeger, H. E., Baten, C. T., & van der Helm, F. C. (2009). Magnetic distortion in motion labs, implications for validating inertial magnetic sensors. *Gait & Posture*, *29*(4), 535-541. DOI: 10.1016/j.gaitpost.2008.12.004.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

DeLeo, A. T., Dierks, T. A., Ferber, R., & Davis, I. S. (2004). Lower extremity joint coupling during running: a current update. *Clinical Biomechanics*, *19*(10), 983-991. DOI: 10.1016/j.clinbiomech.2004.07.005.

Dierks, T. A., & Davis, I. (2007). Discrete and continuous joint coupling relationships in uninjured recreational runners. *Clinical Biomechanics*, *22*(5), 581-591. DOI: 10.1016/j.clinbiomech.2007.01.012.

Dierks, T. A., Davis, I. S., & Hamill, J. (2010). The effects of running in an exerted state on lower extremity kinematics and joint timing. *Journal of Biomechanics*, *43*(15), 2993-2998. DOI: 10.1016/j.jbiomech.2010.07.001.

Derrick, T. R., Dereu, D., & McLean, S. P. (2002). Impacts and kinematic adjustments during an exhaustive run. *Medicine and Science in Sports and Exercise*, *34*(6), 998-1002.

Dingwell, J. B., Cusmano, J. P., Cavanagh, P. R., & Sternad, D. (2001). Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *Journal of Biomechanical Engineering*, *123*(1), 27-32.

Dingwell, J. B., & Cusumano, J. P. (2010). Re-interpreting detrended fluctuation analysis of stride-to-stride variability in human walking. *Gait & Posture*, *32*(3), 348-353. DOI: 10.1016/j.gaitpost.2010.06.004.

Dugan, S. A., & Bhat, K. P. (2005). Biomechanics and analysis of running gait. *Physical Medicine & Rehabilitation Clinics of North America*, *16*, 603-621.

Edwards, S., Brooke, H. C., & Cook, J. L. (2017). Distinct cut task strategy in Australian football players with a history of groin pain. *Physical Therapy in Sport*, *23*, 58-66. DOI: 10.1016/j.ptsp.2016.07.005.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Edwards, R. B., Tofari, P. J., Cormack, S. J., & Whyte, D. G. (2017). Non-motorized treadmill running is associated with higher cardiometabolic demands compared with overground and motorized treadmill running. *Frontiers in Physiology*, *8*, 914. DOI: 10.3389/fphys.2017.00914.

Favre, J., Jolles, B. M., Aissaoui, R., & Aminian, K. (2008). Ambulatory measurement of 3D knee joint angle. *Journal of Biomechanics*, *41*(5), 1029-1035. DOI: 10.1016/j.jbiomech.2007.12.003.

Fellin, R. E., Rose, W. C., Royer, T. D., & Davis, I. S. (2010). Comparison of methods for kinematic identification of footstrike and toe-off during overground and treadmill running. *Journal of Science and Medicine in Sport*, *13*(6), 646-650. DOI: 10.1016/j.jsams.2010.03.006.

Ferber, R., McClay Davis, I., Williams III, D. S., & Laughton, C. (2002). A comparison of within- and between-day reliability of discrete 3D lower extremity variables in runners. *Journal of Orthopaedic Research*, *20*(6), 1139-1145. DOI: 10.1016/S0736-0266(02)00077-3.

Ferber, R., Hreljac, A., & Kendall, K. D. (2009). Suspected mechanisms in the cause of overuse running injuries: a clinical review. *Sports Health*, *1*(3), 242-246. DOI: 10.1177/1941738109334272.

Firminger, C. R., & Edwards, W. B. (2016). The influence of minimalist footwear and stride length reduction on lower-extremity running mechanics and cumulative loading. *Journal of Science and Medicine in Sport*, *19*(12), 975-979. DOI: 10.1016/j.jsams.2016.03.003.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Firminger, C. R., Vernillo, G., Savoldelli, A., Stefanyshyn, D. J., Millet, G. Y., & Edwards, W. B. (2018). Joint kinematics and ground reaction forces in overground versus treadmill graded running. *Gait & Posture*, *63*, 109-113. DOI: 10.1016/j.gaitpost.2018.04.042.

Floría, P., Sánchez-Sixto, A., Ferber, R., & Harrison, A. J. (2018). Effects of running experience on coordination and its variability in runners. *Journal of Sports Science*, *36*(3), 272-278. DOI: 10.1080/02640414.2017.1300314.

Fuller, J. T., Amado, A., van Emmerik, R. E. A., Hamill, J., Buckley, J. D., Tsiros, M. D., & Thewlis, D. (2016). The effect of footwear and footfall pattern on running stride interval long-range correlations and distributional variability. *Gait & Posture*, *44*, 137-142. DOI: 10.1016/j.gaitpost.2015.12.006.

Fuller, J. T., Bellenger, C. R., Thewlis, D., Arnold, J., Thomson, R. L., Tsiros, M. D., Robertson, E. Y., & Buckley, J. D. (2017). Tracking performance changes with running-stride variability when athletes are functionally overreached. *International Journal of Sports Physiology and Performance*, *12*(3), 357-363. DOI: 10.1123/ijspp.2015-0618.

Gabbett, T. J. (2016). The training-injury prevention paradox: should athletes be training smarter and harder? *British Journal of Sports Medicine*, *50*(5), 273-280. DOI: 10.1136/bjsports-2015-095788.

García-Pérez, J. A., Pérez-Soriano, P., Llana Belloch, S., Lucas-Cuevas, A. G., & Sánchez-Zuriaga, D. (2014). Effects of treadmill running and fatigue on impact acceleration in distance running. *Sports Biomechanics*, *13*(3), 259-266. DOI: 10.1080/14763141.2014.909527.

Ghosh, A. K. (2004). Anaerobic threshold: its concept and role in endurance sport. *Malaysian Journal of Medical Sciences*, *11*(1), 24-36.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Giandolini, M., Pavailler, S., Samozino, P., Morin, J. B., & Horvais, N. (2015). Foot strike pattern and impact continuous measurements during a trail running race: proof of concept in a world-class athlete. *Footwear Science*, *7*(2), 127-137.

Giandolini, M., Horvais, N., Rossi, J., Millet, G. Y., Samozino, P., & Morin, J. B. (2016). Foot strike pattern differently affects the axial and transverse components of shock acceleration and attenuation in downhill trail running. *Journal of Biomechanics*, *49*(9), 1765-1771. DOI: 10.1016/j.jbiomech.2016.04.001.

Gindre, C., Lussiana, T., Hebert-Losier, K., & Morin, J. B. (2016). Reliability and validity of the Myotest® for measuring running stride kinematics. *Journal of Sports Sciences*, *34*(7), 664-670. DOI: 10.1080/02640414.2015.1068436.

Gittoes, M. J. R., & Wilson, C. (2010). Intralimb joint coordination patterns of the lower extremity in maximal velocity phase sprint running. *Journal of Applied Biomechanics*, *26*(2), 188-195.

Godwin, A., Agnew, M., & Stevenson, J. (2009). Accuracy of inertial motion sensors in static, quasistatic, and complex dynamic motion. *Journal of Biomechanical Engineering*, *131*(11), 114501. DOI: 10.1115/1.4000109.

Gómez-Molina, J., Ogueta-Alday, A., Stickley, C., Cámara, J., Cabrejas-Ugartondo, J., & García-López, J. (2017). Differences in spatiotemporal parameters between trained runners and untrained participants. *Journal of Strength & Conditioning Research*, *31*(8), 2169-2175. DOI: 10.1519/JSC.0000000000001679.

González, R. C., López, A. M., Rodriguez-Uría, J., Álvarez, D., & Alvarez, J. C. (2010). Real-time gait event detection for normal subjects from lower trunk accelerations. *Gait & Posture*, *31*(3): 322-325. DOI: 10.1016/j.gaitpost.2009.11.014.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Greene, B. R., McGrath, D., O'Neill, R., O'Donovan, K. J., Burns, A., & Caulfield, B. (2010). An adaptive gyroscope-based algorithm for temporal gait analysis. *Medical & Biological Engineering & Computing*, *48*(12), 1251-1260. DOI: 10.1007/s11517-010-0692-0.

Hafer, J. F., Freedman-Silvernail, J., Hillstrom, H. J., & Boyer, K. A. (2016). Changes in coordination and its variability with an increase in running cadence. *Journal of Sports Sciences*, *34*(15), 1388-1395. DOI: 10.1080/02640414.2015.1112021.

Hafer, J. F., Brown, A. M., & Boyer, K. A. (2017). Exertion and pain do not alter coordination variability in runners with iliotibial band syndrome. *Clinical Biomechanics*, *47*, 73-78. DOI: 10.1016/j.clinbiomech.2017.06.006.

Hafer, J. F., & Boyer, K. A. (2017). Variability of segment coordination using a vector coding technique: reliability analysis for treadmill walking and running. *Gait & Posture*, *51*, 222-227. DOI: 10.1016/j.gaitpost.2016.11.004.

Hamann, N., Zaucke, F., Heilig, J., Oberländer, K. D., Brüggemann, G. P., & Niehoff, A. (2014). Effect of different running modes on the morphological, biochemical, and mechanical properties of articular cartilage. *Scandinavian Journal of Medicine & Science in Sports*, *24*(1), 179-188. DOI: 10.1111/j.1600-0838.2012.01513.x.

Hamill, J., van Emmerik, R. E., & Heiderscheit, B. C. (1999). A dynamical systems approach to lower extremity running injuries. *Clinical Biomechanics*, *14*(5), 297-308.

Hamill, J., Palmer, C., & van Emmerik, R. E. (2012). Coordinative variability and overuse injury. *Sports Medicine, Arthroscopy, Rehabilitation, Therapy & Technology*, *4*(1), 45. DOI: 10.1186/1758-2555-4-45.

Hanlon, M., & Anderson, R. (2009). Real-time gait event detection using wearable sensors. *Gait & Posture*, *30*(4), 523-527. DOI: 10.1016/j.gaitpost.2009.07.128.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Harbourne, R. T., & Stergiou, N. (2009). Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Physical Therapy*, *89*(3), 267-282. DOI: 10.2522/ptj.20080130.

Harms, H., Amft, O., Winkler, R., Schumm, J., Kusserow, M., & Tröster, G. (2010, November). Ethos: miniature orientation sensor for wearable human motion analysis. In *Sensors*, 2010 IEEE (pp. 1037-1042). IEEE.

Hausdorff, J. M. (2005). Gait variability: methods, modelling and meaning. *Journal of NeuroEngineering and Rehabilitation*, *2*, 19. DOI: 10.1186/1743-0003-2-19.

Hausdorff, J. M. (2007). Gait dynamics, fractals and falls: finding meaning in the stride-to-stride fluctuations of human walking. *Human Movement Science*, *26*(4), 555-589. DOI: 10.1016/j.humov.2007.05.003.

Heiden, T., & Burnett, A. (2008, March). Determination of heel strike and toe-off in the running stride using an accelerometer: application to field-based gait studies. In: *ISBS-Conference Proceedings Archive* (Vol. 1, No. 1).

Heiderscheit, B. C., Hamill, J., & van Emmerik, R. E. A. (1999). Q-angle influences on the variability of lower extremity coordination during running. *Medicine and Science in Sports and Exercise*, *31*(9), 1313-1319.

Heiderscheit, B. C. (2000). Movement variability as a clinical measure for locomotion. *Journal of Applied Biomechanics*, *16*(4), 419-427.

Heiderscheit, B. C., Hamill, J., & van Emmerik, R. E. A. (2002). Variability of stride characteristics and joint coordination among individuals with unilateral patellofemoral pain. *Journal of Applied Biomechanics*, *18*(2), 110-121.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Heiderscheit, B. C., Chumanov, E. S., Michalski, M. P., Wille, C. M., & Ryan, M. B. (2011). Effects of step rate manipulation on joint mechanics during running. *Medicine and Science in Sports and Exercise*, *43*(2), 296-302. DOI: 10.1249/MSS.0b013e3181ebedf4.

Hein, T., Schmeltzpfenning, T., Krauss, I., Maiwald, C., Horstmann, T., & Grau, S. (2012). Using the variability of continuous relative phase as a measure to discriminate between healthy and injured runners. *Human Movement Science*, *31*(3), 683-694. DOI: 10.1016/j.humov.2011.07.008.

Hobara, H., Sato, T., Sakaguchi, M., & Nakazawa, K. (2012). Step frequency and lower extremity loading during running. *International Journal of Sports Medicine*, *33*(4), 310-313. DOI: 10.1055/s-0031-1291232.

Hollman, J. H., McDade, E. M., & Petersen, R. C. (2011). Normative spatiotemporal gait parameters in older adults. *Gait & Posture*, *34*(1): 111-118. DOI: 10.1016/j.gaitpost.2011.03.024.

Hreljac, A. (2000). Stride smoothness evaluation of runners and other athletes. *Gait & Posture*, *11*(3), 199-206.

Hreljac, A., & Marshall, R. N. (2000). Algorithms to determine event timing during normal walking using kinematic data. *Journal of Biomechanics*, *33*(6), 783-786.

Hreljac, A., Marshall, R. N., & Hume, P. A. (2000). Evaluation of lower extremity overuse injury potential in runners. *Medicine and Science in Sports and Exercise*, *32*(9), 1635-1641.

Hreljac, A. (2005). Etiology, prevention, and early intervention of overuse injuries in runners: a biomechanical perspective. *Physical Medicine and Rehabilitation Clinics*, *16*(3), 651-667. DOI: 10.1016/j.pmr.2005.02.002.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Hughes, D. C., Ellefsen, S., & Baar, K. (2018). Adaptations to endurance and strength training. *Cold Spring Harbor Perspectives in Medicine*, *8*(6), a029769. DOI: 10.1101/cshperspect.a029769.

Hunter, J. P., Marshall, R. N., & McNair, P. J. (2004). Interaction of step length and step rate during sprint running. *Medicine and Science in Sports and Exercise*, *36*(2), 261-271. DOI: 10.1249/01.MSS.0000113664.15777.53.

Hunter, J. P., Marshall, R. N., & McNair, P. J. (2005). Relationships between ground reaction force impulse and kinematics of sprint-running acceleration. *Journal of Applied Biomechanics*, *21*(1), 31-43.

Hunter, I., Lee, K., Ward, J., & Tracy, J. (2017). Self-optimization of stride length among experienced and inexperienced runners. *International Journal of Exercise Science*, *10*(3), 446-453.

James, C. R., Dufek, J. S., & Bates, B. T. (2000). Effects of injury proneness and task difficulty on joint kinetic variability. *Medicine and Science in Sports and Exercise*, *32*(11), 1833-1844.

Jasiewicz, J. M., Allum, J. H., Middleton, J. W., Barriskill, A., Condie, P., Purcell, B., & Li, R. C. (2006). Gait event detection using linear accelerometers or angular velocity transducers in able-bodied and spinal-cord injured individuals. *Gait & Posture*, *24*(4), 502-509. DOI: 10.1016/j.gaitpost.2005.12.017.

Jordan, K., Challis, J. H., & Newell, K. M. (2006). Long range correlations in the stride interval of running. *Gait & Posture*, *24*(1), 120-125. DOI: 10.1016/j.gaitpost.2005.08.003.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Jordan, K., Challis, J. H., & Newell, K. M. (2007). Speed influences on the scaling behavior of gait cycle fluctuations during treadmill running. *Human Movement Science*, *26*(1), 87-102. DOI: 10.1016/j.humov.2006.10.001.

Juen, J., Cheng, Q., Prieto-Centurion, V., Krishnan, J. A., & Schatz, B. (2014). Health monitors for chronic disease by gait analysis with mobile phones. *Telemedicine and e-Health*, *20*(11), 1035-1041. DOI: 10.1089/tmj.2014.0025.

Kadaba, M. P., Ramakrishnan, H. K., Wootten, M. E., Gainey, J., Gorton, G., & Cochran, G. V. (1989). Repeatability of kinematic, kinetic, and electromyographic data in normal adult gait. *Journal of Orthopaedic Research*, *7*(6), 849-860. DOI: 10.1002/jor.1100070611.

Kawabata, M., Goto, K., Fukusaki, C., Sasaki, K., Hihara, E., Mizushina, T., & Ishii, N. (2013). Acceleration patterns in the lower and upper trunk during running. *Journal of Sports Science*, *31*(16), 1841-1853. DOI: 10.1080/02640414.2013.805884.

Khandelwal, S., & Wickström, N. (2016). Gait event detection in real-world environment for long-term applications: incorporating domain knowledge into time-frequency analysis. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *24*(12), 1363-1372. DOI: 10.1109/TNSRE.2016.2536278.

Khandelwal, S., & Wickström, N. (2017). Evaluation of the performance of accelerometer-based gait event detection algorithms in different real-world scenarios using the MAREA gait database. *Gait & Posture*, *51*:84-90. DOI: 10.1016/j.gaitpost.2016.09.023.

Kim, H. K., Mirjalili, S. A., & Fernandez, J. (2018). Gait kinetics, kinematics, spatiotemporal and foot plantar pressure alteration in response to long-distance running: systematic review. *Human Movement Science*, *57*: 342-356. DOI: 10.1016/j.humov.2017.09.012.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Kindred, J., Trubey, C., & Simons, S. M. (2011). Foot injuries in runners. *Current Sports Medicine Reports*, *10*(5), 249-254. DOI: 10.1249/JSR.0b013e31822d3ea4.

Kipp, K., & Palmieri Smith, R. M. (2012). Principal component based analysis of biomechanical inter-trial variability in individuals with chronic ankle stability. *Clinical Biomechanics*, *27*(7), 706-710. DOI: 10.1016/j.clinbiomech.2012.02.005.

Kitagawa, N., & Ogihara, N. (2016). Estimation of foot trajectory during human walking by a wearable inertial measurement unit mounted to the foot. *Gait & Posture*, *45*, 110-114. DOI: 10.1016/j.gaitpost.2016.01.014.

Kluitenberg, B., van Middelkoop, M., Diercks, R., & van der Worp, H. (2015). What are the differences in injury proportions between different populations of runners? A systematic review and meta-analysis. *Sports Medicine*, *45*(8), 1143-1161. DOI: 10.1007/s40279-015-0331-x.

Knapik, J. J., Orr, R., Pope, R., & Grier, T. (2016). Injuries and footwear (Part 2): minimalist running shoes. *Journal of Special Operations Medicine*, *16*(1), 89-96.

Koblbauer, I. F., van Schooten, K. S., Verhagen, E. A., & van Dieën, J. H. (2014). Kinematic changes during running-induced fatigue and relations with core endurance in novice runners. *Journal of Science and Medicine in Sport*, *17*(4), 419-424. DOI: 10.1016/j.jsams.2013.05.013.

Köse, A., Cereatti, A., & Della Croce, U. (2012). Bilateral step length estimation using a single inertial measurement unit attached to the pelvis. *Journal of NeuroEngineering and Rehabilitation*, *9*, 9. DOI: 10.1186/1743-0003-9-9.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Lebel, K., Boissy, P., Hamel, M., & Duval, C. (2013). Inertial measures of motion for clinical biomechanics: comparative assessment of accuracy under controlled conditions - effect of velocity. *PLOS ONE*, *8*(11), e79945. DOI: 10.1371/journal.pone.0079945.

Lebel, K., Boissy, P., Hamel, M., & Duval, C. (2015). Inertial measures of motion for clinical biomechanics: comparative assessment of accuracy under controlled conditions - changes in accuracy over time. *PLOS ONE*, *10*(3), e0118361. DOI: 10.1371/journal.pone.0118361.

Lebel, K., Boissy, P., Nguyen, H., & Duval, C. (2016). Autonomous Quality Control of Joint Orientation Measured with Inertial Sensors. *Sensors*, *16*(7), E1037. DOI: 10.3390/s16071037.

Lebel, K., Boissy, P., Nguyen, H., & Duval, C. (2017). Inertial measurement systems for segments and joints kinematics assessment: towards an understanding of the variations in sensors accuracy. *BioMedical Engineering OnLine*, *16*(1), 56. DOI: 10.1186/s12938-017-0347-6.

Lebel, K., Hamel, M., Duval, C., Nguyen, H., & Boissy, P. (2018). Camera pose estimation to improve accuracy and reliability of joint angles assessed with attitude and heading reference systems. *Gait & posture*, *59*, 199-205. DOI: 10.1016/j.gaitpost.2017.10.016.

Lee, J. B., Mellifont, R. B., Burkett, B. J. (2010). The use of a single inertial sensor to identify stride, step, and stance durations of running gait. *Journal of Science and Medicine in Sport*, *13*(2), 270-273. DOI: 10.1016/j.jsams.2009.01.005.

Leitch, J., Stebbins, J., Paolini, G., & Zavatsky, A. B. (2011). Identifying gait events without a force plate during running: a comparison of methods. *Gait & Posture*, *33*(1), 130-132. DOI: 10.1016/j.gaitpost.2010.06.009.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Lenhart, R., Thelen, D., & Heiderscheit, B. (2014). Hip muscle loads during running at various step rates. *Journal of Orthopaedic & Sports Physical Therapy*, *44*(10), 766-774. DOI: 10.2519/jospt.2014.5575.

Li, Q., Young, M., Naing, V., & Donelan, J. M. (2010). Walking speed estimation using a shank-mounted inertial measurement unit. *Journal of Biomechanics*, *43*(8), 1640-1643. DOI: 10.1016/j.jbiomech.2010.01.031.

Lieberman, D. E., Venkadesan, M., Werbel, W. A., Daoud, A. I., D'andrea, S., Davis, I. S., ... & Pitsiladis, Y. (2010). Foot strike patterns and collision forces in habitually barefoot versus shod runners. *Nature*, *463*(7280), 531-535. DOI: 10.1038/nature08723.

Lilley, T., Herb, C. C., Hart, J., & Hertel, J. (2018). Lower extremity joint coupling variability during gait in young adults with and without chronic ankle instability. *Sports Biomechanics*, *17*(2), 261-272. DOI: 10.1080/14763141.2017.1287215.

Lindsay, T. R., Noakes, T. D., & McGregor, S. J. (2014). Effect of treadmill versus overground running on the structure of variability of stride timing. *Perceptual and Motor Skills*, *118*(2), 332-346. DOI: 10.2466/30.26.PMS.118k18w8.

Lipsitz, L. A. (2002). Dynamics of stability: the physiologic basis of functional health and frailty. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *57*(3), B115-B125.

Liu, K., Liu, T., Shibata, K., Inoue, Y., & Zheng, R. (2009). Novel approach to ambulatory assessment of human segmental orientation on a wearable sensor system. *Journal of Biomechanics*, *42*(16), 2747-2752. DOI: 10.1016/j.jbiomech.2009.08.008.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Lopes, A. D., Hespanhol, L. C., Yeung, S. S., & Costa, L. O. P. (2012). What are the main running-related musculoskeletal injuries? A systematic review. *Sports Medicine*, *42*(10), 891-905. DOI: 10.2165/11631170-000000000-00000.

Lucas-Cuevas, A. G., Encarnación-Martínez, A., Camacho-García, A., Llana-Belloch, S., & Pérez-Soriano, P. (2017). The location of the tibial accelerometer does influence impact acceleration parameters during running. *Journal of Sports Science*, *35*(17), 1734-1738. DOI: 10.1080/02640414.2016.1235792.

Maas, E., De Bie, J., Vanfleteren, R., Hoogkamer, W., & Vanwanseele, B. (2017). Novice runners show greater changes in kinematics with fatigue compared with competitive runners. *Sports Biomechanics*, *July 21*, 1-11. DOI: 10.1080/14763141.2017.1347193.

Mann, R., Malisoux, L., Nührenbörger, C., Urhausen, A., Meijer, K., & Theisen, D. (2015a). Association of previous injury and speed with running style and stride-to-stride fluctuations. *Scandinavian Journal of Medicine & Science in Sports*, *25*(6), e638-645. DOI: 10.1111/sms.12397.

Mann, R., Malisoux, L., Urhausen, A., Statham, A., Meijer, K., & Theisen, D. (2015b). The effect of shoe type and fatigue on strike index and spatiotemporal parameters of running. *Gait & Posture*, *42*(1), 91-95. DOI: 10.1016/j.gaitpost.2015.04.013.

Mansfield, A., & Lyons, G. M. (2003). The use of accelerometry to detect heel contact events for use as a sensor in FES assisted walking. *Medical Engineering & Physics*, *25*(10), 879-885.

Masci, I., Vannozzi, G., Bergamini, E., Pesce, C., Getchell, N., & Cappozzo, A. (2013). Assessing locomotor skills development in childhood using wearable inertial sensor devices: the running paradigm. *Gait & Posture*, *37*(4), 570-574. DOI: 10.1016/j.gaitpost.2012.09.017.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Malisoux, L., Delattre, N., Urhausen, A., & Theisen, D. (2017). Shoe cushioning, body mass and running biomechanics as risk factors for running injury: a study protocol for a randomised controlled trial. *BMJ Open*, *7*(8), e017379.

Mayagoitia, R. E., Nene, A. V., & Veltink, P. H. (2002). Accelerometer and rate gyroscope measurement of kinematics: an inexpensive alternative to optical motion analysis systems. *Journal of Biomechanics*, *35*(4), 537-542.

McCamley, J., Donati, M., Grimpampi, E., & Mazzà, C. (2012). An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data. *Gait & Posture*, *36*(2):316-8. DOI: 10.1016/j.gaitpost.2012.02.019.

McClay, I., & Manal, K. (1997). Coupling parameters in runners with normal and excessive pronation. *Journal of Applied Biomechanics*, *13*(1), 109-124.

McGrath, D., Greene, B. R., O'Donovan, K. J., & Caulfield, B. (2012). Gyroscope-based assessment of temporal gait parameters during treadmill walking and running. *Sports Engineering*, *15*(4), 207-213.

McGrath, D., Patterson, M., Persson, U. M., & Caulfield, B. (2017). Frontal-plane variability in foot orientation during fatiguing running exercise in individuals with chronic ankle instability. *Journal of Athletic Training*, *52*(11), 1019-1027. DOI: 10.4085/1062-6050-52.11.20.

Meardon, S. A., Hamill, J., & Derrick, T. R. (2011). Running injury and stride time variability over a prolonged run. *Gait & Posture*, *33*(1), 36-40. DOI: 10.1016/j.gaitpost.2010.09.020.

Mercer, J. A., Bates, B. T., Dufek, J. S., & Hreljac, A. (2003). Characteristics of shock attenuation during fatigued running. *Journal of Sports Science*, *21*(11), 911-919. DOI: 10.1080/0264041031000140383.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Mercer, J. A., Dufek, J. S., Mangus, B. C., Rubley, M. D., Bhanot, K., & Aldridge, J. M. (2010). A description of shock attenuation for children running. *Journal of Athletic Training*, *45*(3), 259-264. DOI: 10.4085/1062-6050-45.3.259.

Miller, R. H., Meardon, S. A., Derrick, T. R., & Gillette, J. C. (2008). Continuous relative phase variability during an exhaustive run in runners with a history of iliotibial band syndrome. *Journal of Applied Biomechanics*, *24*(3), 262-270.

Mizrahi, J., Verbitsky, O., & Isakov, E. (2000). Fatigue-related loading imbalance on the shank in running: a possible factor in stress fractures. *Annals of Biomedical Engineering*, *28*, 463-469.

Mizrahi, J., Verbitsky, O., & Isakov, E. (2001). Fatigue-induced changes in decline running. *Clinical Biomechanics*, *16*(3), 207-212.

Muro-de-la-Herran, A., Garcia-Zapirain, B., & Mendez-Zorrilla, A. (2014). Gait analysis methods: an overview of wearable and non-wearable systems, highlighting clinical applications. *Sensors*, *14*(2), 3362-3394. DOI: 10.3390/s140203362.

Nakayama, Y., Kudo, K., & Ohtsuki, T. (2010). Variability and fluctuation in running gait cycle of trained runners and non-runners. *Gait & Posture*, *31*(3), 331-335. DOI: 10.1016/j.gaitpost.2009.12.003.

Newell, K. M., & Corcos, D. M. (1993). Variability and motor control. Champaign, IL: Human Kinetics Publishers.

Newell, K. M., & Vaillancourt, D. E. (2001). Dimensional change in motor learning. *Human Movement Science*, *20*(4-5), 695-715.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Ni, G. X., Liu, S. Y., Lei, L., Li, Z., Zhou, Y. Z., & Zhan, L. Q. (2013). Intensity-dependent effect of treadmill running on knee articular cartilage in a rat model. *BioMed Research International*, *2013*, 172392. DOI: 10.1155/2013/172392.

Nielsen, R. O., Buist, I., Parner, E. T., Nohr, E. A., Sørensen, H., Lind, M., & Rasmussen, S. (2013). Predictors of running-related injuries among 930 novice runners: A 1-year prospective follow-up study. *Orthopaedic Journal of Sports Medicine*, *1*(1), 2325967113487316. DOI: 10.1177/2325967113487316.

Nigg, B. M., de Boer, R. W., & Fisher, V. (1995). A kinematic comparison of overground and treadmill running. *Medicine and Science in Sports and Exercise*, *27*(1), 98-105.

Norris, M., Anderson, R., & Kenny, I. C. (2014). Method analysis of accelerometers and gyroscopes in running gait: a systematic review. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology*, *228*(1), 3-15. DOI: 10.1177/1754337113502472.

Norris, M., Kenny, I., & Anderson, R. (2016). Comparison of accelerometry stride time calculation methods. *Journal of Biomechanics*, *49*(13), 3031-3034. DOI: 10.1016/j.jbiomech.2016.05.029.

Novacheck, T. F. (1998). The biomechanics of running. *Gait & Posture*, *7*(1), 77-95.

Panascì, M., Lepers, R., La Torre, A., Bonato, M., & Assadi, H. (2017). Physiological responses during intermittent running exercise differ between outdoor and treadmill running. *Applied Physiology, Nutrition, and Metabolism*, *42*(9):973-977. DOI: 10.1139/apnm-2017-0132.

Paquette, M. R., Milner, C. E., & Melcher, D. A. (2017). Foot contact angle variability during a prolonged run with relation to injury history and habitual foot strike pattern. *Scandinavian Journal of Medicine & Science in Sports*, *27*(2), 217-222. DOI: 10.1111/sms.12647.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Perry, J., & Burnfield, J. M. (2010). *Gait analysis. Normal and pathological function*. Thorofare, NJ: Slack Incorporated.

Peruzzi, A., Della Croce, U., & Cereatti, A. (2011). Estimation of stride length in level walking using an inertial measurement unit attached to the foot: a validation of the zero velocity assumption during stance. *Journal of Biomechanics*, *44*(10), 1991-1994. DOI: 10.1016/j.jbiomech.2011.04.035.

Picerno, P., Cereatti, A., & Cappozzo, A. (2008). Joint kinematics estimate using wearable inertial and magnetic sensing modules. *Gait & Posture*, *28*(4), 588-595. DOI: 10.1016/j.gaitpost.2008.04.003.

Pribut, S. (2008). The top five running injuries seen in the office. *Podiatry Management*, *27*(4), 117.

Purcell, B., Channells, J., James, D., & Barrett, R. (2006, January). Use of accelerometers for detecting foot-ground contact time during running. In: *BioMEMS and Nanotechnology II* (Vol. 6036, p. 603615). International Society for Optics and Photonics.

Reenalda, J., Maartens, E., Homan, L., & Buurke, J. J. (2016). Continuous three dimensional analysis of running mechanics during a marathon by means of inertial magnetic measurement units to objectify changes in running mechanics. *Journal of Biomechanics*, *49*(14), 3362-3367. DOI: 10.1016/j.jbiomech.2016.08.032.

Riley, P. O., Dicharry, J., Franz, J., Della Croce, U., Wilder, R. P., & Kerrigan, D. C. (2008). A kinematics and kinetic comparison of overground and treadmill running. *Medicine and Science in Sports and Exercise*, *40*(6), 1093-1100. DOI: 10.1249/MSS.0b013e3181677530.

Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2017a). Validation of inertial measurement units with an optoelectronic system for whole-body motion analysis. *Medical*

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

& Biological Engineering & Computing, *55*(4), 609-619. DOI: 10.1007/s11517-016-1537-2.

Robert-Lachaine, X., Mecheri, H., Larue, C., & Plamondon, A. (2017b). Effect of local magnetic field disturbances on inertial measurement units accuracy. *Applied Ergonomics*, *63*, 123-132. DOI: 10.1016/j.apergo.2017.04.011.

Roetenberg, D., Baten, C. T., & Veltink, P. H. (2007). Estimating body segment orientation by applying inertial and magnetic sensing near ferromagnetic materials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *15*(3), 469-471. DOI: 10.1109/TNSRE.2007.903946.

Rueterbories, J., Spaich, E. G., & Andersen, O. K. (2014). Gait event detection for use in FES rehabilitation by radial and tangential foot accelerations. *Medical Engineering & Physics*, *36*(4): 502-508. DOI: 10.1016/j.medengphy.2013.10.004.

Sabatini, A. M., Martelloni, C., Scapellato, S., & Cavallo, F. (2005). Assessment of walking features from foot inertial sensing. *IEEE Transactions on Biomedical Engineering*, *52*(3), 486-494. DOI: 10.1109/TBME.2004.840727.

Sainton, P., Nicol, C., Cabri, J., Barthelemy-Montfort, J., Berton, E., & Chavet, P. (2015). Influence of short-term unweighing and reloading on running kinetics and muscle activity. *European Journal of Applied Physiology*, *115*(5), 1135-1145. DOI: 10.1007/s00421-014-3095-3.

Schache, A. G., Bennell, K. L., Blanch, P. D., & Wrigley, T. V. (1999). The coordinated movement of the lumbo-pelvic-hip complex during running: a literature review. *Gait & Posture*, *10*(1), 30-47.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Scheerder, J., Breedveld, K., & Borgers, J. (2015). Who is doing a run with the running boom? The growth and governance of one of Europe's most popular sport activities. In J. Scheerder, K. Breedveld. & J. Borgers (Eds.), Running across Europe (pp. 1-27). London, UK: Palgrave Macmillan.

Schmidt, R. A. (2013). Motor schema theory after 27 years: reflections and implications for a new theory. *Research Quarterly for Exercise and Sport*, *74*(4), 366-375. DOI: 10.1080/02701367.2003.10609106.

Schmitz, A., Russo, K., Edwards, L., & Noehren, B. (2014). Do novice runners have weak hips and bad running form? *Gait & Posture*, *40*(1), 82-86 DOI: 10.1016/j.gaitpost.2014.02.014.

Schubert, A. G., Kempf, J., & Heiderscheit, B. C. (2014). Influence of stride frequency and length on running mechanics: a systematic review. *Sports Health*, *6*(3), 210-217. DOI: 10.1177/1941738113508544.

Seay, J. F., van Emmerik, R. E. A., & Hamill, J. (2011). Low back pain status affects pelvis-trunk coordination and variability during walking and running. *Clinical Biomechanics*, *26*(6), 572-578. DOI: 10.1016/j.clinbiomech.2010.11.012.

Seay, J. F., Van Emmerik, R. E., & Hamill, J. (2014). Trunk bend and twist coordination is affected by low back pain status during running. *European Journal of Sport Science*, *14*(6), 563-568. DOI: 10.1080/17461391.2013.866167.

Selles, R. W., Formanoy, M. A., Bussmann, J. B., Janssens, P. J., & Stam, H. J. (2005). Automated estimation of initial and terminal contact timing using accelerometers; development and validation in transtibial amputees and controls. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *13*(1), 81-88. DOI: 10.1109/TNSRE.2004.843176.

The Education University of Hong Kong Library
For private study or research only.
Not for publication or further reproduction.

Sheehan, F. T., & Mitiguy, P. (1999). In regards to the "ISB recommendations for standardization in the reporting of kinematic data". *Journal of Biomechanics*, *32*(10), 1135-1136.

Shipway, R., & Holloway, I. (2016). Health and the running body: Notes from an ethnography. *International Review for the Sociology of Sport*, *51*(1), 78-96.

Simon, J., Doederlein, L., McIntosh, A. S., Metaxiotis, D., Bock, H. G., & Wolf, S. I. (2006). The Heidelberg foot measurement method: development, description and assessment. *Gait & Posture*, *23*(4), 411-424. DOI: 10.1016/j.gaitpost.2005.07.003.

Sinclair, J., Hebron, J., & Taylor, P. J. (2014). The influence of tester experience on the reliability of 3D kinematic information during running. *Gait & Posture*, *40*(4), 707-711.

Slawinski, J., & Billat, V. L. (2004). Difference in mechanical and energy cost between highly, well, and nontrained runners. *Medicine and Science in Sports and Exercise*, *36*(8), 1440-1446.

Smith, S. L. (1998). Athletes, runners, and joggers: Participant-group dynamics in a sport of "individuals". Sociology of Sport Journal, 15(2), 174-192. DOI: 10.1123/ssj.15.2.174.

Soligard, T., Schwellnus, M., Alonso, J. M., Bahr, R., Clarsen, B., Dijkstra, H. P., ... & Van Rensburg, C. J. (2016). How much is too much? (Part 1) International Olympic Committee consensus statement on load in sport and risk of injury. *British Journal of Sports Medicine*, *50*(17), 1030-1041. DOI: 10.1136/bjsports-2016-096581.

Stergiou, N., Bates, B. T., & James, S. L. (1999). Asynchrony between subtalar and knee joint function during running. *Medicine and Science in Sports and Exercise*, *31*(11), 1645-1655.

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Stergiou, N., Harbourne, R., & Cavanaugh, J. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *Journal of Neurologic Physical Therapy*, *30*(3):120-129.

Stergiou, N., & Decker, L. M. (2011). Human movement variability, nonlinear dynamics, and pathology: is there a connection? *Human Movement Science*, *30*(5), 869-888. DOI: 10.1016/j.humov.2011.06.002.

Storm, F. A., Buckley, C. J., & Mazzà, C. (2016). Gait event detection in laboratory and real life settings: accuracy of ankle and waist sensor based methods. *Gait & Posture*, *50*, 42-46. DOI: 10.1016/j.gaitpost.2016.08.012.

Strohrmann, C., Harms, H., Kappeler-Setz, C., & Tröster, G. (2012). Monitoring kinematic changes with fatigue in running using body-worn sensors. *IEEE Transaction on Information Technology in Biomedicine*, *16*(5), 983-990. DOI: 10.1109/TITB.2012.2201950.

Strohrmann, C., Rossi, M., Arnrich, B., & Troster, G. (2012b, May). A data-driven approach to kinematic analysis in running using wearable technology. In: *2012 Ninth International Conference on Wearable and Implantable Body Sensor Networks* (pp. 118-123). IEEE. DOI: 10.1109/BSN.2012.1.

Takeda, R., Tadano, S., Natorigawa, A., Todoh, M., & Yoshinari, S. (2009). Gait posture estimation using wearable acceleration and gyro sensors. *Journal of Biomechanics*, *42*(15), 2486-2494. DOI: 10.1016/j.jbiomech.2009.07.016.

Tao, W., Liu, T., Zheng, R., & Feng, H. (2012). Gait analysis using wearable sensors. *Sensors*, *12*(2), 2255-2283. DOI: 10.3390/s120202255.

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For private study or research only.
Not for publication or further reproduction.

TarniȚă, D. (2016). Wearable sensors used for human gait analysis. *Romanian Journal of Morphology and Embryology*, *57*(2):373-82.

Tessutti, V., Ribeiro, A. P., Trombini-Souza, F., Sacco, I. C. (2012). Attenuation of foot pressure during running on four different surfaces: asphalt, concrete, rubber, and natural grass. *Journal of Sports Science*, *30*(14), 1545-1550. DOI: 10.1080/02640414.2012.713975.

Thomson, A., Einarsson, E., Witvrouw, E., & Whiteley, R. (2017). Running speed increases plantar load more than per cent body weight on an AlterG® treadmill. *Journal of Sports Sciences*, *35*(3), 277-282. DOI: 10.1080/02640414.2016.1163401.

Trojaniello, D., Cereatti, A., & Croce, U. D. (2014). Accuracy, sensitivity and robustness of five different methods for the estimation of gait temporal parameters using a single inertial sensor mounted on the lower trunk. *Gait & Posture*, *40*(4), 487-492. DOI: 10.1016/j.gaitpost.2014.07.007.

Trojaniello, D., Ravaschio, A., Hausdorff, J. M., & Cereatti, A. (2015). Comparative assessment of different methods for the estimation of gait temporal parameters using a single inertial sensor: application to elderly, post-stroke, Parkinson's disease and Huntington's disease subjects. *Gait & Posture*, *42*(3), 310-316. DOI: 10.1016/j.gaitpost.2015.06.008.

Tschopp, M., & Brunner, F. (2017). Diseases and overuse injuries of the lower extremities in long distance runners. *Zeitschrift fur Rheumatologie*, *76*(5), 443-450. DOI: 10.1007/s00393-017-0276-6.

van der Worp, H., Vrielink, J. W., & Bredeweg, S. W. (2016). Do runners who suffer injuries have higher vertical ground reaction forces than those who remain injury-free? A systematic review and meta-analysis. *British Journal of Sports Medicine*, *50*(8):450-7. DOI: 10.1136/bjsports-2015-094924.

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van Emmerik, R. E. A., Rosenstein, M. T., McDermott, W. J., & Hamill, J. (2004). A nonlinear dynamics approach to human movement. *Journal of Applied Biomechanics*, *20*(4), 396-420.

van Gent, B. R., Siem, D. D., van Middelkoop, M., van Os, T. A., Bierma-Zeinstra, S. S., & Koes, B. B. (2007). Incidence and determinants of lower extremity running injuries in long distance runners: a systematic review. *British Journal of Sports Medicine*, *41*(1), 469-480. DOI: 10.1136/bjsm.2006.033548.

van Sint Jan, S. (2007). Color atlas of skeletal landmark definitions: guidelines for reproducible manual and virtual palpations. Belgium: Churchill Livingstone.

Wang, L., Hong, Y., Li, J. X., & Zhou, J. H. (2012). Comparison of plantar loads during running on different overground surfaces. *Research in Sports Medicine*, *20*(2), 75-85. DOI: 10.1080/15438627.2012.660816.

Wank, V., Frick, U., & Schmidtbleicher, D. (1998). Kinematics and electromyography of lower limb muscles in overground and treadmill running. *International Journal of Sports Medicine*, *19*(7), 455-461. DOI: 10.1055/s-2007-971944.

Warne, J. P., Kilduff, S. M., Gregan, B. C., Nevill, A. M., Moran, K. A., & Warrington, G. D. (2014). A 4-week instructed minimalist running transition and gait-retraining changes plantar pressure and force. *Scandinavian Journal of Medicine & Science in Sports*, *24*(6), 964-973. DOI: 10.1111/sms.12121.

Wasserman, K., Whipp, B. J., Koyal, S. N., & Beaver, W. L. (1973). Anaerobic threshold and respiratory gas exchange during exercise. *Journal of Applied Physiology*, *35*(2), 236-243. DOI: 10.1152/jappl.1973.35.2.236.

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Not for publication or further reproduction.

Watari, R., Hettinga, B., Osis, S., & Ferber, R. (2016). Validation of a torso-mounted accelerometer for measures of vertical oscillation and ground contact time during treadmill running. *Journal of Applied Biomechanics*, *32*(3), 306-310. DOI: 10.1123/jab.2015-0200.

Wheat, J. S. (2005). The measurement of variability in coordination during locomotion (Unpublished Doctoral dissertation). Sheffield Hallam University, UK.

Willemsen, A. T., Bloemhof, F., & Boom, H. B. (1990a). Automatic stance-swing phase detection from accelerometer data for peroneal nerve stimulation. *IEEE Transactions on Biomedical Engineering*, *37*(12):1201-8. DOI: 10.1109/10.64463.

Willemsen, A. T., van Alste, J. A., & Boom, H. B. (1990b). Real-time gait assessment utilizing a new way of accelerometry. *Journal of Biomechanics*, *23*(8), 859-863.

Willson, J. D., Sharpee, R., Meardon, S. A., & Kernozek, T. W. (2014). Effects of step length on patellofemoral joint stress in female runners with and without patellofemoral pain. *Clinical Biomechanics*, *29*(3), 243-247. DOI: 10.1016/j.clinbiomech.2013.12.016.

Willson, J. D., Ratcliff, O. M., Meardon, S. A., & Willy, R. W. (2015). Influence of step length and landing pattern on patellofemoral joint kinetics during running. *Scandinavian Journal of Medicine & Science in Sports*, *25*(6), 736-743. DOI: 10.1111/sms.12383.

Willy, R. W., & Davis, I. S. (2014). Kinematic and kinetic comparison of running in standard and minimalist shoes. *Medicine and Science in Sports and Exercise*, *46*(2):318-23. DOI: 10.1249/MSS.0b013e3182a595d2.

Willy, R. W., Halsey, L., Hayek, A., Johnson, H., & Willson, J. D. (2016). Patellofemoral joint and Achilles tendon loads during overground and treadmill running. *Journal of Orthopaedic & Sports Physical Therapy*, *46*(8), 664-672. DOI: 10.2519/jospt.2016.6494.

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Winter, S., Gordon, S., & Watt, K. (2017). Effects of fatigue on kinematics and kinetics during overground running: a systematic review. *The Journal of Sports Medicine and Physical Fitness*, *57*(6), 887-899. DOI: 10.23736/S0022-4707.16.06339-8.

Wixted, A. J., Thiel, D. V., Hahn, A. G., Gore, C. J., Pyne, D. B., & James, D. A. (2007). Measurement of energy expenditure in elite athletes using MEMS-based triaxial accelerometers. *IEEE Sensors Journal*, 7(4), 481-488.

Wu, G., & Cavanagh, P. R. (1995). ISB recommendations for standardization in the reporting of kinematic data. *Journal of Biomechanics*, *28*(10), 1257-1261.

Wu, G., Siegler, S., Allard, P., Kirtley, C., Leardini, A., …, & Standardization and Terminology Committee of the International Society of Biomechanics. (2002). ISB recommendation on definitions of joint coordinate system of various joints for the reporting of human joint motion--part I: ankle, hip, and spine. International Society of Biomechanics. *Journal of Biomechanics*, *35*(4), 543-548.

Yang, S., Mohr, C., & Li, Q. (2011). Ambulatory running speed estimation using an inertial sensor. *Gait & Posture*, *34*(4), 462-466. DOI: 10.1016/j.gaitpost.2011.06.019.

Yang, S., Laudanski, A., & Li, Q. (2012). Inertial sensors in estimating walking speed and inclination: an evaluation of sensor error models. *Medical & Biological Engineering & Computing*, *50*(4), 383-393. DOI: 10.1007/s11517-012-0887-7.

Zhang, J., Lockhart, T. E., & Soangra, R. (2014). Classifying lower extremity muscle fatigue during walking using machine learning and inertial sensors. *Annals of Biomedical Engineering*, *42*(3), 600-612. DOI: 10.1007/s10439-013-0917-0.

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Zhang, J. T., Novak, A. C., Brouwer, B., & Li, Q. (2013). Concurrent validation of Xsens MVN measurement of lower limb joint angular kinematics. *Physiological Measurement*, *34*(8), N63-N69. DOI: 10.1088/0967-3334/34/8/N63.

Zhang, J. H., McPhail, A. J., An, W. W., Naqvi, W. M., Chan, D. L., Au, I. P., ... & Cheung, R. T. (2017). A new footwear technology to promote non-heelstrike landing and enhance running performance: Fact or fad? *Journal of Sports Sciences*, *35*(15), 1533-1537. DOI: 10.1080/02640414.2016.1224915.

Zijlstra, W., & Hof, A. L. (2003). Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. *Gait & Posture*, *18*(2), 1-10.

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Appendices

Appendix A	Submissions and Publications Arising from and Related to the Thesis
Appendix B	Ethical Approval
Appendix C	Consent Form
Appendix D	Information Sheet
Appendix E	PAR-Q & YOU
Appendix F	General & Medical History Questionnaire
Appendix G	Borg's RPE Scale Instructions
Appendix H	Raw Data of Chapter 3
Appendix I	Raw Data of Chapter 4
Appendix J	Raw Data of Chapter 5
Appendix K	Matlab Codes

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Appendix A. Submissions and Publications Arising from and Related to the Thesis

Peer-reviewed journal articles

Mo, S., & Chow, D. H. K. (2018). Accuracy of three methods in gait event detection during overground running. *Gait & Posture*, *59*, 93-98. DOI: 10.1016/j.gaitpost.2017.10.009.

Mo, S., & Chow, D. H. K. (2018). Stride-to-stride variability and complexity between novice and experienced runners during a prolonged run at anaerobic threshold speed. *Gait & Posture*, *64*, 7-11. DOI: 10.1016/j.gaitpost.2018.05.021.

Mo, S., & Chow, D. H. K. Differences in lower limb coordination and coordination variability between novice and experienced runners during a prolonged treadmill run at anaerobic threshold speed. (*Journal of Sports Science*, under review)

Peer-reviewed conference publications:

Mo, S. (2016). Evaluation of landing consistency in distance running. *International Postgraduate Roundtable and Research Forum cum Summer School 2016*. Hong Kong, 1st–5th July 2016.

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Mo, S., & Chow, D. H. K. (2016). The pattern of impact acceleration during distance running. *5th HKASMSS Student Conference on Sports Medicine, Rehabilitation and Exercise Science 2016—Health and Life Quality Enhancement through Application of Science*. Hong Kong, 26th November 2016.

Mo, S., & Chow, D. H. K. (2017). Evaluation of the accuracy of gait events detected using three different methods during running. *35th International Society of Biomechanics in Sports Conference*. Cologne, Germany, 14th–18th June 2017.

Mo, S., & Chow, D. H. K. (2017). Effect of running experiences on the characteristics of stride time series during treadmill running. *The 8th WACBE World Congress on Bioengineering*. Hong Kong, 30th July–2nd August 2017.

莫仕围.（2018）. 不同经验跑者长时间无氧阈速度跑时下肢动作协调性及协调变异性的差异. *第 12 届全国生物力学大会*，西安，中国，2018 年 8 月 17–21 日.

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Appendix B. Ethical Approval

香港教育大學
The Education University of Hong Kong

29 July 2016

Mr MO Shiwei
Doctor of Philosophy Programme
Graduate School

Dear Mr Mo,

Application for Ethical Review <Ref. no. 2015-2016-0346>

I am pleased to inform you that approval has been given by the Human Research Ethics Committee (HREC) for your research project:

Project title: Evaluation of Landing Consistency in Distance Running

Ethical approval is granted for the project period from 1 August 2016 to 1 August 2018. If a project extension is applied for lasting more than 3 months, HREC should be contacted with information regarding the nature of and the reason for the extension. If any substantial changes have been made to the project, a new HREC application will be required.

Please note that you are responsible for informing the HREC in advance of any proposed substantive changes to the research proposal or procedures which may affect the validity of this ethical approval. You will receive separate notification should a fresh approval be required.

Thank you for your kind attention and we wish you well with your research.

Yours sincerely,

Connie Fung (Ms)
Secretary
Human Research Ethics Committee

c.c. Professor WANG Wen Chung, Chairperson, Human Research Ethics Committee

香港新界大埔露屏路十號
10 Lo Ping Road, Tai Po, New Territories, Hong Kong
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Appendix C. Consent Form (English Version)

THE EDUCATION UNIVERSITY OF HONG KONG

Department of Health and Physical Education

INFORMED CONSENT TO PARTICIPATE IN HUMAN RESEARCH

<Evaluation of Landing Consistency in Distance Running>

I ____________________ hereby consent to participate in the captioned research supervised by Prof. Daniel H. K. CHOW, Dr. Feng Hua SUN, Dr. Peggy P. Y. CHEUNG and conducted by Mr. Shiwei MO.

I understand that information obtained from this research may be used in future research and may be published. However, my right to privacy will be retained, i.e., my personal details will not be revealed.

The procedure as set out in the **attached** information sheet has been fully explained. I understand the benefits and risks involved. My participation in the project is voluntary.

I acknowledge that I have the right to question any part of the procedure and can withdraw at any time without negative consequences.

Name of participant ____________________

Signature of participant ____________________

Date ____________________

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Consent Form (Chinese Version)

香港教育大學

健康與體育學系

知情同意書

<Evaluation of Landing Consistency in Distance Running>

本人___________________同意參加由周鴻奇教授負責監督，莫仕圍負責執行的研究項目。

本人理解此研究所獲得的資料可用於未來的研究和學術發表。然而，本人有權保護自己的隱私，本人的個人資料將不能洩漏。

本人對所附資料的有關步驟已經得到充分的解釋。本人理解可能會出現的風險。

本人是自願參與這項研究。

本人理解我有權在研究過程中提出問題，並在任何時候決定退出研究，更不會因此引致任何不良後果。

參加者姓名: ____________________

參加者簽名: ____________________

日期: ____________________

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Appendix D. Information Sheet

THE EDUCATION UNIVERSITY OF HONG KONG
Department of Health and Physical Education
INFORMED CONSENT TO PARTICIPATE IN HUMAN RESEARCH
<FOR PARTICIPANTS>

You are invited to participate in a research project supervised by Professor Daniel H. K. CHOW, Dr. Feng Hua SUN, Dr. Peggy P. Y. CHEUNG, and conducted by Mr. Shiwei MO, who are staff/postgraduate students of the Department of Health and Physical Education at The Education University of Hong Kong.

Title of Project: Evaluation of Landing Consistency in Distance Running

I. Objective

The objective of this project is to improve our knowledge in running-related injuries prevention among distance runners. This study will (a) compare the accuracy of different inertial measurement unit (IMU) methods for gait events predication during overground running, (b) investigate the effect of running experience on landing consistency in distance running, (c) study the effect of fatigue on landing consistency in distance running and (d) study the interaction effect of running experience and fatigue on landing consistency in distance running. The participants will help us obtain data to address three primary concerns: (a) the most accurate IMU method for gait events prediction during overground running; (b) whether the runners maintain consistent landing pattern during distance running, and (c) whether the running experience affects landing consistency during distance running.

II. Procedures

This study contains two parts. The first part is a project introduction (~ 0.5 h). You will familiarise yourself with measurement setups and experimental protocols. You will also be required to respond to questionnaires. The second part is data collection, which involves three different experiments (an indoor 10-m overground run and a 31-min treadmill run at anaerobic threshold speed) and are each expected to last for approximately 1.5 hours. You will be expected to finish one of them. For the treadmill running, a drop of blood from the index finger will be used for each test to measure blood lactate accumulation before and after the running test.

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III. Risk and Benefits

The risks of this study are considered minimal. You may experience fatigue accompanied by minor muscle weakness because you will be asked to run 31 min at your anaerobic threshold speed. The required running test is similar to those that might be performed during your daily running training. In additional, these types of tests have been used previously by other researchers and no injury incidents were reported. The whole testing procedure is safe and you can stop immediately whenever you feel any discomfort during the running test. A health professional will provide first aid and you can seek support and advice whenever you require it during the experiment.

Although there are no direct benefits promised to the participant, your participation will help improve research regarding the prevention of running-related injuries.

IV. Extent of Anonymity and Confidentiality

Your personal information and identify will be kept confidential. A unique testing code will be assigned to you, and all data, questionnaire responses, and experiment check sheets will be identified using only this testing code. Your name and any personal information you provide will never be connected with your unique data set. All individual information will be collected in a file and locked when not being used. Only the investigators have access to the data. All the collected data will be locked in the supervisor's (Prof. Daniel CHOW) office with a lock and key, and kept for 3 years after the research project is finished.

It is possible that the Human Research Ethics Committee may view this study's collected data for auditing purposes. The Human Research Ethics Committee is responsible for the oversight of the protection of human subjects involved in research.

V. Informed Consent

You will receive two copies of this informed consent document. One will be signed and kept on file with the research team, and the second is for your records.

VI. Compensation

You will be compensated for your participation at a rate of HK$50 per hour. Compensation will be limited to time spent in the testing session (e.g., you will not be compensated for your training course, or your travel to or from the study). Your total payment will vary, depending on the length of time for your testing, and portions of an hour will be compensated by rounding up to the nearest half hour.

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VII. Freedom to Withdraw

You are free to withdraw from this study at any time without giving a reason, and there will be no penalty for doing so. If you choose to withdraw, you will be compensated for the testing time you have already completed. Furthermore, you are free not to answer any questions or to choose not to respond to experimental situations without penalty. There may be circumstance under which the investigator may determine that the experiment should not be continued. In this case, you will be compensated for the portion of the project completed.

VIII. Approval of Research

The Department of Health and Physical Education has approved this research, as well as the Human Research Ethics Committee for Research Involving Human Participants at The Education University of Hong Kong.

IX. Participant's Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities:

i. To read and understand the above instructions.
ii. To answer questions, surveys, etc. honestly and to the best of my ability.
iii. Be aware that I am free to ask questions or end my participation at any point in time.

X. Participant's Permission

I have read and understand the informed consent and conditions of this research project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent for participation in this project.

If I participate, I reserve the right to withdraw at any time without negative consequences. I agree to fulfil the responsibilities, noted above, to the best of my ability, or to inform the investigators if I am unable to do so.

Thank you for your interest in participating in this study.

Prof. Daniel H.K. CHOW

Principal Investigator

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Appendix E. PAR-Q & YOU

Physical Activity Readiness
Questionnaire - PAR-Q
(revised 2002)

PAR-Q & YOU

(A Questionnaire for People Aged 15 to 69)

Regular physical activity is fun and healthy, and increasingly more people are starting to become more active each day. Being more active is very safe for most people. However, some people should check with their doctor before they start becoming much more physically active.

If you are planning to become much more physically active than you are now, start by answering the seven questions in the box below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and you are not used to being very active, check with your doctor.

Common sense is your best guide when you answer these questions. Please read the questions carefully and answer each one honestly: check YES or NO.

YES	NO	
☐	☐	**1. Has your doctor ever said that you have a heart condition and that you should only do physical activity recommended by a doctor?**
☐	☐	**2. Do you feel pain in your chest when you do physical activity?**
☐	☐	**3. In the past month, have you had chest pain when you were not doing physical activity?**
☐	☐	**4. Do you lose your balance because of dizziness or do you ever lose consciousness?**
☐	☐	**5. Do you have a bone or joint problem (for example, back, knee or hip) that could be made worse by a change in your physical activity?**
☐	☐	**6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition?**
☐	☐	**7. Do you know of any other reason why you should not do physical activity?**

If you answered

YES to one or more questions

Talk with your doctor by phone or in person BEFORE you start becoming much more physically active or BEFORE you have a fitness appraisal. Tell your doctor about the PAR-Q and which questions you answered YES.

- You may be able to do any activity you want - as long as you start slowly and build up gradually. Or, you may need to restrict your activities to those which are safer for you. Talk with your doctor about the kinds of activities you wish to participate in and follow his/her advice.
- Find out which community programs are safe and helpful for you.

NO to one or more questions

If you answered NO honestly to all PAR-Q questions, you can be reasonably sure that you can:

- start becoming much more physically active - begin slowly and build up gradually. This is the safest and easiest way to go.
- take part in a fitness appraisal - this is an excellent way to determine your basic fitness so that you can plan the best way for you to live actively. It is also highly recommended that you have your blood pressure evaluated. If your reading is 144/94, talk with your doctor before you start becoming much more physically active.

DELAY BECOMING MUCH MORE ACTIVE:

- If you are not feeling well because of a temporary illness such as a cold or a fever - wait until you feel better; or
- If you are or may be pregnant - talk to your doctor before you start becoming more active.

PLEASE NOTE: If your health changes so that you then answer YES to any of the above questions, tell your fitness or health professional. Ask whether you should change your physical activity plan.

Informed Use of the PAR-Q: The Canadian Society for Exercise Physiology, Health Canada and their agents assume no liability for persons who undertake physical activity, and if in doubt after completing this questionnaire, consult your doctor prior to physical activity.

No changes permitted. You are encouraged to photocopy the PAR-Q but only if you use the entire form.

NOTE: If the PAR-Q is being given to a person before he or she participates in a physical activity program or a fitness appraisal, this section may be used for legal or administrative purposes.

"I have read, understood and completed this questionnaire. Any questions I had were answered to my full satisfaction."

NAME:

SIGNATURE: **DATE:**

SIGNATURE OF PARENT: **WITNESS:**

or GUARDIAN (participants under the age of majority)

Note: This physical activity clearance is valid for a maximum of 12 months from the date it is completed and becomes invalid if your condition changes so that you would answer YES to any of the seven questions.

CSEP SCPE © Canadian Society for Exercise Physiology Supported by: Health Canada Santé Canada

With regard to the provisions of the Privacy Act, I hereby give my permission for HSG Health Systems Group Limited to collect any personal information contained in this document, maintain personal information already on file and to collect further information for the purpose of contacting me by mail, fax, telephone and/or email.

NAME: **DATE:**

SIGNATURE:

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Appendix F. General & Medical History Questionnaire

PART I. Data Collection Sheet

Date: ______D______M______Y

Testing Code:________________.

Gender	
Age (Month/Year)	
Height (cm)	
Body Weight (kg)	
Dominate Side (Right/Left)	
Right Lower Limb Length (cm)	
Left Lower Limb Length (cm)	
Marks:	

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PART II: General Questions

Do you partake running regularly? (if yes, please fill the following table)	Yes [ ]	No [ ]
Running Experience		
How many years/months?		
Months Run of Last One Year		
Do you partake running regularly during last one year? (If yes, please answer)	Yes [ ]	No [ ]
1. How many times per week?		
2. How long per time?		
Best Record		
Do you partake any distance running race?	Yes [ ]	No [ ]
5 K		
10 K		
½ marathon		
marathon		
others (please list)		

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PART III: Medical Questions

Have you ever experienced a running related injuries?	Yes [ ]	No [ ]
Are you currently experiencing pain or have chronic pain in		
Either ankle?	Yes [ ]	No [ ]
Either knee?	Yes [ ]	No [ ]
Either hip?	Yes [ ]	No [ ]
Back?	Yes [ ]	No [ ]
Others (please list)	Yes [ ]	No [ ]
Do you have surgery on any joints of the lower limb?	Yes [ ]	No [ ]
Have you ever been diagnosed with neuropathy?	Yes [ ]	No [ ]
Have you been diagnosed with a vestibular or balance disorder?	Yes [ ]	No [ ]
Are you taking any medications that interfere with balance?	Yes [ ]	No [ ]
Have you ever been diagnosed any cardiovascular diseases?	Yes [ ]	No [ ]
Others (Please list)		

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Appendix G. Borg's RPE Scale Instructions

Borg's RPE Scale Instructions

While exercising we want you to rate your perception of exertion, i.e., how heavy and strenuous the exercise feels to you. The perception of exertion depends mainly on the strain and fatigue in your muscles and on your feeling of breathlessness or aches in the chest.

Look at this rating scale; we want you to use this scale from 6 to 20, where 6 means "no exertion at all" and 20 means "maximal exertion."

9 corresponds to "very light" exercise. For a normal, healthy person it is like walking slowly at his or her own pace for some minutes.

13 on the scale is "somewhat hard" exercise, but it still feels OK to continue.

17 "very hard" is very strenuous. A healthy person can still go on, but he or she really has to push him- or herself. It feels very heavy, and the person is very tired.

19 on the scale is an extremely strenuous exercise level. For most people this is the most strenuous exercise they have ever experienced.

Try to appraise your feeling of exertion as honestly as possible, without thinking about what the actual physical load is. Don't underestimate it, but don't overestimate it either. It's your own feeling of effort and exertion that's important, not how it compares to other people's. What other people think is not important either. Look at the scale and the expressions and then give a number.

Any questions?

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Appendix H. Raw Data of Chapter 3

Table C3.1. Characteristics of each participant.

Participant	Age (years)	Height (cm)	Body mass (kg)	Jogging speed (km/h)	Running speed (km/h)
1	30	178	66	3.4	4.6
2	24	155	50	2.9	4.0
3	30	165	55	3.0	4.0
4	28	168	58	3.1	4.0
5	23	177	61	3.2	4.2
6	32	159	57	3.0	3.7
7	27	178	62	3.1	4.0
8	20	177	61	3.1	4.3
9	20	168	58	3.1	3.9
10	25	172	67	3.2	4.6
11	22	154	52	2.9	3.7
Mean	**25.5**	**168.3**	**58.8**	**3.1**	**4.1**
SD	**4.2**	**9.1**	**5.3**	**0.1**	**0.3**

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Table C3.2. Relative difference for initial contact prediction during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)	
	Jogging	Running	Jogging	Running	Jogging	Running
1	9.6	0.0	–26.4	–8.0	–1.9	–1.5
2	–6.3	7.2	–43.3	–0.8	–8.3	2.7
3	–4.3	5.3	–45.8	0.8	–6.8	2.8
4	–2.5	16.6	–34.0	–16.0	–6.5	13.6
5	1.6	13.2	–45.4	–16.3	–1.9	11.2
6	–8.2	2.1	–45.7	–14.4	–12.2	1.1
7	–7.0	4.4	–44.5	–12.6	–12.0	1.4
8	–2.2	2.9	–13.7	–31.1	–8.2	–0.1
9	–2.6	2.7	–32.1	–30.8	–8.1	–0.3
10	–5.4	5.2	–38.4	–31.3	–8.4	2.7
11	–1.6	2.3	–49.1	–26.7	–6.6	1.8
Mean	**–2.6**	**5.6**	**–38.0**	**–17.0**	**–7.3**	**3.2**
SD	**4.9**	**5.0**	**10.7**	**11.7**	**3.3**	**4.8**

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Table C3.3. Absolute difference for initial contact prediction during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)	
	Jogging	**Running**	**Jogging**	**Running**	**Jogging**	**Running**
1	9.6	2.0	26.4	8.0	5.6	1.5
2	10.8	7.2	23.3	3.6	6.5	3.3
3	7.5	5.4	15.8	3.0	4.8	2.9
4	12.5	16.6	14.0	16.0	10.5	15.8
5	12.0	13.2	15.4	16.3	12.3	11.2
6	8.2	3.2	25.7	14.4	2.2	1.4
7	7.0	5.5	24.5	10.1	2.0	2.1
8	8.2	3.7	10.1	31.3	3.2	2.5
9	8.1	2.9	12.1	30.8	2.6	1.3
10	8.4	5.2	18.4	31.3	5.4	2.7
11	6.6	3.6	29.1	26.7	2.8	2.0
Mean	**9.0**	**6.2**	**19.5**	**17.4**	**5.2**	**4.2**
SD	**2.0**	**4.6**	**6.5**	**11.0**	**3.4**	**4.7**

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Table C3.4. Relative difference for toe-off prediction during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)	
	Jogging	Running	Jogging	Running	Jogging	Running
1	25.6	4.5	–3.9	–12.0	–54.4	–59.0
2	2.1	–15.3	4.1	–8.8	–16.9	–49.3
3	11.0	–5.1	–3.0	–8.1	–32.0	–34.1
4	–4.9	29.0	–3.9	11.0	–41.4	–36.5
5	–3.2	24.9	–2.7	11.4	–43.6	–36.1
6	10.1	9.4	–3.9	1.4	–31.9	–53.6
7	3.8	8.9	2.8	12.9	–43.2	–49.1
8	18.5	17.0	9.0	0.5	–9.0	–50.5
9	–2.1	13.0	2.4	1.5	–22.1	–49.5
10	5.4	13.7	–0.1	3.7	–29.1	–44.8
11	17.7	2.3	–0.8	2.3	–29.3	–52.7
Mean	**7.7**	**9.3**	**0.0**	**1.4**	**–32.1**	**–46.8**
SD	**9.9**	**12.7**	**4.2**	**8.4**	**13.1**	**8.0**

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Table C3.5. Absolute difference for toe-off prediction during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)	
	Jogging	Running	Jogging	Running	Jogging	Running
1	25.6	6.5	4.8	13.0	34.4	39.0
2	12.0	22.3	7.5	8.8	22.6	28.2
3	14.3	31.1	5.2	11.5	24.8	32.0
4	11.4	32.4	5.0	13.0	21.4	36.5
5	7.1	27.3	2.8	11.4	13.7	31.6
6	13.8	9.4	5.3	5.6	26.8	13.6
7	13.2	17.8	3.3	13.5	40.0	24.4
8	18.5	17.0	9.6	3.7	16.3	20.5
9	13.2	17.2	6.4	5.3	22.1	19.5
10	19.9	24.2	3.2	6.5	29.1	31.8
11	17.7	17.9	2.9	5.1	23.9	26.7
Mean	**15.2**	**20.3**	**5.1**	**8.8**	**25.0**	**27.6**
SD	**5.0**	**8.2**	**2.1**	**3.7**	**7.5**	**7.6**

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Table C3.6. Relative difference for stance time estimation during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)		MS-method (ms)	
	Jogging	Running	Jogging	Running	Jogging	Running	Jogging	Running
1	16.0	4.5	22.5	107.0	–52.5	–57.5	–2.0	–10.5
2	8.4	–22.4	47.4	–7.9	–8.6	–70.9	12.4	–11.4
3	15.2	–10.4	42.7	–8.9	–25.3	–50.4	3.7	–8.9
4	–2.4	12.5	30.1	27.0	–34.9	–50.0	2.6	–2.5
5	–4.8	11.7	42.7	27.7	–41.8	–72.8	–0.8	0.2
6	18.4	7.3	41.9	15.8	–19.6	–54.7	8.4	0.3
7	10.7	4.6	47.2	17.1	–31.3	–56.4	14.7	5.6
8	20.7	13.6	22.7	77.2	–0.8	–51.8	17.2	–0.9
9	0.5	21.3	34.5	43.3	–14.0	–38.2	10.5	12.8
10	10.8	8.4	38.3	35.0	–20.7	–54.5	8.3	1.0
11	19.3	0.0	48.4	29.0	–22.6	–58.5	5.9	0.5
Mean	**10.3**	**4.6**	**38.0**	**32.9**	**–24.7**	**–56.0**	**7.3**	**–1.3**
SD	**8.9**	**12.1**	**9.4**	**34.1**	**14.8**	**9.6**	**6.2**	**7.1**

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Table C3.7. Relative difference for stance time estimation during jogging and running.

Participant	L-method (ms)		M-method (ms)		S-method (ms)		MS-method (ms)	
	Jogging	Running	Jogging	Running	Jogging	Running	Jogging	Running
1	16.9	7.5	22.5	36.0	52.5	27.5	6.4	12.5
2	13.8	24.5	47.4	10.2	20.7	30.9	12.5	11.7
3	16.6	31.4	42.7	11.2	29.6	31.7	7.3	12.1
4	9.6	21.9	30.1	27.0	34.9	50.0	5.1	5.9
5	7.8	16.2	42.7	27.7	41.8	32.8	3.9	4.6
6	21.6	7.3	41.9	17.5	24.9	24.7	8.4	6.7
7	14.5	15.4	47.2	23.6	34.4	26.4	14.7	13.1
8	20.7	15.3	37.6	78.9	15.6	51.8	17.2	7.1
9	12.4	26.1	34.5	43.3	15.0	47.5	10.5	13.8
10	21.5	22.3	38.3	35.0	20.7	24.5	8.3	5.6
11	19.3	17.3	48.4	29.0	32.7	28.5	6.1	3.8
Mean	**15.9**	**18.7**	**39.4**	**30.9**	**29.3**	**34.2**	**9.1**	**8.8**
SD	**4.7**	**7.5**	**8.0**	**18.9**	**11.5**	**10.4**	**4.2**	**3.8**

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Table C3.8. Estimated stance time during jogging and running.

Participant	Reference (s)		L-method (s)		M-method (s)		S-method (s)		MS-method (s)	
	Jogging	Running	Jogging	Running	Jogging	Running	Jogging	Running	Jogging	Running
1	0.245	0.219	0.261	0.224	0.267	0.326	0.192	0.162	0.243	0.208
2	0.259	0.207	0.267	0.185	0.307	0.199	0.251	0.136	0.272	0.196
3	0.254	0.199	0.270	0.189	0.297	0.191	0.229	0.149	0.258	0.191
4	0.232	0.220	0.230	0.232	0.262	0.247	0.198	0.169	0.235	0.217
5	0.246	0.212	0.241	0.224	0.289	0.240	0.205	0.139	0.246	0.213
6	0.250	0.218	0.268	0.225	0.292	0.234	0.230	0.163	0.258	0.219
7	0.255	0.221	0.265	0.226	0.302	0.239	0.223	0.165	0.269	0.227
8	0.263	0.223	0.283	0.237	0.286	0.300	0.262	0.171	0.280	0.223
9	0.268	0.219	0.268	0.240	0.302	0.262	0.254	0.181	0.278	0.232
10	0.249	0.218	0.260	0.226	0.287	0.253	0.228	0.164	0.257	0.219
11	0.258	0.214	0.277	0.213	0.307	0.242	0.236	0.155	0.264	0.214
Mean	**0.252**	**0.215**	**0.263**	**0.220**	**0.291**	**0.248**	**0.228**	**0.159**	**0.260**	**0.214**
SD	**0.010**	**0.007**	**0.015**	**0.018**	**0.015**	**0.039**	**0.023**	**0.014**	**0.014**	**0.012**

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Table C3.9. Percentage difference for stance time estimation during jogging and running.

Participant	L-method (%)		M-method (%)		S-method (%)		MS-method (%)	
	Jogging	Running	Jogging	Running	Jogging	Running	Jogging	Running
1	6.9	3.4	9.3	51.6	21.5	26.3	2.6	5.7
2	5.5	12.1	18.2	5.0	8.2	35.1	4.8	5.7
3	6.6	15.9	16.7	5.7	11.8	26.0	2.9	6.1
4	4.1	9.8	12.9	12.3	15.1	22.8	2.2	2.7
5	3.1	7.6	17.3	13.0	17.1	34.4	1.6	2.2
6	8.6	3.3	16.8	7.9	10.2	25.0	3.4	3.1
7	5.7	6.9	18.6	10.8	13.6	25.7	5.8	5.9
8	7.9	6.9	14.3	35.4	5.9	23.3	6.5	3.2
9	4.8	11.6	12.8	19.6	5.9	21.9	3.9	6.0
10	8.6	10.1	15.3	16.0	8.4	25.2	3.4	2.5
11	7.6	8.1	18.7	13.5	12.8	27.4	2.4	1.8
Mean	**6.3**	**8.7**	**15.6**	**17.3**	**11.9**	**26.6**	**3.6**	**4.1**
SD	**1.8**	**3.7**	**3.0**	**14.1**	**4.8**	**4.3**	**1.5**	**1.8**

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Appendix I. Raw Data of Chapter 4

Table C4.1. Characteristics of each participant of experienced runner group.

Participant	Age (years)	Height (cm)	Body mass (kg)	Body mass index (kg/m^2)	AT speed (km/h)
1	24	172	68	23.1	13
2	37	169	68	23.8	13
3	25	173	61	20.4	13
4	35	178	90	28.4	10
5	23	154	45	19.1	11
6	20	163	56	21.1	11
7	18	167	57	20.4	11
8	24	172	68	23.1	13
9	21	170	56	19.2	13
10	23	177	61	19.5	14
11	21	175	65	21.2	13
12	33	178	72	22.7	14
13	20	174	63	20.8	14
14	21	165	60	22.0	13
15	37	168	61	21.6	14
16	24	173	70	23.4	13
17	18	167	57	20.4	11
Mean	**24.9**	**170.3**	**63.4**	**21.8**	**12.6**
SD	**6.4**	**6.1**	**9.5**	**2.3**	**1.3**

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Table C4.2. Characteristics of each participant of the novice runner group.

Participant	Age (years)	Height (cm)	Body mass (kg)	Body mass index (kg/m^2)	AT speed (km/h)
1	20	174	65	21.5	11
2	21	168	63	22.3	12
3	28	172	60	20.2	11
4	21	185	82	24.0	12
5	24	184	53	15.7	11
6	19	166	57	20.7	11
7	21	174	60	19.9	11
8	28	172	60	20.2	11
9	20	166	65	23.6	10
10	36	157	44	17.7	9
11	28	168	58	20.7	12
12	28	172	60	20.2	11
13	21	185	82	24.0	12
14	19	166	57	20.7	11
15	28	172	60	20.2	11
16	21	177	59	18.8	11
17	21	185	82	24.0	12
Mean	**23.8**	**173.1**	**62.8**	**20.9**	**11.1**
SD	**4.7**	**8.0**	**10.4**	**2.3**	**0.8**

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Table C4.3. Number of strides for experienced runners.

Participant	TI1	TI2	TI3	TI4	TI5	TI6
1	402	401	402	406	405	405
2	428	427	422	421	429	427
3	457	447	446	445	445	454
4	434	436	436	435	435	431
5	436	436	434	436	433	435
6	444	438	429	427	428	429
7	441	447	451	452	453	453
8	479	473	473	470	467	461
9	438	436	437	435	420	421
10	439	443	446	448	447	446
11	464	465	469	467	462	464
12	413	418	417	419	417	417
13	427	425	421	420	421	421
14	440	435	437	435	434	437
15	437	439	435	435	438	441
16	435	433	435	428	430	430
17	427	425	421	428	421	421
Mean	**438**	**437**	**436**	**436**	**434**	**435**
SD	**18**	**17**	**18**	**17**	**16**	**16**

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Table C4.4. Number of strides for novice runners.

Participant	TI1	TI2	TI3	TI4	TI5	TI6
1	422	420	422	426	426	427
2	428	430	430	432	430	427
3	430	427	426	423	421	422
4	404	415	414	413	414	416
5	406	407	409	409	409	404
6	441	434	428	426	427	430
7	432	417	407	404	406	410
8	488	474	468	468	470	472
9	427	420	418	415	412	408
10	436	425	419	418	420	421
11	416	416	414	415	416	417
12	416	422	421	422	421	419
13	473	474	477	478	469	460
14	434	426	426	429	425	429
15	420	416	425	423	421	425
16	421	418	417	417	415	425
17	426	424	422	423	424	426
Mean	**431**	**427**	**426**	**426**	**425**	**426**
SD	**21**	**19**	**19**	**19**	**18**	**17**

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Table C4.5. Stride interval for experienced runners.

Participant	TI1 (s)	TI2 (s)	TI3 (s)	TI4 (s)	TI5 (s)	TI6 (s)
1	0.746	0.749	0.746	0.741	0.739	0.740
2	0.735	0.734	0.745	0.746	0.751	0.756
3	0.655	0.670	0.673	0.674	0.678	0.662
4	0.693	0.689	0.688	0.687	0.690	0.691
5	0.688	0.688	0.691	0.689	0.693	0.691
6	0.674	0.682	0.698	0.702	0.701	0.699
7	0.681	0.671	0.666	0.663	0.663	0.663
8	0.628	0.635	0.633	0.639	0.637	0.651
9	0.685	0.688	0.687	0.688	0.716	0.696
10	0.686	0.677	0.674	0.671	0.672	0.672
11	0.613	0.591	0.607	0.621	0.607	0.608
12	0.744	0.754	0.756	0.754	0.754	0.756
13	0.755	0.759	0.767	0.770	0.767	0.767
14	0.679	0.689	0.685	0.689	0.692	0.684
15	0.687	0.683	0.690	0.690	0.686	0.677
16	0.688	0.693	0.689	0.700	0.695	0.698
17	0.755	0.759	0.767	0.770	0.767	0.767
Mean	**0.694**	**0.695**	**0.698**	**0.700**	**0.700**	**0.699**
SD	**0.04**	**0.05**	**0.05**	**0.04**	**0.04**	**0.04**

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Table C4.6. Stride interval for novice runners.

Participant	TI1 (s)	TI2 (s)	TI3 (s)	TI4 (s)	TI5 (s)	TI6 (s)
1	0.747	0.771	0.767	0.760	0.739	0.739
2	0.703	0.697	0.701	0.694	0.696	0.702
3	0.697	0.699	0.703	0.708	0.711	0.712
4	0.739	0.759	0.762	0.763	0.763	0.756
5	0.742	0.735	0.736	0.734	0.732	0.741
6	0.679	0.688	0.698	0.704	0.702	0.696
7	0.693	0.717	0.733	0.743	0.741	0.732
8	0.609	0.627	0.639	0.644	0.638	0.643
9	0.700	0.712	0.718	0.724	0.725	0.735
10	0.682	0.706	0.713	0.718	0.714	0.713
11	0.722	0.719	0.726	0.723	0.721	0.719
12	0.722	0.712	0.712	0.711	0.712	0.714
13	0.687	0.703	0.704	0.699	0.706	0.701
14	0.713	0.724	0.705	0.709	0.710	0.704
15	0.708	0.717	0.720	0.719	0.721	0.710
16	0.726	0.725	0.747	0.746	0.752	0.755
17	0.754	0.762	0.764	0.763	0.763	0.756
Mean	**0.707**	**0.716**	**0.721**	**0.721**	**0.720**	**0.719**
SD	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**	**0.03**

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Table C4.7. Coefficient of variance of stride interval for experienced runners.

Participant	TI1 (%)	TI2 (%)	TI3 (%)	TI4 (%)	TI5 (%)	TI6 (%)
1	1.16	1.13	1.18	1.41	1.46	1.73
2	1.21	1.09	1.35	1.38	1.48	1.80
3	1.33	1.30	1.18	1.22	1.40	1.35
4	1.13	0.95	0.91	1.00	1.06	1.16
5	1.09	1.15	1.08	1.04	1.15	1.13
6	1.19	1.15	1.34	1.26	1.26	1.37
7	1.15	1.09	1.18	1.11	1.12	1.19
8	1.69	1.86	2.37	2.15	2.61	2.36
9	1.20	1.14	1.06	1.04	2.44	1.61
10	1.70	1.63	1.36	1.18	1.21	1.18
11	2.92	2.34	2.90	3.72	3.10	4.35
12	1.12	0.95	1.02	0.94	1.14	1.19
13	0.93	0.96	0.93	1.08	1.09	1.15
14	1.89	1.36	1.53	1.19	1.24	1.21
15	1.46	1.49	1.63	1.70	1.60	1.66
16	2.05	1.56	1.54	1.53	1.55	1.46
17	1.01	1.06	1.02	1.07	1.15	1.28
Mean	**1.43**	**1.37**	**1.39**	**1.41**	**1.53**	**1.60**
SD	**0.50**	**0.37**	**0.53**	**0.67**	**0.60**	**0.78**

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Table C4.8. Coefficient of variance of stride interval for novice runners.

Participant	TI1 (%)	TI2 (%)	TI3 (%)	TI4 (%)	TI5 (%)	TI6 (%)
1	1.21	1.81	1.81	1.73	1.78	1.54
2	1.29	1.12	1.14	1.46	1.31	1.25
3	1.15	1.44	1.36	1.16	1.17	1.22
4	1.69	1.55	1.57	1.30	1.43	1.53
5	1.66	1.20	1.16	1.16	0.97	1.16
6	1.13	1.10	1.23	1.60	1.18	1.07
7	1.85	1.59	1.58	1.57	1.49	1.58
8	2.25	1.82	1.61	2.04	1.71	1.86
9	1.04	1.16	1.04	1.06	1.02	0.93
10	1.84	1.44	1.35	1.21	1.12	0.97
11	1.10	1.21	1.20	1.21	1.20	1.21
12	1.74	1.81	1.63	1.82	1.74	1.67
13	1.58	1.61	2.06	1.96	1.77	1.63
14	1.57	1.62	1.44	1.48	1.43	1.56
15	1.60	1.50	1.56	1.52	1.47	1.75
16	1.50	1.41	1.14	1.04	1.03	0.99
17	1.76	1.54	1.54	1.49	1.55	2.04
Mean	**1.53**	**1.47**	**1.44**	**1.46**	**1.38**	**1.41**
SD	**0.33**	**0.24**	**0.27**	**0.31**	**0.28**	**0.33**

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Table C4.9. Scaling exponent alpha of stride interval for experienced runners.

Participant	TI1	TI2	TI3	TI4	TI5	TI6
1	0.76	0.77	0.73	0.76	0.78	0.85
2	0.86	0.67	0.64	0.53	0.62	0.71
3	0.66	0.70	0.70	0.67	0.86	0.83
4	0.74	0.66	0.61	0.63	0.69	0.64
5	0.74	0.69	0.73	0.70	0.79	0.94
6	0.75	0.69	0.66	0.62	0.76	0.71
7	0.66	0.64	0.65	0.63	0.72	0.74
8	0.85	0.79	0.72	0.74	0.75	0.76
9	0.86	0.77	0.70	0.80	0.92	0.87
10	0.69	0.66	0.64	0.61	0.78	0.69
11	0.77	0.65	0.72	0.83	0.92	0.92
12	0.69	0.72	0.76	0.59	0.85	0.78
13	0.65	0.76	0.66	0.64	0.71	0.68
14	0.77	0.68	0.74	0.60	0.73	0.68
15	0.67	0.64	00.63	0.81	0.65	0.64
16	0.75	0.67	0.66	0.58	0.73	0.74
17	0.67	0.62	0.61	0.64	0.69	0.64
Mean	**0.74**	**0.69**	**0.68**	**0.67**	**0.76**	**0.75**
SD	**0.07**	**0.05**	**0.05**	**0.09**	**0.09**	**0.10**

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Table C4.10. Scaling exponent alpha of stride interval for novice runners

Participant	TI1	TI2	TI3	TI4	TI5	TI6
1	0.68	0.86	0.71	0.64	0.59	0.63
2	0.69	0.68	0.59	0.53	0.63	0.69
3	0.73	0.83	0.73	0.70	0.64	0.70
4	0.80	0.86	0.65	0.67	0.70	0.83
5	0.63	0.74	0.67	0.56	0.58	0.66
6	0.80	0.73	0.75	0.79	0.75	0.72
7	0.75	0.61	0.61	0.55	0.56	0.61
8	0.82	0.69	0.58	0.84	0.74	0.77
9	0.74	0.78	0.58	0.68	0.72	0.63
10	0.87	0.88	0.75	0.75	0.77	0.63
11	0.65	0.69	0.67	0.56	0.58	0.63
12	0.65	0.69	0.56	0.60	0.76	0.61
13	0.76	0.71	0.57	0.57	0.57	0.57
14	0.69	0.82	0.61	0.63	0.56	0.73
15	0.70	0.68	0.71	0.75	0.77	0.82
16	0.61	0.75	0.55	0.50	0.61	0.62
17	0.71	0.62	0.74	0.60	0.71	0.81
Mean	**0.72**	**0.74**	**0.65**	**0.64**	**0.66**	**0.69**
SD	**0.07**	**0.08**	**0.07**	**0.10**	**0.08**	**0.08**

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Appendix J. Raw Data of Chapter 5

Table C5.1. Characteristics of each participant of the experienced runner group.

Participant	Age (years)	Height (cm)	Body mass (kg)	Body mass index (kg/m^2)	AT speed (km/h)
1	37	169	68	23.8	13
2	25	173	61	20.4	13
3	35	178	90	28.4	10
4	23	154	45	19.1	11
5	18	167	57	20.4	11
6	24	172	71	24.0	13
7	21	170	56	19.2	13
8	23	177	61	19.5	14
9	21	175	65	21.2	13
10	33	178	72	22.7	14
11	20	174	63	20.8	14
12	21	165	60	22.0	13
13	37	168	61	21.6	14
14	24	173	70	23.4	13
15	40	174	75	24.8	12
16	22	177	67	21.4	14
17	21	160	52	20.2	11
Mean	**24.5**	**170.8**	**63.7**	**21.7**	**12.8**
SD	**5.5**	**6.7**	**10.1**	**2.3**	**1.2**

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Table C5.2. Characteristics of each participant of the novice runner group.

Participant	Age (years)	Height (cm)	Body mass (kg)	Body mass index (kg/m^2)	AT speed (km/h)
1	20	174	65	21.5	11
2	21	168	63	22.3	12
3	28	172	60	20.2	11
4	21	185	82	24.0	12
5	24	184	53	15.7	11
6	19	166	57	20.7	11
7	21	174	60	19.8	11
8	28	172	60	20.2	11
9	20	166	65	23.6	10
10	28	172	60	20.2	11
11	23	177	59	18.8	11
12	30	179	63	19.7	11
13	28	176	68	22.0	12
14	21	169	71	24.9	10
15	31	178	65	20.5	12
16	28	177	68	21.7	13
17	21	177	59	18.8	11
Mean	**22.5**	**173.5**	**62.6**	**20.8**	**11.0**
SD	**3.3**	**6.0**	**7.3**	**2.5**	**0.7**

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Table C5.3. Running pattern for experience and novice runners at each interval.

Variables of running pattern		Beginning		Middle		End		Two-way repeated measures ANOCVA					
								Group * time		Group		Time	
		Experienced runners	Novice runners	Experienced runners	Novice runners	Experienced runners	Novice runners	*F*	*p*	*F*	*p*	*F*	*p*
Hip angle at IC (°)	θH_{IC}	40.3 (6.5)	36.7 (6.3)	40.9 (7.7)	38.0 (7.3)	39.9 (6.1)	38.1 (7.7)	0.01	0.99	0.58	0.45	2.54	0.10
Hip angle at TO (°)	θH_{TO}	1.3 (4.8)	0.4 (7.3)	0.1 (5.7)	0.8 (6.9)	–1.2 (5.8)	0.6 (6.9)	1.20	0.31	0.001	0.98	0.79	0.43
Peak hip angle (°)	θH_{MAX}	41.5 (6.6)	38.0 (5.8)	41.7 (7.8)	39.3 (6.8)	40.7 (6.6)	39.4 (7.2)	0.12	0.89	0.27	0.61	1.91	0.17
ROM of hip motion (°)	θH_{ROM}	40.2 (4.5)	37.6 (4.6)	41.6 (4.4)	38.5 (4.4)	41.9 (6.0)	38.8 (4.7)	0.61	0.55	0.53	0.47	0.81	0.42
Time to peak hip angle (ms)	tH_{MAX}	28.3 (21.2)	28.2 (21.8)	19.7 (18.6)	27.3 (22.7)	17.0 (18.3)	25.1 (21.5)	4.15	**0.020**	1.39	0.25	1.79	0.19
Knee angle at IC (°)	θK_{IC}	19.3 (6.5)	18.4 (4.1)	20.3 (5.7)	19.1 (6.2)	19.5 (6.2)	20.2 (7.0)	0.55	0.58	0.04	0.85	0.20	0.77
Knee angle at TO (°)	θK_{TO}	22.5 (4.0)	21.6 (6.0)	22.6 (3.8)	22.3 (7.0)	21.8 (5.3)	22.5 (7.3)	0.001	1.00	0.02	0.88	1.72	0.19
Peak knee angle (°)	θK_{MAX}	45.7 (4.1)	43.7 (4.8)	46.5 (4.8)	45.1 (6.2)	45.7 (4.6)	45.7 (6.7)	0.21	0.81	0.02	0.90	1.34	0.27
Minimum knee angle (°)	θK_{MIN}	17.9 (5.0)	17.2 (4.5)	18.7 (4.5)	17.8 (6.5)	17.6 (5.4)	18.7 (7.2)	0.16	0.85	0.02	0.90	1.04	0.35
ROM of knee motion (°)	θK_{ROM}	27.8 (3.7)	26.5 (4.2)	27.9 (3.1)	27.3 (3.9)	28.1 (2.9)	27.0 (4.2)	0.24	0.79	0.001	0.99	0.07	0.88
Time to peak knee angle (ms)	tK_{MAX}	84.6 (12.6)	91.1 (14.2)	84.8 (9.6)	92.4 (13.7)	84.5 (10.6)	90.6 (13.2)	0.53	0.59	0.01	0.92	0.55	0.51
Ankle angle at IC (°)	θA_{IC}	5.2 (4.8)	6.5 (4.4)	4.0 (4.7)	4.6 (4.3)	4.2 (5.2)	5.0 (4.3)	0.58	0.56	0.001	0.99	0.98	0.36
Ankle angle at TO (°)	θA_{TO}	–18.1 (5.8)	–16.7 (7.6)	–20.1 (6.2)	–19.0 (7.5)	–19.6 (6.0)	–19.6 (6.7)	2.40	0.10	1.42	0.24	1.66	0.20
Peak ankle angle (°)	θA_{MAX}	19.6 (4.4)	20.0 (4.7)	19.6 (4.7)	19.9 (4.8)	19.8 (4.5)	20.3 (4.8)	0.28	0.76	0.002	0.97	0.45	0.58
ROM of ankle motion (°)	θA_{ROM}	37.8 (4.9)	36.7 (7.6)	39.7 (5.5)	38.9 (6.9)	39.4 (5.2)	39.9 (5.8)	1.41	0.25	1.90	0.18	0.61	0.55
Time to peak ankle angle (ms)	tA_{MAX}	117.1 (17.3)	128.2 (16.3)	119.0 (18.3)	129.6 (15.9)	119.1 (18.7)	128.2 (15.8)	0.86	0.43	0.01	0.94	0.90	0.37
Pelvis rotation angle at IC (°)	θP_{IC}	–17.5 (4.2)	–15.6 (4.7)	–17.0 (4.2)	–15.8 (5.4)	–16.8 (4.0)	–15.4 (5.2)	0.26	0.78	0.53	0.47	1.29	0.28
Pelvis rotation angle at TO (°)	θP_{TO}	–20.0 (4.6)	–18.2 (5.4)	–19.6 (4.9)	–18.9 (6.1)	–18.9 (4.9)	–18.8 (5.8)	2.66	0.078	0.09	0.77	0.10	0.90
Peak pelvis rotation angle (°)	θP_{MAX}	–15.4 (4.3)	–13.3 (5.4)	–14.7 (4.8)	–13.1 (6.3)	–14.1 (4.7)	–12.8 (6.2)	0.97	0.39	0.02	0.90	0.48	0.56
Minimum pelvis rotation angle (°)	θP_{MIN}	–20.3 (4.7)	–18.4 (5.2)	–20.0 (4.9)	–19.1 (5.9)	–19.5 (4.6)	–19.0 (5.7)	1.37	0.26	0.001	0.98	0.18	0.80
ROM of pelvis rotation (°)	θP_{ROM}	4.9 (1.4)	5.1 (2.2)	5.4 (1.8)	6.0 (2.4)	5.4 (1.9)	6.2 (2.3)	0.46	0.64	0.17	0.68	2.58	0.084
Thigh rotation angle at IC (°)	θT_{IC}	22.0 (3.5)	20.6 (4.2)	23.1 (4.1)	21.7 (5.1)	22.2 (3.4)	22.2 (5.7)	0.05	0.95	0.19	0.67	1.80	0.18
Thigh rotation angle at TO (°)	θT_{TO}	–19.0 (3.0)	–17.8 (5.2)	–19.7 (3.1)	–18.1 (5.1)	–20.4 (5.3)	–18.2 (5.3)	0.09	0.91	0.22	0.65	1.08	0.34
Peak thigh rotation angle (°)	θT_{MAX}	24.1 (3.3)	23.1 (3.9)	24.7 (4.1)	24.2 (4.5)	23.9 (3.8)	24.6 (5.2)	0.06	0.94	1.97	0.16	0.001	0.98
ROM of thigh rotation (°)	θT_{ROM}	43.1 (4.7)	40.9 (5.2)	44.4 (4.8)	42.3 (5.1)	44.3 (5.5)	42.8 (5.3)	0.13	0.88	0.15	0.70	0.19	0.78
Foot rotation angle at IC (°)	θF_{IC}	14.5 (7.1)	14.8 (5.6)	13.3 (6.2)	13.2 (5.4)	13.2 (6.5)	13.1 (4.7)	0.06	0.94	0.03	0.86	0.08	0.85
Foot rotation angle at TO (°)	θF_{TO}	–53.8 (6.6)	–49.8 (8.1)	–56.5 (7.3)	–53.1 (7.1)	–56.2 (6.8)	–54.0 (5.9)	1.22	0.30	0.44	0.51	0.50	0.58
ROM of foot rotation (°)	θF_{ROM}	68.3 (9.9)	64.6 (8.4)	69.8 (8.8)	66.3 (6.2)	69.4 (8.6)	67.1 (5.5)	0.57	0.57	0.17	0.69	0.65	0.46

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Table C5.4. Running variability for experienced and novice runners at each interval.

Variables of running variability		Beginning		Middle		End		Two-way repeated measures ANOCVA					
								Group * time		Group		Time	
		Experienced runners	Novice runners	Experienced runners	Novice runners	Experienced runners	Novice runners	***F***	***p***	***F***	***p***	***F***	***p***
Hip angle at IC (°)	$SD\theta H_{IC}$	0.97 (0.40)	1.25 (0.38)	1.16 (0.58)	1.46 (0.61)	1.27 (0.47)	1.41 (0.54)	0.08	0.93	2.66	0.11	0.94	0.40
Hip angle at TO (°)	$SD\theta H_{TO}$	0.68 (0.22)	0.77 (0.29)	0.69 (0.21)	0.84 (0.38)	0.90 (0.37)	0.84 (0.27)	0.74	0.48	0.19	0.67	2.79	0.069
Peak hip angle (°)	$SD\theta H_{MAX}$	0.98 (0.36)	1.26 (0.39)	1.06 (0.45)	1.39 (0.46)	1.21 (0.46)	1.41 (0.58)	0.03	0.97	4.71	**0.038**	0.24	0.79
ROM of hip motion (°)	$SD\theta H_{ROM}$	1.09 (0.33)	1.35 (0.45)	1.23 (0.53)	1.43 (0.33)	1.47 (0.57)	1.43 (0.47)	0.25	0.78	1.34	0.26	0.29	0.75
Time to peak hip angle (ms)	$SDtH_{MAX}$	7.19 (8.35)	7.96 (7.07)	8.94 (8.32)	6.10 (6.66)	8.90 (9.50)	7.33 (7.34)	0.16	0.85	0.14	0.71	2.21	0.13
Knee angle at IC (°)	$SD\theta K_{IC}$	1.64 (0.36)	1.69 (0.65)	1.57 (0.54)	1.71 (0.68)	1.73 (0.81)	1.79 (0.64)	0.09	0.91	0.001	0.99	0.02	0.98
Knee angle at TO (°)	$SD\theta K_{TO}$	1.19 (0.30)	1.39 (0.59)	1.14 (0.45)	1.45 (0.63)	1.39 (0.64)	1.31 (0.54)	1.83	0.17	1.01	0.32	3.31	**0.043**
Peak knee angle (°)	$SD\theta K_{MAX}$	0.85 (0.28)	1.21 (0.31)	0.85 (0.26)	1.30 (0.37)	0.92 (0.30)	1.22 (0.43)	1.69	0.20	9.30	**0.005**	1.17	0.32
Minimum knee angle (°)	$SD\theta K_{MIN}$	1.41 (0.37)	1.55 (0.64)	1.31 (0.42)	1.55 (0.49)	1.52 (0.63)	1.56 (0.58)	1.15	0.29	0.77	0.39	1.45	0.24
ROM of knee motion (°)	$SD\theta K_{\square OM}$	1.48 (0.49)	1.69 (0.78)	1.39 (0.53)	1.68 (0.55)	1.57 (0.57)	1.85 (0.68)	1.14	0.33	0.68	0.42	2.18	0.12
Time to peak knee angle (ms)	$SDtK_{MAX}$	3.82 (0.97)	5.32 (1.68)	3.81 (1.23)	4.89 (1.68)	3.64 (1.04)	5.12 (2.29)	0.09	0.91	3.45	0.073	1.24	0.30
Ankle angle at IC (°)	$SD\theta A_{IC}$	0.69 (0.26)	0.72 (0.26)	0.84 (0.59)	0.72 (0.32)	1.11 (1.76)	0.73 (0.34)	1.65	0.20	1.53	0.23	1.12	0.30
Ankle angle at TO (°)	$SD\theta A_{TO}$	1.36 (0.33)	1.60 (0.54)	1.15 (0.33)	1.60 (0.41)	1.41 (0.65)	1.67 (0.80)	1.31	0.28	1.08	0.31	1.11	0.33
Peak ankle angle (°)	$SD\theta A_{MAX}$	0.66 (0.23)	0.87 (0.25)	0.62 (0.23)	0.91 (0.29)	0.69 (0.20)	0.88 (0.43)	1.67	0.20	2.56	0.12	1.81	0.18
ROM of ankle motion (°)	$SD\theta A_{ROM}$	1.45 (0.46)	1.78 (0.49)	1.24 (0.32)	1.88 (0.50)	1.59 (0.67)	1.82 (0.65)	2.12	0.16	1.50	0.23	0.30	0.74
Time to peak ankle angle (ms)	$SDtA_{MAX}$	4.19 (1.25)	5.63 (1.39)	4.18 (1.69)	4.87 (1.46)	4.17 (1.88)	5.49 (1.93)	0.25	0.63	4.07	0.052	0.48	0.62
Pelvis rotation angle at IC (°)	$SD\theta P_{IC}$	0.77 (0.27)	0.82 (0.34)	0.85 (0.28)	0.87 (0.30)	1.0 (0.30)	1.00 (0.44)	0.14	0.88	0.21	0.65	0.72	0.49
Pelvis rotation angle at TO (°)	$SD\theta P_{TO}$	0.66 (0.24)	0.80 (0.32)	0.67 (0.21)	0.89 (0.22)	0.90 (0.22)	0.87 (0.33)	1.64	0.20	0.41	0.53	2.91	0.062
Peak pelvis rotation angle (°)	$SD\theta P_{MAX}$	0.68 (0.16)	0.78 (0.41)	0.73 (0.19)	0.83 (0.26)	0.84 (0.25)	0.90 (0.43)	0.50	0.61	0.03	0.87	1.23	0.30
Minimum pelvis rotation angle (°)	$SD\theta P_{MIN}$	0.71 (0.31)	0.79 (0.30)	0.72 (0.22)	0.85 (0.23)	0.96 (0.24)	0.87 (0.31)	0.79	0.38	0.10	0.75	0.55	0.58
ROM of pelvis rotation (°)	$SD\theta P_{ROM}$	0.72 (0.22)	0.74 (0.27)	0.64 (0.23)	0.77 (0.22)	0.79 (0.31)	0.88 (0.37)	0.65	0.43	0.38	0.54	0.10	0.91
Thigh rotation angle at IC (°)	$SD\theta T_{IC}$	0.70 (0.24)	0.98 (0.20)	0.72 (0.31)	1.09 (0.47)	0.85 (0.38)	0.92 (0.29)	0.62	0.54	6.35	**0.017**	0.41	0.67
Thigh rotation angle at TO (°)	$SD\theta T_{TO}$	0.70 (0.23)	0.96 (0.33)	0.79 (0.26)	0.91 (0.30)	1.01 (0.33)	1.01 (0.35)	0.10	0.91	0.20	0.66	1.66	0.20
Peak thigh rotation angle (°)	$SD\theta T_{MAX}$	0.65 (0.22)	0.94 (0.23)	0.69 (0.31)	1.03 (0.36)	0.77 (0.26)	0.90 (0.33)	1.26	0.29	10.38	**0.003**	1.15	0.32
ROM of thigh rotation (°)	$SD\theta T_{ROM}$	0.91 (0.29)	1.27 (0.43)	1.00 (0.34)	1.29 (0.39)	1.23 (0.39)	1.38 (0.53)	0.31	0.74	3.67	0.065	0.16	0.85
Foot rotation angle at IC (°)	$SD\theta F_{IC}$	1.31 (0.35)	1.60 (0.47)	1.57 (1.02)	1.52 (0.50)	1.94 (2.10)	1.66 (0.79)	1.66	0.21	0.15	0.70	1.01	0.33
Foot rotation angle at TO (°)	$SD\theta F_{TO}$	1.85 (0.51)	2.13 (0.63)	1.57 (0.34)	2.31 (0.78)	1.87 (0.68)	2.14 (0.84)	2.16	0.12	2.20	0.15	0.57	0.57
ROM of foot rotation (°)	$SD\theta F_{ROM}$	2.25 (0.60)	2.83 (0.68)	2.24 (0.81)	3.02 (0.93)	2.60 (1.34)	2.97 (1.00)	1.85	0.18	1.34	0.26	1.54	0.22

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Table C5.5. Coordination variability for experienced and novice runners at each interval.

Couplings	Variables of coordination variability	Beginning		Middle		End		Two-way repeated measures ANOCVA					
								Group * time		Group		Time	
		Experienced runners	Novice runners	Experienced runners	Novice runners	Experienced runners	Novice runners	*F*	*p*	*F*	*p*	*F*	*p*
Hip–Knee flexion/extension	Stance phase (°)	2.6 (0.6)	3.1 (0.6)	2.6 (0.6)	3.1 (0.5)	3.0 (0.9)	3.3 (1.0)	0.64	0.53	0.55	0.46	1.54	0.23
	Loading stance (°)	2.7 (2.0)	2.9 (1.0)	2.4 (1.2)	2.9 (0.8)	3.0 (1.4)	3.0 (1.0)	1.66	0.20	0.99	0.33	2.73	0.092
	Midstance (°)	3.9 (1.0)	5.1 (1.0)	4.0 (1.4)	4.8 (1.1)	4.5 (2.1)	4.7 (1.8)	1.06	0.35	0.79	0.38	0.89	0.42
	Terminal stance (°)	1.8 (0.7)	1.3 (0.3)	1.8 (0.4)	1.4 (0.5)	2.0 (0.6)	1.6 (0.5)	0.01	0.99	4.82	**0.036**	0.28	0.76
	Pre-swing (°)	2.5 (0.4)	2.5 (0.7)	2.4 (0.5)	2.6 (0.7)	2.7 (0.6)	3.2 (1.5)	0.46	0.63	0.77	0.39	0.45	0.64
Knee–Ankle flexion/extension	Stance phase (°)	8.2 (2.4)	10.1 (2.1)	9.6 (4.0)	9.5 (3.5)	10.3 (5.3)	10.8 (4.7)	0.80	0.46	0.001	0.97	0.76	0.45
	Loading stance (°)	27.7 (11.8)	34.9 (9.3)	34.4 (18.2)	32.6 (16.4)	37.7 (23.5)	38.0 (19.4)	1.10	0.34	0.05	0.82	0.50	0.61
	Midstance (°)	4.5 (1.2)	5.4 (1.1)	5.0 (1.7)	5.2 (1.5)	5.1 (2.1)	5.5 (2.4)	0.27	0.77	1.89	0.18	1.18	0.32
	Terminal stance (°)	3.6 (1.1)	4.2 (1.6)	3.3 (0.9)	3.8 (1.3)	3.5 (1.3)	4.0 (1.7)	0.30	0.74	0.88	0.36	1.21	0.30
	Pre-swing (°)	1.3 (0.2)	1.3 (0.8)	1.3 (0.3)	1.3 (0.3)	1.2 (0.3)	1.4 (0.4)	1.62	0.21	0.02	0.90	0.62	0.54
Pelvis–Thigh sagittal rotation	Stance phase (°)	9.9 (4.4)	11.4 (5.3)	11.1 (4.2)	12.4 (5.2)	12.6 (5.9)	11.4 (4.6)	1.74	0.18	0.81	0.38	0.66	0.52
	Loading stance (°)	29.0 (22.2)	30.8 (24.7)	39.5 (20.6)	40.9 (27.2)	45.1 (28.8)	37.6 (21.5)	1.22	0.30	0.66	0.42	0.94	0.40
	Midstance (°)	10.5 (7.3)	13.5 (8.3)	7.7 (6.7)	10.5 (7.3)	8.2 (6.4)	9.3 (6.5)	0.13	0.88	0.03	0.87	0.53	0.59
	Terminal stance (°)	1.6 (0.7)	2.1 (1.6)	1.7 (1.1)	1.8 (0.5)	2.1 (1.2)	1.8 (0.7)	0.82	0.45	0.12	0.73	0.15	0.80
	Pre-swing (°)	2.4 (0.9)	2.8 (1.1)	2.2 (0.5)	2.6 (0.8)	2.7 (1.2)	2.9 (1.1)	0.58	0.56	0.14	0.72	0.84	0.41
Thigh–Shank sagittal rotation	Stance phase (°)	1.9 (0.4)	2.4 (0.5)	2.0 (0.4)	2.4 (0.5)	2.1 (0.7)	2.6 (0.7)	0.41	0.66	0.98	0.33	1.85	0.17
	Loading stance (°)	2.4 (0.9)	3.2 (1.2)	2.4 (0.9)	3.2 (1.0)	2.7 (1.3)	3.4 (1.1)	0.46	0.64	0.54	0.47	0.65	0.53
	Midstance (°)	2.1 (0.5)	2.7 (0.5)	2.2 (0.7)	2.6 (0.6)	2.2 (0.9)	2.6 (0.9)	0.52	0.60	1.04	0.32	1.17	0.32
	Terminal stance (°)	1.4 (0.4)	1.6 (0.4)	1.5 (0.4)	1.7 (0.5)	1.7 (0.5)	2.1 (0.7)	1.01	0.37	0.77	0.39	2.34	0.12
	Pre-swing (°)	2.0 (0.3)	2.1 (0.6)	2.1 (0.5)	2.1 (0.7)	2.1 (0.6)	2.4 (0.5)	0.09	0.92	0.05	0.82	0.05	0.96
Shank–Foot sagittal rotation	Stance phase (°)	2.6 (3.9)	2.1 (0.3)	2.2 (1.9)	2.0 (0.5)	3.2 (4.7)	2.1 (0.8)	0.69	0.51	4.46	**0.04**	0.49	0.61
	Loading stance (°)	2.0 (0.7)	2.9 (0.7)	2.7(2.2)	2.9 (1.1)	7.1 (19.6)	3.1 (1.6)	2.41	0.098	1.30	0.26	1.68	0.21
	Midstance (°)	4.5 (10.8)	2.2 (0.5)	3.3 (5.7)	2.1 (0.7)	3.6 (6.2)	2.2 (1.2)	0.24	0.79	4.01	0.054	0.13	0.74
	Terminal stance (°)	2.3 (2.3)	2.4 (0.8)	1.7 (0.5)	1.9 (0.4)	1.8 (0.8)	2.0 (0.7)	1.40	0.25	0.43	0.52	3.34	0.066
	Pre-swing (°)	0.9 (0.2)	0.9 (0.2)	0.8 (0.3)	0.9 (0.3)	0.9 (0.3)	1.1 (0.3)	2.62	0.081	1.71	0.20	0.72	0.49

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Appendix K. Matlab Codes

Gait Events Detection

```
clc; clear;
STEP=140;
Time = xlsread('Time of Vertical Displacement of Heel Marker.xlsx' ,'a:a');
Data = xlsread('Vertical Displacement of Heel Marker.xlsx’,'b:b');
highcut = 0.07;
[b,a] = butter(2,highcut,'low');
Data = filtfilt(b,a,Data);
LENGTH = length(Time);
Time = Time(1:LENGTH);
Data = Data(1:LENGTH);
plot(Time,Data);
hold on
% p=find(Datafilt>6);
% plot(Time(p),Datafilt(p),'or')
spot = Step2(Data,STEP,LENGTH);
spotx = Time(spot);
spoty = Data(spot);
plot(spotx,spoty,'or')
myspot = Step3(spot,Data);
myspotx = Time(myspot);
myspoty = Data(myspot);
plot(myspotx,myspoty,'*')
hold off
xlswrite(‘Initial Contact.xlsx',{'Time', ‘Marker Displacement'},'IC','d1');
xlswrite('Initial Contact.xlsx',[myspotx,myspoty],'IC','d2');

function Spot = Step2(Datafilt,STEP,LENGTH)
   N = 0;
   Begin = 1;
   End = STEP;
   while 1
      if Begin > LENGTH
         break;
      end
```


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```
        if End > LENGTH
           BlockD = Datafilt(Begin:LENGTH);
        else
           BlockD = Datafilt(Begin:End);
        end
        Datay = max(BlockD);
        Position = find(BlockD==Datay,1);
        if Datay < 0.1||isempty(Position)
           Position1 = Begin+Position-1;
           Begin = Position1+1+STEP/2;
           End = Position1+3*STEP/2;
           continue;
        end
        N = N+1;
        Position1 = Begin+Position-1;
        Begin = Position1+1+STEP/2;
        End = Position1+3*STEP/2;
%       Spotx=Time(Position1);
%       Spoty=Data(Position1);
        Spot(N,1) = Position1;
    end
end

function myspot = Step3(spot,Datafilt)
    myspot = [];
    n = length(spot);
    for i = 1:n-1
        S = spot(i);
        W = Datafilt(spot(i):spot(i+1));
        P = find(W==min(W),1);
        myspot = [myspot;S+P-1];
        continue
    end
end
```


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Detrended Fluctuation Analysis

```
clear all; close all; clc
x=xlsread('stride time series.xlsx', 'a141:a740');
N=length(x);
for i=1:N
    y(i)=sum(x(1:i)-mean(x));
end
q=1;
j=floor(N/9);
for n=16:1:j
    nn=floor(N/n);
    N1=nn*n;
    for m=1:nn
        [pt(m,:),stx1]=polyfit(1:n,y((m-1)*n+1:(m-1)*n+n),1);
        y1((m-1)*n+1:(m-1)*n+n)=polyval(pt(m,:),1:n);
    end
%      plot(y1(1:N1),'r');hold on; plot(y(1:N1))
     F(q)=sqrt(sum((y1-y(1:N1)).^2)/N1);
     q=q+1;
     clear y1
end
plot(log2(16:1:j),log2(F),'ro');
[pt2,stx2]=polyfit(log2(16:1:j),log2(F),1);
F1=polyval(pt2,log2(16:1:j));
hold on; plot(log2(16:1:j),F1,'b');
a=pt2(1);
```


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