Facoltá di Ingegneria dei Sistemi
Dipartimento di Bioingegneria
Dottorato di Ricerca in Bioingegneria

Innovative Methods for the Analysis of Sports Movements and for the Longitudinal Monitoring of Individual Motor Skills

Doctoral Dissertation by:
Ezio Preatoni

Tutor:
prof. Giorgio Cesare Santambrogio ....

Advisor:
prof. Renato Rodano ....

Supervisor of the Ph.D. Program:
prof. Maria Gabriella Signorini ....

XIX edition
2004-2007

PUBLICATION DATA:
Innovative Methods for the Analysis of Sports Movements and for the Longitudinal Monitoring of Individual Motor Skills
Ezio Preatoni
Politecnico di Milano
Dipartimento di Bioingegneria
P.zza Leonardo da Vinci, 32
20133 Milano
e-mail: ezio.preatoni@polimi.it

Not everything that can be counted counts, and not everything that counts can be counted.

–Albert Einstein

ABSTRACT

Coaches, trainers and physicians are increasingly turning to biomechanics to improve the individual evaluation of the athlete. Competition results, field tests and qualitative visual inspection are not enough to understand how the performance is achieved: a quantitative analysis of the movement and of the factors that generated it is needed. Biomechanical research in sports has usually produced interesting descriptions of the basic kinematic and kinetic features of specific athletic movements, in order to find possible solutions for performance enhancement and technique proficiency. Unfortunately, these surveys have often lacked either in providing a sound theoretical rationale or in presenting results that could be directly understood and practically used by trainers and athletes. Therefore, there is the need for extensive indications that could let biomechanists exploit the potentialities of motion analysis technologies by setting proper experimental protocols, by using effective data processing and analysis and, finally, by producing reports that may turn useful "on the field".

Hence, the aim of this research was to propose a set of comprehensive guidelines that may drive the analysis of sports movements and the longitudinal assessment of individual motor characteristics. In this context three main issues were identified and investigated.

First, the need for a robust representation of the athlete's motor skills was managed by exploring traditional and innovative analytical methodologies. The comprehension and consequent depiction of individual motor behaviours is strongly affected by the presence of motor biovariability, which originates from many sources, and which is inherently present both within and between individuals. Therefore, the problem of motion variability was extensively analysed by studying kinematic and kinetic variables of race walking, which was chosen as the paradigmatic movement to be investigated. The intraindividual variability of the most important parameters and continuous measures was quantitatively evaluated. It often resulted as being considerable thus confirming that multiple trial protocols would be advisable. Intraclass correlation coefficients were used to assess continuous curves reproducibility and were proposed as an interesting strategy to select the curves that better depict the motor signature of the individual. Different statistical methods for analysing and summarising motion variables (parametric/non parametric estimators, PCA, bootstrap) were compared, and the most consistent and suitable solutions were suggested. All these indications were used to propose indications that may drive the definition of monitoring protocols. Furthermore, the complexity of race walking time series was evaluated by using non linear dynamics tools (sample entropy). Results confirmed that race walking variability is not only the product of noisy processes, but also contains information about the locomotor system health, about its evolution and about its flexibility to variable external conditions.

Once that consistent data have been obtained from quantitative motion analysis, there is the need for interpreting them. This knowledge may arise from the definition of a reference, whose characteristics have been previously interpreted and described. Individual measures may be compared with information coming either from former analyses on the same subject or from the general characteristics of the movement under investigation, by deriving them from a group of homogeneous individuals. Hence, the second step of the work consisted in an extensive investigation of race walking biomechanics concerning both the whole population and longitudinal case studies. The analysis included: traditional representations and assessments of kinematic and kinetic variables; dynamic system theory studies of coordinative factors; creation and exploration of moment-angular velocities plots to gain more insight in the joints kinetics and in their contribution to the movement.

Finally, the extraction of feed-back information was the outcome of the whole process. Some quantitative tools that could support trainers in their typically qualitative assessment of technique were created and some examples of practical interaction between the research world and field needs were presented as well.

The proposed results could represent an actual aid to the longitudinal monitoring of the subject, to coaching programs and even to decisions in terms of injury prevention or recovery.

Acknowledgements

I tre anni di lavoro che hanno portato alla realizzazione di questa ricerca sono stati indimenticabili. Molte persone hanno contribuito, in vario modo affinchè riuscissi ad affrontare con entusiasmo e dedizione questa avventura, che mi ha profondamente arricchito dal punto di vista professionale ed umano. Anche a loro, quindi, va il merito dei risultati raggiunti e la mia infinita riconoscenza. Vorrei pertanto ricordarli e ringraziarli, consapevole che le poche parole scritte non rendano in modo efficace il sentimento di stima, riconoscenza e sincero affetto che nutro nei loro confronti.

Grazie...

...a *Renato*, perchè sei un grande maestro, una splendida persona e soprattutto un sincero amico. Lavorare con te è per me un piacere ed un grande onore, che spero duri ancora per diversi anni;

...a *Giorgio*, perchè fin dai primi giorni della mia avventura da dottorando mi hai dato fiducia, dimostrato stima ed offerto supporto;

...a *Beppone*, perchè nei primi giorni della mia avventura da dottorando mi hai tolto da una cantina fredda e senza finestre, offrendomi una scrivania, la tua esuberante disponibilità e la tua simpatia;

...ad *Antonio, Ruggero, Davide, Matteo, Federica, Sabrina, Daniele, Martina e Stefano*, perchè avete partecipato con impegno ed entusiasmo al lavoro, aiutandomi a capire gli aspetti fondamentali della marcia e offrendovi come "cavie". Spero che i risultati raggiunti da questa ricerca possano al più preso dare un contributo alla vostra attività e al raggiungemento dei vostri sogni sportivi;

...a *Giulia*, perchè lungo il percorso hai portato nuove energie al progetto,

dimostrandoti un'amica e una brillante compagna d'avventura;
... a *Veronica*, perchè mi hai supportato e sopportato durante le lunghe sedute in laboratorio;
... a *Irene e Francesca*, perchè dopo essere state le mie prime tesiste mi avete sempre seguito con simpatia e incoraggiato nel mio lavoro;
... a *tutti i dottorandi e tesisti "di via Garofalo"*, perchè avete colorato le giornate passate in ufficio, rendendole più piacevoli, e perchè con molti di voi ho stretto rapporti di amicizia e condiviso momenti piacevoli;
... ad *Alessia*; perchè hai impreziosito il nostro lavoro realizzando la bella copertina del libretto;
... a *Daniele, Lorenzo, Michele, Marco e Stefano*, perchè siete i miei amici da una vita, e anche da lontano ho sempre sentito la vostra presenza e il vostro supporto;
... a *Valentina, Tiziana, Pino, Francesca e Andrea*, perchè siete stati parte della mia famiglia per tanti anni, dandomi calore ed affetto. Mi avete sempre incoraggiato e supportato. La riuscita di questo percorso è anche merito vostro;
... a *Betta, Manuela, Martin e Salvo*, perchè giorno per giorno avete condiviso con me questa grande avventura, affrontando spesso le stesse difficoltà e vivendo le stesse emozioni. In voi ho trovato non solo dei grandi colleghi, ma degli splendidi, insostituibili amici. Vorrei dirvi tante cose, ma forse una sola le riassume più di tutte: "ce l'abbiamo fatta!". Sono sicuro che il futuro vi riserverà grandi soddisfazioni, io vi rivolgo i miei più siceri "in bocca al lupo";

L'ultimo pensiero va a *mamma, papà, Sara e nonni.* Non trovo parole per esprimere la riconoscenza e i sentimenti che provo nei vostri confronti. Se sono qui è senza alcun dubbio grazie a voi, a ciò che mi avete dato, a quello che mi avete insegnato e a quello che avete fatto per me. Vi dico *grazie*. Lo dico così, semplicemente, ricordando la semplicità e la discrezione che vi contraddistinguono e reppresentano le prime delle vostre infinite qualità.

Contents

List of Figures

List of Tables

Chapter 1

INTRODUCTION

1.1 Relevant Issues of Biomechanical Research in Sports

Sports biomechanics and sports science are currently going through a very crucial phase of their evolution: they should be able to match the increasing interest of physicians, coaches, athletes and even recreational sportsmen, in the quantitative assessment of the athlete's motor characteristics. Competition results, field tests and qualitative visual inspection are the traditional tools that trainers commonly use in daily practice to understand how proficiently the athlete performs his motor task and how effective his training program is. Despite their being readable and easy to use, these monitoring procedures usually score the global performance but they lack in describing how the movement outcome is achieved. Thus, as far as motion analysis is concerned, further research is required to support the need for athletes' monitoring throughout their training.

The problem is no more mainly related to technology, because many powerful, reliable and accurate devices are currently available for most of biomechanical studies and for motion analysis in particular [49, 23, 29, 7]. Three-dimensional motion analysis has now become widespread and represents an invaluable potential for the acquisition of new skills (e.g. through the use of virtual representations and environments), and for performance enhancement [10, 87]. However, the most challenging issue rather concerns the effective exploitation of those technologies, by setting an appropriate experimental design, by applying proper data processing, by interpreting the numerical outcome and its relation with observed phenomena, and, finally, by returning suitable information to athletes and trainers [10, 87, 121, 126, 127, 9, 56].

In physiology, clinics and ergonomics the search for solutions to many common issues concerning people's health has produced significant results. The need for aids to relevant clinical decisions and the availability of considerable funds has pushed toward standardised testing procedures and interchangeable results. Standard protocols and reports have helped the integration of experiences from different research groups and has encouraged the multidisciplinary debate among engineers, physicians, physical therapists. These factors, in turn, have led to a better understanding of motor patterns, of their characteristics, and of their relation with normal biomechanical aspects or pathological behaviours. Consequently, motion analysis has represented an effective aid to clinical practice concerning the neuro-muscular-skeletal system.

If the focus is gradually shifted from the above mentioned areas to the sports one, an increasing number of disciplines and an overwhelming heterogeneity of survey questions emerge. The passage from the investigation of basic daily life movements such as normal walking, to the analysis of a multitude of highly technical motor task, often involving the use of specific equipment, has scattered resources and has hindered the spread of standard procedures. The consequence of this situation is a gap of knowledge that has still to be filled [10]. Every sports action, in fact, relies on distinctive performance factors that may consist in executing a "one shot" movement (e.g. long jump), in repeating cyclic actions (e.g. running), in interpreting the game context (e.g. tennis), in interacting with other players (e.g. basketball). Each of these characteristics would request a specific experimental protocol.

Significant investigations into sports movements and common field tests have been carried out in literature, but basic phenomena and average motor behaviour have usually been preferred to longitudinal individual studies. Sports biomechanists have usually been too descriptive, and have generally aimed at analysing general kinematic and kinetic properties of a specific athletic event [10, 8, 9, 60, 55]. The search for average motor behaviours relates to group design approaches and the descriptive effectiveness of group designs strongly depends on the homogeneity of the analysed sample. Unfortunately, homogeneity does not always fit sports research. Sports field needs may meet clinical ones, but are undoubtedly different. The most relevant issue in clinics could be roughly resumed as "turning a pathological state into a physiological one". This necessarily involves the concept of normality as the primary goal. In contrast, the most important purpose in sports is exalting the athlete's potentialities. This often involves the search for physiological limits. Sportsmen do not usually aim at being safely included in a normality range, but rather strive to reach its upper boundaries. They have not just to do something, but they are thought to do it better and better, concerning both performance and execution technique. In agonistic contests they are thought to do it even better than any other competitor. Furthermore, this continuous search for excellence may subject the neuro-muscular-skeletal system to excessive loads or to overuse injuries due to the repetition of detrimental actions [103, 10, 89, 9]. Therefore, in an apparent dichotomy, the athlete's potentialities should be exalted but his wellness should be contextually granted and injury prevention pursued.

1.2 Individual Analysis through Longitudinal Monitoring and Feed-back

If the aim of the survey is high-level performance, technical improvement, injury prevention or rehabilitation monitoring, individual characteristics should not be neglected by aggregating them in a mean curve [12, 45, 11, 8, 13]. When a group is studied and a mean behaviour is extracted, this average subject is very likely to represent none of the members of the population [12, 45, 11, 13] (Figure 1.1).

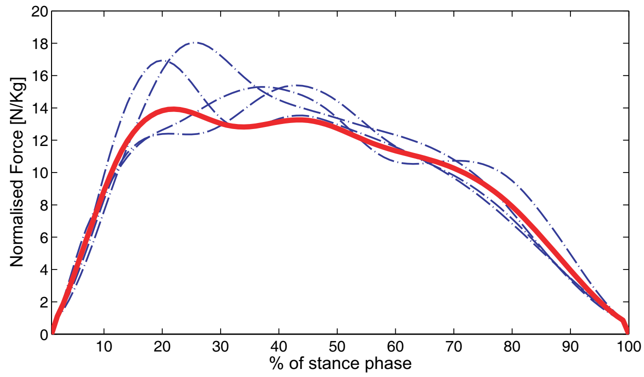


Figure 1.1: *example of average versus individual patterns concerning vertical ground reaction force during race walking. The solid red line represents the mean curve drawn from set of 22 patterns. Dash-dot blue lines correspond to a subset of the individual curves.*

In fact, sports activities are performed by both outstanding and amateur athletes. Many different skill levels and goals (maximal performance rather than wellness) are present, not only between these categories but also within them. Furthermore, although elite athletes possess consistent mastery of the movement, similar performances can result from significantly different motor strategies even among equally skilled individuals. Due to the "seemingly infinite" number of functional degrees of freedom of the neuro-muscular-skeletal system [11] there is a huge variety of independent performance solutions both among and within individuals [66, 45, 11, 10, 63, 126, 8, 13, 77, 93, 127, 9, 60, 61]. The exact repetition of stereotyped movements does not seem possible, either, because the neuro-muscular-skeletal system and the external forces and torques acting on it are subjected to continuous variation [66, 45, 10, 63, 126, 8, 13, 93, 127, 9, 60, 61]. Hence, biovariability should be taken into account before setting experimental protocols and it should be considered with the successive data processing and analysis [8].

The main focus of researches should not only be the identification of the general characteristics of a motor task or the best strategy for the "mythical" average athlete, but even the extraction of the peculiarities and of the most proficient strategy for a single individual. It is always the individual that is of primary importance, not the need of creating a rule that aims at describing the whole group by creating an abstract average man [12, 45, 11, 13].

The passage from a horizontal to a longitudinal experimental design turns the typical deductive approach of group analysis into an inductive one. The individual behaviour is no more compared to a predetermined normality range, but the single subject is analysed independently and, in case, common features or general laws are resumed a posteriori. This could seem an excessive, time consuming, waste of resources, but some prominent authors in the field of injury prevention and motor learning have increasingly encouraged prospective longitudinal studies because they may represent a promising chance for finding relations between causes and effects [10, 89, 8, 9, 60, 61], and for identifying one person's optimal performance [10, 87]. When, for instance, groups of healthy people are compared to injured ones, it is not possible to determine whether the differences that emerge are the consequence of the injury or its cause [89, 78, 60, 61].

Since every athlete is characterised by his own abilities and deficiencies, trainers and coaches might get more effective results by applying and monitoring individual training programs rather than using the same strategy for every member of the team.

A way to improve personalisation may consist in implementing a feedback loop (Figure 1.2), through which the single subject is observed while performing a motor task, through which his actual motor skill level is somehow described, and, finally, through which some useful information are sent back toward either him or someone he interacts with [10, 87, 133, 126, 127]. This cyclic flow of information is based on a longitudinal single subject (SS) design [45, 11, 117, 13, 106], and could provide athletes, trainers, etc., with a powerful instrument to monitor motor behaviour trends, to check on possible anomalies, to make comparisons with other athletes or theoretical models, to plan and monitor training programs or rehabilitative procedures.

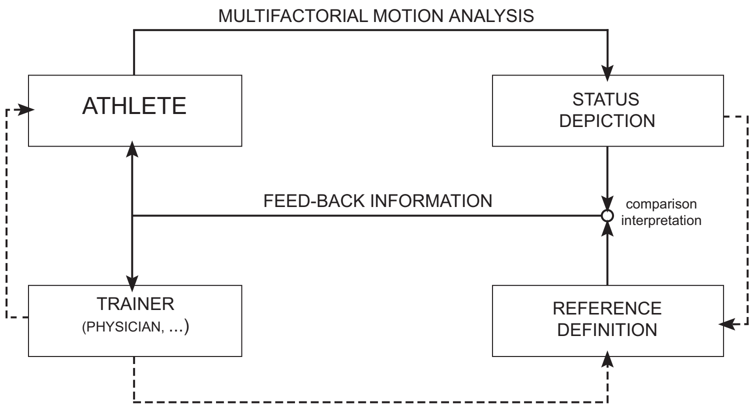


Figure 1.2: *longitudinal monitoring schema.*

1.3 Capturing the Athlete's Actual Motor Characteristics

Each point of the monitoring process shown in Figure 1.2 is addressed in the following chapters: Chapter 4 faces the problem of motor performance depiction; Chapter 5 deals with the definition of references, which the actual characteristics should be compared to; Chapter 6 presents some issues and examples concerning the restitution of information.

However, among the aforementioned topics, this work reserved particular attention to the first one. The problem of drawing an actual description of motor skills is not trivial, and immediately arises when one tries to capture and describe individual peculiarities. This is a crucial point of the whole process because before giving back any advice on how the athlete could improve performances, it should be clear what the athlete is actually able to do and how he does it. The consistent comprehension of the individual motor status is strongly hindered by the presence of biovariability (BV), which is particularly annoying in sports analysis, because it may conceal the little progresses that the athlete achieves and that might give important indication for coaching [73, 72]. Furthermore, BV may contain itself some useful information about the inherent propriety of the neuro-muscular-skeletal system.

1.3.1 What is a Motor Skill?

Exceptional events may be of great importance for the athlete. The ability of achieving impressive results by exceeding personal expectation is often what makes the difference between obtaining a success and wondering about the reason of failures. The causes of an outstanding performance may be manifold, and may involve many aspects: psychological factors, physiological condition, environmental influence, etc. However, regardless of what have determined them, exceptional exploits are by definition unpredictable and thus very difficult to be captured and described. Furthermore, the observation of unusual performances does not give a clear representation of the actual status of the system, rather it might give some clues about its potentialities. Hence, it may confuse the trainer's perception of the athlete's mastery and, thus, it may negatively alter the interventions (e.g. training programs) derived thereof.

Therefore, the core of investigations should not be "one shot" events (e.g. competition performance) but the individual motor skill. Motor skill may be defined as the ability of obtaining the desired goal with a high degree of certainty and maximum proficiency [127]. Namely, a skilled athlete is able to achieve the desired result, independently from the possible perturbations that may act on the system. When a particular movement has to be learned or consistently improved in terms of energy expenditure or execution speed, only the capability of producing a stable performance under different conditions reflects an effective enhancement. To resume: only "repeated motor performance makes motor learning" [127].

1.3.2 The Problem of Motion Variability

If the aim of the work is the description of individual motor skills, many repetitions of the same task should be registered and analysed. Every time that a subject tries to carry out the same movement, a certain amount of changes may be registered between the successive trials. Variability is inherently present throughout the multiple levels of movement organisation and remarkably occurs not only between but even within individuals [66, 11, 10, 8, 13, 77, 93, 9, 60, 114, 101]. BV is the consequence of the extreme complexity of the locomotor system and of the redundancy of its degrees of freedom. The neuro-muscular-skeletal system is always subjected to perturbations, that may originate from both internal processes and external influences: biomechanical, morphological/anatomical, environmental and task constraints may all be factors that affect the final outcome [66, 13, 77, 93, 127, 101].

According to a control theory approach, movement variability is seen as a negative propriety of the motor system, which is not able to organize the multiple degrees of freedom and to make the final output match the planned program. BV is thus reduced to the concept of error.

In contrast with this view, new interpretations of BV have been proposed. Variability is no more seen as detrimental instability but as a combination of random fluctuations (i.e. error, V_e) and of nonlinear dynamical proprieties of the neuromotor system (V_{nl}) [77]:

$$V_{tot} = V_{nl} + V_e \tag{1.1}$$

where V_e may in turn be partitioned into the biological noise that is present within the locomotor system (V_{eb}), into measurement and data processing errors (V_{em}), and into other external sources of variation (V_{ee}) that may come from changes in the environment or in goal settings.

$$V_e = V_{eb} + V_{em} + V_{ee} \tag{1.2}$$

V_{nl} may be read as the flexibility of the system that is able to explore different strategies in order to find out the most proficient one among many available. This elasticity allows for learning a new movement or adjusting the already known one, by gradually selecting the most appropriate pattern for the actual task [68, 40, 41, 100, 39, 119, 20, 36, 65, 99, 77, 93, 127, 135, 137, 60, 67, 91, 101]. The subject is thus able to gradually release the degrees of freedom that have been initially freezed to gain a greater control over an unfamiliar situation. This process may play a very important role for athletes monitoring. The evolution of the amount of variability and of the components it originates from, may in fact provide some useful indication about motor learning and skills acquisition.

1.4 Aims of the Work

The aim of this research was to propose a set of comprehensive guidelines for the consistent depiction of the athlete's performance and of the factors that generated it. In this context, the issue of biovariability was extensively explored, by studying kinematic and kinetic variables of race walking, which was chosen as the paradigmatic mean of investigation. Different analytical methodologies were tested and some solutions for a consistent representation of the athlete's motor-skill state were studied. Some examples of practical interaction between the research world and trainers were presented as well. The proposed results should represent an actual aid to the longitudinal monitoring of the subject, to coaching programs and even to decisions for injury prevention or recovery.

Chapter 2

RACE WALKING

This chapter provides a description of the sport of race walking (RW) and of its main features.

In Section 2.1 the most relevant issue concerning RW technique are reported. In Section 2.2 the reasons that led to the selection of this motor task as the paradigmatic mean of investigation are presented.

2.1 Race Walking Description

The sport of Race Walking (RW) is included in every track-and-field main event. According to the International Association of Athletics Federations (IAAF)[1]:

> *"Race Walking is a progression of steps so taken that the walker makes contact with the ground, so that no visible (to the human eye) loss of contact occurs. The advancing leg shall be straightened (i.e. not bent at the knee) from the moment of first contact with the ground until the vertical upright position."*

In other words, two rules must be strictly respected to perform a correct action: the advancing foot must make contact with the ground before the

[1] IAAF HandBook, section VII - Race Walking Events, rule 230 [104].

rear foot leaves it, so that double support period is established during each gait cycle and the movement can be defined as "walking"; second, the supporting leg must be maintained with the knee fully extended until the trunk overpasses the foot that is in contact with the ground. If these simple indications are not observed in any part of the competition, the athlete may incur cautioning, be sanctioned with up two red cards, and eventually be disqualified [104].

The representation of a correctly performed race walking action is reported in Figure 2.1, where the six principal stages of the movement are indicated by roman numerals (I–VI). The whole gait cycle can be divided

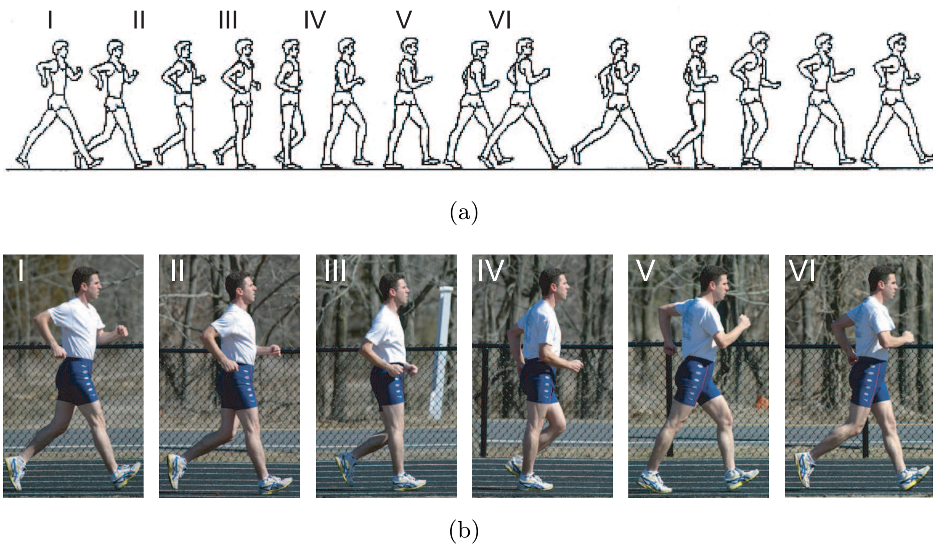


Figure 2.1: *race walking technique during the complete gait cycle (a) and stance phase (b).*

into three principal phases: the front leg support phases (FSP: I–III), the rear leg support phase (RSP: IV–VI) and the double support phase (DSP: VI/I).

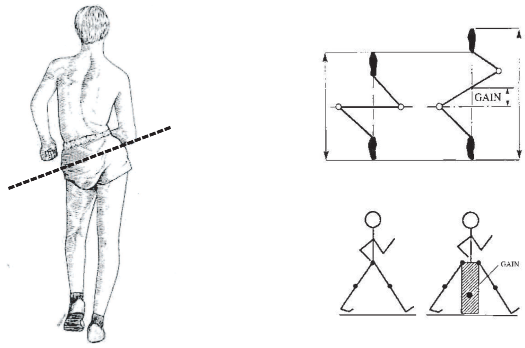
The FSP begins at heel strike (I) and it ends when the supporting leg passes beyond the vertical projection of the center of mass (III/IV).

During this phase the leg approaches the ground after the knee has just been straightened. The foot strikes on the heel, with toes as high as possible. Then the body moves forward over the leg. The advancement is carried out by rolling onto the midsection of the sole and through to the forefoot, always maintaining the knee in a fully extended position. This phase of the stride should represent a rapid transition from load absorbtion to propulsion, therefore the athlete should minimise the loss of progression velocities by performing a "smooth" action.

The RSP begins when the stance leg passes the vertical upright position (III/IV) and ends with toe-off (VI). Rules allow knee flexion during this phase. Nevertheless, the longer it is kept locked, the more effective propulsion is, with a better exploitation of the lever arm and an increased step length. After push-off the leg swings forward to complete the gait cycle. This passage should be performed by driving the knee as low to the ground as possible, in order to minimise energy expenditure, to preserve the horizontal speed and to give a better appearance of correct technique.

The transition between RSP and FSP is the double support phase (VI/I), which is necessarily present, to respect the first of the two rules, but it is extremely reduced (less than 1% of the overall cycle) in comparison with the normal walking one [97, 21]. Hence, race walking might be seen as an uninterrupted succession of stance phases. When the DSP is established the legs do not form a symmetrical triangle, but the rear foot is more behind the body than the front foot is ahead of it. This is one of the aspect that trainers look at for evaluating the correctness of propulsive action, which should be mostly determined by the "backward push" of the stance leg rather than by the "forward pull" of the contralateral one. This strategy is accomplished through proper hip and pelvis motion, and should allow a smoother load absorbtion with reduced articular strain and minimal braking action.

The pelvic motion is fundamental, too. A good mastery of the coordination between movements in the sagittal plane and in the secondary ones significantly improves the proficiency of race walking progression. In fact, in normal walking, the vertical excursion of the center of mass is mainly controlled by the alternating wave of knee flexion and extension. In contrast, this mechanism is not allowed during race walking. Hence, the locked position of the knee is compensated by the increased obliquity of the pelvis in the frontal plane (Figure 2.2(a)). Furthermore, greater pelvic rotations in the horizontal plane (Figure 2.2(b)) concur in improving the step length.



(a) (b)

Figure 2.2: *race walking technique concerning pelvic rotations in the frontal (a) and in the horizontal (b) plane. Figure (a) is taken from [97].*

2.2 Why Race Walking?

Despite the particular requirements that the race walker has to follow, and that make this motor task be very interesting from a biomechanical point of view, few researches have thoroughly addressed the issue of describing race walking biomechanics [97, 21]. These surveys, though very interesting and appropriate, are rather old and used very essential instrumentation in comparison with the currently available technologies.

Among the huge variety of sports disciplines race walking was chosen as the mean of investigations due to its unique peculiarities. RW is not an inborn motor strategy, because at the progression speed that racewalkers are able to achieve (Section 3.1), the man would naturally turn from

NW into running [26, 25, 58]. The specific constraints that the above mentioned rules impose, generate very particular biomechanical and coordinative demands and make this motor task be highly technical and thus very interesting for the purposes of this research. Furthermore, those restrictions add further control over the execution and make race walking appear as rather stereotyped. The analysis of individual biovariability was one of the main topic of this research. Therefore, the choice of a very repeatable movement seemed a good basis for gaining more insight into a particularly complex and little known issue. Finally, RW is the motor task that mostly resemble normal walking (NW), thus giving the chance of a straight comparison with one of the most studied movements in literature.

Chapter 3

EXPERIMENTAL PROTOCOL DESCRIPTION

This chapter contains the "materials and methods" information that is common to all the studies presented in this thesis. A dedicated space was here reserved not to annoy the reader later on, in encountering many times the same descriptions about the adopted procedures.

3.1 Participants

Four male and three female young race walkers of national and international class were the subjects of this study. Their age, height and body mass were (mean±standard deviation): $19.7 \pm 2.1\, years$; $1.75 \pm 0.10\, m$; $58.3 \pm 8.3\, kg$. Detailed information about the anthropometric characteristics and the agonistic results are reported in Table 3.1 and Table 3.2 respectively. From data in Table 3.2 and information provided by coaches, it emerged that the race walking progression velocity of the analysed athletes could range from 3.34 to 4.17 $\frac{m}{s}$ during competitions and approximately from 2.75 to 5 $\frac{m}{s}$ during training, depending on the intensity of the exercise they were accomplishing. All subjects used to undergo from a minimum of 6 to a maximum of 12 training sessions a week. They did not show any remarkable lower limb injury or dysfunction at the time of the experiments.

Table 3.1: *anthropometric characteristics of the analised population. μ is the mean value and σ is the standard deviation.*

		s1	s2	s3	s4	s5	s6	s7	μ	σ
sex	[m,f]	m	m	f	f	m	f	m		
age	[yrs]	23	18	18	18	22	20	19	19.7	2.1
height	[m]	1.87	1.90	1.68	1.72	1.74	1.62	1.72	1.75	0.10
weight	[kg]	67.0	61.0	53.0	56.0	64.0	43.0	64.0	58.3	8.3

Table 3.2: *athletes' personal best over the most common distances of race walking competitions. The performances achieved over the* 5, 10 *and* 20 km *events are reported in the following format:* h:mm:ss, *where* h *stands for hours,* m *for minutes and* s *for seconds. Slashes mean that the athlete did not compete over that distance.* $\overline{v}$ *represents the average progression speed, in* $\frac{m}{s}$. μ *is the mean value and* σ *is the standard deviation.*

	5 km		10 km		20 km	
	t	$\overline{v}$	t	$\overline{v}$	t	$\overline{v}$
s1	20:06.61	4.14	42:59.95	3.88	/	/
s2	21:03.68	3.96	42:22.59	3.93	/	/
s3	23:25.60	3.56	48:34.43	3.43	1:39:47.0	3.34
s4	24:04.61	3.46	/		/	/
s5	19:58.00	4.17	40:56.74	4.07	1:25:39.0	3.89
s6	22:55.20	3.64	46:38.53	3.57	/	/
s7	21:56.33	3.80	44:24.97	3.75	1:33:06.0	3.58
μ		3.82		3.77		3.60
σ		0.28		0.24		0.28

Every athlete was properly informed about testing procedures, personal data treating and aims of the research, so that he/she could provide written informed consent before participation.

3.2 Instrumentation

The kinematics and kinetics of race walking were investigated through motion analysis techniques.[1]

An eight TV-cameras optoelectronic system (ELITE2002, BTS, Milan, Italy) was used to capture the three-dimensional coordinates of anatomical landmarks; its sampling rate was fixed at $100\,Hz$. TVCs were positioned and set so that their field of view properly covered the acquisition volume and so that markers on both side of the subject could be simultaneously detectable by the largest number of sensors. Before each experimental session, accuracy was assessed while calibrating the system: a maximum mean error of $1.5\,mm$ concerning the length of a $600\,mm$ rigid bar was tolerated.

Ground reaction force (R) was measured by a force platform (AMTI OR6-7-1000, Watertown, USA) at a sampling frequency of $500\,Hz$.

The setup of TVCs and force place is shown in Figure 3.1. The reference frames relative to kinematics and R were different; therefore, they were reconducted to a common convention: the x axis was oriented to the direction of progression (antero-posterior axis); the z axis was oriented to the vertical direction; the y axis was the cross-product of x and z and defined the medio-lateral direction.

3.3 Data Collection

Some tests with Davis [34] and SAFLo[2] [53] protocols were initially performed to understand which marker set was the most suitable for the purposes of this research. The preliminary trials showed that the the impulsive approach to the ground that occurs in normal walking at heel strike, was magnified, in race walking, by the increased dynamics of the action and by

[1] All experimental session were carried out at *Laboratorio di Analisi della Postura e del Movimento "Luigi Divieti"*, Department of Bioengineering, Politecnico di Milano, Italy. The author would like to thank dr.Veronica Cimolin for her support during data acquisition.

[2] Servizio di Analisi della Funzionalità Locomotoria.

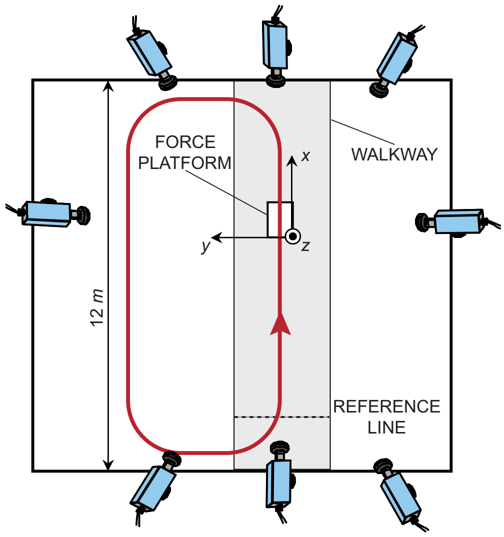
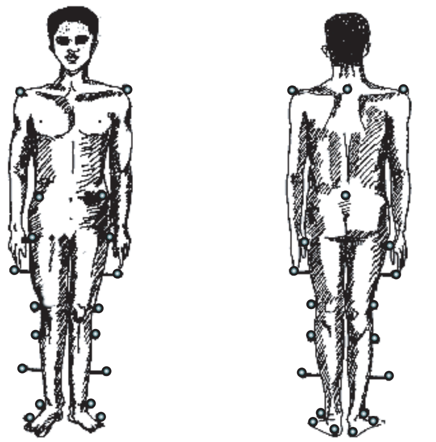


Figure 3.1: *experimental setup.*

the position of the knee, that must be kept fully extended in accordance with the rules. When the Davis configuration was adopted (Figure 3.2), a sensitive oscillation of the markers placed on bars could be visually appreciated and noisy data were its unavoidable outcome. Furthermore the presence of markers on the centre of the greater trochanter was particularly annoying: the athlete was not allowed to wave the arms as close to the trunk as he would naturally do, and a sudden detachment of those markers was often reported. Therefore the SAFLo protocol (Figure 3.3) was preferred. This marker set allowed for the measurement of the total body kinematics, focusing on the lower limbs in particular. The absence of markers both on critical points (e.g. the great trochanters) and on bars (Figure 3.3 and Figure 3.4(a)), let the athlete move naturally and limited the noise that vibration from racewalkers' action might induce.

The subjects were prepared by gluing 19 retroreflective hemispherical markers (15 mm diameter), with a 1 cm pin support, onto the following anatomical landmarks (Figure 3.4(a)): lower prominence of the sacrum,



(a) (b)

Figure 3.2: *the Davis marker set. Front view (a) and back view (b).*

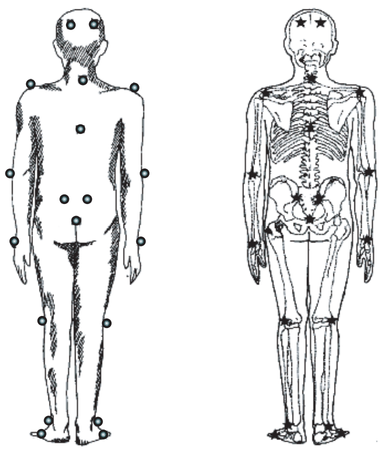
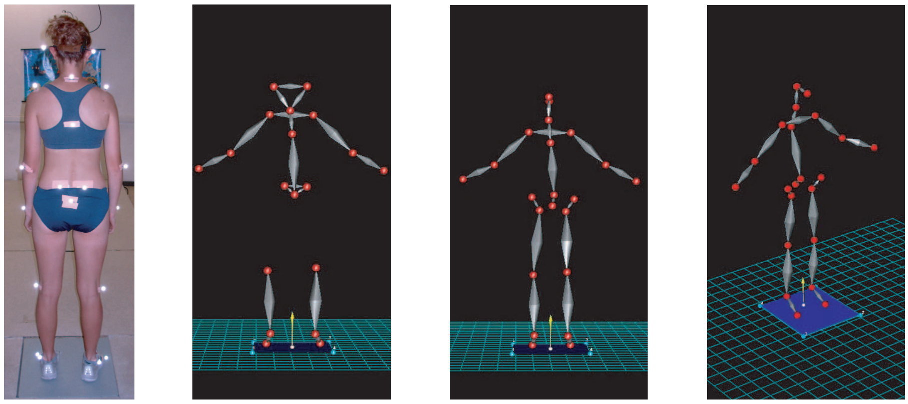


Figure 3.3: *the SAFLo marker set. All markers are visible from the back view.*

posterior superior iliac spines, lateral femoral condyles, lateral malleoli, and fifth metatarsal heads (for the pelvis and lower limbs section); seventh cervical vertebra and point of maximum kyphosis (for the column); acromion bones, lateral homerus epicondyles and stiloideus processes (for the upper limbs section); parieto-occipital areas of the head. Particular care was devoted to fixing the marker to the skin, so that both rapid movements and sweating could not threaten their correct and stable position on the selected anatomical references.



(a) (b) (c) (d)

Figure 3.4: *example of subject prepared with the SAFLo marker set (a) and the corresponding body model: (b) reports the technical markers reconstruction, (c) and (d) two different views of the stick diagram built on estimated joint centers.*

After a standard 20 minutes warm up routine, and a proper number of trials to better familiarise with the experimental settings, each athlete was asked to racewalk across a 12 m long walkway (Figure 3.1). The dimension of the laboratory were big enough to let subjects perform their action continuously and to maintain an adequate, approximately constant, speed while being acquired. The force platform was positioned at two-thirds of the available path, in order to have enough space to accelerate and reach a stable progression. The athletes had previously been instructed not to alter or adjust their pace by looking at the plate: only the trials in which they randomly put their left or right foot on it were recorded. A personal reference line was placed at the beginning of the walkway, as far as possible from the force platform, in order to increase the occurrence of successful passages. As many as 20 suitable race walking trials, performed at a self-selected training pace and supervisioned by the trainer, were collected for each athlete's left and right side. 6 normal walking gaits performed at natural cadence (three for the left limb and three for right one) were acquired as well, to allow for comparison. Two testing sessions, recorded in different periods of the agonistic season, were carried out for four subjects.

The chance of using a treadmill was taken into account, but it was later discarded. It would have not allowed the estimation of ground reaction forces[3] and, consequently, of lower limb joints kinetics. Furthermore, the constraints imposed by that device might have altered the natural movement of race walkers and might have influenced the outcoming motion variability which was one of the most relevant issues of this research. Some authors have investigated the influence of treadmill over kinematic and kinetic variables [143, 2, 146, 39, 92, 147, 120], but contrasting conclusions emerge from their studies. Riley and colleagues [120] observed that treadmill gait is qualitatively and quantitatively similar to overground gait. In contrast, many other authors questioned the assumption that treadmill locomotion effectively reproduce overground locomotion. The differences may concern kinematic and temporal variables [2, 146], electromyographic patterns [146] and coordination variability [39, 147].

3.4 Data Processing

The pipeline of data processing is reported in Figure 3.5. A three level control was applied on the performed trials. First, the athletes' trainer always supervisioned the gaits to check the goodness of performance in terms of both technique and intensity. Then, the balance between anterior and posterior R areas was monitored: under the hypothesis of substan-

[3]Treadmills instrumented with embedded force platforms are a rather novel technology [15, 107] and were not available for this research.

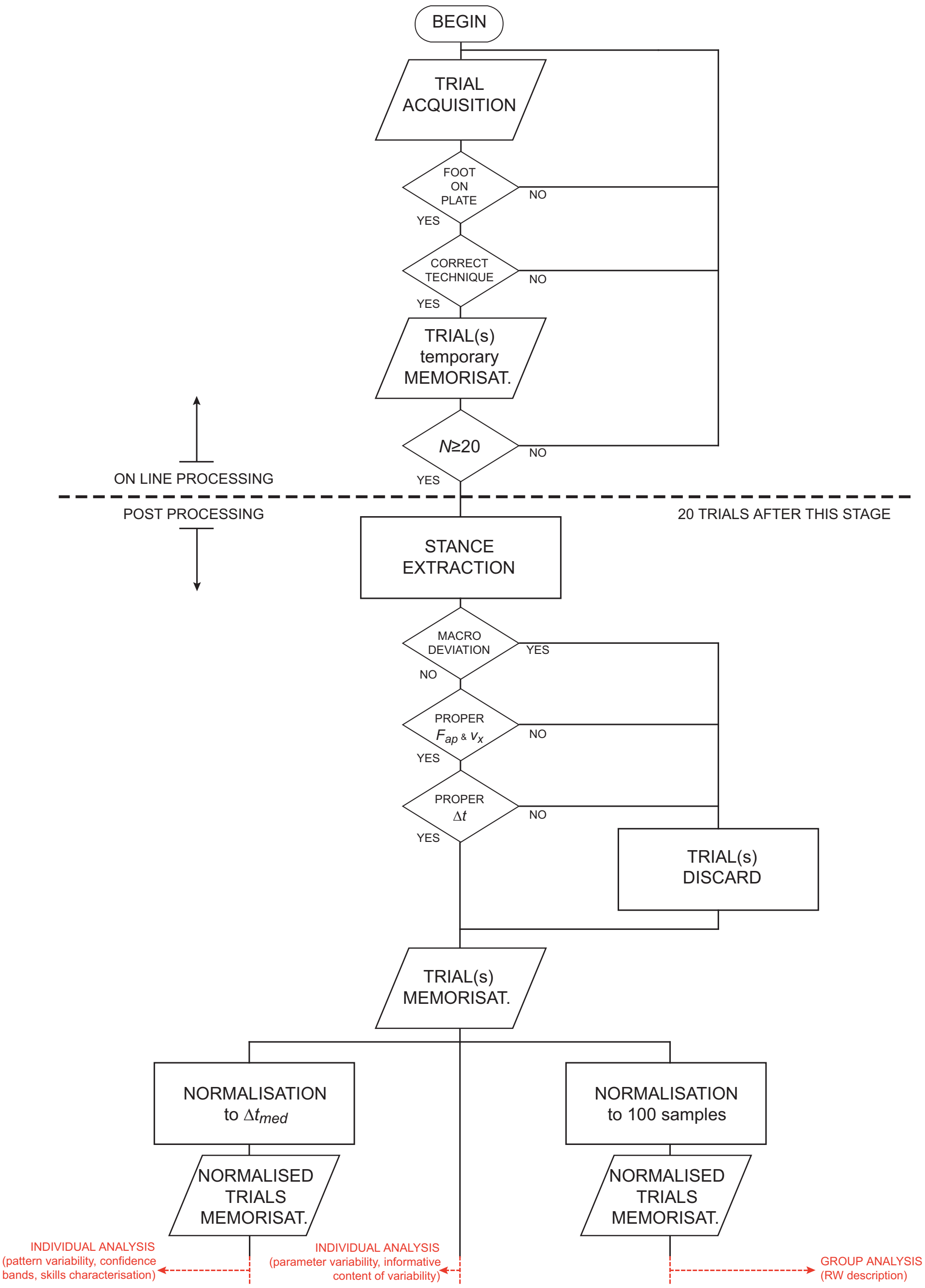


Figure 3.5: *flowchart of data collection and data processing.*

tial symmetry between left and right limb action, the similarity between breaking and propulsive impulse of ground reaction force would imply the maintenance of an almost constant speed. Finally, a post-processing control was carried out directly on the progression speed (v_x), which had to be similiar at heel strike and toe off, and whose average over the stance phase ($\overline{v}_x$) had to resemble usual training speed. v_x was determined from the velocity of the medial point between the two ASIS[4], which will be hereafter referred to as the “fictitious” centre of mass (COM). The extraction of the “true” centre of mass (COM*) (and of its trajectories, velocities and accelerations) from total body kinematics was carried out as well, but the use of the former was preferred because its estimation procedure was still under validation. Even if COM and COM* do not necessarily overlap, preliminary results showed no significative differences between COM and COM*, concerning the measures of interest (e.g. mean progression velocity, vertical displacement range). Furthermore the medial point between the two ASIS approximately corresponds to the navel, which is what trainers qualitatively look at when they have to evaluate the behaviour of the athlete’s centre of mass.

Anthropometric measures and specially designed algorithms [33, 109] were used to estimate and filter three dimensional coordinates of internal joint centres (Figure 3.4(c) and Figure 3.4(d)), joint angles (Figure 3.6) and their derivatives. Net joint moments at the three main joints (M_{hs}, M_{ks}, M_{as})[5] of the lower limb were computed by using the Newton-Euler free body dynamic equilibrium equations. The regression equations proposed by Zatsiorsky and Seluyanov [150] were used to estimate each body segment mass, inertial moments, and gravity center positions. Hip and knee extension and plantar flexion moments were defined as positive. Net joint powers (P_{hs}, P_{ks}, P_{as}) were calculated by multiplying net joint moments and joint angular velocities. Positive values of P were associated to concentric articular actions, negative ones related to eccentric efforts.

[4]Anterior Superior Iliac Spines.

[5]Notation: the first letter of the subscript refers to the articular joint, the second one to the reference plane, e.g. M_{ks} is the knee moment in the sagittal plane.

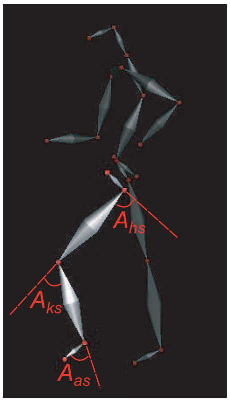


Figure 3.6: *conventions for angles definition in lower limb joints. Average values from the whole population, during standing, were:* $A_{hs} \simeq 25\,deg$, $A_{ks} \simeq 5\,deg$, $A_{as} \simeq 70\,deg$.

R data were normalised by body weight and the other kinetic variables by body weight and height [70, 95], to let interindividual comparison or aggregation be possible.

Besides the three dimesional coordinates of internal landmarks, as many as 15 time varying measures were considered: antero-posterior, medio-lateral and vertical ground reaction forces ($R_{ap}(t)$, $R_{ml}(t)$, $R_v(t)$); hip, knee and ankle joint angles in the sagittal plane ($A_{hs}(t)$, $A_{ks}(t)$, $A_{as}(t)$); hip, knee and ankle joint torques in the sagittal plane ($M_{hs}(t)$, $M_{ks}(t)$, $M_{as}(t)$); hip, knee and ankle joint powers in the sagittal plane ($P_{hs}(t)$, $P_{ks}(t)$, $P_{as}(t)$); pelvic tilt, pelvic obliquity and pelvic rotation angles ($A_{pt}(t)$, $A_{po}(t)$, $A_{pr}(t)$). These variables were chosen because they are supposed to be the most consistent measures of lower limb motion analysis [148, 80, 79, 57, 31, 88, 50, 35, 115] and they were judged, at this stage, as being among the most important ones relating to race walking description.

Only the stance phase of every acquisition was used. This choice derived from some consideration about one of the primary aims of the survey. Biovariability of motion variables had to be extensively investigated; hence, a high accuracy in determining the beginning and the end of the movement was necessary. If the complete gait cycle had been evaluated, the first frame[6] should have been selected by looking at kinematic variables, because only one force platform was available. That estimation would not be trivial and its reliability should be demonstrated [54, 64, 74, 75]. In contrast, the identification of the stance phase was much more consistent: it came from ground reaction force measures, which are generally more accurate and were sampled at higher frequency than kinematics (Section 3.2). Furthermore, in RW, the rear foot usually leaves the ground as soon as the front one approaches it, so that the stance phase approximately covers half of the gait cycle (Section 2.1). Therefore the analysed movement was defined as the interval (Δt) between heel strike, when $R_v(t)$ starts raising from zero, and toe off, when $R_v(t)$ reaches the base line again.

After extracting the stance phase from the selected variables of each repetition, a double control was performed to recognise and discard unrepresentative trials (figure 3.5). The first selection was intended to eliminate macroscopically anomalous curves that could originate either from bad raw data or bad elaboration. The second check was on stance duration; in this case outliers were identified on a temporal basis. Trials that differed more than 1.5 interquartile ranges from the sample median Δt were removed. This threshold is considered a common outlier definition [28].

At this stage curves were saved both in their original and normalised form, ready for further analysis that will be presented in the next chapters. Normalisation was carried out by applying cubic spline interpolation to original data. The number of resampling point was both 100, independently from the stance duration, and the median number of frames concerning the whole set of trials of the analised subject. The former procedure, which is the one commonly adopted in literature, is useful when, for example, interindividual characterisation has to be performed; its main drawback consists in the loss of temporal reference, since time is represented as a percentage of the whole event. The latter was here introduced to maintain temporal information when curves of the same subject were assembled; this operation was allowed by the low intraindividual variability

[6] If the cycle starts outside the force plate and ends on it.

of Δt (Section 4.1).

Chapter 4

CAPTURING MOTOR CHARACTERISTICS: THE ISSUE OF BIOVARIABILITY

If the final aim of the work is to realise the monitoring process described in Section 1.2, the first goal that must be achieved is a consistent description of the actual motor skills of the athlete (Figure 4.1). This might concern

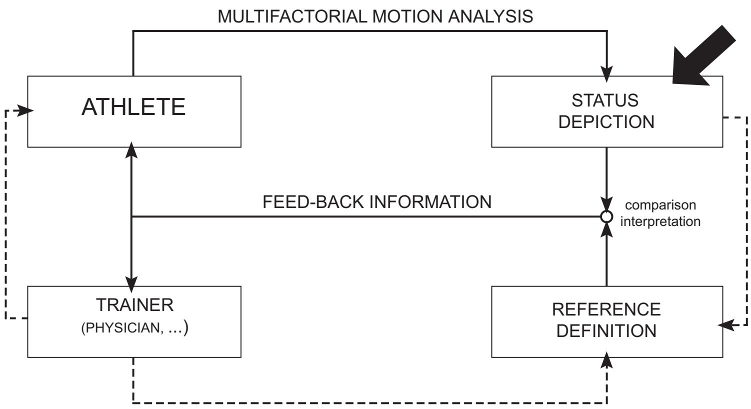


Figure 4.1: *longitudinal monitoring schema. The first phase of the process (i.e. the status depiction) is highlighted.*

either the extraction of parameters or the description and representation of time-varying variables. Quantitative motion analysis typically produce large amounts of data, that consist of parameters (e.g. maximal ground reaction force) and continuous curves (e.g. ground reaction force vs. time or percentage of gait cycle). Both single point and continuous measures have been used for answering research questions about performance enhancement, for gaining more insight into injury prevention, for supporting clinical decisions and for enhancing equipment design.

The most relevant problem in depicting the athlete's status is motor variability. Its quantification, its synthesis, as well as its meaning could deeply affect practical decisions in sports.

In Chapter 4 the issue of biovariability is extensively explored at four different levels, and some solution concerning reliable data reduction are proposed. Section 4.1 and Section 4.2 deal with parameter and pattern variability in order to understand how large they are and how to treat them. The problem of creating a consistent confidence band from a bunch of individual trials is faced in Section 4.3 where both traditional and innovative methods are assessed and compared. Finally, Section 4.4 contains a survey about the informative content of BV, trying to understand whether the fluctuations that occur in repeating the same motor task are only the reflection of noisy measures and random processes, or they represent inherent characteristics of the dynamics of locomotion.

4.1 Assessment of Parameter Variability

4.1.1 Introduction

Quantitative motion analysis often involves the extraction of parameters from kinematic and kinetic curves. The assessment of discrete measures is commonly carried out to understand the characteristics of a particular motor task, to outline the differences between different populations, to select proper therapeutic procedures and to monitor their effectiveness. In sports field, besides all the aforementioned applications, indexes have been used for performance evaluation or enhancement [76, 44, 9, 18], for injury prevention [103, 89, 78, 9, 113, 61], and as an aid to equipment design [144, 19, 47, 102, 122].

The presence of BV in motion variables may alter the evaluation of parameters and drive to misleading conclusions if proper experimental design is not used and robust statistics are not applied. In fact, the changes in observed data might be a consequence of fluctuations and not of emerging features of the phenomenon under investigation. When the individual is examined, the greater movement variability, the higher risk of incurring in unrepresentative results, with this chance being enlarged by the use of few trials during experimental sessions. Some authors suggest that although individuals can be seen as random trials generators and that there is a "seemingly infinite" number of independent performance solutions even to rather stereotyped motor tasks [66, 45, 11, 10, 63, 126, 8, 13, 93, 127, 9, 60, 61]: the exact repetition of movements is impossible [66]. However, variability is not unbounded, but stabilises within certain ranges [77] that may depend on the subject, on the variable, on the movement and on the experimental conditions being considered [37, 42]. Therefore BV should be assessed before proceeding with any kind of biomechanical evaluation and a proper number of trials should be selected in defining the experimental procedures for data collection.

While several researches have thoroughly investigated the reliability of normal walking variables [148, 80, 79, 57, 16, 138, 134, 38, 28], relatively few studies have been conducted to assess the variability of kinematics and kinetics for sports movements. This lack is amplified by the huge variety of motor tasks that are performed by athletes in many different sports disciplines. Jumping [124, 78, 114] and running [14, 37, 85, 42, 50, 115] exercises are the most studied among them.

By registering the variable nature of human movement many scientist agree in suggesting that multiple trials protocols and proper statistics are necessary for reliable analyses [14, 148, 37, 62, 12, 42, 124, 77, 28, 114, 113], but practical applications do not always follow theoretical suggestions. Experimental sessions, data processing and data interpretation are time consuming, thus making researchers often use few or even single trials [17, 71]. Sometimes the intrinsic uniqueness of sports events (e.g. during a competition [149]) makes this choice be unavoidable, however, as suggested by Bates and colleagues [12], the validity and reliability of using a single performance trial as representative of generalized performance outcomes must be questioned.

Therefore the aims of this section were manifold. Since it appeared that BV in race walking gait had never been studied in literature, the variability of a large selection of kinematic and kinetic parameters was investigated by using coefficients of variation (CV). Then, the sequential estimation procedure [14, 62, 124, 77] was used to determine the minimum number of consecutive repetitions that are necessary in an experiment. Finally, the consistency of different central-tendency and spread estimators was tested to understand which are the most robust statistics for summarising variability in discrete data.

4.1.2 Materials and Methods

All available trials, of each subject and side, were considered for the assessment of parameter variability. At this stage variables were taken before being previously normalised by stance duration (Figure 3.5). As many as 70 parameters ($P_i \quad i = 1, \ldots, 70$) were automatically extracted from time-distance data and from the investigated kinematic and kinetic waveforms (Section 3.4) by a dedicated algorithm developed in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.). The selection of these discrete measures was based on literature [16, 42] and on the purpose of fully describing the characteristics of the movement and of its genesis. Table 4.1 reports the whole list of parameters, their abbreviation and their brief description.

Table 4.1: *description of the estimated race walking gait parameters.*

Time-distance data		**Pelvis rotations**		**Lower limb moments**	
Δt:	stance duration	$A_{pt}@hs$:	pelvic tilt at heel strike	M_{hs-MAX}:	max of flex-ext hip moment
$\overline{v}_x$:	mean progression velocity	$A_{pt}@to$:	pelvic tilt at toe off	M_{hs-MIN}:	min of flex-ext hip moment
Δx:	step length	$A_{pt}ROM$:	pelvic tilt range of motion	M_{ks-MAX}:	max of flex-ext knee moment
		$A_{pr}@hs$:	pelvic rotation at heel strike	M_{ks-MIN}:	min of flex-ext knee moment
Ground Reaction Forces		$A_{pr}@to$:	pelvic rotation at toe off	M_{as-MAX}:	max of flex-ext ankle moment
R_{ml-MAX}:	max of med-lat force	$A_{pr}ROM$:	pelvic rotation range of motion	M_{as-MIN}:	min of flex-ext ankle moment
R_{ml-MIN}:	min of med-lat force	$A_{po}@hs$:	pelvic obliquity at heel strike		
R_{ap-MAX}:	max of fore-aft force	$A_{po}@to$:	pelvic obliquity at toe off	$t@M_{hs-MAX}$:	time at max of flex-ext hip moment
R_{ap-MIN}:	min of fore-aft force	$A_{po}ROM$:	pelvic obliquity range of motion	$t@M_{hs-MIN}$:	time at min of flex-ext hip moment
R_{v-MAX}:	max of vert force			$t@M_{ks-MAX}$:	time at max of flex-ext knee moment
		Lower limb angles		$t@M_{ks-MIN}$:	time at min of flex-ext knee moment
$t@R_{ml-MAX}$:	time at max of med-lat force	$A_{hs}@hs$:	hip flex-ext at heel strike	$t@M_{as-MAX}$:	time at max of flex-ext ankle moment
$t@R_{ml-MIN}$:	time at min of med-lat force	$A_{hs}@to$:	hip flex-ext at toe off	$t@M_{as-MIN}$:	time at min of flex-ext ankle moment
$t@R_{ap-MAX}$:	time at max of fore-aft force	$A_{hs}ROM$:	hip flex-ext range of motion		
$t@R_{ap-MIN}$:	time at min of fore-aft force	$A_{ks}@hs$:	knee flex-ext at heel strike	**Lower limb powers**	
$t@R_{ap-zero}$:	time at zero fore-aft force	$A_{ks}@to$:	knee flex-ext at toe off	P_{hs-MAX}:	max of flex-ext hip power
$t_{\%}@R_{ap-zero}$:	% at zero fore-aft force	$A_{ks}ROM$:	knee flex-ext range of motion	P_{hs-MIN}:	min of flex-ext hip power
$t@R_{v-MAX}$:	time at max of vert force	$A_{as}@hs$:	ankle flex-ext at heel strike	P_{ks-MAX}:	max of flex-ext knee power
		$A_{as}@to$:	ankle flex-ext at toe off	P_{ks-MIN}:	min of flex-ext knee power
I_+:	impulse of propulsive force	$A_{as}ROM$:	ankle flex-ext range of motion	P_{as-MAX}:	max of flex-ext ankle power
I_-:	impulse of braking force			P_{as-MIN}:	min of flex-ext ankle power
$I_{+/-}$:	braking-propulsive impulse ratio	**Parameters concerning technique**			
		$t_{\%}@unl$:	% at knee unlocking	$t@P_{hs-MAX}$:	time at max of flex-ext hip power
		$t_{\%}@vup$:	% at vertical upright position	$t@P_{hs-MIN}$:	time at min of flex-ext hip power
		$\Delta t_{unl-vup}$:	$t_{\%}@unl - t\%@vup$	$t@P_{ks-MAX}$:	time at max of flex-ext knee power
		Δz_{cnt}:	"loss of contact" (Section 6.1)	$t@P_{ks-MIN}$:	time at min of flex-ext knee power
		$\Delta x_{fl}@hs$:	"forward pull" (Section 6.1)	$t@P_{as-MAX}$:	time at max of flex-ext ankle power
		$\Delta x_{rl}@to$:	"backward push" (Section 6.1)	$t@P_{as-MIN}$:	time at min of flex-ext ankle power
		$\Delta x_{rl/fl}$:	$\Delta x_{rl}@to/\Delta x_{fl}@hs$		
		Δz_{COM}:	vert excursion of the COM		
		Δy_{COM}:	med-lat excursion of the COM		
		$\Delta z_{kst-ksw}$:	"knee swing" (Section 6.1)		

Quantification of parameter variability

Coefficients of variation were used for the quantitative assessment of parameter variability. This statistics is commonly adopted to evaluate the reproducibility of unidimensional gait data [148, 80, 57, 134, 28, 115], and is defined as the ratio of the standard deviation (σ) to the mean value (μ):

$$CV = \frac{\sigma}{\mu} \tag{4.1}$$

or, if expressed in percentage:

$$CV\% = \frac{\sigma}{\mu} \cdot 100 \tag{4.2}$$

CVs are dimensionless, thus being very suitable for comparing variability of measures irrespective of calibration, scaling or different units of measurement [72].

The intraindividual CV of every parameter, for each session, subject and side was estimated. Basic statistics were then applied to every set of 22 CVs for describing the distribution among the analysed subjects.If the CV value was less than 10%, the intraindividual variability concerning the parameter of interest was considered as being relatively low [148, 90, 115].

Parameter stability

The sequential estimation procedure [14, 62, 124, 77] was used to determine the minimum number of consecutive trials that are necessary to obtain a stable mean for each considered variable, subject and side ($\#t^s_{X_i} \quad s = 1, \ldots, 22;\ i = 1, \ldots, 70$)[1]. This method consists in calculating the cumulative mean of the selected parameter by adding one trial at a time. Stability is recognised when the successive mean deviations

[1]Notation: the subscript X_i refers to the considered parameter, the superscript to the subject. Note that s ranges to 22 and not to 7 because two testing session were available for four subjects. Furthermore, left and right limbs were considered separately (Section 3.3).

fall within a band built around the overall average (Figure 4.2). Table 4.2 shows an example of estimation of $\#t$ for the variable and subject presented in Figure 4.2. In this study the bandwidth was defined as $\mu \pm 0.25\sigma$ [14, 62, 124, 77], where μ is the mean over the whole set of trials and σ the corresponding standard deviation.

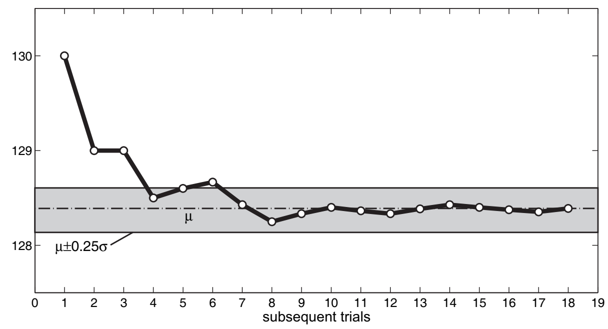


Figure 4.2: *example of sequential estimation on a single individual parameter. The numerical passages are shown in Table 4.2.*

Since the outcoming $\#t^s_{X_i}$ could vary depending on each subject (s) and on the variable under investigation (X_i), basic statistics were applied to their distribution among analysed athletes and then considered for discussion.

Consistency of variability indexes

Due to the presence of motor variability, spatio-temporal parameters or measures extracted from kinematic or kinetic curves should be regarded as stochastic rather than deterministic variables [27, 28]. Hence, the focus in summarising unidimensional motor measures consists in depicting location and spread that match the underlying data distribution and that are not significantly altered by unrepresentative observation [28]. As previously mentioned, the use of coefficients of variation as spread estimators is very common in quantitative motion analysis [148, 80, 57, 134, 28, 115], and is strongly supported by some authors [72]. However, it relies on some hypotheses that should be initially verified [6]. Among them the most

Table 4.2: *example of determination of parameter stability through sequential estimation for a given measure and subject. Here data about $t@R_{ap-MAX}$ (frames) are reported. μ_{cum} and σ_{cum} are the cumulative mean and cumulative standard deviation. μ_{tot} and σ_{tot} are the 18-trials mean and standard deviation. δ is the deviation (absolute value) between μ_{cum} and the overall mean. The trial after which μ_{cum} stabilises within $\mu \pm 0.25\sigma$ bands is highlighted.*

trial #	parameter	μ_{cum}	σ_{cum}	δ
1	130	130.00	0.00	1.61
2	128	129.00	1.41	0.61
3	129	129.00	1.00	0.61
4	127	128.50	1.29	0.11
5	129	128.60	1.14	0.21
6	129	128.67	1.03	0.28
7	127	128.43	1.13	$\triangleright$**0.04**
8	127	128.25	1.16	0.14
9	129	128.33	1.12	0.06
10	129	128.40	1.07	0.01
11	128	128.36	1.03	0.03
12	128	128.33	0.98	0.06
13	129	128.38	0.96	0.00
14	129	128.43	0.94	0.04
15	128	128.40	0.91	0.01
16	128	128.38	0.89	0.01
17	128	128.35	0.86	0.04
18	129	128.39	0.85	0.00
			μ_{tot}:	128.39
			σ_{tot}:	0.21

relevant is the assumption of normality, which is not granted and is not always easily assessable, especially when populations under analysis are not numerous. Furthermore, CVs may lead to erroneous interpretations when data are not bounded to positive values by zero but range around it. In this case, high CVs are not necessarily indicators of high variability (i.e. low repeatability), because their increased values may derive from measures that vary between negative and positive values and whose average approximates zero. Finally, some authors have warned that CVs may be deeply influenced even by single outliers and, consequently, that the resulting variability description may be altered; others have questioned the arbitrary choice of 10% as the correct reference for discriminating between good and poor reproducibility [6].

Therefore the issue of summarising motor variability through proper and robust statistics was investigated at different stages. Tests of normality were performed on the intraindividual distribution of every parameter through Lilliefors test ($\alpha = 0.05$). Central tendency and spread estimators were calculated. Mean (μ) and median (med) were considered for location. Standard deviation (σ), coefficient of variation (CV), interquartile range (IQR) and median absolute deviation (MAD) for spread. Besides μ, med, and σ, which are commonly known, and CV, whose description is reported in (4.1) and (4.2), IQR and MAD are defined as:

$$IQR(X_i) = x_{i,0.75} - x_{i,0.25} \tag{4.3}$$

where $x_{i,0.75}$ and $x_{i,0.25}$ are the 75^{th} and 25^{th} percentiles for the probability distribution of parameter X_i;

$$MAD(X_i) = med(|X_i - med(X_i)|) \tag{4.4}$$

The consistency of estimators to the presence of contaminants was estimated: all the aforementioned statistics were calculated both for original distributions ($X_i^s \quad s = 1, \ldots, 11;\ i = 1, \ldots, 70$) and for the same dataset after outlying values removal ($\hat{X}_i^s \quad s = 1, \ldots, 11;\ i = 1, \ldots, 70$). Outliers were identified, according to Chau and colleagues [28], as the values that differed more than 1.5 interquartile ranges from the sample median.

Non-parametric within groups tests (Wilcoxon, $\alpha = 0.05$), were applied to test for significant differences concerning each estimator with and without contaminants (a total of $i = 70$ tests were carried out for each one of the 6 statistics).

All the procedures exposed in Section 4.1 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

4.1.3 Results

Table 4.3 and Table 4.4 report the intraindividual $CV\%$s of the whole set of parameters, in terms of median and 95^{th} percentile. Looking at the former, 36 out of 70 measures showed a relatively low variability (<10%); among them, ankle angle at heel strike (2.0%), average progression velocity (2.6%), stance phase duration (3.0%), step length (2.4%), occurrence of maximal propulsive force (3.2%) and some variables related to technique (e.g. $t_{\%}@unl$). When the 95^{th} percentile was considered, things dramatically changed: only 11 parameters maintained good reproducibility, while as many as 41 measures assumed $CV\%$ greater than 20%, thus manifesting considerably low repeatability. Kinetic variables were mostly the ones that presented poor repeatability by looking at both median and extreme values, with the exception of R_{v-MAX} and of some parameters concerning the ankle joint. ROMs, which are commonly used kinematic descriptor, had median $CV\%$ lower than 10% ($A_{hs}ROM$, $A_{as}ROM$, $A_{pr}ROM$, $A_{po}ROM$) or close to it ($A_{ks}ROM$), but showed increased variability with some athletes, so that the resulting 95^{th} percentiles were sensitively greater than 10% ($A_{as}ROM$, $A_{po}ROM$) or even 20% ($A_{pr}ROM$, $A_{hs}ROM$, $A_{ks}ROM$).

Table 4.3: *median values of intraindividual CV% distributions over the whole population.*

median $CV\%$							
<5%		5%–10%		10%–20%		>20%	
$A_{hs}@hs$	2.0%	$A_{hs}ROM$	5.3%	$t@P_{hs-MIN}$	10.2%	$\Delta z_{kst-ksw}$	20.7%
$\Delta x_{rl}@to$	2.3%	$\Delta x_{rl/fl}$	5.7%	$A_{ks}ROM$	10.5%	P_{hs-MAX}	20.7%
$t_{\%}@unl$	2.3%	$t@M_{ks-MAX}$	5.8%	R_{ap-MIN}	10.7%	P_{hs-MIN}	22.5%
Δx	2.4%	$t@R_{v-MAX}$	6.1%	I_{+}	11.6%	$A_{po}@to$	22.8%
$\overline{v}_x$	2.6%	A_{as-ROM}	6.7%	M_{hs-MAX}	12.2%	P_{as-MIN}	24.1%
Δt	3.0%	$A_{pt}@to$	6.8%	$A_{ks}@to$	13.1%	Δz_{COM}	24.6%
Δt	3.0%	$A_{pr}ROM$	7.7%	$A_{pr}@to$	13.4%	$A_{ks}@hs$	25.7%
$t@R_{ap-MAX}$	3.2%	M_{hs-MIN}	7.8%	$A_{pr}@hs$	13.7%	P_{ks-MAX}	26.0%
$\Delta t_{unl-vup}$	3.3%	$t@R_{ap-zero}$	8.0%	I_{-}	14.3%	$I_{+/-}$	26.4%
R_{v-MAX}	3.3%	$t_{\%}@R_{ap-zero}$	8.7%	M_{as-MIN}	14.4%	$A_{pt}ROM$	26.5%
$t@P_{ks-MIN}$	3.4%	$A_{po}ROM$	8.7%	M_{ks-MIN}	16.7%	Δy_{COM}	31.3%
$t@M_{as-MAX}$	3.5%	P_{as-MAX}	9.3%	M_{ks-max}	16.9%	$t@P_{as-MIN}$	31.7%
$t@P_{as-MAX}$	3.6%	$t@M_{hs-MAX}$	9.3%	$t@M_{ks-MIN}$	17.1%	R_{ml-MAX}	32.5%
$t@R_{ml-MIN}$	3.7%	R_{ap-MAX}	9.8%	$A_{po}@hs$	17.8%	$t@P_{ks-MAX}$	35.1%
$A_{hs}@hs$	3.8%			R_{ml-MIN}	19.0%	Δz_{cnt}	44.2%
$A_{pt}@hs$	4.2%			P_{ks-MIN}	19.2%	$A_{hs}@to$	44.5%
$A_{as}@to$	4.4%					$t@P_{hs-MAX}$	53.2%
$t@M_{hs-MIN}$	4.5%					$t@R_{ml-MAX}$	63.8%
$t_{\%}@vup$	4.8%						
$t@M_{as-MIN}$	4.8%						
M_{as-MAX}	4.8%						
$t@R_{ap-MIN}$	4.8%						
$\Delta x_{fl}@hs$	5.0%						

Table 4.4: *95^{th} percentiles of intraindividual CV% distributions over the whole population.*

95^{th} percentile of $CV\%$							
<5%		5%–10%		10%–20%		>20%	
$\Delta x_{rl}@to$	3.3%	$t@R_{ap-MAX}$	5.5%	$A_{as}@hs$	10.2%	$A_{pr}ROM$	20.1%
$\overline{v}_x$	4.6%	$t_{\%}@unl$	6.0%	$A_{hs}@hs$	12.0%	I_+	24.0%
R_{v-MAX}	4.8%	Δt	6.5%	$\Delta x_{rl/fl}$	12.2%	R_{ap-MIN}	24.2%
		Δt	6.5%	Δx	12.6%	$A_{pt}@to$	25.1%
		$t@P_{as-MAX}$	7.2%	M_{hs-MIN}	13.1%	$A_{hs}ROM$	25.3%
		$\Delta t_{unl-vup}$	7.2%	P_{as-MAX}	13.8%	$t@P_{ks-MIN}$	26.1%
		M_{as-MAX}	8.8%	$\Delta x_{fl}@hs$	13.9%	$A_{ks}ROM$	28.8%
		$A_{pt}@hs$	9.2%	$A_{po}ROM$	14.0%	M_{ks-MIN}	29.6%
		$t@M_{as-MAX}$	9.3%	$A_{as}ROM$	14.3%	$t@M_{hs-MIN}$	32.8%
				$A_{as}@to$	14.4%	M_{ks-MAX}	35.3%
				$t_{\%}@vup$	14.6%	$A_{ks}@to$	35.3%
				$t@M_{as-MIN}$	15.5%	P_{ks-MIN}	36.4%
				$t_{\%}@R_{ap-zero}$	16.9%	$t@M_{hs-MAX}$	37.0%
				$t@R_{ap-MIN}$	17.0%	M_{as-MIN}	38.5%
				R_{ap-MAX}	17.3%	$A_{pr}@hs$	39.0%
				M_{hs-MAX}	18.3%	I_-	39.1%
				$t@R_{ap-zero}$	18.4%	P_{as-MIN}	40.9%
				$t@R_{ml-MIN}$	19.5%	P_{ks-MAX}	43.9%
						$A_{pr}@hs$	44.5%
						R_{ml-MIN}	44.7%
						$A_{pt}ROM$	46.6%
						$t@P_{hs-MIN}$	47.5%
						$A_{po}@to$	52.9%
						P_{hs-MAX}	53.4%
						$t@R_{v-MAX}$	55.9%
						Δz_{COM}	56.0%
						$I_{+/-}$	58.3%
						$A_{po}@hs$	63.2%
						Δy_{COM}	63.4%
						$t@P_{ks-MAX}$	72.3%
						P_{hs-MIN}	81.0%
						$t@M_{ks-MAX}$	87.4%
						$t@P_{as-MIN}$	89.4%
						$A_{ks}@hs$	108.8%
						$t@M_{ks-MIN}$	119.1%
						$\Delta z_{kst-ksw}$	123.9%
						R_{ml-MAX}	133.2%
						$t@R_{ml-MAX}$	156.1%
						$t@P_{hs-MAX}$	205.3%
						$A_{hs}@to$	262.9%
						Δz_{cnt}	224.8%

Table 4.5: *summary of the minimum number of trials for parameter stability, estimated through sequential estimation. Each element in the table ($\#t^s_{X_i}$) is the outcome of the processes shown in Figure 4.2 and Table 4.2. Only a small subset of the 70 considered parameters is here presented.* min_{tot}, max_{tot}, med_{tot} *are statistics calculated over both the whole population and the whole set of parameters.*

subj	side	Δt	$A_{hs}ROM$	R_{v-MAX}	M_{ks-MAX}	P_{hs-MAX}	$\overline{v}_x$	Δx	$t_{\%}@unl$	+61 par	med_{tot}	min_{tot}	max_{tot}
s1	L1	4	5	4	4	4	4	4	3				
s1	R1	4	4	9	8	5	9	7	11				
s2	L1	13	6	8	9	9	12	11	10				
s2	R1	12	2	11	13	5	12	10	6				
s2	L2	15	9	6	14	10	15	14	6				
s2	R2	3	11	5	11	8	9	7	11				
s3	L1	11	10	4	6	3	8	8	6				
s3	R1	6	9	7	7	6	5	12	8				
s4	L1	12	6	9	11	7	11	9	8				
s4	R1	11	9	14	15	8	9	9	7				
s5	L1	4	3	9	6	4	8	7	4				
s5	R1	8	6	7	7	6	4	7	8				
s5	L2	6	4	7	6	4	6	4	7				
s5	R2	6	6	6	7	8	9	8	8				
s6	L1	15	7	16	18	5	9	16	12				
s6	R1	9	13	5	10	4	14	13	8				
s6	L2	13	12	12	10	8	13	8	6				
s6	R2	10	14	11	13	8	5	12	14				
s7	L1	14	12	10	8	6	14	1	13				
s7	R1	12	11	13	3	11	8	5	12				
s7	L2	11	10	9	10	6	8	11	3				
s7	R2	10	11	10	4	9	8	7	8				
	min	3.0	2.0	4.0	3.0	3.0	4.0	1.0	3.0	···	3.0	1.0	4.0
	max	15.0	14.0	16.0	18.0	11.0	15.0	16.0	14.0	···	15.0	11.0	18.0
	med	10.5	9.0	9.0	8.5	6.0	9.0	8.0	8.0	···	8.0	5.5	11.0
	$95^{th}prct$	15.0	13.5	15.0	16.4	10.5	14.5	15.0	13.5	···	14.0	10.5	16.4

Table 4.5 shows summary statistics of sequential estimation over the whole set of parameters. If the 95^{th} percentiles of $\#t_{X_i}$ distributions among subjects were considered, the number of trials required to obtain stable means of parameters ranged between 10.5 (P_{hs-MAX}) and 16.4 (M_{ks-MAX}), with a median value of 14.0.

Lilliefors tests were carried out on 1540 data sets ($X_i{\cdot}s = 1540 \qquad X_i = 70$, $s = 22$) and evidenced that 1206 out of 1540 intraindividual samples were not normally distributed. Kinetic measures were the ones that showed a higher recurrence of non-normal populations (41.1%), but kinematic parameters were not always Gaussian, either (hypothesis of normality was rejected in 40 out of 356 cases).

Results concerning the consistency of central tendency and spread estimators to the presence of contaminants are resumed in Table 4.6. μ was slightly less robust than *med*. The former showed to be significantly affected by the presence of unrepresentative data in 9 cases out of 70 (87% of robustness), the latter in 4 out of 70 (94% of robustness). Non parametric spread estimators were remarkably more consistent than the corresponding parametric ones. In fact, only 8 times out of 62, μ and CV were not affected by unrepresentative values in the distribution. Figure 4.3 shows

Table 4.6: *consistency of central tendency and spread estimators to the presence of outliers. Test of robustness were performed on 70 parameters (total). The second column (robust) indicates the number of parameters for which the estimate was not significantly affected by contaminants. The third column (non robust) represents the number of parameters for which the estimate was remarkably altered by outliers. % is the percentage of robustness.*

estimator	robust	non robust	total	%
μ	61	9	70	87
med	66	4	70	94
σ	8	62	70	11
CV	8	62	70	11
IQR	29	41	70	41
MAD	27	43	70	39

a bar graph representing the normalised values of central tendency and spread estimators for a single measure ($t@P_{hs-MAX}$) out of the 70 considered, before and after outliers removal.

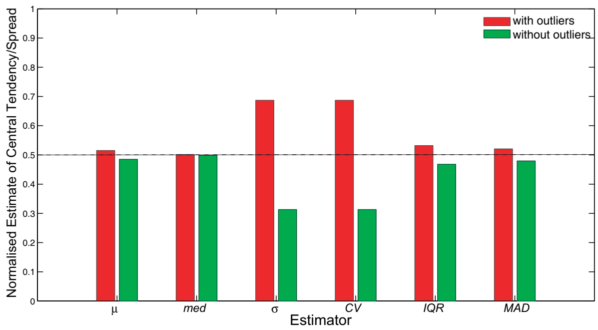


Figure 4.3: *estimation of central tendency and spread through different statistics. The bar graph shows the normalised values before and after outliers removal. The example is referred to a single parameter among the 70 considered.*

4.1.4 Discussion

Race walking is apparently a very repeatable motor task: it is similar to normal walking and it is defined by rules that add external constraints to the movement (Section 2.1), thus making it more controlled and, seemingly, more stereotyped. When data were acquired, data collection (Section 3.3) and data processing procedures (Section 3.4), were set in order to get the athlete's performance to be technically correct and to get trials to be as reproducible as possible. Hence, a low intraindividual variability would be expected.

"Global" parameters, i.e. measures that describe the output of the whole system, gave evidence of the aforementioned homogeneity. In fact, every athlete was able to race walk with very homogeneous progression velocity and showed a significantly high reproducibility in terms of stance duration. Queen and colleagues [115] reported that in most studies on running, subjects are usually asked to maintain speed within a 5–8% variability range, and that treadmills are often used to standardise progression velocity. In the present work, the treadmill was not employed (Section 3.3). Nevertheless, $\overline{v}_x$ resulted very reproducible (4.6% for the 95^{th} percentile) and aligned with the levels of variability that other authors found about normal gait [80, 57, 134]. The low variability of $\overline{v}_x$ during RW was not the outcome of a too controlled movement, in fact magnitudes of $\overline{v}_x$ were comparable with training pace (Section 3.1). Progression velocities ranged between 2.41 $\frac{m}{s}$ and 3.30 $\frac{m}{s}$, and were even not far from speeds registered in many studies on running [42, 50, 115]. Δt was very repeatable, too (6.5% for the 95^{th} percentile); in fact, few trials were discarded for manifesting anomalous duration (Figure 3.5 and Section 3.4).

The good repeatability in spatio-temporal parameters did not correspond to equally reproducible behaviours concerning kinematic and kinetic measures. Most of the variables showed $CV\%$s over 10%, with many of them producing variability far above 20% (Table 4.3 and Table 4.4). In some cases very high BV derived from parameter means close to zero coupled with single trial measures that could range from negative to positive. For instance, median and 95^{th} percentile of $CV\%$ for knee angle at heel strike were 25.7% and 108%. These high values were not necessarily an indication of low reproducibility, rather a consequence of joint angles that could be either slightly positive (knee flexion) or negative (knee hyperextension), and that were always very close to zero (knee completely extended). This phenomenon produced anomalous values that could lead to misleading interpretations if data were not properly read (e.g. $A_{ks}@hs$, $A_{hs}@hs$, R_{ml-MAX}, $\Delta z_{kst-ksw}$). However, there were many variables for which high coefficients of variation reflected effective fluctuation in motor strategies (e.g. $t@R_{v-MAX}$, Δz_{COM}, maxima and minima of joint moments and powers). Figure 4.4 shows an example of how different values of a parameter, $t@R_{v-MAX}$, could reflect different movement organisation when global variables were very similar. In fact, in the reported case, vertical GRF were nearly the same, but curve patterns were remarkably different.

A considerable number of subjects manifested low reproducibility even in kinematic variables (e.g. ROM), that some authors, in contrast, de-

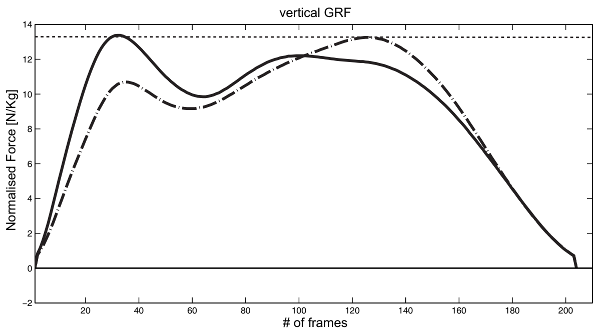


Figure 4.4: *example of GRF patterns, produced by the same subject, that manifested very similar maxima but noticeably different patterns.*

scribed as being rather repeatable [148, 80, 57].

The registered variability in most of the analysed parameters confirmed the need to use proper number of trials. $\overline{v}_x$, Δt, as well as R_{v-MAX}, just represent the global output of the whole neuro-muscular-skeletal system and they give no exhaustive information about how this goal is achieved. Therefore, if the operator has interest in shifting from those "global" measures to the ones that better describe the individual motor strategy and the genesis of performance (typically joint kinematics and kinetics) [124, 114, 113], there is the need to use proper number of trials. The acquisition of a single gait or the selection of the most representative among the registered ones would not be reasonable rather it might produce erroneous interpretations due to the occurrence of false positives or false negatives. Many authors have tried to understand haw many trials should be performed to give a consistent description of the unidimensional kinematic and kinetic measures during walking, running and jumping activities. Kadaba and colleagues [80] said that a single registration might be used for significant clinical decisions. This author's conclusions are in opposition to what many other scientist have found. Winter [148] proposed the employment of at least 3 trials. Bates and colleagues [14] suggested a minimum of 8 successful trials for representing individual GRFs during overground running. De Vita and Bates [37] found that at least 25 acquisitions were necessary to obtain stable means. James [77] observed that ground reaction force parameters were less stable in landing activities than during running, and that the actual number of trials required for performance stability could be affected by the overall number of parameters used to define the stabilisation bandwidth. Other authors used multiple trials protocols but gave no rationale for their choice [3, 4, 57, 42, 115].

Kinetic variables have given clues of relevant potentialities in providing diagnostic information about the locomotor system conditions [17, 124, 114, 113]. Rodano and Squadrone investigated stability of joint kinetics in vertical jump exercises and found that a 12-trials protocol was needed to reach a reliable estimate for hip, knee and ankle moments and powers.

However, it appeared from literature review that a consistent number of acquisition should be carried out, and that the actual $\#t$ needed to depict a stable performance could be a consequence of the activity, of the subject and of the variable under investigation. This was the reason why the sequential estimation procedure was carried out on the whole set of spatio-temporal, kinematic and kinetic parameters.

Results of the present work substantially agreed with previous findings by other authors. If the criterion of looking at the greatest of median $\#t_{X_i}$ (for $i = 1, \ldots, 70$) [124, 77] was followed, 11 trials would be necessary to obtain stable estimates for every parameter (Table 4.5). When a more strict evaluation was performed, and the maximum of 95^{th} percentiles were considered, 16 successful acquisition were needed to reach stable performances.

In this study the reference bandwidth for data stability was defined as $\mu \pm 0.25\sigma$ (Section 4.1.2). The choice of a slightly different bandwidth, however, would not have altered results. Sequential estimations were performed with $\mu \pm 0.2\sigma$ and $\mu \pm 0.3\sigma$, as well, but no significant discrepancies with $\mu \pm 0.25\sigma$ choice emerged.

Test of normality over every set of intraindividual measures produced unexpected results: Lilliefors test ($\alpha = 0.05$) were often positive, thus rejecting the hypothesis of a Gaussian distribution of discrete data collected in successive trials. According to this observation, the use of parametric descriptors, which have been extensively used in literature, appeared as being rather arbitrary. Therefore, a comparison between different estimators of central tendency and variability was implemented.

μ and med were both rather robust to the presence of outliers. In contrast sound differences emerged from comparison between spread estimators (Table 4.6). Non-parametric statistics, σ and CV, were deeply affected by unrepresentative values. These results agreed with what Chau and colleagues found by analysing stride periods [27, 28]. Hence, the issue of summarising location and variability of unidimensional measures should not be addressed by using parametric estimates indiscriminately. CV could inflate variability assessment, thus diminishing the chance of detecting significant differences when they do in fact exist [28]. CV is easily readable, due to its being dimensionless, and thus very suitable for comparisons, but some of the drawbacks this coefficient entails (Section 4.1.2) were actually encountered in this work. However, MAD and IQR were not totally free from being altered by contaminants. They manifested a nearly 50% occurrence of statistically significant changes due to contaminants. Therefore, an effective removal of unrepresentative performances would be advisable. This procedure might be carried out directly on discrete measures, if only one discrete variable is the aim of the investigation, otherwise outliers elimination should be performed directly on continuous waveforms, since anomalous trials regarding a particular point might not correspond to misrepresenting trials concerning another parameter. The issue of trial selection on a continuous measures base is explored in Section 4.2.

4.2 Assessment of Pattern Variability

4.2.1 Introduction

Discrete data analysis is a powerful instrument but is not enough to carry out an exhaustive description of the observed movement. When single measurements are extracted from continuous variables, a large amount of data is discarded and potentially relevant information may not have been accounted [139, 115, 125]. The shape of the whole pattern or other peculiar features may in fact contain other useful indications. In clinics, for example, waveform analysis may help physicians in classifying patients' behaviour as physiological or pathological. In sports monitoring, which is the focus of this research, it may give indications about the athlete's inherent characteristics and about their evolution.

By repeating the same motor activity, athletes do not generate kinematic or kinetic patterns that perfectly overlap, thus evidencing a single waveform, but produce a family of curves, each one (slightly) different from the other. Despite the relevance of continuous measures for a correct description of time-varying kinematics and kinetics, the issue of assessing pattern variability is far less common, in literature, than studies on parameter reliability. In particular, some authors have investigated the reproducibility of gait variables, but have generally focused on the influence of instrumentation and acquisition protocols on data repeatability [80, 57], or on the differences between normal and pathological subjects [134]. In those studies, the coefficient of multiple correlation (CMC) was used to assess the within-day, between-day and overall variability of continuous variables during normal walking. Result showed that lower limb kinematics and kinetics had better reproducibility in the sagittal plane, with CMC values very close to 1[2] both for intraday and for interday variability. In contrast, reliability on secondary planes of motion was less good, with the exception of pelvic rotation and obliquity, for which CMC values were fair. Hence, authors concluded that repeatability for sagittal plane variables is good enough for their use in clinical examinations, provided that operators are very careful in marker placement and experimental settings. Queen and colleagues [115] explored running activities and assessed both the reliability of many kinetic and kinematic variables and the influence of progression velocity on their variability. They confirmed previous findings concerning normal gait [80, 57, 134] and evidenced little effects of running speed on coninuous measures reproducibility. Repeatability of sagittal plane data was greater than repeatability of frontal and transverse plane patterns.

[2] CMC ranges between 0 (totally dissimilar curves) and 1 (perfect reproducibility).

Reliability of GRF variables was better than the one for other kinetic and kinematic measure, with the exception of the medio-lateral component of ground reaction force, for which CMC values were poorer.

Since waveforms variability in sports, and in race walking in particular, has not been thoroughly studied in literature, the work presented in this section aimed at investigating intraindividual repeatability of RW gait data during a single testing session. The use of coefficient of multiple correlation was not suitable for that purpose (Section 4.2.2), therefore a different statistic, the intraclass correlation coefficient (ICC) [131, 94, 130, 50, 46] was applied. ICC was adopted to recognise and discard unrepresentative waveforms, too, so that a family of curves more typical of the athlete's characteristics could be extracted and considered for further analysis. This would concur with the first need of the monitoring process, namely, giving the motor portrait of the athlete (Figure 4.1).

4.2.2 Materials and Methods

Normalised waveforms were used for the assessment of intraindividual pattern variability (Figure 3.5). Pelvic tilt, rotation and obliquity, ankle, knee and hip flex-extension angles, moments and powers, and ground reaction forces were the variables under analysis (Section 3.4).

Quantification of curve variability through ICC

The coefficient of multiple correlation could not be adopted in this study. Its application would require an experimental design with multiple testing session on different days, even if intrasession variability was the only aim of the survey. Growney and colleagues [57], for instance, used 3 trials collected on each of 3 separate days; Queen and colleagues [115] adopted 2 separate testing sessions with as many as 6 trials each. Within day CMC ($wCMC$) are, in fact, defined as [80, 57]:

$$wCMC = \sqrt{1 - \frac{\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\frac{(X_{mn}(t)-\overline{X}_m(t))^2}{M\cdot T\cdot(N-1)}}{\sum_{m=1}^{M}\sum_{n=1}^{N}\sum_{t=1}^{T}\frac{(X_{mn}(t)-\overline{X}_m)^2}{M\cdot(N\cdot T-1)}}} \tag{4.5}$$

where M is the number of days (sessions), N is the number of trials, and T is the number of time points. $\overline{Y}_m(t)$ and $\overline{Y}_m$ are, respectively, the “daily running mean curve” and the “daily grand mean”:

$$\begin{aligned}\overline{Y}_m(t) &= \frac{1}{N} \cdot \Sigma_{n=1}^{N} Y_{mn}(t) &(4.6)\\ \overline{Y}_m &= \frac{1}{N \cdot T} \cdot \Sigma_{n=1}^{N} \Sigma_{t=1}^{T} Y_{mn}(t) &(4.7)\end{aligned}$$

Therefore, another statistic estimator of curve variability was employed: the intraclass correlation coefficient [131, 94, 130, 50, 46]. ICC is “typically a ratio of the variance of interest, over the sum of variance of interest plus error” [131]. When it is applied to continuous data, the intraclass coefficient can be read as the “proportion of variance due to the time-to-time variability in the total variance” [46]. Namely, this index measures whether the N registered curves of an individual are similar enough to suppose that their mean correctly represents the unknown characteristic pattern of the subject. If $X(t)$ is the variable under investigation, this model can be considered [46, 28]:

$$X^j(t) = \overline{X}(t) + \varepsilon^j(t) \tag{4.8}$$

where j is the j^{th} trial out of the N recorded, $\overline{X}$ is the “true underlying” mean of the N repetitions, and ε^j is the residual error. Hence, ICC may be estimated as [46]:

$$ICC_X = \frac{MSB - MSW}{MSB + (N-1) \cdot MSW} \tag{4.9}$$

where MSB is the between-time mean square, i.e. variation of $\overline{X}(t)$ about the overall cycle mean μ, and MSW is the within-time mean square, i.e. variation of $X^j(t)$ about $\overline{X}(t)$.ICCs usually range between 0 (extremely poor repeatability) and 1 (perfect reproducibility). Some authors [131, 130, 72, 90] have tried to set standard values of this coefficient for assessing good reliability (ICC_{min}). Shrout [130] proposed the following conventional labels for the quality of discrete measures reliability:

0.00–0.10, virtually none; 0.11–0.40, slight; 0.41–0.60, fair; 0.61–0.80, moderate; 0.81–1, substantial. Other works [6, 46] have questioned those pre-set references, presenting counterexamples to show their weakness. They suggested that more efforts should be spent to define categories of agreement based on the ICC and that ICC_{min} (i.e. the value above which repeatability is considered good) is likely to depend on the analytical goals of the survey it has been employed for.

No references about ICC "cut-off" are present in sports and exercise science literature [6]. Furthermore ICC_{min} is most likely to be different when continuous curves are examined. In particular, Duhamel and colleagues [46] argued that each motion variable of the anlysed population could have different limits for ICC goodness. This approach was adopted in the present study.

Therefore the ICC of every aforementioned motion variable was calculated for each subject, and the resulting distribution among race walkers was evaluated. The probability density function was estimated by using a non-parametric fitting with a Gaussian kernel [46]. ICC_{min} was defined for every variable as the median value of the estimated distribution concerning the measure under investigation. Figure 4.5 and Table 4.7 report an example of this procedure, referring to knee angle curves.

Outliers detection

The intraclass coefficient was exploited, through an iterative procedure, to identify outliers and gradually discard them. The procedure consisted in calculating the ICC over all available trials, and in successively eliminating the most deviant curve (i.e. the pattern that made ICC decrease most) till ICC was equal or greater than ICC_{min} (Figure 4.6).

All the procedures exposed in Section 4.2 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

Table 4.7: *example of ICC_{min} definition. The ICC of individual knee flex-extension curves during RW are reported. med, $5^{th}prct$ and $95^{th}prct$ are, respectively, the median, the 5^{th} and 95^{th} percentiles of the ICCs distribution among the subjects (as shown in Figure 4.5). The median value was selected as ICC_{min}.*

A_{ks}		
subject	side	ICC
s1	l	0.650
s1	r	0.502
s2	l	0.825
s2	r	0.706
s3	l	0.751
s3	r	0.714
s4	l	0.236
s4	r	0.600
s5	l	0.269
s5	r	0.504
s6	l	0.608
s6	r	0.524
s7	l	0.585
s7	r	0.619
	med	0.604
	$5^{th}prct$	0.243
	$95^{th}prct$	0.810

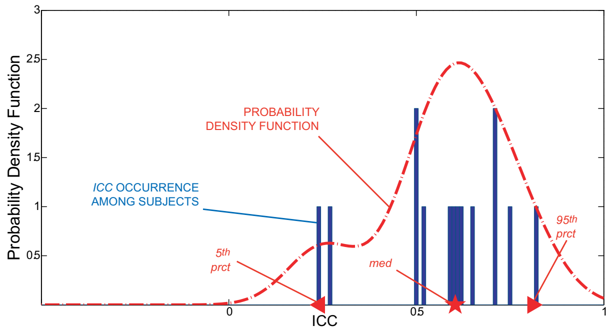


Figure 4.5: *example of ICC_{min} definition. ICC distribution concerning knee flex-extension curves (blue bars) is shown together with its estimated probability density function (red dash-dot line). med, 5^{th}prct and 95^{th}prct are, respectively, the median, the 5^{th} and 95^{th} percentiles of the ICCs distribution among subjects. The median value was selected as ICC_{min}.*

4.2.3 Results

Summary statistics of ICC distributions among analysed athletes are presented in Table 4.8. Antero-posterior and vertical GRF, together with ankle moment, were the variables that presented higher median ICC, with values equal to 0.74, 0.85 and 0.83, respectively. Values of the medio-lateral component of ground reaction force were sensibly lower than R_v and R_{ap} ones. Pelvis and lower limbs angles ranged between 0.51 (pelvic rotation) and 0.73 (hip flex-extension), with the exception of pelvic tilt, which showed very bad reproducibility (0.05). Power curves were always less repeatable than moment ones.

Figure 4.6 represents an example of outliers detection with reference to a single individual variable (R_{ap} for s1, left side). The family of N curves initially generated an ICC equal to 0.52, that became 0.80 after 3 outlying curves removal. ICC_{min} for antero-posterior ground reaction force was set at 0.74 (Table 4.8).

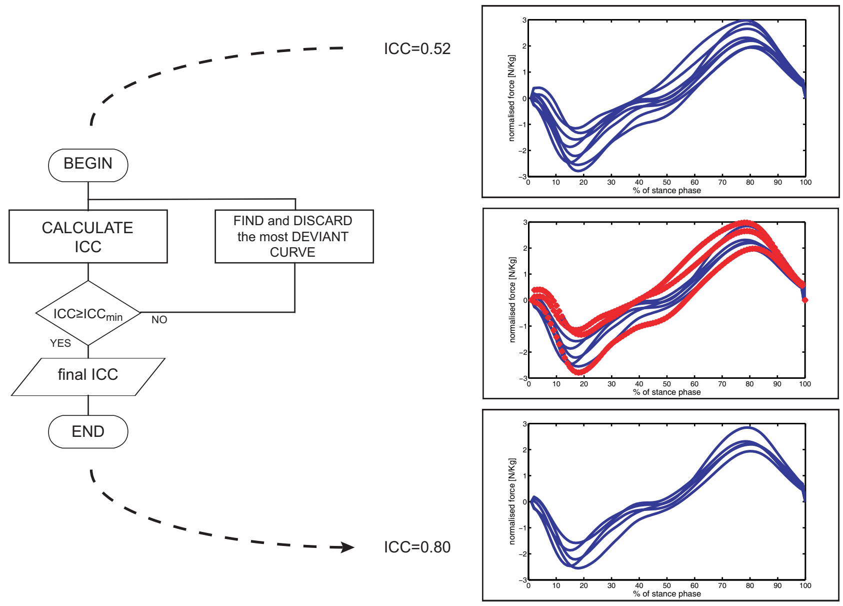


Figure 4.6: *algorithm for outliers detection through ICC. The most outlying curves are gradually discarded until ICC is greater than ICC_{min} (0.74).*

4.2.4 Discussion

The reasons for assessing curve repeatability were manifold. First, it provides more information about the reliability of different continuous measures of quantitative gait analysis. Second, it helps in understanding how much an athlete is able to reproduce the same motor pattern and, consequently, it could represent an effective aid in understanding whether selected training procedures and motor learning can modify curve variability. Anomalies or sudden changes in pattern reproducibility might be related to hidden anomalies and, thus, could serve as monitoring tool for injury prevention. Finally, it allows a more focused depiction of the athlete's motor peculiarities, by selecting a bunch of representative patterns from the original family of trials.

Despite the analysed movement was more dynamical than normal gait, and different reliability estimators were used, results concurred with other

Table 4.8: *summary of ICC distributions descriptors.*

variable	$med\ (ICC_{min})$	$5^{th}prct$	$95^{th}prct$
A_{pt}	0.05	0.00	0.28
A_{po}	0.53	0.23	0.80
A_{pr}	0.51	0.29	0.77
A_{hs}	0.73	0.08	0.90
A_{ks}	0.60	0.24	0.81
A_{as}	0.62	0.10	0.79
R_{ml}	0.24	0.12	0.45
R_{ap}	0.74	0.52	0.85
R_{v}	0.85	0.76	0.90
M_{hs}	0.62	0.36	0.74
M_{ks}	0.38	0.12	0.59
M_{as}	0.83	0.71	0.90
P_{hs}	0.20	0.02	0.51
P_{ks}	0.34	0.15	0.57
P_{as}	0.68	0.40	0.77

authors' findings [80, 57, 134, 115]: absolute values of ICC and CMC could not be compared; nevertheless, some observations on intrasubject reproducibility could be proposed. Pelvic tilt, medio-lateral GRF and hip power were the ones with the lowest ICC values. The small range of motion of the pelvis in the sagittal plane, coupled with errors deriving from the kinematic model adopted, could be the source of poor repeatability in pelvic tilt. Small magnitudes and medio-lateral instability, in particular at heel strike, could be the causes of bad values for transversal ground reaction forces. Whereas, power waveforms reliability could be affected by propagation of errors in the estimation of derivatives.

Hence, antero-posterior and vertical GRF, flex-extension of lower limb joints, pelvis obliquity and rotation, represented the most reliable continuous measures for motor assessment. However, despite RW could be considered as stereotyped as normal walking or even more, results showed that ICC distributions were pretty different from what Duhamel and colleagues [46] found for knee angle pattern in NW gait. Figure 4.7 compares those authors’ findings with the outcomes of the present research concerning the same variable. Probability density function (PDF) of ICC

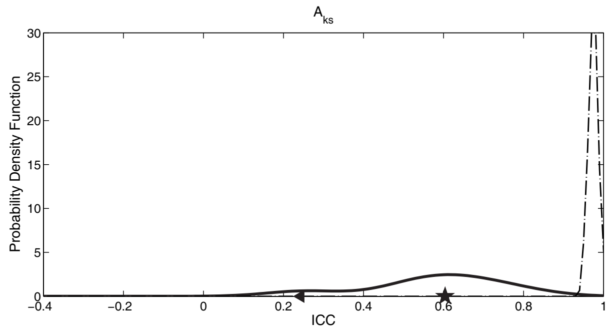


Figure 4.7: *probability density function concerning ICC of knee angles in the sagittal plane. The data obtained in the present study from race walkers’ gaits (solid black line) are compared to results from [46], where normal walking was studied (dash-dot black line).*

distributions were left shifted compared to Duhamel’s data [46], thus indicating that race walkers generally produced less repeatable curves. This was the reason why the same criterion for defining ICC_{min} could not be followed in the present work. Duhamel and colleagues registered [46] that median ICC for knee flex-extension was 0.98 with a minimum of 0.67. Consequently, the resulting PDF manifested a strong increase above 0.95, which was therefore taken as reference limit for assessing good reliability. Despite race walking gaits were very homogeneous in terms of duration and progression speed (Section 4.1) two observation could be registered: first, athletes produced less repeatable $A_{ks}(t)$; second, the resulting ICCs were less homogeneously distributed among subjects. ICC for knee flex-extension ranged from 0.23 to 0.82, with a median value of 0.60 and a 5^{th} percentile equal to 0.24 (Table 4.8). If the 5^{th} percentile had been chosen as ICC_{min}, resembling this way the point were PDF of ICC distribution started increasing, few or even no curves would have been discarded by the recursive algorithm for outliers detection (Figure 4.6). In contrast, when a more constraining boundary, i.e. the median value, was used, the selection of representative individual curves was more effective (Figure 4.6).

Duhamel and colleagues [46] focused only on knee flex-extension during normal gait. Conversely, in the present work a problem related to the contemporary analysis of 15 variables emerged. In fact, the recursive algorithm could eliminate different trials when applied to different variables. For instance, outliers concerning knee angles could be different from unrepresentative trials concerning vertical ground reaction force. Hence, there was the need for defining a selection criterion that could keep only trials that were representative of the individual. Lower limb angles and forces in the sagittal plane have been recognised by many authors as being reliable measures for gait analysis [80, 134, 57]; futhermore, these variables might be considered the bases of both race walking genesis and description. Therefore, only trials that had not been discarded by the recursive algorithm in relation to any of these 5 variables, were kept for further analysis. Anecdotal experience sustained the proposed method, that represents an extension of the procedure presented in Figure 3.5. The output of the whole process would be, for every considered variable, a family of curves that aims at depicting the motor signature of the individual.

A further step would consist in synthesize the information brought by these ensemble of waveforms. This issue is examined in Section 4.3.

4.3 Definition of Confidence Bands

4.3.1 Introduction

The works presented in Section 4.1 and Section 4.2 evidenced the presence of intraindividual variability in many discrete and continuous gait variables. BV causes fluctuation in data coming from the repetition of the same motor task, indipendently from its being a stereotyped movement. Therefore the acquisition of a proper number of trials and the application of suitable and consistent data processing are necessary.

After a family of curves has been collected, and the assessment of their reproducibility has been performed, there is the need to summarise the information they contain, thus characterising the motor signature of the individual. The creation of confidence bands may be an answer to this necessity. The aim of their application may be twofold [105, 139, 86, 46, 77, 28]. The first may be the purpose of classifying new observations as belonging to the reference population or not; this typically occurs in clinical analysis, where patients' curve are usually compared to ranges of normality. The second may consist in understanding whether differences emerge from the comparison of two populations of curves, for example originating from two different subject groups (horizontal design) or from different testing session of the same subject (longitudinal design).

This work shifts its attention onto the individual, thus its principal aim is not the definition of prediction bands for assessing "normality". Nevertheless, the depiction of the athlete's actual status needs the collection of many trials not to fall into erroneous interpretations (Section 4.1 and Section 4.2). Hence, the creation of a consistent confidence regions, in this case from a bunch of individual trials is still fundamental to monitor the boundaries within which the individual motor patterns evolve.

Confidence bands are traditionally created from a set of curves by normalising them to the movement duration and by applying the Gaussian theory to each point of the cycle. Hence, the confidence interval for data at each time position is estimated by creating boundaries of ± 1 standard deviation (68% coverage probability) or ± 1.96 standard deviation (95% coverage probability) about the mean. Unfortunately, statistical methods that are suitable for the analysis of discrete data, are not appropriate if applied to continuous curves. In fact, this point-to-point parametric approach may encounter some relevant critics [139, 86, 46]. First, it assumes that curve values concerning each single instant are normally distributed. Then, it consider each time point independently from the others, neglecting the curve as a whole, and not accounting for the correlation that may exist between the measurements. Finally, some authors have warned about the risk that the use of this method may produce a significant number of clinical misclassifications [105, 139]. Olshen and colleagues [105] and Sutherland and colleagues [139] reported that the use of standard deviation to set boundaries of confidence bands may cause many II type errors (false positives) in evaluating joint angular rotations during gait. Namely, there may be the risk of classifying normal subjects as pathological. Those authors [105, 139] and some others [86, 46, 28] suggested the use of different statistics in order to overcome the drawbacks of parametric point-by-point approaches, and to generate prediction bands with a more consistent coverage probability.

This section therefore aims at exploring innovative methods for the creation of confidence bands from a family of curves, at comparing their effectiveness quantitatively, and at suggesting which appears the most suitable for sports monitoring.

4.3.2 Materials and Methods

All available normalised curves were used for the creation and evaluation of individual confidence bands (Figure 3.5). The whole set of 15 kinematic and kinetic variables (angle of pelvis and lower limb joints, ground reaction force, articular moments and powers, Section 3.4) was analysed; therefore as many as 15 prediction regions were created for each subject and side.

Besides the widespread mean±standard deviation method (MSTD, Figure 4.8(a)), three other statistics were investigated: median and percentiles, bootstrapping and principal component analysis.

Median and percentiles (PRCT)

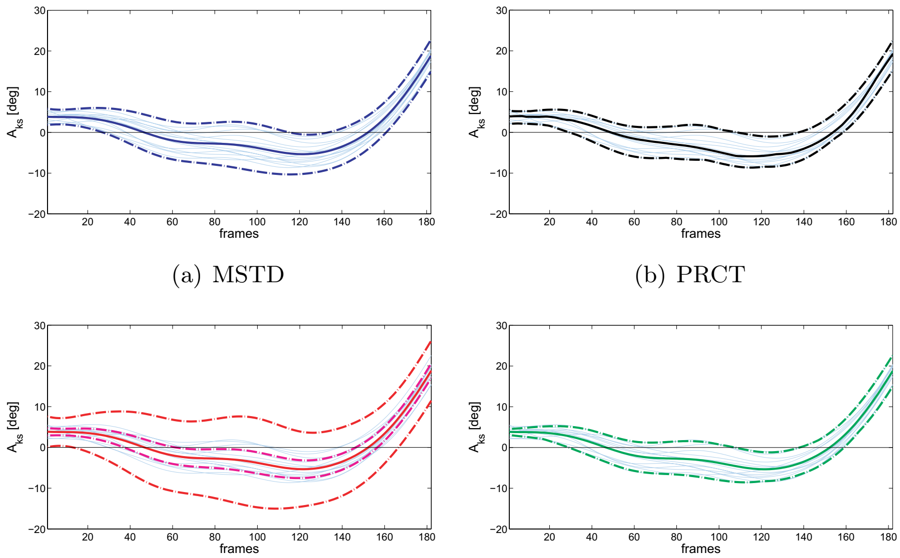
Given a family of N curves of variable $X(t)$, upper and lower limits of confidence bands, according to this technique, were defined as:

$$U_X^{PRCT}(t) = x_{0.975}(t) \tag{4.10}$$

$$L_X^{PRCT}(t) = x_{0.025}(t) \tag{4.11}$$

where $x_{0.975}(t)$ and $x_{0.025}(t)$ were, respectively, the 97.5^{th} and 2.5^{th} percentiles of the distribution of variable $X(t)$ at each time point of the movement cycle (Figure 4.8(b)).

PRCT was still a point-by-point procedure and might suffer from not taking into account possible correlations between successive data over the stance phase. However, it did not rely on the assumption of normality at each t, which was the other main drawback of MSTD.



(a) MSTD (b) PRCT

(c) BOOT (d) PCA

Figure 4.8: *confidence bands created with point-by-point mean and standard deviation (a), point-by-point median and percentiles (b), bootstrapping (c) and principal component analysis (d). This example refers to knee flex-extension angles of a single athlete. Thin lines are the original family of curves. Large dash-dot ones are confidence bands limits. In (b), BOOT-P (larger) and BOOT-C (tighter) bands are represented in red and magenta, respectively.*

Bootstrap (BOOT)

Bootstrap is a rather new technique [48], whose basic idea consists in creating an arbitrary large number (b) of subsets, called "pseudosamples", from the original population. Pseudosamples are generated by randomly drawing N elements with replacement from the initial sample (where N is the size of the original population). Statistics of interest (e.g. the mean) and sampling distributions (e.g. the sampling distribution of the mean) are thus derived from the previously created b subsamples. In particular, when confidence intervals of an estimate are searched, BOOT aims at reducing the coverage error by using simulations to avoid the assumptions which classical procedures rely on [151, 24, 152]. In fact this statistic does not care of how the population is distributed and, thus, it is particularly suitable for small samples with unpredictable distribution. Although it is rather easily applicable to single-measure data sets, bootstrapping becomes a non trivial challenge when populations consist of continuous variables. The reader is referred to [105, 139, 86, 46, 28] for a detailed mathematical description of how bootstrap confidence bands were estimated. However, what BOOT does, is either predicting the boundaries within which any curve drawn from the "true" population is likely to vary with a pre-set probability (BOOT-P)[3], or estimating the confidence bands for the mean curve of the initial ensemble (BOOT-C)[4]. In other terms, "the bootstrap assesses the relationship between the true population and the sample by studying the relationship between the given curves treated as pseudo-population and pseudo-samples drawn from these curves" [86].

Few authors have applied BOOT to gait patterns [105, 139, 86, 46, 28] and have compared the true achieved coverage of bands thus created with the one of traditional techniques. They all agreed in suggesting boostrapping as the most trustworthy method for deriving prediction bands in clinical evaluation.

Conversely, it appears that no studies have investigated the creation and evaluation of boostrapping bands for the assessment of individual sports movements. Therefore, both BOOT-P and BOOT-C were applied to race walkers' families of curves and prediction bands were estimated. The consistency of bootstrapping results may depend on the number of generated pseudosamples. Some researchers have indicated that their number should be between 1000 and 2000. Hence b was set at 2000. Figure 4.8(c)

[3]Notation for upper and lower boundaries: $U_X^{BOOT-P}(t)$–$L_X^{BOOT-P}(t)$.

[4]Notation for upper and lower boundaries: $U_X^{BOOT-C}(t)$–$L_X^{BOOT-C}(t)$.

shows an example of individual bootstrapping bands concerning knee flex-extension angle.

Principal component analysis (PCA)

Several studies in literature have made use of principal component analysis for the assessment of locomotion in healthy and pathological subjects [30, 32, 5, 51, 22, 43] and have tried to understand whether this method can give some information about inherent characteristics of movement organisation (e.g. motor coordination). Due to the high complexity and redundancy of the neuro-muscular-skeletal system it is likely that the large number of kinematic and kinetic measures that come from quantitative motion analysis contain a certain degree of correlation.

PCA is an assumption-free data reduction technique, whereby variables which are believed to be somehow related, are reduced to a few underlying components which adequately account for the structure of the data. Therefore its aim is to reduce the dimensionality of a recorded data set, by projecting the multidimensional space where variables lie into a smaller number of orthogonal axes containing the maximal variation. The reader is referred to [32] for a detailed description of PCA principles and procedures. However, the key passages that were followed are hereafter proposed.

Let $X^j(t)$ be the variable under investigation, where j indicated the j^{th} trial registered ($j = 1, \ldots, N$), and t varied between 1 and T[5]. M_X was the matrix containing original data series:

$$M_X = \begin{pmatrix} X^1(1) & \ldots & X^1(T) \\ \vdots & \ddots & \vdots \\ X^N(1) & \ldots & X^N(T) \end{pmatrix} \tag{4.12}$$

where each waveform was in a row, and column contained the successive time points over the stance phase. After calculating the normalised covariance matrix (C), eigenvectors ($\overrightarrow{v}^k$) and eigenvalues (λ_k) were estimated

[5] T could be either 100 or the median duration of the N trials, depending on whether the stance phase was normalised to 100 points or to the median Δt (Section 3.4).

by solving the following equation:

$$C \cdot \overrightarrow{v}^k = \lambda_k \cdot I \cdot \overrightarrow{v}^k \tag{4.13}$$

where I is the identity matrix. The unique solution of this system determined the N eigenvectors, which represented the new set of orthogonal axes onto which original data were projected. Hence, the resulting principal components, were a linear combination of the original values, but contained no redundancies. Eigenvalues magnitudes were in decreasing order, and their sum equalled 1:

$$1 \geq \lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N \geq 0 \qquad with \qquad \sum_{k=1}^{N} \lambda_k = 1 \tag{4.14}$$

Furthermore, λ_k contained information about the percentage of the original variability explained by the corresponding principal components:

$$\frac{\lambda_k}{\sum_{k=1}^{N} \lambda_k} \tag{4.15}$$

was the portion of total variation described by the k^{th} mode.

The procedure was then followed backward (Figure 4.9), and the original time series were reconstructed by using only the first p components that accounted for at least 95% of total variance ($\widetilde{X}^j(t)$). Upper and lower boundaries of confidence bands were finally defined as:

$$U_X^{PCA}(t) = \max_{j=1}^{N} \widetilde{X}^j(t) \tag{4.16}$$

$$L_X^{PCA}(t) = \min_{j=1}^{N} \widetilde{X}^j(t) \tag{4.17}$$

Two observations must be evidenced. First, differently from common application of PCA, where the different rows of the original data matrix contain different variables (e.g. trajectories of different body landmarks [32]), here rows consisted of the waveforms from the same measure registered over subsequent trials. The reason was that, in this case, the

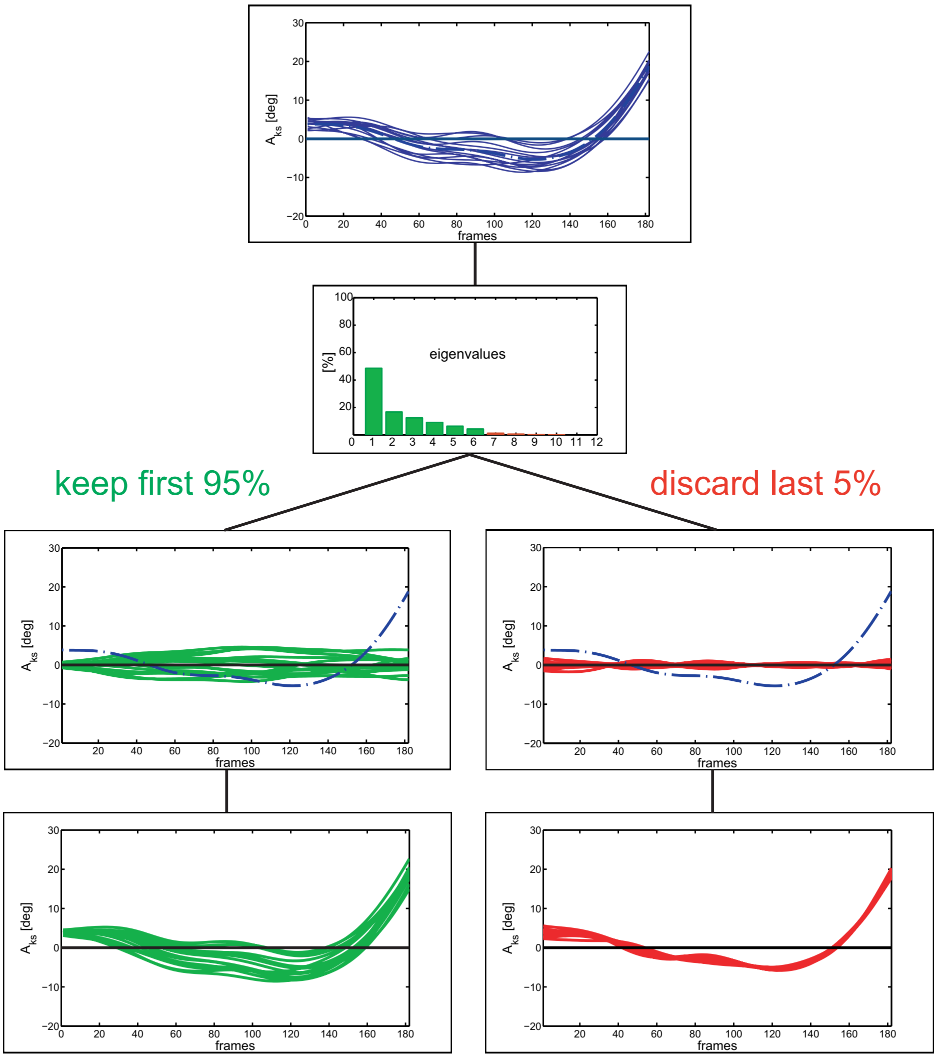


Figure 4.9: *procedure for creating confidence bands through PCA. The principal components are estimated from the original set of curves. Then only the first modes that account for at least 95% of the overall variability are kept and used for reconstructing curves (green plots). The remaining modes are discarded (5%, red). The final result is shown in Figure 4.8(d).*

possible correlation within fluctuation of the same variables were searched, rather than covariance between different kinematic or kinetic variables. Second, the choice of building prediction bands from the first p modes was based on the assumption [32] that the discarded components accounted for variation that mainly came from noisy factors rather than from individual motor peculiarities.

Independently from the statistical method by which they were created, boundaries of confidence bands were set in order to have a theoretical prediction coverage of 95%, i.e. the probability that a new curve drawn from the same population is fully contained within its limits. Therefore, the actual prediction probability could be evaluated by means of crossvalidation, and results from different procedures (MSTD, PRCT, BOOT, PCA) compared.

Crossvalidation measures the chance that an arbitrary curve of the original sample is fully covered by the confidence bands derived from the remaining patterns of the ensemble. The procedure was repeated N times, and the actual coverage probability was given by:

$$CP = \frac{\sum_{j=1}^{N} c^j}{N} \tag{4.18}$$

where c^j was either 1 or 0 depending on whether the j^{th} curve was fully contained by bands created from the remaining $N-1$ patterns.

All the procedures exposed in Section 4.3 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

4.3.3 Results

Confidence bands were estimated for every subject and variable, thus a total of 330 prediction regions (15 variables, 7 subjects, left and right side, 2 session for 4 athletes) were created by using MSTD, PRCT, BOOT, and PCA from as many bunches of individual curves. The same procedure was

Table 4.9: *results of crossvalidation before outliers removal. Median true coverage probability, for nominal 95% prediction bands, of lower limb angles and GRF in the sagittal plane. Values were estimated over the whole population. Results concerning the other 7 variables (Section 3.4) are not here reported, but evidenced very similar behaviour.*

method	A_{hs}	A_{ks}	A_{as}	R_{ap}	R_v
MSTD	23.1	33.0	36.0	22.8	15.3
PRCT	44.3	57.7	57.6	41.1	38.0
PCA	22.6	32.6	33.7	22.1	12.2
BOOT-C	12.0	10.8	8.8	9.8	10.4
BOOT-P	100.0	100.0	100.0	100.0	100.0

Table 4.10: *results of crossvalidation after outliers removal. Median true coverage probability, for nominal 95% prediction bands, of lower limb angles and GRF in the sagittal plane. Values were estimated over the whole population. Results concerning the other 7 variables (Section 3.4) are not here reported, but evidenced very similar behaviour.*

method	A_{hs}	A_{ks}	A_{as}	R_{ap}	R_v
MSTD	12.4	22.6	23.3	11.0	6.7
PRCT	34.5	42.6	50.4	32.8	25.2
PCA	11.9	23.1	23.3	11.0	6.5
BOOT-C	22.9	26.7	26.4	24.1	30.0
BOOT-P	100.0	100.0	100.0	100.0	100.0

carried out both before and after outliers removal (Section 4.2). Figure 4.8 shows an example of extraction of prediction boundaries according to the different methods.

Results concerning crossvalidation are summarised in Table 4.9 (before outliers removal) and in Table 4.10 (after outliers detection and elimination).

4.3.4 Discussion

Traditional methods for creating confidence bands from a family of curves present some important drawbacks that may hinder a correct synthesis of intraindividual variability. They consider each point of a curve as being indipendent from the rest of the pattern and they hypothesize a Gaussian distribution among different trials. These assumptions are not straightforward and should be verified. In fact, some test on the curves coming from race walkers showed that data were not always normally distribute at each t over the stance phase.

Therefore, it emerged the need for exploring different techniques to recognise the boundaries within which individual variables could range over different repetition of the same task.

Some authors [105, 139, 86, 46, 28] have proposed the use of bootstrapping as a valuable tool in clinical biomechanics. By analysing normal gait, Lenhoff and colleagues [86] and Duhamel and colleagues [46] found that BOOT was more reliable than mean±standard deviation method. In fact, the true coverage probability for MSTD was very different from the pre-specified one (54% vs. 90% in [86]; 73% vs. 95% and 67% vs. 95% in [46] for young and elderly groups, respectively). In contrast BOOT showed higher values (86% vs. 90% in [86]; 93% vs. 95% and 90% vs. 95% in [46] for young and elderly groups, respectively). Furthermore, Olshen and colleagues [105] and Sutherland and colleagues [139] evidenced that many cases of misclassification (i.e. healthy judged as pathological) were registered when MSTD was used for depicting “normality”.

Therefore, in this section, 4 different methods for the estimation of individual confidence bands were implemented and compared. The pre-set coverage probability of all the methods was 95%. That’s why, as concerns non parametric point-by-point techniques, $2.5^{th} - 95^{th}$ percentiles intervals were preferred to IQR and MAD.

Results presented in Table 4.9 and Table 4.10 confirmed other authors’ findings: for nominal 95% prediction bands, the estimated true coverage for BOOT was always greater, both when the original set of trials contained ouliers, and after unrepresentative patterns removal. In contrast, the estimated achieved true coverage for MSTD, PRCT and PCA were far below the desired goal. Among them, traditional mean±standard deviation method was the one with best performances. Differently from BOOT, they were sensibly affected by the presence of contaminants. In fact, after outlying curves elimination, actual prediction coverage always worsened.

These evidences would suggest that bootstrapping is undoubtedly the best choice for the synthesis of variability in individual motor patterns. However, the quantitative evaluation performed through crossvalidation should be followed by a qualitative one, that couples the observation of created bands with the aims they are generated for. Bootstrapping bands were consistent but were undoubtedly very broad (Figure 4.8(c)), too. Sutherland and colleagues [139] already evidenced this characteristic, but still remarked that although BOOT bands might appear too wide, they were well set for successful clinical practice. The question is whether they are proper even for individual monitoring in sports. Anecdotal experience and some authors [73, 72] have suggested that the subtle changes that occur in individual evolution over practice could be hardly detectable by using large bands. In contrast, small changes in performance may be worthwhile and should be accounted, especially for top athletes [73, 72]. The aims and the procedures for longitudinal sports analysis are soundly different from clinical ones (Section 1.1). The former should involve comparison between bands of the same subject. The latter typically states if the individual curve matches the ranges of normality and can not afford erroneous interpretations not to compromise the patient's health.

Since a higher chance of "misclassification" might be afforded in sports, it appeared that BOOT-C bands could be a good solution. BOOT-C boundaries predicted, with a preset probability (95% in the present work), the limits within which mean curves of the b pseudosamples might fall; roughly, they described how the mean curve was likely to vary. The performance they achieved in crossvalidation was poor, but this did not come out unexpected. They were not thought to be predictors of how an arbitrary curve, drawn from the "true" population could vary; they indicated where the average curve was likely to be. Furthermore, the true prediction coverage improved after outliers removal (Table 4.9 and Table 4.10), thus suggesting BOOT-C might be suitable for data sets that consist of repeatable waveforms and that contain few elements. BOOT-C resulted very tight (Figure 4.8(c)), so that they appeared as being rather suitable even for comparison where subtle changes are expected. Since they describe the possible location of the core of individual waveforms (i.e. means over many repetition) they might be thought as the descriptors of the motor signature of individuals.

Among the other three methods, MSTD showed the best predictive power, both with and without outliers. However, the poor performance of PRCT and PCA should not be entirely addressed to macroscopically bad prediction bands: during cross-validation many curves ran right on the margins of bands created from the remaining patterns, with only few points falling outside the allowed range. This caused the low score achieved.

Nevertheless, other PCA potentialities could represent an effective tool for longitudinal monitoring. Differently from clinics, macroscopical anomalies and evident changes rarely emerge in longitudinal evaluations of skilled athletes. Hence the usual time domain description of waveforms might not be enough for a through analysis. PCA may provide further indications for interpreting motor skills. Important information could be drawn by inspecting the variability explained by single principal components or by using functional principal component analysis[6] [116, 43, 125].

4.4 The Informative Content of Motion Variability

4.4.1 Introduction

Consecutive repetitions of the same motor task make the outcoming kinematic or kinetic variables appear as pseudo-periodic time series. Variability is inherent within the locomotor system and these fluctuations may appear as noise, but recent investigations have supported the idea that inter-trial

[6]Functional Principal Component Analysis and its relation with biomechanical factors and performance will be further investigated by Giulia Donà, MSc, (Department of Information Engineering, University of Padova, Padova, Italy) in her Ph.D. dissertation. The author would like to thank her for the precious support she provided in investigating the potentialities of functional PCA.

variability does not contain only randomness but also informative content about the system health, about its evolutions, and about its flexibility and adaptability to variable external conditions [68, 40, 41, 100, 39, 119, 20, 36, 65, 99, 135, 137, 67, 91, 101] (Section 1.3.2).

Motor variability might represent either uncertainty or adaptability, depending on its inner nature. Unfortunately, it's not possible to discriminate the different source of variation by using traditional, linear techniques: non-linear dynamics tool must be exploited. In an extensive review about non-linear tools for the analysis of human movement, Stergiou and colleagues [135] evidenced four reasons for sustaining non-linear dynamics as an alternative approach to the analysis of motion variability. First, traditional linear tools (e.g. standard deviation, coefficient of variation) may conceal the structure of BV. They usually imply averaging and normalising processes that alter the temporal variation of motor patterns; conversely, non-linear tools aim at gauging how motion changes over time. Second, linear tools assume that fluctuations between successive repetition of the same task are random and independent. This hypothesis has been questioned by recent studies, that evidenced a likely deterministic origin of those variation and distinguished them from random noise. Third, traditional tools can only quantify the overall variability (see (1.1) in Section 1.3.2), without giving any indication about the stability and complexity of the analysed time series. Fourth, the neuromotor system is characterised by a high degree of complexity and by the presence of many interacting elements and control systems. This make it be very similar to other systems (e.g. cardiovascular) whose variability has been described as possessing intrinsic deterministic dynamics.

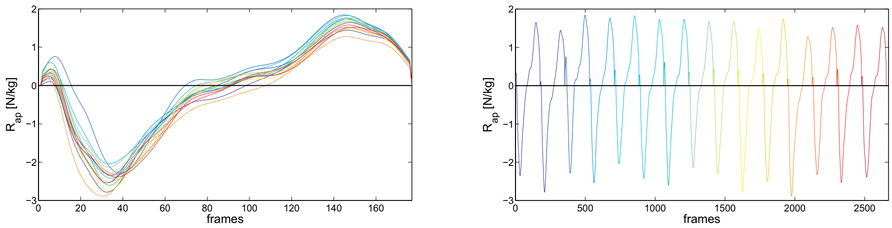
The Lyapunov exponent [1] (LyE) and the approximate entropy [112, 111] ($ApEn$) have usually been adopted as means of exploration of the structure and complexity of variability. However, only recently [135, 101] some authors have associated changes of those indexes to pathologies [40, 41, 96, 140, 141, 135, 137, 101] or behavioural development concerning human posture and locomotion [39, 20, 65, 135, 100, 99, 101]. Those surveys evidenced that a change in the regularity of motor patters may be a sign of motor learning or of a different reorganisation of motor strategies.

Non-linear tools may turn very useful even in the field of sports movements, where the subtle enhancements due to motor learning or the little anomalies due to latent pathologies or detrimental motor behaviours may be easily masked by BV. The traditional quantification of variability in kinematic and kinetic measures may be not enough, but the study of its inherent structure may reveal important information for the evaluation of training programs and for injury prevention. In fact modifications in the time-dependent structure of motor variability may emerge even when there is no apparent change in the overall magnitude of BV and in the modal frequency of the data set [101].

Therefore, the aim of the present study was to assess the complexity of race walking time series by using entropy measures both in their absolute value and in comparison with the same indexes extracted from surrogates. Surrogation is a technique that creates a new sequence of values, removing the deterministic structure of original data but keeping their mean, variance and power spectra. Hence, some conclusions on whether variability is noisy or not may be drawn [132, 135, 91] by analysing the differences between regularity in original measures and in surrogates.

4.4.2 Materials and Methods

Non-normalised waveforms were used for non-linear analyses of motion variability (Figure 3.5). This was done to avoid any kind of alteration that resampling to a common number of point might have induced in the dynamics of time series [135]. Individual kinematic and kinetic time series were created by aligning the N curves available (Figure 4.10), so that they composed a continuous sequence of similar events (stance phases) with an overall length that was consistently longer than the natural timescale of the single movement [101]. Measures concerning hip, knee, ankle flex-extension angles and GRF components in the sagittal plane were considered for this survey. These variables were chosen because they appeared as being the most consistent measures of lower limb motion analysis (Section 4.2). Furthermore, they may be considered, at this stage, among the most important ones for race walking description.



(a) (b)

Figure 4.10: *example of creation of an individual pseudo-periodic time serie. The original N curves concerning the stance phase (a) were aligned to form a continuous sequence of similar events (b). The reported variable was R_{ap} for s2 left limb.*

The regularity of each sequence of data was assessed by using approximate entropy ($ApEn$) [112, 111] and sample entropy ($SampEn$) [118]. $ApEn$ and $SampEn$ are non-linear methods for the quantification of the entropy of a system. Namely, they gauge the complexity of a time series and thus express how regular and predictable it is: the higher $ApEn$ or $SampEn$, the greater complexity[7].

Given a series, $Y(t)$, of M points ($t = 1, \ldots, M$), $ApEn(m, r, M)$ and $SampEn(m, r, M)$ measure the logarithmic probability that two similar sequences of m points extracted from $Y(t)$, remain similar (i.e. within tolerance given by r) on the next incremental comparison (i.e. for $m + 1$ sequences) [112, 111, 118, 135].

$ApEn$ has been considered, among other non-linear tools, as being particularly suitable for the analysis of biological systems whose variability is typically of both deterministic and stochastic origin [135]. $ApEn$ advantages have been summarised [135] as follows:

- it is not affected by noise of magnitude below r
- it is not affected by outliers

[7] $ApEn$ and $SampEn$ values usually range from 0, for greater periodicity, to about 2, for greater irregularity.

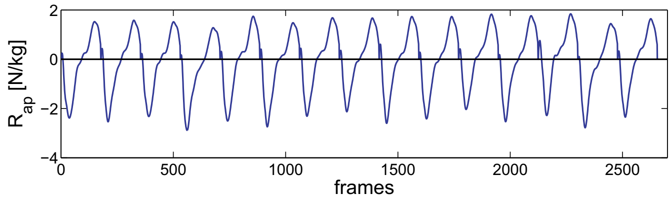
- it can be used even on small data sets with good statistical validity
- its increase/decrease indicates increased/decreased complexity in the series it is estimated from.

Sample entropy differs from approximate entropy in the way it calculates similarities within time series. Furthermore, it shows a more consistent behaviour than *ApEn* for different choices of m and r, and it is largely independent of record length [118]. That is the reason why, although approximate entropy is more common in scientific research on regularity of motor patterns, *SampEn* was preferred for reporting results about race walking gait variables. Since the analysed data sequences showed an apparent great regularity, m was set to 1 and r to 0.1 standard deviation [118, 135].

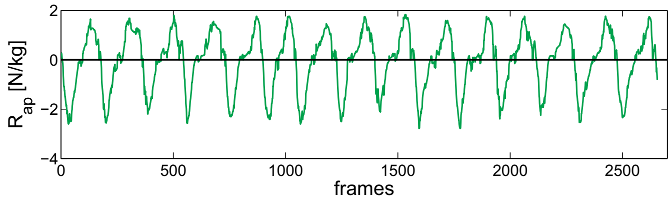
The estimation of time series complexity was carried out both on original data sets and on their surrogates. Surrogation methods are usually applied to test the hypothesis that an observed data series is the outcome of a certain type of dynamics of the anlysed system [132, 135, 91]. A particularly suitable surrogation algorithm, the pseudo-periodic surrogate method[8] (PPS) [132, 91] was found and applied for the analysis. This procedure provides a robust method to test pseudo-periodic time series data against the null hypothesis of a periodic sequence with uncorrelated noise. Its advantages consist in destroying the eventual non-linear structure that characterises time series, without eliminating their periodic nature. Figure 4.11 shows an example of surrogation performed by PPS and by a different method proposed by Schreiber and Schmitz [129].

Different levels of analysis concerning the complexity of time series were carried out. First, regularity of original data and surrogates was assessed and compared. Then the N trials performed by each subject were split into two groups based on the execution order (i.e. first $\frac{N}{2}$ and last $\frac{N}{2}$ repetitions), so that eventual changes in the variability structure over the testing session could be detected. Finally, the regularity of more and less skilled athletes was evaluated. Race walker were divided, in terms of

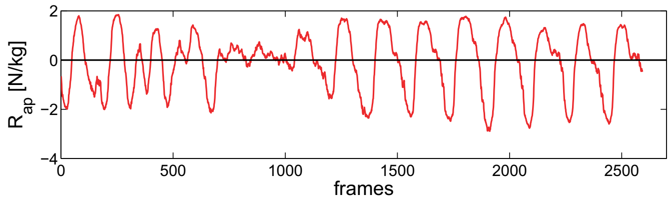
[8] free software is available online at: `http://small.eie.polyu.edu.hk/`



(a) original



(b) PPS



(c) iterative AAFT

Figure 4.11: *antero-posterior GRF values versus time, concerning an individual testing session (subject s2, left limb). The original time series (a) can be compared to its surrogate forms estimated by PPS (b) and by the iterative AAFT algorithm proposed by Schreiber and Schmitz (c). The surrogate in (c) has lost the original temporal geometry, while PPS surrogate maintained its overall temporal structure.*

athletic ability, according to competition results and to the judgment of an expert trainer.

Wilcoxon test ($\alpha = 0.05$) and Mann-Whitney test ($\alpha = 0.05$) were applied for the assessment of within and between groups differences.

4.4.3 Results

Results concerning *SampEn* estimation in race walking time series are reported in Table 4.11 and Figure 4.13. Both angular and GRF measures

Table 4.11: *sample entropy (SampEn) from original (orig) and pseudo-periodic (PPS) time series data. med is the median value of the population; IQR is the interquartile range. † indicates that Wilcoxon test evidenced statistically significant ($p < 0.05$) differences between original sequences and surrogates.*

		A_{hs}†		A_{ks}†		A_{as}†		R_{ap}†		R_v†	
subject	side	orig	PPS	orig	PPS	orig	PPS	orig	PPS	orig	PPS
s1	l	0.133	0.168	0.167	0.402	0.155	0.222	0.287	0.511	0.169	0.356
	r	0.070	0.217	0.133	0.166	0.131	0.196	0.297	0.514	0.211	0.435
s2	l	0.068	0.190	0.048	0.073	0.196	0.409	0.235	0.476	0.186	0.373
	r	0.083	0.213	0.062	0.078	0.221	0.385	0.198	0.283	0.173	0.418
s3	l	0.073	0.168	0.067	0.131	0.166	0.181	0.229	0.444	0.182	0.396
	r	0.066	0.102	0.086	0.127	0.150	0.204	0.241	0.429	0.145	0.326
s4	l	0.074	0.214	0.187	0.229	0.139	0.240	0.216	0.424	0.186	0.320
	r	0.057	0.107	0.126	0.181	0.156	0.257	0.223	0.400	0.144	0.260
s5	l	0.230	0.218	0.213	0.249	0.125	0.151	0.190	0.418	0.212	0.369
	r	0.195	0.287	0.238	0.252	0.125	0.055	0.176	0.327	0.205	0.406
s6	l	0.139	0.182	0.161	0.217	0.142	0.158	0.181	0.345	0.254	0.414
	r	0.131	0.328	0.113	0.119	0.152	0.240	0.176	0.358	0.230	0.438
s7	l	0.059	0.066	0.102	0.112	0.192	0.298	0.206	0.387	0.194	0.381
	r	0.068	0.178	0.126	0.130	0.126	0.139	0.169	0.358	0.178	0.391
	med	0.074	0.186	0.126	0.148	0.151	0.213	0.211	0.409	0.186	0.386
	IQR	0.065	0.048	0.075	0.105	0.030	0.089	0.050	0.082	0.035	0.053

revealed higher regularity in the original series than in their surrogate counterparts: Wilcoxon tests were always positive, thus evidencing statistically significant differences in terms of complexity of time sequences. *SampEn* median values ranged from 0.074 (A_{hs}) to 0.213 (R_{ap}) referring to the former; from 0.148 (A_{ks}) to 0.409(R_{ap}) when the latter were considered.

Antero-posterior GRF was the variable who showed both the greatest values of entropy and the largest mean difference between original data and surrogates (0.189).

Table 4.12 and Figure 4.15 show values of *SampEn*, discriminating between the first and the last half trials that every subject performed during the testing session. Results outlined a substantial invariance between

Table 4.12: *sample entropy (SampEn) from first-half and last-half session trials. med is the median value of the population; IQR is the interquartile range. ‡ indicates that Mann-Whitney test evidenced statistically significant ($p < 0.05$) differences between time series.*

	A_{hs}		A_{ks}		A_{as}		R_{ap}‡		R_v	
subject	first $\frac{N}{2}$	last $\frac{N}{2}$	first $\frac{N}{2}$	last $\frac{N}{2}$	first $\frac{N}{2}$	last $\frac{N}{2}$	first $\frac{N}{2}$	last $\frac{N}{2}$	first $\frac{N}{2}$	last $\frac{N}{2}$
862	0.133	0.070	0.167	0.133	0.155	0.131	0.287	0.297	0.169	0.211
866	0.083	0.068	0.062	0.048	0.221	0.196	0.198	0.235	0.173	0.186
868	0.073	0.066	0.067	0.086	0.166	0.150	0.229	0.241	0.182	0.145
869	0.074	0.057	0.187	0.126	0.139	0.156	0.216	0.223	0.186	0.144
882	0.195	0.230	0.238	0.213	0.125	0.125	0.176	0.190	0.205	0.212
883	0.131	0.139	0.113	0.161	0.152	0.142	0.176	0.181	0.230	0.254
884	0.068	0.059	0.126	0.102	0.126	0.192	0.169	0.206	0.178	0.194
med	0.083	0.068	0.126	0.126	0.152	0.150	0.198	0.223	0.182	0.194
IQR	0.058	0.042	0.087	0.053	0.028	0.038	0.046	0.040	0.020	0.046

indexes calculated over the first and last $\frac{N}{2}$ repetitions. *SampEn* significantly increased only for R_{ap}: median values changed from 0.198 to 0.223.

Figure 4.12 represents median values of *SampEn* for the considered variables, as a function of athletic skill. s2, s5 and s6 formed the skilled group, while s1, s3, s4 and s7 constituted the less skilled one. A_{hs}, A_{ks}, A_{as} and R_v manifested higher complexity for skilled athletes (0.141 vs. 0.075; 0.139 vs.0.124; 0.160 vs. 0.152; 0.210 vs. 0.176). In constrast, *SampEn* concerning R_{ap} was greater for less skilled ones (0.193 vs. 0.233). However the Mann-Whitney tests evidenced significant differences only for A_{hs}, R_{ap} and R_v.

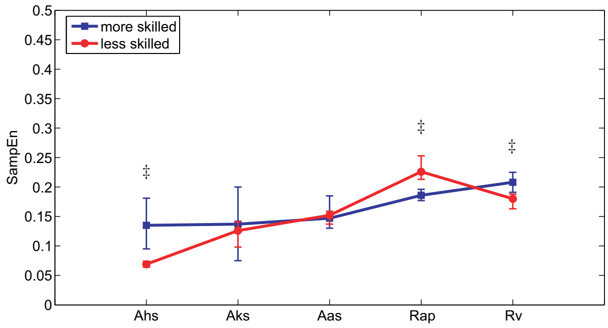


Figure 4.12: *SampEn in more (blue squares) and less skilled (red circles) athletes. Results are presented in terms of median values. Errorbars depict interquartile ranges. ‡ indicates that Mann-Whitney test evidenced statistically significant ($p < 0.05$) differences between time series.*

4.4.4 Discussion

The aim of this section was to evaluate the regularity of race walking time series in order to understand whether the fluctuation that occurred over many repetitions of the same task were the outcome of noisy processes or were induced by non linear properties of neuromotor dynamics [135, 101].

Individual kinematic and kinetic time series were created by aligning angular and GRF patterns of successive stance phases. Sample entropy of those data set were estimated and compared to the same index extracted from PPS surrogates [132, 91]. Results (Table 4.11 and Figure 4.13) showed that *SampEn* values were pretty low for every variable, thus supporting the presence of a high level of regularity over subsequent repetitions of the same motor task. However, significant differences between original time series and their surrogates were reported for all the considered kinematic and kinetic measures. This confirmed the hypothesis that race walking variability was not only the product of random noise, but contained even non-linear structure that surrogation had eliminated.

SampEn revealed decreasing regularity from proximal to distal joints, in contrast with what Stergiou and colleagues reported from other authors' works on normal and pathological gait [135]. This inverted trend might

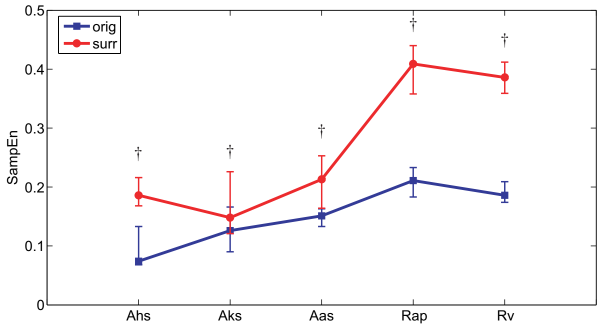


Figure 4.13: *SampEn in original (blue squares) and PPS surrogate (red circles) time series. Results are presented in terms of median values. Errorbars depict interquartile ranges. † indicates that Wilcoxon test evidenced statistically significant ($p < 0.05$) differences between original sequences and surrogates.*

be related to RW rules, that impose an unnatural pattern for knee flex-extension and shift to the hip and to the pelvis the task of absorbing the initial impact and accepting the load of body wait and inertial forces (Section 5.1). The change from normal gait might thus imply an increased control over proximal districts and consequently a reduced complexity of related time series.

Regularity of data sets was also studied as a function of athletic ability (Figure 4.12). After dividing race walkers on the bases of competition results and of the technical evaluation of an expert trainer, $SampEn$ differences between more and less skilled groups were evaluated. Besides R_{ap} that manifested lower regularity for less skilled athletes and A_{as} that was very similar in the two groups, the other variables evidenced an increased complexity for subject with better athletic ability. In particular the regularity of A_{hs} was significantly more consistent with less skilled athletes thus suggesting that those subject maintained an increased control over the proximal joint. These observations agreed with previous findings in literature [140, 141, 65, 135, 101]. Those authors interpreted greater values of $SampEn$ as a better flexibility and adaptability to unpredictable environmental changes. Namely, subject that are more confident and possess an improved coordinative ability have a better control over the body’s degrees of freedom.

The same results, in terms of athletic ability characterisation were not detected by looking at kinematic and kinetic patterns through *ICC* (Figure 4.14). This evidenced that non-linear tools might be able to characterise athletic proficiency when traditional methods are not able to evidence them. In fact, ICC did not point out any significant dissimilarity between the two groups, except for antero-posterior ground reaction force, which appeared as being more repeatable for skilled race walkers.

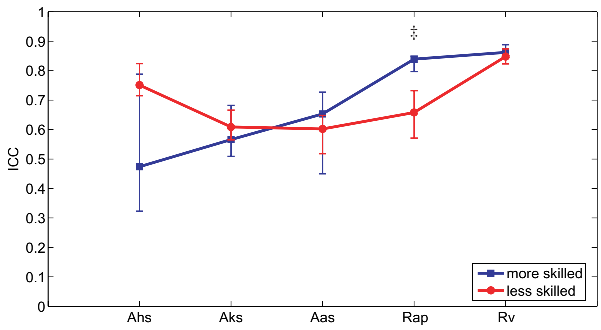


Figure 4.14: *ICC in more (blue squares) and less skilled (red circles) athletes. Results are presented in terms of median values. Errorbars depict interquartile ranges. ‡ indicates that Mann-Whitney test evidenced statistically significant ($p < 0.05$) differences between time series.*

Finally, a comparison between first and last trials executed over a single testing session was carried out. The purpose of this analysis was to understand whether the structure of variability changed over subsequent repetition of the same motor task. Namely, the effects of possible learning effects were investigated. In fact, athletes might progressively become more familiar with the experimental setting and thus modify the complexity of their motor strategy. Results showed that the first acquisition and the last ones did not differ significantly in terms of pattern regularity (Table 4.12 and Figure 4.15). This could sustain the validity of the adopted experimental protocol which let walkers be acquainted with testing procedures yet from the beginning.

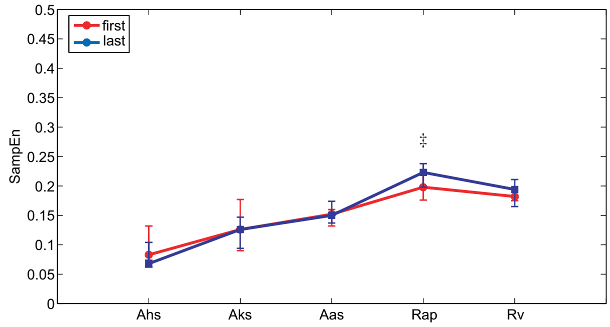


Figure 4.15: *SampEn in first (red circles) and last (blu squares) experimental trials over the same testing session. Results are presented in terms of median values. Errorbars depict interquartile ranges. ‡ indicates that Mann-Whitney test evidenced statistically significant ($p < 0.05$) differences between time series.*

Despite the interesting results and the promising interpretation derived thereof, further efforts should be spent in order to fully exploit the potentialities of non-linear dynamics tools. In particular these innovative methods may represent an important mean of investigation concerning motor learning and injury prevention. Therefore they might be included in longitudinal monitoring of athletes in order to quantitatively support training procedures.

Chapter 5

BIOMECHANICS OF RACE WALKING

What has been presented so far relates to the problem of describing the actual motor skills of athletes. Once that consistent data have been obtained from quantitative motion analysis, there is the need for interpreting them. This knowledge may arise from the definition of a reference (Figure 5.1), whose characteristics have been previously interpreted and described.

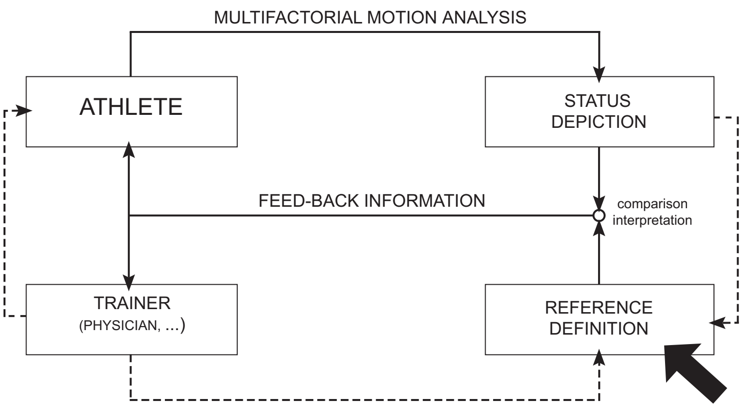


Figure 5.1: *longitudinal monitoring schema. The second phase of the process (i.e. reference definition and data interpretation) is highlighted.*

Individual measures may be compared with information coming either from former analyses on the same subject or from the general characteristics of the movement under investigation, by deriving them from a group of homogeneous individuals. The latter is not the main focus of longitudinal monitoring, but it is still fundamental for understanding features and implications of the analysed movement, particularly when literature is lacking. Since very few authors have addressed the issue of describing race walking biomechanics, its analysis and comparison with normal walking features are extensively carried out in Chapter 5. Both traditional (Section 5.1) and dynamic system (Section 5.2) approaches are presented, and some examples of possible applications concerning horizontal (Section 5.1 and Section 5.2) longitudinal monitoring (Section 5.3) are proposed.

5.1 Kinematics and Kinetics of Pelvis and Lower Limbs during Race Walking Gait

5.1.1 Introduction

As previously mentioned in Chapter 2 it appears there is little published research documenting the kinematics and kinetics of race walking. Some authors have analysed particular aspects of RW [108, 123, 52, 71, 98] or have studied its efficiency from a physiological point of view [26, 25, 58]. However, Cairns and colleagues [21] and Murray and colleagues [97] were the only ones who analysed RW patterns and who tried to interpret their relations with motor factors and execution technique. Although very interesting and appropriate, these surveys are rather old and used very essential instrumentation in comparison with the currently available technologies.

Therefore, this section of the work aimed at analysing the kinematic and kinetic variables of pelvis and lower limbs in a population of young but skilled race walkers, and at understanding their common strategies and average features. Results were compared with normal gait patterns of the same athletes, thus allowing the description of differences and analogies.

5.1.2 Materials and Methods

All available normalised curves after outliers removal (Section 3.4 and Section 4.2) were used to extract a selection of 70 kinematic and kinetic parameters (Section 4.1) and to estimate the individual bootstrapping averages for each variable. Individual mean curves were then employed to calculate the mean patterns and the confidence bands of the whole population both in RW and NW[1]. Overall mean curves and boundaries of prediction bands were computed by the traditional mean$\pm$1.96 standard deviation procedure (MSTD). This choice came from observations in Section 4.3.4. Bootstrapping appeared not very suitable in this case: BOOT-P bands were robust but too wide even for understanding macroscopical differences between race walking and normal walking characteristics (Figure 5.2); BOOT-C ones were not adequate because the purpose of the work was not to understand the motor signature of the individual but to depict the characteristics of the whole population of athletes. MSTD was thus chosen since it was the most consistent method among the remaining ones. Confidence bands derived thereof were graphically compared to detect the peculiarities of the two different gait conditions.

Whenever comparisons of parameters were necessary, non-parametric within groups tests (Wilcoxon, $\alpha = 0.05$), were applied to check for significant differences between RW and NW discrete measures.

All the procedures exposed in Section 5.1 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

5.1.3 Results

A summary of spatio-temporal measures is presented in Table 5.1. The mean stance duration resulted 0.63$\pm$0.03 s for NW and 0.37$\pm$0.04 s for RW.

[1]Since only 3 gaits were available for each subject's side, common averaging procedures were applied instead of bootstrapping for the extraction of individual mean curves during normal walking.

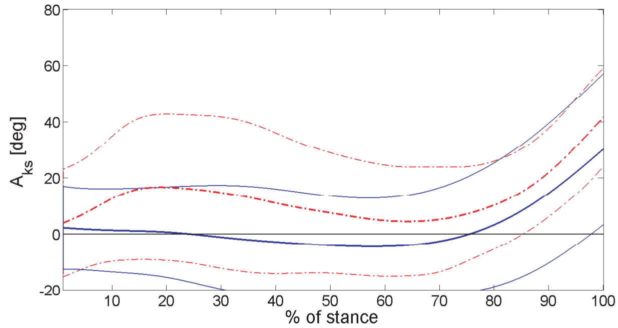


Figure 5.2: *average bootstrapping (BOOT-P) knee flex-extension from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands. Despite the two gait conditions imply very different knee angular displacements, bootstrapping bands do not evidence this dissimilarity clearly enough.*

Mean progression velocities were, respectively: $1.57 \pm 0.09\,\frac{m}{s}$ and $2.85 \pm 0.40\,\frac{m}{s}$. The step length increased significantly from NW to RW, and this trend was registered even for $\Delta x_{rl/fl}$ and $\Delta z_{kst-ksw}$. The vertical excursion of the COM was lower in RW while Δy_{COM} did not show sensitive changes.

Table 5.2 reports data concerning angular analysis. Pelvic obliquity in the frontal plane and pelvic rotation in the transverse plane exhibited greater range of motion during race walking. The mean excursion of hip flex-extension increased, too. Conversely, knee and ankle joints showed lower ROM in RW than in NW.

Measures concerning kinetic variables are resumed in Table 5.3. The mean peak vertical GRF increased significantly from race walking ($14.89 \pm 1.51\,\frac{N}{kg}$) to normal gait ($11.60 \pm 0.48\,\frac{N}{kg}$). The posterior component of ground reaction forces evidenced higher values (breaking action) in RW, while positive peaks (propulsion) were not statistically different. Hip flexion, knee flexion and dorsiflexion moments exhibited greater mean maxima (negative values) during RW. Peak hip extension moments were significantly higher in race walking. In contrast, plantar flexion ones decreased from NW to RW. Peak joint powers revealed significant discrepancies for

Table 5.1: *spatio-temporal components of gait under race walking (RW) and normal walking (NW) conditions. Data are expressed as mean±standard deviation. Duration (Δt) and speed ($\overline{v}_m$) are in s and $\frac{m}{s}$, respectively. Other measures are in mm. A description of parameter abbreviations can be found in Table 4.1. † indicates that Wilcoxon test evidenced statistically significant ($p < 0.05$) differences between the two progression modalities.*

parameter	RW	NW	
Δt	0.37±0.04	0.63±0.03	†
$\overline{v}_x$	2.72±0.23	1.57±0.09	†
Δx	1009.6±73.3	827.2±44.9	†
Δz_{COM}	32.0±20.3	48.8±9.5	†
Δy_{COM}	53.0±23.6	39.9±12.5	
$\Delta x_{fl}@hs$	235.3±41.1	284.6±28.9	†
$\Delta x_{rl}@to$	-485.9±41.4	-438.4±29.0	†
$\Delta x_{rl/fl}$	2.1±0.4	1.5±0.1	†
$\Delta z_{kst-ksw}$	25.3±17.9	2.2±17.1	†

hip maxima and minima, and for knee minima. The other kinetic variables were not statistically different across the two gait modalities.

5.1.4 Discussion

The passage from normal walk to race walk gait determined a significant variation of stance duration, speed and step length (Table 5.1). Δt became about half that of NW; $\overline{v}_x$ nearly doubled normal progression velocity; mean step lengths were also influenced and sensibly increased from a mean of 827.2 mm to 1009.7 mm. RW determined modification in other spatio-temporal parameters, too. The advancement of the front leg at heel strike respect to the vertical projection of the COM ($\Delta x_{fl}@hs$) decreased. Conversely, the rear foot moved back with greater extent at toe-off ($\Delta x_{rl}@to$). All these changes reflected the increased intensity of race walking action, and represented the output of modified kinematic and kinetic strategies.

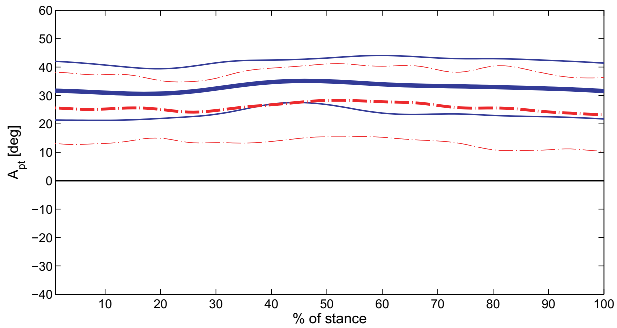
Cairns and colleagues [21] reported that, during RW, the ankle reached greater dorsiflection angles at heel strike and plantar flection angles at toe-off than during normal gait. The same results appeared in the present

Table 5.2: *angular parameters of gait under race walking (RW) and normal walking (NW) conditions. Data are expressed as mean±standard deviation. All measures are expressed in deg. A description of parameter abbreviations can be found in Table 4.1. † indicates that Wilcoxon test evidenced statistically significant ($p < 0.05$) differences between the two progression modalities.*

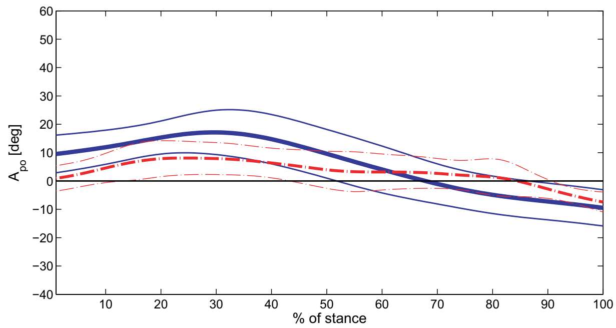
parameter	RW	NW	
$A_{pt}@hs$	33.9±8.7	25.6±6.4	†
$A_{pt}@to$	33.1±7.8	23.4±6.6	†
$A_{pt}ROM$	13.4±11.0	10.2±6.2	
$A_{po}@hs$	11.2±7.2	0.9±2.3	†
$A_{po}@to$	-10.0±5.1	-7.4±1.8	
$A_{po}ROM$	29.0±9.9	16.4±3.4	†
$A_{pr}@hs$	-15.0±4.9	-7.0±2.0	†
$A_{pr}@to$	14.6±4.5	5.6±4.1	†
$A_{pr}ROM$	32.0±7.5	15.9±4.7	†
$A_{hs}@hs$	59.5±12.9	52.6±9.5	
$A_{hs}@to$	9.7±12.1	12.2±9.1	
$A_{hs}ROM$	59.6±11.2	52.5±8.0	†
$A_{ks}@hs$	3.8±4.8	3.9±5.2	
$A_{ks}@to$	30.4±8.0	41.7±4.7	†
$A_{ks}ROM$	34.8±5.4	39.3±5.8	†
$A_{as}@hs$	65.7±4.1	63.4±4.7	
$A_{as}@to$	44.5±7.3	45.5±6.0	
$A_{as}ROM$	27.3±5.8	32.2±5.0	†

study (Table 5.2 and Figure 5.4(c)), even if they did not reached statistical significance. However, these phenomena, coupled with significant lower flexion of the knee at toe-off (Figure 5.4(b)) and greater rotation of the pelvis in the horizontal plane (Figure 5.3(c)), might be interpreted as the effort to gain a more effective "functional lengthening", i.e. increased stride length [97]. Thus, athletes would maximise the use of their lever system while conserving mechanical energy [21].

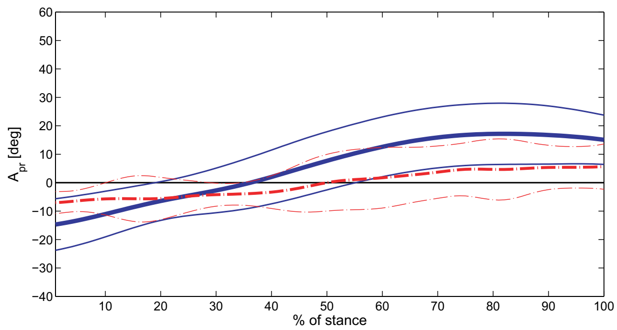
Due to the constraints of the International Federation rules (Section 2.1), the athlete has to keep the supporting leg in a straight position. This demand made the knee angles differ significantly between RW and NW. Both mean $A_{ks}ROM$ and $A_{ks}@to$ sensibly decreased (Table 5.2). However it was



(a)

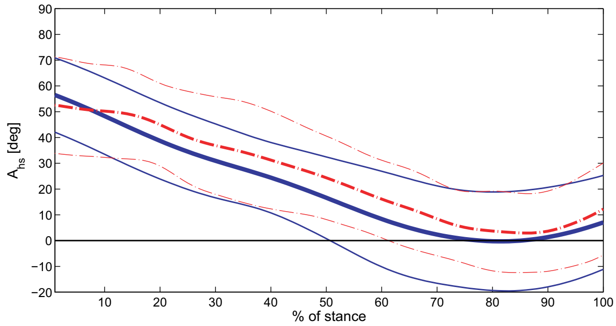


(b)

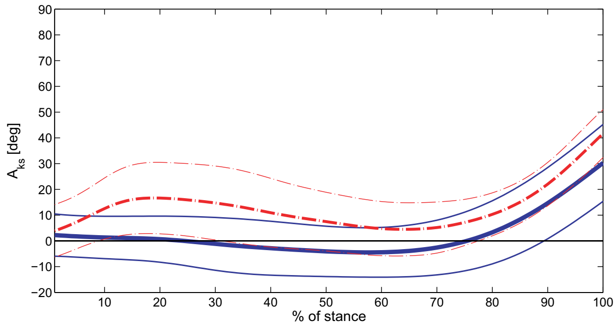


(c)

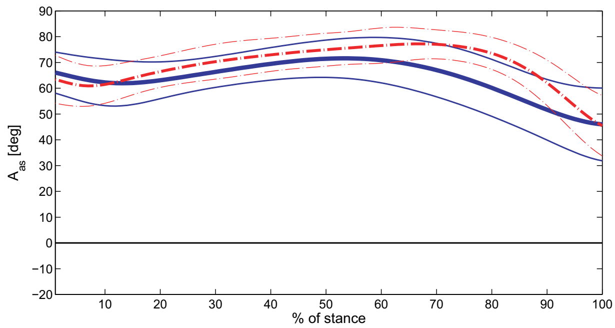
Figure 5.3: *average patterns concerning pelvic tilt (a), obliquity (b), and rotation (c), from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands.*



(a)



(b)



(c)

Figure 5.4: *average flex-extension patterns concerning the hip (a), knee (b), and ankle (c) joint from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands.*

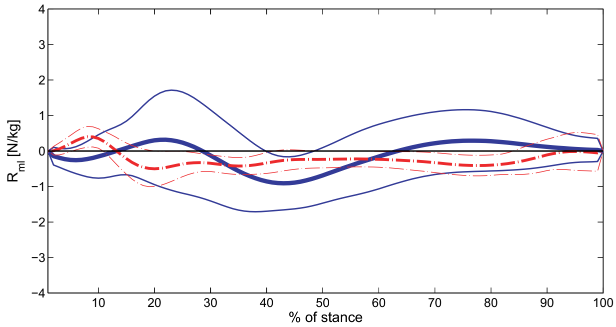
Table 5.3: *kinetic parameters of gait under race walking (RW) and normal walking (NW) conditions. Data are expressed as mean±standard deviation. Ground reaction forces are normalised by body weight and are expressed in* $\frac{N}{kg}$*. Joints moments and powers are normalised by body weight and height, and expressed in* $\frac{N}{kg}$ *and* $\frac{W}{kg \cdot m}$*. A description of parameter abbreviations can be found in Table 4.1.* † *indicates that Wilcoxon test evidenced statistically significant* ($p < 0.05$) *differences between the two progression modalities.*

parameter	RW	NW	
R_{ml-MAX}	0.56±0.55	0.41±0.15	
R_{ml-MIN}	-1.00±0.33	-0.59±0.18	
R_{ap-MAX}	1.49±0.30	2.12±0.20	†
R_{ap-MIN}	-2.83±0.64	-2.17±0.34	†
R_{v-MAX}	14.89±1.51	11.60±0.49	†
M_{hs-MAX}	0.72±0.19	0.46±0.12	†
M_{hs-MIN}	-1.10±0.24	-0.84±0.12	†
M_{ks-MAX}	0.45±0.13	0.52±0.16	
M_{ks-MIN}	-0.32±0.09	-0.21±0.05	†
M_{as-MAX}	0.78±0.11	0.86±0.06	†
M_{as-MIN}	-0.28±0.07	-0.22±0.06	†
P_{hs-MAX}	3.02±1.82	1.20±0.59	†
P_{hs-MIN}	-3.65±1.91	-1.18±0.51	†
P_{ks-MAX}	0.49±0.26	0.55±0.15	
P_{ks-MIN}	-1.82±0.65	-1.31±0.41	†
P_{as-MAX}	2.52±0.78	2.55±0.50	
P_{as-MIN}	-0.39±0.15	-0.33±0.17	

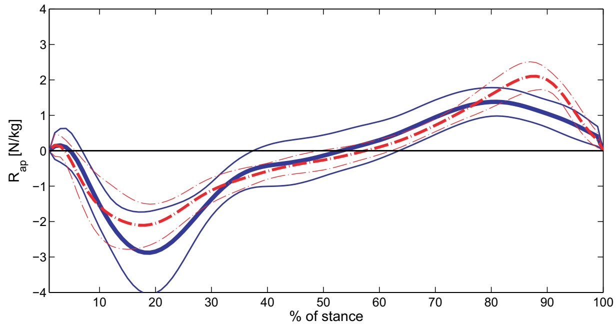
during load acceptance and midstance that the most relevant discrepancies could be found (Figure 5.4(b)). The knee flexion that occurred in the first phase of stance during normal walking disappeared, and an hyper-extension angle (here defined for angles <0 degrees) was maintained for about 50% of the contact time (25 to 75%). Since A_{hs} was substantially comparable in both gait modes over that phase (Figure 5.4(a)), the fully extended knee would cause a sensitive excursion of the center of mass in the vertical direction. Δz_{COM} was, in contrast, significantly lower during race walking gate (Table 5.1), thus suggesting the presence of other mechanisms for controlling the vertical excursion of the center of gravity.

Cairns and colleagues [21] suggested that the alternating wave of knee extension and flexion of NW is compensated, in RW, by the large increase of pelvic rotations in the frontal plane. Results agreed with this interpretation: pelvic obliquity had greater range of motion during race walking (Table 5.2 and Figure 5.3(b)), with particularly higher magnitudes at heel strike. The vertical component of ground reaction force was significantly higher during race walking than during normal gait, except for the last 25% of the stance (Table 5.3 and Figure 5.5(c)). Furthermore, in RW, a central plateau replaced the typical walking curve with 2 peaks and a midstance valley. This confirmed that race walkers were able to reduce the vertical accelerations of the COM, thus achieving a less expensive action [25].

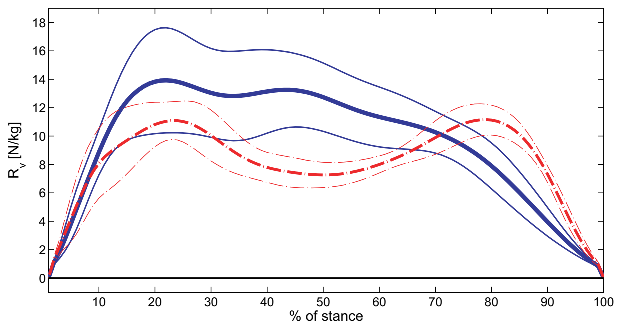
The transition from posterior (breaking) to anterior (propulsive) GRF was anticipated in RW compared to NW (Figure 5.5(b)). Values turned from negative to positive at 52% and 57% of contact time, respectively, in agreement with Cairns' findings [21]. During normal gait the breaking phase was longer in duration, thus requesting a more intense forward pushing to maintain the horizontal velocity. Peak anterior GRF, in fact, was significantly higher ($2.12 \pm 0.20\,\frac{N}{kg}$ vs. $1.49 \pm 0.30\,\frac{N}{kg}$) and occurred later (88±1% vs. 79±9%) in NW. RW showed increased breaking force, in accordance with what Payne [108] found but in contrast with results by Cairns and colleagues [21], who reported very similar R_{ap} extreme values between the two gait conditions. The greater magnitude of race walking breaking action, that appeared rather "impulsive", might be attributed to different angles and a higher stiffness of the limb that approaches the ground and to the increased velocity and dynamics of the movement. However, differently from NW, R_{ap} assumed a smoother shape after load acceptance. Gradual increases and decreases of R_{ap} mean reduced accelerations and decelerations of the COM. Therefore, even with respect to this variable, subjects seemed to achieve a more efficient strategy during race walking. Medio-lateral forces resulted higher in magnitude during race walking (Figure 5.5(a)). In particular, race walkers achieved an increased medial reaction in the mid-stance to contrast the lateral shift of the COM, due to the pelvis lateral drop and hip adduction [21]. Although RW involved a much



(a)



(b)



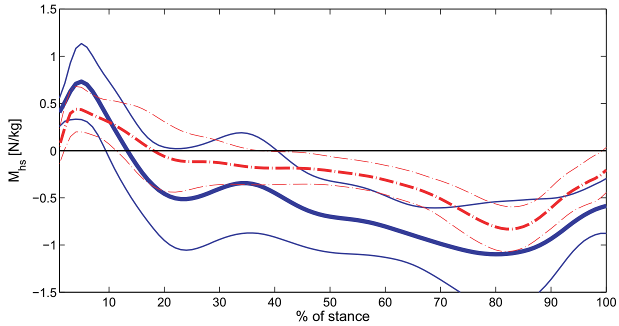
(c)

Figure 5.5: *average ground reaction forces concerning the medio-lateral (a), antero-posterior (b), and vertical (c) component, from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands.*

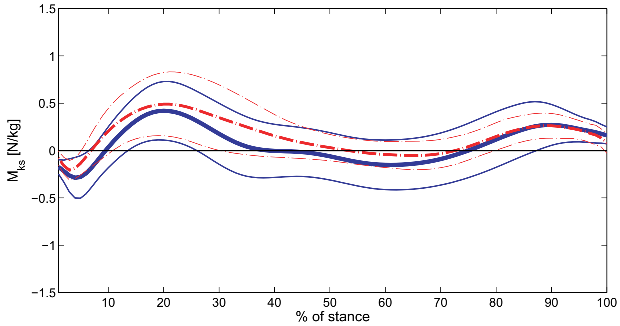
sensitive oscillation in the medio-lateral direction, the sum of positive and negative areas resulted nearly close to zero. That indicates that the subject had a correct technique, with straight progression and symmetry between the two limbs.

Cairns and colleagues [21] reported a greater peak dorsiflexion and plantar flexion moments at the ankle. These findings were not confirmed by the present study, in which the magnitude of M_{as-MAX} resulted significantly lower, with a higher peak to peak rate in RW mode (Table 5.3 and Figure 5.6(c)). This might depend on the need to contrast a greater angular acceleration of the tibia [97, 110] by exploiting as soon as possible the contribution of the gastrocnemius. In fact, the early intervention of the gastrocnemius is facilitated, during race walking, by the straight position of the knee. M_{ks} was quite different in the two gait modes for most of the stance time (Figure 5.6(b)), though without enhancing progression speed. The extension action exerted in NW between 6% and 54% of the stance period could be interpreted as the opposition to gravity force during load acceptance. This hypothesis is supported by the knee power plot (Figure 5.7(b)): during the first 20% of contact in normal gait, an eccentric work (negative area) could be clearly recognised. In contrast, the positive M_{ks} during RW might be seen as the effort exerted by knee extensor muscles to keep that joint straight, just like rules impose, and the P_{ks} close to zero or slightly positive for three quarters of stance confirmed this extended or even hyper extended position. The knee extension moment, was followed, between 40% and 75%, by a flexion one, greater in RW than in NW, that some authors [97, 21], interpreted as the outcome of passive structures (posterior capsule and ligaments) rather than active muscular forces. P_{hs} showed higher excursions in RW (Figure 5.7(a)). This, coupled with the greater magnitude of M_{hs}, denotes a higher involvement of proximal joints and pelvis in the achievement of a more performing action.

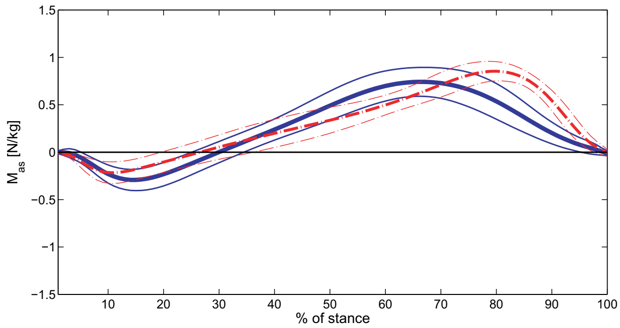
Although very interesting, the analysis that was carried out in this section and the conclusions derived thereof did not taken into coordinative factors, that may be very important for the execution of an efficient



(a)

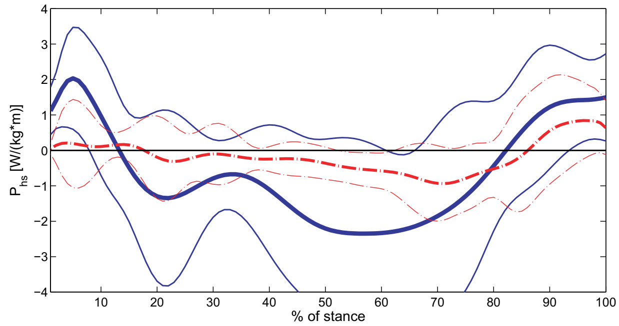


(b)

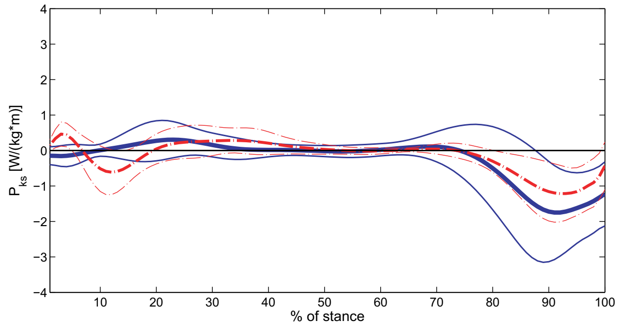


(c)

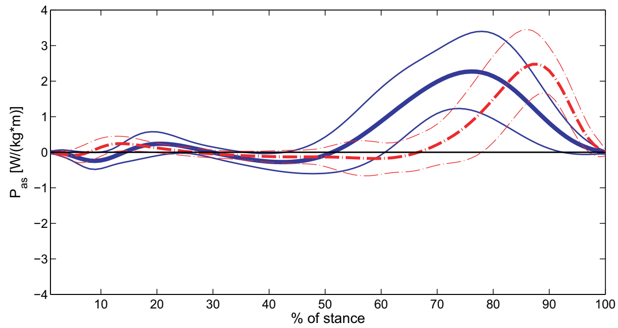
Figure 5.6: *average patterns concerning the hip (a), knee (b), and ankle (c) moment, from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands.*



(a)



(b)



(c)

Figure 5.7: *average patterns concerning the hip (a), knee (b), and ankle (c) power, from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands.*

movement. This issue is addressed in Section 5.2.

5.2 A Dynamic System Analysis of Race Walking Biomechanics

5.2.1 Introduction

Coordination in sports activities plays a fundamental role for the achievement of successful performances [10, 60]. Sports movements usually involve a large number of body segments, which have to act synergically in order to produce the desired outcome [10, 60]. A poor organisation of the elements that concur to the realisation of an harmonious action may cause a bad result and may increase the risk of injury, too. The athlete's neuro-muscular-skeletal system, in fact, often undergoes high intensity biomechanical demands and, at the same time, is required to carry out precise tasks at a considerable speed. Sometimes athletes have to interact with other competitors or to make use of equipment. In some other cases they have to repeat the same (submaximal) action cyclically over a considerable lapse of time. It is therefore clear that an effective coupling of the multiple degrees of freedom of the locomotor system is essential for both executing an healthy movement and for reaching the desired goal [83, 60].

Traditional biomechanical analyses make use of kinematic and kinetic variables to describe the characteristics of the movement and to understand the underlying factors that generated it. Although very useful, these approaches are not very effective in addressing motor coordination, because they describe measures from single joints or segments rather than investigating the interaction between multiple elements of the system.

Dynamic systems theory (DST) has given new means for inspecting the organisation of the locomotor system and for gaining more insight into the multifactorial nature of human motion [128, 63, 69, 136, 81, 142, 83, 60, 61, 84]. According to DST human limbs are seen as a system of coupled pendulums that oscillate about joints. Quantitative information regarding how joint coordination evolves may be drawn by observing the continuous phasing relationships (CRP) between the different elements that participate to the movement. Changes in the mutual relations between body segments or adjacent joints may give important indications about the inherent coordinative factors of the locomotor system. In particular, the amount of variability in the relative phase relationships over many repetition of the same task has been used by many authors to understand how external perturbations, developmental stages, pathologies or detrimental behaviours may influence the choice of a particular motor solution (the reader is referred to [83] for a detailed review).

DST may be exploited for the analysis of sports movements, too. Similar performances in sporting events are often the result of different motor strategies, both within and between individuals [66, 45, 10, 126, 8, 13, 77, 127, 9, 60, 114, 113]. These subtle discrepancies are typically less detectable than the ones that emerge in clinical studies, and are often concealed by the presence of variability (Chapter 4). Hence, the observation of discrete variables and time varying measures are not always effective, while the exploration of motor coordination might unveil either hidden changes or anomalous functionalities. The athlete's phase portraits and CRP measures derived thereof are very likely to be influenced by training programs and motor learning. Furthermore, they may manifest the presence of detrimental behaviour. Therefore, DST tools may represent a valuable tool either for gauging the progresses that are achieved over time or for injury prevention purposes [10, 63, 60, 8, 9, 61].

The aim of this section was to complete the biomechanical description presented in Section 5.1 by analysing race walking features from a dynamic system point of view. RW coordinative aspects were investigated by means of phase portraits and continuous relative phase (CRP) measures. Results were compared with the corresponding characteristics of normal walking gait. The hypothesis was that the constraints imposed by the rules (Chapter 2) and the higher dynamics of race walking would cause different motor strategies and adaptations during the stance period.

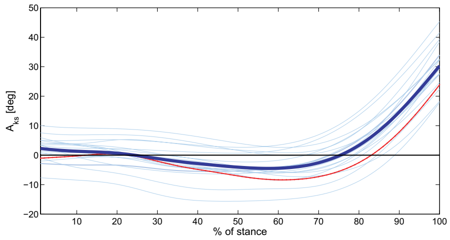
Finally, moment-angular velocities plots (MAV) were proposed as an additional instrument for the depiction of the motor factors that generate the final performance. In fact, phase plots analyse coordinative aspects, but they give no information about the kinetic determinants of the outcoming action. MAV plots were therefore calculated for gaining more insight into the possible relations between the resulting movement (kinematic characteristics) and the causes that generated it (kinetic factors). They might somehow remind of the maps that are used to describe torques-rpm couplings in car engines.

5.2.2 Materials and Methods

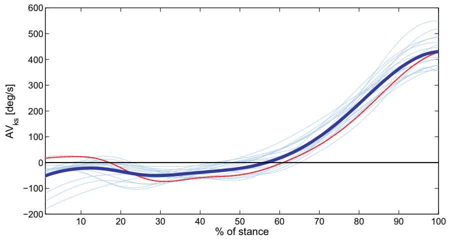
All available normalised curves after outliers removal (Section 3.4 and Section 4.2) were used to estimate the individual bootstrapping averages for each variable. Individual mean curves concerning angular displacement and angular velocity were then employed for the creation of phase portraits of the whole population during both RW and NW[2]. Each phase plot consisted of the angle ($A(t)$) on the horizontal axis, with its first derivative, the angular velocity ($AV(t)$), on the vertical axis. Angular velocity-angle plots (AVA) were estimated for the three main lower limb joints (Figure 5.8); their mean pattern and confidence bands in the state space were calculated as described in [77]. RW and NW phase portraits of the population were graphically compared to detect the peculiarities of the two gait conditions.

The organisation of the neuromuscular system during stance was investigated by looking at continuous relative phase measures. Phase angles ($\phi(t)$) were extracted from every individual phase plot, which had not been previously normalised, according to some authors' suggestions [82, 83]. Normalisation would adjust for amplitude differences in the range of motion and center the phase plot about the origin [69, 63, 59, 60]. However Kurz and Stergiou [82, 83] concluded that normalisation techniques are not necessary because amplitude differences between oscillators do not affect CRP measures. $\phi(t)$ was defined at each time point ($t = 1, \ldots, 100$) as the

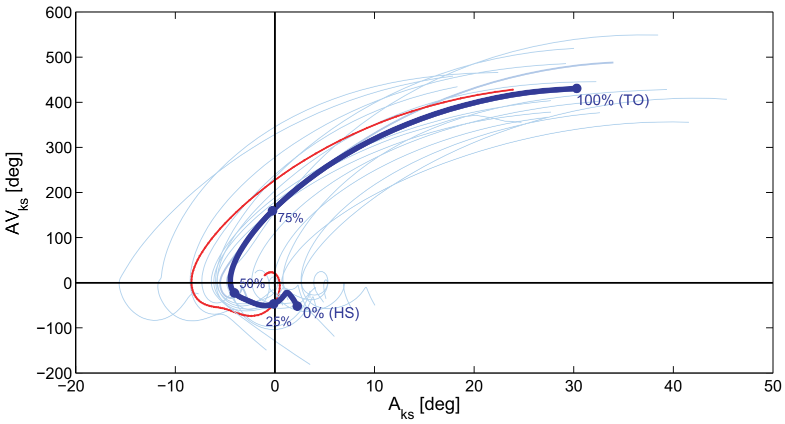
[2]Since only 3 gaits were available for each subject's side, common averaging procedures were applied instead of bootstrapping for the extraction of individual mean curves during normal walking.



(a)



(b)



(c)

Figure 5.8: *example of mean individual phase portraits concerning the knee joint during RW. Each trajectory represent a subject. The 22 mean boostrapping curves of knee angular displacement, $A_{ks}(t)$ (a), and of angular velocity, $AV_{ks}(t)$ (b), were coupled to obtain the corresponding phase plot (c). The curve of one of the subjects is highlighted (red line). The thick blue line is the overall mean (whole population). Stance phase was normalised to 100 points ($t = 1, \ldots, 100$). HS and TO are "heel strike" and "toe off". Numbers indicate the percentage of stance phase.*

angle between the right horizontal axis and a line drawn from the origin to that specific data point $((A(t),AV(t))$, using a four quadrant arctangent function [63, 60] (Figure 5.9):

$$\phi(t) = \begin{cases} [arctan(\frac{AV(t)}{A(t)})] \cdot 57.3 & I\,quad \\ 180 + [arctan(\frac{AV(t)}{A(t)})] \cdot 57.3 & II\,quad \\ 180 - [arctan(\frac{AV(t)}{A(t)})] \cdot 57.3 & III\,quad \\ |[arctan(\frac{AV(t)}{A(t)})] \cdot 57.3| & IV\,quad \end{cases} \quad (5.1)$$

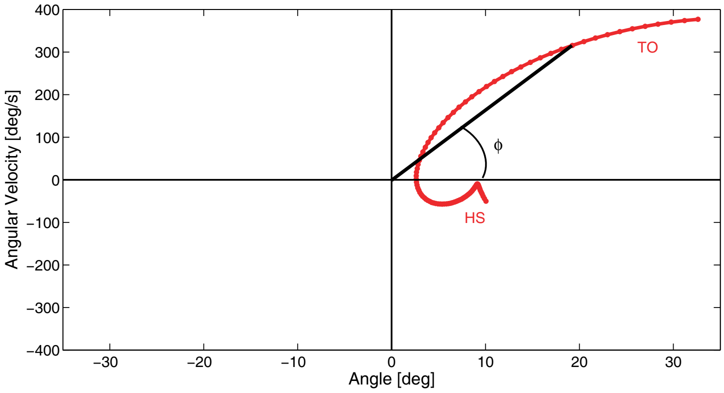


Figure 5.9: *phase angle definition ($\phi(t)$) based on a phase portrait. The resulting ϕ ranged between 0 and* 180 *deg* (5.1).

The continuous relative phase between two adjacent joints was then calculated as:

$$\vartheta_{dp}(t) = \phi_d(t) - \phi_p(t) \quad (5.2)$$

where $\phi_d(t)$ is the phase angle of the distal joint at time t and $\phi_p(t)$ is the phase angle of the proximal joint at time t. $\vartheta_{dp}(t)$ values close to zero meant that the two elements were moving in phase at the t^{th} percentage point of the stance period, while relative phase values that approached 180° indicated out of phase relations. CRP functions were estimated for knee-hip ($\vartheta_{kh}(t)$) and for ankle-knee ($\vartheta_{ak}(t)$) couplings. Continuous relative phase patterns were then averaged across trials to generate mean ensemble curves ($\overline{\vartheta}_{kh}(t)$ and $\overline{\vartheta}_{ak}(t)$) for each individual (Figure 5.10):

$$\overline{\vartheta}_{kh}(t) = \sum_{j=1}^{N} \frac{\vartheta^j_{kh}(t)}{N} \tag{5.3}$$

$$\overline{\vartheta}_{ak}(t) = \sum_{j=1}^{N} \frac{\vartheta^j_{ak}(t)}{N} \tag{5.4}$$

where N is the number of gaits considered for that particular subject.

The phasing relationships between between couples of joints were summarised over the stance phase by extracting mean absolute relative phase ($MARP$) indexes from individual $\overline{\vartheta}_{dp}(t)$. $MARP$ [136, 83] was defined as:

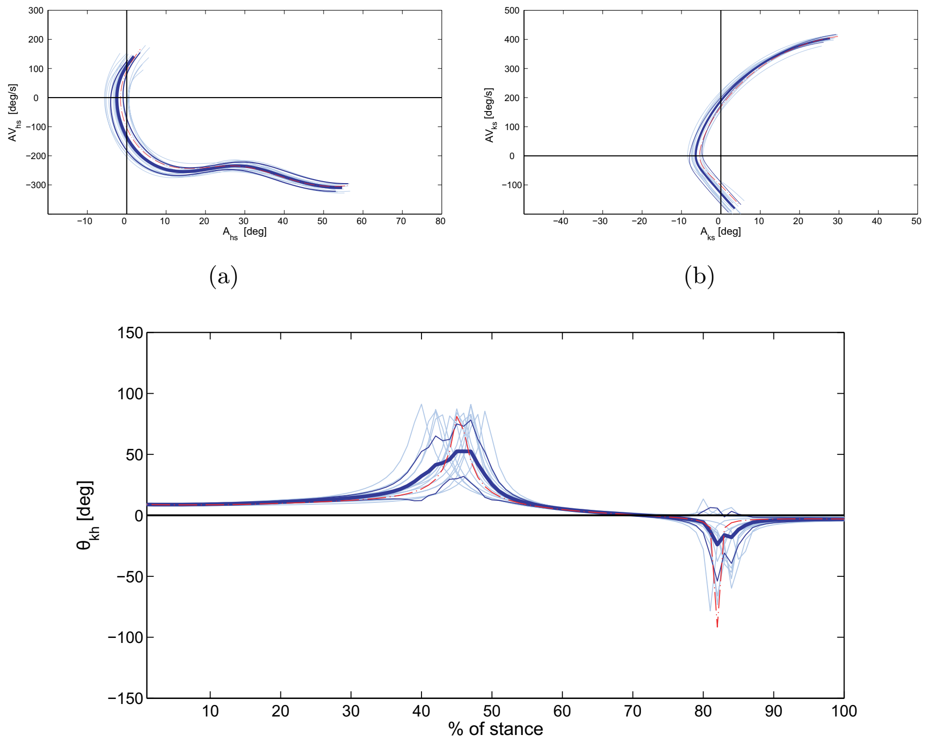
$$MARP_{dp} = \sum_{t=1}^{100} \frac{|\overline{\vartheta}_{dp}(t)|}{100} \tag{5.5}$$

Non-parametric within groups tests (Wilcoxon, $\alpha = 0.05$), were applied to check for significant differences between race walking and normal walking $MARP$s.

Intrasubject coordinative stability was assessed by using the deviation phase index (DP) over individual CRP curves. DP is a measure of the overall variability of CRP throughout the movement cycle, thus it gives quantitative indications about the stability of relative phase patterns over many repetitions of the same motor task [63, 136, 83]:

$$DP_{dp} = \sum_{t=1}^{100} \frac{|\sigma_{dp}(t)|}{100} \tag{5.6}$$

where $\sigma_{dp}(t)$ is the standard deviation of the N individual ϑ_{dp} at time t. A low value of DP indicates a more stable organisation of the neuro-muscular-skeletal system in repeating the same action. DP concerning both knee-hip and ankle-knee relations were calculated for each subject during RW. Unfortunately, due to the lack of trials in normal walking



(a) (b)

(c)

Figure 5.10: *example of individual CRP diagram concerning the knee-hip coupling during RW. AVA plots concerning the hip (a), the knee (b), were used to calculate the continuous relative phase,* ϑ_{kh}*, of the knee-hip coupling (c). Solid blue lines are the mean curve and confidence bands. Thinner grey lines represent single trials, among which one has been highlighted (dash-dot red line)).*

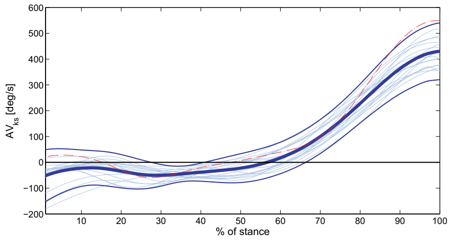
condition, the standard deviation of relative phase could not be estimated and, consequently, the outcoming phase deviation could not be derived. Therefore, statistical comparison between the two progression modalities could not be performed for this index.

Phase portraits depict coordinative aspects inherent to the locomotor system by plotting kinematic variables (angular velocity) versus other kinematic measures (angular displacement). No indication on the kinetic determinants of the outcoming action could be drawn from their observation. Moment-angular velocity plots (MAV) were therefore calculated and proposed (Figure 5.11) as an additional mean of investigation about the possible relations between the resulting movement (kinematic characteristics) and the causes that generated it (kinetic factors). The procedure for creating MAV plots was equivalent to the one that was followed for phase portraits. In this case internal joint moments were on the vertical axis, while angular velocities were on the horizontal one. Positive values of angular velocities corresponded to hip and knee flexion and plantar flexion; positive moments to extension action. Therefore, the first and third quadrant of MAV plots depicted eccentric efforts, while the second and the fourth concentric ones.

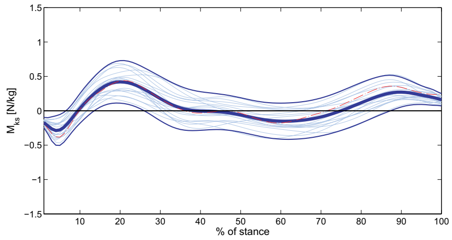
All the procedures exposed in Section 5.2 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

5.2.3 Results

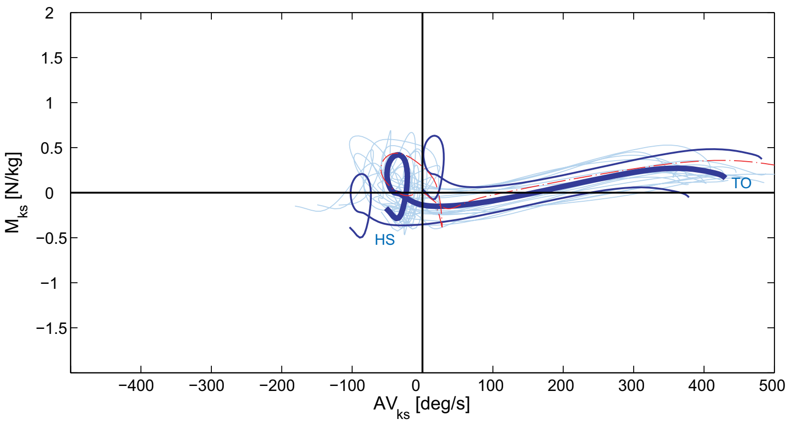
The average phase plots of race walking and normal walking stance concerning hip, knee and ankle flex-extension are presented in Figure 5.12. The patterns of hip and ankle joints maintained an appearently similar profile in the two gait condition throughout the contact time, while the phase portraits of knee joint were remarkably different. Race walking action at the hip and knee was characterised by increased dynamics. The hip (Figure 5.12(a)) had greater extension velocity during NW till about 75% of Δt. Then, angular velocity turned from negative to positive with



(a)

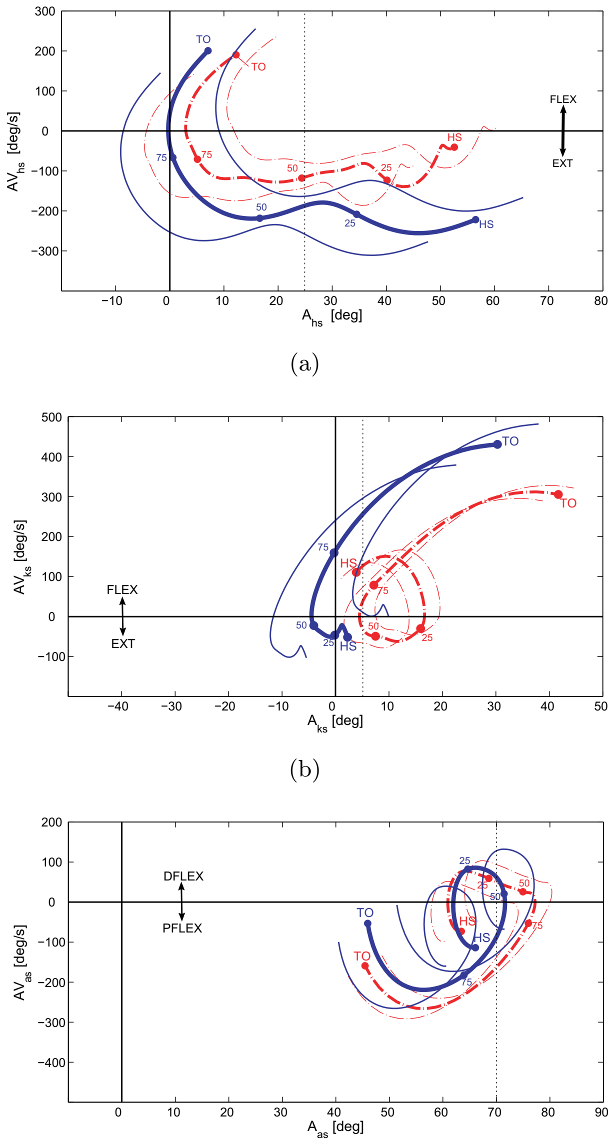


(b)



(c)

Figure 5.11: *example of mean individual MAV concerning the knee joint during RW. Each trajectory represent a subject. The 22 mean boostrapping curves of knee angular velocity, $AV_{ks}(t)$ (a), and of joint moment, $M_{ks}(t)$ (b), were coupled to obtain the corresponding MAV plot (c). The curve of one of the subjects is highlighted (dash-dot red line). Solid blue lines are the overall means and confidence bands (whole population). Stance phase was normalised to 100 points ($t = 1, \ldots, 100$). HS and TO are "heel strike" and "toe off".*



(a)

(b)

(c)

Figure 5.12: *average phase portrait of hip (a), knee (b) and ankle (c) flex-extension from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands. HS and TO are "heel strike" and "toe off". Numbers indicate the percentage of stance phase. The vertical dotted line is approximatively the mean angular value during standing.*

a similar rate both in RW and NW. The range of motion was significantly wider in RW, too. The knee (Figure 5.12(b)) described a plot that ran about the origin for half the duration of stance; then it increased very quickly and reached flexion velocity that was sensibly greater than during NW. Angles excursions were very different as well. During normal walking angles started at HS from the average knee angle of stance and they did never significantly overcome that extended position throughout the movement. In contrast, race walking action generated negative values between load acceptance and final propulsion. Assuming $0\,deg$ as the limit for complete knee extension, values of A_{ks} lower than zero might be read as a fully extended or even hyperextended position. Flexion began right after midstance in both modalities, but, in RW, the knee became more flexed than in standing only after three quarters of stance duration. Differently from the hip, the knee registered decreased ROM during RW. The ankle (Figure 5.12(c)) manifested both lower dynamics and smaller angular excursion during race walking. From HS to 25%, patterns were pretty similar; then, angles increased more intensively in NW (25%–50%). Finally, between 50% and TO, the correspondence was lost both for angular position and velocity, with RW that made the athlete anticipate plantar flexion, and NW that manifested an increased plantar flexion in the last phase of stance (75%–100%). Race walking variability was generally greater (larger confidence bands) than normal walking one. The proximal joint was the one that showed poorer reproducibility in AVA plots.

Table 5.4 reports data concerning mean absolute relative phase and deviation phase. $MARP$ values were higher for distal joint couplings. Significant differences emerged between NW and RW concerning phasing relationship of knee and hip ($MARP_{kh}$). Median phase deviation were $17.35\,deg$ and $17.94\,deg$ for knee-hip and ankle-knee couplings, respectively. Figure 5.13 reports the ensemble CRP variability over the stance phase. σ_{kh} was about $20\,deg$ for almost all the stance phase, with slight decreases between 20% and 40%, 60% and 80%, 90% and TO, and with a modest peak between 80% and 90%. In contrast, σ_{ak} was less homogeneous, and manifested increased variability in the first 70% of Δt, with greater values

Table 5.4: *mean absolute relative phase (MARP) and deviation phase (DP) of the population. Data are expressed in terms of median (med) and interquartile range (IQR). The subscripts $\cdot_{kh}$ and $\cdot_{ak}$ refer to knee-hip and ankle-knee joint couplings. † indicates that Wilcoxon test evidenced statistically significant ($p < 0.05$) differences between normal walking (NW) and race walking (RW) gait. Data are expressed in degrees.*

	$MARP_{kh}$†		$MARP_{ak}$		DP_{kh}		DP_{ak}	
	NW	RW	NW	RW	NW	RW	NW	RW
med	16.68	11.58	40.81	39.28	/	17.35	/	17.84
IQR	5.08	4.82	8.93	10.09	/	9.50	/	7.19

between 10% and 20%, 40% and 60% and even a final peak at TO.

The average moment-angular velocity plots of hip, knee and ankle joints from the whole population are represented in Figure 5.14. Besides the ankle (MAV_{as}), that showed similar shape during NW and RW, the proximal joints, hip and knee, evidenced noticeable dissimilarities between the two gait conditions. MAV_{hs} (Figure 5.14(a)) had greater magnitudes during RW both for moments and for angular velocities. M_{hs} described a greater extension action at heel strike and later became comparable to NW one. AV_{hs} manifested increased absolute velocity until hip extension turned into flexion (just after 75% of Δt). The hip joint alternated eccentric actions, at load acceptance and push off, and concentric one, over most of the stance phase (i.e. between about 12% and 82%). A cusp was present, in RW, between 25% and 50%. This sharp change was determined by a simultaneous decrease of both angular extension and articular flexion moment. It corresponded to the phase during which the stance leg overcame the vertical projection of the COM; namely, at approximately 30% of Δt. MAV_{ks} (Figure 5.14(a)) was remarkably different during the two progression conditions. Knee action formed a wide ring over the four quadrant of moment-angular velocity plane, and went through 6 different phases[3],

[3]Notation: the capital letters, C or E, refer to eccentric or concentric articular actions; superscripts, $\cdot^E$ or $\cdot^F$, to flexion or extension; subscripts to sequence number. Therefore, the four possible combinations, indicate which quadrant the plot falls in. For example, C^F evidence concentric actions when the joint is flexing, and thus refers to

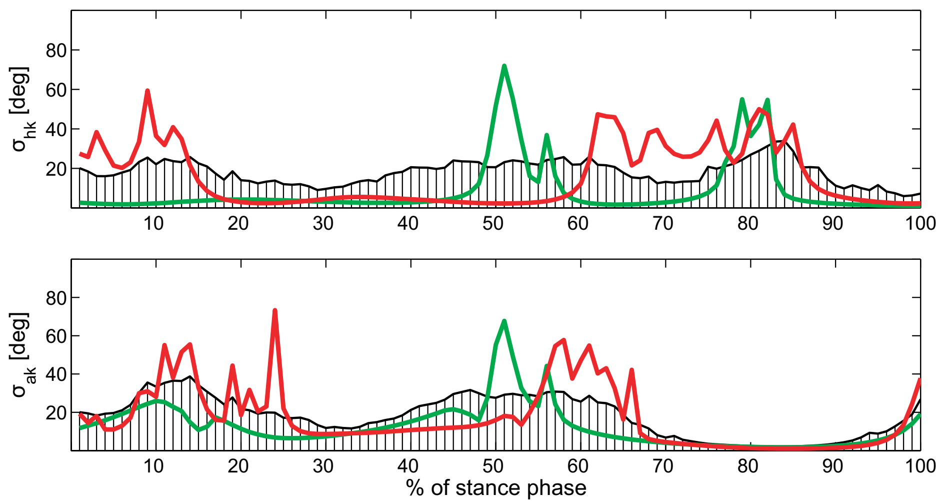
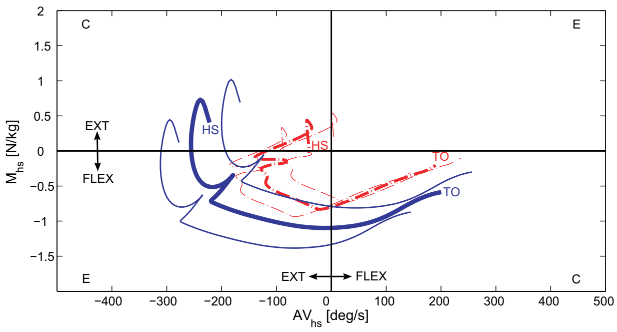
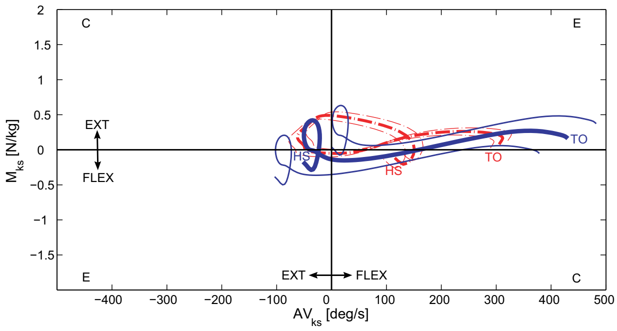


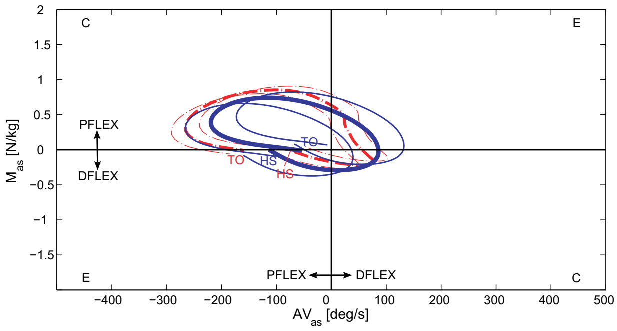
Figure 5.13: *variability of lower extremities couplings (CRP variability) during race walking for the whole population (black striped area). Green and red lines represent variability of a very skilled and less skilled individual, respectively.* $\cdot_{kh}$ *and* $\cdot_{ak}$ *subscripts stand for knee-hip and ankle-hip couplings.*



(a)



(b)



(c)

Figure 5.14: *average moment-angular velocity (MAV) plots of hip (a), knee (b) and ankle (c) flex-extension from the whole population during race walking (solid blue lines) and normal walking (dash-dot red lines). Thinner lines represent confidence bands. HS and TO are "heel strike" and "toe off". Letters C and E in the corners of quadrants stand for "eccentric" and "concentric".*

$C_1^F - E_2^F - C_3^E - E_4^E - C_5^F - E_6^F$, during NW, and through 5 phases, $E_1^E - C_2^E - E_3^E - C_4^F - E_5^F$, during RW. The range of moment values was comparable, but both angular velocities and correspondence between $AV_{ks}(t)$ and $M_{ks}(t)$ at each time point of the cycle were sensibly dissimilar. Race walking variability determined larger confidence bands than normal walking one. In particular, the greatest variability was registered at the hip, for which individual patterns (not reported in figure) often evidenced appreciable irregularity and thus did not necessarily resemble the average plot.

5.2.4 Discussion

The aim of this section was to carry out the description of race walking stance from a DST point of view, and to gain more insight into how lower limb joints interact to perform an efficient movement. Phase plots of hip, knee and ankle joints and continuous relative phases were thus estimated and evaluated for assessing coordination. Furthermore, moment-angular velocity diagrams were proposed as an additional tool for inspecting the relation between kinematic and kinetic factors of joint motion.

Both AVA and MAV plots appeared ad being very useful in analysing race walking gait features and in comparing them with normal walking ones. In fact, the shape of trajectories was quite different in the two progression condition and their observation often evidenced distinctive peculiarities that, in contrast, did not emerge by looking only at single variables versus time. Furthermore, they helped in interpreting quantitative measures.

Phase portraits generally depicted increased dynamics for race walking progression. Angular velocities manifested wider ranges during race walking than during normal walking, with the exception of the ankle. The phase plot of the knee (Figure 5.12(b)) was the one that evidenced the greatest dissimilarities between the two gait conditions. During NW the damping role of this joint determined alternation of flexion and extension

---

the IV quadrant.

during early and central midstance, followed by another flexion phase before toe-off. This behaviour, coupled with angles that never extended to values close to zero (i.e. full extension) made the corresponding plot form a loop about the positive axis. This particular profile disappeared in RW: the phase plot collapsed about the origin of axes for almost 50% of Δt. The rules of RW, in fact, impose to maintain the knee straight at least till vertical upright position, which occurred almost at 30% of stance for all the athletes (mean $t@vup$ was 29%). Therefore, the representation of a correctly performed movement should concentrate on the origin for at least one third of Δt.

Knee MAV plots manifested significant differences between RW and NW, too (Figure 5.14(b)). The intensity of internal moments had comparable magnitude, but the association of $M_{ks}(t)$ and $AV_{ks}(t)$ determined distinctive strategies. Again, normal walking originated a wide loop, but in this case the trajectory spanned the four quadrants before ending in the first one. 6 subsequent different actions could be recognised: an initial sequence of concentric-eccentric flection that corresponded to load acceptance and reaction to gravity force (C_1^F-E_2^F); an early midstance concentric extension (C_3^E) that concluded the normal wave of the knee during the first half of stance; two successive phases of eccentric extension (E_4^E) and concentric flexion (C_5^F) that were characterised by very low moment values and that prepared for the final eccentric flection (E_6^F) during which the knee angle was sustained until the other foot touched the ground. Race walking still produced a loop, but this was narrower and passed through different quadrants with different modalities. In particular, the initial eccentric phase due to load absorbtion disappeared. The succession was: eccentric (hyper)extension at heel strike and during the first 10% of contact time (E_1^E); concentric (hyper)extension (C_2^E) in early midstance (approximatively from 10% and 50%); two subsequent phases of eccentric (hyper)extension (E_3^E) and concentric flexion (C_4^F) that were similar to NW ones but more appreciable because they manifested increased flexion moments; the final eccentric flexion (E_5^F) that reached greater angular velocities and did not show the sudden decrease of both M_{ks} and AV_{ks} that was present in the terminal stance of NW. If C_2^E might be explained by the locking activity exerted to maintain the knee straight over the first half of Δt, some question may arise concerning the first, third and fourth phases, during which negative moments were registered. Murray and colleagues [97] and Cairns and colleagues [21] assumed this negative M_{ks} to be partially due to posterior capsule and ligament forces, rather than to active flexor muscle force. They justified this interpretation by reading electromyographic recordings and by observing that the knee in extended position was subjected to external hyperextension moments. Their interpretation might be undoubtedly true for E_1^E and E_3^E but might encounter some criticism concerning C_4^F. In fact, when the MAV plot is in the fourth quadrant, angular velocities are positive, and , consequently, the knee is flexing. Therefore, in that situation, kinetic factors were contributing to the kinematic outcome and could not be interpreted as the passive opposition to external solicitation. Rather, the negative moment might be related to a "grasping" action that arises when race walkers are close to the unlocking phase (approximatively at 75% of stance). This interpretation finds support in EMG recordings reported in [97]: between 50% and 75% calf muscles and hamstrings were active. Since the gastrocnemius is a biarticular muscle and acts in terms of knee flexion, its contribute might concur in determining negative M_{ks}. MAV plots revealed increased dynamics at the hip (Figure 5.14(a)) both for angular velocities and moments, thus confirming that proximal joints were much more involved than in normal walking. Ankle patterns, in contrast, did not evidenced remarkably different behaviours.

Some authors [83] have suggested that zeros and cusps in phase plots might give initial indications about neuromuscular control features, and may help in discriminating between physiological and pathological behaviours. Zeros are the points where trajectories cross the x-axis and are associated to changes in the dynamics of a segment/joint. Cusps correspond to sudden changes in the movement pattern. Despite the increased angular velocities, both ensemble and individual phase portraits were generally smoother during RW for all three lower limb joints. MAV plots were smoother in RW, too. This might indicate that athletes were able to produce a more fluid and efficient action during race walking. The only exceptions were for knee phase portrait during load acceptance and for knee MAV plot during early midstance, where cusps related to RW could be clearly recognised. The former was probably determined by the forced position that knee angle had to keep at heel strike. The latter might be related to the passage of the stance leg under the vertical projection of the COM. This phase is particularly critic because the pelvis must compensate the increasing excursion of the center of mass (Section 5.1).

The phasing relation between adjacent joints was investigated through mean absolute deviation indexes. MARP is an indicator of phasing relationships between coupled elements. The greater MARP is, the more out of phase joints are [136, 83, 84]. Proximal joints manifested significantly lower MARP values than distal ones (Table 5.4). This findings were in contrast with reports from other authors [83, 84], who registered increasing in-phase relationships from proximal to distal segments both in walking and in running. During RW, hip and knee coupling produced lower MARP values than during NW. In contrast, no differences were found for ankle and knee couplings. Therefore race walking seemed to improve the tuning between proximal districts and the knee. This might be a need that arised for achieving an effective compensation of the altered knee behaviour during RW. In Section 4.4 results concerning regularity of time series showed that sample entropy of the hip was lower than *SampEn* of distal joints. Higher regularity was interpreted as increased control. Hence results concerning time series complexity and joint phasing relationship seem to concur in indicating that, during race walking, athlete were likely to augment the control over proximal joints. Differences between more and less skilled athletes supported this interpretation. In fact, subjects with better athletic ability had lower MARP values for hip-knee coupling: median values were $10.27\,deg$ and $13.23\,deg$ for the more and less skilled groups respectively.

Stability in the organisation of the neuromuscular system was assessed by means of continuous relative phase variability (Table 5.4 and Figure 5.13). Variability of relative phase presents the advantage that it can continuously monitor coordination throughout the entire movement. This is particularly interesting because biomechanical demands might change over the subsequent phases of the action. Increased variability has been assumed to correspond to transitions during which the neuromotor system is in search for the most appropriate motor strategy by exploring different coordinative solutions. Despite it might appear as instability, higher variability in relative phase has been interpreted as a form of flexibility to overcome local and global perturbations or to redistribute detrimental loads [63, 81, 83, 84, 61]. CRP variations over the stance phase did not present the typical “U shape” that was reported by Kurz and Stergiou [83] for foot-shank and shank-thig couplings. RW manifested slight increases of σ_{kh} in correspondence to load acceptance, to late midstance and to knee unlocking phase. While the first and the third raise of variability might be related to peculiar features of race walking action, and might serve as exploration of different strategies, the second raise of variability, that was registered between 40% and 70% of stance, was more difficult to be interpreted. However, by looking at MAV plots, that phase coincided with E_3^F, namely, when the passive structures of the knee were thought to act against external hyperextension moments. A more flexible strategy might thus represent a form of preservation against excessive or repetitive loads over ligaments and posterior capsule. The final increase of CRP variability disappeared in ankle-knee coupling. This was not surprising; in fact, during late stance, the knee recovered from imposed straight position and followed normal walking behaviour. Phasing variation was low and increased only for final transition from stance to swing, as reported by other authors [63, 83].

Although some interesting speculation could be drawn from the presented results, further efforts should be spent to identify reference levels for CRP variability [83, 60] above or below which caution would be advisable. In fact, anomalous magnitudes or unusual distribution of CRP variation might be signs of ineffective or even detrimental coordinative behaviours. Figure 5.13, for example, reports two different distributions from a very skilled and less skilled athlete. Many dissimilarities are present, but their interpretation is not straightforward and might derive only after systematic analyses of many longitudinal case studies. In fact, as mentioned in the introduction, the principal drawback of horizontal investigation is the difficulty in assessing whether the difference between groups is the cause or the result of the related phenomenon [10, 89, 8, 60, 61].

Finally, a further positive note on the DST approach to human movements could be presented. AVA, MAV and CRP measures and representations have the propriety to synthesize information. In fact they do not address single measures versus time, but they condense two or more variables within one, to capture the dynamic organisation of the neuromuscular system. Therefore, synergies between interacting elements are investigated in low-dimensional terms [83].

5.3 Example of Longitudinal Monitoring

5.3.1 Introduction

The previous sections addressed the description of race walking in a group of young athletes: Section 5.1 described the biomechanics of RW through a traditional approach; Section 5.2 exploited innovative tools to outline peculiarities of the neuromuscular organisation during RW. Furthermore RW characteristics were compared with normal walking ones (Section 5.1 and Section 5.2) and some conclusions about groups of athletes with different skill level were proposed (Section 4.4, Section 5.1 and Section 5.2). All those observations were based on a horizontal experimental design, according to which subjects with apparently similar characteristics were associated and their average behaviour was depicted.

Although this approach is essential for understanding the basis of the movement under investigation, many reasons (Section 1.2) suggest the use of individual longitudinal monitoring. Therefore an example of such an approach is hereafter presented. For this purpose, a subject among all the analysed ones was chosen, and results from two different testing session were analysed.

5.3.2 Materials and Methods

Two testing session were available for the analysed subject. The former was carried out in March, when the outdoor season was beginning, the latter in September, during the last phase of the competitive season. The athlete had not manifested any particular dysfunction at the time of both experimental session, but some week after the first one she was subjected to athletic pubalgia, that disturbed her training programs and negatively affected her competition results. Hence her season best in the 10 Km event was far from her expectations, with performances that were pretty constant over the agonistic season: 49 : 20.0 in March, 49 : 54.9 in September.

Data collection, processing and analysis were performed according to the guidelines that were proposed throughout the previous sections (Chapter 3 and Chapter 4). Therefore, as many as 20 suitable trials were registered. Stance phases were extracted and outliers concerning duration eliminated. After temporal normalisation, unrepresentative curves were discarded by using intraclass correlation coefficient (Section 4.2). Kinematic and kinetic measures were estimated (Section 4.1 and Section 4.2), and individual boostrapping (BOOT-C) confidence bands created (Section 4.3). Sample entropy was calculated (Section 4.4), and dynamical system tools (Section 5.2) used to address the issue of neuromuscular system organisation. The Mann-Whitney test ($\alpha = 0.05$) was used, whenever necessary, to test for significant differences between groups of data.

These procedures were applied to both testing sessions and for both the left and the right side of the subject. However, only data concerning the right side are hereafter reported in order to present some examples of the potentialities of the proposed methodologies for longitudinal monitoring.

5.3.3 Results and Discussion

Global parameters from the two testing sessions concurred with competition results: stance duration, mean progression velocity, step length and peak values of ground reaction force did not show any significant change (Table 5.5). Although bootstrapping confidence bands were pretty tight

Table 5.5: *global parameters from two different testing session of the same subject. Data are expressed as median (med) and interquartile range (IQR). Duration (Δt) and speed ($\overline{v}_m$) are in s and $\frac{m}{s}$, respectively. Step length (Δx) is in mm. Forces (R) are normalised to body weight and measured in $\frac{N}{kg}$. Mann-Whitney test did not evidence statistically significant ($p < 0.05$) differences between March and September. A description of parameter abbreviations can be found in Table 4.1.*

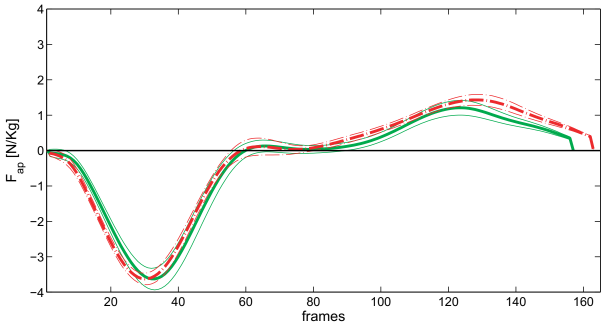
	Mar		Sep	
parameter	*med*	*IQR*	*med*	*IQR*
Δt	0.33	0.01	0.32	0.01
$\overline{v}_x$	2.82	0.09	2.83	0.09
Δx	963.03	26.54	956.41	35.58
R_{ap-MAX}	1.38	0.16	1.21	0.42
R_{ap-MIN}	-3.70	0.19	-3.59	0.41
R_{v-MAX}	17.22	0.73	18.13	1.07

(Section 4.3) R_{ap} and R_v patterns were very similar (Figure 5.15), and overlapped for most of the stance duration. The GRF components in the sagittal plane essentially represent the output of the whole action. In fact, ground reaction forces and accelerations of the center of mass are directly related. Hence, it seemed that physical problems had not altered race walking in terms of global performance: the athlete always determined the same progression of her COM.

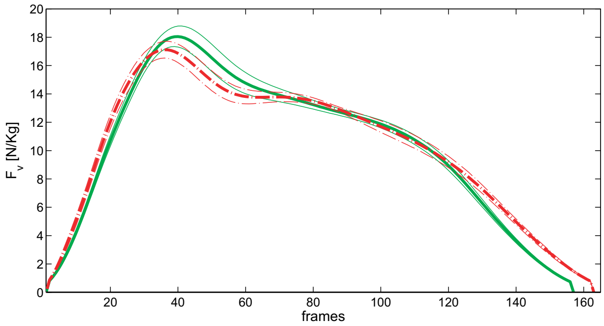
Unfortunately, the stability of those measures did not reflect an equally homogeneous motor organisation. In fact, many discrepancies emerged when the attention was shifted to other kinematic and kinetic factors and to measures concerning joint coordination.

Range of motion of pelvis obliquity, and of hip and ankle flex-extension decreased consistently from the first to the second session. Knee moments and hip, knee and ankle powers showed reduced maxima in September. Data concerning the measures that manifested significant evolutions are reported in Table 5.6.

However, the most evident differences appeared by exploiting the tools presented in Section 5.2.



(a)



(b)

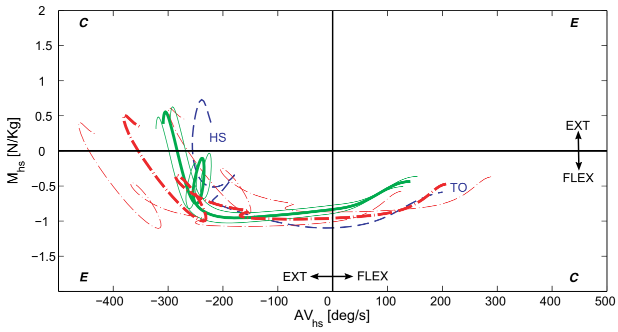
Figure 5.15: *antero-posterior (a) and vertical (b) ground reaction force from two different testing session of the same subject. Dash-dot red lines represent March session. Solid green ones depict September session. Thinner lines represent confidence bands.*

Table 5.6: *kinematic and kinetic parameters from two different testing session of the same subject. Data are expressed as median (med) and interquartile range (IQR). Angles (A) are expressed in deg; moments (M) and powers (P) are normalised to body weight and height and are measured in $\frac{N}{kg}$ and $\frac{W}{kg \cdot m}$. Only measures for which Mann-Whitney test evidenced statistically significant ($p < 0.05$) differences between March and September are reported. A description of parameter abbreviations can be found in Table 4.1.*

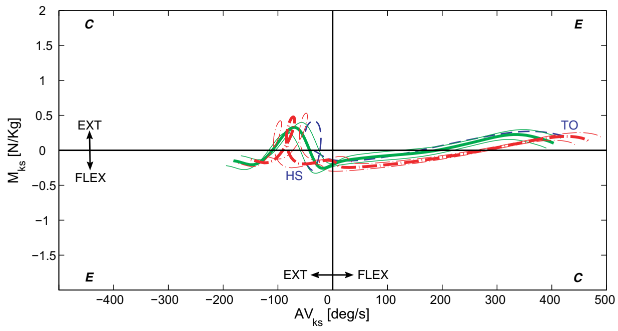
	Mar		Sep	
parameter	med	IQR	med	IQR
$A_{po}ROM$	27.99	3.28	19.76	3.66
$A_{hs}ROM$	62.97	5.48	57.59	2.45
M_{hs-MAX}	0.47	0.07	0.34	0.10
P_{hs-MAX}	2.74	1.48	2.01	0.26
P_{ks-MAX}	0.74	0.41	0.40	0.15
P_{as-MAX}	2.81	0.28	2.28	0.15

MAV plots of all the lower limb joints were significantly different between the two testing session (Figure 5.16), thus indicating that both kinetic and kinematic features had undergone remarkable changes. Moment-angular velocity patterns of the ankle manifested lower magnitudes in September and described a smaller loop in the state space (Figure 5.16(c)). Proximal joints (Figure 5.16(b) and Figure 5.16(a)) also evidenced differences in terms of shape. Hip patterns were evidently more irregular in March, thus giving the idea of a less harmonious action, with many sudden changes (cusps).

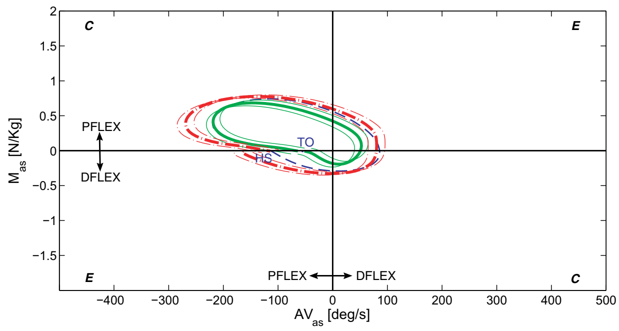
Phasing relations between joint couplings confirmed the presence of a less consistent coordination in the first testing session (Figure 5.17). Angular velocity-angle plots again manifested increased dynamics and reduced smoothness (Figure 5.17(a) and Figure 5.17(b)). Continuous relative phase diagrams showed that knee-hip coupling was less in-phase and had less stability (Figure 5.17(c)). In fact, mean absolute relative phase was 18.14 deg in March and 12.42 deg in September; deviation phase was 18.28 deg and 9.90 deg. The distribution of CRP variability throughout the contact time is reported in Figure 5.18. In March there were many periods



(a)



(b)



(c)

Figure 5.16: *MAV plots concerning the hip (a), the knee (b), and the ankle (c), from two different testing session of the same subject. Dash-dot red lines represent March session. Solid green ones depict September session. Thinner lines represent confidence bands. The dashed blue line is the mean behaviour of the whole population. HS and TO are "heel strike" and "toe off". Letters C and E in the corners of quadrants stand for "eccentric" and "concentric".*

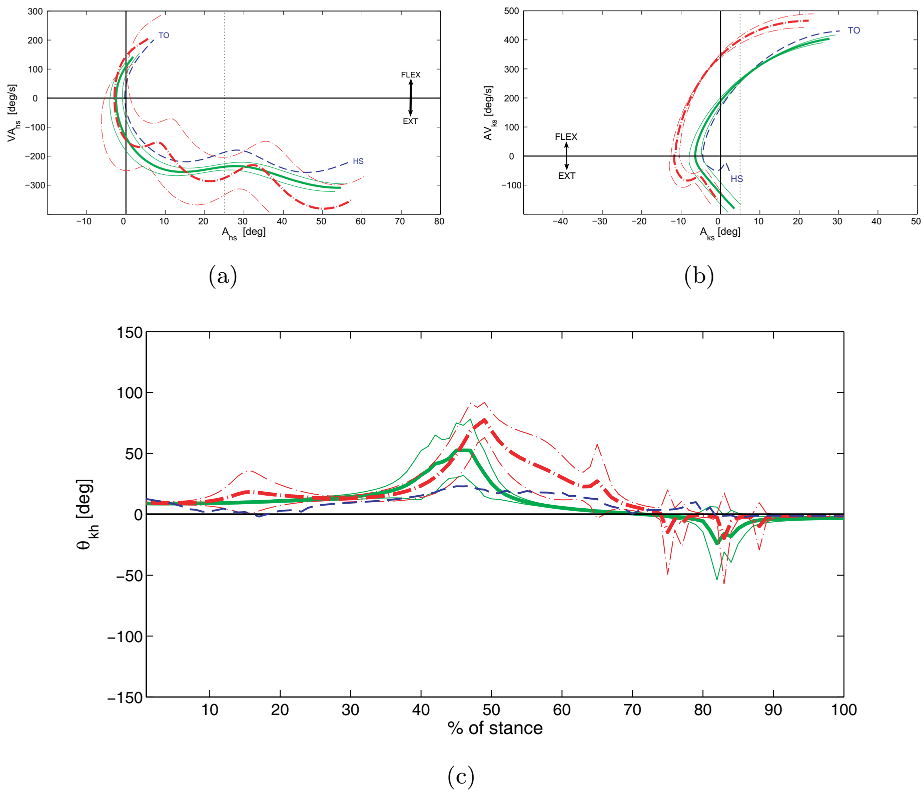
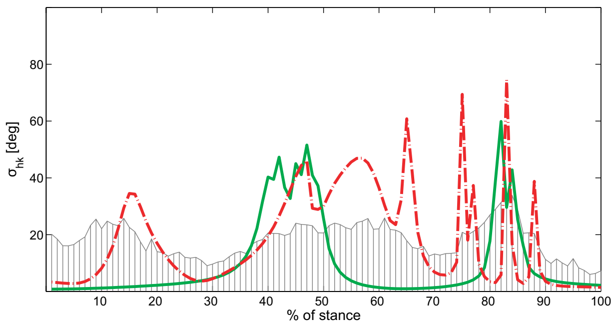
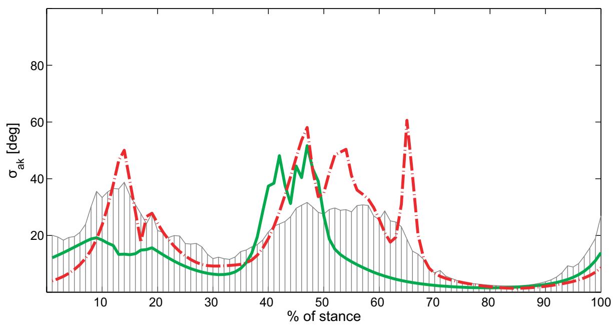


Figure 5.17: *AVA plots concerning the hip (a), the knee (b), and the resulting continuous relative phase of the knee-hip coupling (c), from two different testing session of the same subject. Dash-dot red lines represent March session. Solid green ones depict September session. Thinner lines are confidence bands. The dashed blue line is the mean behaviour of the whole population.*



(a)



(b)

Figure 5.18: *CRP variability for the knee-hip (a) and ankle-knee (b) couplings from two different testing session of the same subject. Dash-dot red lines represent March session. Solid green ones depict September session. The grey striped are is the mean behaviour of the whole population.*

of the stance, during which both the knee-hip and ankle-knee couplings manifested increased fluctuations. σ_{kh} and σ_{ak} were remarkably higher at load acceptance and in late midstance; σ_{kh} reported greater coordinative instability in the knee unlocking phase, too.

Therefore, all the reported results outlined that, although the global performance appeared unchanged, important modifications took place in motor organisation. These changes might be associated to many causes. However, a pathology that typically affects motor structures of great importance for race walking action was present. Its insurgence or its consequences might be associated to the remodeling of motor strategies. In particular, it seemed that, during the second testing session, the athlete exerted an increased control over lower limbs, thus determining better and more stable phasing relations between joint couplings. This was reflected by parameters that monitored execution technique (Section 6.1). The vertical excursion of the center of mass decreased (median Δz_{COM} was $34.16\,mm$ in March and $19.39\,mm$ in September), and many other actions appeared as being less accentuated, for example with decreased range of motion (Table 5.6) and anticipated unlocking of the knee (median $t@unl$ was 91.82% in March and 84.94% in September). Result concerning the estimation of sample entropy agreed with this interpretation: $SampEn$ passed from 0.131 to 0.057 (hip flex-extension) and from 0.119 to 0.021 (ankle plantar-dorsiflexion), while it remained almost constant for knee angles and ground reaction force. Less complexity in angular time series could imply greater control over degrees of freedom of the locomotor system.

To conclude: this was a brief example to show that very similar performances in terms of global output, are not always the outcome of equally homogeneous motor strategies, even within the same individual. Latent pathologies, incomplete recoveries or training procedures may affect the organisation of the neuromuscular system. Sometimes these influences are evident; in some other cases, like the one just exposed, they are subtle and not easily detectable by using traditional analysis. Thus, different tools are needed. Non-linear methods or dynamical system theory approaches may be fundamental, because they help in understanding how the different elements of the system operate and interact. This new information may reveal very useful for injury prevention and for monitoring the effectiveness of training procedures. However further efforts must be spent to gain more insight into the the relation between those measures and the phenomenon of interest. For instance, referring to the exposed case study, it would be very useful to understand whether the greater instability and lack of coordination was the cause of the injury, or, in contrast, whether the increased control during the post-injury session was an abnormal behaviour induced by the pathology.

The answers to these kind of issues might be found only by systematically monitoring athletic activities and by creating consistent data bases. This would be possible only through the creation of standard testing procedures and the enhancement of cooperation between different research groups.

Chapter 6

BRIDGING THE GAP BETWEEN THEORETICAL ISSUES AND PRACTICAL NEEDS

What have been presented so far is evidently theoretical and, although very important, it hardly answers many practical needs "on the field". The robust description of biomechanical characteristics (Chapter 4) and their correct interpretation (Chapter 5) are the basis for an effective analysis of the athlete's motor skills, but a further step must be performed to turn information into tools that may be directly exploited by athletes and trainers [10]. Quantitative motion analysis concerning sports movements have usually been too descriptive and somehow too "cryptic" for sports practitioners. Biomechanists, thus, should improve the way they return information to coaches and athletes by understanding how data should be provided. The feed-back of research results (Figure 6.1) should convey useful information, with proper modalities and in a easily understood format [10, 87, 9].

Trainers need quantitative tools that could support and enhance their

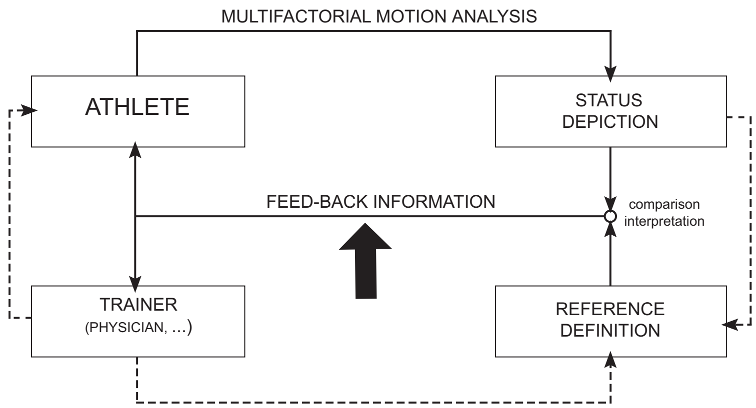


Figure 6.1: *longitudinal monitoring schema. The third phase of the process (i.e. feed-back) is highlighted.*

typically qualitative evaluation of athletes. Athletes need indications for perceiving what they are doing, and how they could improve their performance. Technologies that allow three-dimensional and multifactorial analysis of human movement are currently very powerful instruments. They easily record and process large amounts of data, and they might even provide real-time representation of motion by creating virtual environments [87]. The availability of such a resources may tempt researchers to give back as many details as they can in the shortest time possible. However, feed-back must not be intended as in classical control theory: registering deviations from a desired reference and repeatedly communicating how to correct them might be not enough or even ineffective when the system under investigation is the athlete [87].

The acquisition of a new skill or the improvement of performance may be affected by many elements that are not necessarily related only to biomechanical factors. Some studies have tried to understand how practice and feed-back may influence motor improvement [126, 93, 127, 56] but a lot of work has still to be done in order to understand how athletes could learn skills and improve in performing complex sports activities [10]. Only the collaboration between different disciplines of sports science (biomechanics, motor control, motor learning, physiology, psychology) might help in addressing these issues and in gaining more insight [10, 87, 8, 9, 55]. However, both anecdotal experience[1] [145] and scientific literature [10, 87, 126, 127] agree in observing that skills acquisition take place only when proprioception matches external information. Namely, when the athlete becomes aware that the feed-back he has been given (be it visual, auditory, numerical, ...) corresponds to what he has experienced through internal perception. This process and the implementation of adequate correction to reach the desired outcome may need time, and may depend on the skill level and experience of the receiver. That is why providing too much information or giving it back too frequently, or too immediately, may be ineffective or even confusing [10, 87, 126, 127].

Therefore technologies should not be used for the production of an overwhelming amount of data, rather they should be seen as a mean for obtaining reliable results, for extracting what is essential and for simplifying the transmission of information.

This work was not intended for investigating whether a particular feedback modality could be more effective than another one, however some efforts were made to turn complex biomechanical analyses into information that answered to trainers' specific request and that could provide them with practical indications about their athletes' peculiarities during race walking. Section 6.1 presents the results of these attempts.

6.1 Quantitative Aids for the Evaluation of Race Walking

Trainers usually assess their athletes' performances by visually observing them. The evaluation of race walking technique is typically qualitative and based on experience. Therefore, although fundamental, this activity might benefit from the availability of quantitative tools. That is why an

[1]This information derived even from personal experience and personal communications with outstanding trainers of elite athletes, Prof.Carlo Vittori and Prof.Ennio Preatoni, whom the author would like to thank.

intensive interaction was carried out to understand what trainer focus on, when they judge the proficiency of race walkers' action, and what they need to improve monitoring procedures[2].

The translation of these aspects into biomechanical measures and easily understood representations was the following step, whose results are hereafter presented.

All the procedures exposed in Section 6.1 were carried out by implementing dedicated algorithms in MATLAB language (MATLAB v7.0, The MathWorks Inc., Natick (MA), U.S.A.).

Respect of defining rules

The maintenance of a correct action throughout the observed movement was the first aspect under investigation. According to the defining rules of this event (Section 2.1), race walkers have to keep their stance leg in a straight position at least until the vertical upright position. Furthermore they must never produce visible loss of contact with the ground during progression. Hence, three measures had to be determined.

First, the period during which the knee joint was kept in an extended position: this was monitored by looking at the flex-extension angle in the sagittal plane. The limit for recognising when the athlete stopped locking the knee was determined by looking at that joint angle during stance phase ($A_{ks}@stn$). $A_{ks}@stn$ (whose mean in the population was about $5\,deg$) is not necessarily the fully extended position, however, rules state that judges have to control the correctness of the movement by visual inspection. Therefore that reference appeared as being a reasonable solution. $t_{\%}@unl$ indicated the percentage of contact time at which the knee started flexing more than $A_{ks}@stn$.

$t@unl$ had to be compared with a second time parameter ($t_{\%}@vup$) in order to understand whether unlocking took place late enough, namely,

[2]This information derived from personal communications with outstanding trainers of elite race walkers, Prof.Antonio La Torre and Prof.Ruggero Sala, whom the author would like to thank.

after the instant at which the stance leg overcame the "vertical upright position". $t_{\%}@vup$ was determined by comparing the coordinates of the center of mass and of the ankle on the longitudinal direction (x axis). Furthermore trainers suggest that the support leg should remain extended as long as possible until final push-off. This would allow a grater propulsion and would concur in increasing stride length. Thus, the difference between time of occurrence of vertical upright position and time of occurrence of knee unlocking was estimated as well ($\Delta t_{unl-vup} = t_{\%}@unl - t_{\%}@vup$). The greater $\Delta t_{unl-vup}$, the more proficient the action.

Third, the possible occurrence of loss of contact was verified by calculating the difference (Δz_{cnt}) between the vertical position of the stance ankle at heel strike and the vertical position of the contralateral ankle at the end of Δt. Since markers on lateral malleoli were supposed to be attached at the same height from the ground, positive values of (Δz_{cnt}) would reveal that the swing leg still had not touched the ground when the stance foot was about to take off. However, small differences (i.e. up to approximately $1\,cm$) were accounted as acceptable, because of possible slight misalignment in marker placing or of deformations related to the compliance of shoe midsoles. The bias due to markers misalignment could be partially compensated by considering the vertical offset between articular centres of the ankle during standing.

Monitoring of technique

Pelvis motion plays a fundamental role for race walking proficiency (Section 2.1, Section 5.1 and Section 5.2): it compensate the unnatural position of the knee by reducing the vertical excursion of the COM and it participates to forward propulsion by increasing stride length. Trainers usually look at the line that virtually links the hips to assess pelvic rotations in the secondary planes. In this context pelvic action was quantitatively assessed by estimating the range of motion of pelvic rotation and pelvic obliquity.

The way race walkers swing the leg forward after push off is another indicator of a correct technique. The knee should be driven forward along the longitudinal direction, as low to the ground as possible. This allows a more proficient progression with lower energy dissipation and preservation of horizontal speed. Furthermore, it concurs in giving the appearance of a more correct action. The advancement of the swing leg was evaluated by comparing the trajectory of its knee to the one of the supporting leg. The difference between minima of the two patterns were evaluated ($\Delta z_{kst-ksw}$). Positive values of $\Delta z_{kst-ksw}$ meant that the minimum of the stance knee trajectory was higher than the corresponding minimum of the swing knee.

The advancing leg should approach the ground not too ahead of the vertical projection of the center of mass (x_{COM}). This would allow a smoother load absorbtion with reduced articular strain and minimal braking action. In contrast, the backward push of the supporting foot should be increased, thus contributing both to forward body propulsion and to step length. The "forward pull" and "backward push" components, were assessed by measuring: the advancement of the front leg (i.e. ankle joint centre) at heel strike respect to the vertical projection of the COM ($\Delta x_{fl}@hs$); the extent the rear foot (i.e. ankle joint centre) moved back from x_{COM} at toe-off ($\Delta x_{rl}@to$); the ratio between the two ($\Delta x_{rl/fl}$). The greater $\Delta x_{rl/fl}$, the more effective the production of driving force for forward locomotion.

Finally, both vertical (Δz_{COM}) and mediolateral Δy_{COM} excursion of the center of mass were considered. Oscillations along those directions would result in increased dissipation of mechanical energy, hence they should be minimised. COM trajectory was used to estimate progression velocities, too.

Reports, that summarised the aforementioned measures and graphically represented them, were implemented and proposed to trainers. These representations were rather intuitive and let trainers get quantitative information concerning aspect they were pretty familiar to. Therefore they were immediately appreciated.

Figure 6.2 reports an example of the graphical interfaces that were used to communicate quantitative data to coaches and athletes. These representations were still far from being very appealing from a graphical point of view and they might be improved a lot[3], but contained all the informa-

[3]Graphical interfaces and representation for athletes and coaches will be further

tion trainers had requested. Furthermore, measures were the outcome of robust data collection and data processing procedures (Chapter 4), thus they represented a consistent depiction of the athlete's characteristics.

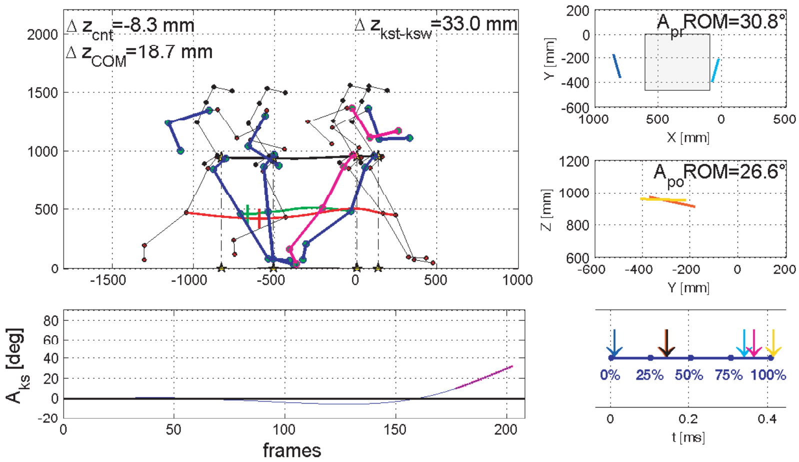


Figure 6.2: *example of graphical interface for the quantitative evaluation of race walking technique. The most important features of race walking technique are reported through both quantitative measures and visual representations: the stick diagram of the four most important phases of the movement (heel strike, vertical upright position, knee unlocking, toe-off); the trajectories of the knee joints and of the center of mass; the knee angle pattern with unlocking phases highlighted; the maximal excursion of the pelvis in the frontal and horizontal plane; the time of occurrence of the those aspects.*

investigated by Giulia Donà, MSc, (Department of Information Engineering, University of Padova, Padova, Italy) in her PhD project.

Chapter 7

CONCLUSION

The assessment of sports movements possesses distinctive characteristic from other scientific fields that make use of quantitative motion analysis (e.g. clinics, ergonomics). When performance enhancements are continuously pursued, each athlete should be assisted both in developing his potentialities and in reducing his deficiencies. Furthermore, injury prevention should be accounted, because athletic activities usually involve maximal biomechanical demands or the repetition of the same movement over a considerable lapse of time.

These aims are hardly achievable by describing average behaviours in groups of apparently homogeneous subjects. Individual peculiarities should not be neglected, because similar performances may be the outcome of different motor strategies, both between and within individuals. In turn, different organisations of the neuromotor system may reveal improvements due to skills acquisition or may warn of possible detrimental behaviours. Hence, after that the general features of the movement have been described, individual longitudinal monitoring should be preferred to the description of mean behaviours through horizontal experimental designs. In fact, it is often very difficult to understand whether differences are the cause or the consequence of the observed phenomenon when two or more groups are compared without any information about time evolutions concerning single subjects.

Biomechanical research in sports have usually been too descriptive and have privileged the analysis of single aspects of athletic activities to the investigation of the neuromuscular and coordinative determinants of the final motor output. Thus, kinematic and kinetic descriptions of specific sports movements have been carried out, in search for possible solutions to technique issues. Unfortunately, results have not always been presented in a way that they could be directly understood and exploited by athletes and trainers. Consequently sports biomechanics has often been suspended between being soundly analytical and providing practical tools for training needs.

Therefore, the aim of this work was to propose a set of comprehensive guidelines (Figure 7.1) that may drive the analysis of sports movements and the longitudinal monitoring of individual motor characteristics. These procedures should allow both to address theoretical questions concerning the organisation of the locomotor system, and to give sports practitioners proper information that may turn useful in everyday practice.

Three main issue were identified and explored for the definition of the monitoring process (Figure 1.2): the consistent depiction of the individual motor characteristics during the execution of the movement (Chapter 4); the interpretation of results (Chapter 5); the translation of biomechanical measures into information that could be easily interpreted by athletes and trainers (Chapter 6). Race walking was chosen as the paradigmatic mean of investigation because its features particularly suited the purposes of this research (Chapter 2). Although very similar to normal walking, which is the most studied movement in literature, race walking is not inborn, and the rules it is governed by impose very peculiar biomechanical and coordinative demands. Those constraints add further control over the execution and make repetitions appear as being rather stereotyped.

The comprehension and consequent depiction of individual motor skills is strongly affected by the presence of variability, which may arise from many different sources and which is inherently present both within and between individuals. Intraindividual fluctuations over consecutive repetitions of the same motor task may hinder the detection of the subtle

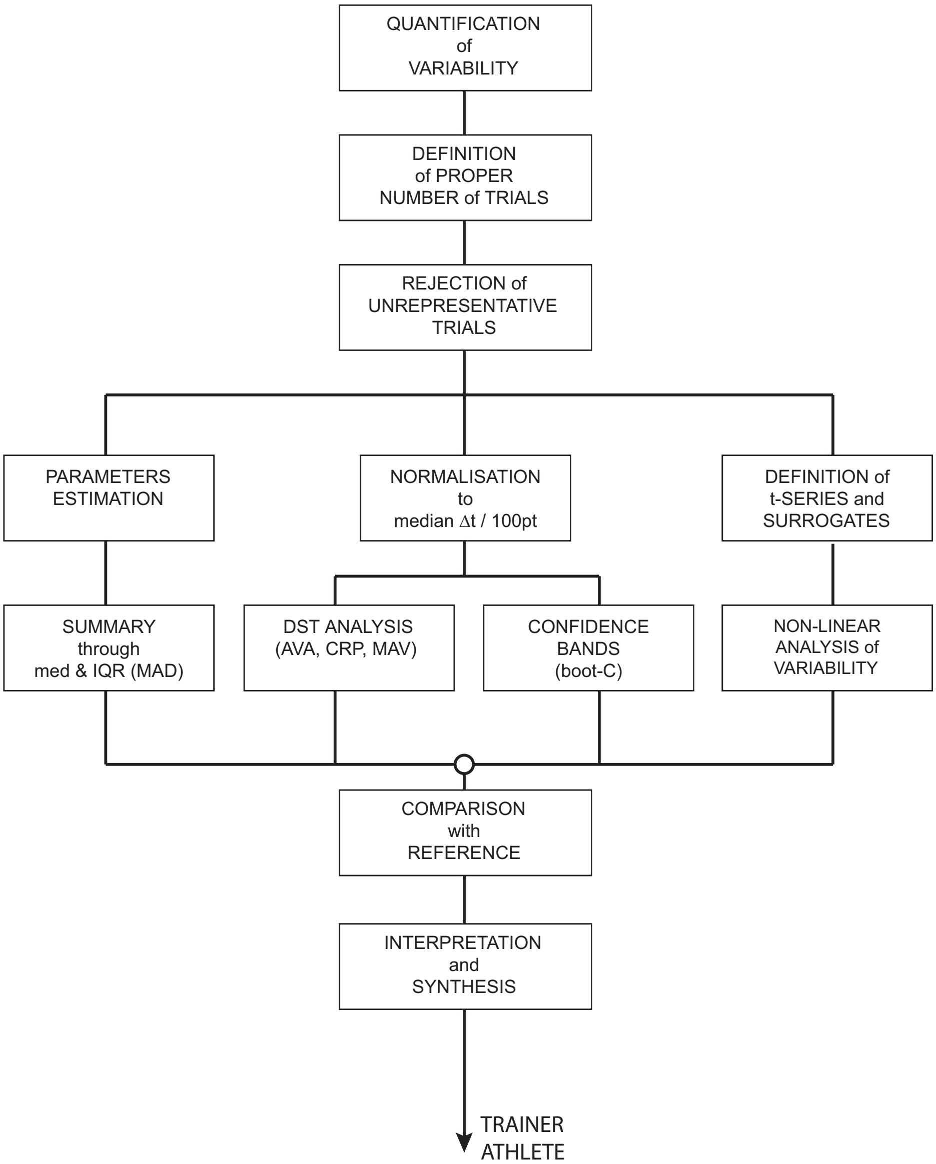


Figure 7.1: *guidelines for individual monitoring in sports.*

changes that either skill enhancements or latent pathologies may induce. Therefore proper acquisition protocols and data processing should be followed in order for the conclusions not to be altered by unrepresentative observations.

Therefore, the first step consisted in the quantification of motion variability. Although race walking was apparently very repeatable in terms of global performance (e.g. stance duration and progression velocity showed great reproducibility), a considerable intraindividual variability was registered in both kinematic and kinetic measures. These findings confirmed that the use of few trials may induce in misleading interpretation due the occurrence of false positives or false negatives. The sequential estimation procedure was used to identify the proper number of repetitions that should be recorded in every experimental session. Results suggested that 11–16 trials were necessary to obtain stable estimates for every considered variable during race walking. When many cycles of the same movement are collected, data sets should be summarised through robust statistics. Different estimators of central tendency and spread were evaluated. Non-parametric statistics (median, interquartile range and median absolute deviation) seemed the most appropriate because they manifested less dependence from contaminants.

Pattern variability was assessed, too. Intraclass correlation coefficient was used for this purpose. It revealed to be a precious tool when it was applied in a recursive algorithm to detect and discard unrepresentative curves. Ground reaction forces, flex-extension of lower limb joints in the sagittal plane and pelvic rotations in the horizontal and frontal plane were the waveforms that manifested better reproducibility.

After a bunch of representative curves has been selected, there is the need of summarising the information they contain, thus depicting the motor signature of the individual. Different procedures for the creation of confidence bands were examined and the best solutions for different applications were proposed. The bootstrapping estimation of the interval within which the mean curve is likely to vary (BOOT-C) appeared as being very suitable for individual monitoring in sports. In contrast, the bootstrapping determination of prediction bands (BOOT-P) or the traditional mean±standard deviation method seemed more appropriate when the description of a group of subject is the aim of the survey. Principal component analysis revealed poor prediction power, but showed clues of interesting potentialities that deserve further investigation. In fact, by decomposing variability along the principal modes it originates from, important indications, for example on movement mastery, may be drawn.

Although variability may appear as a negative propriety of the locomotor systems, it is not exclusively the outcome of random, noisy processes, but contains also information about the system health, about its evolutions and about its flexibility to unstable external conditions. Non-linear dynamics tools were used to investigate fluctuations in kinematic and kinetic time series. Results confirmed that race walking variability was not only the product of random noise. Furthermore they allowed some speculations on neuromuscular control over lower limb joints and on the differences that emerged between more and less skilled subjects.

Once that a consistent representation of the individual has been performed, data should be correctly read and interpreted. This knowledge may derive from the comparison with a reference, whose characteristics have been already evaluated and described. In longitudinal monitoring the reference typically consist in past recordings of the same subject. However, when there is lack of information concerning the general features of the movement, group analysis is fundamental as well. Therefore a detailed description of race walking biomechanics and a comparison with normal walking features were carried out, through both traditional and innovative methods. The former involved the exploration of kinematic and kinetic measures; the latter investigated the organisation of the neuromuscular system through a dynamic system theory perspective. Results outlined the peculiar features of race walking biomechanics and tried to understand their relations with distinctive aspect of execution technique. Furthermore the analysis of phasing relationships between adjacent joints tried to gain more insight into coordinative factors and into the stability of neuromotor organisation. Results seemed to concur with the aforementioned findings on time series regularity and evidenced an increased control over proximal joints. In some cases, a direct comparison with normal walking data, though useful, was not possible: the experimental protocol contained an insufficient number of normal walking trials. Unfortunately, this lack was somehow imposed by time constraints. In fact the acquisition of an equal number of gaits in the two progression conditions would require a considerable lapse of time that could be not compatible with regular monitoring and athletes' individual needs.

The final phase of the process is the restitution of information to trainers and athletes, who both need quantitative aids for improving everyday practice and performances derived thereof. The results of the previous two steps of the monitoring process should not be given back directly. Feedback should contain only essential information in an easily understood format. Therefore some efforts were spent to understand what trainers focus on during the assessment of the athlete's technique and to translate qualitative visual evaluations into biomechanical measures and easily understood representations.

To resume, this work aimed at answering some unsolved issues in the assessment of sports biomechanics, by proposing comprehensive guidelines concerning experimental protocols, data processing and analysis. The results of this survey may represent the heuristic bases for both investigating theoretical questions, and providing practical information to athletes and trainers who should be actively involved in the process. Theoretical issues include injury prevention, motor coordination and skills learning. For example, they may provide useful information to establish to most effective way in which feed-back should be presented to achieve the required outcome of improved performance. However those issues are inherently multidisciplinary and thus need a more intensive collaboration between different research groups.

Bibliography

[1] H.D.I. Abarbanel, R. Brown, J.J. Sidorowich, and L.S. Tsimring. The analysis of observed chaotic data in physical systems. *Rev Mod Phys*, 65(4):1331–1392, 1993.

[2] F. Alton, L. Baldey, S. Caplan, and M.C. Morrissey. A kinematic comparison of overground and treadmill walking. *Clin Biomech*, 13(6):434–440, 1998.

[3] L.F. Aragon-Vargas and M.M. Gross. Kinesiological factors in vertical jump performance: differences among individuals. *J Appl Biomech*, 13(1):24–44, 1997.

[4] L.F. Aragon-Vargas and M.M. Gross. Kinesiological factors in vertical jump performance: differences within individuals. *J Appl Biomech*, 13(1):45–65, 1997.

[5] J.L. Astephen and K.J. Deluzio. Changes in frontal plane dynamics and the loading response phase of the gait cycle are characteristic of severe knee osteoarthritis application of a multidimensional analysis technique. *Clin Biomech (Bristol, Avon)*, 20(2):209–217, 2005.

[6] G. Atkinson and A.M. Nevill. Statistical methods for assessing measurement error (reliability) in variables relevant to sports medicine. *Sports Med*, 26(4):217–238, 1998.

[7] S. Barker, R. Craik, W. Freedman, N. Herrmann, and H. Hillstrom. Accuracy, reliability, and validity of a spatiotemporal gait analysis system. *Med Eng Phys*, 28(5):460–467, 2006.

[8] R. Bartlett. Is movement variability important for sports biomechanics? In M. Lamontagne, D.G.E. Robertson, and H. Sveistrup, editors, *Proceedings of the XXII Internation Symposium on Biomechanics in Sports*, pages 521–524, Ottawa, August 2004. Faculty of Health Science.

[9] R. Bartlett. Future trends in sports biomechanics - reducing injury risk or improving performance? In Q. Wang, editor, *Proceedings of the XXIII International Symposium on Biomechanics in Sports*, volume 1, pages 1–11, Beijing, August 2005. The China Institute of Sport Science.

[10] R.M. Bartlett. Current issues in the mechanics of athletic activities. a position paper. *J Biomech*, 30(5):477–486, 1997.

[11] B. T. Bates. Single-subject methodology: an alternative approach. *Med Sci Sports Exerc*, 28(5):631–638, 1996.

[12] B.T. Bates, J.S. Dufek, and H.P. Davis. The effect of trial size on statistical power. *Med Sci Sports Exerc*, 24(9):1059–1065, 1992.

[13] B.T. Bates, C.R. James, and J.S. Dufek. *Innovative analysis of human movement*, chapter 1, pages 3–28. Human Kinetics, Champaign (IL), 2004.

[14] B.T. Bates, L.R. Osternig, J.A. Sawhill, and S.L. James. An assessment of subject variability, subject-shoe interaction, and the evaluation of running shoes using ground reaction force data. *J Biomech*, 16(3):181–191, 1983.

[15] A. Belli, P. Bui, A. Berger, A. Geyssant, and J.R. Lacour. A treadmill ergometer for three-dimensional ground reaction forces measurement during walking. *J Biomech*, 34(1):105–112, 2001.

[16] M.G. Benedetti, F. Catani, A. Leardini, E. Pignotti, and S. Giannini. Data management in gait analysis for clinical applications. *Clin Biomech*, 13(3):204–215, 1998.

[17] M.F. Bobbert and G.J. van Ingen Schenau. Coordination in vertical jumping. *J Biomech*, 21(3):249–262, 1988.

[18] E.J. Bradshaw, P.S. Maulder, and J. Keogh. Biological movement variability during the sprint start. In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 2, pages 785–789, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[19] G.P. Bruggerman. *Biomedical engineering in exercise and sports*, chapter 10, pages 135–142. Edizioni Minerva Medica, Torino (Italy), 2006.

[20] U.H. Buzzi, N. Stergiou, M.J. Kurz, P.A. Hageman, and J. Heidel. Nonlinear dynamics indicates aging affects variability during gait. *Clin Biomech (Bristol, Avon)*, 18(5):435–443, 2003.

[21] M.A. Cairns, R.G. Burdett, J.C. Pisciotta, and S.R. Simon. A biomechanical analysis of racewalking gait. *Med Sci Sports Exerc*, 18(4):446–453, 1986.

[22] G. Cappellini, Y.P. Ivanenko, R.E. Poppele, and F. Lacquaniti. Motor patterns in human walking and running. *J Neurophysiol*, 95(6):3426–3437, 2006.

[23] A. Cappello and R. Stagni. Errori e artefatti in stereofotogrammetria e loro compensazione. In A. Cappello, A. Cappozzo, and P.E. Di Prampero, editors, *Bioingegneria della postura e del movimento*, pages 103–129. Gruppo Nazionale di Bioingegneria, Patron editore, 2003.

[24] J. Carpenter and J. Bithell. Bootstrap confidence intervals: when, which, what? a practical guide for medical statisticians. *Stat Med*, 19(9):1141–1164, 2000.

[25] G.A. Cavagna and P. Franzetti. Mechanics of competition walking. *J Physiol*, 315:243–251, 1981.

[26] G.A. Cavagna and M. Kaneko. Mechanical work and efficiency in level walking and running. *J Physiol*, 268(2):467—81, 1977.

[27] T. Chau and K. Parker. On the robustness of stride frequency estimation. *IEEE Trans Biomed Eng*, 51(2):294–303, 2004.

[28] T. Chau and S. Redekop. Managing variability in the summary and comparison of gait data. *J Neuroengineering Rehabil*, 2:22, 2005.

[29] L. Chiari, U. Della Croce, A. Leardini, and A. Cappozzo. Human movement analysis using stereophotogrammetry. part 2: instrumental errors. *Gait Posture*, 21(2):197–211, 2005.

[30] G. Courtine and M. Schieppati. Tuning of a basic coordination pattern constructs straight-ahead and curved walking in humans. *J Neurophysiol*, 91(4):1524–1535, 2004.

[31] U. Della Croce, A. Cappozzo, and D. C. Kerrigan. Pelvis and lower limb anatomical landmark calibration precision and its propagation to bone geometry and joint angles. *Med Biol Eng Comput*, 37(2):155–161, 1999.

[32] A. Daffertshofer, C.J.C Lamoth, O.G. Meijer, and P.J. Beek. Pca in studying coordination and variability: a tutorial. *Clin Biomech (Bristol, Avon)*, 19(4):415–428, 2004.

[33] M. D'Amico and G. Ferrigno. Technique for the evaluation of derivatives from noisy biomechanical displacement data using a model-based bandwidth-selection procedure. *Med Biol Eng Comput*, 28(5):407–415, 1990.

[34] R.B. Davis, S. Ounpuu, D. Tyburski, and J.R. Gage. A gait analysis data collection and reduction technique. *Hum Mov Sci*, 10(5):575–587, 1991.

[35] U. Della Croce, A Leardini, L. Chiari, and A. Cappozzo. Human movement analysis using stereophotogrammetry. part 4: assessment of anatomical landmark misplacement and its effects on joint kinematics. *Gait Posture*, 21(2):226–237, 2005.

[36] K.M. Deutsch and K.M. Newell. Deterministic and stochastic processes in children's isometric force variability. *Dev Psychobiol*, 43(4):335–345, 2003.

[37] P. DeVita and B.T. Bates. Intraday reliability of ground reaction force data. *Hum Mov Sci*, 7:73–85, 1988.

[38] J. B. Dingwell and P.R. Cavanagh. Increased variability of continuous overground walking in neuropathic patients is only indirectly related to sensory loss. *Gait Posture*, 14(1):1–10, 2001.

[39] J. B. Dingwell, J.P. Cusumano, P.R. Cavanagh, and D. Sternad. Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *J Biomech Eng*, 123(1):27–32, 2001.

[40] J.B. Dingwell and J.P. Cusumano. Nonlinear time series analysis of normal and pathological human walking. *Chaos*, 10(4):848–863, 2000.

[41] J.B. Dingwell, J.P. Cusumano, D. Sternad, and P.R. Cavanagh. Slower speeds in patients with diabetic neuropathy lead to improved local dynamic stability of continuous overground walking. *J Biomech*, 33(10):1269–1277, 2000.

[42] C.E. Diss. The reliability of kinetic and kinematic variables used to analyse normal running gait. *Gait Posture*, 14(2):98–103, 2001.

[43] O. Donoghue, A.J. Harrison, N. Coffey, and K. Hayes. Functional data analysis of the kinematics of gait in subjects with a history of achilles tendon injury. In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 1, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[44] J.J. Dowling and L. Vamos. Identification of kinetic and temporal factors related to vertical jump performance. *J Appl Biomech*, 9:95–110, 1993.

[45] J.S. Dufek, B.T. Bates, N. Stergiou, and C.R. James. Interactive effects between group and single-subject response patterns. *Hum Mov Sci*, 14(3):301–323, 1995.

[46] A. Duhamel, J.L. Bourriez, P. Devos, P. Krystkowiak, A. Destée, P. Derambure, and L. Defebvre. Statistical tools for clinical gait analysis. *Gait Posture*, 20(2):204–212, 2004.

[47] J.V. Dura, E. Alcantara, D. Rosa, J. Gamez, and J.C. Gonzalez. *Biomedical engineering in exercise and sports*, chapter 11, pages 143–166. Edizioni Minerva Medica, Torino (Italy), 2006.

[48] B. Efron. Bootstrap methods: another look at the jackknife. *The Annals of Statistics*, 7(1):1–26, 1979.

[49] Y. Ehara, H. Fujimoto, S. Miyazaki, M. Mochimaru, S. Tanaka, S. Yamamoto, S. Barker, R. Craik, W. Freedman, N. Herrmann, and H. Hillstrom. Accuracy, reliability, and validity of a spatiotemporal gait analysis system. *Gait and Posture*, 5(3):251–255, 1997.

[50] R. Ferber, I. McClay Davis, D.S. Williams, and C. Laughton. A comparison of within- and between-day reliability of discrete 3d lower extremity variables in runners. *J Orthop Res*, 20(6):1139–1145, 2002.

[51] A. Forner-Cordero, O. Levin, Y. Li, and S.P. Swinnen. Principal component analysis of complex multijoint coordinative movements. *Biol Cybern*, 93(1):63–78, 2005.

[52] P.R. Francis, N.M. Richman, and P. Patterson. Injuries in the sport of racewalking. *J Athl Train*, 33(2):122–129, 1998.

[53] C. Frigo, M. Rabuffetti, D.C. Kerrigan, L.C. Deming, and A. Pedotti. Functionally oriented and clinically feasible quantitative gait analysis method. *Med Biol Eng Comput*, 36(2):179–185, 1998.

[54] S. Ghoussayni, C. Stevens, S. Durham, and D. Ewins. Assessment and validation of a simple automated method for the detection of gait events and intervals. *Gait Posture*, 20(3):266–272, 2004.

[55] P.S. Glazier, J.S. Wheat, D.L. Pease, and R.M. Bartlett. *Movement system variability*, chapter 3, pages 49–69. Human Kinetics, Champaign (IL), 2006.

[56] D. Graham and A.J. Harrison. An investigation of schema theory applied to the biomechanics of the sprint starts in athletics. In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 2, pages 513–516, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[57] E. Growney, D. Meglan, M. Johnson, T. Cahalan, and K.-N. An. Repeated measures of adult normal walking using a video tracking system. *Gait Posture*, 6(2):147–162, 1997.

[58] J.M. Hagberg and E.F. Coyle. Physiologic comparison of competitive racewalking and running. *Int J Sports Med*, 5(2):74–77, 1984.

[59] J. Hamill, J.M. Haddad, and W.J. McDermott. Issues in quantifying variability from a dynamical systems perspective. *J Appl Biomech*, 16(4):407–418, 2000.

[60] J. Hamill, J.M. Haddad, and E.A. Van Emmerik. Using coordination measures for movement analysis. In Q. Wang, editor, *Proceedings of the XXIII International Symposium on Biomechanics in Sports*, volume 1, pages 33–38, Beijing, August 2005. The China Institute of Sport Science.

[61] J. Hamill, J.M. Haddad, and E.A. Van Emmerik. Overuse injuries in running: do complex analysis help our understanding? In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 1, pages 27–32, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[62] J. Hamill and S.L. McNiven. Reliability of selected ground reaction force parameters during walking. *Hum Mov Sci*, 9:117–131, 1990.

[63] J. Hamill, R.E. van Emmerik, B.C. Heiderscheit, and L. Li. A dynamical systems approach to lower extremity running injuries. *Clin Biomech (Bristol, Avon)*, 14(5):297–308, 1999.

[64] A.H. Hansen, D.S. Childress, and M.R. Meier. A simple method for determination of gait events. *J Biomech*, 35(1):135–138, 2002.

[65] R.T. Harbourne and N. Stergiou. Nonlinear analysis of the development of sitting postural control. *Dev Psychobiol*, 42(4):368–377, 2003.

[66] H. Hatze. Motion variability–its definition, quantification, and origin. *J Mot Behav*, 18(1):5–16, 1986.

[67] J.M. Hausdorff. Gait variability: methods, modeling and meaning. *J Neuroengineering Rehabil*, 2:19, 2005.

[68] J.M. Hausdorff, L. Zemany, C. Peng, and A.L. Goldberger. Maturation of gait dynamics: stride-to-stride variability and its temporal organization in children. *J Appl Physiol*, 86(3):1040–1047, 1999.

[69] B.C. Heiderscheit, J. Hamill, and R.E. Van Emmerik. Q-angle influences on the variability of lower extremity coordination during running. *Med Sci Sports Exerc*, 31(9):1313–1319, 1999.

[70] A.L. Hof. Scaling gait data to body size [1]. *Gait Posture*, 4(3):222–223, 1996.

[71] K. Hoga, M. Ae, Y. Enomoto, T. Yokozawa, and N. Fujii. Joint torque and mechanical energy flow in the support legs of skilled race walkers. *Sports Biomech*, 5(2):167–182, 2006.

[72] W.G. Hopkins. Measures of reliability in sports medicine and science. *Sports Med*, 30(1):1–15, 2000.

[73] W.G. Hopkins, J.A. Hawley, and L.M. Burke. Design and analysis of research on sport performance enhancement. *Med Sci Sports Exerc*, 31(3):472–485, 1999.

[74] A. Hreljac and R. N. Marshall. Algorithms to determine event timing during normal walking using kinematic data. *J Biomech*, 33(6):783–786, 2000.

[75] A. Hreljac and N. Stergiou. Phase determination during normal running using kinematic data. *Med Biol Eng Comput*, 38(5):503–506, 2000.

[76] M. Hubbard and L.W. Alaways. Rapid and accurate estimation of release conditions in the javelin throw. *J Biomech*, 22(6-7):583–595, 1989.

[77] C.R. James. *Innovative analysis of human movement*, chapter 2, pages 29–62. Human Kinetics, Champaign (IL), 2004.

[78] C.R. James, J.S. Dufek, and B.T. Bates. Effects of injury proneness and task difficulty on joint kinetic variability. *Med Sci Sports Exerc*, 32(11):1833–1844, 2000.

[79] M. P. Kadaba, H. K. Ramakrishnan, and M. E. Wootten. Measurement of lower extremity kinematics during level walking. *J Orthop Res*, 8(3):383–392, 1990.

[80] M.P. Kadaba, H.K. Ramakrishnan, M.E. Wootten, J. Gainey, G. Gorton, and G.V. Cochran. Repeatability of kinematic, kinetic, and electromyographic data in normal adult gait. *J Orthop Res*, 7(6):849–860, 1989.

[81] J.C. Kao, S.D. Ringenbach, and P.E. Martin. Gait transitions are not dependent on changes in intralimb coordination variability. *J Mot Behav*, 35(3):211–214, 2003.

[82] M.J. Kurz and N. Stergiou. Effect of normalization and phase angle calculations on continuous relative phase. *J Biomech*, 35(3):369–374, 2002.

[83] M.J. Kurz and N. Stergiou. *Innovative analysis of human movement*, chapter 4, pages 93–119. Human Kinetics, Champaign (IL), 2004.

[84] M.J. Kurz, N. Stergiou, U.H. Buzzi, and A.D. Georgoulis. The effect of anterior cruciate ligament reconstruction on lower extremity relative phase dynamics during walking and running. *Knee Surg Sports Traumatol Arthrosc*, 13(2):107–115, Mar 2005.

[85] A. Lees and J. Bouracier. The longitudinal variability of ground reaction forces in experienced and inexperienced runners. *Ergonomics*, 37(1):197–206, 1994.

[86] M.W. Lenhoff, T.J. Santner, J.C. Otis, M.G. Peterson, B.J. Williams, and S.I. Backus. Bootstrap prediction and confidence bands: a superior statistical method for analysis of gait data. *Gait Posture*, 9(1):10–17, 1999.

[87] D.G. Liebermann, L. Katz, M.D. Hughes, R.M. Bartlett, J. McClements, I.M. Franks, D.G. Liebermann, L. Katz, M.D. Hughes, R.M. Bartlett, J. McClements, and I.M. Franks. Advances in the application of information technology to sport performance. *Journal of Sports Sciences*, 20(10):755–769, 2002.

[88] K. Manal, I. McClay, S. Stanhope, J. Richards, and B. Galinat. Comparison of surface mounted markers and attachment methods in estimating tibial rotations during walking: an in vivo study. *Gait Posture*, 11(1):38–45, 2000.

[89] I. McClay. The evolution of the study of the mechanics of running. relationship to injury. *J Am Podiatr Med Assoc*, 90(3):133–148, 2000.

[90] H.B. Menz, M.D. Latt, A. Tiedemann, M.M.S. Kwan, and S.R. Lord. Reliability of the gaitrite walkway system for the quantification of temporo-spatial parameters of gait in young and older people. *Gait Posture*, 20(1):20–25, 2004.

[91] D.J. Miller, N. Stergiou, and M.J. Kurz. An improved surrogate method for detecting the presence of chaos in gait. *J Biomech*, 39(15):2873–2876, 2006.

[92] A.E. Minetti, L. Boldrini, L. Brusamolin, P. Zamparo, and T. McKee. A feedback-controlled treadmill (treadmill-on-demand) and the spontaneous speed of walking and running in humans. *J Appl Physiol*, 95(2):838–843, 2003.

[93] M. Müller and D. Sternad. Decomposition of variability in the execution of goal-oriented tasks: three components of skill improvement. *J Exp Psychol Hum Percept Perform*, 30(1):212–233, 2004.

[94] R. Müller and P. Büttner. A critical discussion of intraclass correlation coefficients. *Stat Med*, 13(23-24):2465–2476, 1994.

[95] K.C. Moisio, D.R. Sumner, S. Shott, and D.E. Hurwitz. Normalization of joint moments during gait: A comparison of two techniques. *J Biomech*, 36(4):599–603, 2003.

[96] S. Morrison and K.M. Newell. Postural and resting tremor in the upper limb. *Clin Neurophysiol*, 111(4):651–663, 2000.

[97] M.P. Murray, G.N. Guten, L.A. Mollinger, and G.M. Gardner. Kinematic and electromyographic patterns of olympic race walkers. *Am J Sports Med*, 11(2):68–74, 1983.

[98] H.F. Neumann, J. Krug, and D. Gohlitz. Coordinative threshold in race walking. In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 1, pages 135–138, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[99] K.M. Newell, M.P. Broderick, K.M. Deutsch, and A.B. Slifkin. Task goals and change in dynamical degrees of freedom with motor learning. *J Exp Psychol Hum Percept Perform*, 29(2):379–387, 2003.

[100] K.M. Newell, S. Challis, and S. Morrison. Dimensional constraints on limb movements. *Human Movement Science*, 19(2):175–201, 2000.

[101] K.M. Newell, K.M. Deutsch, J.J. Sosnoff, and G. Mayer-Kress. *Movement system variability.*, chapter 1, pages 3–23. Human Kinetics, Champaign (IL), 2006.

[102] B. Nigg. New ideas and concepts in sport shoe development. In H. Schwameder, G. Strutzenberger, V. Fastenbauer, S. Lindinger, and E. Muller, editors, *Proceedings of the XXIV International Symposium on Biomechanics in Sports*, volume 1, pages 33–38, Salzburg, August 2006. Department of Sport Science and Kinesiology - University of Salzburg, Austria.

[103] B.M. Nigg and M. Bobbert. On the potential of various approaches in load analysis to reduce the frequency of sports injuries. *J Biomech*, 23 Suppl 1:3–12, 1990.

[104] IAAF (International Association of Athletics Federations). *IAAF Competition Rules 2006-2007.* 2006.

[105] R.A. Olshen, E.N. Biden, M.P. Wyatt, and D.H. Sutherland. Gait analysis and the bootstrap. *The Annals of Statistics*, 17(4):1419–1440, 1989.

[106] P. Onghena and E.S. Edgington. Customization of pain treatments: single-case design and analysis. *Clin J Pain*, 21(1):56–68; discussion 69–72, 2005.

[107] G. Paolini, U. Della Croce, P.O. Riley, F.K. Newton, and D. Casey Kerrigan. Testing of a tri-instrumented-treadmill unit for kinetic analysis of locomotion tasks in static and dynamic loading conditions. *Med Eng Phys*, 29(3):404–411, 2007.

[108] A.H. Payne. A comparison of ground reaction forces in race walking with those in normal walking and running. In E. Asmussen and K. Jorgensen, editors, *Biomechanics VI: proceedings of the Sixth International Congress of Biomechanics*, volume VI-A of *International series on biomechanics*, pages 293–302, Baltimore, MD, 1978. University Park Press.

[109] A. Pedotti and C. Frigo. Quantitative analysis of locomotion for basic research and clinical applications. *Functional Neurology*, 7(4 SUPPL.):47–56, 1992.

[110] J. Perry. *Gait Analysis. Normal and pathological function.* Slack Incorporated, 1992.

[111] S. Pincus. Approximate entropy (apen) as a complexity measure. *Chaos*, 5(1):110–117, 1995.

[112] S.M. Pincus. Approximate entropy as a measure of system complexity. *Proc Natl Acad Sci U S A*, 88(6):2297–2301, 1991.

[113] E. Preatoni, I. Di Giulio, and R. Rodano. Asymmetries in vertical jump: a support for functional motor evaluation? In P. Kneppo and J. Hozman, editors, *Proceedings of the 3rd European Medical & Biological Engineering Conference*, volume 11, Prague, November 2005. International Federation for Medical and Biological Engineering.

[114] E. Preatoni, R. Squadrone, and R. Rodano. Biovariability: the starting point for delveloping reliable motor feed-back procedures in sports. In Q. Wang, editor, *Proceedings of the XXIII International Symposium on Biomechanics in Sports*, volume 1, pages 773–777, Beijing, August 2005. The China Institute of Sport Science.

[115] R.M. Queen, M.T. Gross, and H. Liu. Repeatability of lower extremity kinetics and kinematics for standardized and self-selected running speeds. *Gait Posture*, 23(3):282–287, 2006.

[116] J.O. Ramsay and B.W. Silverman. *Functional data analysis.* Springer series in statistics. Springer, New York, 1997.

[117] D.M. Reboussin and T.M. Morgan. Statistical considerations in the use and analysis of single-subject designs. *Med Sci Sports Exerc*, 28(5):639–644, 1996.

[118] J.S. Richman and J.R. Moorman. Physiological time-series analysis using approximate entropy and sample entropy. *Am J Physiol Heart Circ Physiol*, 278(6):H2039–H2049, 2000.

[119] M.A. Riley and M.T. Turvey. Variability of determinism in motor behavior. *J Mot Behav*, 34(2):99–125, 2002.

[120] P.O. Riley, G. Paolini, U. Della Croce, K.W. Paylo, and D. Casey Kerrigan. A kinematic and kinetic comparison of overground and treadmill walking in healthy subjects. *Gait Posture*, 2006.

[121] R. Rodano. Bioingegneria dello sport. In A. Cappello, A. Cappozzo, and P.E. Di Prampero, editors, *Bioingegneria della postura e del movimento*, pages 513–529. Gruppo Nazionale di Bioingegneria, Patron editore, 2003.

[122] R. Rodano. *Biomedical engineering in exercise and sports*, chapter 9, pages 119–134. Edizioni Minerva Medica, Torino (Italy), 2006.

[123] R. Rodano and G.C. Santambrogio. Quantitative comparison of locomotor performance in different race walkers. In L. Tsarouchas, J. Terauds, B.A. Gowitzke, and L.E. Holt, editors, *Biomechanics in Sports*, volume V, pages 122–134. Hellenic Sports Research Institute, 1989.

[124] R. Rodano and R. and Squadrone. Stability of selected lower limb joint kinetic parameters during vertical jump. *J Appl Biomech*, 18(1):83–89, 2002.

[125] W. Ryan, A. Harrison, and K. Hayes. Functional data analysis of knee joint kinematics in the vertical jump. *Sports Biomech*, 5(1):121–138, 2006.

[126] R.A. Schmidt. Motor schema theory after 27 years: reflections and implications for a new theory. *Res Q Exerc Sport*, 74(4):366–375, 2003.

[127] R.A Schmidt and C.A. Wrisberg. *Motor learning and performance.* Human Kinetics, Champaign (IL), 3rd edition, 2004.

[128] J.P. Scholz and J.A. Kelso. A quantitative approach to understanding the formation and change of coordinated movement patterns. *J Mot Behav*, 21(2):122–144, 1989.

[129] T. Schreiber and A. Schmitz. Surrogate time series. *Physica D*, 142:346, 2000.

[130] P. E. Shrout. Measurement reliability and agreement in psychiatry. *Stat Methods Med Res*, 7(3):301–317, 1998.

[131] P.E. Shrout and J.L. Fleiss. Intraclass correlation: uses in assessing rater reliability. *Psychological Bullettin*, 86(2):420–428, 1979.

[132] M. Small, D. Yu, and R.G. Harrison. Surrogate test for pseudoperiodic time series data. *Phys Rev Lett*, 87(18):188101–, 2001.

[133] R.M. Smith and C. Loschner. Biomechanics feedback for rowing. *Journal of Sports Sciences*, 20(10):783–791, 2002.

[134] G. Steinwender, V. Saraph, S. Scheiber, E.B. Zwick, C. Uitz, and K. Hackl. Intrasubject repeatability of gait analysis data in normal and spastic children. *Clin Biomech (Bristol, Avon)*, 15(2):134–139, 2000.

[135] N. Stergiou, U.H. Buzzi, M.J. Kurz, and J. Heidel. *Innovative analysis of human movement.*, chapter 3, pages 63–89. Human Kinetics, Champaign (IL), 2004.

[136] N. Stergiou, J. L. Jensen, B. T. Bates, S. D. Scholten, and G. Tzetzis. A dynamical systems investigation of lower extremity coordination during running over obstacles. *Clin Biomech (Bristol, Avon)*, 16(3):213–221, 2001.

[137] N. Stergiou, C. Moraiti, G. Giakas, S. Ristanis, and A.D. Georgoulis. The effect of the walking speed on the stability of the anterior cruciate ligament deficient knee. *Clin Biomech (Bristol, Avon)*, 19(9):957–963, 2004.

[138] H. Stolze, J.P. Kuhtz-Buschbeck, C. Mondwurf, K. Jöhnk, and L. Friege. Retest reliability of spatiotemporal gait parameters in children and adults. *Gait Posture*, 7(2):125–130, 1998.

[139] D. Sutherland, K.R. Kaufman, K. Campbell, D. Ambrosini, and M. Wyatt. Clinical use of prediction regions for motion analysis. *Dev Med Child Neurol*, 38(9):773–781, 1996.

[140] D.E. Vaillancourt and K.M. Newell. The dynamics of resting and postural tremor in parkinson's disease. *Clin Neurophysiol*, 111(11):2046–2056, 2000.

[141] D.E. Vaillancourt, A.B. Slifkin, and K.M. Newell. Regularity of force tremor in parkinson's disease. *Clin Neurophysiol*, 112(9):1594–1603, 2001.

[142] R.E.A. Van Emmerik, M.T. Rosenstein, W.J. McDermott, and J. Hamill. A nonlinear dynamics approach to human movement. *J Appl Biomech*, 20(4):396–420, 2004.

[143] G. J. van Ingen Schenau. Some fundamental aspects of the biomechanics of overground versus treadmill locomotion. *Med Sci Sports Exerc*, 12(4):257–261, 1980.

[144] R. Vigano, P. Cova, A. Mason, and R. Rodano. Football footwear. *Italian Journal of Sports Traumatology*, 11(4):247–255, 1989.

[145] C. Vittori. *L'allenamento del giovane corridore dai 12 ai 19 anni.* Suppl. Atleticastudi 1-2/97, 1997.

[146] V. Wank, U. Frick, and D. Schmidtbleicher. Kinematics and electromyography of lower limb muscles in overground and treadmill running. *International Journal of Sports Medicine*, 19(7):455–461, 1998.

[147] J.S. Wheat, V. Baltzopoulos, C.E. Milner, R.M. Bartlett, and D. Tsaopoulos. Coordination variability during overground, treadmill and treadmill-on-demand running. In Q. Wang, editor, *Proceedings of the XXIII International Symposium on Biomechanics in Sports*, volume 1, pages 781–784, Beijing, August 2005. The China Institute of Sport Science.

[148] D.A. Winter. Kinematic and kinetic patterns in human gait: Variability and compensating effects. *Hum Mov Sci*, 3(1-2):51–76, 1984.

[149] M. Young and L. Li. Determination of critical parameters among elite female shot putters. *Sports Biomech*, 4(2):131–148, 2005.

[150] V. Zatsiorsky and V. Seluyanov. The mass and inertia characteristics of the main segments of the human body. In H. Matsui and K. Kobayashi, editors, *Biomechanics*, volume B 4B of *VIII*, pages 1152–1159, Champaign (IL), 1983. International Series on Biomechanics, Human Kinetics.

[151] W. Zhu. Making bootstrap statistical inferences: a tutorial. *Res Q Exerc Sport*, 68(1):44–55, 1997.

[152] W. Zhu and S. Zhang. *Innovative analysis of human movement*, chapter 7, pages 207–222. Human Kinetics, Champaign (IL), 2004.