ALMA MATER STUDIORUM
UNIVERSITÀ DEGLI STUDI DI BOLOGNA

DEPARTMENT OF ELECTRICAL, ELECTRONIC AND INFORMATION ENGINEERING "GUGLIELMO MARCONI" - DEI

SCUOLA DI DOTTORATO IN BIOINGEGNERIA - CICLO XXV
SETTORE CONCORSUALE: 09/G2
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ING-INF/06

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Ai miei genitori

There are these two young fish swimming along, and they happen to meet an older fish swimming the other way, who nods at them and says, ‘Morning, boys, how's the water?’ And the two young fish swim on for a bit, and then eventually one of them looks over at the other and goes, ‘What the hell is water?’

[…]

The real value of a real education […] has almost nothing to do with knowledge, and everything to do with simple awareness. Awareness of what is so real and essential, so hidden in plain sight all around us, all the time, that we have to keep reminding ourselves over and over: ‘This is water. This is water.’

David Foster Wallace, commencement speech to a graduating class at Kenyon College, Ohio, May 21 2005.

We are at the very beginning of time for the human race. It is not unreasonable that we grapple with problems. But there are tens of thousands of years in the future.

Our responsibility is to do what we can, learn what we can, improve the solutions, and pass them on.

Richard P. Feynman

ABSTRACT

The research field of the Thesis is the evaluation of motor variability and the analysis of motor stability for the assessment of fall risk. Since many falls occur during walking, a better understanding of motor stability could lead to the definition of a reliable fall risk index aiming at measuring and assessing the risk of fall in the elderly, in the attempt to prevent traumatic events. Several motor variability and stability measures are proposed in the literature, but still a proper methodological characterization is lacking. Moreover, the relationship between many of these measures and fall history or fall risk is still unknown, or not completely clear.

The aim of this thesis is hence to: i) analyze the influence of experimental implementation parameters on variability/stability measures and understand how variations in these parameters affect the outputs; ii) assess the relationship between variability/stability measures and long- short-term fall history.

Several implementation issues have been addressed. Following the need for a methodological standardization of gait variability/stability measures, highlighted in particular for orbital stability analysis through a systematic review, general indications about implementation of orbital stability analysis have been showed, together with an analysis of the number of strides and the test-retest reliability of several variability/stability numbers. Indications about the influence of directional changes on measures have also been provided. Association between measures and long/short-term fall history has also been assessed. Of all the analyzed variability/stability measures, Multiscale entropy and Recurrence quantification analysis demonstrated particularly good results in terms of reliability, applicability and association with fall history. Therefore, these measures should be taken in consideration for the definition of a fall risk index.

SUMMARY

I. INTRODUCTION

I.1. FALLS IN THE ELDERLY

"A fall […] is an event which results in a person coming to rest unintentionally on the ground or lower level, not as a result of a major intrinsic event (such as a stroke) or overwhelming hazard." [1]

Considered to be one of the so-called *geriatric giants*, falls place a heavy economic burden on society, and are also responsible for a considerable loss of life quality. In 2009 alone, falls led to costs ranging between 0.85 and 1.5 per cent of the total healthcare expenses within the USA, Australia, EU and the UK [2]. Falls also have a critical influence on health status, with approximately 81-98% of hip fractures caused by falls [3,4], and are the leading cause of injury-related visits to emergency departments in the USA [5].

Risk of a falling increases with age [6,7]; falls are and the primary etiology of accidental deaths in persons over the age of 65 years. The mortality rate for falls increases dramatically with age, with falls accounting for 70 percent of accidental deaths in persons 75 years of age and older [5]. The main associated costs therefore tend to occur in higher age groups and in the wake of fractures, a problem that is further exacerbated by the increasing proportion of elderly among the population [8].

There are currently over 400 known risk factors for falls [9], classified into extrinsic (or environmental), intrinsic (or personal) and task-related factors [10,11]. Extrinsic factors comprise all external influences and might include factors such as poor lighting, surface elevation, surface roughness, obstacles, clothing/footwear, lack of equipment or aids, or external perturbations. Task-related factors include task complexity and speed, fatigue, load handling. Intrinsic factors reflect individual differences in, among others, age and gender, muscular strength, reaction time, visual impairment (e.g. glaucoma, macular degeneration, retinopathy), ethnicity, use of drugs and medications (e.g. polypharmacy, sedatives, cardiovascular medications), living alone, sedentary behavior, psychological status, impaired cognition (e.g. dementia), cardiovascular issues and foot problems. In addition, history of falls as well as impaired stability and mobility (e.g. as a result of stroke, parkinsonism, arthritic changes, neuropathy, neuromuscular disease or vestibular disease) can be considered as higher level factors owing to their interdependency with both intrinsic and extrinsic factors. While knowledge of the environment is known to play a role in minimizing the effect of intrinsic and task-related factors on instability, extrinsic factors cannot generally be controlled, tested or accounted for in clinical assessment. Intrinsic factors have also been identified as major risk factors for falling. In particular, gait instability is considered to be a major fall risk factor, particularly in geriatric patients [12–14]; however, the quantification of gait stability is still an issue [8].

Several interventions to prevent falling (and associate injuries) have been proposed [15], but in order to correctly select individuals to which prescribe appropriate interventions, a reliable identification of individuals at risk of falling is needed [16]. Since many falls in the elderly occur during walking [17,18], assessment of gait stability represents a fundamental aspect.

I.2. ASSESSMENT OF GAIT STABILITY

The most established techniques to quantify fall risk are (i) motor function tests, (ii) questionnaires, and (iii) biomechanical laboratory-based measurements. However, since motor function tests and questionnaires are generally not capable of providing a quantitative predictive assessment of gait stability or fall risk [19,20], biomechanical laboratory-based measurements can help defining subject-specific methods with high sensitivity and specificity for gait stability assessment [8].

As said above, assessment of gait stability can allow the identification of subjects at risk of falling, being an important and necessary precondition for walking without falling. However, while stability is a well-defined concept in mechanics, there still is no complete consensus on how to measure stability of gait. Several methods are currently available, each one having advantages and disadvantages.

The term gait stability is comprehensive of both *indirect* as well as *direct* biomechanical aspects of stability during gait. These aspects can be measured and quantified, and hence could contribute to the definition of a subject-specific fall risk index. *Indirect* assessment of gait stability is represented by kinematic variability measures; when error corrections during a motor task become less effective, variability increases. It can therefore be assumed that variability is related to fall risk, because increased variability may bring the dynamic state of the person closer to the limit of stability [8]. On the other hand, *direct* stability measures not only provide information regarding the disturbances in the motor task performance, but also explicitly quantify the performance of the dynamic error correction. In addition, other *stability-related measures* have been recently associated with gait stability.

Mathematical details about *indirect*, *direct* and *stability-related* measures can be found in Chapter IX (Appendix).

I.2.1. Indirect assessment of gait stability

Kinematic variability measures represent the magnitude of variability of a certain kinematic parameter over strides during gait. One of the most established variability measure is stride time variability, expressed in terms of Standard deviation (SD) or Coefficient of variation (CV) [17].

Somehow complementary measures of stride-to-stride variability are the Inconsistency of the variance of the stride time (IV) and the Nonstationary index (NI) [21], which measure the fluctuation dynamics of the stride time.

The Poincaré plot is a widely accepted method for the analysis of 2-D dynamic systems [22]; it has been extensively applied in the study of heart rate variability as a qualitative visualization tool, but can also be applied to other physiological signals (for example stride time). Stride time data plots between successive gait cycles show variability of stride time. Plots are used to extract indices, such as length (PSD2) and width (PSD1) of the long and the short axes describing the elliptical nature of the plots.

Whereas variability measures have been shown to be positively correlated with the probability of falling in the elderly [17,23], decreased variability has also been reported for mobility-impaired subjects, suggesting that these subjects are less stable due to a less flexible system [24,25]. Moreover, analyzing the effects of walking speed on stability and variability, no relationship between variability and the time needed to recover from a perturbation has been found, leading to the conclusion that locomotion variability measures may not be dependable indicators of locomotion stability [26] and are not able to quantify how the locomotor system responds to perturbations [27]. Hence, the relationship between gait variability and stability is not as straightforward as it may seem.

I.2.2. Direct assessment of gait stability

Human locomotion is, in all respects, a dynamical system. To test the stability of a dynamical system, several tools have been developed, since dynamical systems are often nonlinear and complex, and human locomotion definitely is. For this reason, some authors applied methods coming from stability analysis of nonlinear dynamic systems to biomechanics [8].

In theoretical mechanics, stability is defined by how the system state responds to perturbations [28]; similarly, an appropriate definition for the stability of a motor task should be based on the quantification of the tendency of a subject to recover from small (natural or artificial) perturbations occurring during the execution of a structurally cyclic task (e.g. gait [29]). However, in mechanics and robotics a state variable is deterministic and can predict the future state of the mechanical system: while the behaviour of walking robots under perturbation conditions can quite easily be predicted [30], dealing with biomechanical time series of human locomotion variables is not as straightforward as in robotics. In fact, when dealing with human locomotion the equations of the system are not known, and such nonlinear techniques have to be applied in a numerical (rather than analytical) fashion.

A motor task can hence be treated as a nonlinear dynamic system: biomechanical variables (e.g. joint angles, angular velocities or accelerations, marker positions, muscle activations and others) vary during the temporal evolution of the task, defining a system that continuously changes over time. In a repetitive task, like walking, biomechanical variables have a cyclic behavior and recur iteratively with almost the same pattern; this pseudo-periodic behavior can be exploited for nonlinear analysis. For example, plotting the temporal evolution of knee angle against hip angle will design an orbit, which will vary dynamically in time but will maintain almost the same trend. In mechanical dynamics, the set of the variables that describe this orbit (two or more) is called *state space*, which can be defined as a vector space where the dynamical system can be defined at any point [31]. The number of task cycles (e.g. strides, commonly defined as the interval of time that starts at the heel strike of one foot and ends at the following heel strike of the same foot [32,33]) will determine how many times the variables will travel around the orbit. The locomotor pattern will force those variables to roughly travel around a fixed orbit, in a sort of limit cycle behavior. If a perturbation occurs during the motor task, the orbit will instantaneously move away from the limit cycle; in case of stability, the orbit will then tend back to the limit orbit, otherwise will diverge from it. For example, if a significant variation in knee angle occurs during walking (because of an obstacle), a coherent variation in hip angle will take place: simply observing the trend of one of these variables during the task could bring to misleading conclusions regarding stability, whereas embedding the two in the state space gives a more complete characterization of the system behavior. If a measure of only one of these time series is available, a proper way to obtain a characterization of the system is to embed in the state space the variable (e.g. knee angle) and its time-delayed copies; again, if an obstacle causes a sudden variation of knee angle, the orbits will reveal if the subject recovered stability after getting ahead of the obstacle, getting back to the limit cycle orbit after the destabilizing time event. Techniques of nonlinear stability analysis consist then in the quantification of the tendency of an orbit to diverge from or converge to the previous one or to an attracting limit cycle. Two main approaches for nonlinear stability analysis are present in literature: local and orbital stability analysis. These measures of orbital and local dynamic stability quantify different properties of system dynamics [34].

Local stability is used for systems that do not necessarily exhibit a discernable periodic structure, and therefore does not exploit the previously described pseudo-periodicity of some motor tasks. It is defined using short-term (sLE) and long-term (lLE) local divergence exponents (Lyapunov exponents). These indicators quantify how the system state responds to very small (local) perturbations continuously in real time [34]; many studies using this approach are present in literature [14,24,27,35–38]. Recently, an association between local stability and fall history have been found [39].

Orbital stability is defined for periodic systems with a limit cycle behavior, and can then be applied to cyclic motor tasks. This approach is extensively used in the study of passive dynamic walking robots [30], and in the last years it has been applied also to biomechanics [40]. Orbital stability analysis can be applied under the hypothesis of periodicity and assuming that motor dynamics (e.g. walking dynamics) are governed by central pattern generator processes yielding repetitive limit cycle behavior [41].

Fundamental indicators of orbital stability are Floquet multipliers (FM) which quantify, discretely from one cycle to the next, the tendency of the system state to return to the periodic limit cycle orbit after small perturbations [34]. If maximum Floquet Multipliers (maxFM) have magnitude < 1, perturbations tend to shrink by the next repetition, and the system remains stable. Every point on the orbit represents an instant of the task cycle. To calculate FM, a section must be defined in some point along the orbit (Poincaré section). In theory, the orbital stability of a deterministic limit cycle process should be the same, regardless of where along the trajectory the Poincaré section is made; however, human walking is not strictly periodic and people respond to perturbations differently during different phases of the gait cycle [34]. Hence, many authors put the Poincaré section in the most significant phases of the motor task (e.g., for gait, maximum sagittal knee flexion, toe off etc.) along the orbit, in order to obtain information about stability in the task phases that are more likely affected by perturbations. According to the literature, orbital stability analysis seems a promising approach for the definition of a reliable motor stability index; it can represent a novel way to predict risk of fall and to identify the most unstable phases of a motor task, in order to plan appropriate rehabilitation therapies. The most interesting feature of this method is the possibility to account for the whole task cycle dynamics, including more variables in the state space characterising the system. With a proper choice of Poincaré section, that is a proper choice of interesting instants during the task, the stability of every phase of the task cycle can be calculated. However, still the use of maxFM as a fall risk index is deemed to be controversial [8].

I.2.3. Stability-related measures

Other measures are present in literature that, whereas not representing a direct assessment of gait stability *per se*, are considered to be related with gait stability as they quantify strictly gait-correlated characteristics (such as smoothness, complexity, recurrence).

Some measures, such as the Index of Harmonicity (IH) and Harmonic Ratio (HR), involve decomposing signals into harmonics by means of Discrete Fourier Transform and then analyze their spectral components [42,43], in order to obtain a measure of smoothness and rhythm of the gait pattern.

HR, derived from trunk acceleration signals and based on amplitudes in frequency spectra, is an indication of smoothness of acceleration patterns and provides information on how smoothly subjects control their trunk during walking and gives an indication of whole body balance and coordination [42,44].

Similarly to HR, IH assesses the contribution of the oscillating components to the observed coordination patterns by means of spectral analysis [43]. It quantifies the contribution of the stride frequency to the signal power relative to higher harmonics.

Other methods that have been associated with gait stability are Multiscale Entropy (MSE) [45,46] and Recurrence Quantification Analysis (RQA) [47,48].

MSE quantifies the complexity or irregularity of a time series. Time series derived from complex systems, like biological systems, are likely to present structures on multiple spatio-temporal scales [45], and MSE has been introduced to this aim.

RQA is a nonlinear technique that has been applied recently to various biological time series, including walking [47]. Based on local recurrence of data points in the reconstructed phase space, it provides a characterization of a variety of features of a given time series, including a quantification of deterministic structure and non-stationarity [48].

I.3. AIM OF THE THESIS

In the last paragraph, several measures of gait variability and stability proposed in the literature have been illustrated; the aim of such measures is quantifying subject specific gait characteristics such as gait impairment, degree of neuromotor control and balance disorders, in both pathologic and healthy subjects.

However, still there is no methodological standardization on how to properly implement variability/stability analysis measures. These measures often come from the analysis of dynamical systems, and depend on many input parameters. The implementation in movement analysis is hence not straightforward, and a methodological standardization is needed in order to obtain reliable, repeatable and easily interpretable outcomes for a fall risk index definition.

Moreover, the relationship between many of these measures and fall history or fall risk is still unknown, or not completely clear. Loss of dynamic stability during gait may be caused by structural changes in gait patterns or by temporary modifications in balance control that could not be displayed while the subject is being tested. An assessment of the association between these measures and the two aforementioned conditions is hence needed, in order to define the capability of the measures to detect long- and short-term stability modification in relation to fall risk.

The aim of this thesis is hence to:

i) analyze the influence of experimental implementation parameters on variability/stability measures and understand how variations in these parameters affect the outputs;

ii) assess the relationship between variability/stability measures and long/short-term fall history.

OUTLINE OF THE THESIS

In Chapter II, a systematic review of orbital stability analysis in biomechanics [49] is presented, to provide an overview of the state of the art and of the questions raised by this relatively new approach. In Chapter III a model- and experimental-based study on the influence of the experimental input of orbital stability analysis is presented, with the aim to analyze the influence of experimental noise and of several implementation parameters on the outputs of orbital stability applied to human gait. Chapter IV is dedicated to the assessment of the number of required strides and the test-retest reliability of variability/stability measures proposed in the literature. In Chapter V an assessment of the association between fall history and several step detection independent nonlinear measures is presented. Chapter VI is dedicated to the influence of directional changes during gait on variability/stability measures. Chapter VII are dedicated to and the association between such measures with long/short-term fall risk. Finally, in Chapter VIII a general conclusion is drawn, and directions for future research are explored.

II. ORBITAL STABILITY ANALYSIS IN BIOMECHANICS: A SYSTEMATIC REVIEW OF A NONLINEAR TECHNIQUE TO DETECT INSTABILITY OF MOTOR TASKS[1]

II.1. INTRODUCTION

The use of maxFM in the assessment of fall risk has been deemed controversial [8], because of some discrepancy and incoherence in the results found in the literature. A possible cause of this controversy could lie in the lack of a “standard” implementation of this technique, being the technique relatively novel in biomechanics. Considering the motor task as a dynamic nonlinear system, orbital stability analysis implies the definition of a state space characterising the system. No unique way of defining the state space of a given motor task (e.g. gait) has been shown in the literature; the most crucial point seems to be the choice of which and how many biomechanical variables (e.g. joint angles, trunk accelerations) have to be inserted into the space. Even the choice of the position of the Poincaré section represents a critical issue when trying to obtain reliable information about orbital stability of a motor task. Another criticality is represented by the minimum and optimum number of task cycles that should be included in the analysis to obtain reliable stability results.

With the aim to summarize the various applications of this approach in biomechanics and to analyse the solution proposed in the literature about the methodological issues stated above, in this paper a systematic review and a critical evaluation of the literature on the application of orbital stability analysis in biomechanics are provided, with particular focus to its application in gait analysis.

II.2. METHODS

II.2.1. Search strategy

In October 2011 an electronic search was performed by one reviewer to find all articles on the topic of orbital stability analysis in biomechanics. The databases included MEDLINE (1966 - October 2011), ISI Web of Knowledge (1986 - October 2011), and Scopus (2004 - October 2011). Keywords used in the search strategy included "orbital stability", "floquet", "biomechanics" and "movement". "And" and "Or" conjunction were

[1] Published. Riva F, Bisi MC, Stagni R. Orbital stability analysis in biomechanics: A systematic review of a nonlinear technique to detect instability of motor tasks. Gait & Posture 2013; 37: 1–11.

used. Only English language article were considered. Some articles investigated other forms of stability in addition to orbital stability; only details from orbital stability analysis were considered. A manual, targeted search of reference lists of relevant studies and other publications from the authors of the electronically found articles was also performed.

II.2.2. Inclusion and exclusion criteria

A single reviewer assessed the titles and abstract of the articles. The articles included in the study satisfied the following criteria: i) investigation of gait, locomotor or functional tasks, ii) clear and documented purpose of the application of orbital stability analysis and iii) full scientific papers. Since this study focused on the application of orbital stability analysis to biomechanics, reports related to robotics were excluded. Studies published only as conference proceedings were excluded from the review.

II.2.3. Data extraction

A customised data extraction form was developed, based on previous systematic reviews on associated areas [50–53]. The data extraction themes were selected to give an exhaustive overview of each article for analysis and assessment of the quality of the scientific literature. Data extraction themes included the description of the sample, details of the experimental and analytical protocol and the key results of the study (Table II.1). Data were obtained independently by three reviewers. In order to compare results from different articles, 95% confidence intervals for each maxFM calculation in preferred/normal gait condition were extracted (when available).

Table II.1 – Data extraction results

Ref	Article	Subjects	Age	Body Mass Index (BMI)	Motion analysis	State space definition	Motor task
[54]	Arellano et al.	23	23.8 ± 4.5	22.1	3d stereophotogrammetry	Angular positions and velocities on the sagittal plane of the right ankle, knee and hip	Treadmill walking
[55]	Arellano et al.	23	23.8 ± 4.5	22.1	3d stereophotogrammetry	Angular positions and velocities on the sagittal plane of the right ankle, knee and hip	Treadmill walking
[56]	Bruijn et al.	9	25.5 ± 3.6	23	3d stereophotogrammetry	First derivatives of anterior posterior, medio lateral and vertical position time-series of the average movements of the thorax markers (delay reconstruction of individual states)	Treadmill walking
[57]	Bruijn et al.	9	–	–	3d stereophotogrammetry, tri-axial accelerometer	Time-normalized 3D acceleration and 3D rotational velocities time series, each with their sample delayed copies, coming from the inertial sensor and the 3d stereophotogrammetry system	Treadmill walking
[34]	Dingwell and Kang	10	27.1 ± 3.2	22	Electrogoniometers, tri-axial accelerometer	Trunk acceleration data (AP, ML, VT) and right leg sagittal plane joint angles (delay reconstruction of individual states)	Overground walking, treadmill walking
[58]	Dingwell et al.	37	61 ± 6.6 (NP), 57.6 ± 7.7 (CO), 27.9 ± 5.1 (young)	30.3 ± 4.4 (NP), 29.4 ± 2.2 (CO), 23.4±3.5 (young)	Electrogoniometers, 3d stereophotogrammetry	1: sagittal joint angles of hip, knee and ankle joints of the right leg; 2: T1 marker motions in the AP, ML and VT directions (delay reconstruction of individual states)	Overground walking, treadmill walking

Table II.1 – *(Continued)*

Ref	Article	Subjects	Age	Body Mass Index (BMI)	Motion analysis	State space definition	Motor task
[59]	Dingwell et al.	13	24.5 ± 3.4	25	3d stereophotogrammetry	Anterior-posterior, medio-lateral and vertical velocity of a marker attached to the skin over C5/T1 (delay reconstruction of individual states)	Treadmill walking
[60]	Gates & Dingwell	20	25.5 ± 2.2	24	3d stereophotogrammetry	Three rotational angles and angular velocities for each joint (shoulder, elbow, wrist)	Saw task, lift task
[61]	Gates & Dingwell	10	27.9 ± 2.2	24	3d stereophotogrammetry	Three rotational angles and angular velocities for each joint (shoulder, elbow, wrist)	Sawing-like task
[13]	Granata et al.	12	26.3 ± 2.1 (young), 71.3 ± 6.5 (elderly); 71.0 ± 3.0 (fall-prone elderly)	23 (young), 26 (elderly), 30 (fall-prone elderly)	3d stereophotogrammetry	3d position and velocity of a point mid-way between the ASIS and the location of the heel-markers (surrogate CoP relative to CoM)	Treadmill walking
[62]	Hidler and Rymer	4	26 ± 4	_	Precision potentiometer and tachometer	Ankle position and ankle velocity	Clonus initiated in the plantar flexor muscles
[40]	Hurmuzlu and Basdogan	20	28 (19-49)	_	Electrogoniometers	Joint angles of ankle, knee and hip of the dominant side, and their time-derivatives	Overground walking
[63]	Hurmuzlu et al.	26	26 ± 4 (healthy), 52 ±10 (polio survivors)	25 (healthy), 24 (polio survivors)	Electrogoniometers	Bilateral rotations and velocities at the hip, knee and ankle	Overground walking

Table II.1 – *(Continued)*

Ref	Article	Subjects	Age	Body Mass Index (BMI)	Motion analysis	State space definition	Motor task
[64]	Kang and Dingwell	35	23.3 ± 2.6 (young), 72.1 ± 6.0 (elderly)	23.8 (young), 25.3 (elderly)	SEMG	SEMG signals from 4 muscles of the left leg, and their time-derivatives	Treadmill walking
[65]	Kang and Dingwell	35	23.3 ± 2.6 (young), 72.1 ± 6.0 (elderly)	23.8 (young), 25.3 (elderly)	3d stereophotogrammetry	Linear velocities and accelerations of the three coordinates of a virtual center marker representing the trunk; angular velocities and accelerations of three dimensional trunk rotations	Treadmill walking
[66]	Kang and Dingwell	35	23.3 ± 2.6 (young), 72.1 ± 6.0 (elderly)	23.8 (young), 25.3 (elderly)	3d stereophotogrammetry	Linear and angular velocities of a virtual center marker, defined as the average location of the markers on each segment (delay reconstruction of individual states)	Treadmill walking
[67]	Marghitu and Hobatho	6	41464	_	Video-based 2d motion analysis system	Rotations of the hip joint, the knee joint, the ankle joint and their corresponding angular velocities on the sagittal plane	Overground walking
[68]	Marghitu et al.	5	_	_	Video-based 2d motion analysis system	Joint angular displacements (coxofemoral angle, femorotibial angle, tarsal angle) and velocities	Overground walking
[69]	McAndrew et al.	12	29 ± 7.5	24	3d stereophotogrammetry	Delay embedding of the AP, ML and vertical velocities of a C7 vertebral marker	Walking in a CAREN system

Table II.1 – *(Continued)*

Ref	Article	Subjects	Age	Body Mass Index (BMI)	Motion analysis	State space definition	Motor task
[70]	Schablowski and Gerner	10	_	_	3d stereophotogrammetry	Joint angles and velocities (ankle, knee, hip)	Treadmill walking
[71]	Scott-Pandorf et al.	10	22.4 ± 2.2	23	3d stereophotogrammetry	Angular positions and velocities of the right ankle, knee and hip	Treadmill walking
[72]	Scott-Pandorf et al.	10	24.6 ± 6.5	24	3d stereophotogrammetry	Angular positions and velocities of the right ankle, knee and hip	Treadmill walking
[73]	van Schooten et al.	12	23.7 ± 2.4	23	Inertial sensors	Linear acceleration and angular velocities of the trunk in all three directions and their time-delayed copies	Treadmill walking

II.2.4. Quality

Quality assessment was performed to limit bias, minimise errors and improve reliability of findings [74]. The quality of a study relates to aspects of the study's design, methods of sample recruitment, the execution of the tests, and the completeness of the study report. It is essential that the quality of the studies included in the review is assessed and reported, so that appropriately cautious inferences can be drawn [75]. Quality can be described as "the extent to which all aspects of a study’s design and conduct can be shown to protect against systematic bias, non-systematic bias, and inferential error" [76]. Some checklists which assist in the assessment of the quality of studies are present in literature [75,77], but no quality assessment tool existed for the evaluation of articles in this field. Therefore, a customised quality assessment tool was developed (Table II.2), based upon general systematic reviews principles and guidelines from other systematic reviews [50,51,77,78]. The tool consisted of 16 questions that concerned the major research purposes. A scoring system was developed to perform an overall evaluation of each article. Each question coming from the questionnaire was scored as follows: 2 = Yes; 1 = Limited detail; 0 = No. Three reviewers (FR, MCB and RS) scored each paper independently.

Table II.2 – Quality analysis form

Question
1. Is the aim of the study clearly described?
2. Is the design of the study clearly described?
3. Are participant characteristics adequately described?
4. Is sampling methodology appropriately described?
5. Is sample size used justified?
6. Are state space definitions accurately described?
7. Is the choice of the variables set justified?
8. Are equipment and setup clearly described?
9. Are motor tasks clearly defined?
10. Is the analytical technique clearly described?
11. Are appropriate statistical analysis methods used?
12. Are the main findings of the study clearly described?
13. Are key findings supported by the results?
14. Are limitations of the study clearly described?
15. Are key findings supported by other literature?
16. Are conclusions drawn from the study clearly stated?

II.3. RESULTS

II.3.1. Search yield

The initial search of the databases, containing all the keywords, yielded 46 results. Eight more articles [13,54,60,63,64,67,71,72] were identified from the manual targeted search. After the application of the inclusion and exclusion criteria, 23 articles related to orbital stability analysis in biomechanics were selected for review. Details of reviewed articles are summarized in Table II.1 and Table II.5.

II.3.2. Quality

Table II.3 summarizes the quality of the reviewed articles. The overall quality of the articles was high, particularly in the areas of aim and design of the study, equipment and setup description, motor task description, reporting of main findings and the drawn conclusions. Participant characteristics were generally well reported, but in many cases information about body mass index (BMI) were not available. Methods for participant sampling were rarely reported. Many articles had limited details about the choice of the variable set and the analytical technique. Also, many articles had limited statistical analysis. Meta-analysis was not performed in this review.

Table II.3 – Quality analysis results. Each question coming from the questionnaire (Table II.2) was scored as follows: 2 = Yes; 1 = Limited detail; 0 = No. Three reviewers (FR, MCB and RS) scored each paper independently.

Ref	Article	Question number															
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
[54]	Arellano et al.	2	2	1,3	0,3	0,3	2	1,3	2	2	1,3	2	1,3	2	1,3	2	1,6
[55]	Arellano et al.	2	2	2	1	0,6	2	1,3	2	2	1,3	2	1,6	2	2	1,3	1,3
[56]	Bruijn et al.	1,3	2	1,3	1	0,6	2	1	2	2	1,3	1,3	2	1,3	2	1,6	2
[57]	Bruijn et al.	2	1,3	1,3	0,3	0,3	1,6	1	2	2	1,6	2	2	2	1,3	1,3	1,3
[34]	Dingwell and Kang	2	2	1,6	0,6	0,3	1,3	1,3	2	2	1,6	1,6	2	2	2	1,6	2
[58]	Dingwell et al.	2	2	1	0,3	0,6	1,3	1,6	1,3	2	1,3	2	1,6	2	1,3	2	1,3
[59]	Dingwell et al.	2	2	1,3	1,3	0,6	2	1,6	2	2	1,3	2	2	2	1,6	1,3	1,3
[60]	Gates & Dingwell	2	2	2	1,6	0,3	2	1,3	2	2	1,6	2	2	2	2	1,3	2
[61]	Gates & Dingwell	2	1,3	1,3	1,3	0,6	2	1,3	2	2	1,6	2	2	2	2	1,6	2
[13]	Granata et al.	2	2	2	1	0,6	1,3	1,6	2	2	1,6	2	2	2	2	2	2
[62]	Hidler and Rymer	2	2	2	1,6	0,3	1,6	1	1,3	2	1,3	0,3	2	2	1	1	1,6
[40]	Hurmuzlu and Basdogan	2	2	1	0,3	0,3	2	1,3	2	1,3	1,3	2	1,3	2	2	0,6	1,3
[63]	Hurmuzlu et al.	2	2	2	1,3	0,3	2	1,3	2	2	1,3	1,6	2	2	0,6	1	1,6
[64]	Kang and Dingwell	2	2	1,3	1,6	0,6	2	1,3	2	2	1,6	2	2	2	1	2	2
[65]	Kang and Dingwell	2	2	2	1,3	0,6	2	1	2	2	1,3	1,3	2	2	0,6	1,6	2
[66]	Kang and Dingwell	2	2	1,3	1	0,6	2	1	1,6	1,3	1,3	1,3	2	2	2	2	2
[67]	Marghitu and Hobatho	1	1	1	0,3	0,6	2	1,3	1	1	1,6	0	1	1,3	0,3	0,3	1
[68]	Marghitu et al.	1,3	1,3	1	1	0,3	1,6	1,3	2	0,6	1,3	0	1	1,3	1,3	0	1,3
[69]	McAndrew et al.	2	2	1,3	0	0,3	2	1,3	1,3	1,3	1,6	2	2	2	1	2	1,6
[70]	Schablowski and Gerner	1,3	1	0,3	0	0,6	1	1,3	1	1,6	1,3	0,6	1,6	2	0,6	1	1,6
[71]	Scott-Pandorf et al.	2	2	2	1,3	1,3	2	1,6	2	2	1,3	2	2	2	1,3	1,3	2
[72]	Scott-Pandorf et al.	2	2	2	1,6	1,3	2	1,6	2	2	1,3	2	2	2	2	2	2
[73]	van Schooten et al.	2	2	1,6	1,3	0,6	1,3	1	2	2	1	2	2	2	1,6	1	2

II.3.3. Participants

The reviewed articles tested participants with different ages and physical characteristics. Some articles provided insufficient data regarding the physical characteristics of tested participants. The reviewed articles tested different sized groups of participants; the largest group consisted of 37 [58] participants, the smallest group of four participants [62]. Ten articles tested ten subjects or less. Age was mostly restricted to young (mean age 25.4 years) or old adults (mean age 71.7). One article involved children (aged 7-9, [67]), another one dogs [68]. Some articles involved pathologic subjects [58,62]. BMI was used to estimate the body composition of participants. The majority of participants had a BMI value lower than 25, indicating that they had a healthy weight in respect to their height. Where not explicitly reported, mean BMI of the participants was calculated.

II.3.4. Orbital stability analysis

All the subjects analyzed in the articles showed orbitally stable motor patterns (maxFM < 1). Hurmuzlu & Basdogan [40] found that normal individuals possess stability measures that are substantially less than unity, confirming the theory regarding the stability of normal gait. Hurmuzlu et al. analyzed gait of post-polio patients [63]; their gait resulted significantly less stable than the gait of normal individuals. Pathologic subjects were involved also in a study by Hidler & Rymer [62]: they examined ankle clonus in spastic subjects, concluding that the periodic motion exhibited during clonus is in fact a stable limit cycle. In two studies orbital dynamic stability was found to be unaffected by small changes in walking velocity, and the authors stated that slowing down does not lead to a higher orbital stability [13,58]. Conversely, a study [64] reported that both younger and older adults exhibited decreased instability by walking slower, in spite of increased variability. Schablowski & Gerner [70] reported a not very strong, yet nevertheless significant, dependence of orbital stability on walking speed, with a weak local minimum at intermediate speeds. One of these studies [13] indicated also that fall-prone elderly show poorer stability of dynamic walking than young adults and healthy old adults. Of the four articles that confronted orbital stability of walking in young and old adults, three concluded that healthy active older adults exhibit significantly increased orbital dynamic instability (kinematic and muscular), independent of walking speed [64–66]. The other one found no significant difference between the healthy old and young adult groups in terms of maxFM [13]. One study [59] showed that performing an attention demanding task while walking on a treadmill does not affect dynamic stability. One study [66] analyzed muscle activation during walking, and found that maxFM measures were only slightly correlated between electromyography (EMG) and kinematics. However, older adults exhibited greater inter-stride dynamic instability of muscle activation patterns. Two studies analyzed sawing task [60,61], concluding that muscle fatigue does not lead to instability of movement. Some works analyzed the orbital stability of walking with an added mass, with contradictory results: one article concluded that walking with an external load of 30% body weight does not influence the stability of the gait pattern in the sagittal plane [54], while the other one stated that increasing body mass alone would lead to a decrease in the stability of the sagittal plane leg kinematics during steady-state walking [55]. Scott-Pandorf et al. [71,72] concluded that added load have little effect on the sagittal dynamic stability while in simulated Martian gravity, but the gait pattern is more dynamically stable with loads (e.g. Portable Life Support Systems) at the side of the torso and low on the body.

Trunk motion dynamics appeared to provide a more sensitive marker of the decline in gait function in healthy older adults compared to other body segments [65]. Trunk segment is known to play a critical role in regulating gait-related oscillations in all directions [79], hence it might also be responsible for major compensation mechanisms aimed to maintain stability of gait.

One study [69] had the purpose to determine if exposing subjects to different types of continuous perturbations would evoke changes in orbital stability; subjects exhibited direction-specific responses perturbations. A study [73] tested whether (combinations of) measures of variability, and local and orbital dynamic stability were sensitive to experimentally induced impaired gait stability, during treadmill walking at several different speeds, concluding that FM cannot be used to assess balance control in gait. In the opinion of the authors this may be due to compensatory changes, and this claim would require additional research. Orbital stability results for young subjects walking at normal or preferred speed are reported in a forest plot (Figure II.1).

Different methods and instruments of movement analysis lead to the acquisition of different locomotor variables; hence, the composition of the state space strongly depends from the chosen method of movement analysis. Different movement analysis techniques were used in the manuscripts. For kinematic measures, 15 articles used 3d stereophotogrammetry [13,54–59,64,65,70–72], two articles used 2d video motion analysis [67,68], four used electrogoniometer systems [34,40,59,63], three articles used tri-axial accelerometers [34,57,73], one article used surface electromyography [66], one used potentiometers and tachometers [62]. Some articles used two or more techniques.

Orbital stability analysis in literature has been applied to different kinds of cyclic motor tasks. Almost every reviewed article involved overground or treadmill walking, at different speeds with/without carrying loads. One article analyzed subjects walking in a Computer Assisted Rehabilitation ENvironment (CAREN) system (Motek, Amsterdam, Netherlands) and exposed to continuous, pseudo-random oscillations of the support surface or visual field [69]. Two articles analyzed sewing task [60,61], one analyzed lifting task [60]. One article was about dogs trotting [68], another one analyzed a subject who was seating while clonus was stimulated [62]. Although the conclusions drawn by these study are hardly exploitable outside their specific research field, we decided to include them in the review as an application example, as some author might want to apply the technique to different biomechanical-related research areas.

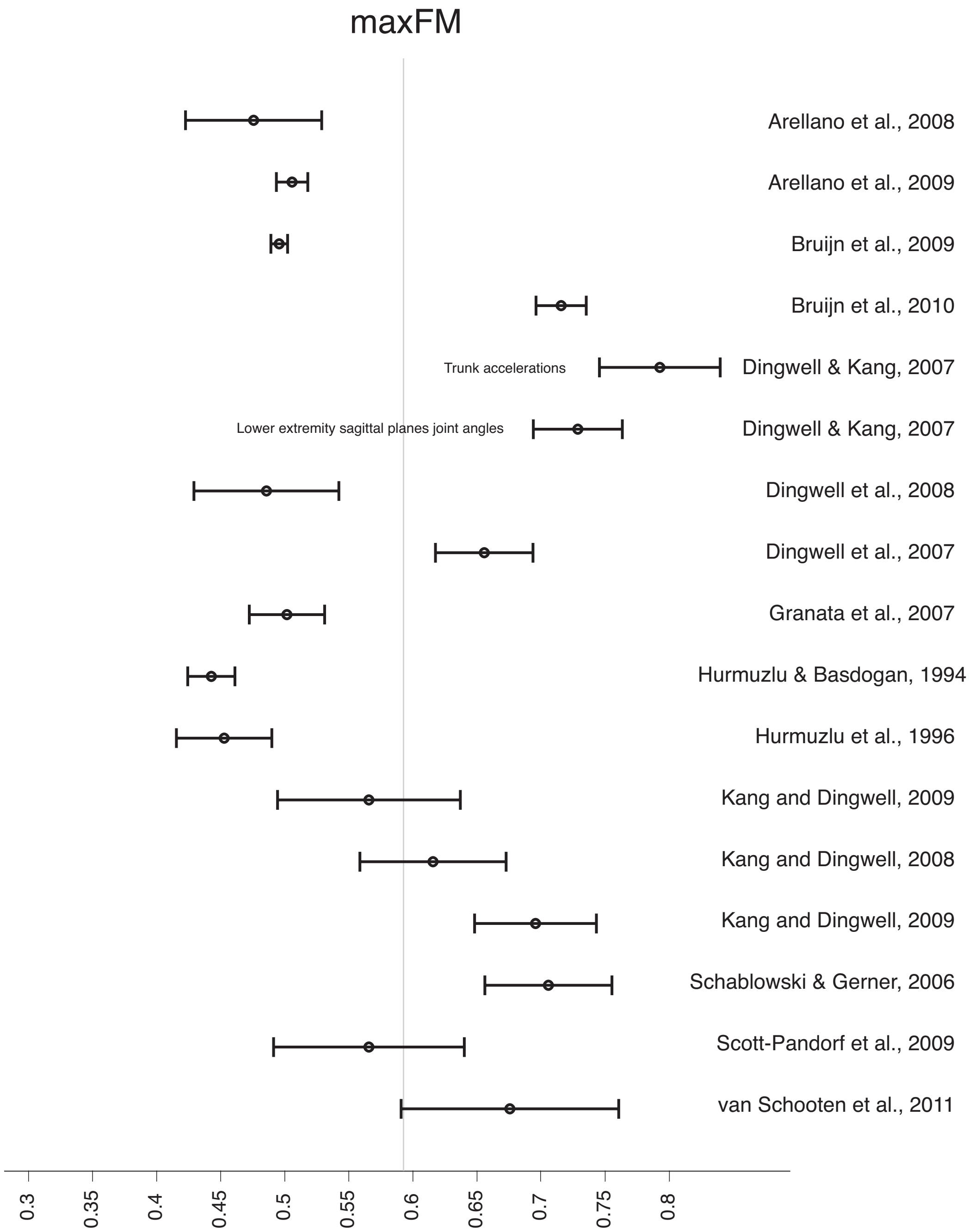

Figure II.1 - maxFM for young healthy subjects walking at preferred (or normal) walking speed. Error bars represent 95% of confidence interval.

All the reviewed articles used the same numerical method for maxFM calculation from time series, referring to the established method by Hurmuzlu et al. [63]. Some articles calculated the dependence on speed of maxFM.

Different state spaces were used in reviewed articles. Many articles included in the state space different combinations of joint angles and their derivatives, including or not their time-delayed copies. Some articles used virtual marker positions, velocities and/or accelerations instead of physical markers [13,64,65]. One article included EMG signals in the state space, and their time derivatives [66]. Articles involving tri-axial accelerometers included in the state space linear acceleration data [34,57,73]. Some articles included in the state space variables coming from both sides, some others just from the dominant side.

Different choices of Poincaré sections were made in the studies. Four articles [63,67,71,72] used maximum sagittal knee flexion to mark the first return data. Two articles [13,40] put Poincaré section at the instant of different foot strike events (left-step, right-step, stride [13] and heel strike, foot flat, heel off, toe off [40]). Two articles [34,58] analyzed the values of maxFM all over the gait cycles, while one [70] took the average values of the maxFM over all the points of the gait cycle. Three articles calculated multipliers at different percentage of the gait cycle [59,64,66]. Five articles calculated all the multipliers in the task cycle; four [56,57,61,69] considered for statistical analysis only the largest FM across all different phases in the cycle, two [69,73] considered the average maxFM value across the cycle. Two articles [54,55] computed maxFM in the instances of heel strike and maximum knee flexion. One article involving spasticity [62] choose the point in the clonus cycle where the ankle acceleration is zero. One article involving dogs trotting [68] put Poincaré maps at the instant of paw strike. Some authors [40] stated that the stability measures are fairly insensitive to the choice of Poincaré section, while other authors stated that the magnitudes of maxFM vary across the gait cycle [34].

Just a few articles [56,63,67,69] stated explicitly the number of cycles upon which the analysis was conducted (Table II.4). The number of cycles analyzed in the articles varied from 4 [63] to 300 [56]. The majority of the articles only indicated the time duration of the trials. One article about precision and sensitivity of orbital stability measures [56] stated that an acceptable value of maxFM for human walking can be estimated within 300 strides; viewing the multiplier as a measure of convergence towards an attractor, using less data could lead to less accurate estimates of the true attractor.

Table II.4 – Number of analyzed cycles

Reference	Article	Cycles number
[54]	Arellano et al.	6 mins walking
[55]	Arellano et al.	6 mins walking
[56]	Bruijn et al.	from 30 to 300 strides
[57]	Bruijn et al.	5 mins walking
[34]	Dingwell and Kang	200 m walkway (overground), 10 mins walking (treadmill)
[58]	Dingwell et al.	10 minutes walking
[59]	Dingwell et al.	3 mins walking
[60]	Gates & Dingwell	-
[61]	Gates & Dingwell	-
[13]	Granata et al.	50s walking (minimum of 35 consecutive steps)
[62]	Hidler and Rymer	–
[40]	Hurmuzlu and Basdogan	pass on a twenty meter walkway (all the gait cycles)
[63]	Hurmuzlu et al.	first 4 gait cycles
[64]	Kang and Dingwell	5 mins walking
[65]	Kang and Dingwell	5 mins walking
[66]	Kang and Dingwell	5 mins walking
[67]	Marghitu and Hobatho	a minimum of 5 gait cycles
[68]	Marghitu et al.	–
[69]	McAndrew et al.	150 continuous strides
[70]	Schablowski and Gerner	90 seconds walking
[71]	Scott-Pandorf et al.	3 mins walking
[72]	Scott-Pandorf et al.	3 mins walking
[73]	van Schooten et al.	2.5 mins / 3 mins / 3.5 mins walking

Table II.5 – Limitations and conclusions reported by the authors

Ref	Article	Limitations	Conclusions
[54]	Arellano et al.	_	Walking with an external load of 30% body weight about the waist did not influence the stability of the gait pattern in the sagittal plane.
[55]	Arellano et al.	The vest may have assisted with the stability of the leg dynamics by providing additional torso control. It is also possible that small horizontal forces were introduced if the subject did not stay directly below the fixed pulley. Potentially, these horizontal forces may have influenced our measures of stability. The vertical lifting forces were more variable as additional mass was added to the subject.	Added mass reduces the stability of the leg kinematics during steady state walking. These results indicate that the inertial state of the body plays a role in the stability of the leg kinematics and may be related to how the body is redirected and accelerated during walking.
[56]	Bruijn et al.	Fatigue and/or boredom may have affected the walking patterns; we cannot exclude the possibility that the observed increase in precision reported was, at least in part, due to the increase in overlap in the samples.	The dependence of the estimates of local and orbital dynamic stability upon the number of strides included in the analysis implies that when estimating stability at different walking speeds, or in different patient groups, a fixed number of strides should be analyzed. The increase in precision with increasing data series length indicates the need to use long data series. The gain in precision tends to be limited when using more than 150 strides.
[57]	Bruijn et al.	The poincaré sections were not sampled at exactly the same time.	The two measurement methods lead to comparable results and thus may be used interchangeably. Inertial sensors may be used as a viable and valid alternative for optoelectronic measurement systems.
[34]	Dingwell and Kang	The additional "states" created were not aligned during the same "phase" of the gait cycle. It is possible this may have led to "averaging out" of differences at individual phases of the gait cycle.	All subjects exhibited orbitally stable walking kinematics during both overground and treadmill walking; the variability inherent in human walking, which manifests itself as local instability, does not significantly adversely affect the orbital stability of walking.
[58]	Dingwell et al.	_	All subjects exhibited orbitally stable walking kinematics, even though these same kinematics were previously shown to be locally unstable. Neuropathic patients do not gain improved orbital stability as a result of slowing down.
[59]	Dingwell et al.	Subjects walked on a motorized treadmill; treadmill walking can reduce the natural variability and enhance the local and orbital stability.	The decreased movement variability associated with the stroop task did not translate to greater dynamic stability.

Table II.5 – *(Continued)*

Ref	Article	Limitations	Conclusions
[60]	Gates & Dingwell	Despite our attempt to make the tasks as similar as possible for the different subjects, significant differences in their responses remained, particularly for the MVC measures. As this task was inherently redundant, subjects could compensate for fatigue by using different muscles or strategies that might allow them to maintain their stability. Different subjects fatigued to different degrees.	When performing multijoint redundant tasks, humans can compensate for muscle fatigue in ways that maintain task precision while increasing movement stability.
[61]	Gates & Dingwell	It was not possible to perform maximum voluntary contractions during this test due to the continuous nature of the task. As such, we were not able to directly quantify decreased force-generating-capacity of subjects' muscles using this protocol. In this paper, we quantified a large number of parameters. It is likely that not all of these were parameters are independent. As such, some caution is likely warranted in interpreting the degree of statistical significance present in some cases.	Subjects significantly altered their kinematic patterns in response to muscle fatigue. These changes were more pronounced when the task was performed at a higher height. Subjects also exhibited increased variability of their movements post-fatigue. Increases in variability and altered coordination did not lead to changes in local or orbital dynamic stability, however. Local stability of the shoulder was lower when movements were performed at a lower height. In contrast, orbital stability of the shoulder and elbow was lower for movements at the higher height. This research showed that people continuously adapt their strategies in multi-joint redundant tasks and maintain stability in doing so.
[13]	Granata et al.	The data represent a pilot study with a small sample size; data were collected while walking on a treadmill; analyses were limited to kinematics of foot-strike with respect to the CoM.	The fall-prone group demonstrated poorer stability of dynamic walking than the other groups.
[62]	Hidler and Rymer	_	The involuntary rhythmic oscillatory movements commonly observed in spastic subjects are driven by peripheral stretch reflexes rather than by a central pattern generator, and the system under these conditions is acting as a stable limit cycle.
[40]	Hurmuzlu and Basdogan	Fewer number joint measurements can be made compared to more advanced optical data acquisition system; it was assumed that the human body is composed of seven segments.	Normal individuals possess stability measures that are substantially less than unity.
[63]	Hurmuzlu et al.	_	With the measure of dynamic stability the gait of post-polio patients is seen to be significantly less stable than the gait of normal individuals.
[64]	Kang and Dingwell	Since muscle activations measured using EMG do not represent muscle forces, it is not yet clear how these muscle activation dynamics result in the muscle forces that lead to the observed kinematics.	Older adults exhibited greater inter-stride variability of muscle activation patterns during gait; multi-dimensional dynamics of muscle activations are reflected in that of kinematics.

Table II.5 – *(Continued)*

Ref	Article	Limitations	Conclusions
[65]	Kang and Dingwell	This study only quantified responses to local perturbations. These results may or may not extend to global stability, where responses to large perturbations, like tripping or slipping would be assessed. The motorized treadmill may not properly reflect overground walking.	Even active older adults who walk at the same preferred speeds as younger adults still exhibit significantly increased orbital dynamic stability, independent of walking speed.
[66]	Kang and Dingwell	_	Superior segments exhibited less local instability but greater orbital instability compared to inferior segments. The superior segments are less sensitive to very small initial perturbations and thus its motion is initially less affected by these small perturbations, compared to inferior segments. Trunk motion dynamics appears to provide a more sensitive marker of the decline in gait function in healthy older adults compared to other body segments.
[67]	Marghitu and Hobatho	_	The techniques of nonlinear dynamics used in this study provide an analytical tool that is easy to use in the clinical diagnosis of human gait abnormalities.
[68]	Marghitu et al.	The 3-angle model for the animal body is a highly simplified model.	The stability index and the measures used will help to clarify and localize the source of the instability and serve to document changes in severity of the condition.
[69]	McAndrew et al.	-	Subjects experienced decreased orbital and short- term local dynamic stability in a direction-specific manner when walking during the continuous pseudo-random perturbations applied in the present study
[70]	Schablowski and Gerner	_	Two different mechanisms regarding dynamic stability of locomotion seem to exist. The increasing instability ad higher speeds may be one reason for the transition from walking to running.
[71]	Scott-Pandorf et al.	True martian gravity cannot be created on the earth's surface; offloading the center of mass of an individual is not likely to be the same as true reduced gravity. Additionally, the body weight suspension system may supply some stabilizing forces.	Adding weight to the walking system while walking in simulated Martian gravity had no effect on the sagittal dynamic stability of the walking pattern.
[72]	Scott-Pandorf et al.	It is possible that the body weight support system may have provided additional stabilizing forces in the frontal plane.	Portable life support system loads at the side of the torso and low on the body improve dynamic stability of the gait pattern in simulated martian gravity.
[73]	van Schooten et al.	The time-normalization that was used was different between the walking speeds. A treadmill was used to control walking speed.	Variability and FM of trunk kinematics cannot be used to assess balance control in gait.

II.4. DISCUSSION

Although the problem of falls in the elderly is gaining increasing clinical and economical attention, assessment methods designed to identify fall-prone individuals remain controversial; biomechanical approaches for assessing gait stability seem to be able to quantify the dynamic stability of locomotion, but they have not been taken up as routine procedures in clinical settings [8]. In particular, orbital stability analysis via FM revealed effective identification of fall-related and age-related differences, but its use in the assessment of fall risk remains controversial [8]. A possible cause of this controversy could be the lack of a "standard" procedure for implementing this kind of analysis in experimental trials; different implementations could in fact lead to different results, and introduce difficulties in their interpretation.

This paper provides a systematic review of the literature in the field of orbital stability analysis application in biomechanics, with particular focus to methodological aspects. 15 articles out of 23 were of very high quality, proving the excellent level of the literature in the field.

MaxFM resulted < 1 for all the analyzed motor tasks (human gait, sewing, dog trotting); hence, those tasks were demonstrated to be orbitally stable. These results showed that the analyzed periodic motor tasks reached a stable condition when equilibrium was attained. MaxFM resulting for young subjects walking at preferred or normal speed, showed in Figure 1, confirm this aspect. Gait of pathologic subjects like post-polio patients, fall-prone elderly, or children with torsional anomalies of the lower limb joints have also been demonstrated to be orbitally stable, even if less stable than gait of healthy young subjects [13,63,67]. On the contrary, subjects with diabetic peripheral neuropathy did not experience any loss of orbital stability as a result of their sensory loss [58]. The increase in risk of falling of these patients may be due to their inability to develop and execute appropriate avoidance and/or response strategies when subjected to large-scale perturbations while walking [58]. Several studies showed how slowing down while walking does not improve orbital stability [13,58] but can eventually worsen it [70]. Only one study reported that older adults exhibited decreased instability by walking slower, in spite of increased variability [64]. These results suggest that the reduction of walking velocity, commonly observed in the elderly, may not be caused by the need to enhance orbital stability [13]. Comparison between orbital stability of gait in young and elderly subjects seems to confirm that old adults tend to be less stable while walking, partially explaining the tendency to fall. The incoherence in the results about walking with added mass does not allow drawing clear conclusions.

In general, a lack of uniformity in the methodological approaches used by the authors was found; this could also explain the different results reported by different authors for basically the same task (Figure 1). Methodological quality of the studies included in this review was in general sufficient, but articles included in the review implemented orbital stability analysis in different manners. Three main factors suffered a general lack of homogeneity between the analyzed studies: state space definition, Poincaré section location and number of cycles analyzed (Tables 3, 4).

Whereas state space composition have been satisfactorily described by most of the manuscripts, the choice of the variables for the state space definition often lacked justification. All the state space defined in the articles seemed appropriate to adequately describe the analyzed dynamical systems; however, an "optimal" set of variables for the definition of state space for orbital stability analysis purposes have not emerged from the analyzed literature. A standardization of the variable set to be used for orbital stability analysis purposes would contribute to the interpretation of stability results and would allow to better compare stability results under different motor conditions.

As stated in the introduction, the orbital stability of a deterministic limit cycle process should be theoretically the same, regardless of the position of Poincaré section along the trajectory. This is not verified when dealing with human cyclic tasks: human cyclic movements are not strictly periodic, and consequently the response to perturbations during different phases of the task is different [34]. This aspect was confirmed by experimental results: different choices for Poincaré section position led to different values of maxFM. All the authors seem to agree that positioning the section in different instants over the task cycle allows to obtain information about orbital stability of the different phases of the task, and that mean value of maxFM across the task cycle give global information about the stability of the task.

One of the most critical issues regarding orbital stability analysis of human locomotion was found to be the number of task cycles necessary to obtain reliable orbital stability results. One article [56] stated that the "true" value of maxFM for human walking could be estimated within 300 strides; most of the articles did not report the number of cycles analyzed, or performed the analysis on a number of task cycles inferior to 300 (Table 4). When dealing with human locomotion (e.g. gait) in a movement analysis laboratory, it is possible to reach a similar number of cycles only by treadmill walking; however, whereas the use of motorized treadmill is generally justified, treadmill walking differs significantly from overground walking [80] and it is also known to enhance orbital stability [58]. Hence, conclusions obtained from treadmill walking, whereas they can be significant and useful in some context, cannot directly be transferred to overground walking.

One of the main goals of research about stability of motor tasks is to understand the mechanisms that underlie motion, particularly in case of falls. Studies included in this review showed the state-of-art in the application of orbital stability analysis via FM calculations in biomechanics.

In summary, the main explanation to the incoherence between some of the results and to the differences in the implementation of the method is believed to be the absence of a generalized methodological procedure to perform orbital stability analysis on biomechanical time series data. This kind of analysis could have a major impact in the prevention of falls. Future research should look for a standardized methodological procedure to implement this kind of analysis, identifying the best experimental setup and analytical procedure to obtain maxFM. In order to obtain more insights on the magnitude of maxFM during human gait, analytical orbital stability analysis of the equations of a full human rigid body model can also represent a promising approach. Another fundamental issue will be the evaluation of the capability of maxFM to predict falls in the elderly.

III. INFLUENCE OF INPUT PARAMETERS ON DYNAMIC ORBITAL STABILITY OF WALKING: IN-SILICO AND EXPERIMENTAL EVALUATION[2]

III.1. INTRODUCTION

The analysis of modelled physiological signals of gait (accelerations, joint angles) could contribute to the assessment of the influence of implementation parameters on FM, in relation to experimental results also. Given the similarity of the signals, influences of different implementations on the stability results are likely to be analogous between model and experimental data analysis. In order to compare model and experimental results, stability in both conditions must be assured. Signals extracted from a stable walking model are hence required.

Some authors performed simulation studies on orbital stability of 1- or 2-link walking models related to fall risk [81–83]. However, these models are rather simple and simulate very peculiar walking condition. Simplicity is both the strength and the limitation of these models: their walking conditions can be easily manipulated, but they generate signals that are far from physiologic conditions of human walking. Stability analysis on a more complex model can give better insight on the orbital stability conditions of human walking, allowing the comparison between model and experimental results. In order to allow adequate comparison, stability condition must be assured for the walking model. The required conditions for the model are hence a continuous walk and the absence of falls or stumbles, in order for the model to produce kinematics as similar as possible to stable human gait.

The aim of the present study was to analyse, from an applicative point of view, the influence on the final results of orbital stability analysis applied to walking of: 1) number of analyzed cycles; 2) selection of the variables for the reconstruction of the state space; 3) experimental measurement noise on a 2-dimensional 5-link walking model [84], providing walking patterns of known stability. Results of in-silico analysis were compared to those obtained experimentally on 10 subjects performing long overground walks.

[2] Under review. Riva F, Bisi MC, Stagni R. Influence of Input Parameters on Dynamic Orbital Stability of Walking: In-silico and Experimental Evaluation. Submitted to Journal of Biomechanical Engineering.

III.2. MATERIALS AND METHODS

III.2.1. Overview

In-silico orbital stability analysis of a 5-link stable walking model [84] was performed. The model showed continuous walking, free of falls or stumbles, for all the simulation period (300 strides). This was also assured by a check on step variability, which was minimal following visual inspection of the phase portraits. The analysis was performed for increasing number of cycles (from 10 to 300), based on differently composed state spaces (including different joint angles and/or accelerations). Simulated experimental error and noise were added to the segmental kinematics of the model and the sensitivity of orbital stability analysis was evaluated. Orbital stability analysis was also performed on data collected experimentally on 10 subjects; given the impossibility to use a stereophotogrammetry system on a long outdoor road, only acceleration data were acquired experimentally. Orbital stability was calculated using an established technique [63].

III.2.2. *In-silico* data

The 2-dimensional, five-link biped walking model analyzed [84] consisted of a trunk, two thigh and two shank segments (Figure III.1). The model orientation was described by supporting and swinging knee angles, supporting and swinging hip angles and upper body angle ($\phi_{k,sw}$, $\phi_{k,st}$, $\phi_{h,st}$, $\phi_{h,sw}$, ϕ_{ub}, all referred to gravity direction).

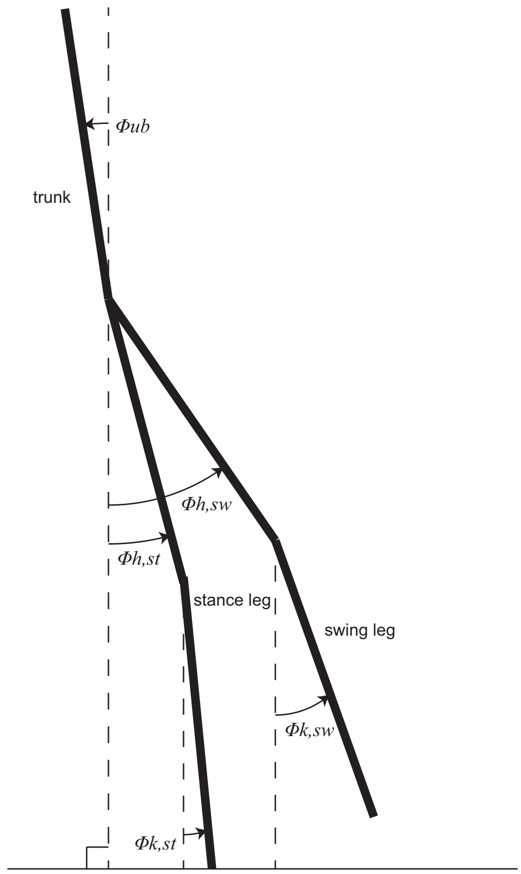

Figure III.1 - Schematic representation of the 5-link 2-dimensional model (Solomon et al., 2010).

In addition to the mentioned joint angles, the model included also the corresponding joint angular velocities. The model was adapted to perform 315 consecutive strides. The first 15 strides of the simulation were discarded in order to assure stable walking condition. The simulation was performed using a MATLAB's (Mathworks, Natwick, NA) fourth- and fifth- order variable time-step Runge-Kutta solver (ode45, with relative error tolerance set to 10^{-12}). Accelerations of the trunk segment at the level of the fifth lumbar vertebra (L5) were obtained as the second derivative of the time history of the position of a point located at 1/8 of the length of the trunk segment.

Table III.1 – Precision of the palpable anatomical landmark position (in millimeters) in the relevant mean anatomical frame obtained by Della Croce et al., 1999. For ME, LE and MM, LM the mean value between the two was used in the analysis.

Anatomical landmark	*x*	*y*
Greater trochanter (GT)	12.2	11.1
Medial Epicondyle (ME)	5.1	5.0
Lateral Epicondyle (LE)	3.9	4.9
Medial Malleolus (MM)	2.2	2.6
Lateral Malleolus (LM)	2.6	2.4

Segmental kinematics data obtained from the model were processed to simulate experimental data from a stereophotogrammetry system (joint angles) and a single inertial sensor located on the trunk (accelerations). Simulated experimental noise and errors were superimposed to segmental kinematics signals obtained from the model.

Clusters of 4 markers were virtually applied to all the segments of the model (trunk, thighs and shanks, for a total of 20 markers) and simulated instrumental normally distributed noise with a standard deviation of 0.2 mm was added to the marker trajectories (or coordinate time histories) in 2-D space. Technical reference frames were calculated from the cluster positions, and the position of the segment extremities relative to these frames was measured. A mislocation error of anatomical landmark positions (Table III.1) was also added to the estimate of the position of segment extremities [85]. Joint angles were then calculated from the relative orientation of the anatomical reference frames [86].

Instrumentation noise (white noise with an SNR of 10 dB and alignment errors with a normal distribution and a standard deviation of 0.1 degrees), compatible with the use of commercial accelerometers, was added to the acceleration signals of the trunk segment at the level of L5. Analyses on lower amounts of noise were also performed, which led to comparable results; hence, we chose to show results in the most potentially critical condition.

III.2.3. Experimental data

10 healthy participants [28 ± 3 years, 174 ± 11 cm, 67 ± 13 kg] were included in the study. Subjects gave informed consent before participating. Two synchronized tri-axial inertial sensors (Opal, APDM, Portland, OR, USA) were placed on the participants at the level of L5 and of the right shank. The range of the accelerometers was ±2g and sample rate was 128 Hz. The participants were instructed to walk straight at self-selected speed on a 250 m dead-end long road.

III.2.4. Data processing

For both model and experimental data, stride cycles were considered as the time between consecutive right heel strikes and were resampled to be 101 samples long, because Floquet theory assumes that the system is strictly periodic. For experimental data, right heel strike instants were estimated from the angular velocity of the lower limb with a method based on wavelet analysis [87]. Angular velocity of the lower limb was measured with the inertial sensor placed on the right shank. Experimental data were analyzed without filtering, in order to avoid the complications associated with the application of linear filtering to nonlinear signals [88]. Orbital stability analysis on model data was performed on six different state spaces (Table III.2). The analysis was conducted for both noise-free and noisy condition. The same analysis was conducted on experimental data. Mean values of maxFM across the gait cycle were calculated on increasing number of strides (from 10 to 300 for model data, from 10 to 160 for experimental data).

III.3. RESULTS

The presence of noise resulted to be critical for state spaces composed by joint angles (WMhk, WMk and WMh). Analysis on WMhk in noise-free conditions led to mean values of maxFM across the gait cycle that decay with the increase of the analyzed stride cycles, until reaching the value 0.3 (for about 250 stride cycles). Standard deviation decreased with the increase of stride cycles. WMk and WMh led to values of 0.34, with low standard deviation (about 0.07), independent of the number of cycles upon which the analysis was conducted (Figure III.2); values of mean maxFM remained stable from 10 to 300 cycles. State spaces composed by noise-affected signals showed a different behavior. For WMhk, maxFM values increased until reaching the value of about 0.7, for 100 stride cycles. For WMk and WMh, mean maxFM value slowly decayed towards zero instead of stabilizing around a fixed value (Figure III.3).

Table III.2- Description of the state spaces. $\phi_{k,st}$ and $\phi_{k,sw}$ are flexion/extension knee angles for supporting and swinging limb; similarly, $\phi_{h,st}$ and $\phi_{h,sw}$ are flexion/extension hip angles. ϕ_t is flexion/extension trunk angle. a_{AP} and a_V are accelerations of the trunk at the level of L5 in anterior-posterior and vertical directions. For delay-embedded state spaces, τ is time delay and d_E is the embedding dimension (τ = 10, d_E = 5).

Acronym	Description	Composition
WMk	Swinging+supporting knee flexion/extension joint angles (model)	$WMk(t) = [\phi_{k,st}(t), \phi_{k,sw}(t)] \in \Re^2$
WMh	Swinging+supporting hip flexion/extension joint angles (model)	$WMh(t) = [\phi_{h,st}(t), \phi_{h,sw}(t)] \in \Re^2$
WMhk	Knees, hips and trunk flexion/extension joint angles (model)	$WMhk(t) = [\phi_{k,st}(t), \phi_{k,sw}(t), \phi_{h,st}(t), \phi_{h,sw}(t), \phi_t(t)] \in \Re^5$
WMaAP	5-dimensional delay embedding of AP accelerations of L5 (model)	$WMaAP(t) = [a_{AP}(t), a_{AP}(t+\tau), \dots, a_{AP}(t+(d_E-1)\tau)] \in \Re^5$
WMaV	5-dimensional delay embedding of V accelerations of l5 (model)	$WMaV(t) = [a_V(t), a_V(t+\tau), \dots, a_V(t+(d_E-1)\tau)] \in \Re^5$
WMa	Accelerations in the AP and V direction of L5 (model)	$WMa(t) = [a_{AP}(t), a_V(t)] \in \Re^2$
EXPa	Accelerations in the AP and V direction of L5 (experimental)	$EXPa(t) = [a_{AP}(t), a_V(t)] \in \Re^2$

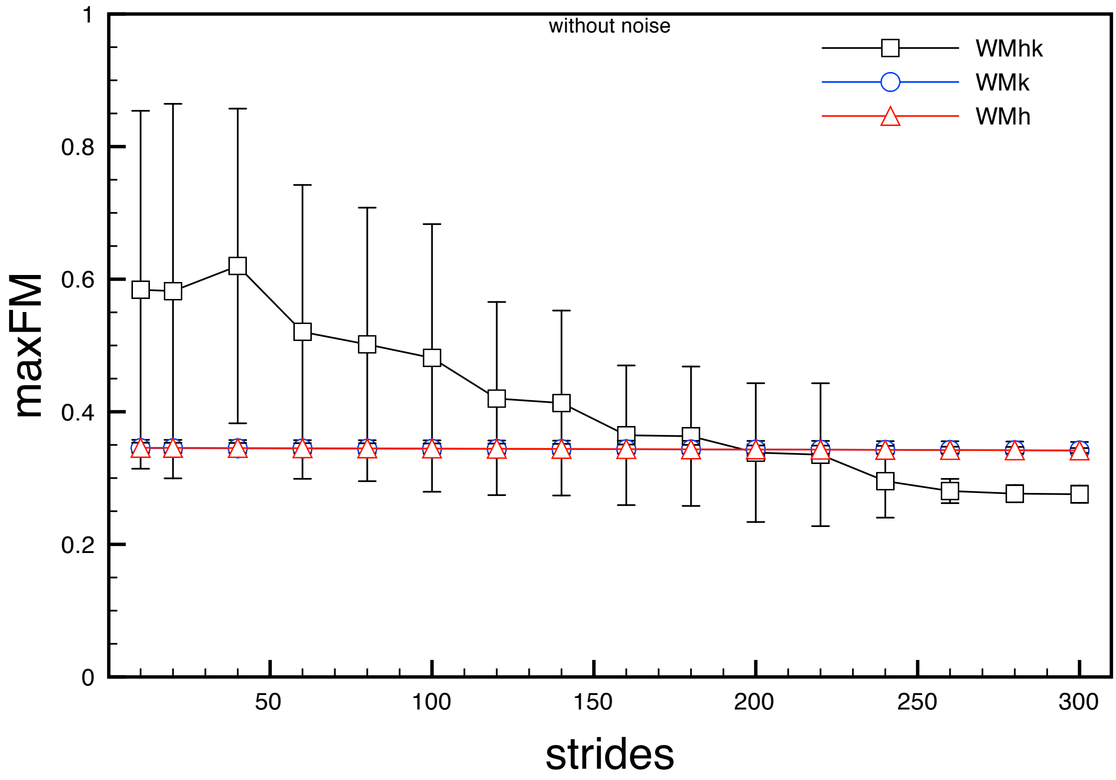

Figure III.2 - Mean maxFM values across the stride cycle calculated on state spaces WMhk, WMk and WMh (clean signals) for increasing number of stride cycles.

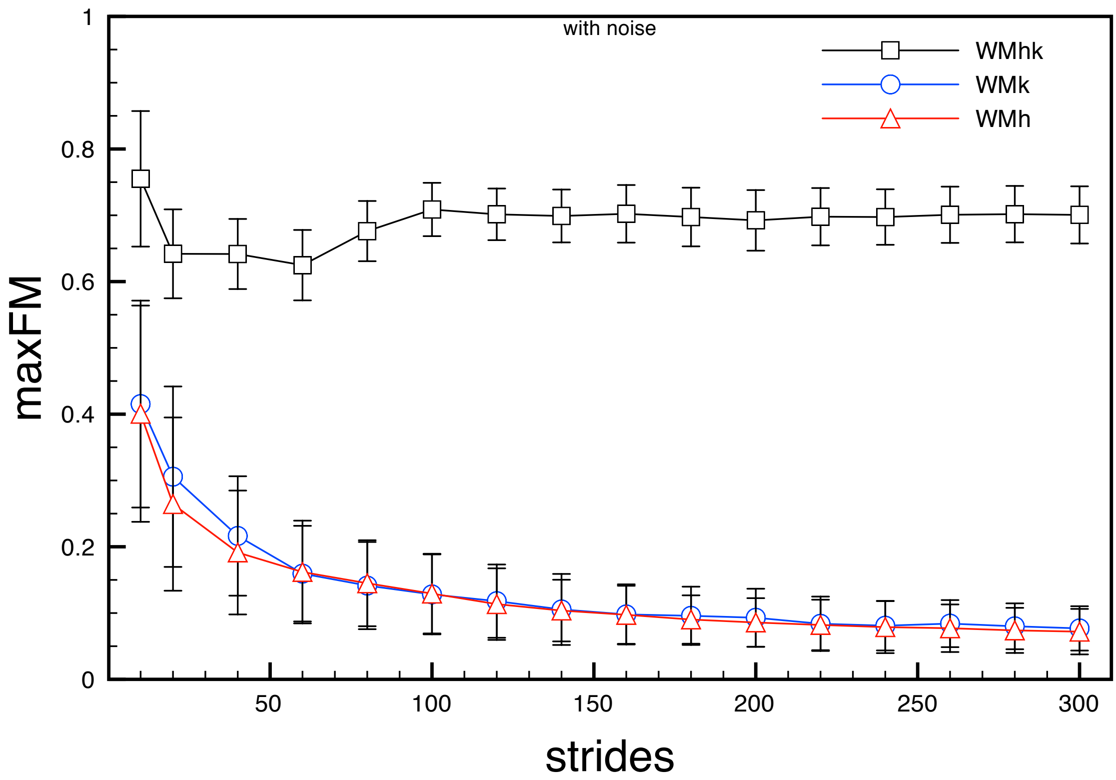

Figure III.3 - Mean maxFM values across the stride cycle calculated on state spaces WMhk, WMk and WMh (noisy signals) for increasing number of stride cycles.

MaxFM calculated on noise-free acceleration state spaces, both 2 and 5 dimensional (WMa, WMaAP and WMaV), behaved similarly: for less than 30 cycles, values of maxFM gradually decreased, starting from values near (or above) one. Starting from about 30 cycles, values of maxFM stabilized around the value previously found for joint angle state spaces (0.34 – 0.4) with a standard deviation of about 0.09 (Figure III.4). Results coming from analysis of noisy accelerations signals were very similar to those obtained from noise-free signals (Figure III.5).

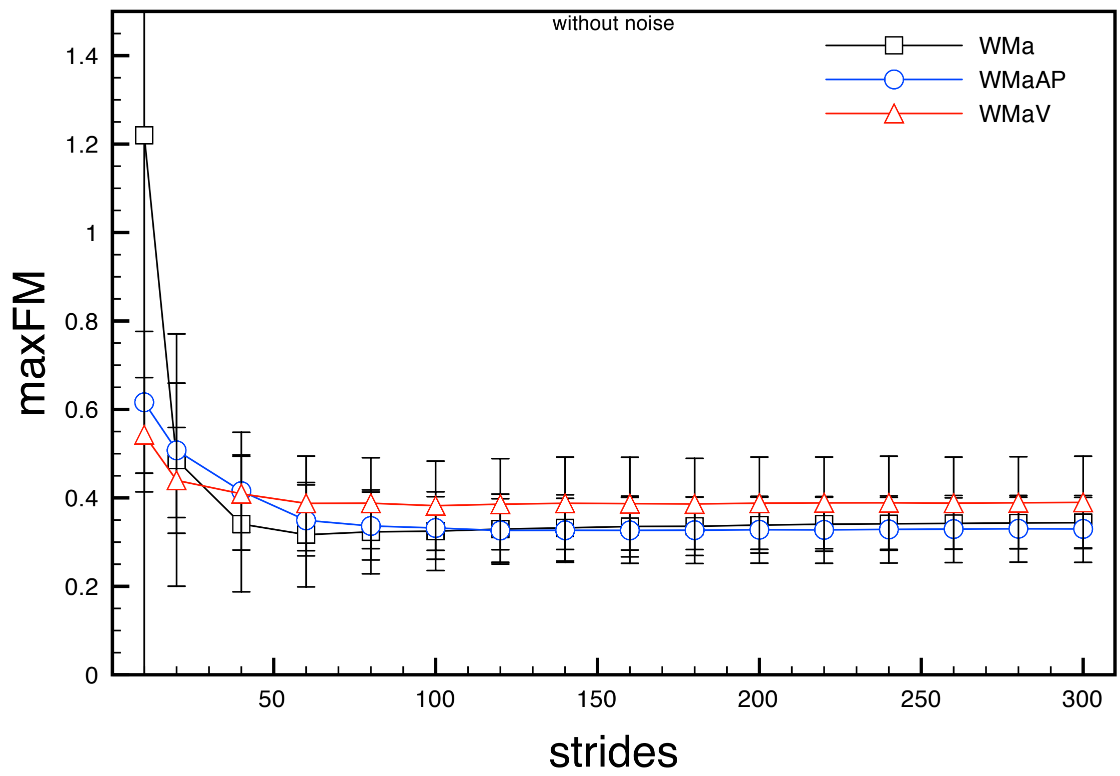

Figure III.4 - Mean maxFM values across the stride cycle calculated on state spaces WMa, WmaAP and WMaV (clean signals) for increasing number of stride cycles.

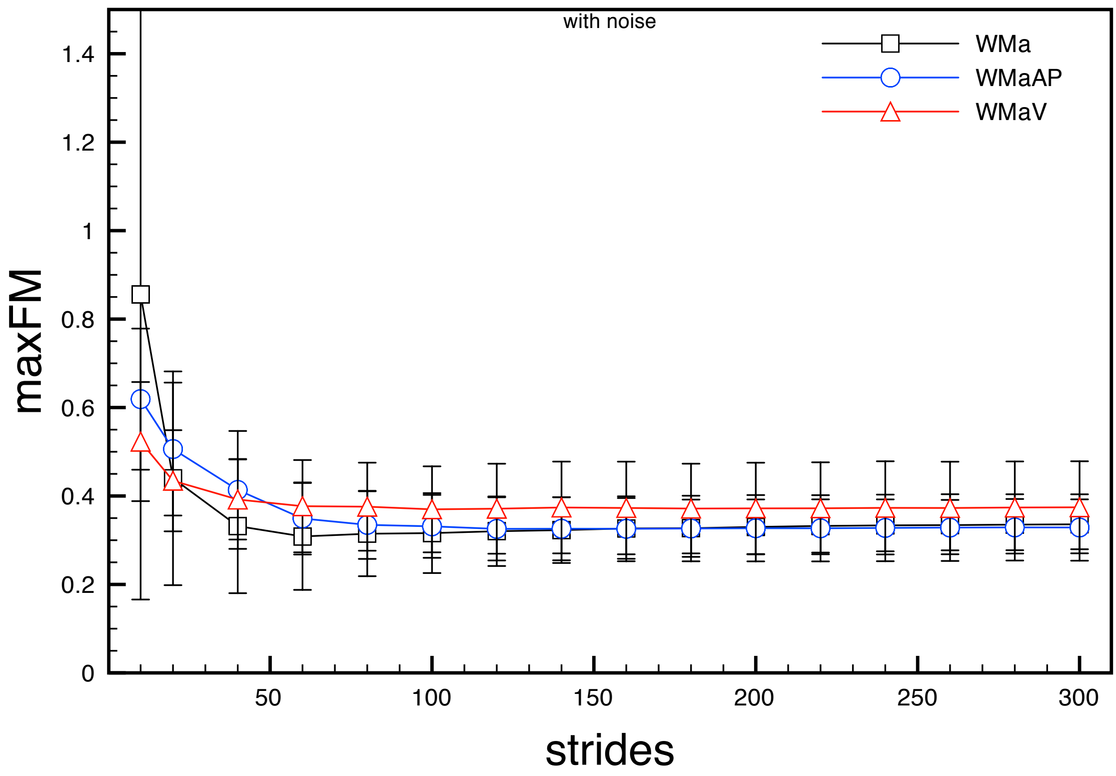

Figure III.5 - Mean maxFM values across the stride cycle calculated on state spaces WMa, WmaAP and WMaV (noisy signals) for increasing number of stride cycles.

MaxFM calculated on experimental acceleration state space (EXPa) showed decreasing value for increasing number of cycles analyzed, reaching values close to 0.4 from 80 cycles on, with a standard deviation of about 0.1 (Figure III.6).

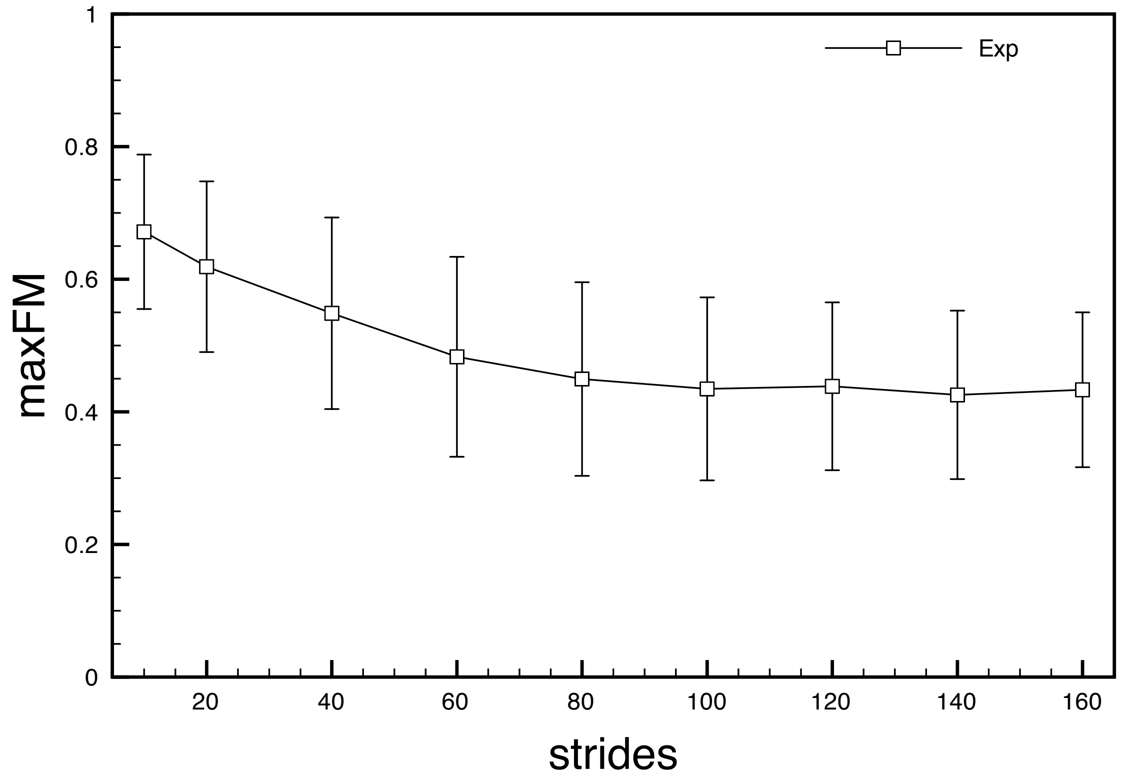

Figure III.6 - Mean maxFM values across the stride cycle calculated on state space EXPa for increasing number of stride cycles.

III.4. DISCUSSION

The possibility to have a reliable locomotor stability index is of fundamental importance in early identification and treatment of older adults with high predisposition to fall, and possibly in real-time gait instability detection also. However, still there is no unique definition of locomotor stability in literature.

Orbital stability analysis via maxFM seems promising for the analysis of cyclic locomotor tasks. When dealing with biomechanical time series, the equations of motion are obviously unknown, thus excluding the possibility to calculate maxFM in an analytical or semi-analytical way. Numerical calculation of maxFM from experimental time series is hence required, but still it is not clear how different implementations of this analysis can influence the stability measure.

Beyond the mathematical implications, it is however important to highlight that applying this analysis to human gait implies several assumptions. Human gait is an inherently stochastic system, while Floquet theory applies to deterministic limit cycle systems. Walking trajectories are continuously being "re-perturbed" by stochastic perturbations, which often are internal to the system. In order to overcome this, the average trajectory is considered to be the limit cycle, but given the likely asymmetrical nature of the basin of attraction of human walking, this is obviously an assumption. However, orbital stability analysis was found to detect gait instability [13,69], hence proving usefulness despite the many theoretical assumptions that must be made.

In this explorative study, orbital stability analysis was applied to a 5-link stable walking model. The walking model was used in order to produce signals (joint angles and trunk accelerations) as similar as possible to real human gait signals. Stability was assumed, since the model didn't show any fall or stumble during the simulation period. Different implementations of numerical orbital stability analysis were then performed on the biomechanical signals obtained from the model. The aim was to better understand the influence of number of analyzed cycles, state space composition and experimental noise on the stability outputs. Given the similarity between model signals and real human gait data, relationships between implementations and stability results are likely to be transferrable to experimental analysis. As a comparison, experimental data of trunk accelerations during gait have also been analyzed.

The magnitude of maxFM obtained in this study was lower than values obtained in simulation studies present in literature [81–83]. Whereas those studies analyzed the behavior of 1- or 2-link walking models in presence of external/internal perturbations, in our study unperturbed walking of a 5-link was analyzed. These two aspects (the absence of perturbations and the higher complexity of the model) are likely to be the major cause of differences in the results. However, as also explicitly stated by Roos and Dingwell [82], the main aim of the cited articles was to show the general relationship between fall risk and stability measures, and not to give exact numerical values.

According to the results of the present study, the number of cycles included in the analysis played a fundamental role when trying to obtain a reliable orbital stability measure from differently composed state spaces. This influence is also correct from a theoretical point of view: for example the number of analyzed cycles cannot be lower than the dimension of the state space otherwise the set of equations would be underdetermined. A possible explanation might be that analyzing more data leads to a better estimate of the true attractor [56]. Orbital stability analysis performed on noise-free signals from the stable walking model resulted in maxFM values that tended to the value of about 0.34 for state spaces composed by joint angles and L5 accelerations. The coherence between these results is encouraging, as it seems to lead to indicate that a repeatable value of the maxFM can be obtained analyzing different state spaces. The main difference between these results was the dependence from the number of cycles considered: a limited number of cycles (about 10) was sufficient to obtain the value 0.34 with WMh and WMk, but at least 30 cycles were necessary to obtain the same result with WMa, WmaAP and WMaV. Using these state spaces for less than 30 cycles, maxFM values resulted to be high (close to or even above 1) and inconsistent, and hence are not believed to be reliable. The number of stride cycles needed to reach the value 0.34 was even higher when analyzing WMhk; it is possible that including a higher number of variables in the joint angle state space introduced redundancy, negatively influencing the results, instead of leading to a better characterization of the system. Whereas a 2-

dimensional representation of a complex system may seem insufficient in order to provide a proper characterization, it may serve the applicative purpose of obtaining a repeatable index of stability. The relationship with the stability index obtained with this implementation and the actual fall risk is, however, still to be determined.

Results coming from the analysis of noisy signals showed again a strong influence of number of cycles and state space composition on the maxFM, with different results between acceleration and kinematic data. Analysis of noisy accelerations of L5 led basically to the same results obtained for noise-free signals, for all the state spaces: simulated experimental noise on inertial sensor data did not influence maxFM calculation. This can lead to the conclusion that orbital stability analysis performed on state spaces composed by accelerations coming from inertial sensors is robust to noise, and that a high dimensional (5) reconstruction of the state space may not be necessary, as a lower dimension (2) state space led basically to the same results for the maxFM. WMk and WMh showed a very different behavior: maxFM tended to gradually decrease towards zero for increasing number of cycles, suggesting that stereophotogrammetric experimental noise and misplacement errors could dramatically influence maxFM calculation, significantly affecting their reliability. Analysis of WMhk led to the same conclusion, even though maxFM showed a different trend: maxFM values seemed to settle around the value 0.7 in about 100 strides. This value indicates very poor stability and is not coherent with results obtained from the analysis of clean signals. This suggests that the influence of noise may have had a negative impact on this result.

A possible explanation for this could be that the peculiar simulated stereophotogrammetric noise characteristics may contribute in hiding the information relative to the distance between the orbits, due to close proximity of the orbits to the limit cycle. This might not happen in an experimental trial, as the orbits defined by joint angles are likely to be less repeatable than those obtained from the model; further experimental analysis on state spaces composed by joint angles obtained from different data acquisition techniques (e.g. inertial sensors) are needed to clarify this aspect. These results are in agreement with Bruijn et al. [57], who found a correlation of 0.66 (defined "low" by the authors) between maxFM obtained from two measurement systems (accelerometers and optoelectronics).

Experimental trial results on the accelerations-based state space showed a similar trend with respect to the ones obtained from the analysis of the same variables derived from the model; nevertheless, the value of maxFM obtained was slightly higher, and so the standard deviation. A limitation of this experimental session was the relatively short length of the walks (160 strides) with respect to the model data; given the high handiness and portability of inertial sensor, however, future studies can analyze orbital stability of very long overground walks. On the other hand, 160 strides seem to be sufficient to reach a steady value for the maxFM.

Based on these results, a reliable implementation of orbital stability analysis could be obtained from an acceleration-based state space (reconstructed with delay-embedding or including in the state space accelerations in different directions) and a number of stride cycles not inferior to 30.

In conclusion, the exploration of the influence of experimental input parameters in orbital stability analysis led to interesting results. One of the main issues relative to this technique is the necessity to properly describe the dynamical system, in order to obtain a reliable orbital stability index; hence, the definition of the state space is of crucial importance for the outputs. The coherence between the results obtained with differently composed state spaces showed that the same stability output can be obtained with different implementations and experimental setup, despite the fact that different numbers of gait cycles are necessary. On the other hand, the number of gait cycles necessary to obtain this result is different among these setups; in particular, analysis conducted on accelerometer data required more gait cycles with respect to analysis conducted on joint angles obtained from stereophotogrammetric data.

Experimental noise and operator errors could represent a critical issue when using orbital stability analysis based on joint angles obtained from stereophotogrammetric systems. Further studies are needed to determine if the stability measures obtained from analysis on these state spaces are really capable to discriminate between known stability conditions. Experimental noise on accelerometer data showed no particular influence on the stability results.

Experimental results were also coherent with the model results supporting the validity of the stability outcomes. This result confirms the possibility to obtain reliable orbital stability measures with a single inertial sensor and could lead to advantages in the development of a simple and fast data acquisition protocol, confirming what was found in literature for treadmill walking [57].

III.5. ACKNOWLEDGMENTS

The authors gratefully thank Dr. Martijn Wisse for his contribution in the implementation of the model.

IV. RELIABILITY OF STABILITY AND VARIABILITY MEASURES[3]

IV.1. INTRODUCTION

In order to perform a proper evaluation of gait variability and stability, standardization of implementation parameters is necessary, as outputs can be influenced by implementation differences (e.g. number of strides). Moreover, the consistency of results in the same experimental conditions between the measures must be ensured. The aim of this study is to assess the minimum number of required strides and the test-retest reliability of 11 temporal variability/stability measures proposed in the literature. Analysis was performed on trunk accelerations acquired on a sample of 10 healthy young participants performing an overground walking task. In general, the overall number of strides necessary to obtain a reliable measure was larger than those conventionally used. For some measures (lLE and RQA max/diverg in the vertical direction) 150 strides were not sufficient to obtain a steady value. MSE and RQA showed excellent reliability.

IV.2. METHODS

Ten healthy participants [28 ± 3 years, 174 ± 11 cm, 67 ± 13 kg] walked straight at self-selected natural speed on a 250 m long dead-end road (about 180 strides), wearing two synchronized tri-axial inertial sensors (Opal, APDM, Portland, OR, USA), one on the trunk at the level of the fifth lumbar vertebra and one on the right ankle. The range of the accelerometers was ±6g and sampling rate 128 Hz. Right foot strikes were obtained from the angular velocity measured by the sensor on the ankle with wavelet analysis based method[87]. The first and the last ten strides (time intervals between two consecutive right heel strikes) were excluded from the analysis, in order to exclude gait initiation and termination phases. The Review Board Committee of the authors' institution approved this study, and informed consent was obtained from the participants.

The following variability measures were applied to stride time:

i. SD [89];
ii. CV [89];
iii. IV [21];
iv. NI [21];
v. PSD1, PSD2 [22].

[3] Under review. Riva F, Bisi MC, Stagni R. Gait variability and stability measures: minimum number of strides and test-retest reliability. Submitted to Gait & Posture.

The following stability measures were calculated on trunk accelerations in vertical (V) medio-lateral (ML) and anterior-posterior (AP) directions.

vi. maxFM [34,49]. Four different state spaces were constructed: one 3-dimensional state space composed by acceleration signals in the V, ML and AP direction and three (one per direction) 5-dimensional state spaces composed by delay-embedding of each acceleration component (delay = 10).
vii. sLE, lLE [34]. The same state spaces constructed for maxFM were analyzed.
viii. RQA [47]. Same state space construction as for maxFM and LE was used. Recurrence rate (rr), determinism (det), averaged diagonal line length (avg), maximum diagonal line length (max) and divergence (diverg) were calculated from the recurrence plot (radius = 40%).
ix. MSE [45]. Sample entropy (consecutive data points $m = 2$, distance $r = 0.2$) was calculated on six consecutively more coarse-grained (scale factor $\tau = 1, \ldots, 6$) time series.
x. HR [42]. HR was not calculated stride by stride, but decomposing the whole signal into its harmonics.
xi. IH [43].

For the quantification of the **minimum number of strides**, measures were calculated on windows of decreasing length (from 150 to 10 strides, 1 stride resolution). Percent interquartile/median ratio (*imr*) was calculated for all the windows, starting from the 150 strides window (which gave the lowest ratio) and proceeding backwards. Thresholds for the *imr* were fixed at 10%, 20%, 30%, 40% and 50%. The required number of strides was defined as the smallest one at which the ratio remained below the lowest possible threshold. The minimum number of strides was first calculated per index and per subject, then for each index the largest number of strides over subjects was selected.

The assessment of **test-retest reliability** was performed calculating variability/stability measures on a window sliding (with 1 stride steps) along the trial. The sliding window was sized at 85 strides because this number of strides comprised the minimum number of strides for most measures (51 out of 57). lLE (tot, V, ML, AP) and RQA V (max, diverg) didn't satisfy this criterion. Interquartile and median values of the measures over the windows were calculated, and the percent *imr* for each measure was calculated. Measures were grouped in five reliability categories, ranging from very poor (*imr* > 40%) to excellent (*imr* < 10%). The maximum inter-subject *imr* was considered for grouping.

IV.3. RESULTS

Measures reached steady values for different number of strides, depending on the threshold. For MSE V ($\tau = 1, \ldots, 4$) and RQA (AP rr, det, avg, ML rr and V rr, det, avg), 10 strides were sufficient to reach a 10% threshold. MSE (AP, ML, V $\tau = 5,6$), RQA (ML det, avg) and sLE V reached a 20% threshold within 10 strides. Other measures showed lower stride number requirement with the increasing of the threshold. lLE required a high number of strides (> 110) even for the 50% threshold. RQA (V max, diverg), never reached steady values in the analyzed range (150 strides). Detailed results are shown in Table IV.1.

Table IV.1 - Number of required strides for each measure at each threshold.

	Thresholds				
Variability/stability	10%	20%	30%	40%	50%
SD	125	59	20	15	10
CV	127	59	49	15	10
NI	143	97	89	78	70
IV	143	91	44	35	29
PSD1	127	52	16	15	10
PSD2	120	106	74	25	19
MSE AP $\tau = 1$	19	10	10	10	10
MSE AP $\tau = 2$	19	10	10	10	10
MSE AP $\tau = 3$	18	10	10	10	10
MSE AP $\tau = 4$	15	10	10	10	10
MSE AP $\tau = 5$	35	10	10	10	10
MSE AP $\tau = 6$	17	10	10	10	10
MSE ML $\tau = 1$	10	10	10	10	10
MSE ML $\tau = 2$	30	10	10	10	10
MSE ML $\tau = 3$	63	10	10	10	10
MSE ML $\tau = 4$	31	10	10	10	10
MSE ML $\tau = 5$	10	10	10	10	10
MSE ML $\tau = 6$	32	10	10	10	10
MSE V $\tau = 1$	10	10	10	10	10
MSE V $\tau = 2$	10	10	10	10	10
MSE V $\tau = 3$	10	10	10	10	10
MSE V $\tau = 4$	10	10	10	10	10
MSE V $\tau = 5$	12	10	10	10	10
MSE V $\tau = 6$	15	10	10	10	10
RQA AP (rr)	10	10	10	10	10
RQA AP (det)	10	10	10	10	10
RQA AP (avg)	10	10	10	10	10
RQA AP (max)	121	75	74	37	36
RQA AP (diverg)	107	95	74	74	74
RQA ML (rr)	10	10	10	10	10
RQA ML (det)	78	10	10	10	10
RQA ML (avg)	55	10	10	10	10
RQA ML (max)	136	129	73	29	29
RQA ML (diverg)	136	135	79	29	29
RQA V (rr)	10	10	10	10	10
RQA V (det)	10	10	10	10	10
RQA V (avg)	10	10	10	10	10
RQA V (max)	150	150	150	150	150
RQA V (diverg)	150	150	150	150	150
HR AP	141	26	15	10	10
HR ML	137	30	10	10	10
HR V	66	29	10	10	10
IH AP	143	141	137	75	10
IH ML	145	141	49	10	10
IH V	140	127	120	18	11
maxFM tot	137	135	23	10	10
maxFM AP	138	137	132	10	10
maxFM ML	137	131	14	10	10
maxFM V	137	51	20	10	10
sLE tot	105	70	10	10	10
sLE AP	90	17	10	10	10
sLE ML	72	10	10	10	10
sLE V	63	10	10	10	10
lLE tot	139	132	130	128	124
lLE AP	141	135	132	131	129
lLE ML	146	125	119	114	110
lLE V	138	123	121	116	113

Table IV.2 - Values of the maximum inter-subjects *imr* with corresponding reliability grouping. Measures have been grouped based on the maximum inter-subject percentage *imr*. Reliability has been labeled as Very poor (*imr* > 40%), Poor (*imr* = 30-40%), Average (*imr* = 20-30%), Good (*imr* = 10-20%), Excellent (*imr* < 10%). As an indication of reference values for the measures, median values of inter-subjects medians and interquartile ranges for variability/stability measures are also shown.

	Variability/stability measures	Median inter-subject value of the medians	Median inter-subject interquartile value	Maximum inter-subject *imr*
Excellent	MSE AP $\tau = 1$	0.38	0.01	0.07
	MSE AP $\tau = 2$	0.56	0.02	0.07
	MSE AP $\tau = 3$	0.65	0.02	0.06
	MSE AP $\tau = 4$	0.76	0.02	0.07
	MSE AP $\tau = 5$	0.81	0.02	0.08
	MSE AP $\tau = 6$	0.85	0.02	0.07
	MSE ML $\tau = 1$	0.59	0.01	0.08
	MSE ML $\tau = 2$	0.86	0.02	0.08
	MSE ML $\tau = 3$	1.09	0.03	0.07
	MSE ML $\tau = 4$	1.31	0.03	0.06
	MSE ML $\tau = 5$	1.46	0.04	0.06
	MSE ML $\tau = 6$	1.55	0.04	0.06
	MSE V $\tau = 1$	0.46	0.01	0.05
	MSE V $\tau = 2$	0.63	0.02	0.05
	MSE V $\tau = 3$	0.74	0.02	0.07
	MSE V $\tau = 4$	0.84	0.03	0.09
	MSE V $\tau = 5$	0.92	0.03	0.07
	MSE V $\tau = 6$	1.00	0.03	0.09
	RQA AP (rr)	15.65	0.06	0.07
	RQA AP (det)	69.3	1.1	0.05
	RQA AP (avg)	8.94	0.12	0.07
	RQA ML (rr)	8.50	0.12	0.03
	RQA ML (det)	49.7	0.8	0.09
	RQA ML (avg)	6.67	0.12	0.07
	RQA V (rr)	13.76	0.22	0.06
	RQA V (det)	81.9	0.5	0.03
	RQA V (avg)	13.58	0.28	0.08
Good	HR AP	3.70	0.14	0.15
	HR ML	2.21	0.11	0.13
	HR V	4.68	0.24	0.16
	PSD1	0.021	0.001	0.14
Average	sLE AP	0.67	0.14	0.26
	sLE ML	0.81	0.14	0.20
	sLE V	0.89	0.19	0.28
	SD	0.02	0.002	0.23
	CV	1.94	0.14	0.23
Poor	IH ML	0.15	0.02	0.37
	PSD2	0.021	0.002	0.34
	sLE tot	0.44	0.10	0.39
	NI	0.52	0.10	0.30
	IV	0.32	0.06	0.37
Very poor	maxFM tot	0.36	0.09	0.57
	maxFM AP	0.43	0.08	0.45
	maxFM ML	0.39	0.06	0.44
	maxFM V	0.48	0.08	0.44
	IH AP	0.04	0.01	0.50
	IH V	0.022	0.003	0.55
	RQA AP (max)	399	51	0.66
	RQA AP (diverg)	0.0025	0.0003	1.64
	RQA ML (max)	281	39	0.88
	RQA ML (diverg)	0.0036	0.0004	0.69
	RQA V (max)	1986	481	0.96
	RQA V (diverg)	0.0005	0.0002	1.76
	lLE tot	0.035	0.007	0.89
	lLE AP	0.035	0.008	1.12
	lLE ML	0.014	0.004	0.52
	lLE V	0.041	0.007	0.57

MSE and RQA (rr, det, avg) showed excellent reliability. HR and sLE demonstrated average to good reliability, with the exception of sLE (tot) that performed poorly. Temporal variability measures (SD, CV, IV, NI and PSD) showed from poor to good reliability. IH showed poor reliability, particularly in AP and V directions. lLE, maxFM and RQA (max, diverg) showed very poor reliability. Reliability results are shown in Table IV.2. Median values of inter-subjects medians and interquartile ranges for variability/stability measures, together with maximum *imr* values, are also shown. These values are meant to give an indication of reference values for the measures.

IV.4. DISCUSSION

The aim of this study was to investigate the minimum number of strides required and the test-retest reliability of a number of gait variability/stability measures. In general, measures showed comparable performances between the reliability indication and the threshold reached for a corresponding number of strides (85).

MSE (ML $\tau = 1, 5$ and V $\tau = 1, \ldots, 4$) and RQA (AP rr, det, avg, ML rr and V rr, det, avg) reached a steady value for a 10% threshold within 10 strides. MSE and RQA (rr, det, avg) also showed excellent reliability. sLE (ML, V) showed that the 10% threshold could be reached for 85 strides, but inter-subject *imr* was slightly higher (0.20 and 0.28 respectively); this is likely due to the influence of the inherent variability of the trial. SD and CV showed average reliability and a quite high number of strides (respectively 125 and 127) to undergo the 10% threshold. This confirms findings from other studies stating that a few number of strides may not be sufficient to obtain reliable measures. While other studies in the past tested the reliability of variability gait parameters, the instrumentation used was different, making it hard to directly extrapolate results from those studies to other instruments. A high number of required strides was found for lLE and RQA (V max, diverg). The former measure required at least 110 strides to reach the 50% threshold, while the latter never reached steady values in the analyzed range. IH, maxFM, sLE and RQA (max, diverg) showed poor or very poor reliability.

In conclusion, of the 11 variability/stability measures that were tested, only MSE and RQA (rr, det, avg) showed excellent reliability. In general, the number of strides necessary to obtain a reliable measure was larger than those conventionally used.

V. ESTIMATING FALL RISK WITH INERTIAL SENSORS USING GAIT STABILITY MEASURES THAT DO NOT REQUIRE STEP DETECTION[4]

V.1. INTRODUCTION

Many gait stability measures proposed in the literature are based on the identification of gait cycles [17,22,34,90,91]. Several methods for step detection have been presented in the literature [87,92,93], based on different techniques and sensor positioning. Errors in step detection can, however, critically affect stability outcomes, making step detection a possible intrinsic source of error for stability calculations; examples are present in the literature of inability in the detection of gait events due to irregular acceleration patterns [94] and incorrect identification of acceleration peaks in correspondence of foot strike [95]. Other temporal parameters detection systems, such as foot switches or pressure sensors attached to the sole, suffer from difficulties in sensor attachment when assessing subjects with abnormal gait; even when correctly done, several problems limit their applicability [87]. Step detection can hence be invalidated by unexpected gait behaviour resulting in atypical signals, which can reflect possible informative gait characteristics or anomalies in the execution of the motor task, such as a shuffling gait. Assuming that such anomalies are more common among people with a high fall risk, such errors may even cause a bias when calculating gait stability measures. To overcome this possible source of error, nonlinear analysis techniques may offer a powerful tool. In particular, some of these stability related measures do not depend on step detection and can provide insights into the mechanisms underlying dynamic stability of walking. In this study the HR [42,44], the IH [43], MSE [45], and RQA measures [48] of trunk accelerations during gait were calculated [42–45,47,48]. The relationship between these measures and fall risk has not been analyzed and reported yet.

The aim of the present study was to investigate the association between fall history and the aforementioned measures during treadmill walking in a large sample of older subjects. The data used have been described earlier in a paper on local dynamic stability and stride variability of gait [39]. Both of these measures were shown to be associated with fall risk, but do rely on step detection.

[4] In press. SIAMOC methodological award 2012. Riva F, Toebes MJP, Pijnappels M, Stagni R, van Dieën JH. Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. Gait & Posture, in press.

V.2. MATERIALS AND METHODS

V.2.1. Participants

A total of 131 healthy subjects (age 62.4 ± 6.1 years; height 171 ± 8 cm; body mass 74 ± 10 kg) aged between 50 and 75 participated in the study, after giving informed written consent. Subjects were recruited and tested at a fair aimed at people of 50 years and older. Subjects were included if they were aged between 50 and 75 years and able to walk on a treadmill without aids. Additional details have been reported by Toebes et al. [39]. Three subjects from the original data set were excluded from the analysis due to technical problems during data acquisition.

V.2.2. Protocol

Participants walked on a treadmill at 4 km/h for 12-17 minutes, wearing an inertial sensor (Dynaport Hybrid, McRoberts B.V., The Hague, The Netherlands) located on the trunk, below the shoulder blades. Sensing range was ± 2g and sample frequency was 100 Hz. The first 5-10 minutes of walking were excluded from the data collection, to allow the subject to familiarize with treadmill walking. Data of the subsequent 3 minutes of walking were acquired. Fall history was obtained by self-report; a subject was classified as a faller if at least one fall had occurred in the 12 months prior to the measurements. 42 subjects (32.1%) experienced at least one fall in the year previous to the experiment. To estimate the habitual physical activity in daily life, the Longitudinal Aging Study Amsterdam Physical Activity Questionnaire (LAPAQ) was used. The LAPAQ data were used to calculate the total physical activity score (in MET·minutes·per day) [96]. Subjects were classified as experienced treadmill walkers if they had walked on a treadmill at least two times previously.

V.2.3. Data analysis

Accelerations of the trunk in the anterior-posterior (AP) and medio-lateral (ML) directions were analyzed. Vertical acceleration signals showed clipping artefacts (on average 0.34% of the signal) in 52% of the subjects, and were therefore not considered in the analysis. HR, IH, MSE and RQA were calculated on AP and ML accelerations of the trunk.

V.2.4. Statistical analysis

To assess differences in demographics, treadmill experience and physical activity between fallers and non-fallers, Mann-Whitney U-test, independent samples t-test and chi-square test were used. SPSS Statistics 20.0 (IBM, Armonk, NY, USA) was used for all statistical tests. Statistical significance for all statistical tests was declared if $p < 0.05$.

A factor analysis was performed to assess to what extent the resulting 24 different measures (HR, IH, MSE at 6 different scales and 4 RQA measures, both in AP and ML directions) reflect different properties of the dynamics. To correct for non-normality, all measures were log transformed and then used as input for factor analysis. The scree plot was used to determine the number of extracted factors, and VariMax rotation was used to optimize the loading of variables onto factors.

Log transformed measures were then used as inputs for univariate logistic regression models, to test if measures were able to classify subjects as fallers or non-fallers, considering self-report as the gold standard. The resulting regression models were then checked for confounders (demographic variables, treadmill experience and physical activity score). In addition, a multivariate, forward step-wise logistic regression model was constructed using the most representative variables of each factor as predictors, i.e. the variable with the highest factor loading for each factor. Potential confounders were added to the models one by one and retained when they changed the coefficients by more than 10%.

V.3. RESULTS

Factor analysis on the 24 log transformed measures led to 7 factors (Table 1), accounting for 89% of the variance (all eigenvalues > 0.8). In general, absolute factor loading values were > 0.5, with the exception of HR in AP direction, which had cross loading on 3 factors and was considered non-specific to a factor. RQA parameters in AP direction showed quite high (absolute value > 0.4) loading on two factors. Parameters of MSE, IH, RQA in the ML direction and HR in the ML direction showed loadings on different factors, reflecting the description of different system dynamics. Furthermore, parameters for the trunk kinematics in the ML and AP were largely independent as reflected in the factor loadings. In summary, Factor 1 mainly reflected AP entropy and recurrence characteristics, Factor 2 reflected ML entropy, Factor 3 reflected ML recurrence characteristics, Factor 4 reflected ML harmonicity, Factor 5 reflected AP harmonic ratio, Factor 6 reflected AP harmonicity, and Factor reflected 7 ML harmonic ratio.

Univariate associations with fall history were found for MSE and RQA measures in the AP direction (Table 2). The best classification results were obtained for MSE with scale factor $\tau = 2$ ($p < 0.001$) and for maximum length of diagonals in RQA ($p = 0.002$), which correctly classified 72,5% (sensitivity 21.4%, specificity 96.6%) and 71% (sensitivity 16.7%, specificity 96.6%) of cases, respectively. All MSE measures in AP direction showed correlations > 70%. Other measures showed no significant association with fall history (Figure V.1, Table V.2). The multivariate model retained only AP direction MSE with $\tau = 3$, and this model yielded slightly worse classification than the model using MSE with $\tau = 2$. All models were checked for possible confounders (demographics, physical activity score, treadmill experience); none of the variables changed the coefficients by more than 10%.

As reported previously by Toebes et al. [39], no significant differences were found between fallers and non-fallers regarding demographic variables, physical activity score and treadmill experience.

Table V.1 - Loading of log transformed variables after factor analysis. Absolute loadings > 0.4 are shown.

Stability measure	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
HR ML							0.951
HR AP	-0.498				0.790		
MSE ML (τ = 1)		0.938					
MSE ML (τ = 2)		0.946					
MSE ML (τ = 3)		0.970					
MSE ML (τ = 4)		0.961					
MSE ML (τ = 5)		0.899					
MSE ML (τ = 6)		0.823					
MSE AP (τ = 1)	0.913						
MSE AP (τ = 2)	0.960						
MSE AP (τ = 3)	0.968						
MSE AP (τ = 4)	0.960						
MSE AP (τ = 5)	0.947						
MSE AP (τ = 6)	0.919						
IH ML				0.860			
IH AP						0.901	
RQA ML rr				0.884			
RQA ML det			0.716				
RQA ML avg			0.848				
RQA ML max			0.764				
RQA AP rr	-0.837						
RQA AP det	-0.721						
RQA AP avg	-0.725		0.448				
RQA AP max	-0.701		0.437				

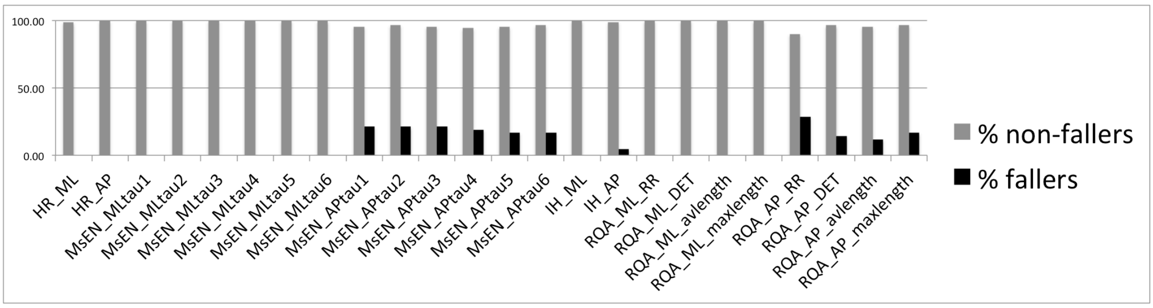

Figure V.1 – Classification results

Table V.2 - Result of the univariate logistic regression models. Regression coefficient (β), p-value (p) and 95% confidence interval of β (95% CIβ) are shown.

Stability measure	β	p	95% CI_β
HR ML	3.135	0.113	-0.74 – 7.01
HR AP	-2.016	0.183	-4.98 – 0.95
MSE ML (τ = 1)	1.579	0.689	-6.15 – 9.31
MSE ML (τ = 2)	0.208	0.951	-6.44 – 6.86
MSE ML (τ = 3)	1.119	0.75	-5.78 – 8.02
MSE ML (τ = 4)	1.915	0.63	-5.87 – 9.70
MSE ML (τ = 5)	3.861	0.376	-4.68 – 12.41
MSE ML (τ = 6)	4.525	0.312	-4.25 – 13.30
MSE AP (τ = 1)	8.994	0.002	3.34 – 14.65
MSE AP (τ = 2)	9.138	0.001	3.68 – 14.60
MSE AP (τ = 3)	9.191	0.001	3.82 – 14.56
MSE AP (τ = 4)	8.594	0.001	3.39 – 13.80
MSE AP (τ = 5)	7.750	0.002	2.80 – 12.70
MSE AP (τ = 6)	7.010	0.004	2.26 – 11.76
IH ML	-3.102	0.105	-6.85 – 0.65
IH AP	-4.072	0.128	-9.32 – 1.17
RQA ML rr	-2.688	0.14	-6.26 – 0.89
RQA ML det	-0.470	0.843	-5.11 – 4.17
RQA ML avg	0.106	0.959	-3.94 – 4.16
RQA ML max	-0.001	0.999	-0.94 – 0.94
RQA AP rr	-8.510	0.999	-13.12 – -3.61
RQA AP det	-4.197	0.001	-7.34 – -1.05
RQA AP avg	-6.485	0.009	-11.04 – -1.94
RQA AP max	-2.410	0.005	-3.90 – -0.92

V.4. DISCUSSION

Nonlinear measures can provide useful insights in the dynamics of gait, and in particular of gait stability. Currently, fall risk is mainly inferred from fall incidence, but this method obviously provides information only after the fact and has proven to be unreliable, especially when dealing with subjects with memory impairments [97]. Alternative fall risk measures are hence needed, and quantitative nonlinear dynamic measures applied to acceleration signals could represent a viable alternative to more traditional fall risk assessment methods; accelerometric systems are very useful for clinical purposes, as they are small, light and portable. Some of these measures (HR, IH, MSE and RQA were analyzed in the present study) do not require stride detection, excluding a possible source of error. This study aimed to explore the relationship of such measures (HR, IH, MSE and RQA were analyzed in the present study) with fall history.

In the literature, one study[39] assessed the association between ’linear and nonlinear measures (namely gait variability and Lyapunov exponents), concluding that these parameters were, individually and combined, positively associated with fall history. Another study [14] investigated the association between Lyapunov exponents and tendency to fall in older adults, but on a significantly smaller sample. The nonlinear measures implemented in our study have already been applied to gait parameters [42,43,45,47], but their relationship with fall history has, to authors' knowledge, not been investigated yet.

The factor analysis on the analyzed measures highlighted a quite sharp separation (Table V.1), supporting the hypothesis that the techniques describe different aspects of the system dynamics; each one of these aspects can reflect different aspects of locomotion features, and could contribute information related to fall risk.

Although previously effects of age were shown for HR in AP direction [98], HR and IH did not show any correlation with fall history in our sample. Harmonicity of oscillations and rhythmicity of the accelerations of the trunk hence seem not to provide useful information for fall risk assessment.

Costa et al. found that the spontaneous output of the human locomotor system during usual walking is more complex than walking under slow, fast or metronome paced protocols [45]. The association between MSE and fall history found in the present study seems to suggest that complexity can also be related to fall risk. Modifications in complexity could reflect alterations in locomotor strategy that affect stability. In particular, MSE with a scale factor $\tau = 2$ led to the best classification results, suggesting that frequencies in the band of 17-25 Hz contribute the most; in fact, operating two coarse graining procedures on gait acceleration signal would filter frequencies higher than 25 Hz, while operating three would filter frequencies higher than 17 Hz.

The present findings seem to suggest higher complexity of gait kinematics in subjects with a fall history, while previous studies have associated higher entropy with better health [46,99]. This is perhaps not surprising, since nonlinear time series analysis often showed contradictory results also when applied in the same context, as it has been demonstrated for FM [49]. Also, non-monotonic relationships could exist. Moreover, results of nonlinear time series analysis of gait accelerations also strongly depend on sensor placement [42].

A previous study [47] used RQA to differentiate healthy and hypovestibular subjects; our findings extend this result, showing that RQA can discriminate between healthy subjects and fall-prone subjects. In the present study, RQA measures, and in particular the maximum length of diagonal structures in recurrence plots, were found to correlate with fall history. RQA (max) is strictly related to the mechanical concept of stability in terms of Lyapunov exponents; in fact, its inverse (called divergence) can roughly reflect the largest Lyapunov exponent [48,100,101]. These results are in line with the existing literature showing an association between short term Lyapunov exponents and fall history [39]. Whereas these two measures express theoretically similar concepts, the calculation process is different; in particular, as stated above, the RQA algorithm does not depend on stride detection.

For all gait variables, specificity of the associations with fall history was low (maximally 21.4%). This may imply that the present methods are not yet suitable to identify individuals at risk of falling and thus the target group for interventions. Combinations with other variables in a multivariate prediction model, e.g. variables that reflect physical capacity, may be necessary. On the other hand, fall history may comprise a substantial number of incidental falls in subjects, exposed to high-risk events, who may not necessarily have an increased risk due to intrinsic factors.

A possible limitation of the present study is the fact that subjects walked on a treadmill; hence, conclusions cannot be directly transferred to over-ground walking, due to the differences between the two motor tasks [38,102]. Moreover, no procedure was applied to precisely standardize the acceleration signals direction, in terms of sensor placement; however, due to the intrinsic nature of the task and the instrumentation, straight walking was assured. Another limitation is the use of self-report as a gold standard for the classification; despite the disadvantages, this method represents the most established technique for fall risk assessment [8], and hence this choice is unavoidable.

In the literature, a standard implementation for the measures studied here is lacking. Due to the lack of methodological studies, there is no consensus on how to deal with methodological aspects such as sample frequency of the signal, instrumentation noise and trial length. For this reason, comparison of results from different implementations of the same measures is not straightforward. With respect to the length of the trials, these measures, particularly RQA, have often been applied to short trials (a few steps). In the opinion of the authors, the analysis of longer trials is preferable for several reasons: effects of long range dynamics, acclimatization time and the probability that occasional gait anomalies show up during the acquisition. On the other hand, also transfer from our results to less controlled acceleration data obtained during daily activities, in which stride detection is a major problem, needs further exploration.

Further research should address the physiological correlates of these measures; whereas the analysis of acceleration time series give useful information about gait dynamics and fall risk, the physiological conditions leading to differences in complexity or recurrence of locomotion acceleration signals are yet unknown. The identification of the physiological correlates could lead to the development of proper targets for therapies or rehabilitation programs aiming at fall prevention.

In conclusion, nonlinear dynamic measures, in particular MSE and RQA are positively associated with fall history and could contribute to the selection of individuals at risk for participation in fall prevention programs.

VI. ARE GAIT VARIABILITY/STABILITY MEASURES INFLUENCED BY DIRECTIONAL CHANGES?[5]

VI.1. INTRODUCTION

Directional changes represent an essential aspect of gait, since 20-50% of steps performed during daily activity are reported to be turns [24]. As a methodological characterization, an assessment of the influence of directional changes on variability/stability measures is needed in order to evaluate the applicability of the measures, both in controlled laboratory trials and in daily life activity analysis. In this study, nine variability/stability measures were calculated on trunk acceleration data of a sample of healthy young subjects walking in straight walking condition and in presence of directional changes. Since large differences in sampling are believed to affect stability measures [37], the influence of sampling frequency of trunk acceleration data on the results was also analyzed.

The aim of this study was to assess the influence of directional changes on variability/stability measures calculated on trunk acceleration data acquired at different sampling frequencies during gait.

VI.2. METHODS

Fifty-one healthy young adults (23 ± 3 years, 172 ± 11 cm, 68 ± 14 kg) volunteered for this study. All subjects were physically active and self-reported no musculoskeletal or neurological disorders that could affect their performance and/or behavior.

Participants were asked to perform one 6-minute walk test [103]. In particular, they were asked to walk back and forth for 6 minutes along a 30m straight pathway, turning by 180 deg at each end of the pathway, and to cover the maximum possible distance over the 6 minutes and, thus, walking as fast as possible. A 180 deg turn was considered in order to test the limit condition, as it represents the most sharp and potentially hazardous directional change. The Review Board Committee of the authors' institution approved this study, and informed consent was obtained from the participants.

An inertial measurement unit (FreeSense, Sensorize s.r.l) was fixed to the lower trunk of the subjects. Only acceleration data was taken into consideration.

[5] Submitted. Riva F, Grimpampi E, Mazzà C, Stagni R. Are gait variability/stability measures influenced by directional changes?. Submitted to Gait & Posture.

Twenty-six trials were acquired with a sampling frequency equal to 100 Hz and twenty-five trials were acquired at 200 Hz. A third set of data was then obtained from the second group, down-sampling acceleration signals from 200 Hz to 100 Hz, and added to the 100 Hz group. Foot strikes were detected from the vertical acceleration using the algorithm proposed by McCamley et al. [104]. Two portions of signals (about 20 strides each) were extracted for each subject and divided in two groups: straight walking (SW) and walking with directional change (DCW). The number of strides was chosen as the maximum number of strides reachable by the subjects in completely straight walking conditions.

Nine variability/stability measures were calculated. Three temporal variability measures were applied to stride time: SD [21], CV [21] and Poincaré plots (PSD1, PSD2) [22]. Stride times were obtained as the time intervals between two consecutive strikes of the same foot. Six stability measures were calculated on trunk acceleration signals in the vertical (V), medio-lateral (ML) and anterior-posterior (AP) directions: maxFM [34], sLE [34], RQA [47], MSE [45], HR [42] and IH [43]. IV [21], NI [21], lLE [34] and RQA (max, diverg) [47] were also considered, but 20 strides were not deemed to be sufficient to draw accurate conclusions having an intrinsic variability > 50%, based on the results illustrated in Chapter IV. Details on the implementation can be found in Chapter IX (Appendix).

In order to assess the influence of directional changes on the measures, significant differences in results between SW and DCW conditions were calculated. Z-scores between the two conditions were calculated for each measure for the two sampling groups (100 Hz and 200 Hz). Bonferroni-corrected p-values for each measure at each sampling condition were then calculated based on the z-scores. Measures were selected based on the capability to discriminate between the two conditions ($p < 0.05$) for the majority (> 20 for 200 Hz group, > 40 for 100 Hz group) of subjects. The increasing or decreasing effect of directional changes has also been assessed, based on the sign of the mean value of the difference between measures obtained in SW and DCT conditions.

VI.3. RESULTS

Only HR was found to be affected by directional changes, both at 200 Hz and at 100 Hz. HR decreased when a directional change was present in the task. HR was affected in the AP and V directions for the 200Hz, but only in AP direction for the 100Hz group.

Other measures (SD, CV, PSD1, PSD2, MSE, RQA, maxFM and sLE) were not found to be affected by directional changes in the walk.

VI.4. CONCLUSION

Variability measures based on stride time were generally found to be not affected by directional changes. It is likely that the stride times suffered minor modifications during the 180 deg turn, hence not significantly influencing measures based on its variability.

HR was the only measure found to be affected by directional change. In particular, it was affected when applied to AP and V accelerations, but not when ML accelerations were analyzed.

IH, maxFM, sLE and RQA were not found to be affected by directional changes. MSE, sLE and RQA also recently proved to be related to fall history in treadmill walking tests [39,105].

The sampling frequency had effects on the measures, but only related to the direction of the acceleration. At 100 Hz, only HR in the AP direction was found to be affected by directional change, while at 200 Hz AP and V directions were affected. This is likely caused by the loss of information induced by the lower sampling frequency.

In conclusion, temporal variability measures were not affected by directional changes. IH, MSE, sLE and RQA were not affected by of directional changes. In particular, MSE, sLE and RQA could contribute to the definition of a fall risk index in free-walking conditions, based on their previously demonstrated association with fall history [39,105]. Further research is needed to assess the capability of these measures to identify fall-prone subjects in an overground walking task.

VII. STABILITY OF WALKING AND SHORT TERM FALL-HISTORY

VII.1. INTRODUCTION

The assessment of the association between variability/stability measures and fall history should highlight if these indicators are capable to detect any eventual *structural* alteration in gait patterns. The application of such measures to portions of acceleration signal that are located in the proximity of a fall should instead assess the capability of such indicators to detect if the gait pattern undergo a particular modification which may cause a critical loss of stability. The detection of this *temporary* modification may become particularly evident in the case of fall-prone pathological subjects, which can experience several falls even in a short period of time.

Ten variability/stability measures were applied to a database of trunk acceleration data acquired during a 24 hour monitoring of 20 parkinsonian fall-prone subjects affected by progressive supranuclear palsy. The subjects experienced a fall during the monitoring, hence allowing to know the temporal distance from the fall episode and the analyzed walking window. The aim of the study was to test if variability/stability measures can i) discriminate between the close-to-a-fall and the far-from-a-fall conditions; ii) discriminate between unfrequent faller and frequent faller subjects; iii) discriminate between the pre-fall and the post-fall conditions. In addition, a case study was analyzed in order to iv) observe the behavior of variability/stability measures in the very proximity (< 30 minutes) of a fall episode compared to a far-from-a-fall condition.

VII.2. METHODS

Twenty elderly subjects (7 unfrequent fallers, 13 frequent fallers) affected by Progressive supranuclear palsy (PSP) were monitored in daily activity for 24h, using an accelerometer located on the trunk (data were supplied by Bagalà et al., University of Bologna). A subject was classified as frequent faller if his fall rate was ≥ 1 fall/month.

Five subjects fell during the registrations. For some subjects, more than one 24h registration was available, and thus were considered to be additional subjects. This led to a total of ten subjects who fell during the registrations that were considered for the analysis. Trunk acceleration signals relative to three windows containing only walking activity were extracted. Each window included a number of strides comprised between 30 and 70. In order to obtain comparable results among the subjects, 30 strides for each window were used for the analysis.

Ten variability/stability measures were calculated on the three windows. Six temporal variability measures were applied to stride time: SD [21], CV [21], IV [21] and Poincaré plots (PSD1, PSD2) [22]. Stride times were obtained as the time intervals between two consecutive strikes of the same foot, detected from the AP trunk acceleration with a peak detection method [92]. Four stability measures were calculated on trunk acceleration signals in the vertical (V), medio-lateral (ML) and anterior-posterior (AP) directions: Recurrence quantification analysis (RQA) [47], Multiscale entropy (MSE) [45], Harmonic ratio (HR) [42] and Index of harmonicity (IH) [43]. NI [21], lLE [34] were also considered, but the number of strides included in the windows (30 strides) was not deemed to be sufficient to draw accurate conclusions, having an intrinsic variability > 50% based on the results illustrated in Chapter IV. Based on the same results, for RQA (max, diverg) [47] only ML direction was considered. Details on the implementation can be found in Chapter IX (Appendix).

Four different analyses were performed on the sample: i) a comparison between the close-to-a-fall (CF) and the far-from-a-fall (FF) conditions; ii) a comparison between variability/stability measures calculated on unfrequent fallers (UnF) and frequent fallers (FrF); iii) an overall analysis on the pre-fall (PrF) and post-fall (PoF) condition; iv) a case study analysis on a subject for which the walking windows were extracted particularly close to a fall (< 30 minutes).

VII.2.1. Close to a fall / Far from a fall

In order to define the CF and FF conditions, a threshold equal to 8 hours was set, being the median of the time distances from the nearest fall of all the extracted windows. Two windows for each subject were considered, one close to the fall and one far from the fall, disregarding if the fall episode occurred before or after the extracted window. Three subjects satisfied this criterion, and hence were selected for the analysis.

Z-scores for each subject were calculated between the results of the measures in the two conditions (CF and FF), using as variance the between-subjects median value of the interquartile obtain in a previous study (see Chapter IV). Bonferroni-corrected p-values were then obtained.

VII.2.2. Unfrequent fallers / Frequent fallers

Two groups were created. The first was composed by measures calculated on unfrequent fallers windows (UnF). The second was composed by measures calculated on the windows that were considered to be far from a fall (time distance > 8 hours) of frequent fallers that experienced a fall during the registrations (FrF). To assess the differences between the two groups, a t-test was performed.

VII.2.3. Pre-fall / Post-fall

Measures calculated on the windows for all the subjects were re-grouped, disregarding the information relative to the subjects, in two groups (PrF and PoF), based only on the sign of the time distance from the nearest fall. To assess the differences between the two groups, a t-test was performed.

VII.2.4. Single subject case study

A single subject with a favorable location of the time windows with respect to the fall episode was analyzed. The three time windows extracted were located at 18m before the fall episode (PrF), 30m (PoF) and 20h after the fall episode (FF).

Z-scores of measures between the PrF/PoF and the FF condition were calculated, using as variance the between-subjects median value of the interquartile obtain in a previous study (see Chapter IV). Bonferroni-corrected p-values of the two conditions in relation to the FF condition were then obtained.

VII.3. PRELIMINARY RESULTS

VII.3.1. Close to a fall / Far from a fall

HR, MSE AP (τ = 2, …, 6), RQA ML (diverg) and IV didn't highlight any difference between the CF and the FF condition for all the three subjects. SD, CV, IH (ML, V), PSD1, PSD2, MSE V (τ = 2, 3, 5), RQA AP (rr, det, avg), RQA ML (rr, det, avg) and RQA V (det) found statistically significant differences between the two conditions for all the three subjects. Results are illustrated in Table VII.1.

VII.3.2. Unfrequent fallers / Frequent fallers

HR (AP, V), IH (AP, V) and RQA (AP det, ML det, V diverg) found statistically significant differences between the UnF and the FrF groups. Other measures didn't find any difference.

VII.3.3. Pre-fall / Post-fall

Only PSD1 was found to be significantly different between the PrF and the PoF condition. Other measures didn't highlight any difference.

VII.3.4. Single subject case study

HR, MSE AP (τ = 4, …, 6) and RQA V (max) didn't highlight any difference between the PrF/PoF and the FF condition. RQA V (avg, diverg) and NI didn't find differences between the PrF condition and the FF condition. MSE AP (τ = 1, …, 3), RQA ML (diverg), RQA V (rr) and IV didn't find any differences between the PoF condition and the FF condition. All other measures were found to be significantly different between the PrF/PoF and the FF condition.

Table VII.1 – Significance of measures between the CF and FF condition

Significantly different for 3/3 subjects	Significantly different for 2/3 subjects	Significantly different for 1/3 subjects	Non significantly different
IH (ML, V)	IH (AP)	MSE AP ($\tau = 1$)	HR (AP, ML, V)
PSD1	MSE ML ($\tau = 1, .., 6$)	RQA ML (max)	MSE AP ($\tau = 2, \ldots, 6$)
PSD2	MSE V ($\tau = 1, 4, 6$)		RQA ML (diverg)
MSE V ($\tau = 2, 3, 5$)	RQA V (rr, avg)		IV
RQA AP (rr, det, avg)			
RQA ML (rr, det, avg)			
RQA V (det)			
SD			
CV			

VII.4. CONCLUSION

A possible limitation of the studies i) and ii) is the large temporal threshold (8 hours) that had to be fixed in order to separate subjects in the CF and FF conditions. Temporal variability measures (SD, CV, PSD1, PSD2) were found to be different in proximity of a fall episode. In particular, PSD1 was also capable to highlight differences between the pre- and post-fall conditions. HR, IH and RQA showed to be sensitive to the frequency of the falls experienced by the subjects, being capable to discriminate between frequent and unfrequent fallers, although not for all acceleration directions. MSE and RQA showed different behaviors, highly influenced by the direction of the trunk acceleration. Particularly interesting is the result of MSE AP ($\tau = 1, \ldots, 3$), which performed poorly in discriminating between CF and FF when the threshold was high, but was able to discern between the two conditions in the very few minutes before a fall. Having been associated with fall history [105], this measure seems capable to reflect potentially critical changes in the gait pattern. However this result has been obtained from a single subject, and conclusions must hence be drawn carefully.

VIII. CONCLUSIONS

Falls in the elderly pose a serious problem in society, both clinically and economically. From a clinical point of view, falls are often associate with injuries (e.g., hip fractures) [4], and have a negative psychological impact on patients [106]. Moreover, older adults may restrict their activities in response to a fall, leading to a loss of independence and ability to carry out life's routine tasks [107].

In this context, reliable methods for quantifying fall risk are needed, in order to adequately select subject to include in fall prevention programs. Since falls often occur during walking [17,18], assessment of gait stability represents a crucial indicator for fall risk. Many methods (*direct*, *indirect* and *stability-related*) to quantify gait stability are presented in literature; however, the relationship between many of these stability measures and fall history/fall risk is still unknown, and there is still no consensus in the literature on how to correctly interpret the stability indicators and how to effectively implement stability analysis methods to obtain reliable stability outcomes.

The aim of this thesis was to analyze the influence of experimental implementation parameters on stability measures and to understand how variations in these parameters affect the outputs. The assessment of the relationship between dynamic stability measures and long/short-term fall risk was also an objective of this thesis.

In Chapter II a systematic review of the literature on the topic of biomechanical applications of a nonlinear dynamic stability measure (namely orbital stability analysis via maximum Floquet multipliers) is presented. The review highlighted an incoherence among the results of the studies present in the literature, believed to be due mainly to the absence of a generalized methodological procedure to implement orbital stability analysis on biomechanical time series data [49] and confirming the uncertainty regarding how to properly apply stability measures in biomechanics and the association of these measures with risk of fall.

As a consequence of the results obtained from the review, an experimental- and model-based study on the influence of experimental input parameters in orbital stability analysis was performed. The results are presented in Chapter III. One of the main issues relative to this technique is the necessity to properly describe the dynamical system, in order to obtain a reliable orbital stability index; hence, the definition of the state space is of crucial importance for the outputs. The coherence between the results obtained with differently composed state spaces shows that the same stability output can be obtained with different implementations and experimental setup, despite the fact that different numbers of gait cycle are necessary. On the other hand, the number of gait cycles necessary to obtain this result is different among these techniques; in particular, analysis conducted on accelerometer data requires more gait cycles. Experimental noise and operator errors could represent a critical issue when using orbital stability analysis based on joint angles obtained from stereophotogrammetric systems, while experimental noise on accelerometer data showed no particular influence on the stability results. Experimental results were also coherent with the model results, supporting the validity of the stability outcomes.

In Chapter IV, an assessment of the minimum number of strides needed and a test-retest reliability analysis performed on several temporal variability/stability measures is presented. Multiscale entropy and Recurrence Quantification Analysis showed excellent reliability. In general, the number of strides necessary to obtain a reliable measure was larger than those conventionally used.

An analysis of the association between nonlinear stability measures and fall history is presented in Chapter V. In particular, in this study measures independent from stride detection were tested, in order to avoid a potentially critical implementation process. Multiscale entropy and Recurrence Quantification Analysis were found to be positively associated with fall history.

In Chapter VI, the influence of directional changes on variability/stability measures was assessed. Only Harmonic ratio was found to be influenced by directional changes, while measures such as short-term Lyapunov exponents, Multiscale entropy and Recurrence quantification analysis were not.

In Chapter VII, the association of variability/stability measures with short-term risk of fall is presented. Preliminary results showed that Multiscale entropy in the AP direction seems to be able to detect modification in the gait pattern immediately before a fall episode.

In conclusion, several implementation issues have been addressed. Following the need for a methodological standardization of gait variability/stability measures, highlighted in particular for orbital stability analysis through a systematic review, general indications about implementation of orbital stability analysis have been shown, together with an analysis of the number of strides and the test-retest reliability of several variability/stability numbers. Indications about the influence of directional changes on measures have also been provided. Association between measures and long/short-term fall history has also been assessed. Of all the analyzed variability/stability measures, Multiscale entropy and Recurrence quantification analysis demonstrated particularly good results in terms of reliability, applicability and association with fall history. Therefore, these measures should be taken in consideration for the definition of a fall risk index.

IX. APPENDIX

IX.1. STANDARD DEVIATION

Standard deviation (SD) of stride time was simply calculated as the standard deviation of the stride times in the analyzed time-window [17].

IX.2. COEFFICIENT OF VARIATION

Coefficient of variation (CV) was calculated as the SD normalized to each subject's mean stride time [21]:

$$\mathrm{CV} = \frac{SD \times 100}{mean\_stride\_time} \tag{IX.1}$$

IX.3. INCONSISTENCY OF THE VARIANCE

Each time series was first normalized with respect to its mean and SD, yielding new time series each with mean = 0 and SD = 1, but with different dynamic properties. This normalized time series was then divided into blocks of five strides each, and in each segment the (local) average and (local) SD were computed. The inconsistency of the variance (IV) is the SD of the local SD [21].

IX.4. NONSTATIONARY INDEX

Similarly to the IV, the nonstationary index (NI) is defined as the SD of the local averages of the normalized time series's five strides blocks. The nonstationary index provides a measure of how the local average values change during the walk, independent of the overall variance (the fluctuation magnitude) of the original time series. A higher nonstationary index indicates greater range among the local averages [21].

IX.5. POINCARÉ PLOTS

Stride time data plots between successive gait cycles, known as Poincaré plots, show variability of stride time data. Brennan *et al.* [108] provided mathematical expressions that relate each measure derived from Poincaré plot geometry to well-understood existing heart rate variability indexes. Using the method described by Brennan [108], these plots were used to extract indices, such as length (PSD2) and width (PSD1) of the long and short axes describing the elliptical nature of the Poincaré plot images. Statistically, the plot displays the correlation between consecutive stride times data in a graphical manner. Points above the line-of-identity indicate strides that are longer than the preceding, and points below the line of identity indicate shorter strides than the previous ones. The Poincaré plot typically appears as an elongated cloud of points oriented along the line-of-identity. The dispersion of points perpendicular to the line-of-identity reflects the level of short-term variability [108]. The dispersion of points along the line-of-identity is shown to indicate the level of long-term variability [22].

IX.6. ORBITAL STABILITY ANALYSIS

The first step of orbital stability analysis via maximum Floquet multipliers (maxFM) is the state space reconstruction. Two approaches were used: direct inclusion of acquired variables (joint angles/acceleration time series) into the state space, delay-embedding reconstruction. Delay embedding is a technique to reconstruct a dynamical system from a sequence of observations. Standard embedding techniques were used [27,109]; an appropriate state space was reconstructed from each time series and its time delayed copies. An embedding dimension of $d_E = 5$ was always chosen; many studies in literature agree in considering this to be an appropriate dimension for gait data [27,37,56]. A fixed time delay $\tau = 10$ was always used [37,56].

Stride cycles were considered as the time between consecutive right heel strikes and were resampled to be 101 samples long, because Floquet theory assumes that the system is strictly periodic. A Poincaré section was defined at each percentage of the gait cycle (0% = right heel strike).

The Poincaré map:

$$S_{k+1} = \mathrm{F}(S_k) \qquad \text{IX.2}$$

defines the evolution of the state S_k to the state S_{k+1} at each Poincaré section, for each stride k.

The limit cycle trajectory was defined as the average trajectory across all strides. This produces a fixed point in each Poincaré section:

$$S^* = \mathrm{F}(S^*) \qquad \text{IX.3}$$

A linear approximation of Eq. IX.1:

$$[S^{k-1} - S^*] \approx J(S^*)[S^k - S^*] \qquad \text{IX.4}$$

allows calculating how system states diverge from or converge to fixed points. The FM are the eigenvalues of the Jacobian matrix J*(S*)*. The maximum FM (maxFM) is believed to govern the dynamics of the system, and hence to be the most representative in terms of instability. maxFM was calculated for each Poincaré section (0 – 100% of the gait cycle). If the maxFM have magnitude < 1, the system remains stable; otherwise, the system tends to diverge from the limit cycle and become unstable. The overall mean value of maxFM across the gait cycle was calculated and used in the analyses.

IX.7. LOCAL STABILITY ANALYSIS

The first step for local stability analysis is the state space reconstruction (see description in Section IX.6). Local dynamic stability of walking is quantified by estimating the average exponential rates of divergence of initially neighboring trajectories in state space as they evolve in real time. These local divergence exponents provide a direct measure of the sensitivity of the system to extremely small (i.e., local) perturbations. Positive exponents indicate local instability, with larger exponents indicating greater sensitivity to local perturbations. Nearest neighbor points on adjacent trajectories in the reconstructed state space represent the effects of small local perturbations to the system. Euclidean distances between neighboring trajectories in state space were computed as a function of time and averaged over all original pairs of initially nearest neighbors. Local divergence exponents were estimated from the slopes of linear fits to these exponential divergence curves:

$$y(i) = \frac{1}{\Delta t}\langle \ln d_j(i) \rangle \qquad \text{IX.5}$$

where *dj(i)* is the Euclidean distance between the *j*th pair of initially nearest neighbors after *i* discrete time steps (i.e., $i\Delta t$ seconds) and ⟨.⟩ denotes the average over all values of *j*. Since the intrinsic time scales were different for each subject (i.e., different average stride times), the time axes of these curves were rescaled by multiplying by the average stride frequency for each subject. Short-term exponents (sLE) were calculated from the slopes of linear fits to the divergence curve between 0 and 1 stride. Long-term exponents (lLE) were calculated as the slope between 4 and 10 strides [34].

IX.8. HARMONIC RATIO

The Harmonic ratio (HR) was calculated by decomposing the AP and ML acceleration signals into harmonics using a discrete Fourier transform [42]; the summed amplitudes of the first 10 even harmonics were then divided by the summed amplitudes of the first 10 odd harmonics for the AP accelerations, and vice-versa for the ML accelerations. This difference is due to the fact that whereas the AP accelerations have two periods every stride, showing a dominance of the second harmonic, representing step frequency and subsequent even harmonics, ML accelerations have only one period per stride, reflecting a dominance of the first (and subsequent odd) harmonics [42]. In order to avoid errors that might be introduced by step-detection, HR was not calculated stride by stride, but decomposing the whole signal into its harmonics. A higher HR is an indication of increased smoothness of gait, which can be interpreted as increased stability.

IX.9. INDEX OF HARMONICITY

Index of harmonicity (IH) was calculated according to Lamoth et al. [43]. The power spectra of the AP and ML acceleration signals were estimated by means of discrete Fourier transform. The peak power at the first six harmonics was estimated and IH was defined as:

$$\mathrm{IH} = \frac{P_0}{\sum_{i=0}^{5} P_i} \qquad \text{IX.5}$$

where P_0 is the power spectral density of the first harmonic and P_i the cumulative sum of power spectral density of the fundamental frequency and the first five super-harmonics. Values close to 1 indicate high harmonicity (e.g. a sine wave has a power ratio of 1, indicating perfect harmonicity). Power spectral density of each peak was averaged over a range of [-0.1…+ 0.1] Hz around the peak frequency value

IX.10. MULTISCALE ENTROPY

Multiscale entropy (MSE) was implemented constructing consecutively more coarse-grained time series; this procedure implies averaging increasing numbers of data points in non-overlapping windows of length τ. Sample entropy (SE) [110] was then calculated for each coarse-grained time series, in order to obtain entropy measures at different scales; SE quantifies the conditional probability that two sequences of *m* consecutive data points similar (distance of data points inferior to a fixed radius *r*) to each other will remain similar when one more consecutive point is included, thus reflecting the regularity of the time series [45]. SE at each time scale τ is hence a function of *m* and *r* and is expressed as the negative of the natural logarithm of the conditional probability *C(r)* that two sequences that are close within a tolerance $r\delta$ for *m* consecutive points remain close at the next point [111], where δ is the standard deviation of the original series:

$$\mathrm{SE} = -\ln \frac{C^{m+1}(r)}{C^{m}(r)} \qquad \text{IX.6}$$

MSE was hence calculated for values of τ ranging from 1 to 6, m = 2 and r = 0.2, as suggested by Pincus [112] and later applied by Richman and Moorman to biological time series [110].

IX.11. RECURRENCE QUANTIFICATION ANALYSIS

The first implementation step of Recurrence quantification analysis (RQA) is the reconstruction of the phase space by means of delay embedding [109]. In this study, an embedding dimension of 5 and a delay of 10 samples were used, based on previous studies [14,56,113]. A distance matrix based on Euclidean distances between normalized embedded vectors was then constructed; the recurrence plot was obtained by selecting a radius of 40% of the max distance, and all cells with values below this threshold were identified as recurrent points. A radius of 40% was chosen to make sure that recurrence rate (rr) responded smoothly and was not too high, and that determinism (det) did not saturate at the floor of 0 or the ceiling of 100, as approaching these limits would tend to suppress variance in the measure [48].

A number of measures can then be obtained by RQA; in this study, rr, det, averaged diagonal line length (avg) and maximum diagonal line length (max) were calculated (Eq. IX.7, IX.8, IX.9, IX.10), reflecting different properties of the system.

$$\mathrm{rr} = \frac{1}{N^2}\sum_{i,j=1}^{N} R_{i,j} \qquad \text{IX.7}$$

where N is the number of points on the phase space trajectory;

$$\mathrm{det} = \frac{\sum_{l=4}^{N} lP_l}{\mathrm{rr}} \qquad \text{IX.8}$$

where l is the length of diagonal lines, represented through a histogram (P_l);

$$\mathrm{avg} = \frac{\sum_{l=4}^{N} lP_l}{\sum_{l=4}^{N} P_l} \qquad \text{IX.9}$$

$$\mathrm{max} = \ (\{l_i; i = 1 \ldots N_l\}) \qquad \text{IX.10}$$

where N_l is the number of diagonal lines in the recurrence plot.

SE was calculated using MATLAB (Mathworks, Natick, MA) software available on Physionet [114]. All other measures were calculated through custom self-made MATLAB (Mathworks, Natick, MA) scripts.

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XI. SCIENTIFIC WRITING

XI.1. PUBLICATIONS IN INTERNATIONAL JOURNALS

1. Riva F, Bisi MC, Stagni R, *"Orbital stability analysis in biomechanics: a systematic review of a nonlinear technique to detect instability of locomotor tasks"*, **Gait & Posture**, 2013; 37(1): 1-11.
2. Bisi MC, Stagni R, Riva F, *"Biomechanical and metabolic responses to seat-tube angle variation during cycling in tri-athletes"*, **Journal of Electromyography and Kinesiology** 2012; 22(6): 845-51.
3. Riva F, Bisi MC, Stagni R, *"Influence of input parameters on dynamic orbital stability of walking: in-silico and experimental evaluation"*, submitted to **Journal of Biomechanical Engineering**.
4. Riva F, Bisi MC, Stagni R, "*Reliability of stability and variability measures*", submitted to **Gait & Posture**.
5. Riva F, Toebes MJP, Pijnappels M, Stagni R, van Dieën JH, "*Estimating fall risk with inertial sensors using gait stability measures that do not require step detection",* **Gait & Posture**, in press, SIAMOC methodological prize 2012.
6. Riva F, Grimpampi E, Mazzà C, Stagni R, "*Are gait variability/stability measures influenced by directional changes?",* submitted to **Gait & Posture**.
7. Riva F et al. "*Stability of walking and short-term fall history*" to be submitted to **Gait & Posture**.

XI.2. ABSTRACTS PUBLISHED IN PROCEEDINGS OF INTERNATIONAL CONFERENCES

1. Bisi MC, Riva F, Stagni R, Gnudi G, *"Energetics of movement: comparison of two different models for the estimation of muscular energy consumption"*. **Proceedings of GCMAS conference,** May 2010, Miami (Florida, USA).
2. Bisi MC, Riva F, Stagni R, Gnudi G, *"Energetics of movement: comparison of two different models for the estimation of muscular energy consumption"*. **Proceedings of the 17th congress of the European Society of Biomechanics (ESB)**, July 2010, Edinburgh (Scotland).
3. Bisi MC, Riva F, Stagni R, Gnudi G, *"Quantification of energy expended during movement starting from biomechanical information"*. **Proceedings of the IUTAM Symposium**, September 2010, Leuven (Belgium).
4. Riva F, Bisi MC, Stagni R, Cristofolini L, *"Orbital stability of step climbing: analysis of muscle activations in young subjects "*. **Proceedings of the VPH Conference**, September/October 2010, Brussels (Belgium).
5. Riva F, Stagni R, Cristofolini L, *"Orbital stability analysis of human movement: in-silico preliminary evaluation for the definition of experimental trials"*. **Proceedings of GCMAS conference**, April 2011, Bethesda (Maryland, USA).
6. Bisi MC, Riva F, Stagni R, "*A non-invasive protocol to estimate muscle tendon lengths and moment arms through ultrasound images*"**. Proceedings of GCMAS conference**, April 2011, Bethesda (Maryland, USA).
7. Stagni R, Bisi MC, Riva F, *"Subject specific muscle tendon length and moment arm quantification for muscle-skeletal modeling: non-invasive estimate using direct and ultra-sound calibration"*.

Proceedings of the XXIIIrd Congress of the International Society of Biomechanics (ISB), July 2011, Brussels (Belgium).

8. Riva F, Stagni R, Cristofolini L, *"Orbital stability analysis of human movement: in-silico and experimental preliminary evaluation on a stair climbing task"*. **Proceedings of the XXIIIrd Congress of the International Society of Biomechanics (ISB)**, July 2011, Brussels (Belgium).

XI.3. ABSTRACTS PUBLISHED IN PROCEEDINGS OF NATIONAL CONFERENCES

1. Bisi MC, Riva F, Stagni R, Gnudi G. *"Kinetics and energetics during exercise: A model evaluation"*. **Proceedings of the Secondo Congresso Nazionale di Bioingegneria** (**GNB)**, July 2010, Torino (Italy).
2. Riva F, Bisi MC, Stagni R, Cristofolini L, *"Orbital stability of muscle activations during step climbing in young subjects"*. **Proceedings of the Secondo Congresso Nazionale di Bioingegneria** (**GNB)**, July 2010, Torino (Italy).
3. Riva F, Cristofolini L, Stagni R, *"Orbital stability of walking: in-silico assessment of a walking model"*, **Proceedings of the Terzo Congresso Nazionale di Bioingegneria** (**GNB)**, June 2012, Roma (Italy).

XI.4. ABSTRACTS PUBLISHED IN INTERNATIONAL JOURNALS

1. Bisi MC, Riva F, Stagni R, Gnudi G. *"Kinetics and energetics during exercise: A model evaluation"*. **Proceedings of the SIAMOC conference**, October 2009, Alghero (Italy), **Gait & Posture**, 30S1, pag. S50, 2009.
2. Riva F, Bisi MC, Stagni R, Cristofolini L, *"Kinematic orbital stability during step climbing in young subjects"*. **Proceedings of the XI SIAMOC conference**, October 2010, Ferrara (Italy), **Gait&Posture** 33S1, pag. S47, 2011.
3. Bisi MC, Riva F, Stagni R, *"A non invasive protocol to estimate muscle tendon lengths and moment arms through ultrasound images"*. **Proceedings of the XI SIAMOC conference**, October 2010, Ferrara (Italy), **Gait&Posture** 33S1, pagg. S28-S29, 2011.
4. Riva F, Bisi MC, Stagni R, 2011. *"Orbital stability analysis of voluntarily altered gait pattern"*. **Proceedings of the XII SIAMOC conference**, September/October 2011, Bosisio Parini (Lecco, Italy), **Gait & Posture** 35S1, Pages S3-S4, 2012.
5. Bisi MC, Ceccarelli M, Riva F, Stagni R, 2011. "*Biomechanical and metabolic responses to seat-tube angle variation during cycling in tri-athletes*". **Proceedings of the XII SIAMOC conference**, September/October 2011, Bosisio Parini (Lecco, Italy), **Gait & Posture** 35S1, Pages S25-S26, 2012.
6. Riva F, Stagni R, *"In-silico assessment of orbital stability analysis applied to walking"*, **Proceedings of the XVIII Congress of the European Society of Biomechanics (ESB),** July 2012, Lisbona (Portogallo). **Journal of Biomechanics** 45S1, Page S226, 2012.
7. Riva F, Mayberry K, Stagni R, *"Comparison between model and experimental orbital stability analysis of gait"*, **Proceedings of the XVIII Congress of the European Society of Biomechanics (ESB),** July 2012, Lisbona (Portogallo). **Journal of Biomechanics** 45S1, Page S227, 2012.
8. Stagni R, Bisi MC, Riva F, *"Quantification of subject specific muscle moment arm and muscle length: an issue for modeling"*, **Proceedings of the XVIII Congress of the European Society of Biomechanics (ESB),** July 2012, Lisbona (Portogallo). **Journal of Biomechanics** 45S1, Page S242, 2012.
9. Bisi MC, Riva F, Stagni R, *"Measures of gait stability: evaluation of the proposed methods comparing adults with infants at the beginning of independent walking"*, **Proceedings of the XVIII Congress of the European Society of Biomechanics (ESB),** July 2012, Lisbona (Portogallo). **Journal of Biomechanics** 45S1, Page S230, 2012.

10. Riva F, Toebes MJP, Pijnapples M, Stagni R, van Dieën JH, *"Fall history: is a minimum setup quantification possible?"*, **Proceedings of the XIII SIAMOC conference**, September 2012, Bellaria (Rimini, Italy), to be published in **Gait & Posture.**

XI.5. AWARDS

1. **SIAMOC Award 2012** for the best methodological work, *"Fall history: is a minimum setup quantification possible?",* **XIII SIAMOC conference**, September 2012, Bellaria (Rimini, Italy)